Macro Stress-Testing Credit Risk in Romanian Banking System

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Abstract

This report presents an application of a macro stress testing procedure on credit risk in the Romanian banking system.

Macro stress testing, i.e. assessing the vulnerability of financial systems to exceptional but plausible macroeconomic scenarios, maintains a central role in macro-prudential and crisis management frameworks of central banks and international institutions around the globe.

Credit risk remains the dominant risk challenging financial stability in the Romanian financial system, and thus this report analyses the potential impact of macroeconomic shocks scenarios on default rates in the corporate and household loan portfolios in the domestic banking system.

A well-established reduced form model is proposed and tested as the core component of the modelling approach. The resulting models generally confirm the influence of macroeconomic factors on credit risk as documented in previous research including applications for Romania, but convey also specific and novel findings, such as inclusion of leading variables and construction activity level for corporate credit risk.

Using the estimated model, a stress testing simulation procedure is undertaken. The simulation shows that under adverse shock scenarios, corporate default rates can increase substantially more than the expected evolution under the baseline scenario, especially in case of GDP shock, construction activity shock or interest rate shocks. Under the assumptions of these adverse

scenarios, given also the large share of corporate loans in the banks' balance sheet, the default rates evolution could have a substantial impact on banks' loan losses.

The households sector stress testing simulation show that this sector is more resilient to macroeconomic adverse evolutions, with stressed default rates higher than expected values under baseline scenario, but with substantially lower deviations.

The proposed macro-perspective model and its findings can be incorporated by private banks in their micro-level portfolio risk management tools. Additionally, supplementing the authorities' stress tests with independent approaches can enhance credibility of such financial stability assessment.

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Abbreviation list

ADL	Autoregressive Distributed Lag (econometric model)
ARMA	Auto-Regressive Moving Average
CPI	Consumer Price Index
EAD	Exposure At Default
E.B.A.	European Banking Association
EL	Expected Loss
E.U.	European Union
F.S.A.P.	Financial Sector Assessment Programs
GDP	Gross Domestic Product
I.M.F.	International Monetary Fund
LGD	Loss Given Default
LLP	Loan Loss Provision
MSCE	Monte Carlo Standard Error
N.A.T.O.	North Atlantic Treaty Organization
N.B.R.	National Bank of Romania
NPL	Non-Performing Loans
OLS	Ordinary Least Square (regression)
PD	Probability of Default
p.p.	Percentage points
Q1, Q2, Q3, Q4	Quarter 1, 2, 3, 4 respectively
RON	Romanian Leu
SUR	Seemingly Unrelated Regression
U.S.	United States of America
UL	Unexpected Loss
VAR	Vector-Autoregression

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1. Introduction

1.1. Macro stress-testing background

Macro stress-testing comprises a set of techniques designed to assess potential vulnerabilities of a financial system, or a sub-set thereof, to “exceptional but plausible” macroeconomic shocks (I.M.F. and the World Bank, 2003, p. 3, Jobst et al, 2013). Whereas stress-testing at micro levels (e.g. at portfolio or institution level) has been extensively used by international banks since 1990, macro stress-testing of entire financial systems is a more recent approach (Borio et al, 2012; Sorge and Virolainen, 2006). It has maintained a key role within Financial Sector Assessment Programs (F.S.A.P.) macro-surveillance framework initiated by International Monetary Fund (IMF) and the World Bank in 1999 (Sorge and Virolainen, 2006) and has gradually become an important part of the macro-prudential toolbox used by authorities around the globe (especially central banks and international financial institutions, F.S.B.-I.M.F.-B.I.S., 2011, Drehmann, 2008). Following the onset of the current crisis, macro stress-testing has gained a new role of effective crisis management and resolution tool, guiding bank recapitalization processes and contributing to restoring confidence within financial systems (I.M.F., 2012a, Borio et al, 2012).

Aside I.M.F.’s F.S.A.P. programs, illustrative examples of usage of macro stress-testing, applied within broader crisis-management stress-testing procedures and focusing on financial institutions of systemic importance, include (i) U.S. Federal Reserve Supervisory Capital Assessment Program performed in 2009, (ii) E.U.-wide stress-testing performed by the

Committee of European Banking Supervisors and the European Banking Association (E.B.A.) in 2010, and (iii) E.B.A. Capital Exercise in 2011-2012. (I.M.F., 2012a; E.B.A. 2011).

The main intended value added of macro stress testing is derived from the consultative approach of the process and the integration of "a forward-looking macroeconomic perspective, a focus on the financial system as a whole, and a uniform approach to the assessment of risk exposures across institutions" (I.M.F. and the World Bank, 2003, p. 3, Foglia, 2009).

1.2. Stress test application in the Romanian banking system

The latest financial stability report issued by the National Bank of Romania (N.B.R. 2012) shows that the Romanian financial system is dominated by the banking system, which accounts for almost 68% of the net assets of the Romania financial systems (N.B.R. 2012). The domestic banking system features a high connectivity with the European banking system as majority E.U.-based foreign capital banks hold more than 80% of total net assets. The report notes that, in spite of the adverse macroeconomic conditions of the last years, local banks register sound capital adequacy levels and comfortable solvency ratio as a result of central bank prudential actions and support from parent banks materialized in substantial new capital contributions.

Two major financial stability vulnerabilities of the Romanian banking system are identified by the report:

- credit risk, which remains the dominant risk as non-performing loans have maintained upward trends in a weak macroeconomic environment, and have generated substantial losses in bank's balance sheets;

- risk related to external financing of foreign capital banks. A gradual reduction of external funding has been registered in the recent years, but generally the central bank considers that current prudential indicators levels strongly mitigate this risk, and that the system can successfully face even massive funding withdrawal.

While there is an impressive amount of research on the development and implementation of macro stress testing around the globe (Foglia, 2009) and in spite of the documented importance of stress testing research in assessing the health of financial systems and addressing crisis effects, applications of macro stress testing for the Romanian financial system is very limited.

Given the predominance of the banking system in the domestic financial system, and the persistent inherent risks, local macro stress testing exercises have focused on the banking system, in both authorities' efforts and independent studies.

The International Monetary Fund and the Romanian central bank use comprehensive stress test frameworks that incorporate estimation of shocks impact on various risk exposures (credit risk, interest rate risk effect on future income, liquidity risk) and combine macro-level with micro, bank-level analysis (N.B.R. 2012, I.M.F. 2010). They generally found that banks have comfortable position in terms of capital and liquidity, but a severe adverse macroeconomic scenario (recession and sharp domestic currency depreciation) could lead to undercapitalization for some banks due mainly to credit risk materialization. The methodological details and the results of the stress tests are not however fully disclosed.

Given also data availability constraints, independent studies have focused on estimating the potential impact of adverse macroeconomic shocks on credit risk at banking system level. Specifically, Chiriacescu (2010) and Trenca and Benyovszky (2008) employ similar reduced-form methodology to capture the link between main macroeconomic variables and default rates in the loan portfolios of the banking system and then simulate the effect of stress scenarios on the loan portfolios losses. Chiriacescu (2010) and Trenca and Benyovszky (2008) incorporate industry-specific corporate default rates, and additionally, the former study models separately the household loan portfolio at county disaggregated level using panel regression technique. While results differ in details, all these studies confirm the negative impact of macroeconomic shocks on credit risk.

1.3. Research objectives and contribution

This study will contribute to this scarce independent body of research by both capturing a more complete period of adverse macroeconomic conditions (a limitation of the two studies above being the overweighed reliance on pre-crisis data, Chiriacescu 2010) and by adopting a broader modelling and testing approach.

The main objectives of the proposed macro stress testing in Romanian banking system are:

(i) Reviewing current research on macro stress testing methodology and practices at international and local level;

(ii) Identifying the main macroeconomic variables that explain the evolution of credit risk variables (default rates) in the local households and corporate sector portfolios, and fully estimating the quantitative explanatory model;

(iii) Identifying the most relevant macroeconomic stress scenarios given the current vulnerabilities of the domestic banking system and taking into consideration the relevant current international practices;

(iv) Based on simulation techniques, the estimated model is to be used to assess the evolution of default rates in the credit portfolios under the assumed adverse stress scenarios.

The methodological approach adopted here comprises an econometric multifactor macro model for determining default rates distributions at the banking system level (corporate and household loan portfolio) and a model for forecasting the evolution of individual macroeconomic time series, based on top-down, reduced-form models. A stress test simulation is carried in the next stage, using the estimated parameters and error terms of these models.

This methodological framework is derived from the well-established non-linear model initially proposed by Wilson (1988) for modelling industry specific probability of default and further used and extended in numerous studies on macro stress testing, applied in various contexts (e.g. Virolainen, 2004; Boss, 2002). A similar methodology is used by the independent studies on the Romanian banking system, Chiriacescu (2010) and Trenca and Benyovszky (2008) for modelling stress testing industry specific probabilities of default.

Taking into consideration the specific features of the credit risk in the local banking system and following a coherent variables selection framework as proposed by recent research in the field, an extended list of macroeconomic variables are tested in order to identify the relevant macroeconomic – credit risk links. The results are consistent with previous research on macro stress testing and credit risk modelling, but the wider approach used here allows for incorporation of new and specifically relevant macroeconomic variables. The corporate sector analysis includes an alternative forward looking model that incorporates leading indicators such as the domestic stock exchange index and the consumer confidence indicator. Additionally, specific macroeconomic variables are tested and included in the model in order to capture the particular vulnerabilities of the local credit portfolio (e.g construction activity level for corporate loans and indebtedness degree proxy for households).

Informed by current international practices on macro stress testing and building on the broader modelling approach, an extended scenarios design approach is undertaken in order to construct the most appropriate stress test scenarios.

While the official stress testing exercises adopt a comprehensive framework, including extended scenarios design approach (full details are not publicly disclosed however), the independent studies use only simple ad-hoc scenario and thus this study further contributes to current research by proposing and testing a wider series of relevant scenarios, carefully designed in accordance with best practices in the field.

The proposed macro-perspective model and its findings can be incorporated by private banks in their micro-level portfolio risk management tools. Additionally, as Drehmann (2008) argues, supplementing the authorities' stress tests with independent approaches can enhance credibility of such financial stability assessment.

The next chapter includes an extended literature review, with focus on methodology approaches, presenting also the current challenges and advancements in the field. Chapter 3 details the specific methodology employed in this study, explains its selection and related background and further discusses several particular modelling choices. The estimation of the credit risk model and the results of the stress testing procedures are reported in Chapter 4. Finally, chapter 5 presents the conclusions of the research.

2. Literature Review

In spite of the wide-spread use of macro stress-testing, and generally of stress-testing in financial systems, accompanied by impressive amount of research and substantial progress on addressing inherent challenges, except for only a rough consensus on the model structure (Drehmann, 2008, Sorge and Virolainen, 2006), the proposed methodology is diverse and heterogeneous and the process involves high degree of complexity, still unsolved difficulties and sometimes conflicting objectives (I.M.F. 2012a; and Drehmann, 2008). Sorge and Virolanein (2006) and more recently Foglia (2009)[1], Drehmann (2009) and I.M.F. (2012a)[2] include comprehensive reviews of current methodologies, while Čihák (2007) presents a useful introduction to application of stress testing. I.M.F. (2012a), Borio et al (2009), Drehmann (2008) extensively discuss challenges faced by most recent methodologies, the typical failings and

[1] Focus on central bank frameworks.
[2] Focus on International Monetary F.S.A.P. framework.

limitations of stress testing, and propose best practices and principles to guideline efforts in constructing effective macro stress testing.

The next section will outline the main structure of macro stress testing with focus on methodology approaches rather than actual results of stress testing, since the latter are usually specific to the context and the subject of the application[3].

