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MODELLING LOANS TO NON-FINANCIAL CORPORATIONS WITHIN THE EUROZONE: A LONG-MEMORY APPROACH

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Abstract

This paper uses fractional integration and cointegration methods to analyse the determinants of the amount of loans provided to non-financial corporations (NFCs) during the last three decades in four Eurozone countries, namely Germany, France, Italy and Spain. More specifically, ARFIMA (AutoRegressive Fractionally Integrated Moving Average) and FCVAR (Fractionally Cointegrated Vector Autoregression) models are estimated and then forecasts are also produced. All series are found to be highly persistent and long-run equilibrium relationships between them are also identified, confirming the role of real GDP and real gross investment as determinants of loans to NFCs. The forecasting accuracy of the FCVAR was also assessed by comparing it to that of the ARFIMA specifications, and the former were found to outperform the latter in all cases.

Keywords: non-financial corporations; loans; Eurozone; long-memory; fractional integration and cointegration

JEL classification: C22, C32, C51, H81

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1. Introduction

Credit plays an important role in the economy. In particular, the amount of loans provided to non-financial corporations (NFCs) is an indicator of the investment and spending decisions of the banking sector and thus also provides useful information to policy makers. Within the Eurozone in particular, bank lending is one of the major sources of financing to NFCs, with European firms heavily relying on bank lending to finance investment, especially in the case of small and medium-sized enterprises that have few alternatives to address their external financing needs (EIB, Revoltella et al, 2014). Credit is normally found to be high correlated with asset prices and hence can help understand financial cycles. It also has an important role in the transmission of monetary policy to the real side of the economy. Loans are a key component on the asset side of the balance sheet of Eurozone banks, and thus a significant counterpart to monetary aggregates. Consequently, corporate lending and, in particular, financing to NFCs is an important measure to consider for assessing the monetary policy stance.

Detailed knowledge of the factors determining corporate loan developments is therefore crucial for understanding monetary developments and the setting of monetary policy in the Eurozone. Credit growth for NFCs in this area is currently trending downwards, especially as a result of the accession of new member states that have been more severely affected by the global financial crisis of 2007-8. Stagnation of bank lending can be a severe constraint on economic growth in Europe where it plays a much more important role in financing the corporate sector than, for instance, in the US. In the wake of the 2007-8 crisis the capacity of many banks to lend to relatively high-risk sectors and to young, innovative firms has been seriously hindered by capital constraints and a strong deterioration in the quality of the assets on their balance sheets. However, prior to the Covid-19 crisis lending to NFCs was showing clear signs of recovery in all the four largest Eurozone countries as a result of the decreasing influence of various demand-side and supply-side factors related to the global financial crisis of 2007-8 which had depressed lending levels.

Given their importance in a European context, this paper analyses the determinants of the amount of loans provided to NFCs in four countries belonging to the Eurozone (Germany, France, Italy and Spain). The empirical framework is based on fractional integration and cointegration methods since most macroeconomic series appear to exhibit long-memory or long-range dependence (namely, their autocorrelations do not decay exponentially but rather according to a hyperbolic shape), which makes I(d) processes the most appropriate to model them since it allows shocks to have long-lasting effects.

The layout of the paper is as follows. Section 2 reviews the literature on modelling loans to NFCs, with a focus on Europe. Section 3 outlines the fractional integration and cointegration methods used for the analysis. Section 4 describes the data. Section 5 discusses the empirical results. Section 6 offers some concluding remarks.

2. Literature Review

Since the early 1990s a vast literature has developed on modelling credit to the private sector, especially within the central banking community given its policy relevance. A common feature of these studies is the econometric framework used. In particular, owing to the typically non-stationary nature of loans and their determinants, a Vector Error Correction Model (VECM) has normally been estimated.

Sørensen et al. (2010) were the first to use Johansen's (1992) methodology to explain the long-term behaviour of loans to NFCs in the Eurozone and identified three cointegrating relationships. Previous studies had generally modelled credit to the private sector as a whole. For instance, Hofmann (2001) estimated a 4-variable VECM for eight Eurozone countries from 1980 to 1998, and was unable to detect any cointegration relationships. Hülsewig (2003) analysed German data using a 5-variable VECM. He found two cointegrating relationships which he interpreted as the credit demand and the credit supply equilibria, with credit demand reverting rather slowly to its long-run equilibrium and supply effects through their impact on lending rates being insignificant. Calza et al. (2006) estimated a 4-variable VECM for the Eurozone and detected one cointegration relationship interpreted as the credit demand equilibrium. Gambacorta and Rossi (2010) investigated possible non-linearities in the response of bank lending to monetary policy shocks in the Eurozone over the period 1985-2005 by means of an Asymmetric Vector Error Correction Model (AVECM) involving four endogenous variables, and found that the effect on credit, GDP and prices of a monetary policy tightening was larger than that of a monetary policy easing. This result supported the existence of an asymmetric credit channel in the Eurozone.

Other studies have focused on business lending in individual Eurozone countries. Focarelli and Rossi (1998) specified a 5-variable VECM model and found three cointegrating relationships, namely loan demand, a relationship between investment and borrowing requirements and the lending rate equalling risk-free government bond yields. Bridgen and Mizen (1999) investigated the interactions between investment, money holding and bank borrowing by private NFCs and identified long-run relationships for investment, money and borrowing, with the dynamics indicating the existence of feedback from money and credit disequilibria onto investment. Bridgen and Mizen (2004) found equilibrium relationships for investment, lending and money with causal linkages running from money and lending to investment and from money to lending in a dynamic model. Kakes (2000) analysed the role of bank lending in the monetary transmission mechanism in Germany following a sectoral approach and distinguishing between corporate lending household lending; they reported that banks respond to a monetary contraction by adjusting their security holdings rather than by reducing their loans portfolio. Finally, Plasil et al. (2013) showed that Czech banks had to restrict credit significantly when the financial crisis hit.

Some more recent studies, such as Busch et al. (2010) and Tamasi and Vilagi (2011), estimate VAR models with theory-based restrictions imposed on the impulse response functions to identify difference types of shocks. Ferrari et . (2013) presented evidence suggesting survey indicators of credit conditions can be useful for macroprudential purposes. De Bondt et al. (2010) examined the information content of the Eurozone Bank Lending Survey for aggregate credit and output growth, which suggests that both price and non-price conditions and terms of credit matter for credit and business cycles. As far as we are aware, ours is the first attempt to carry out an analysis of loans to European NFCs using fractional integration and cointegration methods.

3. Methodology

Our analysis involves two steps. First the stochastic properties of loans to NFCs and their determinants are examined by means of both standard unit root tests and fractional integration methods (specifically, Sowell's (1992) exact maximum likelihood (EML) estimator and Robinson's (1994) tests based on the Lagrange multiplier (LM) principle. Second, the economic relationships linking them are investigated in the context of both standard and fractional cointegration multivariate models (in the latter case, the recently introduced fractionally cointegrated VAR (FCVAR) approach of Nielsen and Johansen, 2012, is implemented). These methods are outlined below.

3.1 Long Memory and Fractional Integration

An important characteristic of many economic and financial time series is their non-stationary nature, which can be described by a variety of models. Until the 1980s the standard approach was to use deterministic (linear or quadratic) functions of time, thus assuming that the residuals from the regression model were I(0) stationary. Later on, and especially after the seminal work of Nelson and Plosser (1982), a general consensus was reached that the non-stationary component of most series was stochastic, and unit roots (or first differences, I(1)) were most appropriate for them. However, the I(1) case is merely one particular model that can describe such behaviour. In fact, the number of differences required to achieve I(0) stationarity is not necessarily an integer value but could be any point on the real line, including fractional values. In the latter case, the process is said to be fractionally integrated or I(d).

Long memory is a feature of observations that are far apart in time but highly correlated. This can be captured by fractionally integrated or I(d) models of the form:

$$(1 - L)^d x_t = u_t, \quad t = 0, \pm 1, ..., \tag{1}$$

where d can be any real value, L is the lag-operator ($Lx_t = x_{t-1}$) and u_t is I(0), defined for our purposes as a covariance-stationary process with a spectral density function that is positive and finite at the zero frequency. Although fractional integration can also occur at other frequencies away from zero, as in the case of seasonal and cyclical fractional models, the series used for our analysis do not have these features and hence we estimate standard I(d) models as in (1). The idea of fractional integration was introduced by Granger and Joyeaux (1980), Granger (1980,1981) and Hosking (1981), though Adenstedt (1974) had already showed awareness of its representation. The polynomial $(1 - L)^d$ in equation (1) can be expressed in terms of its binomial expansion, such that, for all real d, x_t depends not only on a finite number of past observations but on the whole of its past history. In this context, d plays a crucial role since it indicates the degree of dependence of the series: the higher the value of d is, the higher the level of association between the observations will be.

