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MASTER'S THESIS

FORECASTING GOVERNMENT BOND SPREADS IN A DATA–RICH ENVIRONMENT USING THE THREE–PASS REGRESSION FILTER

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“Prediction is very difficult, especially if it's about the future.”

(Quote by Niels Bohr, in Ellis, K. A. 1970, p. 431)

INTRODUCTION

Unstable government bond spreads in the euro area represent an important feature for dynamic econometric modelling and forecasting. Recent financial turmoil has disturbed European economies of both peripheral and core countries and raised widespread concerns over the plausible increase of government bond spreads and the fate of the euro.

The connection between macroeconomic and fiscal determinants, country–specific fundamentals, and international factors driving **10–year government bond spreads** has yet to be studied formally in academic literature. Current literature focuses on the relation between sovereign default, credit risk, and liquidity risk. Consequently, the objective of presented work is to empirically examine which macroeconomic and fiscal factors, country–specific fundamentals, and international factors drive 10–year government bond spreads and may therefore prove useful for countries affected by the European debt crisis and their policy makers.

Government bond spreads are closely related to economic activity and global financial risk and hence serve as a valuable economic and financial indicator of a country's economy. For example: spreads can reach a high value of basis points (hereinafter: bps) due to rapid changes in inflation expectations driven by hopes for fiscal stimulus, which affects forex markets. The euro weakens as bond yields fall and spreads against the German *Bunds* widen.

The dynamic evolution of the yield– and spread curve is essential for pricing financial assets and their derivatives, managing financial risk, allocating portfolios, structuring fiscal debt, conducting monetary policy, and valuing capital goods. A wide variety of models for investigating yield– and spread curve dynamics are provided in literature.

Rising spreads reflect growing concerns of financial markets about the ability of given countries to service their future debts. In addition to increasing borrowing costs, a rise in spreads signalises investors’ discouragement to lend funds, which jeopardizes a country’s access to the international capital market. Spreads are immensely significant for fiscal policy. One of the objectives when studying the impact of fiscal conduct on spreads is to demonstrate the correct choice of fiscal policy instruments to save essential sums. Government bond spreads substantially influence interest rates, that is, the borrowing price for all the other economy sectors.

The explanation of government bond spreads is particularly complex for two reasons. Firstly, spreads depend on the relative strength of the factors in different countries. In other words, changes in factors that affect bond yields cannot be examined for individual countries. The relative strength of separate factors must initially be observed within a broader group of countries. The relevant category of countries and regions are those with considerable flows of capital. Secondly, bond prices, similarly to the prices of all other financial assets, are subject to intricate fluctuations, as they occur due to the sentiment changes of market players. Expectations are variable and occasionally depend on the action of irrational factors ("information cascades" are capable of inciting imitation and herd behaviour). Luckily, bonds, unlike stocks, have maturity dates, which essentially mitigate the effects of fluctuations in the perception of risks on bond prices. Regarding government bonds, the credit risk is relatively small in comparison with other financial instruments and issuers of the same kind of bonds. However, it is never entirely absent therefore yields and spreads are more stable than in other financial instruments of long maturity periods and greater degrees of risk. Hence the idea that yields or spreads could be explained by the variables that fundamentally affect them. Fiscal policy is one such variable.

Fiscal policy could be among the most important determinants of government bond yields and spreads. It can foster or hamper economic growth. The direction of public expenditure can encourage private investments in capital projects, and increase productivity by improving production techniques (e.g., through consistent enforcement of the law, respect for contracts and deadlines, and adequate regulations of the financial market). Investment in infrastructure and human capital also positively affects the productivity of work and capital. Taxation system can distort the allocation of resources, reducing economic growth and welfare. Economic, political, and institutional environments influence the efficacy of public spending that might foster growth. The creators of fiscal policy ought to increase tax revenue and take on credit to finance public expenditure, and at the same time minimise the costs that can diminish economic growth. Accordingly, a more trustworthy fiscal policy is expected to reduce risks, organize public debt instruments and, in general, underpin economic growth. Consequently, investors' expected yields on investments in government bonds will be smaller, and vice versa. It is recommended that a credible fiscal policy is pursued for the government borrowing cost to be drastically reduced (Žigman & Cota, 2011, 385–412).

Concerning economic and monetary policy, the movement of spreads is also a vital research question. Extracting a small amount of potential drivers, especially the relevant factors closely connected to proxies, from a significantly larger set presents a methodological challenge. Consequently, it is difficult to appropriately interpret relevant results.

According to different models and methodologies of recent academic papers (Rowland & Torres, 2004, pp. 3–55; Favero, Pagano & von Thadden, 2005, pp. 107–134; Remonola, Scatigna & Wu, 2007, pp. 27–39; Beber, Brandt & Kavavejc, 2009, pp. 10–51; Attinasi, Checherita & Nickel, 2009, pp. 4–45; Gerlach, Schulz & Wolff, 2009, pp. 1–68; Bernoth & Erdogan, 2010, pp. 1–20; Giordano, Linciano & Soccorso, 2012, pp. 7–19; De Grauwe & Ji, 2012, pp. 1–32; Di Cesare, Grande, Manna & Taboga, 2012, pp. 5–35; Maltriz, 2012, pp. 657–672; Poghosyan, 2012, pp. 2–26; Haan, Hessel & van den End, 2013, pp. 49–68; D'Agostino & Ehrmann, 2013, pp. 4–30; Dorgan, 2015, July 13, SNB, and De Santis, 2016, pp. 5–76) macroeconomic variables prove useful for explaining and/or forecasting government bond spreads. An extensive amount of empirical literature has documented a declining role of fiscal fundamentals in determining spreads. According to some authors, country–specific risk factors are dominated by international financial markets' developments in determining bond yield differentials.

At the same time, other studies argue that an increased macroeconomic uncertainty has loosened the relation between macro– and fiscal fundamentals and bond spreads, with differentials mostly driven by shifts in beliefs (De Grauwe & Ji, 2012, pp. 1–32). Most of these empirical studies do not treat expectations explicitly, though, as they observe the reaction of realized spreads to actual fiscal fundamentals.

However, some studies include the expected outlook for fiscal policy to explain realized spreads, either implicitly by considering the fiscal overhang of bank–bailouts (Gerlach et al., 2009, pp. 1–68), or explicitly by using deficit forecasts. The main idea is that actual market prices incorporate the expectations regarding the future path of fiscal and economic fundamentals, rather than their current or past values. Overall, actual bond prices tend to react to expected developments in fiscal variables and other macroeconomic fundamentals (Attinasi et al., 2009, pp. 5–49)

Surprisingly, only very small macroeconomic information sets are being exploited for the analysis. Commonly, the models include a measure of the output gap and of inflation, two other variables, and one or more latent yield curve factors. State–of–the–art affine term structure models estimate numerous parameters, thereby considerably restricting the number of explanatory variables in a model.

Pseudo real–time forecasting would clearly indicate if public debt, differentials in wage and labour productivity, real–effective exchange rate, exchange rates, current account balance, inflation, economic growth and government gross debt (drivers of spreads according to authors mentioned above) were also determinants of euro area bond spreads during global financial crisis.

Why forecasting bond yield spreads? Many economic decisions made by policymakers, firms, investors, or consumers are often based on the forecasts of relevant macroeconomic variables. The accuracy of these forecasts can thus have crucial repercussions. In theory, the optimal forecast of a variable under quadratic loss is its expectation conditional on information available. In practice, the relevant information set might be substantial. For instance, central banks are known to monitor hundreds of macroeconomic indicators, each potentially carrying useful additional information.

It is common to identify two broad forecasting approaches in a data–rich environment: *(a)* one can try to reduce the dimensionality of the problem by extracting the relevant information from the initial datasets, and then use the resulting factors for forecasting the variable of interest. Factor models with different techniques and **the Three–Pass Regression Filter** (hereinafter: **the 3PRF**) are examples of the first approach; *(b)* one can select the relevant information from the individual forecasts provided by numerous models that usually do not contain more than a few variables for each model. Classical forecast combination, Bayesian Model Averaging (hereinafter: BMA), and Bootstrapping Aggregation (Bagging) represent this forecasting approach in a data–rich environment.

As discussed by Stock and Watson (2006), there are several forecasting techniques with many predictors, e.g. dynamic factor models, ridge regression, Bayesian techniques, partial least squares, and combinations of forecasts, which have been used in macroeconomic forecasts. Diffusion Index (hereinafter: DI) or Factor–Augmented Regression (hereinafter: FAR) use factors estimated from a large panel of data to help forecast the series of interest, so that information of various variables can be used while the dimension of the forecasting model remains small. Many studies have proved that dynamic factor models are particularly powerful in forecasting economic time series.

While the availability of more data provides the opportunity to understand economic phenomena and anomalies better, researchers can also suffer from an information overload without some way to organize the data into an “easy–to–interpret” manner. In the last 15 years, the analysis of large dimensional data has received much attention of theoretical and empirical researchers. The early focus has been on the use of factor models as a means of dimension reduction.

When forecasting an economic variable, it is often necessary to incorporate information from a large set of potential explanatory variables into the forecasting model. Most traditional macroeconomic prediction approaches, however, are unsuitable, either because it is inefficient or impossible to incorporate large numbers of variables in a single forecasting model and estimate it using standard econometric techniques. As an alternative approach to this problem, the FAR has gained a prominent place.

Traditionally, the FAR model indicates that the Principal Components Analysis (hereinafter: PCA) is applied. The distinctive feature of the FAR is to add factors estimated by the Principal Components (hereinafter: PC) method to an otherwise standard regression $Y_{t+h} = \alpha^{'} \tilde{F}_t + \beta^{'} W_t + e_{t+h}$. The crucial problem when using the PCA factors is its inability of economic interpretation.

The 3PRF eliminates this by estimating relevant factors of variables, which is used as a factor proxy. By searching among all sets of possible proxies, I get the **possibility of economic interpretation of factors as relevant predictors of spreads**. The 3PRF has the advantage of being expressed in closed form and virtually instantaneous to compute.

As already explained, the 3PRF allows focus on factors through proxies and the focus in the 3PRF is on using latent variables to predict some target. Compared to the PCA, relevant factors enable an economic interpretability of forecast results through automatic or theory–motivated proxies. The resulting estimates reveal important facts of the time series of expected future government bond spreads that may be used to guide future monetary policy.

A new estimator is calculated in closed form and conveniently represented as a set of Ordinary Least Squares regressions (hereinafter: OLS). 3PRF forecasts are consistent for the infeasible best forecast when both the time dimension and cross–section dimension become large. This requires specifying only the number of relevant factors driving the cross–section of predictors. The 3PRF is a constrained least squares estimator and reduces to partial least squares as a special case. Simulation evidence (see Kelly & Pruitt, 2014, pp. 21–30) confirms the 3PRF's forecasting performance relative to the alternatives.

This study makes theoretical, computational, and empirical contributions: empirically assesses the determinants of 10–year government bond spreads in the euro area (with Germany as a benchmark) and especially focuses on the period following the collapse of Lehman in September 2008. I examine which macroeconomic and fiscal determinants, country–specific fundamentals, and international factors drive the spreads of four of the most important economic euro area countries (i.e., France, Italy, the Netherlands, and Spain).

The purpose is to represent the 3PRF as a new approach to forecasting, using many predictors, its advantages compared to other procedures in the sense of factor models (the

PC and constrained least squares) and its performance over a simple univariate autoregressive model (hereinafter: AR). This master's thesis illustrates the forecasting performance of the 3PRF with real financial example.

A survey–based quarterly dataset of individual forecasters is employed in the analysis focusing on the relation between fiscal and macroeconomic variables, and government bond spreads from January 2000 to December 2015. Regarding pseudo real time, one–, two–, three–, and four – quarters ahead estimations for four countries are made.

The key empirical research questions in the master's thesis are the following:

1) Conceptually, what is the sole subject and the fundamental objective of this forecast? How to gain a better understanding of bond yields' movement during turbulent periods?

2) Descriptively, how do government bond spreads "behave"? Is it possible to obtain simple yet accurate dynamic characterizations and forecasts?

3) Theoretically, how are the shape and the evolution of the yield– and the spread curve governed and restricted? Is it possible to relate spread curves to macroeconomic fundamentals and central bank behavior?

4) In comparison to other estimation methods, what are the key advantages of the new approach (the 3PRF) to forecasting with many predictors developed by Kelly and Pruitt (2014)?

5) Which macroeconomic and fiscal variables determine the government bond spreads?

6) What is the relative role of domestic factors and is their role more important than that of international factors in forecasting government bond spreads?

7) Are these findings the same as suggestions in current academic literature?

These challenging multifaceted questions are vitally important. Accordingly, there are various literature attempts to address them. Numerous statistical and economic "currents" and "cross–currents" flow through literature. There is no simple linear thought progression, but rather self–contained with each step logically following forming a tangled web; hence it is not our intention to produce a "balanced" yet unhelpful and meaningless survey of yield curve modelling.

These are the main results from the 3PRF forecasting: pseudo out–of–sample forecasting for different selected subperiods, beginning in 2008 with the bankruptcy of the US investment bank Lehman Brothers, shows the FAR's performance compared to the AR model for all countries except Spain. There were altogether 96 forecasts for one–, two–, three–, and four–quarters ahead forecast horizons for the period 2008Q3–2015Q4 (48 forecasts), and for the subperiods 2008Q3–2011Q2, 2011Q3–2013Q4, and 2014Q1–2015Q4 (48 forecasts). The FAR outperforms the benchmark AR model in 52 forecasts, and vice versa in 44 forecasts. In the period 2008Q3 to 2015Q4, the FAR evidently outperforms the AR on 27 occasions. On the other hand, the AR prevails in 21 instances. In the matter of subperiods, the candidate FAR dominates in forecasting spreads on 25 occasions, and the benchmark AR model prevails 23 times.

With regard to different forecasting horizons, the best results in terms of relative forecasting performance for the 3PRF forecast models are generally for one– and two–steps ahead forecasts. I observed that the 3PRF outperforms the AR model and can function as a useful complement to central banks' current forecasting tools, especially at shorter horizons.

The results therefore show that the 3PRF model usually outperforms the AR model. The average gain for one–step ahead forecast, for example, is close to six percent. Furthermore, relative performance of the 3PRF model in the quarterly examples is improved for shorter forecasting horizons. Forecasting results show that the FAR model generally provides smaller relative Mean Square (forecast) Errors (hereinafter: relative MSEs) than the simple autoregressive. The baseline model outperforms the FAR model in the case of peripheral countries (i.e., Italy and Spain), but only during the European debt crisis and the Greek crisis and only when forecasting spreads three–, and four–quarters ahead. When the baseline model outperforms the candidate FAR model (i.e., three– and four–quarters ahead), the AR outperforms the FAR decidedly. Moreover, I found that the FAR model with the 3PRF makes worse predictions than the AR model in the four–step ahead forecasting for all countries except the Netherlands.

I investigate whether the differences between the models are systematic or not in each forecast horizon. The results of Diebold–Mariano test statistic (1995, pp. 252–263) show that the differences in the relative MSE between the factor forecasts and autoregressive forecasts are generally statistically significant. Therefore, the 3PRF forecast slightly outperforms the baseline forecasting model. Principal conclusion when considering gain in forecasting precision from pseudo real–time forecasting is that the 3PRF demonstrates competitive out–of–sample forecasting performance in finite samples under a wide range of specifications.

Empirically, I have found that the following fundamentals are pivotal in explaining spreads: **the Gross Domestic Product** (hereinafter: **GDP)**, **government expenditure, inflation, hourly earnings in manufacturing** and **in private sector, government gross debt, industrial production index – manufacturing, producer price index – total durable consumer goods, producer price index – total investment goods, stock prices – stock index,** narrow money (hereinafter: **M1**), intermediate money (hereinafter: **M2**), and broad money (hereinafter: **M3**), **real–effective exchange rate based on manufacturing CPI** (hereinafter: REER). Other essential drivers are exchange rates **US/EUR, CHF/EUR**, and **one–year EURIBOR.**

My findings also point to significant interaction of general risk aversion and domestic macroeconomic fundamentals. Domestic factors have become clearly more important in times of financial stress when international investors started to discriminate more between countries. The combination of high risk aversion and deteriorated current account positions particularly tends to magnify to a significant extent the incidence of deteriorated public finances on government bond yield spreads. The importance of current account deficits for yield spreads provides support to the idea that the distinction between private and public debt becomes blurred in times of financial stress as investors account for the possibility that the government is forced to take over private debt.

Overall, results suggest that an improvement in global risk perception will lead to a further narrowing of intra–euro area bond yield differentials. This is because the strong rise in financing costs by sovereign issuers since September 2008 maybe explained, to a certain extent, by the correction of abnormally narrow spreads in the pre–crisis period, when domestic risk factors resulted in small yield differentials. Moreover, spreads can be expected to remain elevated compared to the pre–crisis period since debt levels have increased significantly in a number of countries (compared to the German benchmark) and the contingent liabilities assumed by the public sector in rescuing the financial sector will continue to weigh on the outlook for public finances.

Looking further ahead, greater market discrimination across countries may provide higher incentives for governments to attain and maintain sustainable public finances. Since even small changes in bond yields have a noticeable impact on government outlays, market discipline may act as an important deterrent against deteriorating public finances. In the medium– and long–run this may thus play in favor of greater sustainability of public finances.

The thesis is comprised of three parts. The first part describes the theoretical background of time series variable to be forecasted: 10–year government bond spreads relative to the German *Bunds*. The second part introduces the econometric framework as the base for the pseudo real–time forecasting evaluation. The third part brings empirical results and a detailed discussion.

The whole master's thesis is constituted of 8 chapters, with the crucial empirical results summarized in the text. Chapter 1 starts with a short theoretical view of financial time series variable to be forecasted and its relation to interest rates, macroeconomic and fiscal fundamentals. It is evident that government bond spreads can be used as an economic indicator of country's macroeconomic wealth and that is why it is useful for policy makers in deciding on policy actions. Through the linkage between government bond spreads and domestic economy, the global financial risk in turn affects the macroeconomic variables significantly. Econometric analysis suggests that a permanent change in these determinants has a more significant and robust impact on spreads than transitory shocks. Chapter 1 continues with a recent academic research of determinants of drivers of spreads.

Chapter 2 offers the basic overview of dynamic factor models. Third and fourth chapter are the most important part of the thesis. Chapter 3 introduces the FAR and its distinctive feature to add factors estimated by the newest method – the 3PRF – to an otherwise standard regression. In chapter 4, one of the most crucial chapters of the thesis, I comprehensively describe the 3PRF as a modern approach to forecasting using many predictors. Chapter 4 concludes with the most important advantages of the 3PRF approach and the facts explaining why this approach may outperform other approaches, while mentioning the future challenges of this new approach for estimate factors. The rest of the paper is structured as follows: the third part of the thesis touches upon the pseudo real–time forecasting evaluation and the empirical research evaluating exactly which model is better for forecasting the government bond spread by using numerous predictors.

Chapter 5 represents the dataset and the main source of data for the empirical research. In chapters 6 and 7, forecasting procedure and forecast comparison are described. The relative MSE compares the performance of a candidate forecast to a benchmark forecast, both of which are computed using pseudo out–of–sample methodology. Chapter 8 is devoted to the presentation of results obtained from the estimation of factors and forecasting. All figures and tables presented in chapter 8 are the results of my empirical study. Finally, I summarize the crucial results and offer the conclusion.

1 THEORETICAL FRAMEWORK OF FORECASTED TIME SERIES VARIABLE: GOVERNMENT BOND SPREADS

This chapter examines the following questions:

1) What is the proper definition of government bond spreads?

2) Which government bonds are used as benchmark bonds?

3) Which macroeconomic and fiscal country–specific factors based on recent literature research are drivers of spreads?

At the end of the chapter, the historical evidence of movements of spreads, meaning, the movements of spreads before financial crisis in 2008 and at the beginning of crisis are examined.

1.1 The Definition of Government Bond Spreads

The term **government bond spreads** (notation used here) or **sovereign spreads** refers to the interest rate differential between two bonds. A yield spread is the difference between the quoted rates of return on two different investments, usually of different credit qualities but with similar maturities. It is often an indication of the risk premium for one investment product over another. In other words, yield spreads refer to the difference between the yields of two fixed income securities. It is related to country risk, which is the contrast between the interest rate on a US Treasury issue and a similar issue of another government.

A government bond spread is the distinction between the yield on a country's bond issue and the yield on a comparable bond issued by a benchmark country, e.g. the United States or Germany. Mathematically, a bond spread is the simple subtraction of one bond yield from another. Spreads are typically expressed in bps. One basis point is one–hundreth of a percentage point, i.e. 1.0 % equals 100 bps. Hence, a one–percentage spread is 100 bps.

Bond spreads are commonly used by market participants to compare values and reflect the relative risks of the bonds being compared. Similarly, "price–earnings ratios" are used for equities. The higher the spread, the higher the risk usually is. Bond spreads are generally viewed as the comparison of the yields on federal government bonds, which are predominantly considered most creditworthy, to the bonds of other issuers such as provinces, municipalities, or corporations.

A clear distinction between sovereign risk and risk premium as the price of that risk is essential for the interpretation of government bond spreads. The spreads can be divided into two components: expected losses from default and risk premium. Risk premium as the mirror of how investors price the risk of unexpected losses is often the larger part of the spread (Remolona et al., 2007, p. 27–39). According to another interpretation, a government bond spread is also the difference between the quoted rates of return on two different investments, i.e. different credit quality. It is often an indication of the risk premium for investing in one investment product over another.

1.1.1 Yield Curve: Facts and Factors

Dozens of yields may be observed at any time, each corresponding to different bond maturities. Nevertheless, yield curves evolve dynamically; hence their cross–sectional and temporal dimension. Modelling and forecasting a time series is on one hand very straightforward, but in another sense rather complex and interesting, as the series of curves is modeled. Yield curves are dynamic, shifting among different shapes: flat, U–shaped, growing and falling at increasing or decreasing rates, etc.

Multivariate models (e.g., a vector autoregression model, etc.) are required for sets of bond yields but unrestricted vector autoregressions are profligate parameterizations, wasteful of degrees of freedom. Fortunately, financial asset returns typically conform to a certain type of restricted vector autoregression, displaying a factor structure. Factor structure is operative in situations with a high–dimensional object (e.g., a large set of bond yields), which is driven by an underlying lower–dimensional set of objects ("factors"). Beneath a seemingly complicated high–dimensional set of observations, lies a much simpler reality (Diebold & Rudebusch, 2012, pp. 4–13.)

Indeed, factor structure is ubiquitous in financial markets, financial economic theory, macroeconomic fundamentals, and macroeconomic theory. Campbell et al. (1997), for example, discuss aspects of empirical and theoretical factor structure in financial markets and financial economic models. Similarly, Aruoba and Diebold (2010) analyse empirical factor structure in macroeconomic fundamentals, and Diebold and Rudebusch (1996) study theoretical factor structure in macroeconomic models.

Factor structure provides a particularly fine description of bond yields' structure and, consequently, spreads. Most early studies involving predominantly long rates (e.g., in Macaulay (1938)) implicitly adopt a single–factor world view, where the factor is the level (e.g., a long rate). Similarly, early arbitrage–free models like Vasicek (1977) involve a single factor. However, this severely limits the scope for interesting term structure dynamics, which rings hollow both in terms of introspection and observation (Diebold & Rudebusch, 2012, pp. 4–13).

1.2 *Bunds* – German Government Bonds

German government bonds are known as *Bunds* (Ger. *Bundesanleihen*). They are the key measure of investor confidence, auctioned solely with original maturities of 10 and 30 years. Other bonds, such as five–year federal notes *Bobls* (Ger. *Bundesobligationen*), two–year maturity federal Treasury notes *Schatze* and federal savings notes *Bundesschatzbriefe* are also purchasable by individuals. Inflation–linked German government bonds have recently been added to bond market offerings.

Bunds are highly liquid debt securities that are eligible to be used as the insurance reserves for trusts and are accepted by the European Central Bank (hereinafter: ECB) as collateral for credit operations. *Bunds* are auctioned in the primary market at volumes by producing several increases, up to about €15 billion, which helps to maintain high level of trading volume for *Bunds*. *Bunds* account for the majority of German government debt, typically around 50 % of all outstanding debt, emphasizing their importance in government funding. By issuing long–term securities such as *Bunds*, German authorities obtain a more stable source of financing without having to roll over debt.

The German government bond issuance is considered a "gold standard" or benchmark in Europe (even after the euro). In Germany, the bond market for individual investors is not particularly "direct", i.e. although an individual investor in Germany has significant amounts of bonds in his or her asset holdings, most of the activity is not a consequence of purchasing individual bonds but rather of holding bonds through mutual funds and in insurance products, i.e. pension and retirement funds, burial funds, etc. *Bunds* represent the key element of the euro zone's debt markets, both to compare against other countries and measure investor risk tolerance (Kuepper, 2016, p. 5). German government bonds may have been relatively niche on a global level before the crisis, but investors now monitor so–called *Bund spreads* to determine how well the euro area countries are doing relative to their strongest member.

A *Bund spread* is the difference between the German Bund's yields and those of other countries. For example, if Germany's 10–year *Bunds* are yielding 1.3 % and Spain's 10–year bonds are yielding 5.5 %, then the *Bund spread* with Spain would be 4.2 %. Germany is depicted as the largest and most stable euro zone country, which means that its *Bunds* are treated as the "gold standard" for comparison. Higher *Bund spreads* tend to signify less risk for the country being compared, since the same interest rates and monetary policy apply throughout (Kuepper, 2016, p. 5).

Germany's *Bunds* came into focus during the European sovereign debt crisis as, because they provided a simple way to calculate performance. Struggling euro area countries saw their spreads widen, while their borrowing costs grew at a faster rate than Germany's. The most important *Bund spreads* to observe are the 10–year *Bunds*, since they fall between short–term and long–term bonds. However, the duration of the bonds can also provide useful insight into investor sentiment across various time horizons. For instance, short–term bonds may signal that everything is in order, but increasing long–term yields could be a sign of trouble ahead. Finally, investors also monitor German *Bunds* without comparison to estimate if the market is seeking a safe haven. For example, negative yields on the 2–year *Bunds* may suggest short–term investor anxiety. In the case of negative yields investors are literally paying the country to house their money for fear of financial loss elsewhere (Kuepper, 2016, p. 5).

1.3 Drivers Based on Recent Literature Research

The literature on government bond spreads determinants has expanded substantially in last 15 years, mainly reflecting concerns for the developments in the European sovereign debt markets during the crisis. The European debt crisis (often also referred to as the euro zone crisis or the European sovereign debt crisis) is a multi–year debt crisis that has been taking place in the European Union (hereinafter: EU) since the end of 2009. Several Eurozone member states, e.g. Greece, Italy, Portugal, Spain and Ireland; hereinafter:

GIPSI, were unable to repay or refinance their government debt or bail out over–indebted banks under their national supervision without the assistance of third parties like other euro zone countries, the European Central Bank (hereinafter: ECB), or the International Monetary Fund (hereinafter: IMF).

The majority of cross–curent literature studies the effects of fiscal and other economic fundamentals on the realized spreads. According to some papers, government's fiscal position plays a role in determining realized spreads in industrialized and emerging economies (e.g., Bernoth et al., 2010, pp. 7–33). Nevertheless, most essays do not identify fiscal variables among the main determinants of spreads for advanced economies. Liquidity risk seems to be relevant only in the times of heightened economic or fiscal stress (Beber et al., 2009, pp. 10–51; Poghosyan, 2012 pp. 2–26).

Substantial empirical studies have researched the determinants of government bond spreads in the euro area since the beginning of the European Monetary Union (hereinafter: EMU). Numerous analyses estimate a reduced form model by regressing spreads at certain maturities on a set of explanatory variables which may be grouped into factors affecting public debt sustainability, other macroeconomic factors, such as external economic position, sovereign bonds liquidity, international risk and global risk aversion indicators (Giordano et al., 2012, pp. 7–19). I am going to observe which factors are the drivers of spreads for a particular country at different forecast horizons and in different subperiods.

Public debt sustainability is affected by fiscal variables, economic growth, inflation rates and interest rates. Rising budget deficit as well as growing primary budget deficit are obvious indicators of increasing fiscal fragility. In addition to that, a high stock of debt weakens public finance sustainability since it implies burdensome debt service payments and, consequently a greater exposure to small changes in interest rates. As deficit and debt grow, sovereign default risk rises too, thus prompting a surge in the risk premium by the investors (Afonso, Arghyrou & Kontonikas 2015, pp. 1–36).

The empirical evidence for the euro area mostly confirms the role of fiscal fundamentals, although its significance varies across countries. At the onset of the EMU the ratio of debt–to–GDP proved relevant for some countries (e.g., Italy and Spain) and affected bond yields according to a non–linear relationship interacted with international risk indicators. The relevance of fiscal fundamentals seems to change not only from country to country but also over time. During the 2008 financial crisis fiscal imbalances were penalized much firmer and general risk aversion played a crucial role. Researchers confirmed that the long–run fluctuations in euro area countries' yield spreads were related to fundamentals but such connection was not constant over time (Giordano et al., 2012, pp. 7–19; Bellas, Papaioannou & Petrova, 2010, p. 281).

A recent study by Di Cesare et al. (2012, pp. 5–35) suggested that after the financial crisis the spreads of several euro countries have increased to a level that can't be justified on the basis of fiscal and macroeconomic fundamentals. Among the possible reasons for this finding the analysis focused on the perceived risk of the euro area breakup. I could assume that the coefficients of the relationship between fiscal fundamentals and spreads had been time invariant until a discrete structural break occurred.

Authors Bernoth and Erdogan (2010, pp. 7–33) departed from the hypothesis above and used a time–varying coefficient model to capture the gradual shift of such relationship affecting 10 EMU countries. They came to the following conclusion: the government debt level along with the global investors' risk aversion were relevant at the onset of the EMU and declined in subsequent years, i.e. two years before the Lehman Brothers fiscal position default emerged, reaching its highest impact during the turmoil period.