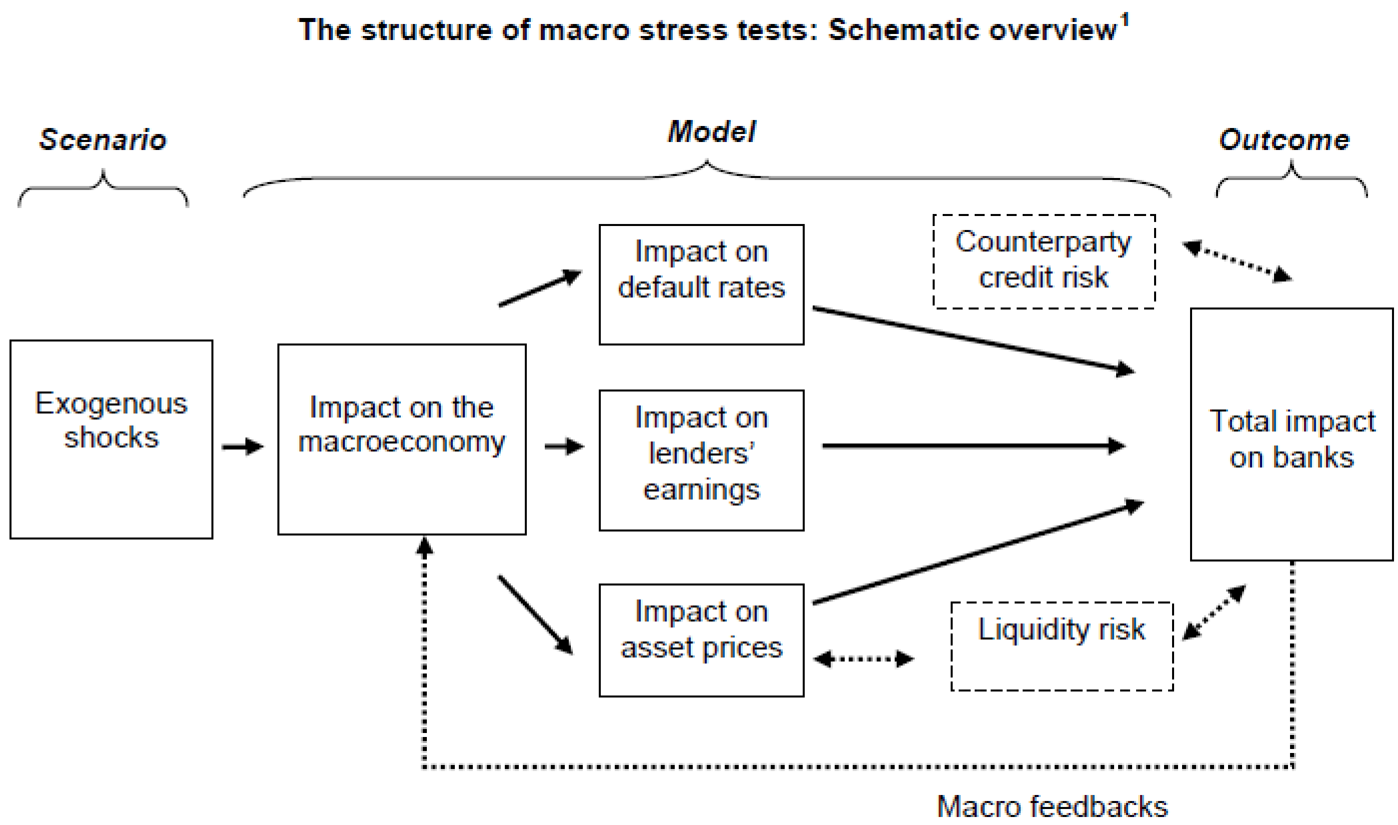
2.1. Main structure of macro stress testing

The basic structure of macro stress test includes (Borio et al, 2012; a schematic overview is presented below[4]):

1. A set of ***risk exposures*** subject to stress testing;
2. The macroeconomic ***scenarios*** that define and calibrate the exogenous stress shocks;
3. The ***model*** that maps the impact of shocks on a measure of outcome, capturing the shocks transmission through the systems;
4. A measure of ***outcome*** which quantifies the impact of the simulated shocks on the financial sector balance sheet;

[3] General conclusion and useful comparisons could be drawn from the various stress tests results (as discussed for example in the "Estimation and results" section for the Romanian banking system), but the main purpose of stress testing is to actually quantify the estimated impact of shocks in the specific context of application rather than confirming general macroeconomic and financial relations.
[4] Alternative but similar presentation/approaches to the main structure of stress-testing can be found in Sorge and Virolainen (2006) and Foglia (2009).

Figure 1 The structure of macro stress tests: schematic overview



[1] Schematic overview of the structure of the current macro stress tests that seek to evaluate the strength of banks. Bold lines represent the components captured by the majority of stress tests; dotted lines indicate the feedback effects that only the more sophisticated versions are able to capture, and even then only partially.

Source: Borio et al. (2012), Graph 1, p. 28

The ***risk exposures*** decision comprises both selection of the set of institutions (banking system, pension funds, insurance companies etc) and the selection of risks and their measurement indicators that should be considered as subject to stress testing (Borio et al, 2012).

Preferably the subject should be the entire financial system, but in practice, the stress test focus usually on sub-sets, especially banking sector, given its weight and central place in the financial systems, but also its potential role in spilling over financial shocks back to real economy (Borio et al, 2012; Drehmann, 2008; Sorge and Virolainen, 2006).

In terms of types of risk considered[5], generally, macro stress testing has focused on credit risk (borrowers' default, especially at domestic level, the most important risk for banks in terms of size), but recent practices have incorporated risk to future incomes, market risk (the potential adjustment of the market value of banks' assets and liabilities due mainly to interest rate risk, but also foreign exchange rate and equity markets risks), cross-border exposure reduction, liquidity risk and sovereign risk (Borio et al, 2012, I.M.F., 2012a). In spite of the substantial progress in terms of assessing and integrating the effect of other risks (including the correlated effects), Borio et al. (2012) note that the core of the analysis remains credit risk and that, given the complexity involved and data availability constraints, fully integrated approaches are still scarce.

Generally, the decision about risk exposure comprises a wide range of options and choices (types of risks analyzed, sets of institutions, assets classes, decision on how to approach

[5] Sorge and Virolainen (2006) consider the option about which risks to include in the stress testing as part of the scenario design stage of the process.

financial conglomerates, use of book or market data etc) and depends on both the scope of stress testing and data availability (Sorge and Virolainen, 2006).

As explained in the introduction, given the specific context of the Romanian financial system and the data constraints, this study will analyse credit risk (default rates) at the overall banking system (corporate and household sectors).

Regarding the design and calibration of "severe but plausible" ***scenarios,*** Borio et al. (2012) document that design scenario is usually based on considering adverse macroeconomic conditions (prolonged and accentuated recessions, drops in property prices, exchange rates etc). The next section will discuss in detail the typical approaches of scenarios design in macro stress testing.

The stress-testing ***model*** comprises actually a range of steps and building blocks (Borio et al, 2012; I.M.F. 2012a). The process could follow (i) a bottom-up approach, where a central authority provides a common scenario to individual banks, which use their own models to forecast the impact and then the central authority aggregates the results; this could entail models inconsistency issues; (ii) a top-down approach, where the central authority/researcher uses exclusively its own models and when available, incorporating detailed individual banks' positions or certain level of disaggregation (industry specific; household – corporate); or (iii) as typically used in practice by central banks, a combined approach (Borio et al., 2012).

Generally, the starting point is a macroeconomic model that estimates the effect of the exogenous factor on the economy. Such macro-models however don't usually include financial variables and thus the output of the macro-model is used as input on an auxiliary / satellite model that links macroeconomic variable to variables relevant for financial risk assessment (Borio et al, 2012; Foglia, 2009). Typical satellite models include credit risk models and frameworks that incorporate a wider set of asset classes and risks (e.g. market risk and future income risk). Basic models usually limits stress-testing to this "first round effect" analysis (from macroeconomic to financial variables, for example recent E.U.-wide adopt such a methodology, E.B.A., 2011), but more advanced stress-testing attempt also to evaluate the impact of potential feedbacks ("second round effect") generated by endogenous behavioural response of the financial systems participants: portfolio optimization attempts, including counterparty credit risk in interbank markets, policy makers response, liquidity risk and financial sector to real economic macro feedback (I.M.F., 2012a; Drehmann, 2008).

Section 2.3. of this chapter presents the main models currently used in practice.

The typical ***outcome*** metrics are portfolio losses, capital adequacy (solvency stress testing), assets quality, earnings or indicators of market liquidity (Sorge and Virolainen, 2006).

Selection of the specific outcome (credit risk variable / indicator) is an essential decision within stress testing procedure, but in many cases it's heavily restricted by data availability for the chosen degree of aggregation (Ferrari et al. 2011; Foglia et al. 2009).

Generally, credit risk stress testing focuses on estimating the Expected Loss (EL) and Unexpected Loss (UL) of a credit portfolio (Boss, 2002). Reflecting the Basel II terminology, at credit portfolio level, the EL can be computed as EL = PD * LGD * EAD, where PD denotes probability of default, LGD – Loss Given Default and EAD – Exposure At Default, respectively (Ferrari et al, 2011; B.I.S. 2006). Exposure at default is routinely reported by banks.

The Expected Loss should reflect the maximum loss based on the best estimation of the worsening of credit portfolio quality (generating an increase in PD and/or LGD). This is the loss that banks should reasonably expect (e.g. at 50% probability level) and they are required to cover the EL on ongoing basis through provisioning and write-offs (B.I.S. 2005; Boss, 2002).

Typically, while PD values are a dynamic component of the stress test procedure (as per above models), the stressed values of LGD and EAD are considered fixed over the horizon of the stress test, although there is evidence of influence from macroeconomic factors on all these credit losses components (Ferrari et al, 2011; Virolainen, 2004).

The Unexpected Loss, on the other hand, relates to potential large losses that occur rarely. It measures the maximum loss that may be incurred taking into consideration very low probability levels, thus raising the confidence level to high values (with a confidence level of 99% or 99.9%, by historical statistics estimation, the unexpected losses should not exceed the estimated level). From a credit risk management perspective, the bank's capital should cover any unexpected loss for a reference period of time that would be required in order to liquidate the portfolio (B.I.S., 2005; Boss et al, 2002). The concept is similar with Value-at-Risk approach in market risk management.

Default probability (credit loss) distribution estimation is thus necessary for estimation of expected and unexpected losses under stressed condition for the typical probability levels (Foglia, 2009).

In practice however, since PD are not usually publicly available, several other credit risk indicators are used to reflect PD and/or LGD (such as NPL ratio, loan loss provision ratio, corporate bankruptcy rates – the subsequent literature review will present several studies exemplifying this issue). Ferrari et al. (2011) and Foglia (2009) discuss at length the comparative advantages and disadvantages of each indicator, while the research presented below comments on the specific chosen credit risk indicators.

2.2. Scenario design

The design of extreme but plausible scenarios is a crucial component of applying a stress test procedure (Boss, 2002).

Jobst et al. (2013) and E.C.B. (2006) document the main technical approaches of constructing such scenarios: the process starts with establishing a baseline (benchmark) scenario given by the high probability forecast of the macroeconomic evolution (e.g. F.S.A.P. framework uses the I.M.F.'s World Economic Outlook projections); the second step involves constructing the alternative adverse scenario, which can be done following the below typical approaches:

(i) historical simulation, e.g. replicating past severe episodes such as "worst in a decade" or the 2008-2009 crisis shock;

(ii) probabilistic approaches, i.e. using shocks scenarios as implied by the tail of the historical distribution of risk factors ("x-standard deviation" or extreme quantiles in the distribution);

(iii) hypothetical scenarios or ad-hoc expert judgment scenarios, with no historical background but having particular relevance for specific vulnerabilities of the systems

Aside being easy to implement, historical based scenarios have the advantage of having a straightforward interpretation (E.C.B., 2006). Nevertheless, especially in the case of applying the stress test in benign times, the historical approach can involve a certain degree of complacency. Historical scenarios obviously miss events that never occurred and they also depend on the chosen historical horizon (I.M.F., 2012a).

Probabilistic approaches, focused on unlikely tail risks, can extend the historical approach but they remain dependent on the selected time period (volatility can be low in the chosen sample).

The qualitative and flexible approach of hypothetical scenarios addresses these disadvantages and thus could prove useful in complementing the usual historical-based scenarios (Oura et al, 2012). Nevertheless, as Borio et al. (2012) point out, the plausibility of hypothetical scenarios or that of extremely unlikely probabilistic scenarios is typically evaluated against historical evolutions.

Similar with other element of stress testing exercise, while several rules of thumbs and guidelines are typically applied in practice, designing the specific scenarios however still involves substantial expert judgment irrespective of the chosen approaches. Furthermore, while a consistent and comparable approach across countries could prove useful, scenario design should remain flexible in order to address the specific vulnerabilities of the analysed financial systems (Jobst et al, 2013).

Additionally, central supervisory authorities are also faced with an important trade-off decision between severity and plausibility, especially in crisis or near-crisis periods. In such circustances, the baseline scenario is already adverse and thus supervisory authorities may be reluctant to use excessively extreme scenarios (I.M.F., 2012a). Since the results of central bank stress testing exercises are typically published, adopting extreme scenarios can trigger "self-fulfilling prophecy" crises. Moreover, conducting stress tests at country, regional or international level in relation to re-capitalization needs of banking systems involves a complicated political and economic context. On the other hand, compromising on severity can greatly affect the credibility of the procedure and this could contribute to prolonging the crisis. Near-crisis stress test should thus not compromise on severity, and instead the central authorities should mitigate potential adverse effect of the stress test findings by making available credible support measures (I.M.F., 2012a)

Current studies (Jobst et al, 2013; I.M.F. 2012a) document several main specific scenarios construction techniques:

1. Constructing GDP shock scenarios (and sometimes other types of shocks scenarios) based on standard deviations from long-term historical averages (20-30 years):
    a. a mild adverse scenario based on one standard deviation (assuming normal distribution, this implies a 15.87% probability of occurrence);
    b. a severe adverse scenario – two standard deviations from historical averages (implying a much lower probability of occurence, i.e. 2.28% under normal distribution assumption).

This approach is a standard practice in I.M.F.'s F.S.A.P. framework and has the advantage of being comparable across countries.

2. Given the magnitude of the 2008-2009 shock, a well-established practice is to design a historical scenarios that replicate this shock;

Typically, as recommended above the scenarios are complemented by hypothetical scenarios designed to incorporate the specific vulnerabilities of the financial system on which the stress test is applied.

The **scenario time horizon** is also an important decision within scenarios design. Longer time horizons are desirable since macro-financial adverse shock trigger typically a lasting effect, distributed on several years (especially for credit risk) and regulatory reform implementation is usually slow (I.M.F. 2012a). For example, F.S.A.P. programs usually have a time horizon of 5 years.