Given the parameterisation in (1) one can distinguish between several cases depending on the value of d. Specifically, if d = 0, $x_t = u_t$, x_t is said to be "short memory" or I(0), and if the observations are (weakly) autocorrelated (e.g. AR), then the values in the autocorrelations decay exponentially fast; if $d > 0$, x_t is said to be long memory, so called because of the strong association between observations far apart in time. In this case, if d belongs to the interval (0, 0.5), x_t is still covariance stationary, while $d \geq 0.5$ implies non-stationarity. Finally, if $d < 1$, the series is mean-reverting and therefore the effects of shocks disappear in the long run, whilst if $d \geq 1$they persist forever. Hence the value of this parameter represents very useful information for policy makers.

There exist several methods to estimate and test the fractional differencing parameter d. Some of them are parametric while others are semi-parametric and can be specified in the time or in the frequency domain. Sowell (1992) analysed the exact maximum likelihood (EML) estimator of the parameters of the ARFIMA model in the time domain using a recursive procedure that allows a quick evaluation of the likelihood function. Doornik and Ooms (2003) refined this likelihood-based procedure, and Doornik and Ooms (2004) then applied this method to modelling inflation data in the UK and the US. We follow their ARFIMA modelling procedure and use the software package Oxmetrics, obtaining a parsimonious data representation to produce out-of-sample forecasts. In particular, the results based on the Exact Maximum Likelihood (EML) estimation were obtained by making use of the ARFIMA-package of Doornik and Ooms (1999), which is a class of procedures in the programming language Ox. The core of the EML method is the computation of the autocovariances as a function of the parameters of a stationary ARFIMA model, such that the levels of the long-range parameter d cannot be above 0.5. Hosking (1981) provided an effective method to compute the ACF for an ARFIMA (1,d,1) process, which was extended by Sowell (1992) to the general case, and then improved by enhancing numerical stability by Doornik and Ooms (2003).

Other parametric methods to estimate d in the frequency domain were proposed by, among others, Fox and Taqqu (1986) and Dalhaus (1989). The small sample properties of these and other estimators were examined by Hauser (1999). A semi-parametric frequency domain estimator is the log-periodogram estimator proposed by Geweke and Porter-Hudak (1983), and other semi-parametric methods have been put forward by Velasco (1999a, 1999b) and Phillips and Shimotsu (2004, 2005) among others. Another approach widely employed in the empirical literature and also in the present study is the parametric testing procedure of Robinson (1994), which is a Lagrange Multiplier (LM) test based on the Whittle function in the frequency domain. Robinson (1994) showed that, under certain very mild regularity conditions, its LM-based statistic converges asymptotically to a standard N(0, 1) distribution, and this limit behaviour holds independently of the use of exogenous regressors (or deterministic terms) and the specific modelling assumptions about the I(0) disturbances. The tests of Robinson (1994) were applied to an extended version of the Nelson and Plosser's (1982) dataset in Gil-Alana and Robinson (1997) to test for unit roots and other long-memory processes when the singularity at the spectrum occurred at the zero frequency, as in the case in the series analysed here. Such tests have not been previously applied to analyse the provision of loans to NFCs.

3.2 The Fractionally Cointegrated Vector AutoRegressive (FCVAR) Model

The Fractionally Cointegrated Vector AutoRegressive (FCVAR) model was introduced by Johansen (2008) and further developed by Johansen and Nielsen (2010, 2012). It is a generalisation of Johansen´s (1995) Cointegrated Vector AutoRegressive (CVAR) model which allows for fractional processes of order d that cointegrate with order d-b. In order to introduce the FCVAR model we start from the well-known, non-fractional, CVAR model. Let $Y_t, t = 1,\ldots T$ be a p-dimensional I(1) time series. Then the CVAR model can be expressed as:

$$\Delta Y_t = \alpha\beta' Y_{t-1} + \sum_{i=1}^{k} \Gamma_i \Delta Y_{t-i} + \varepsilon_t = \alpha\beta' L Y_t + \sum_{i=1}^{k} \Gamma_i \Delta L^i Y_t + \varepsilon_t \, . \qquad (2)$$

The simplest way to derive the FCVAR model is to replace the difference and lag operators Δ and L in (2) by their fractional counterparts, Δ^b and $L_b = 1 - \Delta^b$, respectively. One then obtains:

$$\Delta^b Y_t = \alpha\beta' L_b Y_t + \sum_{i=1}^{k} \Gamma_i \Delta^b L_b{}^i Y_t + \varepsilon_t, \qquad (3)$$

which is applied to $Y_t = \Delta^{d-b} X_t$ such that:

$$\Delta^d X_t = \alpha\beta' L_b \Delta^{d-b} X_t + \sum_{i=1}^{k} \Gamma_i \Delta^b L_b{}^i Y_t + \varepsilon_t, \qquad (4)$$

where ε_t is p-dimensional independent and identically distributed with mean zero and covariance matrix Ω.

The parameters have the same interpretation as in the CVAR model. In particular, α and β are $p \times r$ matrices, where $0 \le r \le p$. The columns of β are the cointegrating relationships in the system, that is to say the long-run equilibria. The parameters Γ_i govern the short-run behaviour of the variables and the coefficients in α represent the speed of adjustment towards equilibrium for each of the variables. Thus, the FCVAR model allows simultaneous modelling of the long-run equilibria, the adjustment responses to deviations from those and the short-run dynamics of the system. As an intermediate step towards the final model, we consider a version of model (2) with d = b and a constant mean term for the cointegration relations. That is to say:

$$\Delta^d X_t = \alpha(\beta' L_d X_t + \rho') + \sum_{i=1}^{k} \Gamma_i \Delta^d L_d{}^i X_t + \varepsilon_t. \qquad (5)$$

Johansen and Nielsen (2012) and Nielsen and Morin (2014) discuss estimation and inference of this model, the latter providing Matlab computer programs for the calculation of estimators and test statistics.

It is noteworthy that fractional differencing is defined in terms of an infinite series but any actual sample will include only a finite number of observations. In order to calculate the fractional differences one can assume that X_t was zero before the start of the sample. The bias introduced by this assumption is analysed by Johansen and Nielsen (2014) using higher-order expansions. They showed that it can be completely avoided by including a level parameter μ that shifts each of the series by a constant.

The estimated empirical model is the following:

$$\Delta^{d}(X_t - \mu) = L_d \alpha \beta^{'}(X_t - \mu) + \sum_{i=1}^{k} \Gamma_i \Delta^{d} L_d{}^{i}(X_t - \mu) + \varepsilon_t. \qquad (6)$$

The asymptotic analysis in Johansen and Nielsen (2012) shows that the maximum likelihood estimators of $(d, \alpha, \Gamma, \ldots. \Gamma_2)$ are asymptotically normal, while the maximum likelihood estimator of (β, ρ) is asymptotically mixed normal when $d_0 < 1/2$ and asymptotically normal when $d_0 > 1/2$. CFVAR models have recently been estimated for forecasting commodity returns by Dolatabadi et al. (2017); for forecasting political opinion polls by Nielsen and Shibaev (2015) and Jones et al. (2014); for commodity futures markets by Dolatabadi et al. (2014).

4. Data

Our analysis focuses on four Eurozone economies, namely Germany, France, Italy and Spain, and the following three quarterly series over the sample period 1980Q1 – 2014Q4 for each of them: real NFC (Non-Financial Corporations) loans, real gross investment and real GDP. The data were obtained from the Economics Department of the Deutsche Bundesbank.

[Insert Figure 1 and Table 1 about here]

Figure 1 displays the time series plots of the three variables for each of the four countries examined and descriptive statistics are reported in Table 1. Real NFC loans trend upwards till the end of the 2000´s except for the case of Germany where a significant decline occurred at the start of that decade, and was followed by an increase and then a sudden decrease by 2010. Similar falls were experienced in the other countries, Spain being the most noticeable case. Real Gross Investment exhibits a similar pattern in France, Italy and Spain, namely a significant increase till the end of the last decade followed by a sharp fall. The exception is Germany, where this series fluctuated throughout the last two decades. Finally, the behaviour of real GDP shows the effects of the 2007-8 global financial crisis: in all four countries it fell significantly and it appears still to be stagnating, with the exception of Germany where there were clear signs of recovery.