Attinasi et al. (2009, pp. 7–47) and Gerlach et al. (2009, pp. 1–68) identified the events that have contributed to the repricing of the sovereign risk for some euro area countries since the eruption of the 2008 financial crisis. Attinasi et al. (2009, pp. 5–49) focused on the announcement of bank rescue packages in 2007 and 2008 and discovered that they had accounted for 9 % of the daily changes in government bond spreads versus a 56 % and a 21 % due to the rise in the international risk aversion and the expected fiscal position.

Gerlach et al. (2010, pp. 1–68) also brought evidence showing that a high level of systemic risk may have lead to an upward reassessment of sovereign risk premium. The authors tested whether the size of domestic banking sector affected sovereign spreads along with macroeconomic fundamentals and global risk. A higher aggregate risk may make banks and public budgets more vulnerable to financial crises. The overall effect of the banking sector on government bond spreads is significant and rises when the aggregate risk factor is high; on the other hand, this effect can reverse in tranquil periods.

Alessandrini et al. (2012, pp. 1–46) showed that not only fiscal variables but also differentials in wage and labour productivity growth played a role: according to their results, poor fundamentals may have fuelled a debt problem independently from country's fiscal responsibility. As recalled above, besides in addition to fiscal fundamentals, the overall state of the economy is crucial in determining the country's ability to meet its payment obligation. In principle, a rising debt does not raise concerns provided that the economy grows at a faster pace than its public debt. In this respect, the empirical evidence is mixed; however, most recent studies have confirmed the relevance of economic growth's negative impact on spreads.

External sector's role has also been investigated in several analyses. Both current account balance, i.e. export minus import, and real–effective exchange rate are noteworthy. Current account balance as the indicator of competitiveness and of a country's ability to raise funds for debt servicing is expected to negatively affect government bond yields; therefore, as it improves, the spreads should decline. Vice versa, as pointed out by De Grauwe and Ji (2012, pp. 1–32), current account deficits signal an increase in net foreign debt which either directly (if spurred by public overspending) or indirectly (if due to private sector's overspending) undermine government's ability to meet its payment obligations.

According to Maltriz (2012, pp. 657–672), the relationship between spreads and current account balance may also have a positive sign. A positive current account surplus, coupled with net capital outflows for the balance of payment identity, might in fact signal either a country's inability to borrow from abroad or a capital flight. In both cases, spread should rise. Such relationship would reflect short–term liquidity issues while the negative sign of the current account recalled above would be related to long–term solvency arguments. Moreover, the movements in the real–effective exchange rate, accounting for price level differences between trading pattern, indicate the evolution of a country's competitiveness. By construction, if this rate increases, the external position of an economy deteriorates since its residents pay relatively more for their imports and raise proportionately less from their exports, thus signalling possible future current account deficits. Therefore, the appreciation of the real–effective exchange rates is likely to lead to an increase in the sovereign risk premium demanded by the investors.

Government yield spreads may also be influenced by the liquidity risk to sell or buy an asset in an illiquid market, at an unfair price, and therefore bearing high transaction costs. Liquidity risk is usually measured either through bid–ask spreads or the size of the government bond markets. The evidence provided so far in empirical researches is controversial (Alexopoulou & Ferrando, 2009, pp. 1–49; D'Agostino et al., 2013, pp. 5–52).

Favero et al. (2005, pp. 107–134) show that apart from country specific variables, there is a strong evidence showing that spreads are driven by a common international factor which is usually captured through a proxy, e.g. the spread between the US corporate bond yields and the US Treasuries yields or as the composite index of several risk measures. There is a proof that the government bond spreads between two countries affect their exchange rate. For example, as the bond spread between two economies widens, the country's currency with a higher bond yield appreciates against the other country's currency with a lower bond yield.

According to Dorgan (2015, July 13, SNB), crucial government bond spreads drivers are inflation expectations and inflation, country's wealth, regular and irregular influences on bond spreads by central banks, foreign debt relative to GDP and changes in the Net International Investment Position, namely a current account balance. The most important criteria are inflation expectations and inflation. High inflation expectations must be compensated via higher bond yields.

Firstly, the main driver behind inflation expectations is the wage development, i.e. the form of inflation that typically persists. Price inflation follows inflation expectations with a certain lag. Secondly, the higher the wealth of a country, the lower the bond yields. High savings typically increase country's wealth. Thirdly, regular influences signify that central banks buy government bonds, particularly in the world reserve currency, the US dollars. Irregular influences indicate that central banks buy bonds of their own government and depress yields: so–called Quantitative Easing (hereinafter: QE), where the central bank buys the bonds of their own government to make them less attractive in comparison to stocks and other risky assets. If a country is relatively poor, foreigners ought to purchase the bonds and, consequently, foreign debt relative to GDP and the international investment position become important. Investors want to be compensated for rising prices and inflation; therefore, government bond yields for countries often increase according to inflation. The main drivers behind inflation expectations are wages and unit labour costs. A strong relationship increases unit labour costs, wages and price inflation in advanced economies: so–called consumption–driven countries. This is different in emerging markets, i.e. countries with a weak capital stock per capita. If a country is relatively poor or has a weak savings rate, foreigners must help with the needed capital formation. Strong GDP growth usually leads to less unemployment (Okun's law), higher wages and finally price inflation (Phillips curve).

As mentioned above, wealthy countries have lower bond yields and governments need to pay less for its debts, which reduces risks; theoretically, governments could collect higher taxes and reduce the debt. Affluence brings more competition for safe assets like government bonds competition among wealthy nations is therefore higher because risk–averse investors typically save in their local currency. Wealth increases with high local savings, current account surpluses or a growth of asset price (Dorgan, 2015, July 13, SNB).

According to Dorgan (2015, July 13, SNB), a weak net investment position and a current account deficit increases government bonds yields. Countries with current account surpluses and a strong international investment position typically have lower government bond yields. Risk has become a very important criterion for the valuation of bonds after the financial crisis. Western governments adopted a version of Keynesian principle, which requires governments to spend during difficult times and save during affluent times. In most countries, debt rose between 1998 and 2007 during prosperous times. However, after the financial crisis governments used Keynes' arguments to increase debt even further.

De Grauwe and Ji's empirical work (2012, p. 1–32) explained the fundamental variables and its expected effects on the spreads. The government debt–to–GDP ratio: when it increases, the burden of the debt service increases, leading to a growing probability of default. This in turn triggers rise in the spread, a risk premium for which investors demand a compensation in case of increased default risk. The accumulated current account measures a country's net foreign debt as a whole (private and official residents). It is computed as a current account accumulated since the selected quartal divided by its GDP level. If an increase in net foreign debt arises from the private sector's overspending, it will lead to the private sector's default risk. However, the government is likely to be affected because this triggers a negative effect on economic activity, inducing a decline in government revenues and an increase in government budget deficits. If an increase in net foreign indebtedness arises from government overspending, it directly increases the government's debt service and thus the default risk.

The real–effective exchange rate as a measure of competitiveness can be considered as an early warning variable indicating that a country that experiences a real appreciation will run into problems of competitiveness, which will in turn lead to future current account deficits and debt problems. Investors may then demand an additional risk premium. Economic growth affects the ease with which a government is capable of servicing its debt. The lower the growth rate, the more difficult it is to raise tax revenues (De Santis, 2016, pp. 5–76).

1.3.1 Fundamentals for Explaining Government Bond Spreads by Rowland &Torres (2004); Haan, Hessel & End (2013); and D'Agostino & Ehrmann (2013)

Rowland and Torres (2004, pp. 3–55) were one of the first empirical researchers who started investigating the most important country fundamentals for explaining spreads. They followed the method of Sala–i–Martin (1997) who started with a small set of variables in previous literature, significant when explaining spreads. Rowland and Torres (2004, pp. 3–55) started with a liquidity and solvency variable, a vulnerability indicator to external shocks and a default dummy. They continued by adding various variables and testing its significance. Trivial variables were then replaced by other variables from the same group. This procedure was continued until they found the robust set of variables. Six significant fundamentals were obtained: real GDP growth, debt–to–GDP, reserves–to–GDP, debt–to–export, export–to–GDP and debt service–to–GDP.

Haan, Hessel and End (2013, pp. 49–68) observed previously used models to identify the most relevant macroeconomic fundamentals that explained government bond spreads. Their variables were limited to four fundamentals: real GDP growth, government gross debt, inflation, and the current account–to–GDP ratio.

D'Agostino and Ehrmann (2013, pp. 5–52) used roughly the same fundamentals to estimate spreads with the difference that they applied the expected values of their fundamentals, i.e real GDP growth, government gross debt, current account, unemployment and inflation.

Finally, government bond spreads are closely related to economic activity and global financial risk and hence serve as a valuable economic and financial indicator of a country's economy (Zakrajšek, Gilchrist & Yue, 2012, p. 1).

As previously stated, the aim of the presented study is to discover which macroeconomic and fiscal variables produce the best forecast of spreads relative to the German *Bunds* for the selected core (i.e., the Netherlands and France) and peripheral countries (i.e., Italy and Spain). Will the 3PRF proxies be the same as described by authors that have been studying determinants of spreads so far or will they be different?

1.4 Euro Area Government Bond Spreads in Historical Perspective

The financial crisis was accompanied by a strong rise in euro area government bond yield spreads, in sharp contrast to the period following the advent of the euro when bond yield spreads had been steadily converging. Starting in summer 2007, and especially after September 2008, spreads vis–à–vis the German *Bunds* increased particularly in peripheral countries, e.g. GIPSI. However, relatively stable and low–risk countries (e.g., the Netherlands and France) also faced higher risk premiums. House prices in the United States (hereinafter: US) stopped increasing with the beginning of the financial crisis marked by the fall of the Lehman Brothers which started the breakdown of the young subprime mortgage market and stopped the development of complex securitization structures like Mortagage Backed Securities.

The main root of the European crisis is an excessive public debt and overall, it has different causes compared to the global subprime mortgage crisis. The European crisis was a consequence of a misallocation of resources within the euro area and the loss of competitiveness of GIPSI countries which resulted in several subsequent events. Secondly, fiscal mismanagement was conducted by GIPSI countries as the tax reveneues increased significantly due to lower borrowing costs and increased demand in domestic products. GIPSI countries' governments chose to spend the increased income instead of recognizing it as a temporary revenue and saving it in case of stagnating market growth.

However, recent European crisis can not entirely be blamed on GIPSI countries. The following two reasons have played the principal role: European banking crisis and sovereign debt crisis. Firstly, assets of the European banks tied to the US mortgages became qustionable in value, preventing the banks to borrow money and, as a consequence, there was an increase in spreads. Secondly, investors demanded different interest rates on government bonds for two reasons, i.e. devaluation or appreciation was not applicable but the chance of default was. If investors expect a government not to be able to repay its debt, a higher interest rate to compensate for the additional default risk will be required.

During the financial turmoil, differences between German and other euro area government bond yields were increasing, with a particularly strong upsurge between February 2007 and mid–March 2008. At that time, spreads reached peaks that were close to or even exceeded the maximum level since the respective country had joined the EMU. The market upheaval and the deterioration in the European financial sector outlook might have contributed to the repricing of sovereign credit risk. In particular, renewed attention was given to countries with large fiscal and external imbalances by market analysts (ECB Monthly Bulletin May, 2008, p. 5–69).

Throughout the global financial crisis in 2009, substantial changes in the path of government bond spreads in euro area countries were made. In months following the collapse of Lehman Brothers, spreads widened significantly (see Figures 1, 2 and 3). Between the second quarter of 2009 and early summer, spreads generally dropped. Since October 2009, the disclosure of a considerable deterioration in Greece's public finances has generated substantial concerns over their sustainability, which has spilled over to other European countries with weaker macroeconomic positions. In Greece, Portugal and, to a lesser extent, Ireland, Spain and Italy, spreads grew noticeably in the first half of 2010. Despite an increase in other countries' spreads, the levels recorded in the months following the bankruptcy of Lehman Brothers were not exceeded. The widening of government bond spreads in the last 15 years can be attributed to both the relative liquidity of the respective bonds and the difference in creditworthiness of the issuers.

Since the beginning of the global crisis, spreads for the peripheral countries have been higher than desired, an indication for market overreacting and investors' proneness to »herding behavior« during periods of recession. On the other hand the opposite is true for some core countries within the EMU, e.g. Germany, France, and the Netherlands that seem to benefit from the global crisis, so–called safe haven or flight–to–quality which may be due to investor's preference in high–rated government bonds. Subsequent to the announcement of the Outright Monetary Transactions (hereinafter: OMT) programme by Mario Draghi, President of the ECB in 2012, the spreads have begun to decline. De Grauwe and Ji (2012, pp. 1–32) proved that the fall is due to a consequence of the positive sentiment triggered by the OMT and is not related to underlying fundamentals, such as public debt, GDP growth or external position that have continued to increase in most countries. European bond spreads jumped again in the beginning of 2015 during Greek referendum. Countries were experiencing political turbulence and yield spreads widened up to the highest level since the start of Public Sector Purchase Programme (hereinafter: PSPP) launched by the ECB in March 2015.

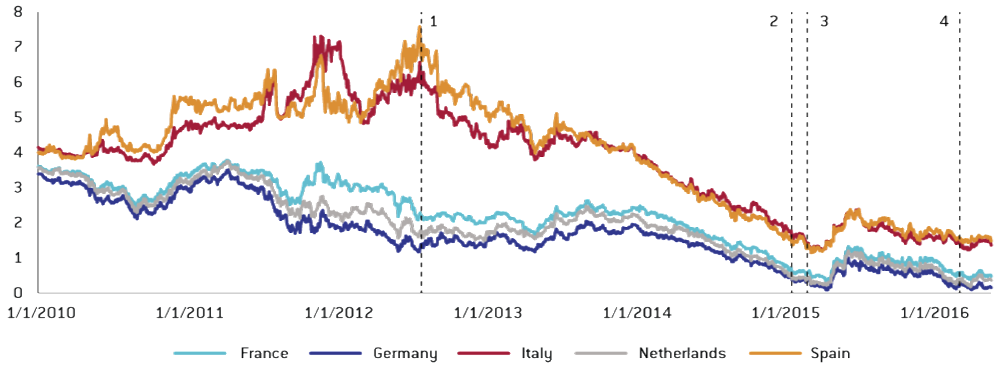
There are three main conclusions when observing the complete spread movements. Firstly, spreads change over time. At the beginning of the EMU, spreads were relatively low. Secondly, spread movements differ between the countries. The yields of the core countries (i.e., France and the Netherlands), compared to the peripheral countries (i.e., Italy and Spain), are less likely to be affected by the crisis (Figure 1 below illustrates this well). Thirdly, a global decrease in the risk appetite of investors can be observed, especially during the later phase of the crisis.

Figures 1, 2, and 3 below show the movements of government bond spreads in the last 15 years (*2000Q1–2015Q4)*. Readers can clearly spot an instantaneous growth of peripheral countries' spreads (i.e., Italy and Spain) since the Lehman Brothers's crash in September 2008 and the sovereign debt crisis at the end of 2011. European government bond yields shot up during the sovereign debt crisis in 2011, especially in the peripheral countries (in Spain and Italy, 10–year bond yields reached 7.6 % and 6.5 %, respectively; see Figure 1).

The highest spread values were attained in summer 2012, by the time of President Draghi's famous "whatever it takes" speech (see Figure 2). Since then bond yields have steadily reduced except for a temporary increase in the summer of 2015 during the Greek crisis which in fact coincided with the first few months of the PSPP's operation. On 22 January 2015, the ECB announced the PSPP, an expansion of the Asset Purchase Programme (hereinafter: APP). In March 2015, the Eurosystem started to purchase sovereign bonds under the PSPP from European governments, and debt securities from European institutions and national agencies. There has been a gradual reduction in yields. While bond yields declined both in core and peripheral countries, the latter fell faster after Draghi's "whatever it takes" speech, thus compressing the spreads against German bonds (see Figure 2).

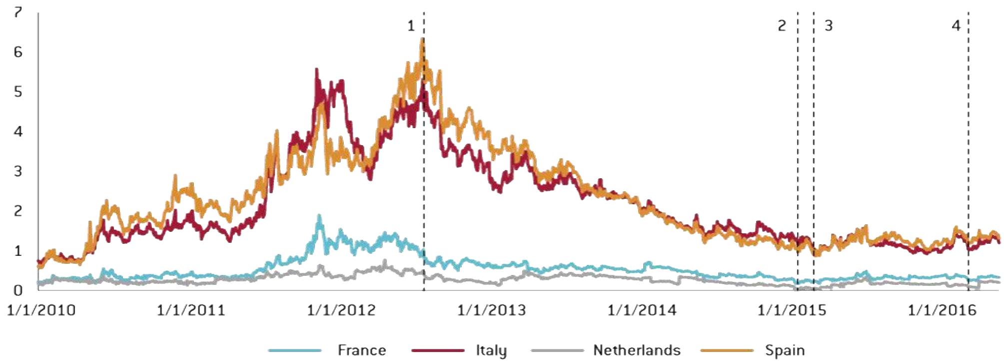
However, the announcement and beginning of the PSPP did not seem to affect the spreads. Two major operation channels of the QE are visible: a weaker exchange rate and lower long–term yields. The latter can be seen in in the following Figures (lower long–term yields since 2012).

Figure 1. 10–Year Government Bond Yields (%)



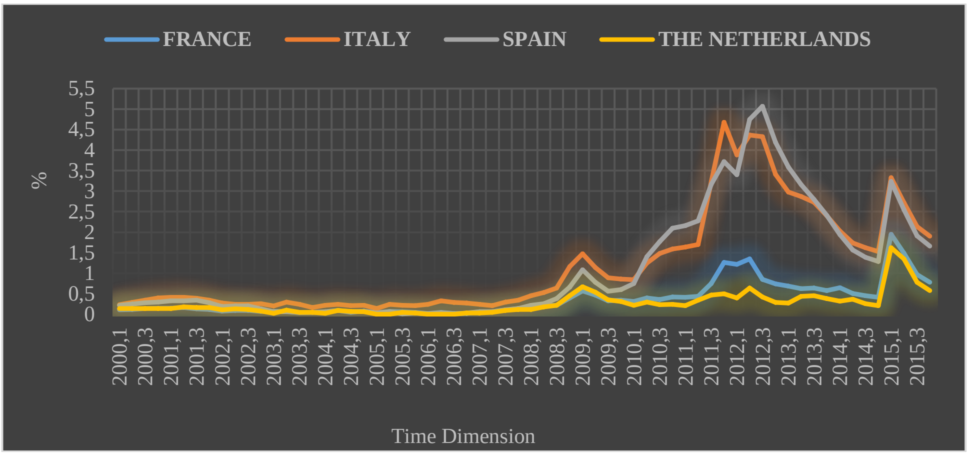
Source: M. Demertzis & G. B. Wolff, *The effectiveness of the European Central Bank's Asset Purchase Programme*, 2016, p. 4.

Figure 2. 10–Year Government Bond Spreads against Germany (%)



Source: M. Demertzis & G. B. Wolff, *The effectiveness of the European Central Bank's Asset Purchase Programme*, 2016, p. 4.

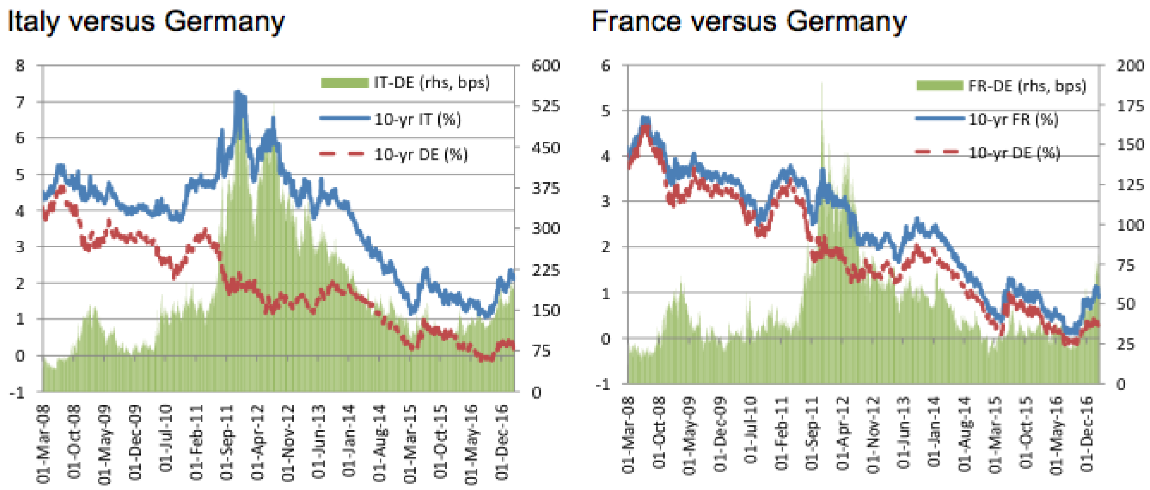
Figure 3. Realized Values of the 10–Year Spreads against Germany (%)



The redenomination or convertibility risk concept was mentioned by Mario Draghi, President of the ECB, in a speech at an investment conference in London on 26 July 2012. He pledged to do "whatever it takes" to protect the Eurozone from collapsing, announcing the possibility to engage in OMTs in secondary sovereign bond markets. A few weeks later in mid–September 2012, Italian and French 10–year government bond spreads fell by approximately 170 and 40 bps, respectively (see Figure 4). Clearly, the prevailing government bond spreads in July 2012 were disconnected from the underlying fiscal fundamentals (Di Cesare et al., 2012, pp. 5–35; De Grauwe & Ji, 2012, pp. 1–32; Dewachter, Lyrio & De Sola Perea, 2014, p. 4; De Santis, 2016, pp. 5–76).

Figure 4 shows the 10–year Italian, French, and German benchmark government bond yields. The government bond spreads vis–à–vis the German *Bunds* are reported on the right–hand scale and in bps. Sample period is 01.03.2008 – 02.03.2017.

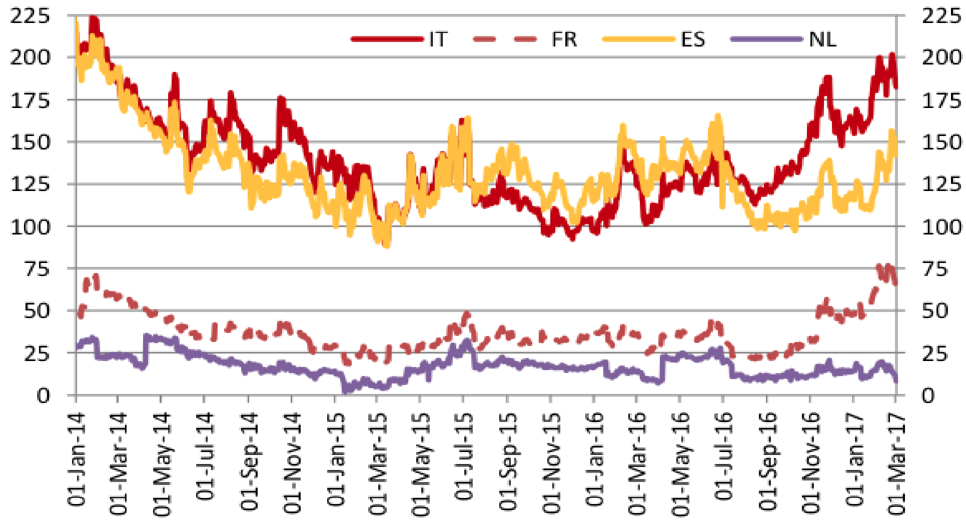
Figure 4. Government Bond Yields: 10–Year Italian, French, and German Benchmark



Source: *Thomson Reuters*, 2017.

Eurozone government bond spreads have recently been increasing, except for countries with more solid fiscal fundamentals. Lately, Italian and French government bond spreads vis–à–vis Germany's measured by the 10–year benchmarks have reached 180 and 60 bps (with peaks in January 2017 of about 200 and 80 bps), respectively – levels were last recorded at the beginning of 2014 (see Figure 5). Figure 5 shows the 10–year Italian, French, Spanish, and Dutch benchmark government yields not including the 10–year German *Bunds* in bps. Sample period is 01.01.2014 – 02.03.2017.

Figure 5. 10–Year Government Bond Spreads in the Largest Eurozone Countries (bps)



Source: *Thomson Reuters*, 2017.

Are these developments the result of macroeconomic and fiscal country–specific factors? And if, which?

1.5 Modelling and Forecasting of Yield Spread's Curve

An essential empirical question prior to forecasting is: Why use factor models for forecasting spreads?

The first disadvantage of structure modelling is its inability to summarize the price information for the large number of traded nominal bonds. Dynamic factor models are appealing for three key reasons.

Firstly, factor structure generally provides a highly–accurate empirical description of yield curve data. Only a small number of systematic risks underlie the pricing of a myriad of tradable financial assets; therefore, nearly all bond price information can be summarized with just a few constructed variables or factors. Yield curve models almost invariably employ a structure that consists of a small set of factors and the associated factor loadings that relate yields of different maturities to those factors.

Secondly, factor models provide a valuable compression of information, effectively collapsing an intractable high–dimensional modelling situation into a tractable low–dimensional situation provided that the yield data are well–approximated with factor structure. Low–dimensional factor structure is essential for statistical tractability.

In relation to that, factor structure is consistent with the "parsimony principle" – even false restrictions that may degrade in–sample fit often help to avoid data mining and produce good out–of–sample forecasts. For example, an unrestricted vector autoregression provides a very general linear model of yields typically with good in–sample fit, but the large number of estimated coefficients may reduce its value for out–of–sample forecasting.

Lastly, financial economic theory suggests, and routinely invokes, factor structure. In the equity sphere, for example, the celebrated *Capital Asset Pricing Model* (hereinafter: CAPM) is a single–factor model. Various extensions (e.g., Fama and French (1992)) invoke a few additional factors but intentionally remain low–dimensional, generally with less than five factors. Yield curve factor models are a natural bond market parallel (Diebold & Rudebusch, 2012, pp. 4–13).

2 ECONOMETRIC FRAMEWORK: MODELS FOR LARGE DATASETS: FACTOR MODELS

According to Stock and Watson (2006), there are several forecasting techniques that use many predictors, e.g. dynamic factor models, ridge regression, Bayesian techniques, partial least squares and combinations of forecasts are possible approaches that have been used in macroeconomic forecasts.

The objective of this part segment is to present the methodology for estimating a few underlying factors based on factor models proposed by Bai and Ng (2008). The factor model is a dimension reduction technique introduced by economists Sargent and Sims (1977). The basic idea is to combine the information of numerous variables into a few representative factors, portraying an efficient way of extracting information from a large dataset. The number of variables employed in most applied papers usually varies from one hundred to four hundred, but in some cases the datasets can be larger. Therefore, the second part of the thesis is devoted to the presentation of the theoretical views of factor models, the FAR model, and the 3PRF. Firstly, I am going to describe the factor model, one of the currently most widespread methodologies, that has been largely used in central banks and research institutions as a forecasting tool.

In future, data will inevitably be available for more series and over an increasingly long span due to improvement in information technology. While more information provide a better understanding of economic phenomena and anomalies, researchers can be affected from an information overload and require strategies to organize the data into an easy–to–interpret manner. The analysis of large dimensional data has received the attention of both theoretical and empirical researchers. The early focus was primarily on the use of factor models as means of dimension reduction. Nevertheless, empirical and theoretical research has grown substantially (Bai & Ng, 2008, p. 91).

Essentially, factor models enable us to reduce the dimension of a large dataset into a smaller group of factors and retain most of the information contained in the original dataset. In the approximate factor model, each variable is represented as the sum of two mutually orthogonal components: the common component (the factors) and the idiosyncratic component.

2.1 Motivation for Using Factor Models

Bernanke and Boivin (2003, pp. 525–546) claim that factor models offer a framework for analyzing clearly specified data, but remain agnostic about the structure of the economy while employing as much information as possible in the construction of the forecasting exercise. The idea that variations in numerous economic variables can be modelled by a small number of reference variables is appealing and therefore used in many economic analyses. In time, the availability of information increases both in terms of time coverage and the number of variables. The crucial question is how to work with this information overload parsimoniously. Factor models have become a popular and viable tool for reduction of the parameter space in a data–rich environment and are used for forecasting, estimation, and macroeconomic modelling. For researchers, the most important benefit of using factor models is an increase both in the scope and efficiency of the analysis. There are five empirical applications of dynamic factor models: forecasting, instrumental variable estimation, policy analysis, panel unit root testing and panel co–integration (Bai & Wang, 2012, p. 5; Masten, 2016).

The main advantage of factor models is that using a small number of factors is a parsimonious and efficient way of capturing information in a data–rich environment. Dynamic factor models can be used in four ways: (i) estimated factors used as predictors in forecasting applications or additional regressors, in the Factor–Augmented Vector Autoregression, (ii) estimated factors used as improved instruments over observed variables, (iii) testing the validity of observed proxies for factors, and (iv) panel unit–root tests.

2.2 Specification and Estimation of Factor Models

In addition to the size of the dataset and the characteristics of the variables, estimation techniques might play an important role in the factor forecast model. The chosen method might also affect the precision of the factor estimates. Boivin and Ng (2005) assert that two leading methods in the literature are the "dynamic" method of Forni, Hallin, Lippi and Reichlin (2000, 2005) and the "static" method of Stock and Watson (2002a, b).

According to Boivin and Ng (2005), the static method is not only easier to construct than the dynamic, it also presents better results in empirical analysis. In the next subsection, the methodology developed by Stock and Watson (2002a, b) is described.

Let's suppose that various time series, collectively denoted X_t, are available to the researcher at date *t*. The word "various" indicates that the number of time series approaches or exceeds the number of observations per series. X_t is transformed to be stationary, and for notational simplicity, each series is assumed to be mean zero (Bernanke & Boivin, 2003, pp. 525–546).

N represents the number of cross–section units and *T* the number of time series observations. Based on this methodology, the amount of observations does not restrict the amount of explanatory variables and therefore *N* can be larger than *T*.