On the other hand, longer time period involve increase uncertainty and although stress testing is not a forecasting exercise (it should be able to capture medium-term effects of shocks), the decision should be adapted to dynamic of the specific environment (I.M.F., 2012a). Specifically, shorter time horizons are usually selected for financial system undergoing rapid changes. For example, most F.S.A.P. application involve a time horizon of 1-3 for emerging market with less mature banking systems (I.M.F., 2012a). Confirming the above argument, recent E.U. stress-testing performed in the volatile context of Euro zone countries debt crisis takes into consideration a two-year time horizon (E.B.A., 2011; C.E.B.S. 2010; C.E.B.S., 2009).

The time horizon decision has also implication on endogenous behaviour and feedback modelling. Models that do not incorporate second round effects should use a short term forecast horizon (Elsinger et al, 2006).

2.3. Main modelling approaches

Generally the models used in macro stress testing are based either on a reduced-form / parsimonious framework, or on a structural model (i.e. model founded on a macroeconomic theory) (Foglia, 2009[6]). Sorge and Virolainen (2006) argue that structural approaches can contribute to an improved understanding of the transmission of initial shocks into the systems and allow the evaluation of policy trade-offs and potential conflicts.

Drehmann (2008) note however that parsimonious models (e.g., based on vector autoregressive specifications) can outperform the "true" model in terms of forecasting accuracy, and that the model type choice should take into consideration the objective of the stress test. Specifically, the technical, reduced-form models are not suitable for policy evaluation and communication (which requires transparent models, accommodating "story telling" on results and methodology), but could be very useful for decision making where accuracy is a primary objective[7].

Aside the technical classification above, Sorge and Virolainen (2006) identify two main macro stress-testing econometric modelling approaches:

[6] The study documents also a third option: pure statistical approach used by the Austrian central bank (System Risk Monitor model), modeling macroeconomic and financial variable through a multivariate t-copula. Such an approach is focused on accuracy and it's not suitable for communication.
[7] Sorge and Virolainen (2006) present the counter-argument of the vulnerability of reduced-form models to endogenous parameter instability (please see section Current challenges and recent advancement).

- The "***piecewise approach***" includes models forecasting the impact of macroeconomic stress shocks on several measure of outcomes/risk (loan losses, non-performing loans etc), taken individually; the overall assessment of financial stability is then derived from adding-up the estimated impact on each indicator;
- The "***integrated approach***" incorporates the assessment of multiple factors of risk into an overall estimate of the probability distribution of aggregate losses.

Both approaches can use reduced-form or structural models.

The ***"piecewise approach"***[8] econometric models typically estimate a direct and linear relation between macroeconomic variable and the risk measure. Generally, while this approach involves intuitive and easy to implement models, its main limitations relate to the assumption of linear relationship and the reduced applicability as it does not capture the entire loss distribution (necessary for estimating unexpected losses), but only the expected losses (Sorge and Virolainen, 2006).

"Integrated approaches" models estimate a conditional probability distribution of losses for each simulated macroeconomic scenario. Typically, Value-at-Risk measure (unexpected losses) is used as a summary statistic of the estimated distribution in order to quantify in a single metric the sensitivity of the portfolio to risk sources (Foglia, 2009). This approach accommodates integration of other risks (e.g. market risk) and allows a more advanced modelling of the relationship between indicators of financial stability and macro variable (e.g. non-linearity, state / time-dependent parameters) (Sorge and Virolainen, 2006).

[8] Sorge and Virolainen (2006) review the main studies implementing this approach. Given the proposed methodology in this report, this section will focus on integrated approach and reduced-from approach designed to address macro feedback effects.

A main strand of literature within this approach is that of modelling default probabilities related to credit risk as a non-linear function of macro-economic variables based on the methodology proposed by Wilson (1998; 1997a and 1997b) for assessing credit quality of banks' portfolio. Generally, the framework comprises a multifactor macro model for determining industry specific default rates distributions and a model for forecasting the evolution of individual macroeconomic time series (typically reduced form models). The next step is to construct stress test simulation using the estimated parameters and error terms of the models. This is the methodology used by the independent studies on the Romanian banking system, Chiriacescu (2010) and Trenca and Benyovszky (2008) and a version of the model is used also in this research. Section 2.5. further details this reduced form modelling framework.

An alternative to Wilson (1998) credit portfolio risk modelling is the firm-level structural framework derived from Merton (1974). Sorge and Virolainen (2006) and Drehman (2005) note that such models start from modelling, in a non-linear fashion, the response of equity prices to macroeconomic variable and then map asset price movement into default probabilities, conditional on the macroeconomic scenario (the theoretical structural assumption being that default case occurs when asset market value falls below liabilities value, as proposed by Merton, 1974). Such a framework is used by Drehman (2005) for UK corporate sector, Pesaran et al. (2006) in a global perspective study and Duellmann and Erdelmeier (2009) on automobile sector German corporate loans.

Sorge and Virolainen (2006) note that approaches based on Wilson (1998) are intuitive and easy to implement. Merton (1997) approach, while involving increased computation efforts, has the advantage of taking a forward-looking perspective based on equity prices and credit ratings. Still, the proposed firm-level theory and the related stress testing procedure imply several important assumption that are not always valid (e.g. , i.e. complete and efficient markets, relevance of equity prices for the entire industry and as proxies for assets fluctuations, see Drehmann, 2005; Pesaran et al 2006; Duellmann and Erdelmeier, 2009). For example, in practice, Merton (1974) based credit risk models[9] are used by banks especially for risk assessment in large corporate credit portfolio and to a lesser extent for SME portfolio (McKinsey, 2009).

2.4. Current challenges and recent advancement

This section discusses the major current challenges faced by macro stress testing methodologies and related proposed solutions as documented in I.MF. (2012a), Drehmann (2008) and Sorge and Virolainen (2006).

[9] Such as Moody's KMV and JP Morgan's Credit Metrics (Crouhy et al, 2000)

2.4.1. Data availability

Generally severe stress events data are scarce. Rapid innovation in financial markets also complicates the issue of data availability. Still, the framework of stress testing accommodates hypothetical scenarios (e.g. to be used on innovative financial products, see Bunn et al, 2004 for an example).

In order to deal with the more difficult case of data constraints that affect model robustness and impose use of several assumption, Čihák (2007) recommends testing the model on different sets of assumptions, while Drehmann (2008) proposes adopting different econometric approaches (including more sophisticated approaches: Bayesian and non-parametric entropy models, as in Segoviano and Padilla, 2006). Alternatively, Ong et al (2010) propose a simple reverse test (finding the system "breaking point") technique to deal with poor data environment.

2.4.2. Incorporating different risks

Elsinger et al. (2006) propose a model that integrates the main risk sources discussed above (credit risk, market risk, including interest rate risk and counterparty risk in interbank markets) based on combining modern risk management tools with a network model of interbank loans. The model innovatively uses credit register data (currently, a practice in many countries, Foglia, 2009). The framework accommodates stress testing but only for short term horizon as it doesn't incorporate second round effects (aside counterparty risk). Boss et al. (2008) have extended the model by further incorporating future income risk and risk from cross-border exposure and accommodating a three-year forecast horizon.

Arguing that stress testing models often ignore the balance between asset and liabilities, Drehmann et al. (2010) propose a new framework that integrates credit and interest rate risk by concurrently modelling the assets, liabilities and off-balance positions of banks so as to ensure the basic accounting equality between them.

2.4.3. The endogeneity of risk

The endogeneity of risk arises mainly due the potential endogenous behavioural reactions of market participants (banks, policy makers) facing stress conditions (feedback or “second round” effects, Drehmann, 2008). The difficulties encountered in attempting to model such behaviours generate the current unsolved challenges of macro stress testing.

Severe shocks may cause structural breaks in models estimated on historical data, leading to parameter instability, with reduced form models being particularly vulnerable to this shortfall (Sorge and Virolainen, 2006). While sometimes they incorporate such “spirals” evolution (when historical data includes such endogenous reactions), without a specific structural modelling of the feedback mechanism, the implicit assumption is that the feedback will simply follow historical patterns. This assumption is not necessarily valid and can restrict the objective of the stress testing (for example, in case a central bank would like to assess different policy options, Drehmann, 2008).

The same studies argue that following severe shocks, market participants will attempt to optimize and hedge their portfolio, but since such reactions are difficult to predict, usually stress testing models assume exogenous portfolio evolution (only impacted by losses generated by the shock not by behavioural response). Drehmann et al. (2007) use simple rule of thumbs as a starting point to partially incorporate this exogenous effect. Alternatively, De Bandt and Oung (2004) propose a parsimonious model that relates demand and supply for credit with the macroeconomic state, and thus account for balance sheet adjustment in a reduced-form fashion.

Drehmann (2008) document that endogeneity of risk can further generate liquidity risk, macro feedbacks from financial systems to real sector, and non-linearity.

2.4.4. Liquidity risk

In time of crisis, liquidity problems arise before solvency issues and thus current stress-testing practice include liquidity risk (I.M.F., 2012a). The Bank of England uses a comprehensive framework, Risk Assessment Model for Systemic Institutions (RAMSI) (Aikman et al, 2009), that incorporates the main type of risks (building also on Drehmann, 2010), including liquidity risk and main second round effects in the financial systems. Alternatively, another approach, used successfully by several central banks (I.M.F., 2012a), is proposed by the Dutch central bank in Van den End (2008). The model focuses on market and funding liquidity risks of banks and incorporates modelling of endogenous behaviour.

2.4.5. Macro feedbacks

There is a wide theoretical and empirical support for such feedbacks from financial sector to real economy, through several specific channels (Sorge and Virolainen, 2006). Drehmann (2008) and Foglia (2009) document however that only a few reduced form models have explicitly incorporated this effect, since large scale macro structural models that include financial variable are still in emerging stages. For example, in a recent study on Italian banking system, Marcucci and Quagliariello (2008) use a vector autoregression that incorporates credit supply and banks' capital adequacy variables to test for transmission channels.

These reduced-form models however were not developed in the specific context of macro stress testing and modelling of macro feedback remains an important concern for future methodology research and practice (I.M.F., 2012a).

2.4.6. Non-linearity

While there seems to be a consensus that Wilson (1998) and Merton (1974) based credit risk models can capture the non-linearity of the relationships between financial system and macroeconomic shocks (Foglia, 2009), Drehmann (2008) argue that such specification could still miss some non-linearity features across the system. I.M.F. (2012a) report increased attempts to incorporate non-linear dependencies into macro-stress testing models.

2.5. General model and related research

The credit risk macro stress test methodology for corporate sector used in this study is similar to that used in Boss (2002) and Boss et al. (2009) for the Austrian financial system (bankruptcy rates at aggregate corporate/households levels and at industry level, respectively), and Virolainen (2004) and Sorge and Virolainen (2006) for Finnish corporate sector (bankruptcy rates at industry level).

The model is based on the framework proposed by Wilson (1998, 1997a and 1997b), as part of CreditPortfolioView® model, initially developed by McKinsey & Co. Within this framework, credit risk is modelled in relation with main macroeconomic variables, following the empirical result that average probabilities of default (PD) tend to be related to business cycle fluctuation (PD increases in recession periods). Additionally, the model incorporates the empirical finding that specific average PD / default rate sensitivity to macroeconomic fluctuation is different across industries /sectors of the economy (Boss, 2002, e.g. construction sector tends to be relatively more sensitive to macro-economic shocks).

The PD of an industry is modelled as a logistic function of an industry-specific macroeconomic index:

$$p_{j,t} = \frac{1}{1+ e^{-y_{j,t}}} \qquad (1)$$

here $p_{j,t}$ is the average PD of industry j at time t, while $y_{j,t}$ denotes the industry-specific macro index. The logistic transformation is broadly used in modelling defaults rates as it ensures that estimates falls in [0,1] range. Additionally, as van den End et al. (2006) note, nonlinear transformation of default rate could improve the ability of the model to capture potential nonlinear relationship between macro variables and default rates, likely in stress test adverse shock situation.

Solving for the macroeconomic index $y_{j,t}$ in the above equation, the $y_{j,t}$ is given by the inverse logit transformation:

$$y_{j,t} = \ln(\frac{p_{j,t}}{1-p_{j,t}}) \tag{2}$$

After computation of $y_{j,t}$ as per equation (2) using the available date on PD, this index is then modelled as follows:

$$y_{j,t} = \beta_{j,0} + \beta_{j,1}x_{j,1,t} + \beta_{j,2}x_{j,2,t} + \cdots + \beta_{j,K}x_{j,K,t} + \varepsilon_{j,t} \tag{3}$$

where $x_{j,t} = (x_{j,1,t}, x_{j,2,t}, \dots, x_{j,K,t})$ is a set of exogenous macroeconomic variables / factors for industry j at time t and $\beta = (\beta_{j,0}, \beta_{j,1}, \beta_{j,2}, \dots, \beta_{j,K})$ denotes the set of parameters to be estimated (e.g. regression coefficients) reflecting the direction and degree of impact of macroeconomic variables on the index $y_{j,t}$ (and thus on PD). The exogenous variables can be common for all industries (e.g. GDP, exchange rate) or specific to certain industries (e.g. indebtedness). Section 3.6. “Macroeconomic variable selection” discusses the variables usually used in this step.