5. Empirical Results

As a first step we carried out standard unit root tests, specifically the ADF test from Dickey and Fuller (1979); the results can be found in the Appendix, with the p-values implying in all cases that the null hypothesis of a unit root cannot be rejected and therefore the series are not stationary in levels. Although there could still exist a linear combination of these series that is stationary, i.e. they could be cointegrated in the sense of Engle and Granger (1987) or Johansen (1995), all such cointegration tests fail to identify any long-run equilibrium relationships linking the variables of interest, possibly as a result of the relatively short data span.

It is well known that unit root tests have very low power against specific alternatives such as structural breaks (Campbell and Perron, 1991); trend-stationary models (DeJong et al., 1992), regime-switching (Nelson et al., 2001), or fractional integration (Diebold and Rudebusch, 1991; Hassler and Wolters, 1994; Lee and Schmidt, 1996). In this paper we focus on fractional integration, noting that it includes the classic unit root models as a particular case of interest.

In particular, we estimate the following model:

$$y_t = \beta_0 + \beta_1 t + x_t, \quad (1 - L)^d x_t = u_t, \quad t = 1, 2, ..., \tag{7}$$

where y_t is the observed time series; β_0 and β_1 are the coefficients on the intercept and the linear time trend respectively, and the disturbance term u_t is I(0) and assumed to be a white noise.[1]

[Insert Table 2 about here]

Table 2 displays the Whittle estimates of d along with the 95% confidence intervals of the non-rejection values of d using Robinson's (1994) parametric approach. We report the estimates of d for the three standard cases of no regressors in the undifferenced regression (i.e., $\beta_0 = \beta_1 = 0$ in (7)), an intercept (β_0 unknown and $\beta_1 = 0$), and an intercept with a linear time trend (both β_0 and β_1 unknown).

It can be noticed that the estimated values of d are very similar for the two specifications including deterministic terms (see Table 2). The coefficients in bold are those for the model selected on the basis of the statistical significance of the regressors; note that Robinson's (1994) approach is based on the null differenced model, which is I(0) by construction, and thus the t-values are still valid in the differenced regression model. In other words, under the null hypothesis:

$$H_o : d = d_o \tag{8}$$

equation (7) becomes $\tilde{y}_t = \beta_0 \tilde{1}_t + \beta_1 \tilde{t}_t + u_t$, where $\tilde{1}_t = (1-L)^{d_o} 1_t$, and $\tilde{t}_t = (1-L)^{d_o} t_t$, and, given that u_t is I(0) by construction, standard t-tests apply. The t-values for the deterministic terms

[1]Note that the I(0) u_t term also allows for (weakly) ARMA-types of autocorrelations, with very similar results in this case.

imply that the selected model should be the one with an intercept only, and the estimated values of d in this case imply lack of mean reversion for all series except German Real Gross Investment, although even in that case this hypothesis cannot be rejected conclusively. Two important points emerge from these results. First, for all these series the effects of shocks persist forever, which is of interest to policy makers. Second, none of the series is covariance-stationary ($d \geq 0.5$) and therefore forecasting based on Robinson´s (1994) long-memory tests is problematic, and one should use instead Sowell´s (1992) long-memory ARFIMA models based on exact maximum-likelihood estimation (EML) on the first differenced processes.

The core of the EML method is the computation of the autocovariances as a function of the parameters of a stationary ARFIMA model, such that the long-range parameter d cannot be above 0.5, this being one of the main differences in comparison to Robinson's (1994) tests. We have estimated parsimonious ARFIMA models for loans to NFCs in each of the four European countries considered using maximum likelihood, using the AIC and BIC criteria to choose the lag length and the MSE criterion to assess the forecasting performance.[2]

[Insert Figure 2 about here]

For each of the four countries we show four different forecasts in Figure 2. Both visual inspection and the MSE criterion indicate that in all four cases the forecasts obtained using a fractionally integrated framework are considerably more accurate than those based on simple autoregressive AR(1) processes. This underlines the importance of taking into account long memory in macroeconomic series.

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[2] Note, however, that these criteria may not necessarily be the best criteria in applications involving fractional differencing. They concentrate on the short-term forecasting ability of the fitted model and may not give sufficient attention to the long-run properties of the ARFIMA models. (see, eg, Hosking, 1981, 1984). For model selection in the case of long- and short-memory processes see also Beran et al. (1998) who propose versions of the AIC, BIC and the HQ (Hannan and Quinn, 1998) criterio in the case of fractional autoregressions but do not consider MA components.

Next we estimate the FCVAR models. The lag length is determined using a general-to-specific testing strategy, namely several lags are initially included and then the insignificant ones on the basis of LR tests are dropped sequentially. In all four cases the selected lag order was 1. The rank of the system, that is to say the number of cointegrating relations, is then determined on the basis of a series of LR tests, whose asymptotic distributions are non-standard and derived in Johansen and Nielsen (2012). In all cases the appropriate rank order turned out to be 2.

[Insert Table 3 about here]

The FCVAR results are reported in Table 3. They include in each case the rank tests and the parameter estimated for the (unrestricted) models. Figure 3 displays instead the forecasts produced by the estimated models, according to which NFCs should increase in Germany and Italy, decrease considerably in Spain and remain relatively stable in France.

[Insert Figure 3 about here]

6. Conclusions

In this paper we have carried out an empirical investigation of the determinants of loans to NFCs in four countries belonging to the Eurozone (Germany, France, Italy and Spain). The findings are of interest not only to academics, but also to practitioners and European policy makers, since this type of financing is much more important for the corporate sector in Europe than elsewhere. Our modelling approach has been based on fractional integration and cointegration methods, which have the advantage of taking into account the possible long-memory properties of the series of interest. Specifically, we have estimated univariate models for the individual series and a FCVAR model to examine linkages between them. All series were found to be highly persistent and long-run equilibrium relationships between them were also identified, confirming the role of real GDP and real gross investment as determinants of loans to NFCs. The forecasting accuracy of the FCVAR models was also assessed by comparing it to that of the ARFIMA specifications, and the former were found to outperform the latter in all cases.

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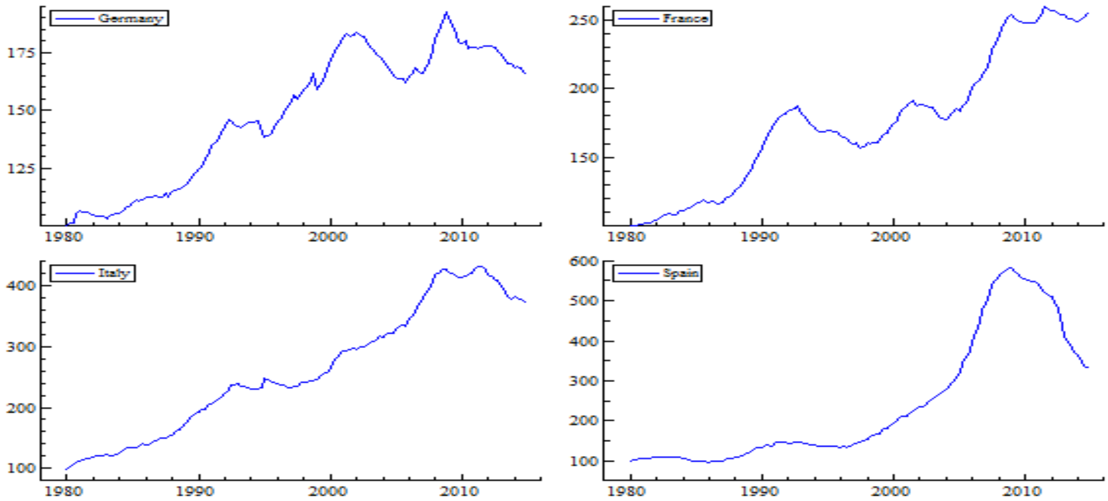
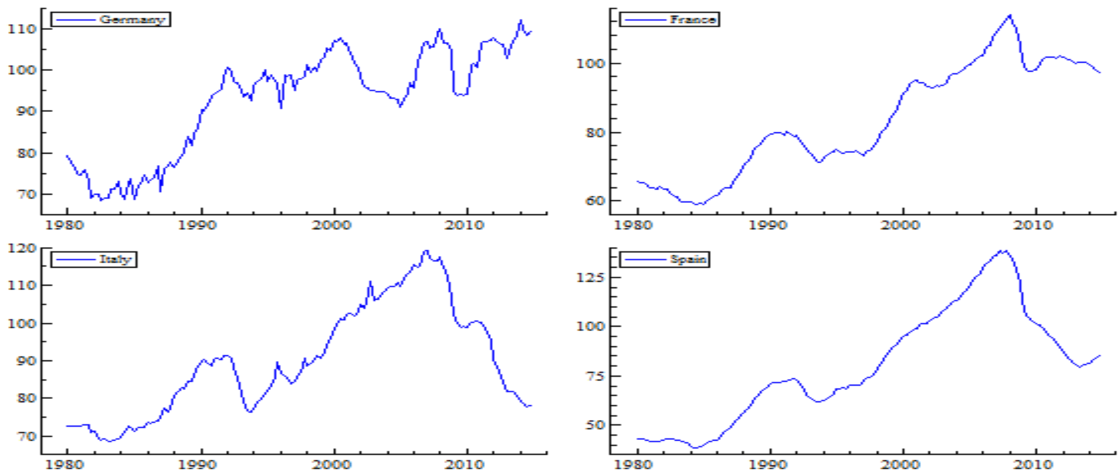
Figure 1:Series graphical representation