Assume that for $i = 1, \ldots, N$, $t = 1, \ldots, T$, a *static* model is defined as

$$X_{it} = \lambda'_i F_t + e_{it} \quad (1)$$

$$= C_{it} + e_{it} \quad (2)$$

Formally, each variable in the $N-$dimensional dataset x_{it}, $i = 1, 2, \ldots, N$ can be decomposed into the sum of a common component C_{it} and an idiosyncratic component e_{it} (Barigozzi et al., 2016, p. 2). In the standard version of the Dynamic Factor Models (hereinafter: DFM), which is adopted here, the common components are linear combinations of an $r-$dimensional vector of common factors $F_t = (F_{1t}, F_{2t}, \ldots F_{rt})'$. X_{it} represents the observed value of explanatory variable i at time t. There are different estimation techniques for the model defined by (1). In addition to the approaches proposed by Stock and Watson (2002a) and Forni et al. (2005) that rely on the static and dynamic PC analysis, Kapetanios and Marcellino (2004) suggest a method based on subspace algorithm. Boivin and Ng (2005) claim that the first approach presents better results in an empirical analysis.

In factor analysis, e_{it} is referred to as the idiosyncratic error and λ_i the factor loading, i.e. the vector of weights that is put on the corresponding *r* (static) common factors F_t by unit *i*. Factor loadings λ_i are in matrix form presented as Λ. The term $C_{it} = \lambda'_i F_t$ is otherwise known as the common component of the model. Factor models arise naturally in economics.

For example, x_{it} is the GDP growth rate for country *i* in period t, F_t a vector of common shocks, λ_i represents the heterogenous shocks, and e_{it} stands for the country–specific growth rate. In finance, x_{it} is the return for asset i in period t, F_t is the vector of systematic risks (or factor returns), λ_i is the exposure to the factor risks, and e_{it} is the idiosyncratic returns (Forni & Lippi, 2005, pp. 830–840; Bai & Ng, 2008, pp. 93–94; Bai & Wang, 2012, p. 5). Assume that $X_t = (x_{1t}, x_{2t}, \ldots, x_{Nt})'$, $F = (F_1, \ldots, F_T)'$, and $\Lambda = (\lambda_1, \ldots, \lambda_N)'$. In vector form, I have:

$$X_t = \Lambda F_t + e_t. \tag{3}$$

Assume also that $X = (X'_1,\ldots, X'_N)$ be a $T \times N$ matrix observations. The matrix representation of the factor model is

$$X = F\,\Lambda' + e, \tag{4}$$

where $e = (e'_1, e'_2,\ldots,e'_N)$ is $T \times N$. Although the model specifies a static relationship between x_{it} and F_t, F_t itself can be a dynamic vector process that evolves according to (Forni & Reichlin, 1996, pp. 27–42; Forni & Reichlin, 1998, pp. 453–473; Forni & Lippi, 2005, pp. 830–840)

$$A\,(L)\,F_t = e_t, \tag{5}$$

where $A\,(L)$ is a polynomial (possibly infinite order) of the lag operator. The idiosyncratic error e_{it} can also be a dynamic process. The assumptions to be stated below also permit e_{it} to be cross–sectionally correlated.

The static model is to be contrasted with a *dynamic r*–factor model, defined as

$$x_{it} = \lambda'_i\,(L)\,f_t + e_{it}, \tag{6}$$

where $\lambda_i\,(L) = (1 - \lambda_{i1} L - \ldots - \lambda_{is} L^s)$ is a vector of dynamic factor loadings of order s. The term *dynamic factor model* is sometimes reserved for the case when s is finite, whereas a "generalized dynamic factor" model allows s to be limitless. In either case, the factors are assumed to evolve according to

$$f_t = C\,(L)\,\varepsilon_t, \tag{7}$$

where ε_t are $i.i.d.$ errors. The dimension of f_t, denoted q, is the same as the dimension of ε_t. I can rewrite the model as

$$x_{it} = \lambda_i\,(L)'\,C\,(L)\,\varepsilon_t + e_{it}\,. \tag{8}$$

In the literature, $q = dim\,(\varepsilon_t)$ is referred to as the number of dynamic factors. Both models have their origin in the statistics literature. Assuming F_t and e_t are uncorrelated and have zero mean, the covariance structure of the static model is given by

$$\Sigma = \Lambda\Lambda' + \Omega, \tag{9}$$

where Σ and Ω are the $N \times N$ population covariance matrix of Y_t and e_t, respectively; the normalization $E(F_t F_t') = I_r$ is assumed. If Ω is diagonal, (2) is referred to as a strict factor model.

In traditional factor analysis, F_t and e_t in (2) are generally assumed to be serially and cross–sectionally uncorrelated under the assumptions that *(i)* e_t is $i.i.d.$ over t; *(ii)* N is fixed as T is limitless (or vice versa); *(iii)* both F_t and e_t are normally distributed and well documented. Classical factor analysis estimates Λ and the diagonal elements of Ω, with which factor scores F_t can also be evaluated. The estimated score cannot be consistent since N is fixed. The limiting distribution is based on asymptotic normality for an estimator of Σ (e.g., the sample covariance matrix). This method is not applicable for large N since Σ ($N \times N$) can not be consistently assessed (Forni & Reichlin, 1996, pp. 27–42; Forni & Reichlin, 1998, pp. 453–473; Forni & Lippi, 2005, pp. 830–840; Bai & Ng, 2008, pp. 94–95).

Traditional factor models have been widely used in psychology and social sciences but less so in economics, perhaps because the factors and errors are serially and cross–sectionally correlated which does not correspond with economic data. The dynamic classical factor model assumes that the errors are independent across i and explicitly recognizes the analyzed data as serially correlated. Sargent and Sims (1977), and Geweke (1977) were amongst the first to apply the dynamic factor approach to macroeconomic analysis (Bai & Ng, 2008, p. 95). Dynamic factor models were originally developed by Geweke (1977), Sargent and Sims (1977), Geweke and Singleton (1981), and Watson and Eagle (1983), and applied in the context of a limited number of variables (Forni et al., 2002, pp. 540–554).

A dynamic factor model with q factors can be written as a static factor model with finite r factors. However, the dimension of F_t will generally be different from the dimension of f_t since F_t includes the leads and lags of f_t. In other words, if one has q dynamic factors, $r = q\ (s + 1) \geq q$ static factors will be acquired.

Although precise calculation of primitive shocks in the economy is useful in some studies, many econometric methods can be developed within the static framework. Consequently, the properties of the estimated static factors are easier to comprehend from a theoretical standpoint.

Empirically, the static and the dynamic factor estimates produce rather similar forecasts. From a practical perspective, the primary advantage of the static framework is simple estimation using the time domain methods and involves quite a few auxiliary parameters. Dynamic factor models are estimated with tools of frequency domain analysis but the proper choice of auxiliary parameters remains an issue requiring further research (Bai & Ng, 2008, p. 96; Forni & Lippi, 2005, pp. 830–840).

An important characteristic of a static model with r factors is that the largest eigenvalues of Σ increase with N, while the remaining eigenvalues of Σ, as well as all eigenvalues of Ω, are bounded. Intuitively, the information of the common component accumulates as the observations across i are summed up and therefore the eigenvalues of the population covariance matrix of the common component increase with N. In contrast, the e_{it} are unit–specific errors and asumming the errors across i does not lead to the same accumulation of information. In other words, the eigenvalues of Ω can not increase without bounds, as N increases.

The difference in the property of the eigenvalues distinguishes the common from the idiosyncratic component. If the eigenvalues of the common component increase with N so do the population eigenvalues of Σ (Bai & Ng, 2008, p. 97). The dynamic factor model has an equivalent static factor model representation, where r–dimensional static factors comprise both current and lagged values of the q dynamic factors. When the number of static and dynamic factors is the same, i.e. $r = q$, static and dynamic factor forms are identical.

2.2.1 Large Dimensional Static Factor Model

The difference between the large dimensional static factor model and the traditional factor model is that the prior relaxes three mentioned assumptions. Research was initiated by Stock and Watson in the late 1990s. Simultaneously, assumptions of the classical dynamic factor model were relaxed, notably by Forni et al. (2005). The new generation of factor models is known as "large dimensional approximate factor models".

The adjective "large" implies that the sample size in both dimensions is boundless in the asymptotic theory. The adjective "approximate" suggests that the idiosyncratic errors can be "weakly" correlated across i and t (Bai & Ng, 2008, pp. 95–97). In other words, relaxed assumptions of a classical static factor model are the following: (i) both T and N are limitless, (ii) F_t is serially correlated (weak serial correlation among factors and idiosyncratic components), (iii) e_{it} are weakly correlated across i and t (i.e., the idiosyncratic errors may be weakly cross–correlated and heteroscedastic (Forni et al., 2002, pp. 540–554; Forni & Lippi, 2005, pp. 830–840).

The only observed quantities in factor analysis are the data x_{it}. Neither the factors and their loadings nor the idiosyncratic errors are detected and separately unidentifiable. Estimation of classical factor models with the sample size fixed in one dimension can also pose difficulties if heterogeneous variables are incorporated (Forni & Reichlin, 1996, pp. 27–42; Forni & Reichlin, 1998, pp. 453–473).

Whereas classical (static or dynamic) factor models can be consistently estimated by methods that rely on sample moments converging to population moments of fixed dimensions, this approach is inappropriate when the dimension of moment matrices increases (Bai & Ng, 2002, pp. 192–195). New evaluations have been developed: the PC estimator and the 3PRF estimator.

3 FACTOR–AUGMENTED REGRESSIONS

When forecasting an economic variable, it is often necessary to incorporate information from a large set of potential explanatory variables into the forecasting model. Most traditional macroeconomic prediction approaches, however, are unappropriate, either because it is inefficient or impossible to include multiple variables in a single forecasting model and estimate them with standard econometric techniques. As an alternative approach to this problem, the FAR has gained a prominent place.

3.1 Characteristics of Factor–Augmented Regressions

In forecasting and regression analysis, it is often necessary to select predictors from a large dataset. Without natural ordering of the predictors, an exhaustive evaluation of all possible predictor combinations can be computationally costly (Bai & Ng, 2009, pp. 608–610). The FAR has received much attention in high–dimensional problems with numerous predictors available over a long period.

Assuming that some latent factors generate the co–movement of all predictors, a particular series can be forecasted using factors rather than the original predictors and hence the dimension is significantly reduced. In the FAR, the factors are determined and ordered according to their importance in driving the covariability of many predictors, which may not be consistent with their forecast power for the particular series of interest, an issue discussed by Bai and Ng (2008, 2009). The model specification is necessary to determine which factors should be used in the forecast regression, in addition to specifying the number of lags of the dependent variable and the factor included. These decisions depend on the particular series of interest and the forecast horizon (Cheng & Hansen, 2015, pp. 280–293).

This study considers forecasting a single time series when there are many predictors (N) and time series observations (T). When the data follow an approximate factor model, the predictors can be summarized by a small number of indexes, which can be estimated by the PC or an alternative, the 3PRF.

The distinctive feature of the FAR is that the factors estimated by the 3PRF are added to an otherwise standard regression:

$$Y_{t+h} = \alpha^{'} \tilde{F}_{t} + \beta^{'} W_t + \epsilon_{t+h} \tag{10}$$

$$= \tilde{z}'_{t+h}\, \delta + \epsilon_{t+h}\,, \tag{11}$$

where W_t are predetermined variables (such as lagged variables) that the researcher includes regardless of $\tilde{F}_t$. W_t is a $m \times 1$ vector of observed variables, which along with F_t is useful for forecasting y_{t+h} (Stock & Watson, 2002b, p. 1167). Equation (10) is an infeasible regression model, where F_t is not observable and replaced by $\hat{F}_t$ estimated under one of the two identification assumptions.

3.2 Assumptions of Factor–Augmented Regressions and Diffusion Index

Assumptions of Factor–Augmented Regressions are described in points *(a)* and *(b)* (Bai & Ng, 2008, p. 115):

a) Assume that $z_t = (F'_t\ W'_t)'$, $E \parallel z_t \parallel^{4} \leq M$; $E\,(\epsilon_{t+h} | y_t, z_t, y_{t-1}, ...) = 0$ for any $h > 0$; z_t and ϵ_t are independent of the idiosyncratic errors e_{is} for all i and s. Furthermore, $\frac{1}{T} \sum_{t=1}^{T} Z_t\, Z_t' \xrightarrow{p} \sum_{ZZ} > 0$

b) $\frac{1}{\sqrt{T}} \sum_{t=1}^{T} z_t\, \epsilon_{t+h} \xrightarrow{d} N\,(0, \sum_{ZZ,\epsilon})$, where $\sum_{ZZ,\epsilon} = plim\, \frac{1}{T} \sum_{t=1}^{T} (\epsilon_{t+h}^{2}\, z_t z'_t) > 0.$

The regression model given by (10) encompasses many applications of interest. If $h = 0$, (10) is merely a regression with generated regressors $\tilde{F}_t$ and $\tilde{z}'_t$, $\hat{\delta}$ is the estimated conditional mean of y_t. For example, if y_t is government bond spreads, then $\tilde{z}'_t\, \hat{\delta}$ is the estimated conditional mean of government bond spreads and if y_t is the volatility of government bond spreads, then $\tilde{z}'_t\,\hat{\delta}$ is the estimated conditional volatility of government bond spreads with conditioning information $\tilde{z}_t$. In this master's thesis there is a case of $h > 0$, (10) is a forecasting equation and forms the basis of the DI forecasting methodology of Stock and Watson (2002a). Diffusion index forecasts, also known as factor–augmented forecasts, have received significant attention from econometricians.

Firstly, factors are estimated from a large number of predictors $(X_{1t}, \dots, X_{Nt})$ using the 3PRF method and then augmented to a linear forecasting equation for y_{t+h} that consists of lags of y (Bai & Ng, 2008, p. 304). The DI methodology is appealing due to its capacity to simply and parsimonously incorporate information in various predictors into the forecast. The DI framework is now used by various government agencies in different countries as well as by independent and academic researchers (Stock & Watson, 1998, 2002a, pp. 147–162; Bai & Ng, 2008, p. 115).

The primary appeal of the FAR is that the factors embody information in many variables. In practice, an FAR analysis is obtained as follows. After acquiring the r–estimated factors $\tilde{F}_t$, $\tilde{z}_t = \left(1, W_t', y_t, y_{t-1}, \dots, \tilde{F}_{t1} \dots \tilde{F}_{t-p,1}, \dots, \tilde{F}_{t-p,r}\right)'$ is the potential set of predictors. The next step is to determine p^* and r_y, p^* being the optimal lag of y_t and r_y the number of estimated factors entering the forecasting equation to yield $\tilde{f}_t = \left(\tilde{F}_{t1}, \dots, \tilde{F}_{tr_y}\right)'$. If y_t is a scalar, equations $Y_{t+h} = \alpha' \tilde{F}_t + \beta' W_t + e_{t+h}$ and $X_{it} = \lambda_i' F_t + e_{it}$ or in matrix form, $X_t = \Lambda F_t + e_t$, constitute the DI forecasting model of Stock and Watson (2002a, b). The DI forecast for an h–period ahead forecast is therefore as follows:

$$\hat{y}^h_{T+h|T} = \hat{\alpha}'\hat{F}_t + \hat{\beta}'W_t. \tag{12}$$

Consistent estimation of the space spanned by F_t enables to obtain $\sqrt{T}$ consistent estimates of α and β and $min\left[\sqrt{N}, \sqrt{T}\right]$ consistent forecasts of the conditional mean, $y^h_{T+h|T}$, if $\sqrt{T}/N \to 0$ as $N, T \to \infty$. These types of analyses exploit the possibility that information in x_{it} can be summarized in a low–dimensional vector F_t. In an economic study, F_t can be interpreted as the common shocks that generate co–movements in the data.

3.3 Linear Factor–Augmented Regressions

This subchapter focuses on the linear Factor–Augmented Regression assumptions proven by Bai and Ng (2002, 2008a, 2008b). All presented assumptions are necessary for stationary data. Assume that assumptions, presented below, hold (Bai & Ng, 2002, p. 196; Bai & Ng, 2008, pp. 102–103, 115):

a) ASSUMPTION A–*Factors:*

> $E\, ||\, F_t^0\, ||^4 \le M$ and $\frac{1}{T}\sum_{t=1}^{T} F_t^0\, F_t^{0\prime} \xrightarrow{p} \sum_F > 0$ for an $r \times r$ non–random matrix $\sum_F$ and where F_t^0 is the true factor and M is a generic positive constant such that $M < \infty$.

b) ASSUMPTION B–*Factor Loadings:*

λ_i^0 is either deterministic such that $||\ \lambda_i^0|| \leq M$, or it is stochastic such that $E\ ||\ \lambda_i^0||^4 \leq M$. In either case, $N^{-1}\ \Lambda^{0\prime}\ \Lambda^0 \xrightarrow{p} \sum_\Lambda > 0$ for an $r \times r$ non–random matrix $\sum_\Lambda$, as $N \to \infty$. λ_i^0 is the true factor the same as F_t^0.

c) ASSUMPTION C–*Time and Cross–Section Dependence and Heterockedasticity:*

c.1) $E\ (e_{it}) = 0, E\ |e_{it}|^8 \leq M$

c.2) $E\ (e_{it}\ e_{js}) = \sigma_{ij,ts},\ \ |\sigma_{ij,ts}|\ \leq \bar{\sigma}_{ij}$ for all (t,s) and $|\sigma_{ij,ts}|\ \leq\ \tau_{ts}$ for all (i,j) such that $\frac{1}{N}\sum_{i,j=1}^{N}\bar{\sigma}_{ij}\ \leq\ M$, $\frac{1}{T}\ \sum_{t,s=1}^{T}\tau_{ts} \leq M$, and $\frac{1}{NT}\sum_{i,j,t,s=1}|\sigma_{ij,ts}|\ \leq\ M$

c.3) For every (t,s), $E\ \left|N^{-1/2}\ \sum_{i=1}^{N}[e_{is}\ e_{it} - E\ (e_{is}\ e_{it})]\right|^4\ \leq\ M$

c.4) For each t, $\frac{1}{\sqrt{N}}\sum_{i=1}^{N}\lambda_i\ \ e_{it} \xrightarrow{d} \mathrm{N}(0,\Gamma_t)$, as $N \to \infty$ where

$$\Gamma_t = lim_{N \to \infty}\frac{1}{N}\ \sum_{i=1}^{N}\sum_{j=1}^{N}E\ \left(\lambda_i\ \lambda'_j\ e_{it}e_{jt}\right)$$

c.5) For each i, $\frac{1}{\sqrt{T}}\sum_{t=1}^{T}F_t\ e_{it} \xrightarrow{d} \mathrm{N}\ (0,\Phi_i)$ as $T \to \infty$ where

$$\Phi_i = lim_{T \to \infty}\ T^{-1}\sum_{s=1}^{T}\sum_{t=1}^{T}E\ (F_t^0 F_s^{\prime 0}e_{is}\ \ e_{it})$$

d) ASSUMPTION D–*Assumption FAR*:

d.1) Assume that $z_t = (F'_t\ W'_t)'$, $E\ \|\ z_t\|^4 \leq M; E\ (\epsilon_{t+h}|y_t, z_t, y_{t-1}, \dots) = 0$ for any $h > 0$; z_t and ϵ_t are independent of the idiosyncratic errors e_{is} for all i and s. Furthermore, $\frac{1}{T}\sum_{t=1}^{T}Zt\ Z't \xrightarrow{p} \sum_{ZZ} > 0;$

d.2) $\frac{1}{\sqrt{T}}\sum_{t=1}^{T}z_t\ \epsilon_{t+h} \xrightarrow{d} N\ (0, \sum_{ZZ,\epsilon})$, where $\sum_{ZZ,\epsilon} = plim\ \frac{1}{T}\sum_{t=1}^{T}(\epsilon_{t+h}^2\ z_t z'_t) > 0$

Assumption A is standard for factor models. Assumption B ensures that each factor has a non–trivial contribution to the variance of X_t. I only consider non–random factor loadings for simplicity. Results still hold when the λ_i are random, provided they are independent of the factors and idiosyncratic errors. Assumption C allows limited time series and cross–section dependence in the idiosyncratic component. Heteroskedasticity in both the time– and cross–section dimension is also allowed. Given Assumption *c.1*, the remaining assumptions are easily satisfied if e_{it} are independent for all i and t. Some correlation in the idiosyncratic components sets up the model to have an approximate factor structure. It is more general than a strict factor model, which assumes e_{it} is uncorrelated across i (Bai & Ng, 2002, p. 196).

Assume that Assumptions A, B, C, and D hold. I get the following *Result A* (Bai & Ng, 2008, pp. 116–119):

Result A.1 If $\sqrt{T}/N \to 0$, then

$$\sqrt{T}\left(\hat{\delta} - \delta\right) \xrightarrow{d} N\,(0, \textstyle\sum_{\delta})^{1},$$

where $\sum_{\delta} = \Phi'^{-1}_{0} \sum_{zz}^{-1} \sum_{zz,e} \sum_{zz}^{-1} \Phi_{0}^{-1}$, $\Phi_{0} = diag\ (V^{-1} Q \sum_{\Lambda}, I)$ is block diagonal, $V = plim\tilde{V}$, Q = plim $\tilde{F}'F/T$, and $\sum_{\Lambda}$ defined in assumption C. A consistent estimator for $Avar(\hat{\delta}) = \sum_{\Lambda}$ is

$$\widehat{Avar}\left(\hat{\delta}\right) = \left(\frac{1}{T}\sum_{t=1}^{T-h} \hat{z}_t\, \hat{z}'_t\right)^{-1} \left(\frac{1}{T}\sum_{t=1}^{T-h} \hat{e}_{t+h}^{2}\, \hat{z}_t\, \hat{z}'_t\right) \left(\frac{1}{T}\sum_{t=1}^{T-h} \hat{z}_t\, \hat{z}'_t\right)^{-1}.$$

Result A.2 Assume that $\hat{y}_{T+h|T} = \hat{\delta}'\hat{z}_T$. If $\sqrt{N}/T \to 0$ and Assumptions A, B and C hold, then for any $h \geq 0$,

$$\frac{\left(\hat{y}_{T+h|T} - y_{T+h|T}\right)}{\sqrt{var\ (\hat{y}_{T+h|T})}} \xrightarrow{d} \mathrm{N}\ (0,1),$$

where $Var\left(\hat{y}_{T+h|T}\right) = \frac{1}{T}\,\hat{z}'_T Avar\left(\hat{\delta}\right)\hat{z}_T + \frac{1}{N}\,\hat{\alpha}' Avar\left(\tilde{F}_T\right)\hat{\alpha}$.

Based on Result A, parameter estimates of equations involving $\tilde{F}_{t+1}$, whether as regressants or regressors, are $\sqrt{T}$ consistent. It also shows how standard errors can be computed and provides a complete inferential theory for Factor–Augmented Regressions.

3.4 The FAR and Generated Regressor Problem

Generated regressors are conventionally obtained as the fitted values from a first–step regression of any observed variable related to the latent variable of interest on a finite set of other observed regressors. As shown in Pagan (1984, pp. 221–247), sampling variability from the first–step estimation is $O_p(1)$ in the second stage. As a consequence, the standard errors of the second–step parameter estimates must account for the estimation error from the first step. According to Result A, adjustment is unnecessary when the generated regressors are $\tilde{F}_t$ if $\sqrt{T}/N \to 0$ because the term $O_p(1)$ in convetional settings, is $O_p\left(\frac{\sqrt{T}}{min[N,T]}\right)$ in the Factor–Augmeted Regression setting, and vanishes if $\sqrt{T}/N \to 0$. However, although the condition $\sqrt{T}/N \to 0$ is not stringent, it does put discipline on when estimated factors can be used in regression analysis (Bai & Ng, 2008, p. 115). Sampling variability from the stage induces bias in the second stage. As proven by Bai and Ng (2006), there is no generated–regressor bias if $\sqrt{T}/N \to 0$. Result A.2 concerns the prediction interval for the conditional mean. There are two terms in *var*

[1] See equation (10).

$(\hat{y}_{T+h|T})$ and the overall convergence rate for $\hat{y}_{T+h|T}$ is $min\ [\sqrt{T}, \sqrt{N}]$. In a standard setting, $var\ (\hat{y}_{T+h|T})$ falls at rate T and for a given T, it increases with the number of observed predictors through a loss in degrees of freedom. In factor forecasts, the error variance decreases at rate $min\ [N, T]$ and for given T, efficiency improves with the number of predictors used to estimate F_t. A large N enables better estimation of the common factors and thus directly affects the efficiency of subsequent estimations involving $\tilde{F}_t$. If the estimation of F_t was based upon a fixed N, consistent estimation of the factor space would not be possible however large T becomes. Result A will not apply if $\tilde{F}_t$ is used to reduce the dimension of an already small set of predictors.

4 THE THREE–PASS REGRESSION FILTER (the 3PRF)

The Principal Component Analysis has got an alternative method, the 3PRF. The procedure presented by Kelly and Pruitt (2014) started from the idea that the factors relevant to y may be a strict subset of all factors driving x. Their method selectively identifies the subset of factors that influence the forecast target while discarding irrelevant factors that may be pervasive among predictors. This section presents the crucial advantages of this method – besides, the 3PRF is expressed in closed form and instantly computed. The principal contribution of this chapter is to present the 3PRF estimator; its asymptotic theory; the importance of proxies (automatic and theory–motivated); and most importantly, advantages of the 3PRF compared to forecasting with many predictors. 3PRF forecasts are consistent for the infeasible best forecast when both the time dimension and cross–section dimension increase. This requires specifying relevant factors driving the cross–section of predictors.

4.1 The Estimator

The sequence of OLS regressions gives the estimator its name, the Three–Pass Regression Filter. A target variable to be forecasted are government bond spreads. There are many useful predictors for the target variable. The number of predictors N may be large or near or more than the available time series observations T which makes OLS problematic. Therefore, the dimension of predictive information must be reduced and to do so the data is assumed to be described by an approximate factor model. The 3PRF uses proxies to forecast, i.e. variables, driven by the factors target–relevant factors in particular which are always available from the target and predictors but may alternatively be supplied to the econometrician on the basis of economic theory.

The target is a linear function of a latent factors subset alongside some unforecastable noise. The optimal forecast is a result of a regression on the true underlying relevant factors which are unobservable and hence called **the infeasible best forecast** (Kelly & Pruitt, 2014, p. 4). Y is written for the $T \times 1$ vector of the target variable time series from $2, 3, \ldots, T+1$. X is the $T \times N$ matrix of predictors $X = (x'_1, x'_2, \ldots, x'_T)' = (x_1, x_2, \ldots, x_N)$ that have been standardized to have unit time series variance. The $T \times L$ matrix of proxies is denoted as Z, which stacks period–by–period proxy data as $Z = (z'_1, z'_2, \ldots, z_T)'$. There is no assumption on the relationship between N and T but I assume L (predictive factors) $<<$ min (N, T) in the spirit of dimension reduction. With this notation in mind, the 3PRF's regression–based construction is defined in Table 1 below.

The first pass runs N separate time series regressions, one for each predictor. In these first–pass regressions, the predictor is the dependent variable, the proxies are the regressors, and the estimated coefficients describe the sensitivity of the predictor to factors represented by the proxies. As shown later, proxies do not need to represent specific factors and may be measured with noise. The important requirement is that their common component spans the space of the target–relevant factors.

The second pass uses the estimated first–pass coefficients in T separate cross–section regressions where the predictors are again the dependent variable while the first–pass coefficients $\hat{\phi}_i$ are the regressors. Fluctuations in the latent factors cause the cross section of predictors to compress over time. First–stage coefficient estimates map the cross–sectional distribution of predictors to the latent factors. Second–stage cross–section regressions use this map to abandon factor estimates at each point in time (Kelly & Pruitt, 2014, p. 5). If coefficients were observable, this mapping would be straightforward since factors could be directly estimated each period with cross–section regressions of predictors on the loadings. While the loadings in this framework are unobservable, the same intuition for recovering the factor space applies to cross–section regressions. The difference is that I use estimated loadings as stand–ins for the unobservable true loadings.

The next step is to transmit the estimated second–pass predictive factors $\hat{F}_t$ to the third pass. This is a single time series forecasting regression of the target variable y_{t+1} on the second–pass estimated predictive factors $\hat{F}_t$. The third–pass fitted value $\hat{ß}_0 + \hat{F}_t \hat{ß}$ is the 3PRF time t forecast. Because the first–stage regression takes an errors–in–variables form, second–stage regressions produce an estimate for a unique but unknown rotation of the latent factors. Since the relevant factor space is spanned by $\hat{F}_t$, the third–stage regression delivers consistent forecasts.

Table 1. Three–Pass Regression Filter Algorithm

Pass	Description
1.	Run time–series regression of $\boldsymbol{x_i}$ on $\boldsymbol{Z}$ for $i = 1, \ldots, N$, $x_{i,t} = \phi_{0,i} + \boldsymbol{z'_t \Phi_i} + e_{it}$, retain slope estimate $\hat{\Phi}_i$ (Time series regression)
2.	Run cross–section regression of $\boldsymbol{x_t}$ on $\boldsymbol{\hat{\phi}_i}$ for $t = 1, \ldots, T$, $x_{i,t} = \phi_{0,t} + \boldsymbol{\widehat{\Phi'}_i} \boldsymbol{F}_t + \varepsilon_{it}$, retain slope estimate $\hat{F}_t$ (Cross–section regression)
3.	Run time–series regression of y_{t+1} on predictive factors $\boldsymbol{\hat{F}_t}$, $y_{t+1} = \beta_0 + \boldsymbol{\hat{F}'_t \beta} + \eta_{t+1}$, delivers forecast $\hat{y}_{t+1}$ (Predictive regression)

* *Note*: All regressions use the OLS

Source: B. Kelly & S. Pruitt, *The Three–Pass Regression Filter: A New Approach to Forecasting Using Many Predictors*, 2014, p. 34.