Random error $\varepsilon_{j,t}$ is assumed to be independent and identically normally distributed:

$$\varepsilon_{j,t} \sim N\left(0, \sigma_{j,\epsilon}\right) \text{ or } \varepsilon_t \sim N(0, \textstyle\sum_{\varepsilon}) \qquad (4)$$

where $\varepsilon_t$denotes the vector of the index innovations in all industries, while $\sum_{\varepsilon}$their covariance matrix.

The system of equations (1)-(4) can be regarded as a multi-factor model for modelling industry-specific default rates, with a systematic risk (non-diversifiable default risk) component captured by macroeconomic variables $x_{j,t}$ and industry-specific shocks captured by the error term $\varepsilon_{j,t}$.

The above formulation follows Boss (2002) with a higher value of $y_{j,t}$ reflecting an worsening state of the economy[10]; the macroeconomic index value increases when the probability of default increases (equation (2)) and we would expect a positive relation with adverse macroeconomic conditions (as reflected by negative GDP growth for example), reflected in a specific corresponding sign in regression (3) (negative sign for GDP growth).

The next step is to estimate the evolution of each macroeconomic variable. The initial Wilson (1997a) framework models each variable time series as a univariate autoregressive process of order 2, AR(2) (thus adding also a dynamic component to the model, Boss (2002)). This is the approach followed by Boss (2002), Virolainen (2004) and Sorge and Virolanein (2006):

[10] Virolanein (2004) use the alternative inverse form $p_{j,t} = \frac{1}{1+ e^{y_{j,t}}}$, as originally formulated by Wilson. This maintains the same positive / negative relation as in a direct PD over macroeconomic factors regression.

$$x_{j,k,t} = \gamma_{k,0} + \gamma_{k,1} x_{j,k,t-1} + \gamma_{k,2} x_{j,k,t-2} + \vartheta_{j,k,t} \quad (5)$$

where $x_{j,k,t}$ denotes the k-th macroeconomic variables in industry j at time t, $\gamma = (\gamma_{k,0}, \gamma_{k,1}, \gamma_{k,2})$ are the parameters to be estimated and $\vartheta_{j,k,t}$ the error term, which is assumed to be an independent random variable, normally distributed:

$$\vartheta_{j,k,t} \sim N(0, \sigma_{k,\vartheta}) \text{ or } \vartheta_t \sim N(0, \textstyle\sum_\vartheta) \quad (6)$$

The system of equations (1)-(6) models the joint evolution of the industry specific default rates and relevant macroeconomic variables, with a $(J+K)\ x\ 1$ vector of error terms / innovations and a $(J+K)\ x\ (J+K)$ variance-covariance matrix of errors ∑ as per below equation, where J denotes the total number of industries taken into consideration (K is the total number of macroeconomic variables as per equation (3)).

$$E = \binom{\varepsilon}{\vartheta} \sim N(0, \textstyle\sum), \sum = \begin{bmatrix} \sum_\varepsilon & \sum_{\varepsilon,\vartheta} \\ \sum_{\vartheta,\varepsilon} & \sum_\varepsilon \end{bmatrix} \quad (7)$$

In the final stage, the estimated equations and the error terms are used to simulate future evolution of joint PDs / default rates for all industries, over a certain time horizon.

Monte Carlo simulation methods can be applied in order to estimate credit loss distribution for credit portfolios, under the assumption that, conditional on the state of the economy (as reflected by the selected macroeconomic variable), industry-specific default rates are independent. Given equation (7), the simulations take into account the correlation between macroeconomic factors and any interdependence with industry specific shocks (Virolanein, 2004).

This can be seen as a baseline scenario, based on historical patterns, and expected and unexpected losses can be computed, where the unexpected loss reflects the scenario of extreme, low probability, scenarios (Chiriacescu, 2010; Virolainen 2004; see section 3.5 "Credit risk variable selection" below for a discussion).

Additionally, using the estimated model and distributions, other hypothetical or expert judgement adverse stress scenarios are usually tested as well (the autoregressive process of the stressed macroeconomic variable is altered to accommodate the scenario).

Sorge and Virolanein (2006) apply this model, but present also the possibility of extending equation (5) to an autoregressive specification of unknown order (*AR(n)*).

Typically, as proposed by Virolainen (2004) the set of equations is estimated using Seemingly Unrelated Regression[11] (SUR), applied for the set of industry-specific equations (3), rather than simply Ordinary Least Square (OLS) separate regressions for each sector. Relative to the latter, the SUR econometric solution improves the efficiency of the estimation in systems of equations that include correlated dependent variables (industry-specific default rates in this case) by adjusting the coefficients of all equations using an estimate of errors variance-covariance

[11] The SUR method, originally developed by Zellner (1962) and sometimes called Joint Generalized Least Square, consist in generalization of the OLS regression for system of equations and improves efficiency in the case equations have different regressors. It gives the same results as single-equation OLS regressions only in the limiting cases of using the same regressors for all equations or when actually the equations errors are not simultaneously correlated.

matrix, since usually correlated dependent variables induce simultaneous error correlations[12] (Fiori et al, 2007).

2.5.1. Applications in the Romanian banking system

Closely similar methodology is used by the independent macroeconomic stress testing studies mentioned above for the Romanian banking system.

Spefically, Trenca and Benyovszky (2008) use this model configuration to analyse the bankruptcies rates in Romania's main industries for the following main sectors: industry, services, construction and services (2002-2007 period). The authors then proceed with simulation of credit loss distribution (expected and unexpected losses) for hypothetically constructed corporate credit portfolios. Equation (5) modelling macroeconomic factors evolution is extended to an *AR(n)* process in their study.

Chiriacescu (2010) cover the same main economic sectors, but includes a separate assessment of household credit risk (credit default rates) using data at county level and applying specific panel regression technique. The study uses SUR method to estimate sectoral equations (3) and extends macroeconomic variables equation (5) to an Auto-Regressive Moving Average (ARMA) process as proposed by Fiori et al. (2007). Box-Jenkins methodology and information criteria are used to select the most appropriate ARMA specifications. The macro stress tests are based

[12] Specifically, Fiori et al. (2007) explain that if the model fully captures the systematic risk, the specific industry component should be uncorrelated, i.e. error terms in equations (3)-(4) should be uncorrelated. Otherwise, a significant correlation between these errors would indicate that the correlation between industry-specific default rates is not exclusively generated by the macro evolution of the multi-factor model, but also by a direct interconnection between companies of different industries, thus violating the assumption behind the distribution simulations.

both on Monte Carlo simulation and ad-hoc expert judgment scenarios, with computation of expected and unexpected losses on hypothetically constructed credit portfolio.

The household portfolio country level assessment is presented also in Chiriacescu (2012), without the stress test component (as a credit risk determinants analysis).

2.5.2. Extensions of the model and other applications

A similar methodology as presented above has been also widely applied for system level macro stress test or NPL ratio / credit losses determinants, including regional panel data studies (Schechtman and Gaglianone, 2010; Foglia, 2009). Generally, depending of the specific context and purpose of the study, the model has many versions and extensions in the literature, with regards to both general specifications and specific chosen econometric solutions.

For example, Schechtman and Gaglianone (2010) present the following general specification for system level models (the previous industry specific notation *j* is thus dropped, but this extended model can be applied also at disaggregated industry level):

$$\begin{cases} CRI = \frac{1}{1+e^{-y_t}} \quad (or\ y_t = \ln(\frac{CRI_t}{1-CRI_t}) \ ) & (8) \\ y_t = \alpha_t + \sum_{l=1}^{s} \alpha_i y_{t-i} + \beta_0 x_t + \sum_{m=1}^{w} \beta_m x_{t-m} + \varepsilon_t & (9) \\ x_t = \gamma_0 + \sum_{q=1}^{z} A_q x_{t-q} + \vartheta_t \ , z > w & (10) \\ (\varepsilon \, , \vartheta) \sim N(0, \Sigma) \ , \ \Sigma = \begin{bmatrix} \Sigma_{\varepsilon} & \Sigma_{\varepsilon,\vartheta} \\ \Sigma_{\vartheta,\varepsilon} & \Sigma_{\varepsilon} \end{bmatrix} & (11) \end{cases}$$

where:

y_t is the macroeconomic index, i.e. the logit transformation of an observable selected credit risk indicator CRI_t with values in range [0,1],

x_t is a vector of macroeconomic variabile at time *t,*

ε_t is a normal error term, homoscedastic and independent with regard to past information and $\vartheta_t$is independent and identically normally distributed error term.

This specification extend the original model presented above, by adding lags of the dependent in equation (2) in order to capture time persistence of default rate following a macroeconomic shock, adding lags of the exogenous macroeconomic variables in the same equation and extending equation (10) to allow for multivariate lag modelling of macroeconomic factors[13].

Kucukozmen and Yuksel (2006) use such an extended version of the model to assess industry-specific NPL rates and inter-sector correlations of several main sectors of Turkey economy, with monthly data. More specifically, equation (9) includes first lag of the dependent variables (the dependent index y_t is used in first difference form in order to achieve stationarity). Their econometric results show that autoregressive patterns are found in the evolution of default rates for all of the analysed sectors.

The study models equation (10) as univariate Autoregressive Moving Average process of unknown order (*ARMA(p,q)*) rather than as a *AR* process.

[13] Schechtman and Gaglianone (2010) explain that the system of equation (9) belongs to the class of Autoregressive Distributed Lag (ADL) econometric models, and it's not strictly a Vector-Autoregression (VAR) model due to the presence of $\sum_{\varepsilon,\vartheta}$.

A similar model is employed in Fiori et al. (2007)[14] for estimating industry-specific credit default rates and inter-sector correlations of six main sectors of Italian economy, with quarterly data. More specifically, equation (9) includes up to 2 quarterly lags of the dependent variables while equation (10) is also specified as an *ARMA(p,q)* process.

Misina et al. (2006) specify equation (10) jointly as a full vector-autoregression specification (VAR) in a research of sectoral probability of defaults (proxied by observed bankruptcies rates) in the Canadian banking system, in order to better capture the indirect impact of macroeconomic factors trough their influence on other macroeconomic variables. The sectoral equations are estimated using the usual logistic regression, with 4 quarter lags of the macroeconomic factors (no lags for the dependent variables).

Simons and Rowels (2009) analyse industry-specific bankruptcy rates for Dutch corporate sector using the first part of the model, with one quarter lag of the dependent in equation (9) (the lag dependent is indented to capture also lagged effect of exogenous variable shocks). There is no dynamic component in their model (equation (10) is not estimated) as the stress scenario is based on hypothetical expert judgment (two quarters of zero GDP growth).

Vazquez et al. (2010) test credit risk (NPL ratio) in Brazilian banking sector for several granular credit portfolio categories, comprising household and corporate loans, in a bottom-up approach starting from bank-level data. Their general specification of the model includes one quarter lag for the dependent variable and several lags of the exogenous variables in equation (8) and a VAR specification for equations (10). The study uses a wide range of more advanced econometric techniques to estimate the equations system.

[14] Fiori et al. (2007) study is preliminary and doesn’t include a macro stress test component.

Variants of the above model are also used as part of more extensive macro stress testing approaches. For example, van den End et al. (2006) utilise a similar configuration in their more comprehensive framework applied for the Dutch banking sector. The research analyses credit risk (modelling default probabilities and their mapping in loan losses) and interest rate risk for a set of large banks in Netherlands. There are no lags in Equation (9), while equations (10) for macroeconomic variables are tested both as univariate process and as a full VAR model.

In a study of Brazilian household sector (based on NPL rates), Schechtman and Gaglianone (2010) use this model as basis for a comparison with an alternative, more flexible model based on quantile regression[15].

Additionally, since the first part of the equations system deals actually with analysing the macroeconomic factors generating credit risk, several studies attempting to identify the determinants of nonperforming loans in the Romania banking system use this methodology (e.g. equations (1)-(4), or (8)-(9) in the extended form, without the stress testing component). Moinescu (2012) recent paper partially applies the methodology to identify the determinants on non-performing loans ratios in a regional context for countries in Central and East Europe using multivariate panel regression techniques. The study analyses non-performing loans rates exclusively at aggregated country level, not on industry level and it doesn't model the evolution of macroeconomic variables (as it would be necessary for the dynamic stress testing component). It uses dynamic panel regression with fixed effects as main econometric

[15] The alternative framework maintains the macroeconomic index logit transformation but specifically models the quantiles of default rates conditional distribution (the tails), using different specifications for all remaining set of equations ((9)-(10)). Their model allows variation of relative importance of macroeconomic factors along the credit risk distribution thus further incorporating uncertainties in default rate correlations. Substantial different configuration notwithstanding, the final stress test results were not so different qualitatively.

technique. Annual statistics are used and there is no lagged dependent included in equation (9) but the exogenous variables are tested for lagged influence.

Moinescu and Codirlasu (2012) apply the above methodology to model the industry-specific default rates for Romania's main activity sectors. Using quarterly data, the paper estimates the model using both SUR and VAR methods, and an alternative linear specification.

3. Methodology

Similar with the recent applications on the Romanian banking system cited above and given the specific vulnerabilities of local banking system presented in the introduction, this study analyses domestic credit risk using a methodology (top down, reduced-form model) derived from Wilson (1998) methodology presented above.