Real NFC loans, index (from stocks)



Real Gross Investment, index



Real GDP, index

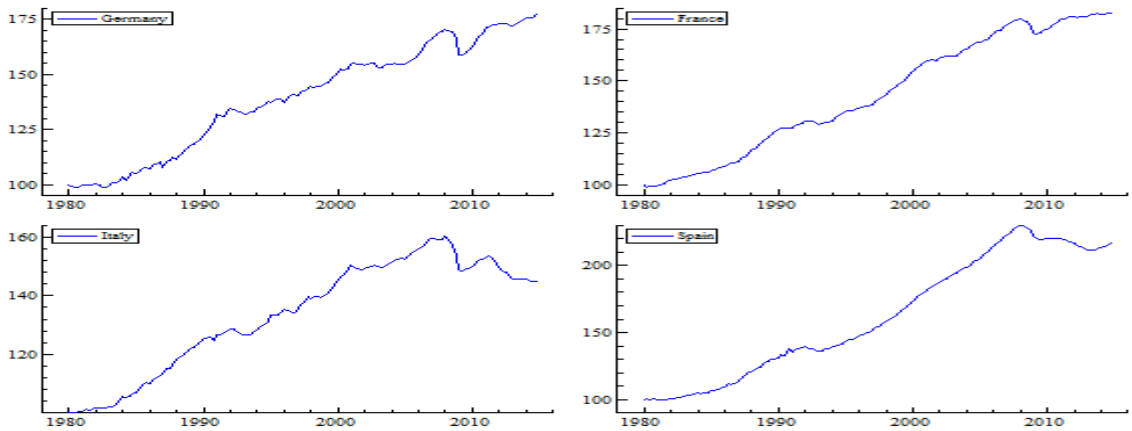
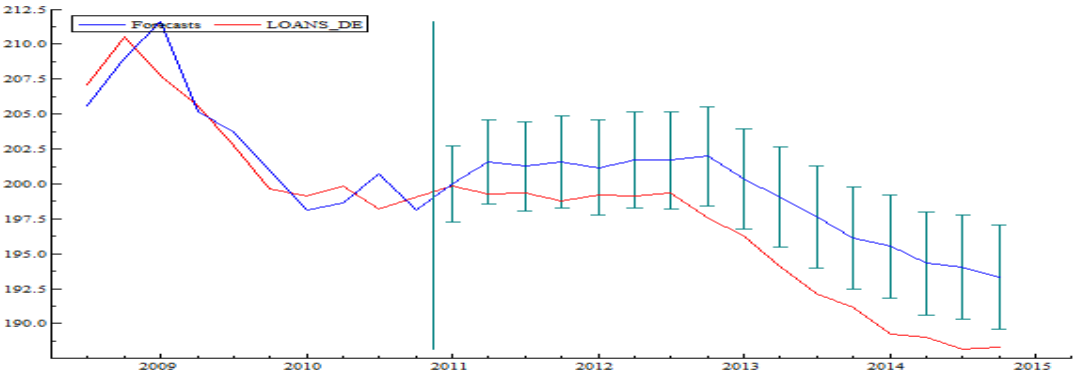
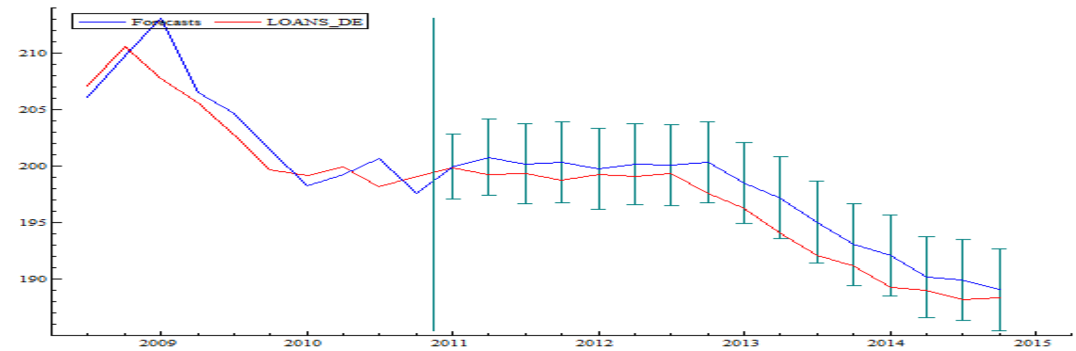


Figure 2: ARFIMA Modelling Forecasts of loans to non financial corporations.