Simultaneously, this can be short–circuited (if you have adequate data with satisfactory values) by a single formula – presented in the following. An alternative representation for the 3PRF is one-step closed form:

$$\hat{y} = \iota_T \bar{y} \; + \; J_T X W_{XZ} (W'_{XZ} S_{XX} W_{XZ})^{-1} W'_{XZ} s_{xy} \; ,$$

where $J_T \equiv \; I_T \, \frac{1}{T} \, \iota_T \iota'_T$ for I_T the T – dimensional identity matrix and ι_T the T–vector of ones (J_N is analogous), $\bar{y} \; = \; \iota'_T y / T$, $W_{XZ} \equiv \; J_N X' J_T Z$, $S_{XX} \equiv X' J_T X$ and $s_{xy} \; \equiv X' J_T y$. J matrices enter because each regression pass is run with a constant. The closed form is central to the theoretical development that follows. Nonetheless, the regressions–based procedure in Table 1 remains useful for two reasons. In practice (particularly with many predictors) unbalanced panels and missing data often occur.

The 3PRF as described in Table 2 easily handles these difficulties. Additionally, it is useful for developing intuition behind the procedure and understanding its relation to partial least squares (Kelly & Pruitt, 2014, p. 6)

4.1.1 Automatic Proxies

In case of one relevant factor ($K_f = 1$) the target variable depends only on the relevant factors and therefore satisfies assumptions 2.4, 3.3, 3.4, and 6 (see Assumptions 2, 3 and 6). However, if $K_f = 1$, the target proxy 3PRF does not extract enough factors to asymptotically attain the infeasible best and in this case by selecting additional proxies that depend only on relevant factors the target proxy 3PRF can be improved. The system can always be recast in terms of single relevant factors $\beta'_f f_t$ and can rotate the remaining factors to be orthogonal but this does not generally alleviate the requirement for as many proxies as relevant factors because rotating of the factors implies a rotation of factor loadings. If both rotations are taken into account, the same amount of relevant proxies and relevant factors is required (Kelly & Pruitt, 2014, p. 16).

The second proxy is obtained when residuals from target–proxy 3PRF forecasts also satisfy Assumption 6 (see Section 4.2) since they (i) have non–zero loading on relevant factors due to the insufficiency of the target–only proxy), (ii) have zero loading on irrelevant factors, and (iii) are linearly independent of the first proxy.

From this point, proxy construction proceeds iteratively: use the residuals from the target proxy 3PRF as the second proxy. This is so–called *automatic proxy–selection algorithm* (see Table 2 for the details). According to definition, the forecaster is called the *L–automatic proxy 3PRF* when automatic proxy–selection algorithm is iterated to construct *L* predictive factors (Kelly & Pruitt, 2014, p. 16).

Table 2. Automatic Proxy–Selection Algorithm

0. Initialize $r_0 = y$.

For k= 1, ..., L:

1. Define the k^{th} automatic proxy to be r_{k-1}. Stop if $k = L$; otherwise proceed.

2. Compute the 3PRF for target y using cross section X using statistical proxies 1 through k. Denote the resulting forecast $\hat{y}_k$.

3. Calculate $r_k = y - \hat{y}_k$, advance k, and go to step 1.

Source: B. Kelly & S. Pruitt, *The Three–Pass Regression Filter: A New Approach to Forecasting Using Many Predictors*, 2014, p. 34.

I can rewrite the forecast as

$$\hat{y} = \iota_T \bar{y} + \hat{F}\hat{\beta} \tag{13}$$

$$\widehat{F'} = S_{ZZ}(W'_{XZ}S_{XZ})^{-1}W'_{XZ}X' \tag{14}$$

$$\hat{\beta} = S_{ZZ}W_{XZ}S_{XZ}(W'_{XZ}S_{XX}W_{XZ})^{-1}W'_{XZ}s_{Xy} \tag{15}$$

where $S_{XZ} \equiv X'J_TZ$. Here I interpret $\hat{F}$ as our predictive factor and $\hat{\beta}$ the predictive coefficient on that factor. Since I have used the N predictors to construct a L–dimensional predictive factor, the 3PRF reduces the dimension of the forecasting problem.
Alternatively, the forecast can be rewritten as

$$\hat{y} = \iota\bar{y} + J_T X\hat{\alpha} \tag{16}$$

$$\hat{\alpha} = W_{XZ}(W'_{XZ}S_{XX}W'_{XZ})^{-1}W'_{XZ}s_{Xy} \tag{17}$$

interpreting $\hat{\alpha}$ as the predictive coefficient on individual predictors. The regular OLS estimate of the projection coefficient α is $(S_{XX})^{-1}s_{Xy}$. This representation suggests that described approach can be interpreted as a constrained version of least squares.

4.2 Assumptions

This subchapter reproduces the assumptions that provide principles for developing asymptotic properties of the 3PRF.

Assumption 1 (Factor Structure)

The data are generated as follows (Kelly & Pruitt, 2014, p. 7):

$$x_t = \phi_0 + \Phi F_t + \varepsilon_t \qquad y_{t+1} = \beta_0 + \beta' F_t + \eta_{t+1} \qquad z_t = \lambda_0 + \Lambda F_t + \omega_t$$

$$X = \iota\phi'_0 + F\Phi' + \varepsilon \qquad y = \iota\beta_0 F\beta + \eta \qquad Z = \iota\lambda'_0 + F\Lambda' + \omega$$

where $F_t = (f'_t\, g'_t)'$, $\Phi = (\Phi_f, \Phi_g)$, $\Lambda = (\Lambda_f, \Lambda_g)$, and $\beta = (\beta'_f, 0')'$with $|\beta_f| > 0$. $K_f > 0$ is the dimension of vector f_t, $K_g \geq 0$ is the dimension of vector g_t, L is the dimension of vector z_t $(0 < L < min(N, T))$, and $K = K_f + K_g$.

The target's factor loadings $(\beta = (\beta'_f, 0)')$ allow the target to depend on a strict subset of factors driving the predictors. This subset is referred to as the relevant factors f_t. In contrast, irrelevant *f*actors g_t do not influence the forecast target but may drive the cross–section of predictive information x_t. The proxies are driven by factors and proxy noise.

Assumption 2 (Factors, Loadings and Residuals)

Assume that $M < \infty$ for any *i*, *s*, *t* (Kelly & Pruitt, 2014, p. 8):

1. $\mathbb{E}\|F_t\|^4 < M$, $T^{-1}\sum_{s=1}^{T} F_s \xrightarrow[T\to\infty]{} \mu$ and $T^{-1}F'J_T F \xrightarrow[T\to\infty]{} \Delta_F$

2. $\mathbb{E}\|\phi_i\|^4 \leq M$, $N^{-1}\sum_{j=1}^{N} \phi_j \xrightarrow[T\to\infty]{} \bar{\phi}$, $N^{-1}\Phi' J_N \Phi \xrightarrow[N\to\infty]{} \mathcal{P}$ and $N^{-1}\Phi' J_N \phi_0 \xrightarrow[N\to\infty]{} \mathcal{P}_1$

$\|\phi_i\| \leq M$can replace $\mathbb{E}\|\phi_i\|^4 \leq M$ *i*f ϕ_i is non–stochastic (Kelly & Pruitt, 2014, p. 8).

3. $\mathbb{E}(\varepsilon_{it}) = 0, \mathbb{E}[\varepsilon_{it}]^8 \leq M$

4. $\mathbb{E}(\omega_t) = 0, \mathbb{E}\|\omega_t\|^4 \leq M$, $T^{-1/2}\sum_{s=1}^{T}\omega_s = O_p(1)$ and $T^{-1}\omega' J_T \omega \xrightarrow[N\to\infty]{} \Delta_\omega$

5. $\mathbb{E}(\eta_{t+1}) = \mathbb{E}(\eta_{t+1}|y_{t,}F_t, y_{t-1}, F_{t-1}, \ldots) = 0$, $\mathbb{E}(\eta^4{}_{t+1}) \leq M$, and η_{t+1} is independent of $\phi_i(m)$ and $\varepsilon_{i,t}$.

Since η_{t+1} is a martingale difference sequence with respect to all information known at time *t*, $\beta_0 + \beta'_f f_t$ gives the best time t forecast. However, it is infeasible since the relevant factors f_t are unobserved.

Factors and loadings ought to be cross–sectionally regular and have well–behaved covariance matrices for large T and N. Assumption 2.4 does not exist in Stock and Watson's or Bai and Ng's work but is required due to the 3PRF's use of proxies to extract factors. The moments of proxy noise ω_t were bounded in the same manner as the bounds on factor moments.

Assumption 3 (Dependence)

Assume that $x(m)$ denotes the m^{th} element of x for $M < \infty$ and any *i*, *j*, *t*, *s*, m_1, m_2 (Kelly & Pruitt, 2014, p. 9):

1. $\mathbb{E}(\varepsilon_{it}e_{js}) = \sigma_{ij,ts}, |\sigma_{ij,ts}| \leq \bar{\sigma}_{ij}$ and $|\sigma_{ij,ts}| \leq \tau_{ts}$, and

   (a) $N^{-1}\sum_{i,j=1}^{N}\bar{\sigma}_{ij} \leq M$

   (b) $T^{-1}\sum_{t,s=1}^{T}\tau_{ts} \leq M$

   (c) $N^{-1}\sum_{i,s}|\sigma_{ii,ts}| \leq M$

   (d) $N^{-1}T^{-1}\sum_{i,j,t,s}|\sigma_{ij,ts}| \leq M$

2. $\mathbb{E}\left|N^{-1/2}T^{-1/2}\sum_{s=1}^{T}\sum_{i=1}^{N}[\varepsilon_{is}\varepsilon_{it} - \mathbb{E}(\varepsilon_{is}\varepsilon_{it})]\right|^2 \leq M$

3. $\mathbb{E}\left|T^{-1/2}\sum_{t=1}^{T}F_t(m_1)\omega_t(m_2)\right|^2 \leq M$

4. $\mathbb{E}\left|T^{-1/2}\sum_{t=1}^{T}\omega_t(m_1)\varepsilon_{it}\right|^2 \leq M.$

Assumption 4 (Central Limit Theorems)

Assume that for any i, t (Kelly & Pruitt, 2014, p. 9):

1. $N^{-1/2}\sum_{i=1}^{N}\phi_i\,\varepsilon_{it} \xrightarrow{d} \mathcal{N}(0,\Gamma_{\Phi\varepsilon})$, where $\Gamma_{\Phi\varepsilon} = \text{plim}_{N\to\infty}N^{-1}\sum_{i,j=1}^{N}\mathbb{E}[\phi_i\,\phi'_j\varepsilon_{it}\varepsilon_{jt}]$
2. $T^{-1/2}\sum_{t=1}^{T}F_t\,\eta_{t+1} \xrightarrow{d} \mathcal{N}(0,\Gamma_{F\eta})$, where $\Gamma_{F\eta} = \text{plim}_{T\to\infty}T^{-1}\sum_{t=1}^{T}\mathbb{E}[\eta_{t+1}^2F_tF'_t] > 0$
3. $T^{-1/2}\sum_{t=1}^{T}F_t\,\varepsilon_{it} \xrightarrow{d} \mathcal{N}(0,\Gamma_{F\varepsilon,i})$, where $\Gamma_{F\varepsilon,i} = \lim_{T\to\infty}T^{-1}\sum_{t,s=1}^{T}\mathbb{E}[F_tF'_s\varepsilon_{it}\varepsilon_{is}] > 0.$

According to Assumption 3, factor structure is approximate in the sense that some cross–section correlation among e_{it} is permitted. Serial dependence among e_{it}, some proxy noise dependence with factors and idiosyncratic shocks are also allowed.

Assumption 4 requires that central limit theorems apply and is satisfied when various mixed conditions hold among factors, loadings, and shocks.

Assumption 5 (Normalization)

(Kelly & Pruitt, 2014, p. 9) $\mathcal{P} = \text{I}, \mathcal{P}_1 = 0$ and Δ_F is diagonal and positive with unique diagonal elements. Assumption 5 recognizes an inherent non–identification between the factors and factor loadings and therefore selects a normalization with orthogonal factors and the covariance of predictor loadings as the identity matrix. This particular normalization is unimportant and ultimately, a vector space spanned by the factors is estimated, which does not depend upon the choice of normalization. Stock and Watson (2002a) summarize this part, but Kelly and Pruitt (2014) have replaced their symbols with the following notation: If $\Phi F_t = \Phi R R^{-1}F_t$ for any non–singular matrix R, a normalization is required to uniquely define the factors. The model with factor loadings ΦR and factors $R^{-1}F_t$ is observationally equivalent to the model with factor loadings Φ and factor F_t. Assumption 5 requires an orthonormal R and a diagonal matrix with diagonal elements of ± 1.

Assumption 6 (Relevant Proxies)

$\Lambda = [\Lambda_f, 0]$ and Λ_f is non–singular. According to Assumption 6, proxies *(i)* have zero loading on irrelevant factors, *(ii)* linearly independent loadings on the relevant factors, and *(iii)* equal number of proxies and relevant factors. If Assumption 6 and 5 are combined, the common proxy component spans the relevant factor space and none of the proxy variation is due to irrelevant factors.

The only conditions involving the proxy variables are Assumptions 2.4, 3.3, 3.4 and 6 (see Assumptions 2 and 3 above). Theorem 7 proves that automatic proxies, generally constructible using X and Y, undoubtedly satisfy these proxy assumptions (Kelly & Pruitt, 2014, p. 10).

4.3 Consistency

Theorem 1. Assume that Assumptions 1–6 hold. The 3PRF forecast is consistent for the infeasible best forecast, $\hat{y}_{t+1} \xrightarrow[T,N\to\infty]{} \beta_0 + F'_t\beta$. The difference between the feasible and the infeasible best forecast vanishes in case of large *N* and *T*. This outcome along with other asymptotic results is based on simultaneous *N* and *T* limits.

As discussed by Bai and Ng (2003), a simultaneous limit implies the existence of coinciding sequential and path–wise limits but the converse doesn't hold. The estimated loadings on individual predictors $\hat{\alpha}$ play an important role in the interpretation of the 3PRF.

Theorem 2. According to authors of the 3PRF, Theorem 2 provides the probability limit for the loading on each predictor *i*. Assume that Assumptions 1–6 hold and $\hat{\alpha}_i$ denote the i^{th} element of $\hat{\alpha}$ for any i (Kelly & Pruitt, 2014, p. 11):

$$N\hat{\alpha}_i \xrightarrow[T,N\to\infty]{} (\phi_i - \bar{\phi})'\beta. \tag{18}$$

The coefficient α maps underlying factors to the forecast target via observable predictors. As a consequence, the probability limit of $\hat{\alpha}$ is a product of the loadings of X and y on the relevant factors f. This arises from the interpretation of $\hat{\alpha}$ as a constrained least squares coefficient estimate. Due to the simultaneous growth of the dimension of $\hat{\alpha}$ with the number of predictors, $\hat{\alpha}$ is multiplied by *N* in order to derive its limit. As *N* grows, the predictive information in f is spread across a large number of predictors, so that each predictor's contribution approaches zero. Standardizing by N is necessary for the identification of the non–degenerate limit.

It is necessary to mention how these results are distinguished from empirical work that uses principal component regressions. This is largely due to the fact that the 3PRF uses the same number of predictive factors as factors relevant to y_{t+1}. On the other hand, the PC regressions forecast is asymptotically efficient with as many predictive factors as the total number of factors driving x_t. The above distinction is pivotal when the number of relevant factors is lower than the number of total factors in the predictor data, and the target–relevant principal components are dominated by other components in x_t. If the factors driving the target are weak and contribute only a small fraction of the total variability in the predictors, then the principal components may have difficulties identifying them. The method of principal components is not assured to first extract predictive factors relevant to y_{t+1} (Kelly & Pruitt, 2014, p. 12).

In contrast, the 3PRF identifies those exact relevant factors in its second–pass factor estimation. The second–step extracts leading indicators that are estimated factors specifically valuable for forecasting a given target. For example, considering there is only one relevant factor and the sole proxy is the target variable y_{t+1}. This is referred to as the target–proxy three–pass regression filter.

Corollary 1. If Assumptions 1–5 hold, with the exception of Assumptions 2.4, 3.3, and 3.4 (see Assumptions 2 and 3), assuming there is only one relevant factor, then the target–proxy three–pass regression filter forecaster is consistent for the infeasible best forecast which is true regardless of the number of irrelevant factors driving X and position of the relevant factor in the principal component ordering for X.

4.4 Asymptotic Distributions

The 3PRF is consistent for the infeasible best forecast, with each forecast having a normal asymptotic distribution. The asymptotic distribution for $\hat{\alpha}$ is presented below.

Theorem 3. Assume that N, $T \to \infty$ and Assumptions 1–6 hold. There is (Kelly & Pruitt, 2014, p. 13)

$$\frac{\sqrt{T}\ N(\hat{\alpha}_i - \tilde{\alpha}_i)}{A_i} \xrightarrow{d} \mathcal{N}(0,1) \tag{19}$$

where A_i^2 is the i^{th} diagonal element of $\widehat{Avar(\hat{\alpha})} = \Omega_\alpha \left(\frac{1}{T}\sum_t \hat{\eta}_{t+1}^2 (X_t - \bar{X})\,(X_t - \bar{X})'\right)\Omega'_\alpha$, $\hat{\eta}_{t+1}$ is the estimated 3PRF forecast error, $\tilde{\alpha}_i \equiv S_i G_\alpha \beta$, where S_i is selects the i^{th} element of vector $G_\alpha \beta$ and

$$G_\alpha = J_N(T^{-1}X'J_T Z)(T^{-3}N^{-2}W'_{XZ}S_{XX}W_{XZ})^{-1}(N^{-1}T^{-2}W'_{XZ}X'J_T F) \tag{20}$$

and

$$\Omega_\alpha = J_N\left(\frac{1}{T}S_{XZ}\right)\left(\frac{1}{T^3N^2}W'_{XZ}S_{XX}W_{XZ}\right)^{-1}\left(\frac{1}{TN}W'_{XZ}\right) \tag{21}$$

Theorem 3 presents a distribution theory including feasible *t*–statistics, for inference, while Theorem 2 shows that $\hat{\alpha}$ may be used to measure the relative forecast contribution of each predictor. The matrix G_α appears because the factors are identified only up to an orthonormal rotation. This is the point from which the asymptotic distribution of the 3PRF forecasts can be derived.

Theorem 4. As $N, T \to \infty$ and Assumptions 1–6 hold, there is (Kelly & Pruitt, 2014, p. 14):

$$\frac{\sqrt{T}(\hat{y}_{t+1} - \mathbb{E}_t y_{t+1})}{Q_t} \xrightarrow{d} \mathcal{N}(0,1) \tag{22}$$

where $\mathbb{E}_t y_{t+1} = \beta_0 + \beta' F_t$ and Q_t^2 is the t^{th} diagonal element of $\frac{1}{N^2} J_T X \widehat{Avar}\ (\hat{\alpha})' X J_T$.

The result above proves that besides being consistent for the infeasible best forecast $\mathbb{E}_t(y_{t+1}) \equiv \beta_0 + \beta' F_t$, the 3PRF forecast is asymptotically normal and provides a standard error estimator for constructing forecast confidence intervals. There is a subtle, but important feature: for the prediction intervals only the asymptotic variance of individual predictor loadings $\widehat{Avar\ (\hat{\alpha})}$ is required. This feature differs from the confidence intervals of principal component regressions forecasts, where an estimate of the asymptotic variance for the predictive factor loadings as well as for the fitted latent factors, $\widehat{Avar}(\widehat{F})$, is required (Kelly & Pruitt, 2014, p. 14). With the help of Kelly and Pruitt's (2014) 3PRF forecasts, loadings on individual predictors can be represented in a convenient algebraic form $\hat{\alpha}$. Variability in $\hat{\beta}$ and $\hat{F}$ is captured by $\widehat{Avar\ (\hat{\alpha})}$.

Theorem 5. Theorem 5 introduces the asymptotic distribution of predictive loadings on the latent factors and a consistent estimator of their asymptotic covariance matrix.

As $N, T \to \infty$ and under Assumptions 1–6 there is (Kelly & Pruitt, 2014, p. 14):

$$\sqrt{T}\left(\hat{\beta} - G_\beta \beta\right) \xrightarrow{d} \mathcal{N}\left(0, \Sigma_\beta\right) \tag{23}$$

where $\Sigma_\beta = \Sigma_z^{-1} \Gamma_{F\eta} \Sigma_z^{-1}$; $G_\beta = \hat{\beta}_1^{-1} \hat{\beta}_2 \hat{\beta}_3^{-1} (N^{-1} T^{-2} Z' J_T X J_N X' J_T F)$ and $\Sigma_z = \Lambda \Delta_F \Lambda' + \Delta_\omega$; furthermore:

$$\widehat{Avar}\ (\hat{\beta}) = \left(T^{-1} \widehat{F}' J_T \widehat{F}\right)^{-1} T^{-1} \textstyle\sum_t \hat{\eta}_{t+1}^2 \left(\widehat{F}_t - \hat{\mu}\right)(F'_t - \hat{\mu})' \left(T^{-1} \widehat{F}' J_T \widehat{F}\right)^{-1} \tag{24}$$

is a consistent estimator of Σ_β.

4.5 Proxy Selection

The 3PRF's success in forecasting – regardless of PCs dominating cross–section variation being irrelevant to the forecast's target and the filter formulation – relies on proxies that depend only on target–relevant factors. The crucial feature of Kelly and Pruitt's 3PRF (2014) is the absence of an *a priori* assumption about the availability of proxies that satisfy the relevance criterion of Assumption 6. Proxies depending only upon relevant factors are obtained from an automatic proxy selection algorithm.

Theorem 6. Under the condition that Assumptions 1– 5 hold except for Assumptions 2.4, 3.3, and 3.4 (see Assumptions 2 and 3), the *L*–automatic–proxy 3PRF forecaster of y naturally satisfies Assumptions 2.4, 3.3, 3.4, and 6 (see Assumptions 2, 3 and 6) when $L = K_f$.

According to Theorem 6, L–automatic–proxy is consistent and asymptotically normal as stated in Theorems 1 and 4 (Kelly & Pruitt, 2014, p. 17). The 3PRF is generally available since the conditions can be satisfied by the construction of automatic proxies. The only variables required to implement the filter are y and x.

4.5.1 Theory–Motivated Proxies

The use of automatic proxies in the 3PRF disciplines dimension reduction of the predictors by emphasizing the covariance between predictors and target in the factor estimation step. The filter may be employed with alternative disciplining variables (factor proxies) which may be distinct from the target and chosen on the basis of economic theory or by statistical arguments. When $K_f = 1$, the target and proxy are given by $y_{t+1} = \beta_0 + \beta f_t + \eta_{t+1}$ and $z_t = \lambda_0 + \Lambda f_t + \omega_t$.

The population R^2 of the proxy equation is supposedly substantially higher than the population R^2 of the target equation. The results or the forecasts are asymptotically identical when z_t or the target are used as proxies. In finite samples, forecasts can be improved using proxy–ng with z_t due to its higher signal–to–noise ratio. 3PRF forecasts have an attractive feature – they embody an economic narrative which makes the forecasts more appealing to policy makers or institutional investors.

4.6 The 3PRF and Related Methods

It is essential to compare the newest forecasting method with many predictors to other similar methods, such as Principal Component Regressions (hereinafter: PCR) for establishing why Kelly and Pruitt's (2014) 3PRF produces powerful forecasts. Although this empirical study compares the 3PRF to the univariate autoregressive model, the difference between the 3PRF and the PCR ought to be explained, particularly since economic literature has relied mainly on the PCR for forecasting issues with many predictors.

4.6.1 The 3PRF and Principal Component Regressions

The PCR as the most used econometrics literature for forecasting with many predictors was developed and exemplified by Stock and Watson (1998, 2002a, b, 2006, 2012), Forni and Reichlin (1996, 1998), and Bai and Ng (2002, 2006, 2008). Both the PCR and the 3PRF can be calculated instantaneously for virtually any *N* and *T*. PCR's key distinction is the ability to condense information from the large cross section into a small number of predictive indices *before* estimating a linear forecast. In other words, the PCR condenses the cross section according to covariance *within the predictors*, identifies the factors driving the panel of predictors, some of whom may be irrelevant for the dynamics of the forecast target and uses those factors to forecast.

The 3PRF condenses the cross section according to *covariance with the forecast target.* Principal component regressions need to estimate all common factors among predictors to achieve consistency, including those irrelevant for forecasting. In contrast, the 3PRF estimates only the relevant factors, whose number is always less than or equal to the total number of factors required by principal component regressions. This contrast is not applicable in large demonstrations, but it can prove crucial in small samples.

4.7 The Importance of the Three–Pass Regression Filter

The 3PRF focuses on relevant factors through proxies (automatic or theory–motivated). Firstly, the 3PRF predominantly uses latent variables to predict targets. Secondly, the 3PRF brings results with economic interpretation. Thirdly, the 3PRF is a fairly clean solution to an important problem, relating to the issue of many predictors in macroeconomic and other business research. The literature's benchmark method extracts factors that are significant drivers of variation in X and then uses these to forecast y. Factors that are relevant to forecast spreads may be a strict subset of all the factors driving X. This new method selectively identifies only the subset of factors that influence the forecast target while discarding factors that are irrelevant for the target but that may be pervasive among predictors.

The 3PRF has the advantage of being expressed in closed form and virtually instantaneous to compute. As already explained, the 3PRF allows focus on factors through proxies and the focus in the 3PRF is on using latent variables to predict some target. Compared to the PCR, relevant factors enable an economic interpretability of forecast results through automatic or theory–motivated proxies.

A new estimator is calculated in closed form and conveniently represented as a set of ordinary least squares regressions. 3PRF forecasts are consistent for the infeasible best forecast when the time dimension and cross–section dimension become larger. This requires specifying relevant factors driving the cross section of predictors. Simulation evidence confirms the 3PRF's forecasting performance relative to the alternatives.

Errors in variables can be avoided using the 3PRF. An error–ridden observable may be used as (a) 3PRF theory proxy for extracting target–relevant information from the cross–section of macroeconomic predictors x at time t. The advantages are: *(1)* the solution can be expressed in closed form as a complicated but easily computable matrix expression, and *(2)* it is not necessary to employ maximum likelihood estimation. Furthermore, *(3)* the 3PRF may outperform other approaches, such as the PCR or partial least squares because the 3PRF allows the data to behave as an approximate factor model – the approximate factor model by Rotschild and Chamberlain allows cross–sectionally correlated errors – the 3PRF as the newest method for factor estimation provides a satisfactory solution to the problem of correlated errors; *(4)* the PCR condenses the cross–section according to covariance within the predictors. This identifies the factors driving the panel of predictors, some of which may be irrelevant for the dynamics of forecast target spreads, and uses those factors to forecast.

The 3PRF on the other hand, condenses the cross–section according to covariance with the forecast target. The PCR must estimate all common factors among predictors to achieve consistency, including those irrelevant for forecasting spreads. The 3PRF estimates only the relevant factors. The number of relevant factors is always less than or equal to the number of factors requaired by the PCR. The 3PRF uses as many predictive factors as the number of factors relevant to y_{t+1}. On the other hand, the PCR forecast is asymptotically efficient when there are as many predictive factors as the total number of factors driving x_t. In contrast, the 3PRF exclusively identifies relevant factors in its second–pass factor estimation. Those estimated factors are specifically valuable for forecasting a given target. *(5)* The 3PRF forecasts are consistent for the infeasible best forecast when time dimension and cross–section dimension become larger. This requires specifying relevant factors driving the cross–section of predictors; *(6)* proxies have zero loadings on irrelevant factors, while they have linearly independent loadings on the relevant factors, and number equal to the number of relevant factors; *(7)* one of the strengths of the 3PRF is the ability to include theory–motivated proxies that effectively favour some factors over others. Theory–motivated proxies help are useful when proxies contain common, persistent components and when some y–components have an unstable relationship with z–components.

In the third part of the thesis the data description, forecasting comparison, and forecasting results are presented. Firstly, the data used in the empirical procedure is described, the chapter then continues with a short description of the importance of euro–area information, forecasting procedure, forecast comparison, subsample analysis and lastly, the empirical results are discussed.

5 FORECASTING FRAMEWORK: DATA DESCRIPTION

In the third part of the thesis the data description, forecasting comparison, and forecasting results are presented. Firstly, the data used in the empirical procedure is described, the chapter then continues with a short description of the importance of euro–area information, forecasting procedure, forecast comparison, subsample analysis and lastly, the empirical results are discussed.

This section briefly presents the treatment of data to obtain the factors using the 3PRF. Dependent variables are bond yield spreads, derived as a difference between 10–year government bond yields of EMU founding countries (along with Greece) and yields of the equivalent German *Bunds*. The sample comprises both core EMU countries (i.e., the Netherlands and France) and peripheral EMU countries (i.e., Spain and Italy). The full dataset collected for Germany, France, Italy, Spain, the Netherlands, and the euro area, explained in Appendix A, contains 63 quarterly time series per country over the sample period 2000Q1–2015Q4. The main data source is Eurostat and the Federal Reserve Bank of St. Louis. The data chosen for the pseudo real–time–forecasting evaluation experiment represents several (i.e., 51) important categories of country–specific macroeconomic and fiscal variables.

The dataset consists of 41 country–specific and 10 international factors. Of all series, 13–time series belong to the output data; one to business tendency surveys; four to retail turnover and sales; the consumer price index (hereinafter: CPI) contains four different price indexes, the Harmonized Index of Consumer Prices (hereinafter: HICP) describes the HICP of all items and eight price indexes belong to the set of the producer price index. The labour market contains six–time series. There are also financial variables: four different exchange rates; five different interest rates, including the interest rate on the 10–year government bond yields; stock prices; and four–time series that belong to monetary aggregates.

The quarterly data, 2000Q1–2008Q2, are used for in–sample estimation. The data 2008Q3–2015Q4 are reserved for pseudo out–of–sample forecasting. The whole dataset includes the GDP and its expenditure components: consumption, fixed capital formation, and gross value added.

The dataset comprises real output variables (GDP, components of the GDP, industrial production), and international trade variables (export, import). It also contains industrial production, received orders and turnover, disaggregated by sectors. Labour market variables taken into consideration are employment, unemployment, and hourly earnings by sectors. Several disaggregated price time series, interest rates, exchange rates, and spreads are also included. Additionally, survey time series, such as business situation and expectations, assessment of stocks, capacity utilization, and other series are used.