Using Merton (1974) based approaches seems inappropriate for the Romanian financial system, since the stock exchange market is small relative to economy size and features reduced liquidity (Vogiazas and Nikolaidou, 2011), which is generally contradictory to the assumption behinds these models (efficient markets and relevance of equity markets).

Additionally, as mentioned in the introduction, Merton (1974) based model are preferred in practice especially for large corporate credit portfolio, while the Romanian banking system credit risk comprises a significant SME component (please see Chapter 4 "Estimation and results" below).

3.1. Specific model

In a study of assessment aggregated default rates at system level in non-stationarity context (please see chapter 4. "Estimation and results" below), Boss (2002) proposes a slightly altered model of the general framework presented in Section 2.5. above.

The non-stationary of the time series is addressed by using the change of the macroeconomic index as dependent variable in regressions of equation (3), instead of the index itself and by transforming the macroeconomic variables (first difference or log-difference) to achieve stationarity. Consequently, Boss (2002) proposes the following model (the notations used in equations system (1) to (7) are maintained, but the industry notation *j* is dropped):

$$p_t = \frac{1}{1+ e^{-(y_{t-1}+\Delta y_t)}},\ or,\ y_{t-1} + \Delta y_t = \ln\left(\frac{p_t}{1-p_t}\right) \tag{12}$$

$$\Delta y_t = \beta_0 + \beta_1 x_{1,t} + \beta_2 x_{2,t} + \cdots + \beta_K x_{K,t} + \varepsilon_t \tag{13}$$

$$x_{k,t} = \gamma_{k,0} + \gamma_{k,1} x_{k,t-1} + \gamma_{k,2} x_{k,t-2} + \vartheta_{k,t} \tag{14}$$

$$E_t = \binom{\varepsilon_t}{\vartheta_t} \sim N(0,\Sigma)\,, \Sigma = \begin{bmatrix} \Sigma_{\varepsilon} & \Sigma_{\varepsilon,\vartheta} \\ \Sigma_{\vartheta,\varepsilon} & \Sigma_{\varepsilon} \end{bmatrix} \tag{15}$$

where $x_t = (x_{1,t}, x_{2,t}, \dots, x_{K,t})$ is a set of exogenous macroeconomic variables or their stationary transformed form and E_t is a *(K+1) x 1* vector of error terms / innovations and Σ their *(K+1) x (1+K)* covariance matrix. This matrix captures the interdependence of shocks in the macroeconomic factors and their influence on the macroeconomic index. It is further used to perform stress tests based on Monte Carlo simulations.

Using annual data, Boss (2002) actually includes in his model also 1 year lag of the exogenous macro variables as documented also in other studies, but finds the lagged factors generally not statistically significant.

Given the data availability restriction (please see section 3.5 “Credit risk variable selection” below) and non-stationarity of the time series this study will use the configuration above for corporate sector, testing also for significant lags of the macroeconomic variables, and using *ARMA(p,q)* specification for equation (10) as proposed by Kucukozmen and Yuksel (2006), Fiori et al. (2007) and Chiriacescu (2010):

$$x_{k,t} = \gamma_{k,0} + \gamma_{k,1}x_{k,t-1} + \cdots + \gamma_{k,p}x_{k,t-p} + \vartheta_{k,0} + \theta_{k,1}\vartheta_{k,t-1} + \cdots + \theta_{k,q}\vartheta_{k,t-q} \qquad (16)$$

where $\gamma_k = (\gamma_{k,0}, \gamma_{k,1} \ldots \gamma_{k,p})$ and $\theta_k = (\theta_{k,1}, \ldots, \theta_{k,q})$ are a set of regression coefficients to be estimated using Box-Jenkins methodology and information criteria.

Households loans portfolio modelling required different specification because default series register low values at the beginning of the series (below 0.5% up to end of 2008) and non-stationarity (Annex B Unit root tests results and discussion). The logit transformation proposed above, followed by first order difference to achieve stationarity create artificial variability of the series when absolute values are low (logit difference transformation generates similar values for an increase of default rate from 0.1% to 0.2%, i.e. 0.1% p.p., as for and increase from 1% to 2%, i.e. 1% p.p.) and the empirical testing was not able to explain this variability based on macroeconomic factor evolutions.

Consequently, as applied for example by Kalirai and Scheicher (2002) and Pesola (2001) (application on Nordic countries credit risk) for system wide credit risk modelling, a linear direct specification is proposed and tested instead. Moinescu and Codirlasu (2012) employ also linear specification in the Romania credit risk context (on industry-specific default rates) and find the model satisfactory.

3.2. Model Simulation

After selection of variables and estimation of the above model, simulation of the dynamic of the model over some time horizon *T* is usually carried out using Monte Carlo method, with a view to determine the distribution of the credit risk indicator (CRI). In case the CRI is a probability of default, its distribution can be further used to estimate the loss distribution (Expected and Unexpected Loss) for a given credit portfolio, when necessary additional data on credit exposure and loss given default are available or can be estimated (please see Section for details); the credit portfolio can be either an arbitrarily constructed portfolio representative for the analyzed financial system, or an actual credit portfolio (assuming necessary date are available).

The simulation procedure typically comprises the following steps (Kucokozmen and Yuksel, 2006; Virolainen, 2004; Boss, 2002):

1. The variance-covariance matrix of equation (7) is decomposed into the product of a lower triangular matrix and its conjugate transpose using Cholesky decomposition, i.e. $\sum = AA^T$;

2. A $(K+1) \times 1$ vector of standard normal pseudo random independent variables $Z_{t+s} \sim N(0,1)$ is drawn, where $s = (1, 2 \dots T)$ denotes each step (period) of the chosen time horizon;
3. Using the lower triangular matrix of Cholesky decomposition above, the uncorrelated random variables are transformed into correlated normal variables, as follows: $Z^*{}_{t+s} = AZ_{t+s}$.
4. Starting with some initial values for the macroeconomic factors $x_{k,t}$, simulated forecasts for all periods $t+s$ are computed for each factor based on equation (5) and adding the correlated residuals $Z^*{}_{t+s}$. Boss (2002) and Kucokozmen and Yuksel (2006) propose to use the current historical values as start values (which is equivalent with computing ARIMA conditional expectation) and then adding the simulated residuals. Depending on the ARMA configuration, for each *s* step-ahead simulated value, the previous *(s-1)*-step-ahead simulated value is used in the equation (5) when historical values become unavailable (similar to dynamic forecasting approach, Brooks, 2008);
5. In the final step, the simulated values generated for the macroeconomic factors in the earlier step are used to simulate the values of the macroeconomic index Δy_t according to equation (13) and adding the corresponding residuals from $Z^*{}_{t+s}$ vector. Equation (12) is then used to compute the simulated values of the credit risk indicator p_{t+s};
6. The above steps are repeated for a desired number of times (typically 20,000 -50,000) and the results are recorded in order to determine the simulated distributions over the chosen simulation horizon.

3.3. Stress Testing

As Boss (2002), Virolainen (2004) and Kucokozmen and Yuksel (2006) document, the model can be used to assess the impact of adverse stress test scenarios by employing Monte Carlo simulations, but applying them on an altered configuration of the model that incorporates the proposed scenario shock. Specifically, the value proposed by the stress test scenario for a certain macroeconomic variable is decomposed into a "normal" part resulting from the ARMA process and an "unexpected" part,

$$x_{k,t+u}^{sc} = E\left(x_{k,t+u} \middle| \Omega_t\right) + \delta_{k,t+u}^{sc} \tag{17}$$

where:

$x_{k,t+u}^{sc}$ denotes the stress test scenario values for a certain macroeconomic factor (k);

$E\left(x_{k,t+u} \middle| \Omega_t\right)$ is the conditional expectation (the forecast) of $x_{k,t+u}$ given all information available up to (and including) time t (Ω_t);

$\delta_{k,t+u}^{sc}$ describes the artificial shock implied by the scenario;

$u = (1, 2 \ldots ST)$ denotes each period (step-ahead) of the scenario time horizon (ST).

The conditional expectations of the ARMA(p,q) equations (16) are computed using the forecast function as described by Brooks (2008):

$$E\left(x_{k,t+u} \middle| \Omega_t\right) = f_{k,t,u} = \gamma_{k,0} + \sum_{i=1}^{p} \gamma_{k,i} f_{k,t,u-i} + \sum_{j=1}^{q} \theta_{k,j} \vartheta_{k,t+u-j} \ldots + \vartheta_{k,0} \tag{18}$$

where $f_{k,t,u-i} = x_{t+u-i}$ for $u - i < 0$ (for past values) and $\vartheta_{k,t+u-j} = 0$ if $u - j > 0$ (for future values).

The Monte Carlo simulation process is then adjusted to incorporate the shock by replacing the corresponding elements $z_{k,t+u}$in the vector Z_{t+u} of independent random numbers described at step 2 above, with the artificial shock $z_{k,t+u}^{sc}$ – the result of standardization of $\delta_{k,t+u}^{sc}$ (division by its standard deviation):

$$z_{k,t+u}^{sc} = \delta_{k,t+u}^{sc} / \sigma_{k,\delta} \tag{19}$$

The above procedure ensures that the next steps of the Monte Carlo simulation incorporate the impact of the stress test scenario on the other macroeconomic variables through the variance-covariance matrix (Boss, 2002).

3.4. Credit risk variable selection

Table 1 below presents and comments the main credit risk variables used in the research on the Romanian banking system (at different levels of aggregation), including studies on credit risk determinants. The table is structured similar to Ferrari et al. (2010) presentation and comments on advantages /disadvantages are based generally on Ferrari et al. 2011, Schechtman and Gaglianone (2010) for NPL ratio and stock variable disadvantages and Misina et al. (2006) for bankruptcy rates.

While a lagged indicator versus PD, NPL ratio seem to hold an important role in assessment of credit risk research, as its definition and treatment of its secondary components is similar across countries (Jakubik and Reininger, 2013). Given its direct impact on banks' profitability, NPL ratio is part of the macro-prudential financial soundness indicators of I.M.F. and a focus of Romanian central bank's stability reports (N.B.R. 2013a).

Table 1 Credit risk variables available for Romanian banking system

Credit risk variable and type	Definition	Content	Advantages	Disadvantages	Studies
I. BANK ACCOUNTING DATA VARIABLES					
Non-performing loan (NPL) ratio **Type: stock variable**	Ratio of NPLs to total loans. As per legal definition (N.B.R. 2013a), NPLs are loans overdue for more than 90 days and/or for which legal proceedings have been initiated (forced sale procedure or bankruptcy/insolvency procedure).	PD	Broadly used in credit risk and stress testing studies. Definition harmonized on bank level by the regulator in Romania (N.B.R. 2013a). Publicly available.	Being a stock measure, it captures performance of loans granted in different periods of time and thus is affected by changes in credit portfolio not necessarily related to credit risk (total granted volumes, maturities, collateral treatment). Affected by write-offs.	Moinescu (2012) – system level NPL determinants study
Loan loss provision ratio (LLP) ratio. Known also as credit risk ratio. **Type: stock variable** [16]	LLPs to total loans ratio. Banks can register new provision following an increase in expected loss, potentially before actual defaults.	PD, LGD	Harmonized definition by regulations. Usually publicly available at aggregated level.	Although the definition is harmonized, banks have some discretion regarding provisioning and thus LLP ratios across banks could lack comparability. Similar disadvantages to NPL – stock variable; also affected by write-offs.	Vogiazas and Nikolaidou (2011) and Nikolaidou and Vogiazas (2012) – system level LLP determinants.
II. DEFAULT DATA					
Default rate **Type: flow variable (ratio of numbers) or stock variable (volume ratio of defaulted loans in total loans)**	Ratio of number of default borrowers to total number of borrowers. Sometimes expressed as volumes ratio. Following Basel II framework a debtor is considered to be in default in case of more than 90 days overdue on any material credit obligation or when the bank considers that the borrower is unlikely to repay the credit in full.	PD (LGD when measured in volumes)	Harmonized definition. Sometimes loans and no of borrowers with overdue amounts of over 90 days are available in central banks' credit register.	Usually not publicly available. Usual disadvantages as described above when used as stock variable	Chiriacescu (2010) and Chiriacesu et al (2012) – flow variable per sector of activity (separately for households). Moinescu and Codirlasu (2012a) – sectoral stock volume ratio for companies as proxy for sectoral NPL.
Bankruptcy rate **Type: flow variable**	Ratio of numbers of companies filing for bankruptcy (entering insolvency proceedings).	PD	Harmonized legal definition. Usually publicly available at sectoral disaggregated levels. Broadly used in stress testing studies.	Usually available only for companies. Complicated net effect on actual PD in banking system. Banks' credit portfolios may not reflect entire sector distribution (credit selection criteria lead to rejection of likely to go bankrupt companies), but, on the other hand, credit default is not always followed or preceded by bankruptcy.	Trenca and Benyovszky (2008)

[16] As Ferrari et al (2011) note LLP ratio can be available as flow variable (new provisioning to a measure of stock of total loans), but this is not the case for Romanian banking system.