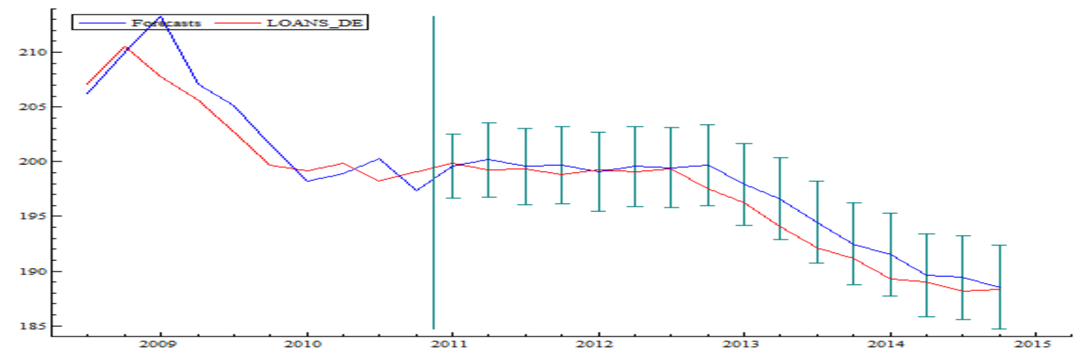
GERMANY



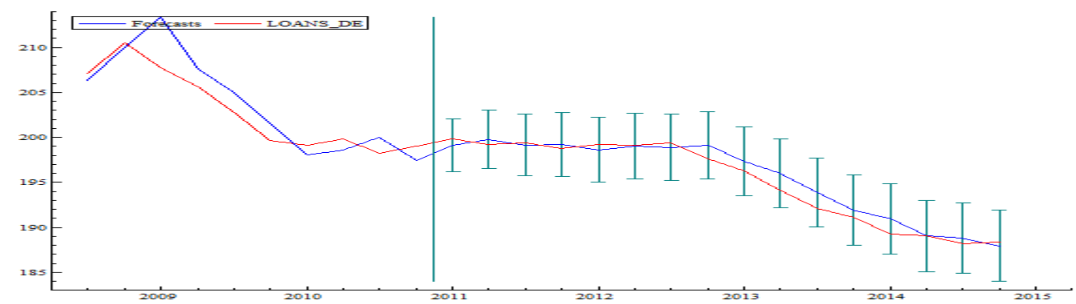
No Fractional Integration MSE= 4.1506



ARFIMA (1,0,0) MSE= 1.8475

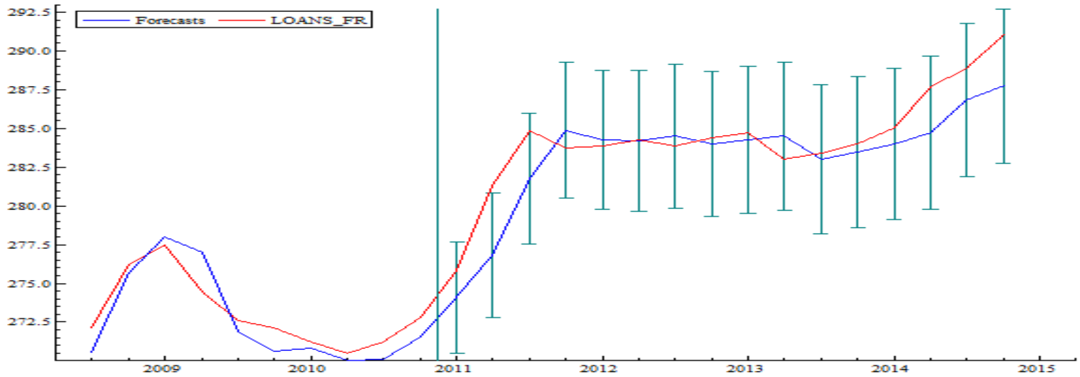


ARFIMA (0,d,1) MSE= 1.3720

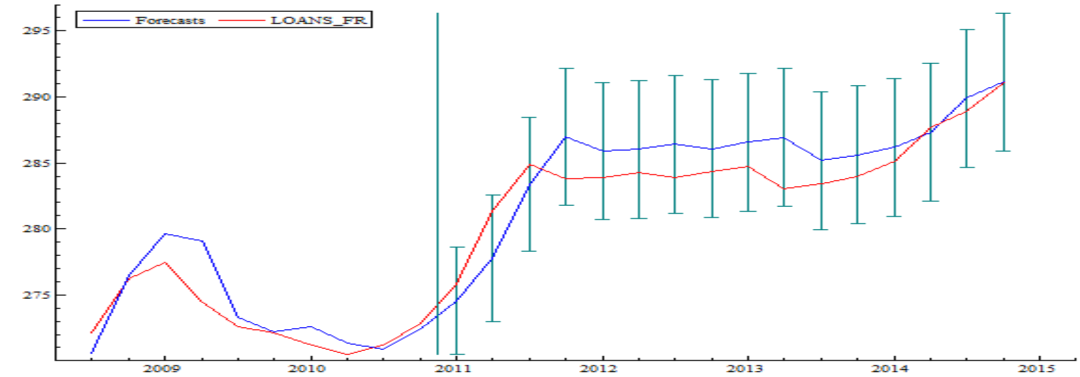


ARFIMA (0,d,0) MSE= 0.9969

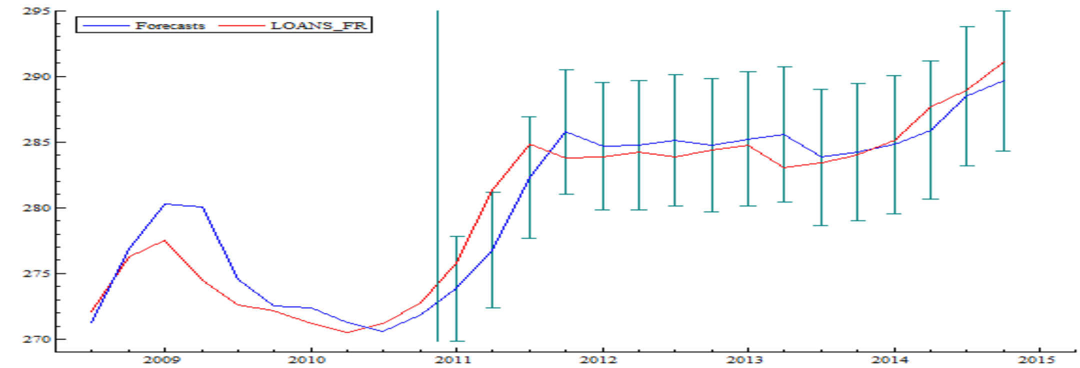
FRANCE



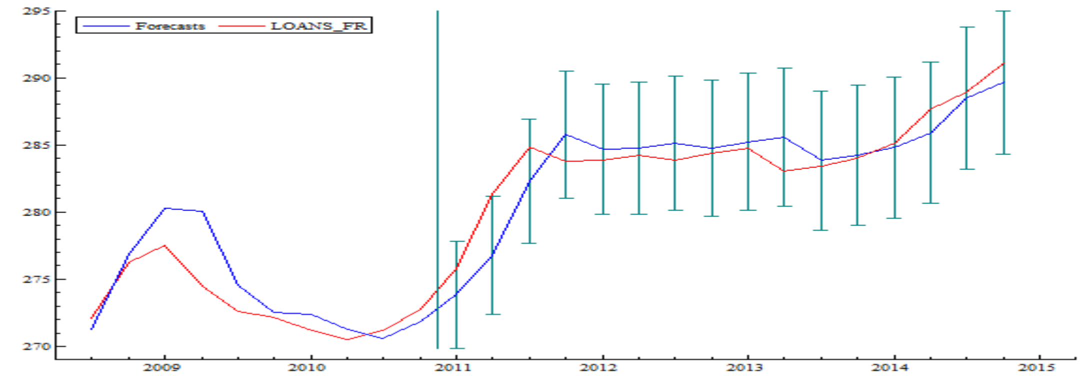
No Fractional Integration MSE=1.9747



ARFIMA (1,0,0) MSE= 2.0997

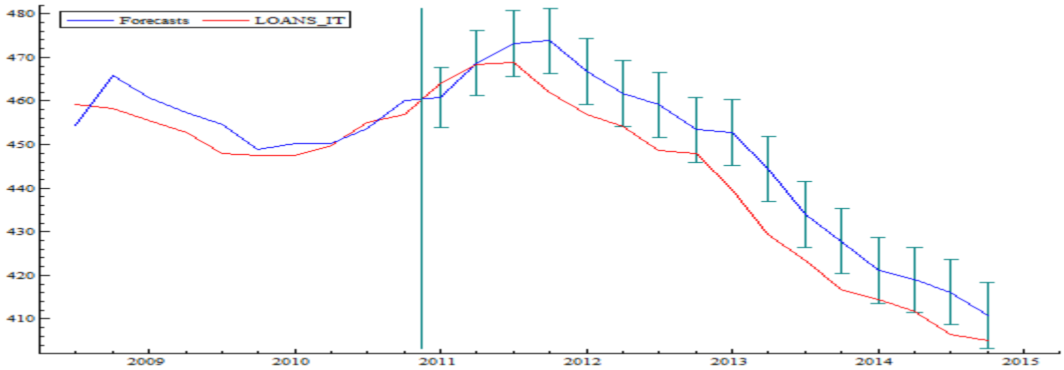


ARFIMA (0,d,1) MSE= 1.7717

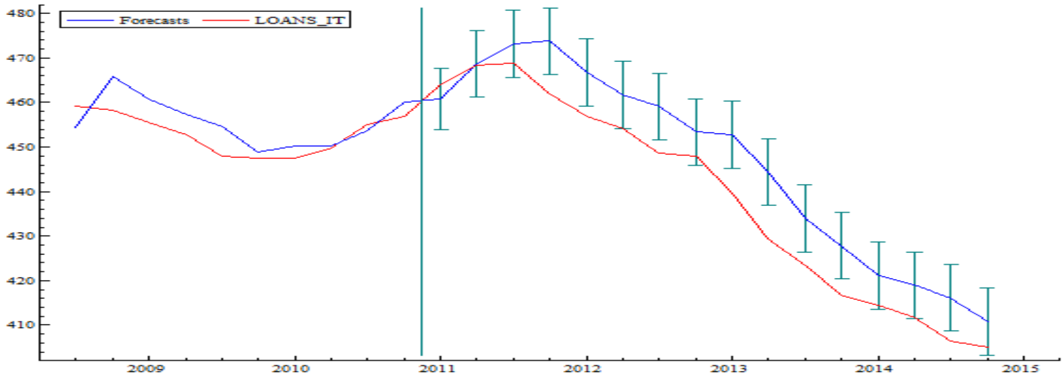