The factors to be used as regressors in forecasting models are extracted from the country–specific datasets. Due to increasing integration within Europe, euro–area information is relevant for forecasting macroeconomic variables. Monetary aggregates M1, M2, and M3 are particularly important. Empirical results would report if my suggestion was correct. The number of variables for each forecast horizon is shown in Table 3. In this exercise, all 3PRF estimations are done for balanced dataset, therefore variables unavailable for the entire sample or data with different frequency from quarterly are not included.

Table 3. Summary of the Variables Employed in the 3PRF Estimation

Sectors	**Number of Variables**
Monetary Aggregates	4
Interest Rates	5
Macroeconomic Variables	10
Price Indices	13
Industrial Production	3
Capacity Utilization	1
Consumption and Sales	4
Employment and Working Hours	6
Exchange Rates	4
Stock Prices	1
Overall	**51**

Factor analysis requires some “pre–treatment” of the data; therefore, the three–stage approach by Marcellino, Stock, & Watson (2003) is applied. Following the standard procedures, similar to those largely used in empirical dynamic factor literature as in Marcellino et al. (2003), the data are transformed in a multi–stage process:

1) Logarithms are taken from all nonnegative series and those characterized by percentage changes, whereas shares or unemployment and interest rates are transformed in the following way: $ln(1 + x/100)$.

2) The series are transformed to account for stochastic or deterministic trends.

3) The time series are corrected for outliers and then seasonally adjusted.

4) Finally, the variables are transformed into series with zero means and unit variance in order to avoid scaling effects.

6 FORECASTING MODELS

In this part, I outline the forecast models to be compared in the analysis as well as the metrics to be used for assessing the forecast accuracy and performance of the models. I begin with a general description of the forecast model.

6.1 The Dynamic Forecast Model

The framework used in this analysis was quite rich, allowing the distributed lags of potentially serially–correlated factors to enter the x and y equations, serially– or cross–correlated error terms, and factor loadings that evolved over time.

Forecast models were specified and estimated as the linear projection of an h–step ahead variable y_{t+h}^{h} onto the t–dated vector of predictors Z_t:

$$y_{t+h}^{h} = \mu + \alpha(L)y_t + \beta(L)'Z_t + e_{t+h}^{h} \tag{25}$$

where $\alpha(L)$ was a scalar lag polynomial, $\beta(L)$ a vector lag polynomial and μ represented a constant. Z_t was a vector of predictor variables at time t and e_{t+h}^{h} was an error term. I set the forecast horizon to $h=1, \ldots, 4$. y_t was a dependent variable 10–year government bond spreads, and vector Z_t was determined with estimated 3PRF factors. This approach is known as dynamic estimation and differs from the standard approach of estimating one–step ahead model and then iterating it to obtain h–step ahead predictions.

There are two main advantages of an h–step ahead projection approach: *(i)* it eliminates the need to estimate additional equations for simultaneous forecast of Z_t, *(ii)* it reduces the potential impact of specification error in one–step ahead model (including the equations for Z_t) by using the same horizon for estimation and forecasting.

The characterization of y_{t+h}^{h} depends on whether the variables of interest, the spreads in this case, are modelled as stationary or not. Regarding the results in section 8, inflation was considered as an *I (0)* process and the relevant variable for most models was

$$y_{t+h}^{h} = ln\left(\frac{Y_{t+h}}{Y_t}\right) \tag{26}$$

The lag length was chosen on the basis of other relevant similar forecasting studies and the particular numbers of lagged variables were 3, 4 and 5.

6.2 Forecasting Procedure

A forecasting experiment denotes the variable to be forecasted, Y_t, and a set of n predictors collected in the $n \times 1$ vector X_t. In the literature of forecasting methods, X_t and Y_t are usually assumed to be stationary. In addition, the predictors X_t need to be pretreated in the same standardized way to have zero mean and unit variance during the entire empirical comparison.

Let h be the forecast horizon and Y_{t+h}^{h} the h–step ahead forecasts. The regular forecasting regressions in which the forecast at time t is denoted by $Y_{t+h|t}^{h}$ project an h–step ahead variable Y_{t+h}^{h} onto t–dated predictors, an intercept, and lagged predictors if necessary. Regarding multiple forecasts, let $Y_{i,t+h|t}^{h}$ be the i^{th} individual of all available predictions.

Forecasting can then be performed in a two–step process. Firstly, the time series of the factors is estimated as predictors; secondly, the relationship between the forecasted variable and the factors is estimated by a linear regression. If the number of predictors is substantial, precise estimates of the latent factors can be constructed using simple methods even under general assumptions about the cross–sectional and temporal dependence in the variables. I estimate the factors using the 3PRF and show that its estimates are consistent in an approximate factor model with idiosyncratic errors that are serially– and cross–sectionally correlated.

To be specific, y_t is the scalar time series variable to be forecasted – spreads and X_t are $N -$ dimensional multiple time series of candidate predictors – all 51 variables (including euro–area variables) from the dataset. It was assumed that (X_t, y_{t+h}) admit a factor model representation with r common latent factors F_t.

Data are available for $\{y_t, X_t, W_t\}_{t=1}^{T}$ and the intention is to forecast y_{T+h}. I allowed error terms to be both serially– and weakly cross–sectionally correlated. Estimated factors including W_t were then used to estimate regression coefficients.

The 3PRF forecasts are based on setting Z_t in (25). The benchmark forecasts are provided by univariate autoregressive models based on (25) excluding Z_t.

7 FORECAST COMPARISON

A variety of simulation experiments are considered to evaluate the empirical performance of one of the forecasting models described. All models are based on out–of–sample forecasting and only in–sample information is used to estimate the factors (Schumacher, 2005, p. 12).

Forecast comparison was conducted in a simulated out–of–sample framework where all statistical calculations were done using a fully recursive methodology. I selected the period after the bankruptcy of the fourth largest US investment bank Lehman Brothers (September 15, 2008) as a representation of out–of–sample or real–time period serving as the time window for the evaluation of pseudo out–of–sample forecasting performance.

Firstly, the models were estimated on data from 2000Q1 to 2008Q2 and h–step ahead forecasts (from 1 to 4) were consequently computed. Secondly, the sample was augmented by one quarter and the corresponding h–quarter ahead forecast was calculated. Pseudo real–time forecasting was 2008Q3 to 2015Q4. Regarding subperiods: 2008Q3–2011Q2, 2011Q3–2013Q4, and 2014Q1–2015Q4, out–of–sample forecasting for four horizons and three–lagged variables was performed, i.e. a total of 48 forecasts.

The forecasting performance of the various methods described was examined by the Relative Mean Square (Forecast) Error (hereinafter: relative MSE). Relative MSE compares the performance of a candidate forecast (forecasting i) to the benchmark autoregressive forecast, where both are computed using the pseudo out–of–sample methodology.

The relative MSE less than one indicates a superior forecasting performance of a model for the chosen forecast horizon $h = 1$. In other words, if the relative MSE of the candidate forecast is less than one, the forecast based on that leading indicator outperforms the AR benchmark. If the relative MSE is smaller than 1, the forecasting squared error generated by the candidate model is generally smaller than that generated by the AR. Specifically, let $\hat{y}_{i,t+h|t}^{h}$ denote the pseudo out–of–sample forecast of $\hat{Y}_{t+h}^{h}$, computed using data through time *t* based on the i^{th} individual indicator.

Let $\hat{Y}_{0,t+h|t}^{h}$ denote the corresponding benchmark forecast using autoregression. As a consequence, the relative MSE of the candidate forecast relative to the benchmark is

$$Relative\ MSE = \frac{\sum_{t=T_1}^{T_2-h}\left(\hat{Y}_{t+h}^{h} - \hat{Y}_{i,t+h|t}^{h}\right)^2}{\sum_{t=T_1}^{T_2}\left(\hat{Y}_{t+h}^{h} - \hat{Y}_{0,t+h|t}^{h}\right)^2} \qquad (27)$$

where T_1 and T_2–h are respectively the first and last dates over which the pseudo out–of–sample forecast is computed (Glažar, Kušar & Masten, 2008, p. 5).

7.1 Testing for Equal Forecast Accuracy

It may be interesting to investigate each forecast horizon and establish whether the differences between the forecasting performances are systematic or not. For the simulation scheme, the test on equal forecast accuracy proposed by Diebold and Mariano (1995) is applied. Therefore, the Diebold–Mariano (hereinafter: DM) test statistics for determining the statistic significance of the superior forecasting performance are used. The relative MSE from the model can be marginally lower than 1, while the superior performance is statistically significant if a model generates a smaller forecasting error than the AR in most periods. The DM test statistics (although based on a non–parametric test statistic) are a frequent and reasonable indicator of a significant difference between two models (Krušec, 2007, p. 59).

The alternative factor models are not tested, therefore Diebold and Mariano's test (1995, pp. 253–263) can be directly applied. The test statistic is constructed as follows: I have two models that both produce forecasts of the spread in period t. The forecasts h periods ahead depend on information available in period $t - h$, and the forecast is the application of the conditional expectation operator $y_{AR,t\ /\ t\ h}$ and $y_{FAR,t\ /\ t\ h}$ for the AR and the FAR model, respectively. A sequence of T forecast errors for both models is calculated.

The DM test for equal forecast accuracy is based on the time series of differences of the squared forecast errors $d_{t,h} = e_{AR,t,h}^2 - e_{FAR,t,h}^2$. Under the null hypothesis, the sample mean is not significantly different from zero.

8 OUT–OF–SAMPLE FORECASTING RESULTS

The results of out–of–sample or pseudo real–time forecasting for each of the selected countries and subperiods at different horizons are presented below. From the whole set of forecasts (96 forecasts: 48 forecasts for the period $2008Q3$ to $2015Q4$; and 48 forecasts for the subperiods), there are 52 forecasts in which the FAR outperforms the baseline AR model, and 44 forecasts where the AR outperforms the FAR model. When observing the period $2008Q3$ to $2015Q4$, the FAR clearly outperforms the AR on 27 occasions. On the other hand, the AR model prevails on 21 occasions. Regarding subperiods, the candidate FAR is more successful at forecasting spreads on 25 occasions, and the benchmark AR model is better on 23 occasions.

Concerning different forecasting horizons, the best results in terms of relative forecasting performance for the 3PRF forecast models are usually for one–step ahead forecasts. The 3PRF outperforms the AR model and can function as a useful complement to the central bank's current forecasting tools, especially at shorter horizons. Furthermore, the proposed data–reduction rule provides superior forecasts at some horizons. The results show that the 3PRF model usually outperforms the AR model. The average gain for one–step ahead forecast, for example, is close to six percent. Furthermore, relative performance of the 3PRF model in the quarterly examples is improved for shorter forecasting horizons. Forecasting results show that the FAR model generally provides smaller relative MSEs than the simple autoregressive.

I investigate whether the differences between the models are systematic or not in each forecast horizon. The results of the DM test statistic show that, on average, the differences in the relative MSE between the factor forecasts and autoregressive forecasts are statistically significant and can be determined. Therefore, the 3PRF forecast performance slightly outperforms the baseline forecasting model.

Empirically, I have found that the following country–specific macroeconomic and fiscal fundamentals are significant in explaining spreads: the GDP growth rate, government expenditure, inflation, hourly earnings in manufacturing and in private sector, government gross debt, industrial production index – construction, producer price index – total durable consumer goods, producer price index – total investment goods, stock prices – stock index, M1, M2, M3, real–effective exchange rate based on manufacturing CPI. International factors, such as exchange rates (US/EUR, CHF/EUR) and one–year EURIBOR are also pivotal. Furthermore, I have found that the effects and significance of country fundamentals have changed notably over time and differ between countries.

The median of the realized spreads is reported in the following Figures (see the green line in Figures.) The values are summarized in Table 17, Subchapter 8.9, together with the highest and the lowest values of realized spreads in the sample period $2000Q1 - 2015Q4$. **All presented figures and tables are the results of my empirical study.**

8.1 Dutch DSL – German Bund 10–Year Spreads

The Netherlands belongs to one of so–called "safe–haven" countries. The Dutch government bond spreads are lower compared to peripheral countries. With very low rate of unemployment, a large and stable current account surplus, low government debt and a budget in surplus, Dutch economy was initially assessed to be relatively well prepared for the financial and economic crisis that arose in mid–2008. In 2008, however, the negative effects of the financial crisis became apparent and economic growth came to a grinding halt. The typical Dutch strengths, such as the funded pension system and the strong position in world trade, then proved to be vulnerabilities in the wake of the crisis and have negatively impacted consumption and investment.

When examining the crisis period, it can be concluded that the Netherlands stayed in a relatively good shape, most importantly because of its flexible labour market and limited dependency on foreign capital. This is the crucial distinction from France, the second core euro-area country, where dependency on foreign capital is at a very high level. Consequently, the Dutch 10–year government bond spreads stay "relatively low" compared to France, Italy, and Spain.

Figures 6 and 7 show movements of the DSL/Bund spreads, where pseudo real–time forecasting begin in the 34th quarter. The following three periods: 2008*Q3–2011Q2, 2011Q3–2013Q4* and *2014Q1–2015Q4* mark movements of Dutch spreads. In all periods, spreads exceed a relatively normal level. Figures 6 and 7 show, that the FAR model displays the best performance for shorter forecasting horizons (i.e., one– and two–steps ahead) as well as for larger horizons (i.e., three– and four–steps ahead).

Figure 6. Forecasting Dutch DSL – Bund 10–Year Spreads h=1, 2008Q3–2015Q4

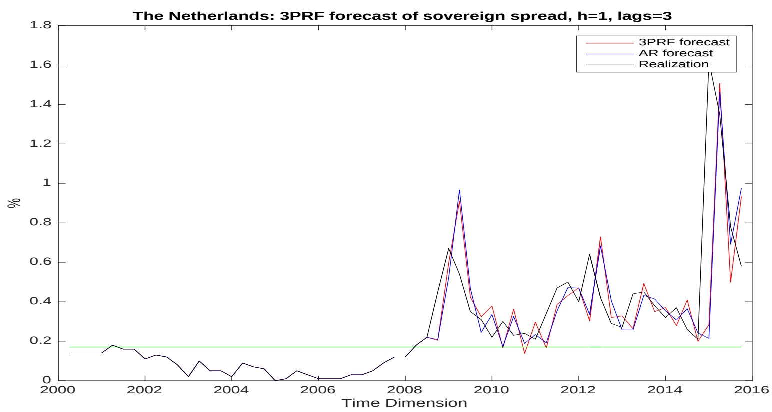
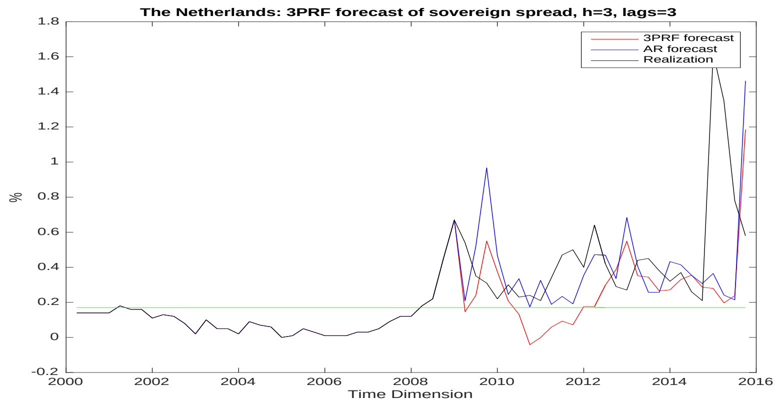


Figure 7. Forecasting Dutch DSL – Bund 10–Year Spreads h=3, 2008Q3–2015Q4



The results of forecasting performance for the Netherlands are displayed in Table 4. The details on which proxy produced the best forecast for each forecast horizon and for different number of lagged variables, relative MSE of the best forecasting model, trace R^2, and the DM test statistics for accuracy of forecast are summarized. The t–statistics of the DM test for forecast accuracy are shown in the fourth column. Figures in italics indicate that the statistic is statistically significant at 10 % significance level.

There are several interesting results in Table 4. Firstly, the FAR model using the 3PRF outperforms the benchmark AR model at all horizons: eleven forecasts out of twelve, show that the FAR model is more effective compared to the AR model when predicting movements of Dutch spreads.

Table 4. Forecasting Performance: the Netherlands

Horizon	*Lagged Variables*	*rMSE*	*DM**	*Trace R^2*	*Gain (%)***	*Proxy*
h=1	3	0.95	*1.72*	0.56	4.17	Hourly Earnings: Private Sector
h=2	3	0.99	*1.84*	0.32	9.05	REER
h=3	3	0.99	*1.74*	0.27	0.68	Employment Rate (15–64)
h=4	3	1.04	*-1.81*	0.27	-4.52	Employment Rate (15–64)
h=1	4	0.96	0.44	0.56	3.35	IPI: Total Industry
h=2	4	0.56	0.12	0.32	1.32	GDP Growth Rate
h=3	4	0.98	*1.69*	0.26	1.82	GDP Growth Rate
h=4	4	0.98	*1.66*	0.26	1.45	Hourly Earnings: Private Sector
h=1	5	0.99	0.39	0.57	1.37	Hourly Earnings: Private Sector
h=2	5	0.97	0.39	0.57	1.28	PPI: Nondurable Consumer Goods
h=3	5	0.96	*1.94*	0.33	0.40	M1
h=4	5	0.99	*1.93*	0.31	0.49	Hourly Earnings: Manufacturing

*Diebold–Mariano test statistic. Italic figures indicate rejection of the null of equal predictive accuracy at 10% significance level respectively.
** Gain: gain in forecasting precision

For one–quarter horizon, the best FAR model with three lagged variables is the one using hourly earnings in private sector as 3PRF factor proxy, with a 4.17 % gain in forecasting precision (see the sixth column in Table 4). When lagged variables are added (four and five) for horizon $h=1$, the FAR model is still more effective. Relative MSE is closer to 1, but still beneath (see the third column in Table 4).

The FAR model shows an improvement compared to the AR, with a relative MSE ranging from 0.56 to 0.99. If I forecast with four lagged variables, the proxy producing the best forecast will become industrial production index: total industrial production. In the case of five lagged variables, the proxy producing the best forecast is again hourly earnings in private sector.

Hourly earnings in private sector, employment rate (15–64), industrial production index: total industrial production and producer price index became the most important determinants of the Dutch government bond spreads after the financial crisis in 2008 (see the seventh column in Table 4). Forecasting of DSL/Bund spreads for all forecast horizons indicates that the FAR model using the 3PRF is clearly superior to the AR model (see the sixth column in Table 4).

26 % to 57 % of the total panel variability of 51 predictors is clarified by the best predictor for different forecast horizons (see the fifth column in Table 4.) In one–quarter ahead forecasting, the proxy producing the best forecast of the Dutch government bond spreads clarifies 56.15 % to 57.08 % of the total panel variability of 51 predictors, in two–quarters ahead forecasting 32 % to 57 %, in three–quarters ahead forecasting 26 %, 27 % and 33 %, and in four–quarters ahead forecasting 26 %, 27 % and 31 % of the total panel variability of 51 predictors (see the fifth column in Table 4).

Statistically significant differences in forecast accuracy could be determined (see the fourth column in Table 5). The results show that the differences in relative MSE between the factor forecasts and autoregressive forecasts are statistically significant. Therefore, the 3PRF forecast performance in the Dutch dataset outperforms the baseline forecasting model. In other words, the 3PRF approach proposed by Kelly and Pruitt (2014) seems to outperform the baseline forecast model systematically. The 3PRF lead me to the conclusion that in comparison to the EU–15, the Netherlands retained its strength during the period of global financial crisis, the period of crisis and Greek referendum, plausibly due to its high degree of labour market flexibility and low dependency on foreign capital.

8.2 Italian BTP – German Bund 10–Year Spreads

The financial crisis will likely have a long–lasting impact on Italy’s economic potential. The Italian economy suffered the worst recession since World War II. Italy has suffered from chronically low economic growth, even before the global financial crisis in 2008. Before the crisis the Italian economy underperformed most of its Euro Area peers. Italy’s GDP moved gradually away from the EU–15 benchmark with the average annual growth almost 1 percent point lower than the average EU–15. Italy’s dismal growth performance was largely due to poor productivity.

Breaking down the GDP growth into labor, capital and total factor productivity (hereinafter: TFP), contributions show that the Italian economy’s anemic growth was mostly explained by the declining TFP. In fact, the TFP contributions decreased substantially over the pre–crisis period: a slowdown which was pervasive across all sectors, especially pronounced in manufacturing and non–tradable sectors. Despite strong household balance sheets, private consumption also declined significantly, possibly reflecting uncertainty, rising unemployment, and tighter consumer credit, and was only marginally offset by the modest rise in government consumption (Morsy & Sgherri, 2010, pp. 3–10). As a result, the Italian government bond yield spreads movements are significantly impacted, and the following figures clearly denote that. But which are the most influential and essential drivers? Figures 8 and 9 show, that the FAR model portrays the best performance for shorter forecasting horizons (i.e., one– and two–steps ahead), whereas larger horizons (i.e., three– and four–steps ahead) are dominated by the AR models.

Figure 8. Forecasting Italian BTP – Bund 10–Year Spreads h=1, 2008Q3–2015Q4

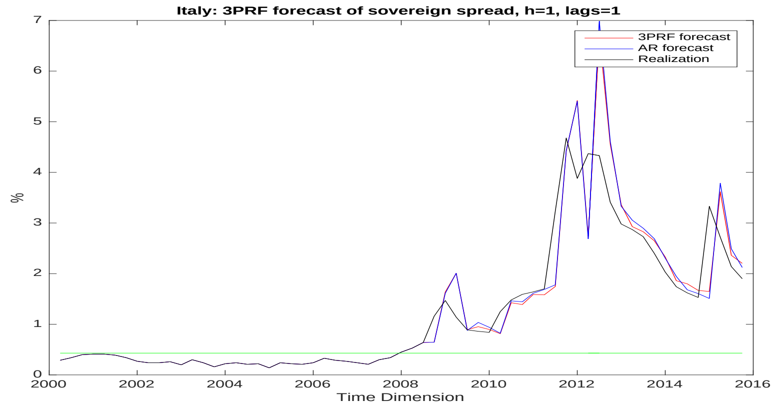
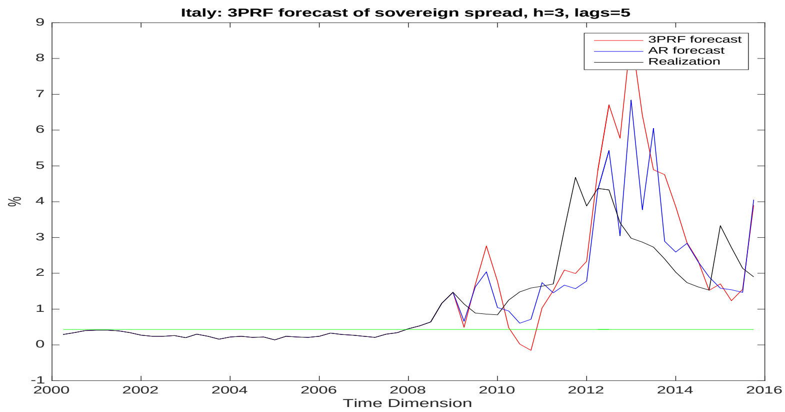


Figure 9. Forecasting Italian BTP – Bund 10–Year Spreads h=3, 2008Q3–2015Q4



According to Figures 8 and 9, volatility in Italian spreads has increased since the middle of 2011. The European debt crisis and country–specific macroeconomic and fiscal events were important drivers of Italian spreads. Sovereign spreads tightened for a short period of time in spring 2012, after the 3–year Long Term Refinancing Operations (hereinafter: LTRO), but then widened in July 2012.

The results of forecasting performance for Italy are reported in Table 5. Summarized are the details on which proxy produced the best forecast for each forecast horizon and for different numbers of lagged variables, the relative MSE of the best forecasting model, trace R^2, and the DM test statistics for accuracy of forecast. The t–statistics of the DM test for forecasts accuracy are shown in the fourth column. Figures in italics indicate that the statistic is statistically significant at 10 % significance level.

Table 5. Forecasting Performance: Italy

Horizon	*Lagged Variables*	*rMSE*	*DM**	*Trace R^2*	*Gain (%)***	*Proxy*
h=1	3	0.90	*0.52*	0.90	9.51	CHF/EUR
h=2	3	0.90	*1.69*	0.90	9.04	CHF/EUR
h=3	3	1.94	*-1.91*	0.76	-88.78	M1
h=4	3	3.29	-1.23	0.68	-222.98	M1
h=1	4	0.88	1.28	0.90	11.54	CHF/EUR
h=2	4	1.07	-1.19	0.76	- 7.00	M1
h=3	4	1.73	*-1.81*	0.69	-73.30	M1
h=4	4	3.53	*-1.94*	0.70	-246.06	US/EUR
h=1	5	0.88	1.32	0.90	11.34	CHF/EUR
h=2	5	0.94	-1.14	0.76	5.29	M1
h=3	5	1.71	*-1.82*	0.69	-71.81	M1
h=4	5	3.60	*-1.90*	0.70	-260.19	CHF/EUR

*Diebold–Mariano test statistic. Italic figures indicate rejection of the null of equal predictive accuracy at 10% significance level respectively.
** Gain: gain in forecasting precision

There are several interesting results to be found in Table 5. Firstly, the FAR model using the 3PRF outperforms the benchmark AR model only at short horizons (i.e., one– and two–step ahead): five forecasts out of twelve portray that the FAR model is more effective compared to the AR model when predicting movements of Italian spreads. In one–quarter ahead forecasting, the best FAR model with three lagged variables is the one using the exchange rate CHF/EUR as the 3PRF factor proxy, with 9.51 % gain in forecasting precision (see the sixth and the seventh column in Table 5).

The performance results of the FAR model still dominate the AR model when I add additional lag and forecast for one– and two– quarters ahead. The relative MSE using a spread as proxy is now marginally higher, that is between 0.88 and 0.94. Forecasting one–quarter ahead with four and five lagged variables, the exchange rate CHF/EUR is still the 3PRF proxy producing the best forecast.

Forecasting three– and four–quarters ahead with four and five lagged variables M1 became the most important driver of Italian spreads (see the seventh column in Table 5). The results surprisingly show the importance of liquidity, cash, and short–term deposits as determinants of Italian government bond spreads during global financial turmoil – the significance of the M1 as a metric for money supply of Italy and includes physical money as well as checking accounts, demand deposits and negotiable order of withdrawal accounts for movements of Italian BTP/Bund spreads.

It is also noticeable that when M1 acts as a proxy producing the best forecast, the benchmark AR model predicts the best movements of BTP/Bund spreads. At horizons 3 and 4, the AR model outperforms the candidate FAR. In three– and four–quarters ahead forecasting, the role of monetary aggregates, especially of M1 (see the seventh column in Table 5), became even more evident.

Financial fundamentals after the financial crisis in 2008, such as M1 and exchange rate CHF/EUR became essential determinants of Italian spreads, signifying the importance of liquidity and monetary certainty when explaining the movement of spreads during the crisis. The three– and four–quarters ahead forecast of BTP/Bund spreads indicates that the FAR is losing performance compared to the AR (see the sixth column in Table 5).

68 % to 90 % of the total panel variability of 51 predictors is clarified by the best predictor for different forecast horizons (see the fifth column in Table 5.). In one–quarter ahead forecasting, the proxy producing best forecast of Italian spreads clarifies around 90 % of the total panel variability of 51 predictors, in two–quarters ahead 76 % and 90 %, in three–quarters ahead 69 % and 76 %, and in four–quarters ahead forecasting, the proxy producing the best forecast of Italian spreads clarifies around 70 % of the total panel variability of 51 predictors (see the fifth column in Table 5).

Statistically significant differences in forecast accuracy could be determined in only a few cases (see the fourth column in Table 5). Overall, the results show that the differences in relative MSE between the factor forecasts and autoregressive forecasts on average are statistically significant. Therefore, the 3PRF forecast performance in the Italian dataset is slightly outperforms the baseline forecasting model. In other words, the 3PRF approach proposed by Kelly and Pruitt (2014) seems to outperform the baseline forecast model systematically. I have observed an increase in the relative MSE through higher forecast horizons, and with this, a lower gain in forecasting precisions of the FAR model.

8.3 French OAT – German Bund 10–Year Spreads

The impacts of the financial crisis in 2008 and the sovereign debt crisis in 2012 affected the French GDP and its components. Company collapses caused higher unemployment rates and lower income therefore people had to adapt their spending. Gross fixed capital formation has fluctuated more than in other core EMU countries. The situation in government gross debt was not the crucial driver of higher spreads values, such as devaluation of the American dollar compared to the Euro, which makes American goods less expensive than French goods.

Figures 10 and 11 show, that the FAR model portrays the best performance for shorter forecasting horizons (i.e., one– and two–steps ahead), whereas larger horizons (i.e., three– and four–steps ahead) are dominated by the AR models.