The studies mentioned above had access to data which are not currently publicly available (e.g. Moinescu and Codirlasu, 2012a; Chiriacescu, 2010) or the series have been discontinued (industry-specific bankruptcy rates used by Trenca and Benyovszky, 2008).

Still, due to data restriction, Moinescu and Codirlasu (2012a) and Chiriacescu (2010) actually use a proxy of the formal default rate as their data series are based on data of loans and number of borrowers, respectively, that register overdue amounts of more than 90 days as reported by National Bank of Romania's credit register and not on actual defaulted borrowers / loans formally declared by banks. Their series however exclude only borrowers / loans for which the bank consider that repayment is unlikely (potentially in advance of any 90 days arrears), which should constituted only exception cases.

While Moinescu and Codirlasu (2012a) and Chiriacescu (2010) used sectoral disaggregated data, Romanian central banks' credit register has publicly available data only for volumes of overdue credit obligations (overdue principal, without interest and other penalties) disaggregated for household and companies[17]. Data on number of borrowers with overdue amounts of more than 90 days are not available (only on number of total borrowers and number of borrowers registering delays of any number of days).

Table 2 below presents the credit risk variables data available for the Romanian banking system, their sample period and level of disaggregation:

[17] The companies sector includes also municipalities.

Table 2 Credit risk variable data availability for Romanian banking system

Credit risk variable	Level of disaggregation	Available sample period (continuous series)	Data frequency	Source
NPL ratio	System level	March 2008 – present	Quarterly	N.B.R. data base and financial stability reports
Disaggregated NPL ratio	Companies and household level	February 2009 – August 2013 for companies	Monthly	N.B.R. financial stability reports
		September 2008 – June 2013 for households	Quarterly	N.B.R. financial stability reports
LLP ratio (credit risk ratio)	Exclusively available at system level	December 2007 – present	Quarterly	N.B.R. data base
Default rates	Companies and household level (proxied by overdue of more than 90 day)	February 2005 – present	Monthly	N.B.R. data base (credit register)
Bankruptcy rate	Main object of activity (usually they are aggregated for main economic sectors of activities)	March 2010 – present	Monthly	National Trade Register Office database

Given the data availability restriction noted above, this study will focus on default rates (in terms of volumes) separately for corporate and household loans. The National Bank of Romania uses the same main disaggregation level for its stress testing procedure (N.B.R. 2013a; Melecki and Podpiera, 2010), of course, complemented by more detailed granular disaggregation based on data that are not publicly available.

Unexpected loss cannot be directly computed based on volume-based default rates simulations (as usually done in such cases as discussed in the literature review); nevertheless, useful macro stress testing can be performed on default rate values directly.

This study will use the full sample available, with quarterly frequency, i.e. 2005 Q1 to 2013 Q3 period (35 observations).

The available samples have the advantage of capturing different business and credit cycle, in a balanced manner: the 2005-2008 upward period (high GDP and credit growth rates, following Romania's accession to N.A.T.O. and E.U.), the late-2008 – 2009 shock generating important GDP downturns and NPL build up, as well as the recent slight macroeconomic improvement (N.B.R. 2013a).

This study complements thus the independent macro stress testing research for credit risk in Romanian banking system since Trenca and Benyovszky (2008) use only pre-crisis data (2002-2007), and although Chiriacescu (2010) and Chiriacescu et al (2012) include also the 2008-2009 macroeconomic shock effects (both studies use 2006-2010 data series), as Chiriacescu (2010) explain, the model could still be biased towards pre-2009 macroeconomic conditions.

3.5. Macroeconomic variables selection

While the selection of exogenous macroeconomic variables can take into consideration many potential candidates, the above mentioned research focuses on several main categories, such as GDP and its main components (industrial production, private consumption, gross capital formation, GDP gap) and monetary conditions or price stability variables (interest rates, spreads, exchange rate, inflation rate, monetary aggregates). Other studies extend the analysis to credit growth, corporate indebtedness, household sector variables (unemployment, disposable income, indebtedness) as well as oil prices and other financial indicators (stock market indexes) and exports (e.g. Boss, 2002).

Being a reduced form approach, the theoretical considerations are typically general and the final selection is performed taken into consideration econometric results. Several variables are included on the basis of their information content rather than direct influence (e.g. stock exchange indexes for their forward looking features). Allen and Saunders (2002) report includes a comprehensive review of these theoretical background. Kalirai and Scheicher (2002) present theoretical justifications for a wide range of potential variables, while Jakubik and Reininger (2013) discuss the most relevant macroeconomic factors affecting credit risk in Central, East and South-eastern Europe.

This study will follow the selection guidelines proposed by Boss (2002): the process starts from a list of candidate variables classified as per Kalirai and Scheicher (2002) structure; a series of uni-variate regressions of the macroeconomic index[18] (logit transformation of the default rate) on each variable is then performed, and only one statistically significant factor from each category is retained for building up the multi-variate model. Additionally, the direction of the statistically significant relation should correspond to the theoretical assumption (the regression coefficient should have the expected sign). A similar procedure is followed by Moinescu (2012) in the Romanian credit risk context.

Of course any non-structural selection approach maintains a certain degree of subjectivity and ambiguity as the macroeconomic series are strongly inter-correlated on different lags, any macroeconomic variables grouping is somewhat arbitrary, and some of the macroeconomic factors exert mixed effect on borrowers' repayment effort (e.g. inflation and exchange rate) and the

[18] Alternatively, Fiori et al. (2007) perform a factor analysis to identify the most significant factors.

influence can change on different time horizons (Jakubik and Reininger, 2013; Kalirai and Scheicher, 2002).

The "Estimation and results" chapter below will discuss in more detail this theoretical background, in comparison with other studies applied for credit risk assessment for the local market.

Annex A presents the variables used in this study, their source and sample range.

The range of variables has been extended compared with Boss (2002) proposals, in order to include variables found relevant in other studies cited above, but on the other hand, some variables have been excluded due to lack of data, generally or at the desired frequency (e.g. disposable income, slope of the yield curve, foreign direct investments). Nevertheless, similar with other studies, proxies are used were possible, and the range is generally wider than the one used in the research done for the Romanian banking system[19].

Due to the method of computation of default rates (total amounts of defaulted loans to total loan amounts), several series were excluded from the models due high correlation implied by the mathematical computation method. For example, monetary aggregates, used in some studies of PD (numbers ratio), were excluded from the models due to high correlation with the denominator (67-70%).

Additionally, although sometimes classified in different categories, several variables can be correlated, sometimes to a high degree (e.g. household consumption is an important part of GDP, i.e. 84%, unemployment is expected to be correlated with GDP as well; interest rates can be

[19] Excluding some variables taking into consideration by Vogiazas and Nikolaidou (2011) and Nikolaidou and Vogiazas (2012) as their research purpose is different. They attempt to identify and quantify cross-border banking systems influence, specifically, correlation between Greek crisis and NPL ratio in Romania.

correlated with exchange rates). The final multi-variate setting will take these correlations into account in order to avoid multi-collinearity.

4. Estimation and results

Aside being informed by previous research on credit risk modelling in the Romanian banking system, the models estimated here take also into consideration several specific features of credit risk (mainly expressed in terms of NPL rate) in the Romanian banking system. A qualitative assessment is thus presented as well and the findings are used to adequately design the proposed models.

4.1. Main recent evolutions in credit risk in the Romanian banking sector

As documented at length mostly in the central bank financial stability report (N.B.R. 2013a, 2012, data as of August 2013 unless otherwise specified), the credit risk in the domestic banking sector is characterized by the below recent evolutions:

- Following the adverse macroeconomic evolution of the last years and in the context of the negative evolution of private lending, the banking system registers high NPL ratio, still on an upward trend, with important negative impact on profitability; this constitutes a major weakness of the system (along with cross-border deleveraging). The NPL ratio is expected to further increase, but at a slower pace. Nevertheless, the levels of solvency, provisioning and liquidity continue to be adequate (89.5% of NPL are covered with provisions), ensuring that banks can cope with moderate unfavourable evolutions without major difficulties;

- The NPL high level is also generated by the fact that banks maintain in their portfolio a substantial share of borrowers with reduced likelihood of debt servicing and extended arrears (arrears over a year for example for around 70% of the household NPL). Loan restructuring / rescheduling and foreclosure were the main NPL management tools applied by the banks, while disposal of claims and debt cancellation were less used;
- More than 60% of household and corporate loans are granted in foreign currency and this entails additional credit risk since the majority of borrowers are unhedged. Loans in foreign currency have been generally riskier for both corporate and households' portfolios; the central bank has continuously implemented regulatory measures to balance the portfolios with moderate, but positive results in the last years (N.B.R. 2013a, 2012);
- A significant part of the overall companies and household portfolio is mortgage-backed (67%) generating exposure on adverse real estate market evolutions;
- The NPL ratio is substantially higher in the corporate portfolio than in households portfolio (23.4% for companies versus 8.2%; companies hold a slightly higher share of total private credit than households);
- The **corporate sector** features a high degree of heterogeneity in its performance on numerous sectoral breakdown criteria:
    - **Size**: SME, and especially micro-enterprises, proved the most vulnerable to adverse macroeconomic evolution (NPL ratio at 23.2% as of December 2012 versus 4.3% for

large corporations). Large corporations have a lower indebtedness degree and a better interest coverage ratio;

- **Main sector of activity**: trade, real estate and construction companies register a higher NPL ratio (39.7% for construction companies as of August 2013) and they typically have a riskier financial profile (continuous losses at aggregate sector level) with higher indebtedness degrees. These sectors account for almost 50% of corporate loans. On the other hand, companies activating in the agriculture sector show positive overall evolution with debt-servicing above average (NPL at 14.9%);
- **Tradables[20] and non-tradables goods sectors:** tradables sector has a relatively lower NPL ratio than non-tradable sector (20.1% versus 25.2%) due to better financial situation at aggregate level;
- **Other criteria**: companies belonging to the medium-high and high tech sub-sectors register a better than average bank debt servicing. Similarly, the NPL ratio for net exporting companies was 13.3% as of August 2013, much lower than system-wide average (23.4%)

- Aside the foreign currency unhedged exposure mentioned above, the **household loans portfolio** main vulnerability is related to high household indebtedness. A slight improvement has been registered in the last two years following the decrease of total financial debt and related debt service, on one hand (decrease of the numerator of indebtedness measure) and the increase of net wealth, GDP and disposable income (the

[20] While not well defined in the available statistics, tradables sectors include agriculture, hunting and forestry, energy and industry and partially international transport, communication, external trade service etc; non-tradables sectors cover construction, domestic trade, warehousing, communication.

denominator), on the other hand. However indebtedness remains high, with a large share of overindebted households and generally higher (debt service / income) ratio than other E.U. countries. Macroeconomic factors such as unemployment, wages, interest rates and exchange rate dynamics are the main drivers of overindebtedness (N.B.R. 2013a).

(N.B.R. 2013a) further explains that indebtedness is specifically generated by high interest rate spreads charged on Romanian households' loans. The overall portfolio includes a substantial share of consumer loans (54%, much higher than E.U. average of 27%), with higher interest rates than mortgage loans. Indebtedness measures that don't include interest expenses, such as (principal debt / gross income) ratio, register lower values than other E.U. countries.

Additionally, borrowers with incomes below minimum wage account for an important part of banks' portfolio (60% of borrowers, 35% of total loans) and they are especially vulnerable to shocks in interest and exchange rates (disposable income is much lower in absolute values).

The research on Romanian banking system mentioned earlier in the text generally confirms the credit risk features described above, at both system-wide and sector levels. Measures of gross value added (GDP, industrial production, construction activity level, sectoral value added etc), interest rates or spreads, the exchange rate, unemployment and measures of indebtedness (including sector-specific) are typically the most significant macroeconomic factors in modelling credit risk.

4.2. Model Estimation

Annex B presents the unit root test results and related discussion. Aside GDP growth and output gap, unit root testing suggest that most of the series are non-stationary and thus transformations are applied in order to achieve stationarity; the approach is similar with most of the research cited here (Boss, 2002; Fiori et al, 2007).

All econometric estimations were performed using Eviews econometric package.

Annex C presents the preliminary uni-variate regression results. Similarly with Boss (2002), since macroeconomic factor are expected to be autocorrelated (as modelled in their specific equation), the Newey-West heteroskedasticity and autocorrelation consistent covariance matrix estimator is used in uni-variate regression stage, in order to accommodate any expected residuals heteroskedasticity and/or autocorrelation of unknown order.

Also in line with Boss (2002) approach and with most of the similar studies cited above (including the ones for the Romanian banking system) the testing includes lags of the independent variables; specifically, the testing includes 8 quarter lags (Boss, 2002 using annual data includes current annual value and 1-year lag).

As expected, the testing confirms the hypothesis of the relation between macroeconomic factors and credit risk, either contemporaneous or lagged [21].

[21] As explained above, a positive sign in the regressions means a direct positive relation between the macroeconomic factor and the default rate (e.g. interest rates hikes will cause default rate to increase, i.e. positive sign, but positive GDP growth should decrease default rate, i.e. negative sign).