ARFIMA (0,d,0) MSE= 1.7713

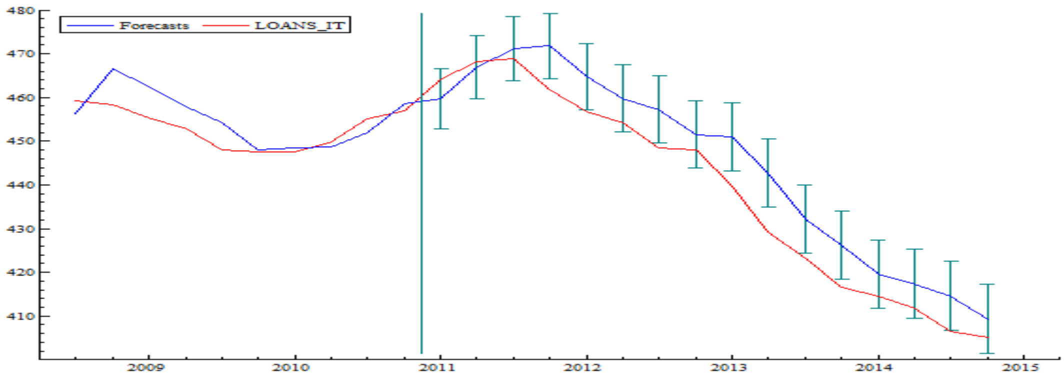
ITALY



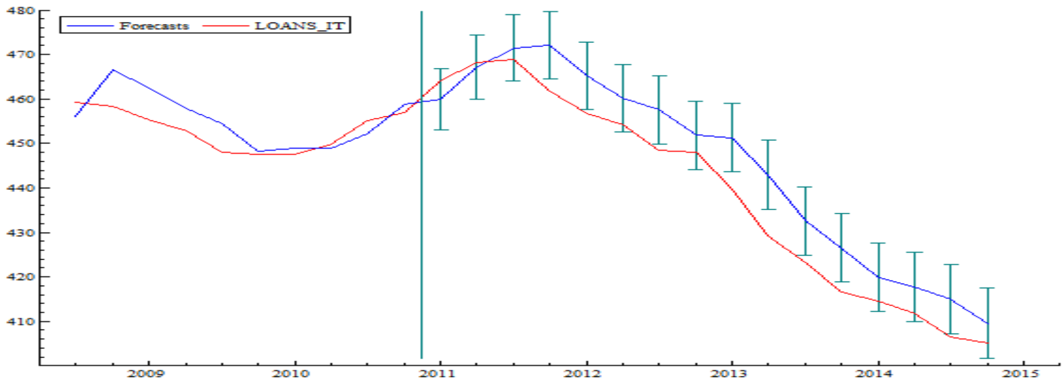
No Fractional Integration MSE= 13.7512



ARFIMA (1,0,0) MSE= 9.1141

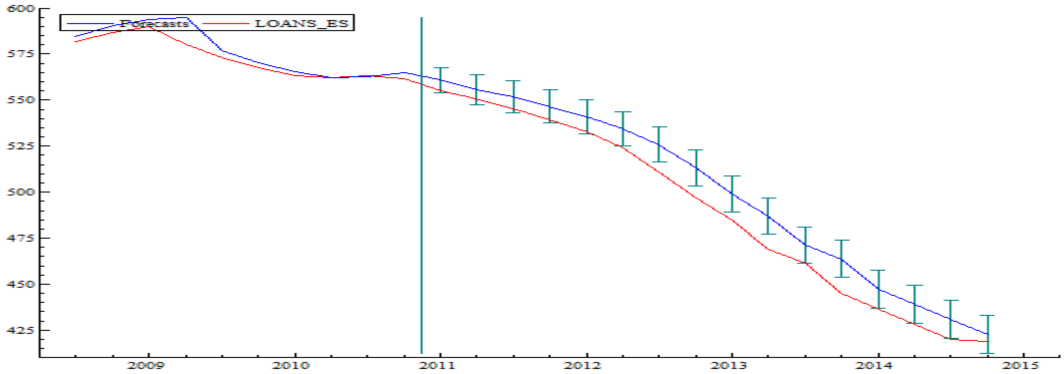


ARFIMA (0,d,1) MSE= 7.6195

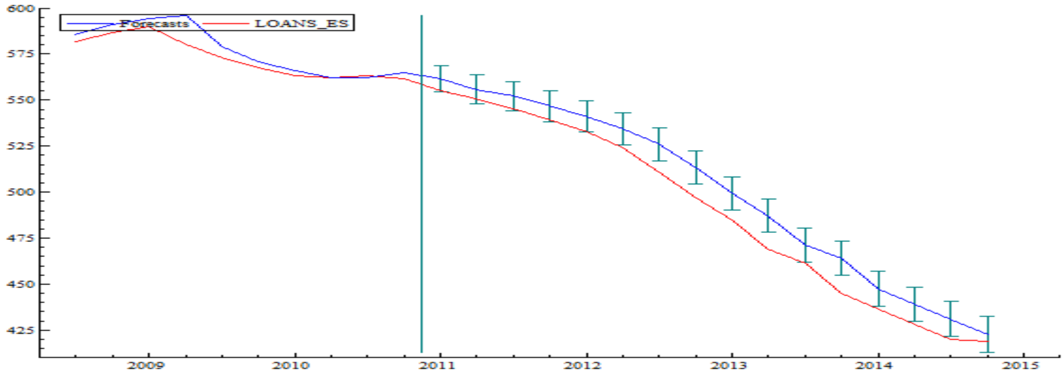


ARFIMA (0,d,0) MSE= 7.8823

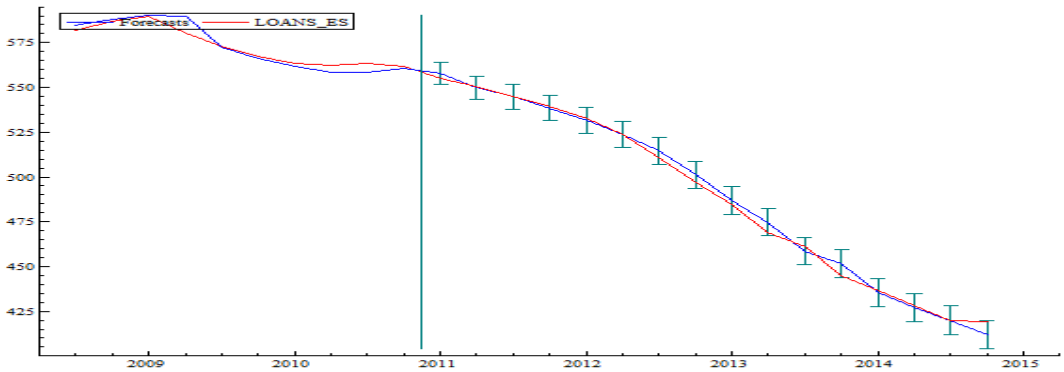
SPAIN



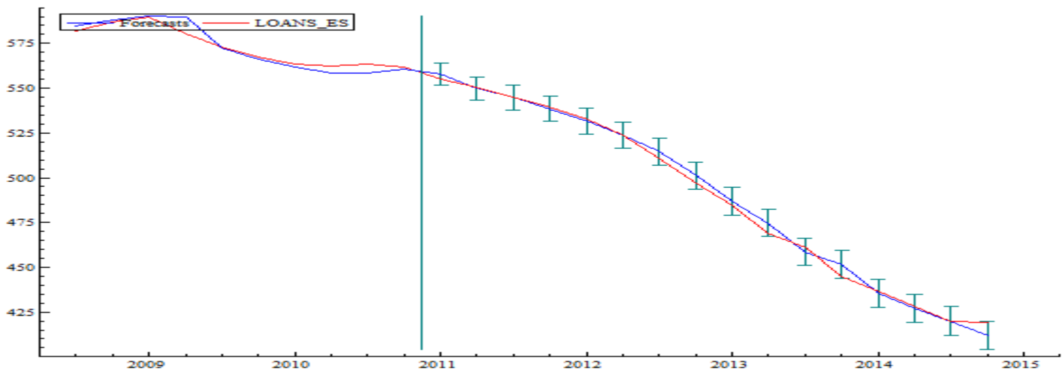
No Fractional Integration MSE= 13.3951



ARFIMA (1,0,0)or AR(1) MSE= 12.575



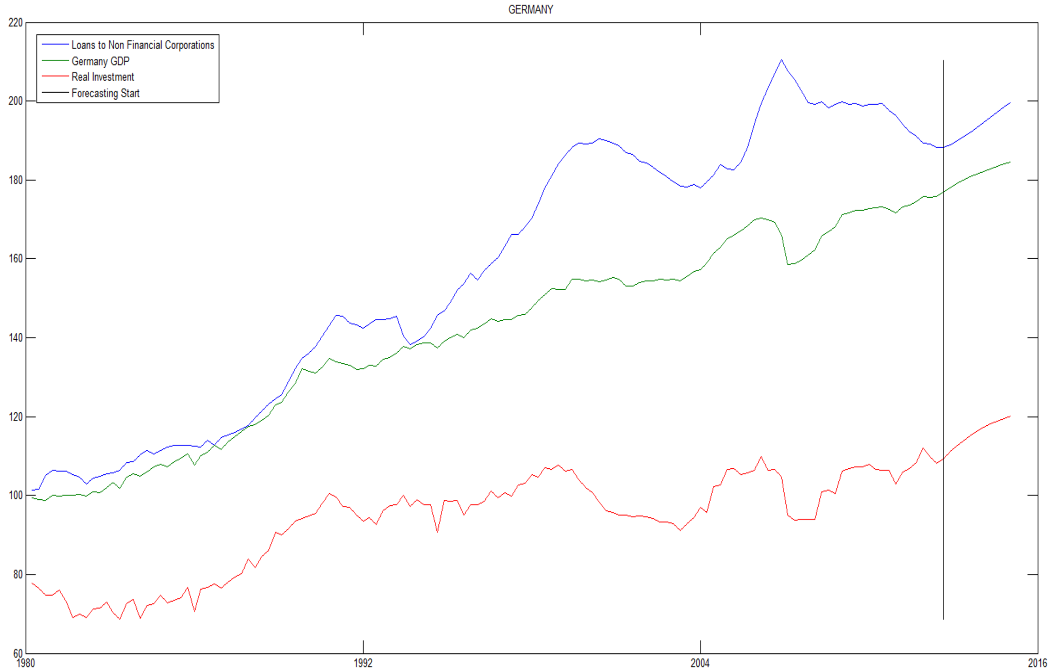