Figure 10. Forecasting French OAT – Bund 10–Year Spreads h=1, 2008Q3–2015Q4

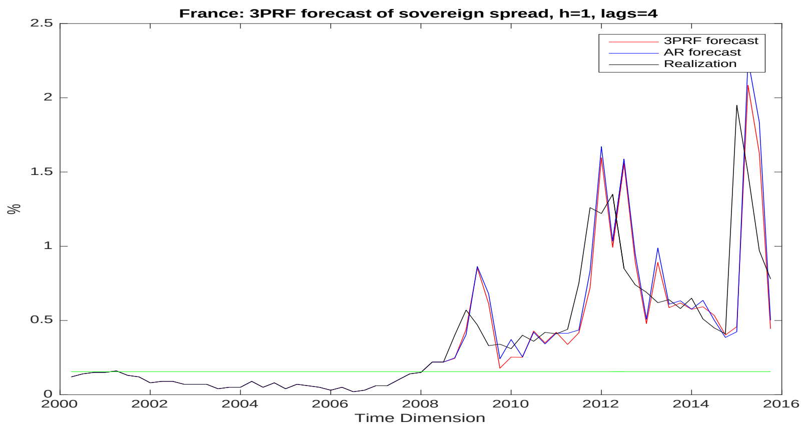
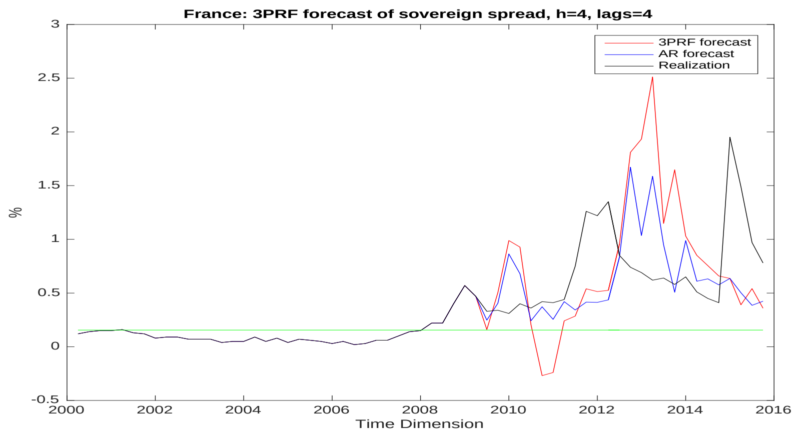


Figure 11. Forecasting French OAT – Bund 10–Year Spreads h=4, 2008Q3–2015Q4



French export and import enormously decreased and its spreads increased again in the middle of 2011 as a response to growth slowdown and financial turmoil (see Figures 10 and 11). The government debt as a percentage of the GDP was higher and French fiscal position was disadvantageous.

The results of forecasting performance for France are displayed in Table 6. The details on which proxy produced the best forecast for each forecast horizon and for different number of lagged variables, relative MSE of the best forecasting model, trace R^2, and the DM test statistics for accuracy of forecast are summarized. The t–statistics of the DM test for forecast accuracy are shown in the fourth column. Figures in italics indicate the significance of the statistic. Bold figures (and italic figures) indicate that the statistic is significant at 5 % (and 10 %) significance level.

There are several interesting results to be found in Table 6. Firstly, the FAR model using the 3PRF outperforms the benchmark AR model only at short horizons (i.e., one– and two–step ahead): eight forecasts out of twelve portray that the FAR model is more effective compared to the AR model when predicting movements of French spreads.

Table 6. Forecasting Performance: France

Horizon	*Lagged Variables*	*rMSE*	*DM**	*Trace R^2*	*Gain (%)***	*Proxy*
h=1	3	0.97	*1.65*	0.71	2.84	US/EUR
h=2	3	0.94	*1.65*	0.71	5.16	US/EUR
h=3	3	1.10	-0.64	0.54	-10.13	M2
h=4	3	0.91	1.28	0.69	8.40	M2
h=1	4	0.89	***1.99***	0.72	10.99	US/EUR
h=2	4	0.90	*1.69*	0.72	9.85	CHF/EUR
h=3	4	0.96	1.22	0.49	3.42	M1
h=4	4	1.41	*-1.68*	0.45	- 41.03	M2
h=1	5	0.97	1.62	0.72	2.58	US/EUR
h=2	5	0.92	**1.99**	0.50	9.46	M3
h=3	5	1.14	-0.70	0.46	-14.46	M3
h=4	5	1.40	*-1.72*	0.51	- 40.02	CHF/EUR

*Diebold–Mariano test statistic. Bold and italic figures indicate rejection of the null of equal predictive accuracy at 5% and 10% significance levels respectively.
** Gain: gain in forecasting precision

The most important drivers of French spreads movements during the global financial crisis became exchange rates US/EUR and CHF/EUR, M1, M2, and M3 (see the seventh column in Table 6). International factors, liquidity, price certainty, long–term deposits, savings deposits, market securities, mutual funds, other time deposits, such as M2, and liquid instruments, such as M3, have become drivers of French spreads. Economists have found close links between money supply, inflation and interest rates. Central banks use lower interest rates to increase the money supply when they want to stimulate the economy.

Conversely, in an inflationary setting, interest rates are raised and the money suplly diminishes, leading to lower prices. In simple terms, if there is more money to go around, the economy tends to accelerate, with businesses having easy drop or stop rising. In this context, broad money is one of the measures that central bankers use to determine waht interventions, if any, they choose to make in the economy. This is thoroughly presented in Table 6. For one–quarter horizon the best FAR model with three lagged variables is the one using exchange rate US/EUR as 3PRF factor proxy, with a 2.84 % gain in forecasting precision (see the sixth and the seventh column in Table 6).

The FAR model outperformed the AR model when I added an additional lagged variable for one– and two–quarters ahead forecast. The FAR model outperforms the AR model by 10.99 % and 9.85 % (see the sixth column in Table 6). Relative MSE of the best model is now marginally lower, between 0.89 and 0.90. In one– and two–quarters ahead forecasting, the best FAR model with four lagged variables is the one using the exchange rates US/EUR and CHF/EUR as 3PRF factor proxy. In three– and four–quarters ahead forecasting, the best FAR model with four and five lagged variables is the one using the exchange rates US/EUR and CHF/EUR, and monetary aggregates M1, M2, and M3 as a 3PRF factor proxy (see the seventh column in Table 6).

The results surprisingly show the importance of exchange rates, liquidity, cash and short–term deposits, two–year maturity deposits, and marketable instruments issued by the

Monetary Financial Institutions (hereinafter: MFIs) sector. These were the determinants of French government bond spreads during global financial turmoil.

45 % to 72 % of the total panel variability of 51 predictors is clarified by the best predictor for different forecast horizons (see the fifth column in Table 6). In one–quarter ahead forecasting, the proxy producing the best forecast of the French spreads clarifies around 72 % of the total panel variability of 51 predictors; in two–quarters ahead 50 %, 71 % and 72 %; in three–quarters ahead 46 %, 49 % and 54 %; and in four–quarters ahead 45 %, 51 % and 69 % of the total panel variability of 51 predictors (see the fifth column in Table 6). I have observed an increase in the relative MSE through higher forecast horizons, and with this, a lower gain in forecasting precisions of the FAR model (see the third and the sixth column in Table 6).

Statistically significant differences in forecast accuracy could be determined in only a few cases (see the fourth column in Table 6). Overall, the results show that the differences in relative MSE between the factor forecasts and autoregressive forecasts on average are statistically significant. Therefore, the 3PRF forecast performance in the French dataset is slightly outperforms the baseline forecasting model. In other words, the 3PRF approach proposed by Kelly and Pruitt (2014) seems to outperform the baseline forecast model systematically.

8.4 Spanish – German 10–Year Bond Yield Spreads

The recent widening in Spanish spreads is being driven by specific factors apart from prevailing political uncertainty. Although political uncertainty is an important driver of increasing spreads in the Spanish government bond market – the surrounding regional Catalan elections in September 2015 – a *de facto* referendum – here I am observing macroeconomic and fiscal drivers of spreads, the explanations for political situation, and the events connected with it.

The Spanish government bond spreads are associated with an enormous government debt, government expenditure, negligible GDP growth rate, and particularly with M1. In 2008, before the Great Recession, Spain's government gross debt was as low as 39.06 % due to rising tax revenues from the real estate bubble to cover increasing government expenditure. The Great Recession led to the real estate bust. Spanish banks went through financial turmoil due to violating accounting standards, hiding losses, misleading regulators and investors, and avoiding government supervision. With the help of the "Troika", the Spanish government had to bail out large banks and incur a huge government debt. The public debt reached 104.52 % in 2014Q2. In addition to that, the Spanish government bonds were downgraded several times from 2010 to 2012, leading to a higher borrowing cost. A relatively high debt is expected to affect the long–term interest rate as the government is competing for limited funds with the private sector.

Spain is the only country where the benchmark AR model outperforms the candidate FAR model. This is represented in the Figures below (Figures 12 and 13) – evidently showing that the AR is better at predicting Spanish government bond spreads movements. According to Figures 12 and 13, neither the AR model nor the FAR using the 3PRF, are able to predict the largest increases in spreads during the financial turmoil period in 2012 and 2013. This applies to forecasts at all horizons except for one–quarter ahead.

Figure 12. Forecasting Spanish – German 10–Year Spreads, h=1, 2008Q2–2015Q4

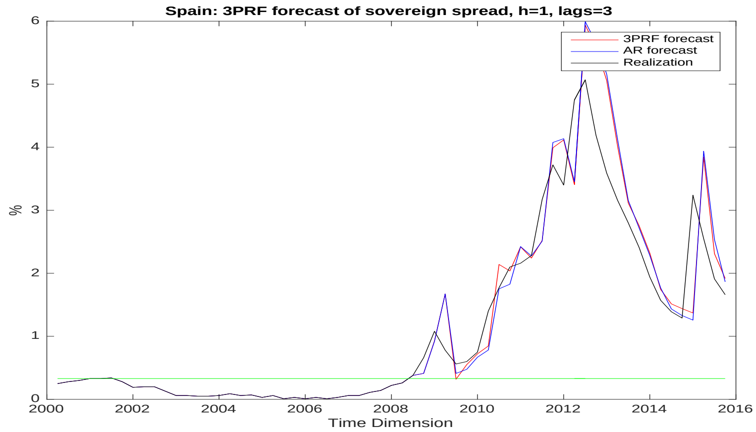
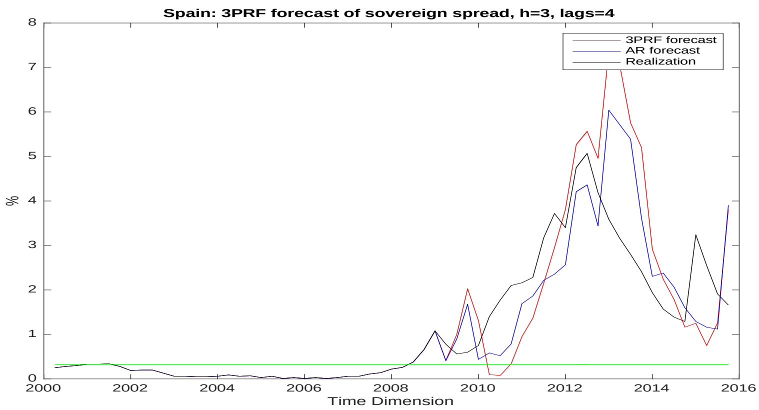


Figure 13. Forecasting Spanish – German 10–Year Spreads, h=3, 2008Q3–2015Q4



The results of forecasting performance for Spain are displayed in Table 7. The details on which proxy produced the best forecast for each forecast horizon and for different number of lagged variables, relative MSE of the best forecasting model, trace R^2, and the DM test statistics for accuracy of forecast are summarized. The t–statistics of the DM test for forecast accuracy are shown in the fourth column. Figures in italics indicate the significance of the statistic. Bold figures (and italic figures) indicate that the statistic is significant at 5 % (and 10 %) significance level.

There are several interesting results in Table 7. Firstly, the FAR model using the 3PRF does not outperform the benchmark AR model: neither at short horizons (i.e., one– and two–steps ahead) nor at longer (i.e., three– and four– steps ahead): according to 12 forecasts, the FAR model is only 3–times better at predicting movements of Spanish spreads compared to the AR model.

Table 7. Forecasting Performance: Spain

Horizon	*Lagged Variables*	*rMSE*	*DM**	*Trace R^2*	*Gain (%)***	*Proxy*
h=1	3	0.91	0.34	0.91	8.21	REER
h=2	3	0.94	0.45	0.80	6.89	Government Gross Debt
h=3	3	1.54	*-1.91*	0.73	-54.30	GDP Growth Rate
h=4	3	2.68	**-2.31**	0.73	-167.56	Government Expenditure
h=1	4	0.92	0.95	0.92	7.84	CHF/EUR
h=2	4	1.37	-0.89	0.80	-31.90	GDP Growth Rate
h=3	4	1.70	*-1.64*	0.73	-70.95	PPI: Total Investment Goods
h=4	4	3.10	-1.42	0.75	-210.22	Government Expenditure
h=1	5	1.08	0.62	0.92	-8.89	REER
h=2	5	1.26	-0.91	0.86	- 26.23	Government Gross Debt
h=3	5	1.58	-1.32	0.73	-58.77	PPI: Total Investment Goods
h=4	5	2.97	*-1.69*	0.75	-197.51	GDP Growth Rate

* Diebold–Mariano test statistic. Bold and italic figures indicate rejection of the null of equal predictive accuracy at 5% and 10% significance levels respectively.
** Gain: gain in forecasting precision

As presented in Table 7, Spanish spreads are mostly determined by general government gross debt, government expenditure, GDP growth rate, and producer price index: total investment goods and real–effective exchange rate (see the seventh column in Table 7). In one–quarter ahead forecasting, the best FAR model with three lagged variables is the one using real–effective exchange rate based on manufacturing CPI as a 3PRF factor proxy, with an 8.21 % gain in forecasting precision (see the sixth and the seventh column in Table 7). For the two–quarter horizon the best FAR model with three lagged variables is the one using government gross debt as a 3PRF factor proxy, with an 6.89 % gain in forecasting precision (see the sixth and the seventh columns in Table 7).

The AR model drastically outperforms the FAR model when I add an additional (four and five) lagged variable in two–, three–, and four–quarters ahead forecasting. The AR model largely outperforms the candidate FAR model (see the sixth column in Table 7): from 31.90 % (four lagged variables, two–steps ahead) and 58.77 % (five lagged variables, three–steps ahead) to 210.22 % (four lagged variables, four–steps ahead). 73 % to 92 % of the total panel variability of 51 predictors is clarified by the best predictor for different forecast horizons (see the fifth column in Table 7. In one–quarter ahead forecasting, the proxy producing the best forecast clarifies around 90 % of the total panel variability of 51 predictors; in two–quarters ahead 80 % and 86 %; in three–quarters ahead 73 %; and in four–quarters ahead forecasting around 75 % of the total panel variability of 51 predictors (see the fifth column in Table 7). I have observed an increase in the relative MSE through higher forecast horizons, and with this, a lower gain in forecasting precisions of the FAR model (see the first, the second, the third and the sixth column in Table 6).

The 3PRF forecasts have a worse performance in terms of relative MSE (see the third column in Table 6) – the statistically significant differences in forecast accuracy are not immense and systematic (see the fourth column in Table 7). Despite the conceptual and theoretical advantages of the 3PRF model, its forecast performance for Spain is considerably weaker than the baseline forecasting model, the AR model. In other words, the results show that the differences in relative MSE between the factor forecasts and autoregressive forecasts are not statistically significant. Therefore, the 3PRF forecast performance does not outperform the baseline forecasting model – the 3PRF approach does not outperform the baseline AR forecast model systematically.

An interesting result is that the recent 15–years of widening of Spanish 10–year *Bonos y Obligaciones del Estado* over the German 10–year *Bunds* yields was so high determinate with the real–effective exchange rate. The object of focus here are the relative prices in manufacturing. Manufactory's price competitiveness got the principal role in explaining Spanish spreads one–quarter ahead. When Spanish manufactory trading partners became more competitive compared to Spanish manufactory producers, Spanish government bond spreads increased largely.

The GDP growth rate is the second driver of Spanish spreads. It is necessary to check trends in four components of the GDP in order to explain its effects on spreads. With the beginning of the Great Depression in 2008, personal consumption, including retail sales, dropped significantly; business investment, including construction and inventory levels, practically stopped. The Spanish government was very extremely uneconomical. Export and import of Spanish goods and services decreased due to value of Euro. While export causes growth, import has a negative impact. Spanish consumers have less money to spend on purchases. The reason for Spanish negative GDP and the contraction of economy was described. As a consequence, Spanish spreads have been jumping. Spanish spreads increased enormously as a result of the country's higher total gross government debt and the changes in government debt over time, which reflects the impact of government deficits. Spanish spreads are an indicator of Spanish economy's bad health and unsustainability of Spanish government finance.

8.5 The Netherlands: Subperiods

Results for the Netherlands report, that the candidate FAR model largely outperforms the benchmark AR model. According to 12 forecasts (subperiods), "quasi" out–of–sample forecasting shows that the FAR is 7–times better at predicting movements of Dutch spreads. Tables 8 and 9 reported the results from out–of–sample forecasting DSL/Bund spreads based on different subperiods and forecast horizons $h = 1,2$. The results for forecast horizons $h = 3,4$ are summarized in Appendix B. Tables 8 and 9 show which 3PRF proxy produces the best forecast for each horizon, relative MSE of the best model, trace R^2, and the DM test statistics for accuracy of forecast. The t–statistics of the DM test for forecast accuracy are shown in the seventh column. In one–step ahead observation, DSL/Bund spreads during Lehman's crisis were identified by the industrial production index – manufacturing, while the consumer credit as monetary aggregate portrays the best movements from July 2011 to October 2013, and from January 2014 to October 2015 (see the third column in Table 8). For the same subperiods and for the forecast horizon $h = 2$ GDP, the 3PRF proxy in the first subperiod is the growth rate, in the second subperiod the exchange rate CHF/EUR, and in the third subperiod the REER. Relative MSE of the best model is lower than one except for the subperiod $2008Q3$–$2011Q2$, where the AR model outperforms the candidate FAR model (see the third column in Table 8).

Table 8. The Netherlands: Subperiods and Forecast Horizon h=1

Forecast horizon	*Time dimension*	*Proxy producing best forecast*	*Gain* (%)*	*rMSE*	*Trace R^2*	*DM***
h=1	2008:3–2011:2	IPI:Manufacturing	4.22	0.95	0.56	0.52
h=1	2011:3–2013:4	Consumer Credit	4.1	0.96	0.58	0.84
h=1	2014:1–2015:4	IPI:Manufacturing	4.77	0.95	0.56	0.56

* Gain: gain in forecasting precision

** Diebold–Mariano test statistic

*** Forecasts with 3 lagged variables

Table 9. The Netherlands: Subperiods and Forecast Horizon h=2

Forecast horizon	*Time dimension*	*Proxy producing best forecast*	*Gain* (%)*	*rMSE*	*Trace R^2*	*DM***
h=2	2008:3–2011:2	GDP Growth Rate	-9.05	1.09	0.32	-0.72
h=2	2011:3–2013:4	CHF/EUR	13.85	0.86	0.33	*1.76*
h=2	2014:1–2015:4	REER	14.74	0.89	0.27	*1.87*

* Gain: gain in forecasting precision

** Diebold–Mariano test statistic. Italic figures indicate rejection of the null of equal predictive accuracy at 10% significance levels respectively.

*** Forecasts with 3 lagged variables

Results suggest that during the global crisis in 2008 and the European debt crisis at the end of 2009, the height of the government gross debt, government expenditure, and the GDP growth rate did not seem to largely affect the DSL/Bunds and monetary aggregates. This is a crucial distinction in comparison to the peripheral countries. With the beginning of the global crisis the most important drivers of the Dutch spreads became the industrial production index – the construction and hourly earnings in the private sector. The FAR model outperforms the AR model at around 4.22 % and 14 % (see the fourth column in Tables 8 and 9). The remaining empirical results for subperiods are summarized in the Appendix B.

8.6 Italy: Subperiods

Results for Italy report, that the candidate FAR model largely outperforms the benchmark AR model. According to 12 forecasts (subperiods), "quasi" out–of–sample forecasting shows that the FAR is 7–times better at predicting movements of Italian spreads. Tables 10, 11 and 12 reported the results of out–of–sample forecasting for Italian spreads relative to the German Bunds based on different subperiods and forecast horizons $h = 1, 2, 4$. The results of horizon $h = 4$ are summarized in Appendix B.

Tables 10, 11 and 12 show which 3PRF proxy produces the best forecast for each horizon, relative MSE of the best model, trace R^2, and the DM test statistics for accuracy of forecast. The t–statistics of the DM test for forecast accuracy are shown in the seventh column.

In one–quarter ahead forecasting, Italian spreads during Lehman's crisis are identified by the M1, while hourly earnings in manufacturing explain the best movements of Italian spreads from July 2011 to October 2013. From January 2014 to October 2015, the most important driver of spreads was the real–effective exchange rate based on manufacturing CPI. For the same subperiods and for the forecast horizon $h = 2$ M1 is the proxy producing best forecast for the first subperiod, the hourly earnings in private sector for the second subperiod, and the hourly earnings in manufacturing the best explains spreads for the third subperiod (see the third column in Tables 10, 11 and 12). Relative MSE is lower than one except for the subperiods $2008Q3$–$2011Q2$, where the AR model outperforms the candidate FAR model in one– and two–quarters ahead forecasting.

When observing three–quarters ahead, the 3PRF proxy in the first subperiod is the GDP growth rate, in the second subperiod hourly earnings in manufacturing, and M1 in the third subperiod. In four–quarters ahead forecasting, general government gross debt, government expenditure, and GDP growth rate are the 3PRF proxies. After the debt crisis and Greek referendum, these determinants became the most important drivers of Italian spreads – a large amount of government expenditure, low GDP growth rate and every quarter deeper government gross debt are sources of higher increases in Italian spreads.

Forecasting performance of the FAR model is clearly seen, but regarding Italy, there is a clearly evidence that the AR is a better forecast model with the 3PRF proxy as a financial variable. The FAR model outperforms the AR model between 2.00 % and 9.36 % $(\mathrm{h} = 1)$ at around 10.28 % and 25.20 % $(\mathrm{h} = 2)$ and at around 5.05 % and 10.98 % $(\mathrm{h} = 3)$ (see the fourth column in Tables 10, 11 and 12).

Table 10. Italy: Subperiods and Forecast Horizon h=1

Forecast horizon	*Time dimension*	*Proxy producing best forecast*	*Gain (%)*	*rMSE*	*Trace R^2*	*DM***
h=1	2008:3–2011:2	M1	- 1.45	1.01	0.80	-0.31
h=1	2011:3–2013:4	Hourly Earnings: Manufacturing	2.00	0.98	0.90	0.66
h=1	2014:1–2015:4	REER	9.36	0.90	0.99	1.53

* Gain: gain in forecasting precision

** Diebold─Mariano test statistic

*** Forecasts with 3 lagged variables

Table 11. Italy: Subperiods and Forecast Horizon h=2

Forecast horizon	*Time dimension*	*Proxy producing best forecast*	*Gain* (%)*	*rMSE*	*Trace R^2*	*DM***
h=2	2008:3–2011:2	M1	-20.2	1.2	0.76	*-1.8*
h=2	2011:3–2013:4	Hourly Earnings: Private Sector	10.28	0.89	0.76	*1.73*
h=2	2014:1–2015:4	Hourly Earnings: Manufacturing	25.2	0.75	0.76	**1.95**

* Gain: gain in forecasting precision

** Diebold─Mariano test statistic. Bold and Italic figures indicate rejection of the null of equal predictive accuracy at 5% and 10% significance levels respectively.

*** Forecasts with 3 lagged variables

Table 12. Italy: Subperiods and Forecast Horizon h=4

Forecast horizon	*Time dimension*	*Proxy producing best forecast*	*Gain* (%)*	*rMSE*	*Trace R^2*	*DM***
h=4	2008:3–2011:2	Gov. Gross Debt	10.98	0.89	0.69	*1.93*
h=4	2011:3–2013:4	Government Expenditure	5.05	0.94	0.69	0.55
h=4	2014:1–2015:4	GDP Growth Rate	-6.15	1.06	0.63	**3.29**

* Gain: gain in forecasting precision

** Diebold–Mariano test statistic. Bold and Italic figures indicate rejection of the null of equal predictive accuracy at 5% and 10% significance levels respectively.
*** Forecasts with 3 lagged variables

8.7 France: Subperiods

Results for France report that the candidate FAR model outperforms the benchmark AR model in 50 % of the forecasts. According to 12 forecasts (subperiods), "quasi" out–of–sample forecasting shows that the FAR is 6–times better at predicting movements of French spreads compared to the AR model.

Tables 13 and 14 reported results of out–of–sample forecasting of French spreads based on different subperiods and forecast horizons $h = 1, 3$. The results of horizons $h = 3, 4$ are summarized in Appendix B. Tables 13 and 14 show which 3PRF proxy produces the best forecast for each horizon, relative MSE of the best model, trace R^2, and the DM test statistics for accuracy of forecasts. The t–statistics of the the DM test for forecast accuracy are shown in the seventh column.

10–year (one–quarter ahead) French – German Bund spreads during Lehman's crisis are identified with the exchange rate CHF/EUR. Meanwhile, the US/EUR indicates the best movements of OAT/Bund spreads from July 2011 to October 2013, and from January 2014 to October 2015. The 3PRF proxies for the same subperiods and for the forecast horizon $h = 2$ are: M1 for the first subperiod, government expenditure for the second subperiod, and producer price index: total durable consumer goods for the third subperiod. In all cases, relative MSE is lower than one except for the subperiod 2008Q3–2011Q2, where the baseline AR model outperforms the candidate FAR model (see the third and fifth column in Tables 13 and 14). In three–quarters ahead forecasting, there are the same 3PRF proxies. For higher forecast horizons, performance of the FAR is not clearly seen (see the Appendix B).

With the beginning of the global crisis, exchange rates US/EUR and CHF/EUR, government expenditure, and producer price index: total durable consumer goods, became the most important drivers of French spreads, in contrast to the Netherlands, the first core country which is less dependent on foreign capital.

French spreads increased enormously in the middle of 2012 and in the first quarter of 2015. The primary sources were the movements in the exchange rate US/EUR – the depreciation of the US dollar indicates that American goods and services were less expensive compared to the French (European). French export of goods and services decreased; consequently, French spreads increased.

The upswing in French spreads is also explained with changes in the producer price index: the total durable consumer goods. However, weak consumer demand along with past appreciation of the Euro and external competition, have moderated these pressures. Producer prices have impacted the consumer price inflation. As the average price for durable consumer goods has changed from the previous month, the producer price index determined French spreads during the past periods. This phenomenon is presented in Tables below. The FAR model outperforms the AR between 5.67 % and 7.36 % (h = 1) and at around 34.45 % (h = 3) while the baseline model makes better forecasts. These amounts are at 16.04 % and 22.87 % (h = 3) and around 67.50 % (h = 4) (see the fourth column in Tables 13 and 14 and Appendix B).

Table 13. France: Subperiods and Forecast Horizon h=1

Forecast horizon	*Time dimension*	*Proxy producing best forecast*	*Gain* (%)*	*rMSE*	*Trace R^2*	*DM***
h=1	2008:3–2011:2	CHF/EUR	5.67	0.94	0.71	0.65
h=1	2011:3–2013:4	US/EUR	5.91	0.94	0.71	0.51
h=1	2014:1–2015:4	US/EUR	7.54	0.92	0.71	0.34

* Gain: gain in forecasting precision
** Diebold–Mariano test statistic
*** Forecasts with 3 lagged variables

Table 14. France: Subperiods and Forecast Horizon h=3

Forecast horizon	*Time dimension*	*Proxy producing best forecast*	*Gain* (%)*	*rMSE*	*Trace R^2*	*DM***
h=3	2008:3–2011:2	M1	- 19.13	1.20	0.44	-0.64
h=3	2011:3–2013:4	Government Expenditure	- 18.17	1.18	0.46	-0.37
h=3	2014:1–2015:4	PPI: Total Durable Consumer Goods	34.45	0.65	0.46	1.40

* Gain: gain in forecasting precision
** Diebold–Mariano test statistic
*** Forecasts with 3 lagged variables

8.8 Spain: Subperiods

Results for Spain report that the baseline AR model slightly outperforms the candidate FAR. According to 12 forecasts (subperiods) "quasi" out–of–sample forecasting shows that the FAR is 7–times better at predicting movements of Spanish spreads compared to the AR model.

Tables 15 and 16 reported the results of out–of–sample forecasting Spanish – German spreads based on different subperiods and forecast horizons $h = 1, 2$. The results of horizons $h = 3, 4$ are summarized in Appendix B. Tables below show which 3PRF proxy produces the best forecast for each horizon, relative MSE of the best model, trace R^2, and the DM test statistics for accuracy of these forecasts. The t–statistics of the DM test for forecast accuracy are shown in the seventh column of Tables 15 and 16.

Table 15. Spain: Subperiods and Forecast Horizon h=1

Forecast horizon	*Time dimension*	*Proxy producing best forecast*	*Gain* (%)*	*rMSE*	*Trace R^2*	*DM***
h=1	2008:3–2011:2	REER	7.21	0.92	0.91	0.34
h=1	2011:3–2013:4	REER	8.28	0.91	0.91	0.59
h=1	2014:1–2015:4	CHF/EUR	6.88	0.94	0.92	0.63

* Gain: gain in forecasting precision
** Diebold—Mariano test statistic
*** Forecasts with 3 lagged variables
**** REER: Real Effective Exchange Rate (2010=1) based on manufacturing CPI

Table 16. Spain: Subperiods and Forecast Horizon h=2

Forecast horizon	*Time dimension*	*Proxy producing best forecast*	*Gain* (%)*	*rMSE*	*Trace R^2*	*DM***
h=2	2008:3–2011:2	M1	-23.89	1.23	0.8	**-2.7**
h=2	2011:3–2013:4	M1	-22.52	1.22	0.8	**-2.65**
h=2	2014:1–2015:4	M1	27.93	0.72	0.8	*1.75*

* Gain: gain in forecasting precision

** Diebold─Mariano test statistic. Bold and Italic figures indicate rejection of the null of equal predictive accuracy at 5%

*** Forecasts with 3 lagged variables

Spanish – German spreads for one–quarter ahead during Lehman's crisis were identified with the REER; the same factor explains the best movements of Spanish spreads from July 2011 to October 2013 and from January to October 2015. The most important driver of spreads was the REER (see the third column in Tables 15 and 16). M1 is the 3PRF proxy for the same subperiods and for the forecast horizon $h = 2$. Relative MSE is lower than 1 in all cases of $h = 1$. However, in two–quarters ahead forecasting, AR outperforms the candidate FAR model (see the fourth column in Tables 15 and 16). In three-quarters ahead forecasting, M1 is the 3PRF proxy for the first and the second subperiod, while the best movements of spreads are explained in the third subperiod by stock prices. In four–quarters ahead forecasting, government expenditure is the 3PRF proxy for all subperiods. The AR is undoubtedly better at forecasting with larger forecast horizons.