In terms of empirical findings regarding lagged relation, an important note should be added Almost all of the uni-variate regressions showed that several closed lags are statistically significant and have high explanatory power rather than only one specific lag of a proposed macroeconomic factor (this is also in line with the auto-regressive assumption for modelling the macroeconomic variables, i.e. shocks are persistent). Since the model is based on quarterly data, the multi-variate model includes one specific quarter lag (the most significant / highest explanatory power) or the contemporaneous value of the series, but this reflects only a general lagged or simultaneous effect and not only a specific quarter influence (i.e. quarter 7 reflects a delayed effect of approx. 1-1.5 year for example).

4.3. Corporate model

4.3.1. Uni-variate results

Real and nominal GDP growth rates are the most important cyclical explanatory factors, with immediate effect on default rates, as typical found in similar research on the Romanian credit risk (Moinescu, 2012; Jakubik and Reininger, 2013; Moinescu and Codirlasu, 2012 who use gross value added for each sector, the main components of GDP; Trenca and Benyovszki, 2008). Industrial production, which in some cases leads economic growth (Boss, 2002) is significant, indeed on lagged values, but has a low explanatory power.

GDP gap seems to act as an early warning indicator with lagged values (5 lags for real output gap) having a direct positive relation with default rate (e.g. economy overheating periods are followed in the next year by increase of default rate). This is contradictory with the result reported by Chiriacescu (2010) how founds an immediate positive relation between output gap and default rate in its industry-specific study on 2006-2010 sample (default rates are nevertheless computed differently based on number of borrowers ratio[22]).

Assessing system-wide NPL dynamics, Moinescu (2012) founds an immediate positive relation between changes in output gap and NPL in several Central and East European countries, including Romania, but univariate regression on level of output gap provided mixed result (changing sign on lag 0 versus lag 1) and low explanatory power.

The forward looking economic sentiment indicator is not significant.

Regarding the price stability indicators, from a theoretical perspective, inflation rate is expected to exert mixed effects on default rates. Generally the research on developed economies cited above (e.g. Fiori et al, 2007; Boss, 2002; Kalirai and Scheicher, 2002) mention an expected negative relation between inflation rate and default rates, as higher inflation decreases both the real value of the debt to be repaid in the future and the real cost of funding (real interest rates). However, for Romanian economy, in order to address persistent relatively higher inflation rates (e.g. around 4.95% at the end of 2012) the central bank has been maintain maintaining contractionary monetary policy stance, even in adverse macroeconomic environment, with high money market RON interest rates (N.B.R. 2013b), entailing an increase direct cost of borrowing. For example, Moinescu (2012) analysis of system-wide NPL ratio report a significant positive relation with inflation rate in uni-variate settings, but the variable is not used in the final multi-variate model.

[22] Additionally, as the author explains, the model used in this study has the limitation of using non-stationary series in a static model (alternative dynamic specification provided poor results, while short sample didn't allow for cointegration modelling).

Uni-variate regression yield mixed results regarding inflation rate influence in this analysis, with different signs on levels series versus first difference series testing, distant lags and relatively low explanatory power. This finding is line with the exclusion of this variable from the model in all the sectoral corporate studies mentioned here.

Household indicators are all significant, showing the expected sign. Real household consumption evolution has the highest explanatory power (even higher than real GDP growth cyclical indicator, with which it is highly correlated), as it probably captures both the real macroeconomic cyclical evolution and the sectoral weaknesses discussed above (trade sector vulnerability). The forward looking consumer confidence index is significant as well.

In the corporate sector indicators, both gross capital formation and construction activity show significant and immediate relation with default rate and high explanatory power.

Construction activity level is not usually included in the models cited for the Romanian corporate sector, but the strong relation identified here confirms the sectoral pattern presented above (construction sector companies register the highest level of NPL ratio). Additionally, this variable could also capture information on real estate market development, in the context of predominant mortgage-based exposure, as detailed above. This factor is found statistically significant in Vogiazas and Nikolaidou (2011) system-wide credit risk study.

Most of the studies mentioned here found an important positive relation of indebtedness degree at industry-specific level. Unfortunately, due to the computation method for corporate aggregate indebtedness, i.e. (total bank debt / total gross value added) and for default rates i.e. (defaulted loan total amount/ total bank debt), the implied partial mathematical negative relation seems to prevail and/or industry-specific different indebtedness compensate at aggregate level and overall indebtedness loses significance.

Somewhat unexpectedly given the low level of development of domestic stock exchange (Jakubik and Reinninger, 2013; Vogiazas and Nikolaidou, 2011), and their typical exclusion from similar research on the Romanian corporate sector, forward looking stock market variable have good explanatory power on lagged values. This is contradictory with Vogiazas and Nikolaidou (2011) finding that stock market index have no explanatory power for corporate defaults.

Nevertheless, Jakubik and Reinninger (2013) multi-variate model incorporates the domestic stock index (fifth lag) for several countries in Central, Eastern and Southeastern Europe, including Romania; they stress the role of this variable as leading indicator for overall economic and financial evolution rather than an potential direct influence on default rate (e.g. through direct wealth effect). Additionally, as Kalirai and Scheicher (2002) suggest, the stock exchange index could capture information typically incorporated in Merton (1974) based structural credit risk assessment frameworks.

Domestic currency money market interest rate (as typically reflected by ROBOR 3M, Moinescu, 2012; N.B.R. 2013a) shows relatively lower explanatory power in its category, while the EURIBOR evolution has a circumstantial negative relation with default rates. Since EUR total interest rate are generally related to EURIBOR in the Romanian credit market (Jakubik and Reininger, 2013) the same unexpected negative relation maintains also for total EUR interest rates. The EUR interest rate spread (which excludes the effect of the counter-cyclical evolution of EURIBOR) has a strong explanatory power and the expected sign.

RON average interest rate on loans however has a strong relation with corporate default rates as it captures overall monetary and financial conditions and concurrently has a direct substantial impact on borrowing costs. The lag for this variable is distant (more than a year) suggesting that increased cost doesn't immediately affect debt servicing but as it accumulates it generates an adverse effect.

Aside the result on EUR money market and total interest rates, the results on interest rate indicators are similar with previous research.

In the external variable, the exchange rate shows a high explanatory power and a significant relation given the unhedged foreign currency credit risk issue discussed above. Similarly with increased interest cost, the lag is distant. Export related variable don't have a strong explanatory power.

Generally, as Boss (2002) and Karilai and Scheicher (2002) explain a depreciation of foreign currency could also improve default rates as it encourages export activity.

While indeed in recent years the export sector performance was strong, positively contributing to GDP growth and net export sector companies have registered relatively better financial standing and debt servicing (N.B.R. 2013a), at the level of average overall corporate level default rate, the uni-variate results suggest that the adverse effect on credit risk outweigh the positive effect generated through export improvement.

Moinescu and Codirlasu (2012) as well as Chiriacescu (2010) similarly include only exchange rate as external variables in their modelling of corporate sector defaults rates. Additionally, Moinescu and Codirlasu (2012) incorporate fuel prices in their model, but they found a statistically significant relation only for agriculture sector.

Oil prices are not significant in the uni-variate testing presented here, but since agriculture sector account only for around 8% of GDP, the result is not inconsistent with Moinescu and Codirlasu (2012) finding.

4.3.2. Multi-factor corporate model

Preliminary multi-variate results showed that household consumption is highly correlated with GDP growth. The latter variable was preferred as it's widely documented in similar research as the main cyclical indicator and provided slightly better fit than specification where household consumption took the role of cyclical indicator. Consequently to this decision, the other significant indicators reflecting household sector were tested in the multi-variate setting.

Based on the uni-variate results and taken into consideration the credit risk features discussed earlier, two alternative preferred multi-variate models are proposed (Table 3): a model including also leading indicators with a slightly higher accuracy (but not suitable for communication as discussed above, Model 1) and one based strictly on main macroeconomic factors (Model 2).

Table 3 Corporate multi-variate model

Variable	**Model 1**		**Model 2**	
	Lag	Coefficient	Lag	Coefficient
Constant		0.1037***		0.1086***
Real GDP growth	0	-1.8264***	0	-2.8949***
Consumer confidence indicator	1	0.0067**		
Construction activity (nominal)	0	-0.8762***	0	-0.7337***
Domestic stock market index (BET)	7	-0.1305***		
Interest rate for RON loans	5	3.3769***	5	4.0000***
Exchange rate			7	0.5160*
R-squared		*0.913*		*0.871*
R-squared adjusted		*0.896*		*0.852*
Durbin-Watson test		*1.987*		*2.020*

*Note: ***, ** and * denote significance level of 1%, 5% and 10%, respectively.*

The inclusion of leading indicators in Model 1 is generally a novel approach in the research on Romanian corporate sector, but a similar result was found in the system-wide study of Jakubik and Reininger (2013) for the domestic stock market index as discussed above.

Since household consumption was excluded, the consumer confidence index proved significant in this multi-variate model. The alternative household indicators were not significant in the multi-variate models (unemployment and indebtedness proxy).

The inclusion of the nominal construction activity as corporate sector indicator follows the result of the univariate testing (and related discussion).

Among interest rate indicators, RON loan interest rate and EUR interest rate spread have similar explanatory power, but the former yielded better result in the multi-variate testing and was thus preferred.

Model 1 excludes the exchange rate; while this variable was actually marginally significant in the model (at 10% significance level), it generated residuals correlation.

The exclusion seems contradictory with the related discussion above, but nevertheless Moinescu and Codirlasu (2012) report multi-factor models without exchange rate as well for several corporate sectors. Aside the considerations outlined earlier on the exchange rate mixed effect, Jakubik and Reininger (2013) further explain that borrowers in foreign currency loans have benefited from the decrease of EUR interest rates (typically indexed to EURIBOR), while domestic currency rates were maintained at high level due to inflationary pressures. Indeed N.B.R. (2013a) notes that, higher risk notwithstanding, at aggregate level NPL ratio for foreign currency loans has only recently exceeded that for domestic currency loans.

Model 2 incorporates only direct macroeconomic factors, including the exchange rate but with a more distant lag (7^{th} lag instead of the 4^{th} lag found the most significant in uni-variate testing[23]; the former lag is significant as well in the uni-variate setting, albeit with a lower explanatory power).

The multi-variate models include both contemporaneous and lagged influence of the macroeconomic factors.

As found also in other studies (Chiriacescu, 2010 for Romanian banking system; Jakubik and Reininger[24], 2013 in panel study, including Romania), GDP influences contemporaneously the NPL in the corporate sector (same quarter), although we could expect some resilience (similarly, the effect of construction activity level, a GDP component, is also simultaneous). As general economic consideration, the GDP evolution reflects the business cycle stage but concurrently, being a value added variable, it constitutes a good proxy of corporate sector profitability (Virolainen, 2004), i.e. the main source of loan and interest repayment. Additionally, specific to the Romanian credit risk, the permissive insolvency legislation for debtor companies could be also an explanation for this immediate effect (Chiriacescu, 2010).

On the other hand, the interest rate for RON loans is included in the models with more distant lags (5^{th} lag) but, as explained above, actually lags from the second/third quarter to eight are statistically significant for both sectors at 91% or at most 95% confidence levels. The selected lags

[23] As already discussed, this doesn't imply a theoretical specific effect of lag 7, since several distant lags are significant in the uni-variate model (3^{rd} –7^{th}) but rather a general delayed effect because the effect of an increase of borrowing cost takes time to accumulate and generate 90 days arrears

[24] Jakubik and Reininger (2013) model includes previous quarter GDP.

are the ones found the most significant / having the highest explanatory power. While GDP and GDP components capture directly and immediately an income decrease and adverse economic conditions, interest rates, on one hand, reflect financial conditions which usually have a lagged impact on private sector, and on the other hand, affect loan cost, but it is reasonable to expect a gradual accumulation rather than an immediate effect. This could be because interest rates are usually fluctuant (and thus debtors are used with some degree of fluctuations; banks usually update interest rates on a monthly basis in the corporate sector, N.B.R. 2013a) and affect only a part of the debt service, while NPL captures 90 days arrears and thus it takes time for an interest rate shock to accumulate[25].

The domestic stock market indicator is also included on a distant lag in corporate Model 1, but as discussed, stock indexes are leading / forward looking indicators and thus this finding seems in line with theoretical background and other study findings (Jakubik and Reininger, 2013 – 5th lag)

Both models show good statistical fit with R-squared adjusted values of 85-90%; Durbin Watson test values indicate no first order autocorrelation of errors. Annex D.1 and D.2 present the diagnostic tests of the models following the guidelines of Brooks (2008), chapter 3. Since the multi-variate specification was based on relatively extensive uni-variate testing (this could affect the usual computation of confidence levels, Brooks, 2008), an out-of-ample forecast evaluation is presented as well, with a holdout sample consisting of the last 4 quarters. The models are estimated for the period excluding the holdout sample and results are then used to construct forecast for the holdout

[25] Specifically, ceteris paribus, a company's default take places quicker when the company is facing decreased profitability in an adverse macroeconomic environment, than in the situation when the company is facing only an interest rate increase and/or financial market turbulences.

period, using actual values for the independent variables. Both models proved satisfactory forecast power, but model 2 yielded relatively better results.

Additionally, since the multi-variate models include macroeconomic series intrinsically related, multi-collinearity could be an issue.

As general observation, Gujarati (2004) and O'Brien (2007) explain that the usual sign of multi-collinearity is a high R-squared combined with non-significant coefficients (although jointly, coefficients seem significant). However, this is not the case in proposed models as all variables are individually statistically significant (the statistical significance of each variable included in the multi-variate models was a criterion in building the model).