ARFIMA (0,d,1) MSE=9.765



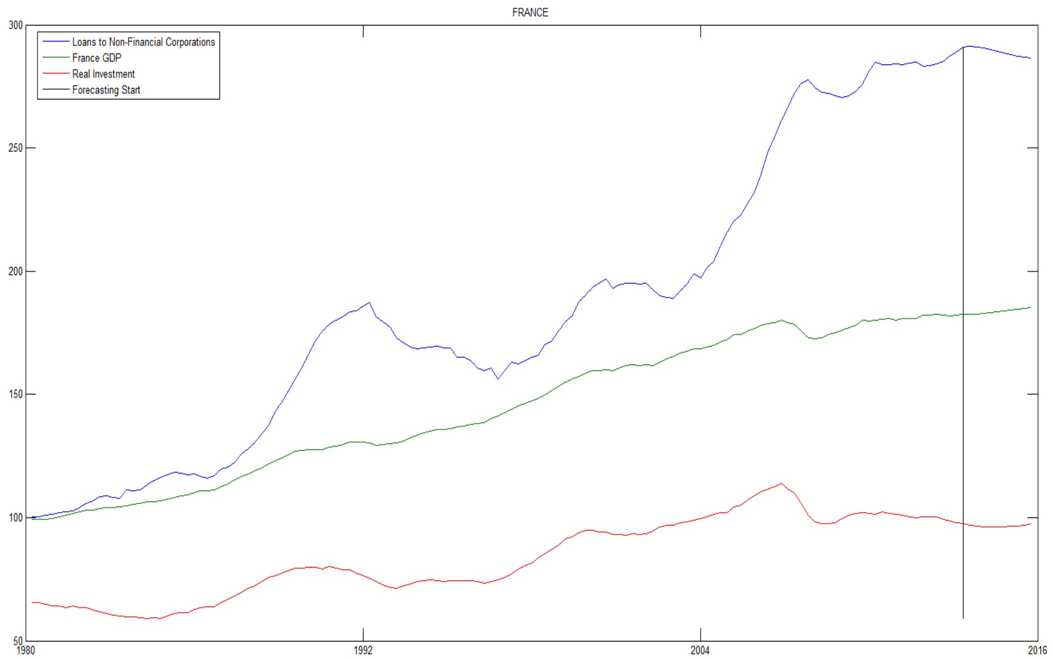
ARFIMA (0,d,0) MSE=9.547

Figure 3: FCVAR Loans to non-financial corporations forecasts.

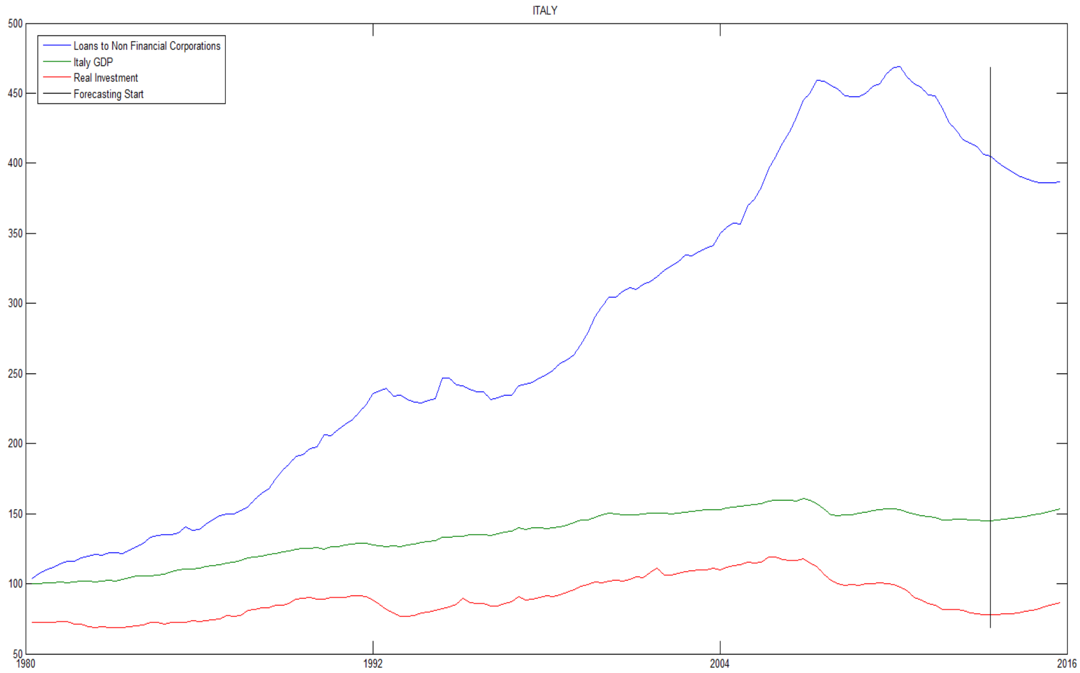
GERMANY



FRANCE



ITALY


ITALY
Loans to Non Financial Corporations
Italy GDP
Real Investment
Forecasting Start
500
450
400
350
300
250
200
150
100
50
1980
1992
2004
2016

SPAIN

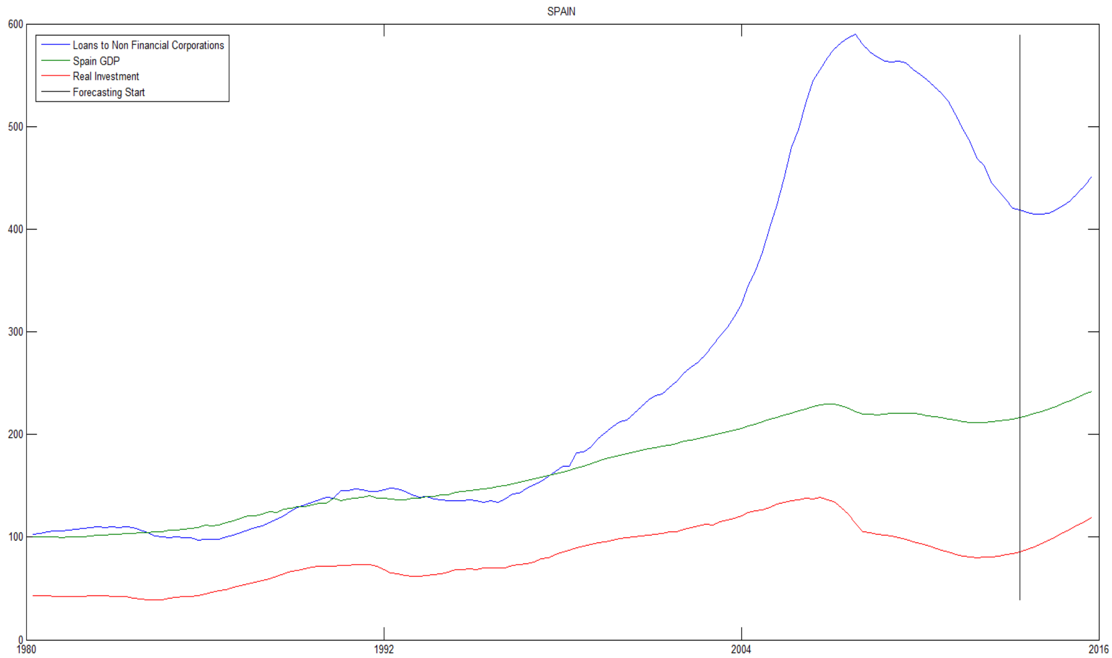

SPAIN
Loans to Non Financial Corporations
Spain GDP
Real Investment
Forecasting Start
600
500
400
300
200
100
0
1980
1992
2004
2016