Regarding the peripheral countries, Italy and Spain, the empirical evidence suggests that before the global crisis in 2008 and the European debt crisis, the height of the government gross debt (as a percentage of the GDP), government expenditure, and the GDP growth rate did not seem to affect the 10–year government bond spreads, relative to the German *Bunds*. This changed with the beginning of the global crisis. The same applies to monetary aggregates, especially M1, which means that liquidity played an enormous role as the driver of spreads in peripheral countries.

Another important driver of Spanish spreads during financial turmoil was the REER. The focus is on relative prices in manufacturing. Manufacturing price competitiveness has the principal role in explaining Spanish spreads one–quarter ahead. Spanish government bond spreads increased significantly when Spanish manufacturer trading partners became more competitive compared to the Spanish manufacturer producers.
General government expenditure is the driver of Spanish spreads when forecasting four–quarters ahead for all subperiods (see Appendix B). A large variation in this indicator

highlights the variety of country's approaches to delivering public goods and providing social protection.

This phenomenon is presented in Tables 15 and 16. The FAR model outperforms the AR between 6.88 % and 8.28 % (h = 1) and at 27.93 % (h = 2) while on average the baseline model makes better forecasts. These amounts are at 22.52 % and 23.89 % (h = 2), 54.30 % and 55.33 % (h = 3) and 167.56 % and 190.76 % (h = 4) (see the fourth column in Tables 13 and 14 and Appendix B).

8.9 The Median of the Realized Spreads

According to Table 17, the highest values of the median of the realized spreads belong to the peripheral countries, Italy (0.43 %) and Spain (0.33 %). The European core countries, the Netherlands (0.17 %) and France (0.16 %), have markedly lower values of the median.

Table 17. The Median of the Realized Spreads

Country	*The Netherlands*	*Italy*	*France*	*Spain*
Median (%)	0.17	0.43	0.16	0.33
The highest value (%)	1.62 (61st)	4.68 (48th)	1.95 (61st)	5.07 (51st)
The lowest value (%)	0.00 (21st)	0.14 (21st)	0.02 (27th)	0.01(27th)

*Note: In the parentehesis are reporeted the quartals of the described value. Sample period: $2000Q1 - 2015Q4$

8.10 The Principal Empirical Results

The principal empirical results connected to macroeconomic and fiscal country-specific fundamentals and international factors driving the 10–year government bond spreads are summarized and presented in Table 18. In Table 19, the effects of fundamentals on the government bond spreads are reported.

Table 18. The Most Important Drivers of 10–Year Government Bond Spreads

1. Industrial Production Index (2010=1): Manufacturing
2. GDP Growth Rate
3. Government Expenditure
4. Stock Prices (Stock Index)
5. Real Effective Exchange Rate based on Manufacturing CPI
6. Money Aggregates: M1 (Narrow Money)
7. Money Aggregates: M2 (Intermediate Money)
8. Money Aggregates: M3 (Broad Money)
9. Hourly Earnings: Manufacturing
10. Hourly Earnings: Private Sector
11. Government Gross Debt (% of GDP)
12. Producer Price Index: Total Durable Consumer Goods
13. Producer Price Index: Total Investment Goods
14. US/EUR
15. CHF/EUR
16. One – Year EURIBOR
17. Inflation

Table 19. The Effects of Fundamentals on Spreads

↑ Industrial Production Index (2010=1): Manufacturing ~ Spreads ↓
↑ GDP Growth Rate ~ Spreads ↓
↑ Government Expenditure ~ Spreads ↑
↑ Stock Prices (Stock Index) ~ Spreads ↓
↑ US/EUR: Depreciation of US ~ ↓ of Spreads of Euro Area Countries
↑ CHF/EUR: Depreciation of CHF ~ ↓ of Spreads of Euro Area Countries
↑ Money Aggregates: M1 (Narrow Money) ~ Spreads ↓
↑ Money Aggregates: M3 (Intermediate Money) ~ Spreads ↓
↑ Money Aggregates: M3 (Broad Money) ~ Spreads ↓
↑ Hourly Earnings: Manufacturing ~ Spreads ↓
↑ Hourly Earnings (2010=1): Private Sector ~ Spreads ↓
↑ Government Gross Debt (% of GDP) ~ Spreads ↑
↑ Producer Price Index (2010=1): Total Durable Consumer Goods ~ Spreads ↓
↑ Inflation ~ ↑ Spreads

CONCLUSION

In this master's thesis, I present a new econometric theory for factor models of large dimensions. This is a modern approach to estimate factors as predictors in a data–rich environment, so–called Three–Pass Regression Filter (hereinafter: the 3PRF). I am using a general and tractable dynamic approximate latent factor model to demonstrate 10–year government bond spreads as a function of economic fundamentals. I adapted a novel, easily implemented filtering procedure to estimate dormant processes. I succeeded in constructing exceptionally accurate in–sample and out–of–sample forecasts of government bond spreads, by merely extracting information from the cross–section. The out–of–sample forecasts are compared to the AR model in terms of the relative MSE. I was able to thoroughly summarize several compelling results and features of empirical results.

Pseudo out–of–sample forecasting for different selected subperiods, beginning in 2008 with the bankruptcy of the US investment bank Lehman Brothers, shows the FAR's performance compared to the AR model for all countries except Spain. There were altogether 96 forecasts for one–, two–, three–, and four–quarters ahead forecast horizons for the period 2008Q3–2015Q4 (48 forecasts), and for the subperiods 2008Q3–2011Q2, 2011Q3–2013Q4, and 2014Q1–2015Q4 (48 forecasts). The FAR outperforms the benchmark AR model in 52 forecasts, and vice versa in 44 forecasts. In the period 2008Q3 to 2015Q4, the FAR evidently outperforms the AR on 27 occasions. On the other hand, the AR prevails in 21 instances. In the matter of subperiods, the candidate FAR dominates in forecasting spreads on 25 occasions, and the benchmark AR model prevails 23 times.

With regard to different forecasting horizons, the best results in terms of relative forecasting performance for the 3PRF forecast models are generally for one– and two–steps ahead forecasts. I observed that the 3PRF outperforms the AR model and can function as a useful complement to central banks' current forecasting tools, especially at shorter horizons. In peripheral countries (Italy and Spain), the AR model outperforms the FAR model in three– and four–quarters ahead forecasting. Moreover, the FAR with the 3PRF is inferior to the AR model in the 4–steps ahead forecasting for all countries, except the Netherlands. The baseline model decidedly outperforms the candidate FAR (three– and four–quarters ahead). According to the results, the 3PRF model is generally superior to the AR model. For example, the average gain for a one–step ahead forecast for quarterly spreads is close to six percent. Furthermore, relative performance of the 3PRF model in the quarterly examples seemingly improves in shorter forecasting horizons.

The results of pseudo real–time forecasting evaluation suggest that the 3PRF performs well under a variety of circumstances, in most cases outperforming the benchmark simple univariate AR model, especially in forecasting one– and two–quarters ahead, where the candidate model using the Kelly and Pruitt's 3PRF is more superior to a simple univariate autoregressive forecast. On average, the FAR model provides smaller relative MSEs than the simple autoregressive. I investigate whether the differences between the models are systematic or not in each forecast horizon. According to the results of the DM test statistic, the differences in the relative MSE between the factor– and autoregressive forecasts are generally statistically significant. Therefore, the 3PRF forecast performance slightly dominates the baseline forecasting model. Principal conclusion when considering the gain in forecasting precision from pseudo real–time forecasting is that the 3PRF demonstrates competitive out–of–sample forecasting performance in finite samples under a wide range of specifications.

Empirically, I have come to the conclusion that the the following country–specific macroeconomic and fiscal fundamentals are pivotal in explaining spreads: the GDP growth rate, government expenditure, inflation, hourly earnings in manufacturing and in the private sector, government gross debt, industrial production index – construction, producer price index – total durable consumer goods, producer price index – total investment goods, stock prices – stock index, M1, M2, M3 and real–effective exchange rate based on manufacturing CPI. International factors, such as exchange rates (US/EUR, CHF/EUR) and one–year EURIBOR are also significant. Furthermore, the effects and significance of country fundamentals have notably changed over time and differ between countries.

At this point, it is necessary to compare my findings with those of the researchers that have already tried to explain which macroeconomic and fiscal fundamentals have the largest impact on the movements of spreads. My empirical results are closely connected to the recent literature research of drivers of government bond spreads. Fundamental predictors (the 3PRF proxies) of spreads are the following: public debt (government gross debt), differentials in wage, variables of the labour market, real–effective exchange rate, international factors, exchange rates, and the GDP growth rate. Ultimately, they strongly resemble those of Rowland and Torres (2004); Remolona et al. (2007); Beber et al. (2009); Favero et al. (2005); Attinasi et al. (2009); Gerlach et al. (2009); Bernoth and Erdogan (2010); Alessandrini et al. (2012); De Grauwe and Ji (2012); Giordano et al. (2012); Di Cesare et al. (2012); Maltriz (2012); Poghsyan (2012); Haan, Hessel and End (2013); D'Agostino and Ehrmann (2013); Dorgan (2015), and De Santis (2016). There is, however, one key distinction compared to my research: monetary aggregates (M1, M2 and M3), the industrial production index and the producer price index also play crucial roles.

My findings also point to significant interaction of general risk aversion and domestic macroeconomic fundamentals. Domestic factors evidently became more important in times of economic hardship when international investors started to discriminate more between countries. The combination of high risk aversion and deteriorated current account tends to magnify the incidence of declining public finances on government bond yield spreads. Current account deficits support the idea that the distinction between private and public debt becomes blurred in times of financial stress as investors account for the possibility that the government is forced to take over private debt. Overall, an improvement in global risk perception will lead to a further narrowing of intra–euro area bond yield differentials. A strong rise in financing costs by sovereign issuers since September 2008 may be explained by the correction of abnormally narrow spreads in the pre–crisis period, when domestic risk factors resulted in small yield differentials.

Moreover, spreads can be expected to remain elevated compared to the pre–crisis period since debt levels have increased significantly in various countries and the contingent liabilities assumed by the public sector in rescuing the financial sector will continue to weigh on the outlook for public finances. Looking further ahead, greater market discrimination across countries may provide higher incentives for governments to attain and maintain sustainable public finances. Since even minor changes in bond yields noticeably impact government outlays, market discipline may act as an important deterrent against deteriorating public finances. This may thus play in favor of greater sustainability of public finances in the medium– and long run. Access to the domestic market and a possibility to rely on both domestic and foreign investors are crucial during the financial crisis. The analysis has shown that countries with a larger percentage of domestic debt within total public debt enjoy greater trust from investors and, consequently, have lower spreads on their bonds. With regard to fiscal policy, financial discipline and the long–term sustainability of public finance should be ensured. According to the financial crisis in the second half of 2008, fiscal policy proves to be the weakest link in the monetary union (i.e., fiscal discipline and public debt management). The market estimate of risks on bonds should be the most reliable mechanism for the introduction of discipline into the handling of fiscal policy. It applies before, during, and after a crisis.

There are, however, some limitations in this study. Firstly, I did not include country's data before January 2000 because of the lack of quarterly information, especially for Germany and Italy. To retain enough observations for in–sample estimation and out–of–sample forecasting, I decided to exclude those macroeconomic and financial variables not found in statistical datasets before the year 2000. Utilization of monthly data may alleviate this problem while I still face the trade–off between the number of variables and time observations.

The performance of the Kelly and Pruitt's (2014) 3PRF method as an alternative to the most widely used PCR depends on macroeconomic variables of study. Moreover, it is supposed to be related to areas and countries of interest, the underlying dataset or subsample, short– and long–term forecast horizons, etc. Future research of the 3PRF is mostly related to the collection of more effective datasets with longer, cleaner, and higher frequency time series; detailed simulation studies to investigate the efficiency of Kelly and Pruitt's (2014) method of factor estimation in panels of non–stationary, the integrated data of order one $I(1)$ and two $I(2)$, and in the environment of "big data cointegration".

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APPENDIXES

TABLE OF APPENDIXES

APPENDIX A: Data Description

Transformation Code: 1= no transformation; 2= first difference; 4= logarithm; 5= first difference of logarithms; 6= second difference of logarithms.

Series No.	Description	Transformation Method	Group
1	Total GDP (Current prices, million EUR)	5, SA[2]	Output Data
2	Gross Value Added (GDP, Current prices, million EUR)	5, SA	Output Data
3	Final Private Consumption (GDP, Current prices, million EUR)	5, SA	Output Data
4	Government Expenditure (GDP, Current prices, million EUR)	5, SA	Output Data
5	Gross Fixed Capital Formation (GDP, Current prices, million EUR)	5, SA	Output Data
6	Exports of Goods & Services (GDP, Current prices, million EUR)	5, SA	Output Data
7	Imports of Goods & Services (GDP, Current prices, million EUR)	5, SA	Output Data
8	General Government Gross Debt (% of GDP)	1, SA	Output Data
9	GDP Growth Rate (GDP, constant prices, %)	2, SA	Output Data
10	GDP Implicit Price Deflator (GDP, 2010=100)	5, SA	Output Data
11	Industrial Production Index (2010=100): Production of Total Industry	5, SA	Output Data
12	Industrial Production Index (2010=1): Mining and Quarrying	5, SA	Output Data
13	Industrial Production Index (2010=1): Manufacturing	5, SA	Output Data
14	Rate of Capacity Utilization (% of Capacity): Manufacturing	1	Business Tendency Surveys
15	Value of Retail Trade and Sales (2010=1): Total	5	Retail Turnover and Sales
16	Value of Retail Trade and Sales (2010=1): Total Manufactured Durable Consumer Goods	5	Retail Turnover and Sales
17	Value of Retail Trade and Sales (2010=1): Total Manufactured Investment Goods	5	Retail Turnover and Sales
18	Value of Retail Trade and Sales (2010=1): Total Manufactured Intermediate Goods	5	Retail Turnover and Sales
19	Consumer Price Index (2010=100): All Items	5, SA	Prices
20	Consumer Price Index (2010=100): Housing	5, SA	Prices
21	Consumer Price Index (2010=100): Energy	5, SA	Prices
22	Consumer Price Index (2010=100): Food	5, SA	Prices
23	Harmonized Index of Consumer Prices (2010=100)	5, SA	Prices
24	Producer Price Index (2010=1): Total Durable Consumer Goods	5, SA	Prices
25	Producer Price Index (2010=1): Total Investment Goods	5, SA	Prices
26	Producer Price Index (2010=1): Total Energy	5, SA	Prices
27	Producer Price Index (2010=1): Total Nondurable Consumer Goods	5, SA	Prices
28	Producer Price Index (2010=1): Total Consumer Goods	5, SA	Prices
29	Producer Price Index (2010=1): Economic Activities: Domestic Industrial Activities	5, SA	Prices
30	Producer Price Index (2010=1): Economic Activities: Manufacture of Food Products	5, SA	Prices
31	Producer Price Index (2010=1): Economic Activities: Mining and Quarrying Activities	5, SA	Prices
32	Real Effective Exchange Rate (2010=1) based on Manufacturing CPI	5	Exchange Rates
33	Exchange Rate: GBP/EUR	5	Exchange Rates
34	Exchange Rate: CHF/EUR	5	Exchange Rates
35	Exchange Rate: US/EUR	5	Exchange Rates
36	Long-Term Government Bond Yields: 10-Years (%)	1	Interest Rates
37	EONIA	1	Interest Rates
38	Three-Month EURIBOR	1	Interest Rates
39	Six-Month EURIBOR	1	Interest Rates
40	One-Year EURIBOR	1	Interest Rates
41	Employment Rate (15-64, %): Total	1, SA	Labor Market
42	Unemployment Rate (15-74, %): Total	1, SA	Labor Market
43	Employment by Economic Activity (All Persons): Agriculture	5, SA	Labor Market
44	Employment by Economic Activity (All Persons): Services	5, SA	Labor Market
45	Hourly Earnings (2010=1): Manufacturing	5, S	Labor Market
46	Hourly Earnings (2010=1): Private Sector	5, SA	Labor Market
47	Stock Prices (Current Prices, EUR)	5	Stock Market
48	M1 (Narrow Money) (End Period, million EUR	5	Money Aggregates
49	M2 (Intermediate Money) (End Period, million EUR)	5	Money Aggregates
50	M3 (Broad Money) (End Period, million EUR)	5	Money Aggregates
51	Consumer Credit (End Period, million EUR)	5	Money Aggregates

[2] SA – Seasonally Adjusted Quarterly Data

APPENDIX B: Forecasting Performance: Subperiods

Table 1. The Netherlands

Forecast horizon	*Time dimension*	*Proxy producing best forecast*	*Gain*(%)*	*rMSE*	*Trace R^2*	*DM***
h=3	2008:3–2011:2	GDP Growth Rate	- 0.68	1.01	0.26	-0.04
h=3	2011:3–2013:4	CHF/EUR	- 6.75	1.08	0.27	*-1.72*
h=3	2014:1–2015:4	Government Expenditure	24.42	0.75	0.27	*1.83*

* Gain: gain in forecasting precision
** Diebold-Mariano test statistic. Italic figures indicate rejection of the null of equal predictive accuracy at 10% significance level respectively.
*** Forecasts with 3 lagged variables

Table 2. The Netherlands

Forecast horizon	*Time dimension*	*Proxy producing best forecast*	*Gain*(%)*	*rMSE*	*Trace R^2*	*DM***
h=4	2008:3–2011:2	Stock Prices (AEX)	-4.52	1.04	0.26	-0.61
h=4	2011:3–2013:4	1-year EURIBOR	-0.57	1	0.27	/
h=4	2014:1–2015:4	Government Expenditure	2.97	0.97	0.27	**1.98**

* Gain: gain in forecasting precision
** Diebold-Mariano test statistic. Bold figures indicate rejection of the null of equal predictive accuracy at 5% significance level respectively.
*** Forecasts with 3 lagged variables

Table 3. Italy

Forecast horizon	*Time dimension*	*Proxy producing best forecast*	*Gain*(%)*	*rMSE*	*Trace R^2*	*DM***
h=3	2008:3–2011:2	GDP Growth Rate	- 18.24	1.18	0.68	*-1.99*
h=3	2011:3–2013:4	Hourly Earnings: Manufacturing	0.24	0.99	0.68	0.23
h=3	2014:1–2015:4	M1	- 1.74	1.03	0.68	/

* Gain: gain in forecasting precision
** Diebold-Mariano test statistic. Bold figures indicate rejection of the null of equal predictive accuracy at 5% significance level respectively.
*** Forecasts with 3 lagged variables

Table 4. France

Forecast horizon	*Time dimension*	*Proxy producing best forecast*	*Gain*(%)*	*rMSE*	*Trace R^2*	*DM***
h=2	2008:3–2011:2	M1	-22.87	1.22	0.78	*-1.67*
h=2	2011:3–2013:4	Government Expenditure	-16.04	1.16	0.49	-0.95
h=2	2014:1–2015:4	PPI:Total Durable Consumer Goods	7.29	0.92	0.5	*1.74*

* Gain: gain in forecasting precision
** Diebold-Mariano test statistic. Italic figures indicate rejection of the null of equal predictive accuracy at 10% significance level respectively.
*** Forecasts with 3 lagged variables

Table 5. France

Forecast horizon	*Time dimension*	*Proxy producing best forecast*	*Gain*(%)*	*rMSE*	*Trace R^2*	*DM***
h=4	2008:3–2011:2	M1	-69.4	1.7	0.49	*-1.78*
h=4	2011:3–2013:4	Government Expenditure	-67.5	1.7	0.45	*-1.73*
h=4	2014:1–2015:4	PPI: Total Durable Consumer Goods	18.96	0.82	0.49	*1.89*

* Gain: gain in forecasting precision
** Diebold-Mariano test statistic. Italic figures indicate rejection of the null of equal predictive accuracy at 10% significance level respectively.
*** Forecasts with 3 lagged variables

Table 6. Spain

Forecast horizon	*Time dimension*	*Proxy producing best forecast*	*Gain*(%)*	*rMSE*	*Trace R^2*	*DM***
h=3	2008:3–2011:2	M1	-54.3	1.54	0.73	-1.41
h=3	2011:3–2013:4	M1	-55.33	1.54	0.73	-1.28
h=3	2014:1–2015:4	Stock Prices (IBEX)	-3.17	1.03	0.73	/

* Gain: gain in forecasting precision
** Diebold-Mariano test statistic.
*** Forecasts with 3 lagged variable

Table 7. Spain

Forecast horizon	*Time dimension*	*Proxy producing best forecast*	*Gain*(%)*	*rMSE*	*Trace R^2*	*DM***
h=4	2008:3–2011:2	Government Expenditure	-167.56	2.70	0.73	-1.31
h=4	2011:3–2013:4	Government Expenditure	-190.76	3.00	0.73	*-1.86*
h=4	2014:1–2015:4	Government Expenditure	25.40	0.74	0.73	**1.99**

* Gain: gain in forecasting precision
** Diebold-Mariano test statistic. Bold and Italic figures indicate rejection of the null of equal predictive accuracy at 5% and 10% significance levels respectively.
*** Forecasts with 3 lagged variables

APPENDIX C: Abbreviations and Acronyms

APP	Asset Purchase Programme
AR	Autoregressive Model
BMA	Bayesian model averaging
BTP	*Buoni del Tesoro Poliennali*
CDS	Credit Default Swap
CPI	Consumer Price Index
DGP	Dynamic Generating Process
DFM	Dynamic Factor Models
DI	Diffusion Index
DM	Diebold–Mariano test statistics
DSL	*Dutch State Loans*
ECB	European Central Bank
EMU	European Monetary Union
EU	European Union
FAR	Factor–Augmented Regressions
GDP	GDP–Gross Domestic Product
GIIPS	Greece, Ireland, Italy, Portugal, Spain
HICP	Harmonized Index of Consumer Prices
IMF	International Monetary Fund
IPI	Industrial Production Index
LTRO	Long Term Refinancing Operation
M1	Narow Money
M2	Intermediate Money
M3	Broad Money
MFIs	Monetary Financial Institutions
MMF	Money Market Fund
OATs	*Obligations Assimilables du Trésor*
PC	Principal Components
PCA	Principal Component Analysis
PCR	Principal Component Regression
PPI	Producer Price Index
REER	Real Effective Exchange Rate (2010=1) based on manufacturing CPI
PSPP	Public Sector Purchase Programme
3PRF	Three–Pass Regression Filter
rMSE	relative Mean Squared Error
OLS	Ordinary Least Squares
OMT	Outright Monetary Transactions
TFP	Total Factor Productivity
QE	Quantitative Easing

APPENDIX D: POVZETEK V SLOVENSKEM JEZIKU

NAPOVEDOVANJE PRIBITKOV 10–LETNIH DRŽAVNIH OBVEZNIC V PODATKOVNO BOGATEM OKOLJU S TRO–STOPENJSKIM REGRESIJSKIM FILTROM (3PRF METODO)

UVOD

Pričujoče magistrsko delo predstavlja ekonometrično študijo *(i)* napovedovanja pribitkov 10–letnih državnih obveznic štirih gospodarsko najmočnejših držav euro območja (Italija, Francija, Nizozemska in Španija) glede na nemške 10–letne državne obveznice, imenovane *Bunds (*v nadaljevanju: Angl. *benchmark),* in predvsem *(ii)* iskanje ključnih determinant (makroekonomskih, fiskalnih, domačih in mednarodnih), ki določajo gibanje in drastične premike vrednosti pribitkov v obdobju po izbruhu svetovne finančne krize septembra leta 2008 (bankrot četrte največje ameriške investicijske banke, Lehman Brothers), pri čemer uporabljam novo metodo ocenjevanja faktorjev, t.i. **tro–stopenjski regresijski filter** (Angl. ***the Three–Pass Regression Filter, the 3PRF***), ki sta ga analitično razvila ameriška teoretična ekonometrika, Bryan Kelly in Seth Pruitt (2014).

Na začetku je nujno izpostaviti vprašanje, zakaj je tako ključnega pomena poznati determinante in vzvode gibanja vrednosti pribitkov z vidika narodnega in nenazadnje globalnega gospodarstva. Povezava med makroekonomskimi in fiskalnimi determinantami, domačimi in mednarodnimi, ki primarno vplivajo na gibanje donosov državnih obveznic in pribitkov je že bila proučevana. Literatura se je osredotočala predvsem na povezavo med pribitki in kreditnim, tržnim, valutnim tveganjem ter tveganjem reinvestiranja. Osrednji predmet pričujočega dela je tako empirično raziskati determinante (3PRF faktorje), ki določajo gibanje pribitkov skozi obdobje svetovne finančne in evropske dolžniške krize.

Pribitki na dolgoročne državne obveznice so ključno povezani z realno ekonomsko aktivnostjo in globalnim finančnim tveganjem, kar posledično pomeni, da so pribitki lahko uporabljeni kot glavni ekonomski in finančni indikator posamezne ekonomije. Na primer: pribitki dosežejo visoke vrednosti baznih točk skozi hitre spremembe v inflacijskih pričakovanjih, ki so jih povzročila upanja po fiskalnih stimulacijah, kar pa ima vpliv na valutne trge. Euro kot valuta slabi, medtem ko donosi na obveznice padajo in pribitki močno narastejo. Razumevanje pribitkov ter faktorjev njihovih naglih porastov je ključnega pomena pri oblikovanju strukture fiskalnega dolga, usmerjanju monetarne politike, vrednotenju kapitalskih dobrin, upravljanju finančnih tveganj, alokaciji portfeljev ter določanju cen finančnih dobrin. Finančni trgi se spopadajo z naraščajočimi pribitki in strategijami nekaterih držav za "krotenje" morebitnih dolgov. Poleg naraščajočih stroškov izposoje tudi porast pribitkov nakazuje na zadržano držo investitorjev pri vlaganju, s tem pa je državi ogrožen dostop do mednarodnega kapitalskega trga. Pribitki so temelji celotne fiskalne politike, ki znatno vplivajo na obrestne mere oziroma na stroške izposoje v vseh gospodarskih sektorjih.

Napovedovanje pribitkov državnih obveznic je težavno iz dveh razlogov. Prvič, pribitki varirajo glede na relativno moč faktorjev v različnih državah. To pomeni, da sprememb v faktorjih, ki vplivajo na donose državnih obveznic, ne moremo posamično preiskovati za določeno državo. Drugič, cene obveznic so podobno kot cene drugih finančnih sredstev podvržene zapletenim nihanjem, ki so posledica nezaupanja udeležencev na trgu. Donose ali pribitke lahko zato pojasnimo s pomočjo spremenljivk, ki v veliki meri vplivajo na njih. Ena izmed njih je fiskalna politika, ki jo prištevam med najpomembnejše determinante pribitkov in donosov državnih obveznic.

Dejstvo je, da fiskalna politika na eni strani spodbuja ali pa ovira gospodarsko rast. Smer javnih odhodkov lahko stimulira zasebne naložbe v kapitalne projekte in poveča produktivnost z izboljšanjem tehnik izdelave (npr. z doslednim izvajanjem zakona, spoštovanjem pogodb in rokov in ustreznimi predpisi finančnega trga). Naložbe v infrastrukturo in človeški kapital tudi pozitivno vplivajo na povečanje produktivnosti dela in kapitala. Po drugi strani pa sistem obdavčitve lahko izkrivlja razporeditev sredstev ter zmanjšuje gospodarsko rast in dobrobit. Gospodarsko, politično in institucionalno okolje vpliva na učinkovitost porabe javnih sredstev, ki morebiti pospešujejo rast. Ustvarjalci fiskalne politike morajo zvišati davčni prihodek in prevzeti kredit za financiranje javne porabe, hkrati pa znižati stroške, ki ogrožajo gospodarsko rast. V skladu s tem bo zanesljivejša fiskalna politika znižala tveganja, uredila instrumente javnega dolga in vzpostavila gospodarsko rast, pričakovani donosi investitorjev pri vlaganju v državne obveznice pa bodo nižji. Verodostojna fiskalna politika je nujna za korenito zmanjšanje državnega dolga. Z vidika monetarne politike je gibanje pribitkov tudi pomembno raziskovalno vprašanje. Izluščiti majhno število možnih faktorjev pribitkov iz velikega nabora podatkov je metodološki izziv, še posebej izluščiti relevantne faktorje, ki so povezani s t.i. *proxy*–ji.

Primarna raziskovalna vprašanja na samem začetku pričujoče emprirične študije so bila naslednja:

1) Konceptualno, definicija finančne spremenljivke, katere napovedovanje in proučevanje determinant me zanima ter nenazadnje, zakaj je opazovanje slednje spremenljivke sploh pomembno z vidika narodnega in globalnega gospodarstva? Kako lahko na podlagi moje študije bolje razumemo premike krivulje donosov dolgoročnih obveznic in s tem pribitkov skozi obdobja ekonomske stagnacije in finančnih kriz?

2) Opisno, kako se pribitki na dolgoročne državne obveznice obnašajo v gospodarsko osrednjih državah (Francija in Nizozemska) in na drugi strani, v gospodarsko perifernih državah (Italija in Španija)? Ali lahko pričakujem preprosto razumljive in hkrati točne napovedi?

3) Teoretično, na podlagi dosedanjih akademskih študij, kateri faktorji oziroma vzvodi povzročajo premike pribitkov in njihovo evolucijo? Lahko slednje povežem z makroekonomskimi determinantami (fiskalnimi in finančnimi), domačimi in mednarodnimi, in z dejanji centralnih bank?

4) Katere so tako teoretične kot praktične prednosti uporabe najnovejše metode 3PRF, napovedovanja v podatkovno bogatem okolju primerjalno z drugimi, doslej najpogosteje uporabljenimi: v teoretičnem smislu primerjava z Metodo Glavnih Komponent ter v praktičnem pomenu primerjava s preprostimi modeli časovnih vrst?

5) Zakaj napovedovati pribitke s faktorskimi modeli, natančneje s Faktorsko–Dodano Regresijo?