Table 1: Descriptive Statistics

GERMANY	Mean	Median	Min	Max	St.dev	Asymetry	Kurtosis
Real NFC Loans	148.21	155.56	100.37	192.36	28.335	-0.332	-1.362
Real Gross Investment	92.751	95.53	68.85	112.15	12.675	-0.601	-0.943
Real GDP	139.32	142.26	98.72	176.94	24.698	-0.263	-1.213
FRANCE	**Mean**	**Median**	**Min**	**Max**	**St.dev**	**Asymetry**	**Kurtosis**
Real NFC Loans	175.67	175.13	100.28	259.52	48.69	0.194	-0.947
Real Gross Investment	83.458	79.615	58.96	113.81	15.932	0.065	-1.333
Real GDP	143.68	140.75	99.27	182.41	27.972	-0.085	-1.405
ITALY	**Mean**	**Median**	**Min**	**Max**	**St.dev**	**Asymetry**	**Kurtosis**
Real NFC Loans	260.54	241.53	99.69	431.43	102.58	0.167	-1.19
Real Gross Investment	89.791	88.45	68.62	119.31	14.43	0.353	-0.98
Real GDP	133.82	137.23	100.00	160.53	18.562	-0.456	-1.084
SPAIN	**Mean**	**Median**	**Min**	**Max**	**St.dev**	**Asymetry**	**Kurtosis**
Real NFC Loans	243.01	147.81	97.13	583.7	160.56	0.964	-0.579
Real Gross Investment	79.941	73.76	38.51	138.42	28.441	0.333	-0.816
Real GDP	133.82	137.23	100.00	160.53	18.562	-0.456	-1.084

Table 2: Long Memory-Fractional Integration Analysis results.

Real GDP, index	No regressors	With Intercept	With Intercept and Trend
Germany	0.96 (0.85, 1.11)	**1.16 (1.03, 1.33)**	1.16 (1.03, 1.33)
France	0.95 (0.84, 1.09)	**>1.50**	>1.50
Italy	0.96 (0.86, 1.11)	**1.41 (1.29, 1.50)**	1.40 (1.28, 1.50)
Spain	0.97 (0.85, 1.12)	**1.37 (1.30, 1.46)**	1.36 (1.29, 1.45)
Real Gross Inv.	No regressors	With Intercept	With Intercept and Trend
Germany	0.93 (0.83, 1.08)	**0.94 (0.85, 1.06)**	0.93 (0.84, 1.06)
France	0.96 (0.84, 1.11)	**>1.50**	>1.50
Italy	0.98 (0.87, 1.13)	**1.30 (1.21, 1.43)**	1.30 (1.21, 1.43)
Spain	1.17 (1.07, 1.30)	**1.50**	>1.50
Real NFC Loans	No regressors	With Intercept	With Intercept and Trend
Germany	0.97 (0.86, 1.11)	**1.39 (1.27, 1.50)**	1.39 (1.27, 1.50)
France	1.03 (0.92, 1.17)	**>1.50**	>1.50
Italy	1.03 (0.91, 1.18)	**1.39 (1.30, 1.50)**	1.39 (1.29, 1.50)
Spain	1.35 (1.26, 1.46)	**>1.50**	>1.50

Results obtained using Robinson (1994) tests. Disturbances were considered as White noise.

Table 3: FCVAR models for Loans to Non-Financial Corporations in Germany, France, Italy and Spain.

GERMANY:

Rank Test	d	Log-Likelihood	LR statistic
0	0.516	-709.279	10.817
1	0.452	-706.792	5.844
2	0.394	-704.487	1.234
3	0.355	-703.870	------

FCVAR model:

$$\Delta^d \left(\begin{bmatrix} loans_t \\ GDP_t \\ inv_t \end{bmatrix} - \begin{bmatrix} 100.547 \\ 99.531 \\ 77.688 \end{bmatrix} \right) = L_d \begin{bmatrix} 0.024 \\ -0.053 \\ -0.058 \end{bmatrix} \upsilon_t + \sum_{i=1}^{2} \Gamma_i \Delta^d L_d{}^i (X_t - \mu) + \varepsilon_t .$$

FRANCE:

Rank	d	Log-Likelihood	LR statistic
0	0.796	-505.419	29.360
1	**0.928**	**-495.626**	**9.773**
2	0.981	-491.998	2.518
3	1.012	-490.739	--------

FCVAR model:

$$\Delta^d \left(\begin{bmatrix} loans_t \\ GDP_t \\ inv_t \end{bmatrix} - \begin{bmatrix} 100.244 \\ 99.159 \\ 65.637 \end{bmatrix} \right) = L_d \begin{bmatrix} 0.008 \\ -0.005 \\ -0.004 \end{bmatrix} \upsilon_t + \sum_{i=1}^{2} \Gamma_i \Delta^d L_d{}^i (X_t - \mu) + \varepsilon_t .$$

ITALY:

Rank	d	Log-Likelihood	LR statistic
0	0.440	-746.845	26.763
1	**0.398**	**-740.351**	**13.775**
2	0.258	-733.995	1.063
3	0.293	-733.464	------

FCVAR model:

$$\Delta^d\left(\begin{bmatrix} loans_t \\ GDP_t \\ inv_t \end{bmatrix} - \begin{bmatrix} 103.275 \\ 99.978 \\ 73.051 \end{bmatrix}\right) = L_d \begin{bmatrix} -0.02 \\ -0.042 \\ -0.077 \end{bmatrix} \upsilon_t + \sum_{i=1}^{2} \Gamma_i \Delta^d L_d{}^i (X_t - \mu) + \varepsilon_t.$$

SPAIN:

Rank	d	Log-Likelihood	LR statistic
0	0.610	-712.889	24.688
1	**0.442**	**-704.577**	**8.065**
2	0.484	-701.266	1.441
3	0.480	-700.545	------

FCVAR model:

$$\Delta^d\left(\begin{bmatrix} loans_t \\ GDP_t \\ inv_t \end{bmatrix} - \begin{bmatrix} 102.194 \\ 100.052 \\ 43.311 \end{bmatrix}\right) = L_d \begin{bmatrix} 0.003 \\ 0 \\ 0.001 \end{bmatrix} \upsilon_t + \sum_{i=1}^{2} \Gamma_i \Delta^d L_d{}^i (X_t - \mu) + \varepsilon_t.$$

Appendix

ADF Unit Root Tests Results

Real GDP,index	No regressors	With Intercept	With Intercept and Trend
Germany	3.556	-0.641	-2.283
France	2.783	-1.079	-1.942
Italy	1.829	-2.031	0.041
Spain	2.018	-0.928	-3.049
Real Gross Inv.	No regressors	With Intercept	With Intercept and Trend
Germany	0.831	-1.327	-2.456
France	0.916	-1.167	-2.188
Italy	-0.126	-1.566	-0.844
Spain	0.092	-1.681	-2.313
Real NFC Loans	No regressors	With Intercept	With Intercept and Trend
Germany	0.862	-1.646	-1.219
France	1.938	-0.841	-3.191
Italy	1.177	-1.156	-3.276
Spain	-0.120	-1.267	-3.408

Test statistics values. In all cases the null hypothesis of the unit root cannot be rejected, meaning that the series cannot be considered stationary.