6) Ali so razlike med primerjalnima modeloma (3PRF v okviru FAR in AR) na podlagi Diebold–Mariano testne statistike statistično značilne ali ne in kaj rezultat pomeni?

7) Na podlagi lastne empirične študije ugotoviti, kateri faktorji oziroma vzvodi povzročajo premike pribitkov in njihovo evolucijo? Katere makroekonomske determinante (fiskalne in finančne), domače in mednarodne, so to?

8) Kakšna je vloga domačih makroekonomskih faktorjev v odnosu do mednarodnih? Kateri nosijo večjo težo?

9) Ali so moji dobljeni rezultati skladni z dognanji avtorjev, ki so doslej proučevali gibanje pribitkov in njihovih determinant?

10) Monetarna ekonomija: Ali na podlagi rezultatov lahko sklepam o znatni povezavi med nenaklonjenostjo tveganju in domačimi makroekonomskimi determinantami? Nadalje, ali nenaklonjenost tveganju in slabo stanje na tekočem računu v veliki meri vplivata na slabe javne finance in s tem posledično na razpon donosov državnih obveznic, torej večje pribitke? Primanjkljaj na tekočem računu igra pomembno vlogo pri razponih donosov, saj je v času finančnih pretresov meja med zasebnim in javnim dolgom zabrisana, vlada pa morebiti primorana prevzeti zasebni dolg, kar gre v prid vlagateljem. Ali si vlade in centralne banke z mojimi rezultati, pridobljenimi s 3PRF ocenjevanjem faktorjev, lahko pomagajo pri oblikovanju monetarne politike?

Faktorsko–Dodana Regresija (Angl. the *Factor–Augmented Regression*, v nadaljevanju: FAR) uporablja faktorje, ocenjene iz velikega nabora podatkov, medtem ko dimenzija napovednega modela ostane nespremenjena oziroma majhna. Doslej se je v okviru metode FAR uporabljala Stock– in Watson–ova (2006) Metoda Glavnih Komponent (Angl. *Principal Component Analysis*, v nadaljevanju: PCA). FAR metoda faktorje, ocenjene z metodo PCA, doda standardni regresiji $Y_{t+h} = \alpha^{'} \tilde{F}_t + \beta^{'} W_t + e_{t+h}$. Osrednji problem pri uporabi PCA metode je njena nezmožnost ekonomske interpretacije.

Tro–stopenjski regresijski filter (v nadaljevanju: 3PRF), ki ocenjuje faktorje kot prediktorje in potem ocenjene faktorje doda standardni regresiji, je učinkovita metoda pri napovedovanju v podatkovno bogatem okolju, kjer je velika količina možnih prediktorjev ali relevantnih faktorjev, ki najbolje napovedujejo gibanje odvisne spremenljivke – pribitkov na 10–letne državne obveznice, in primarno uporablja približni dinamični faktorski model kot teoretični okvir, v katerem majhno število prikritih faktorjev povzema informacije o prediktorjih. Empirična študija se torej osredotoča na napovedovanje finančne spremenjivke kot časovne serije z uporabo velikega števila možnih prediktorjev in nato iz tega bogatega nabora možnih prediktorjev izlušči majhen nabor relevantnih 3PRF *proxy*–jev.

Teoretični oziroma ekonometrični okvir 3PRF metode kot novega pristopa za ocenjevanje faktorjev oziroma baze geometrijskega prostora faktorjev ter povzemanje le tistih, ki relevantno določajo gibanje finančne spremenljivke, ki jo napovedujem, predstavlja Chamberlain–ov in Rotschild–ov (1983) ter Bai–jev in Ng–in (2008, 2009, 2013) približni dinamični faktorski model. Faktorji, ocenjeni kot prediktorji, so kot že rečeno, dodani standardni regresiji, FAR.

Približna faktorska struktura kot sinonim za manj stroge predpostavke klasičnega statičnega faktorskega modela se nanaša na naslednje specifikacije modela: (i) idiosinkratične napake so lahko šibko korelirane okoli i in t, (ii) T in $N \rightarrow \infty$, (iii) F_t je serijsko koreliran (dovoljena šibka serijska korelacija med faktorji in idiosinkratičnimi komponentami), (iv) e_{it} komponente so lahko heteroskedastične.

3PRF ocene so izračunane v zaprti obliki in predstavljajo zaporedje regresij po metodi najmanjših kvadratov (Angl. *Ordinary Least Squares,* v nadaljevanju: OLS). 3PRF napovedi so konsistentne za neizračunljive najboljše napovedi v pogojih, ko časovna dimenzija T (Angl. *time dimension*) in obseg reprezentativnega vzorca N (Angl. *cross–section dimension*) gresta v neskončnost. Slednje zahteva specifikacijo le tistega števila faktorjev, ki so relevantni za napovedovanje.

3PRF predstavlja alternativo PCA, ki je doslej najbolj uporabljena metoda v faktorski napovedni literaturi. Tekom študije se je ugotavljalo, katere prednosti ima FAR model z uporabo 3PRF metode glede na preprosti model časovnih vrst.

1 PODATKOVNA BAZA IN METODOLOGIJA

Glavna vira podatkov sta bili podatkovni bazi Eurostat–a in Federal Reserve Bank of St. Louis. Pregled uporabljenih spremenljivk je prikazan v Prilogi A, medtem ko tabela 1 v nadaljevanju povzema število uporabljenih spremenljivk v 3PRF ocenjevanju glede na gospodarski sektor, kateremu pripada spremenljivka.

1.1 Podatkovna baza

Podatkovna baza sestoji iz 63 čertletnih serij, katerih časovno obdobje zajema čas od 2000Q1 do 2015Q4 za gospodarsko najpomembnejše države članice euro območja: Nemčija, Italija, Francija, Nizozemska in Španija. Podatki, uporabljeni za napovedovanje pribitkov dolgoročnih državnih obveznic, predstavljajo 51 makroekonomskih spremenljivk, potencialnih *proxy*–jev – relevantnih faktorjev, ki najbolje napovedujejo gibanje pribitkov.

Makroekonomske determinante narodnega gospodarstva kot možne 3PRF faktorje lahko združimo v naslednje skupine: spremenljivke, ki kažejo rezultate gospodarske rasti, zunanje ravnotežje, spremembe na kapitalskem trgu, javnofinančno ravnotežje ter notranje ravnotežje (inflacija). Del podatkovne baze so tudi finančne spremenljivke: štirje različni menjalni tečaji; pet različnih obrestnih mer; vključno z obrestno mero na donos 10–letnih državnih obveznic; delniški indeks; in štiri spremenljivke, ki spadajo med monetarne agregate. Trinajst spremenljivk pripada narodno–gospodarskim podatkom; bruto domači proizvod – v nadaljevanju: BDP; in njene komponente, kot so potrošnja in bruto naložbe v osnovna sredstva, kot tudi bruto dodana vrednost; ena spremenljivka pripada napovedi poslovnih gibanj; štiri spremenljivke pripadajo fluktuaciji v maloprodaji in razprodajah; indeks cen življenjskih potrebščin obsega štiri različne spremenljivke; harmonizirani indeks življenjskih potrebščin opisuje vse življenjske potrebščine; in osem cenovnih indeksov spada v sklop cen industrijskih proizvodov pri proizvajalcih; in nenazadnje trg dela, ki opisuje šest spremenljivk.

Tabela 1. Povzetek števila uporabljenih spremenljivk v 3PRF ocenjevanju

Sektor	**Število uporabljenih spremenljivk**
Monetarni agregati	4
Obrestne mere	5
Makroekonomske spremenljivke	10
Cenovni indeksi	13
Industrijska proizvodnja	3
Napoved poslovnih gibanj	1
Potrošnja in razprodaje	4
Trg dela	6
Menjalni tečaji	4
Delniški indeks	1
Seštevek	**51**

Gledano podrobneje, podatkovna baza obsega BDP, in njene potrošniške komponente kot so državni izdatki in bruto naložbe v osnovna sredstva, kot tudi bruto dodana vrednost. Spremenljivke realnega outputa so celotni BDP, stopnja rasti BDP, industrijska proizvodnja, mednarodna blagovna in storitvena menjava (izvoz, uvoz). Podatkovna baza prav tako zajema delež javnega dolga v BDP, implicitni cenovni deflator, poslovne fluktuacije in spremenljivke, povezane z obsegom maloprodaje in razprodaj ter industrijski proizvodni indeks (razdeljen po izbranih industrijskih sektorjih). Indeks cen življenjskih potrebščin med drugim zajema cene energije in hrane. Indeks cen industrijskih proizvodov pri proizvajalcih je prav tako razčlenjen po segmentih. Trg dela predstavljajo spremenljivke, kot so: stopnja zaposlenosti glede na starost, stopnja nezaposlenosti in urna postavka po sektorjih. Različne obrestne mere (EONIA, EURIBOR, itd.), menjalni tečaji, delniški indeksi in nenazadnje ključni monetarni agregati, kot so: primarni denar (v nadaljevanju: M1), širši denar (v nadaljevanju: M2) in obveznosti poslovnih bank (v nadaljevanju M3:) so prav tako del podatkovne baze.

1.2 Metodologija napovedovanja

V procesu pre–selekcije spremenljivk sem sledila pristopu, ki ga uporabljajo Marcellino, Stock in Watson (2003). Vse spremenljivke so sezonsko prilagojene, da ne prihaja do osamelcev. Nestacionarne časovne serije so primerno diferencirane, in sicer so diferencirane reda nič. Serije so transformirane z namenom, da se izloči stohastični oziroma deterministični trend. Končno, serije so normalizirane, da imajo matematično upanje enako nič in enako statistično razpršenost oziroma varianco enako ena.

30 kvartalnih časovnih serij, 2000Q1–2008Q2, je uporabljenih v t.i. ocenjevanju znotraj vzorca (Angl. *in–sample estimation*). Podatki za obdobje 20008Q3–2015Q4 so vključeni v t.i. izven–vzorčno ocenjevanje (Angl. *pseudo out–of–sample forecasting*). Specifikacija napovednega modela je povzeta po avtorjih Bai in Ng (2008, 2009, 2013) ter Stock in Watson (2002a) in predstavlja napovedno enačbo $y_{t+h}^{h} = \mu + \alpha(L)y_t + \beta(L)'Z_t + \varepsilon_{t+h}^{h}$, kjer je y_{t+h}^{h} odvisna spremenljivka v času $t + h$, tj. pribitek na 10–letne državne obveznice, Z_t vektor prediktorjev v času t, $\alpha(L)$ skalarni polinom odlogov, $\beta(L)$ vektorski polinom odlogov, μ konstanta in ε_{t+h}^{h}, idiosinkratične napake. Napovedni horizonti, ki so me zanimali, so $h = 1, \dots, 4$. V primeru avtoregresijskega modela (v nadaljevanju: AR) vektor prediktorjev Z_t ne vključim, medtem ko je vektor prediktorjev

prisoten v FAR modelu, kjer uporabim 3PRF kot metodo ocenjevanja faktorjev. Primerjalni (Angl. *benchmark*, *baseline*) model je torej avtoregresijski, medtem ko je FAR model z uporabo 3PRF konkurenčni model (Angl. *candidate*). Za oba modela (AR in FAR) z rekurzivno metodologijo izračunam simulirane izven–vzorčne napovedi za obdobje po bankrotu četrte največje ameriške investicijske banke, Lehman Brothers (torej obdobje po septembru 2008). Napovedno moč modelov primerjam na podlagi relativnih povprečnih kvadratov napak (Angl. *Relative Mean Squared Error, relative MSE*) konkurenčnega modela. V AR modelu je številu odlogov določeno na podlagi primerjalne literature s področja ekonometričnega napovedovanja, kjer je število odlogov določeno z BIC kriterijem (Angl. *Bayesian Information Criterion*). In sicer, je število odlogov enako 3, 4 in 5 v primeru pseudo napovedovanja za obdobje 2008Q3–2015Q4, in 3 v primeru pseudo napovedovanja za podobdobja.

V nadaljevanju na kratko povzemam metodologijo novega pristopa ocenjevanja faktorjev. Želim napovedovati gibanje posamezne finančne spremenljivke in imam veliko število potencialnih regresorjev $x_i \in X, i = 1, \dots, N$. Dokler velja $N > T$ OLS napovedi niso učinkovite. Nadalje, imam *proxy* $z_j \in Z$, $I = 1, \dots, L$ – kjer je L[3] znatno manj kot T. Ti *proxy*–ji so skriti faktorji (determinante), ki jih ekonomska teorija predpostavlja kot vzvode, ki določajo gibanje proučevane spremenljivke. Končno, tukaj je še odvisna spremenljivka, ki jo proučujem, y_t, ki je stolpični vektor s T observacijami. Skriti faktorji v matriki F[4] določajo *proxy*–je v Z in prediktorje v X. Temelječ na makroekonomskih raziskavah dinamičnih faktorjev, le nekaj od teh skritih faktorjev določa y_t. Kako lahko potem raziskovalec učinkovito uporabi ta nabor podatkov? Rešitev znana v napovedni literaturi izhaja iz modela, v katerem skriti faktorji določajo spremembe napovedne spremenljivke, y_t in matrike prediktorjev, X. Kot rezultat je zahtevano faktorsko ocenjevanje. Iztisniti oziroma izluščiti je potrebno faktorje, ki znatno in pomembno določajo spremembe v X in so na ta način ključne gonilne sile sprememb v X in potem uporabljeni za napovedovanje y. Metoda Kelly–ja in Pruitt–a (2014) izhaja iz ideje, da so faktorji, ki so relevantni za y, lahko skrita podmnožica vseh faktorjev, ki so gonilna sila X. 3PRF metoda tako selektivno identificira le tisto podmnožico faktorjev, ki dejansko pomembno vpliva na gibanje spremenljivke, ki jo napovedujem, medtem ko zanemari faktorje, ki so irelevantni ali nepomembni za y.

1.2.1 3PRF algoritem

Če na kratko povzamem tabelo 1 iz poglavja 4, v kateri je opisan postopek 3PRF metode, sestavljene iz treh zaporednih OLS regresij:

1 **Prvi korak** pomeni N regresijo časovnih serij za vsakega prediktorja. V prvem koraku je prediktor odvisna spremenljivka, *proxy*–ji so regresorji, in ocenjeni koeficienti opisujejo občutljivost prediktorjev do faktorjev, predstavljenih v *proxy*–jih. *Proxy*–ji ni nujno, da predstavljajo specifične faktorje in so lahko opazovani z matematičnim upanjem nič in upoštevajoč, da ni korelacije med vrednostmi pri različnih vrednostih t (Angl. *white noise*). Pomembna zahteva je, da njihova skupna komponenta obsega relevantne faktorje za napovedno spremenljivko (Angl. *target*–

[3] $L\ (napovedni\ faktorji) \ll min\ (N, T)$

[4] $Y_{t+h} = \alpha' \tilde{F}_t + \beta' W_t + \epsilon_{t+h}$ Ali $\tilde{z}'_{t+h}\,\delta + \epsilon_{t+h}$

relevant factors). Gre za OLS regresijo x_i iz matrike X na z_j v matriki X. To je t.i. regresija časovnih vrst (Angl. *time series regression*). Jaz v mojem empiričnem primeru iteriram čez vse možne *proxy*–je (51 možnih prediktorjev).

2 **V drugem koraku** upoštevam ocenjene koeficiente in njhove konstante iz prvega koraka v T ločeni regresiji reprezentativnega vzorca. To pomeni, da za vsako periodo t, vrednosti reprezentativnega vzorca $x_{i,t}$ jemljem kot odvisno spremenljivko. Povedano drugače: v drugem koraku so prediktorji še enkrat odvisna spremenljivka, medtem ko so koeficienti $\widehat{\Phi_i}$ iz prvega koraka zdaj regresorji. Fluktuacija skritih faktorjev povzroči, da se prediktorji zgostijo skozi čas. Koeficienti, ki so bili ocenjeni v prvem koraku, določijo razporeditev prediktorjev do skritih faktorjev. To je t.i. regresija reprezentativnega vzorca (Angl. *cross–section regression*).

3 V drugem koraku ocenjene napovedne faktorje, $\widehat{F_t}$, zdaj prenesem v **tretji korak**. Tukaj gre za posamezno napovedno regresijo časovnih serij spremenljivke, ki jo napovedujem, y_{t+1}, na, v drugem koraku ocenjene napovedne faktorje, $\widehat{F_t}$. Vrednosti, dobljene v tretjem koraku, $\widehat{\beta_0} + \widehat{F}_t'\hat{\beta}$, so 3PRF napovedi v času t. To je t.i. napovedna regresija (angl. *predictive regression*). Ker regresija v prvem koraku upošteva napake v spremenljivkah, drugo–stopenjska regresija producira ocene za edinstvene, ampak neznane rotacije skritih faktorjev. Dokler relevantni faktorski prostor zavzema prostor $\widehat{F_t}$, tretji korak prinaša konsistentne napovedi.

2 EMPIRIČNI REZULTATI IN ZAKLJUČEK

Rezultati potrjujejo večjo napovedno moč FAR modela, v okviru katerega ocenjujem faktorje z metodo 3PRF, v primerjavi s preprostimi modeli časovnih vrst. Prednosti uporabe nove metode ocenjevanja faktorjev pridejo še posebej do izraza v primeru napovedovanja enega četrtletja in dveh četrtletij naprej, in sicer, v primeru napovedovanja pribitkov gledano celotno časovno obdobje kot tudi za naslednji podobdobji: obdobje globalne finančne krize po bankrotu ameriške investicijske banke Lehman Brothers, 2008Q3–2011Q2 ter napovedi gibanja pribitkov v obdobju po dolžniški krizi, 2014Q1–2015Q4.

2.1 Rezultati izven–vzorčnega ocenjevanja

FAR je v povprečju torej boljši napovedni model v primerjavi s preprostimi modeli časovnih vrst: za napovedni horizont eno četrtletje na primer FAR v povprečju za 6 % bolje napove dinamiko pribitkov. Relativna moč napovedovanja je značilna le za krajše napovedne horizonte (1. in 2. napovedno četrtletje), medtem ko je primerjalni model časovnih vrst (AR) boljši v primeru daljših napovednih horizontov (3. in 4. napovedna četrtletja), in še to prepričljivo le v primeru perifernih držav, kot sta Italija in Španija. V celotnem naboru 96 testiranih napovedi v 52 primerih FAR z uporabo 3PRF bolje napoveduje dogajanje pribitkov na dolgoročne državne obveznice izbranih držav, medtem ko so modeli časovnih vrst boljši v 44 primerih. Ko ta nabor napovedi razdelimo v dva dela: *(1)* 2008Q3–2015Q4 in *(2)* tri izbrana podobdobja v primeru napovedovanja za obdobje 2008Q3–2015Q4 FAR (3PRF) model bolje napoveduje višino pribitkov na 10–letne državne obveznice v 27 testiranih napovedih, AR model kot primerjalni model na drugi strani pa v 21 primerih. Gledano podobdobja rezultati kažejo, da FAR (3PRF) model natančneje napoveduje gibanje pribitkov v 25 testiranih napovedi od 48, medtem ko AR model natančneje napoveduje v 23 testiranih napovedi od 48. Empirični rezultati kažejo, da je FAR model statistično boljši od AR modela in je na podlagi tega primerno orodje za napovedovanje pribitkov 10–letnih državnih obveznic držav euro območja. Iz pseudo napovedovanja lahko zaključim, da 3PRF predstavlja konkurenčno izven–vzorčno napovedno moč v verjetnostni porazdelitvi v pogojih širokega nabora specifikacij. Končno, gledano celotni nabor napovedi, FAR v povprečju bolje napoveduje gibanje pribitkov, saj so relativne povprečne napake kvadratov v 52–tih napovedih manjše od 1. S svojo napovedno močjo torej lahko služi kot učinkovito napovedno orodje centralnih bank, še posebej v primeru krajših napovednih horizontov.

Za vsak napovedni horizont obenem preverjam, ali so razlike med modeloma statistično značilne ali ne. Rezultati Diebold–Mariano (v nadaljevanju: DM) testne statistike kažejo, da razlike v relativnih povprečnih napakah kvadratov v povprečju so statistično značilne. Torej, 3PRF napoved predstavlja nekoliko boljšo sistematično metodo.

2.2 Ključni 3PRF faktorji–determinante pribitkov

Skozi empirično študijo dosežem cilj določiti domače makroekonomske (in izmed njih tudi finančne) in fiskalne vzvode pribitkov na 10–letne državne obveznice in faktorje mednarodnega okolja, ki najbolje določajo gibanje pribitkov dolgoročnih obveznic. Empirične rezultate prikazuje tabela 2.

Tabela 2. 3PRF faktorji pribitkov na 10–letne državne obveznice

1.	Indeks industrijske proizvodnje: predelovalne dejavnosti
2.	Stopnja rasti BDP
3.	Državni izdatki
4.	Cene delnic (delniški indeks)
5.	Realni efektivni menjalni tečaj
6.	Monetarni agregati: M1
7.	Monetarni agregati: M2
8.	Monetarni agregati: M3
9.	Urna postavka: predelovalne dejavnosti
10.	Urna postavka: zasebni sektor
11.	Javni dolg (kot odstotek BDP)
12.	Producentov cenovni indeks: trajne potrošne dobrine
13.	Producentov cenovni indeks: Investicijske Dobrine
14.	US/EUR
15.	CHF/EUR
16.	Eno−Letni EURIBOR
17.	Inflacija

Rast BDP, državna potrošnja, javni dolg kot odstotek BDP, inflacija, urna postavka v predelovalnih dejavnostih in zasebnem sektorju, producentov cenovni indeks – vse trajne potrošne dobrine, producentov cenovni indeks – vse investicijske dobrine, indeks industrijske proizvodnje – predelovalne dejavnosti, delniški indeks, monetarni agregati M1, M2 in M3 so 3PRF faktorji, ki kot determinante najbolje opisujejo dogajanje na trgu dolgoročnih obveznic in pripadajočih pribitkov po nastopu svetovne finančne krize septembra leta 2008. Ugotavljam, da veliko vlogo nosijo tudi faktorji mednarodnega okolja, kot na primer menjalni tečaji (US/EUR, CHF/EUR) in eno–letni EURIBOR. Kot eno izmed ključnih ugotovitev lahko izpostavim, da se učinki in pomembnost posameznega faktorja spreminjajo skozi čas, skozi posamezna obdobja proučevanja in razlikujejo med državami. Skladno z rezultati študije, lahko povzamem naslednje 3PRF faktorje pribitkov po izbranih državah, predstavljenih v tabeli 3.

Tabela 3: 3PRF faktorji pribitkov po izbranih državah

1. **Nizozemska:** Urna postavka v zasebnem sektorju, stopnja zaposlenosti (15–64), producentov cenovni indeks – trajne potrošne dobrine in producentov cenovni indeks – investicijske dobrine
2. **Francija:** Menjalni tečaj (US/EUR, CHF/EUR) in eno–letni EURIBOR
3. **Italija:** Stopnja rasti BDP, državna potrošnja, javni dolg (kot odstotek BDP) in monetarni agregati M1, M2 in M3
4. **Španija:** Realni efektivni menjalni tečaj, stopnja rasti BDP, državni izdatki in javni dolg (kot odstotek BDP).

Učinki in pomembnost posameznega faktorja se spreminjajo skozi čas, skozi posamezna obdobja proučevanja in razlikujejo med državami. Študija izbranih držav je torej pokazala, da na primer javnofinančno ravnotežje močno vpliva na pribitke državnih obveznic v perifernih članicah EU, precej manj pa v centralnih državah, kar pomeni, da je pri gospodarsko osrednjih oziroma najbolj razvitih državah euro območja ta učinek statistično nesignifikanten/neznačilen. Na stopnje pribitkov gospodarsko najbolj razvitih držav euro območja zelo vplivajo menjalni tečaji (US/EUR, CHF/EUR), urna postavka v zasebnem sektorju, producentov cenovni indeks – trajne potrošne dobrine in producentov cenovni indeks – investicijske dobrine. Očitno je presoja kupcev obveznic gospodarsko razvitih držav odvisna od gospodarske rasti in dinamike na trgu kapitala v teh narodnih gospodarstvih. Javni dolg (kot odstotek BDP), razlike v urni postavki in spremenljivke trga dela (stopnja nezaposlenosti), realni efektivni menjalni tečaj, menjalni tečaji in rast BDP so 3PRF faktorji, ki se ujemajo z analizo determinant pribitkov dosedanjih akademskih študij – Rowland in Torres (2004, 3–55); Favero, Pagano in von Thadden (2005, 107–134); Remonola, Scatigna in Wu (2007, 27–39); Beber, Brandt in Kavavejc (2009, 10–51); Attinasi, Checherita in Nickel (2009, 4–45); Gerlach, Schulz in Wolff (2009, 1–68); Bernoth in Erdogan (2010, 1–20); Giordano, Linciano in Soccorso (2012, 7–19); De Grauwe in Ji (2012, 1–32); Di Cesare, Grande, Manna in Taboga (2012, 5–35); Maltriz (2012, 657–672); Poghosyan (2012, 2–26); Haan, Hessel in van den End (2013, 49–68); D'Agostino in Ehrmann (2013, 4–30); Dorgan (2015, Julij 13, SNB) in De Santis (2016, 5–76). Ključna razlika v primerjavi s študijami omenjenih avtorjev nastopa v monetarnih agregatih, kot so M1, M2 in M3, ter v determinantah: indeks industrijske proizvodnje – predelovalne dejavnosti ter producentov cenovni indeks, ki se v moji študiji prav tako pojavljajo kot 3PRF faktorji pribitkov.

Na podlagi rezultatov lahko sklepam o znatni povezavi med nenaklonjenostjo tveganju in domačimi makroekonomskimi determinantami. Domači faktorji so postali ključnega pomena tekom finančne krize, ko so mednarodni investitorji začeli diskriminirati med državami. Nenaklonjenost tveganju in slabo stanje na tekočem računu v veliki meri vplivata na slabe javne finance in razpon donosov državnih obveznic. Primanjkljaj na tekočem računu igra pomembno vlogo pri razponih donosov, saj je v času finančnih pretresov meja med zasebnim in javnim dolgom zabrisana, vlada pa morebiti primorana prevzeti zasebni dolg, kar gre v prid vlagateljem.

2.3 Ključne prednosti 3PRF metode

Naj zaključim s ključnimi prednostmi nove metode. Napovedi s 3PRF metodo so konsistentne za neizračunljive oziroma neizvedljive najboljše napovedi (Angl. *infeasible best forecast*) ko oba, časovna dimenzija in obseg reprezentativnega vzorca postaneta velikih dimenzij. Napovedovanje z uporabo metode **3PRF prinaša lažjo ekonomsko razlago faktorjev**, ki pojasnjujejo spremembe v gibanju odvisne spremenljivke in učinkovito uporabo ekonomske teorije pri iskanju možnih determinant pribitkov na 10–letne državne obveznice. Identificirani so faktorji, tako da se jim lahko dodeli ekonomska interpretacija. Slednjega PC metoda v okviru FAR ne prinaša. Skratka, odpravlja to slabost PC faktorjev. 3PRF oceni relevantne faktorje za spremenljivko, ki se uporabi kot faktor *proxy*. S tem povežem faktorje in pripadajoči *proxy*, torej dobim možnost ekonomske interpretacije faktorjev kot relevantnih prediktorjev za pribitke, če pri tem uporabim/iščem prek večjega nabora možnih *proxy*–jev.

V nadaljevanju povzemam izstopajoče prednosti 3PRF metode: *(1)* 3PRF rešitev je izražena v enostavno izračunljivi matrični obliki, *(2)* ni potrebe po uporabi ocenjevanja t.i. največjega verjetja (Angl. *Maximum Likelihood Estimation)*, *(3)* 3PRF predstavlja učinkovito alternativo Regresiji Glavnih Komponent (Angl. *Principal Components Regression*, v nadaljevanju: PCR) glede koreliranih idiosinkratičnih napak, saj predpostavlja, da se podatki obnašajo kot približni dinamični faktorski model po Rotschild–u in Chamberlain–u (1983), *(4)* PCR uporablja reprezentativni vzorec podatkov glede na kovarianco *znotraj* prediktorjev. PCR torej zajame informacije iz velikega nabora v majhno skupino prediktorjev pred ocenjevanjem linearne napovedi. To pomeni, da identificira tudi prediktorje, ki so irelevantni za dinamiko napovedne spremenljivke. 3PRF na drugi strani, povzema reprezentativni vzorec podatkov glede na kovarianco z napovedno tarčo – spremenljivko, ki jo napovedujem. PCR mora ocenjevati faktorje čez vse prediktorje, da doseže konsistentnost, tudi tiste, ki so irelevantni. **3PRF ocenjuje le relevantne faktorje.** 3PRF uporabi le toliko faktorjev, kot je potrebno za napovedovanje y_{t+1} – pribitkov. Na drugi strani je PCR asimptotično učinkovit le, če je prediktorjev toliko kot celotno število faktorjev, ki določajo x_t, *(5)* 3PRF napovedi so konsistente za najboljše neizračunljive napovedi v primeru, ko tako časovna dimenzija kot dimenzija reprezentativnega vzorca podatkov postaneta velikih obsegov, *(6) proxy*–ji imajo ničelno faktorsko utež na irelevantne faktorje, medtem ko imajo linearno neodvisno faktorsko utež na relevatne faktorje, (7) število *proxy*–jev je enako številu relevantih faktorjev, in *(8)* veliko prednost 3PRF predstavlja njegova zmožnost vključevanja *proxy*–jev na podlagi ekonomske teorije.

2.3.1 Napotki prihodnjim študijam v okviru 3PRF napovedovanja

Zanimivi napotki prihodnjim študijam v kontekstu 3PRF napovedne metode v podatkovno bogatem okolju so povezani z boljšo vsebino podatkovne baze, z daljšimi, čistejšimi in pogostejšimi frekvencami časovnih serij. Velik izziv vsekakor predstavlja tudi proučevanje uspešnosti oziroma učinkovitosti 3PRF v primeru nestacionarnih podatkov in podatkov integriranih reda $I\,(1)$ in reda $I\,(2)$ v pogojih kointegracije podatkovno bogatega okolja.