Nevertheless, following the guideline provided by Gujarati (2004), the diagnostic tests annexes include a Variance-Inflating Factor analysis for all models which confirms that multi-collinearity level is not problematic for the models.

4.4. Households model

4.4.1. Uni-variate results

Annex E includes the results of uni-variate regression for the households sector, again using Newey-West covariance matrix estimator.

Among cyclical indicators, GDP growth maintains the highest explanatory power also in the household model, but with a significant lag (3-4 quarters). This finding is similar with the results reported by Chiriacescu (2010), who suggest that the lack of a household bankruptcy law that would offer protection to distressed households, can be an explanation for the delayed effect (compared with corporate sector, where the bankruptcy procedure is heavily used by debtors facing financial difficulties, N.B.R. 2013a). Alternatively, it could show simply that households maintain better repayment even when facing income decreases. An explanation could be the higher level of savings in the households sector: at system level as of September 2013, households' savings amount to around RON 126.5 billion versus RON 64.7 billion in the corporate sector, while loans to corporate sector reach RON 170.9 billion versus RON 87.8 billion loans to households.

Again, inflation rate yielded mixed results in the uni-variate regressions.

Similarly with the corporate model, but on 3-4 quarters lagged values, real household consumption has a good explanatory power (higher than GDP growth rates). It probably captures, at aggregate level, the business cycle evolutions concurrently with other household sector dynamics affecting debt servicing (unemployment, disposable income etc). Given the features of the households credit risk detailed above, net nominal wage, unemployment rate and interest payment service show significant relation as well, albeit with lower explanatory power.

The leading indicators regarding economic sentiment and consumer confidence are not statistically significant, but stock market indexes maintain a significant relation with default rate, but on more distant lags (8 quarters).

Money market, interest rate and external variables testing yielded similar result with the corporate model.

4.4.2. Households multi-factor model

As expected household consumption has an important explanatory power; it is consequently assigned the role of main cyclical indicator and it's preferred over GDP growth in the multi-factor model (Table 4 below) since it reflects directly the household sector macroeconomic evolution and yielded better fit.

The alternative household specific indicator incorporated in the model is the disposable income proxy (aggregate interest service payment). Total interest rate for RON loans is also included in model.

The important relations of these two factors (disposable income and interest rate) with default rate is in line with the households credit risk feature outlined above, i.e. over-indebtedness generated also by high interest rates.

The disposable income proxy is computed as (interest payments / nominal wage in RON) ratio at aggregate level, specifically taking into account different interest rates per currency, i.e. EUR interest rates and EUR loan balances (in RON equivalent, thus capturing exchange rate dynamics). The correlation between this proxy variable and the RON interest rate is limited (0.28 correlation coefficient) as an effect of the large share of foreign currency denominated loans in the portfolio and the additional information captured by the proxy regarding wages (the denominator of the proxy).

Table 4 Household multi-variate model

Variable	Lag	Coefficient
Constant		0.3555***
Household consumption	4	-3.6359***
Interest rate payment service	6	1.1208***
Interest rate for RON loans	8	9.9010***
R-squared		*0.761*
R-squared adjusted		*0.731*
Durbin-Watson test		*1.72*

*Note: ***, ** and * denote significance level of 1%, 5% and 10%, respectively.*
The DW test shows a lower value but still higher than the 95% confidence level critical value (1.650) and thus the hypothesis of no first order auto-correlation cannot be rejected. Nevertheless, the coefficient covariance matrix is estimated based on Newey-West heteroskedasticity and autocorrelation consistent (HAC) covariance estimator.

The model doesn't include directly the exchange rate as its inclusion yielded poor results, but its effect on household loan debt servicing capacity is captured by the disposable income proxy and household consumption (the latter is expected to capture unemployment as well) and probably total interest rate (since they reflect also money market and financial risk conditions).

The interest rate and the disposable income proxy are included with distant lags, reflecting the above explained resilience of the household sector and the gradual accumulation of borrowing cost (interest rate and exchange rate effects). The interest rate lag is even more distant than in the corporate models because banks typically update interest rate on quarterly basis for households loans (versus monthly basis for corporate loans; N.B.R. 2013a, Chiriacescu, 2010).

Stock exchange market index maintain statistical significance in the multi-variate model but induce an increase in residual auto-correlation.

The final multi-factor model shows a good fit (R-squared adjusted of 73%). Annex F reports the diagnostic test, with generally satisfactory results, but relatively less conclusive than the corporate model (residuals normality assumption and functional form). The out-of-sample forecast evaluation however yielded good results.

The only available research specifically assessing household credit risk portfolio is found in Chiriacescu (2010) and Chiriacesu et al (2012). The model proposed by these studies includes industrial production as the main cyclical indicator due to chosen frequency of the data (monthly, while GDP related data are available only quarterly). Unemployment, indebtedness, exchange rate and interest rate spreads are found statistically significant in the multi—variate setting.

4.5. Estimation of macroeconomic variables equations (ARMA)

This section presents the methodology employed to estimate the *ARMA (p,q)* specifications (equation (16), Section 3.1 Specific Model) of the explanatory macroeconomic variables and the results of this estimation.

The ARMA equations are estimated using Box-Jenkins approach, with information criteria at the identification stage, following the guidelines proposed by Brooks (2008) and Gujarati (2004). In the context of the broader modelling methodology used in this study, similar approaches to ARMA estimation can be found in Kucukozmen and Yuksel (2006), Fiori et al (2007) and Chiriacescu (2010).

Generally, the Box-Jenkins ARMA estimation approach is an iterative process comprising three steps (Brooks, 2008):

1. *Identification* – this step involves finding the appropriate order for the ARMA (determining the value for *p*, i.e. the number of auto-regressive terms and *q,* i.e. the number of moving average terms*).* This can be done by inspecting the graphical correlogram (the autocorrelation function) and partial correlogram (partial autocorrelation function) of the series in order to identify patterns similar to those implied by theoretical ARMA configuration. Since real data series don't usually display the simple theoretical patterns, current practice however involves using information criteria in this stage; this concurrently implies that the identification decision is less subjective than simply interpreting the correlograms (Brooks, 2008).
2. *Estimation of parameters* – having identified the adequate values for *p* and *q,* the ARMA parameters can be estimated using usual least squares technique or other non-linear techniques (e.g. maximum likelihood).
3. *Model checking* – determining whether the identified specification and related estimation fit the date reasonably well. This is typically done through residual diagnostic, i.e. checking if the residuals display linear dependence (auto-correlations, partial autocorrelation and Ljung-Box test), which would imply that the chosen model doesn't fully capture the feature of the series[26]. In such a case the model is rejected and the process starts over from step 1. Alternatively, in case the residuals exhibit withe noise properties, the model is considered appropriate and the process stops.

[26] As Brooks (2008) notes usually the residuals diagnostic testing in the Box-Jenkins approach comprise only autocorrelation tests (not the full standard package of residual diagnostics).

Additionally, especially for relatively small samples, the goals is usually to identify and estimate a *parsimonious model* that captures the features of data using as few estimated parameters as possible, (Brooks, 2008). This preserves degrees of freedom and avoids building large model that fit the date only in in-sample estimation, while performing poorly in out-of-sample estimation.

Annex G presents the results of the ARMA estimation[27] and testing for the selected macroeconomic variables using the approach described above; table 5 below summarizes the results. Several series showed no auto-regressive or moving average patterns (no significant auto-correlation / partial auto-correlation) and thus they will be treated as non-zero white noise processes (Brooks, 2008).

As recommended by Brooks (2008), since the sample is relatively small, the Ljung-Box Q-Statistics portmanteau test has been taking into consideration within the model checking step, for 3-8 quarterly lags (along with the usual auto-correlation and partial auto-correlation function significance levels).

Table 5 ARMA estimation results

Models	Macroeconomic variable	Selected specification
Corporate models	Real GDP Growth	AR(1)
	Consumer Confidence Indicator	Non-zero white noise
	Construction activity (nominal)	ARMA (4,2)
	Domestic stock market index (BET)	Non-zero white noise
	Interest rate for RON loans (corporate sector)	ARMA (2,1)
	Exchange rate	Non-zero white noise
Household model	Household consumption (real)	ARMA (1,2)
	Interest rate payment service	Non-zero white noise
	Interest rate for RON loans (household sector)	ARMA (1,3)

[27] Similar to the studies quoted above (e.g. Kucukozmen and Yuksel, 2006 who use 12 monthly lags; Chiriacescu, 2010 – 3 quarterly AR terms and 2 MA terms in the final specification) a maximum number of autoregressive and moving average terms of 4 were taken into consideration in the ARMA estimation procedure (up to 4 quarters lags);

4.6. Specific scenarios

The table below summarises the scenarios used in the few Romania recent stress testing applications:

Table 6 Scenarios design in recent Romanian stress testing application

Study / Report	Context	Scenarios	Time Horizon
N.B.R. (2013a)	Central bank supervisory stress testing	Comprehensive adverse macroeconomic scenario involving a strong and persistent domestic currency depreciation (20%), negative economic growth (prolonged recession), substantial rise in funding cost and euro area recession. Probabilities of default considered in the scenario are comparable with their historical maximum registered in 2009 (higher actually in the case of mortgage loans). Full scenarios details are not disclosed.	2 years (2013-2015)
N.B.R. (2012)	Central bank supervisory stress testing	Comprehensive adverse macroeconomic scenario involving a double dip recession (-1.5% GDP decrease each year), strong and persistent domestic currency depreciation (14% in the first year) and worsening funding condition. Full scenarios details are not disclosed.	2 years (2012-2014)
Chiriacescu (2010)	Independent research	Baseline scenario given by model forecasting (autoregressive equations). Adverse alternative hypothetical scenario involving: ➢ 17% depreciation of local currency ; ➢ Rise in unemployment (for household sector): consecutive quarter increases (1.5%, 1%, 0.5% and 0.2%). Expected and unexpected losses are computed under both baseline and adverse scenarios.	1 year (2010 – 2011)
Trenca and Benyovszky (2008)	Independent research	Baseline scenario given by model forecasting (autoregressive equations). Hypothetical adverse scenario comprising a 2% percentage points interest increase for four consecutive quarters. Expected and unexpected losses are computed under both baseline and adverse scenarios.	1 year (2007-2008)

The table shows that generally both Romanian central bank and the few independent studies use hypothetical scenarios. However, N.B.R. doesn't fully disclose the methodology details and thus the assumed adverse scenarios could be based on certain historical evolution or probabilistic approaches. Generally, the N.B.R. stress test framework is comprehensive, covering all relevant risks of the financial system and consequently their scenarios design reflects this broader approach.

Given the data availability constraints and the reduced form methodology employed (similar to the one used in this report), the two independent studies use simple ad-hoc hypothetical scenarios, without clear historical or probabilistic background. Trenca and Benyovszky (2008) calibrate the model on pre-crisis period (2002 to early 2007) when defaults rates were very low and test only a simple hypothetical scenario based on interest rate cost shocks, without addressing specific financial system vulnerabilities. The model proposed by Chiriacescu (2010) covers also post-crisis data and the adverse scenarios include shocks of relevant credit risk factors, specific to the Romanian banking system (local currency rate depreciation and unemployment).

Both independent studies lack a GDP shock scenario (although Chiriacescu, 2010 includes a related unemployment shock for household segment), a standard practice in stress testing as explained above. Furthermore, the absence of the usual historical or probabilistic scenarios affects the comparability of their findings.

Given the findings of the modelling sections and the discussion is Section 2.2. regarding current practices on scenarios design, this study includes the scenarios presented in Table below. The scenarios approach is much broader than the one used in the other independent studies.

Since the analyzed sample is relatively reduced (around 8 years), historical approaches based on 2008-2009 shocks are preferred over probabilistic approaches (the latter should be based on longer term averages and deviations). However, the historical scenarios values are compared with the values implied by the usual probabilistic scenarios. A hypothetical scenario is proposed for household sector to address specific risks within the sector.

Several variables (stock market index and exchange rate for corporate sector and interest rate for household in the households sector) were not specifically included in the stress test scenarios due to their distant lags in the model.

Table 7 Scenarios proposed for corporate models

Adverse scenarios	Historical background	Comparison with usual probabilistic approach
GDP shock: decrease of -7.54% over a year (equally distributed over four quarters, -1.94% decrease/quarter)	-7.6% decrease observed in 2008Q3-2009Q3 period	The series seems to have a non-normal distribution. The scenario is similar with four consecutive shocks of 1.5 standard deviation from GDP growth sample mean. The quarterly decrease is slightly lower than the 5% quantile.
Consumer confidence shock: decrease (worsening) of consumer confidence index from its current value (-34.6) to its minimum registered value (-63 in 2010Q2) – gradual uniform quarterly evolution of +16.3% per quarter (+83% in year)	the lowest historical value of the index is -63 (registered in 2010Q2, after a decrease from its peak value of -12 registered in 2008Q3)	The differenced (% change) series seems to have a non-normal distribution and features high variance. One or two standard deviation/s would imply much larger decreases (but the generated final value would be substantially below historical minimum of the index).
Construction activity shock: decrease of 16.63% over a year (equally distributed over four quarters, -4.16% decrease/quarter)	-16.63% decrease observed in 2009Q1-2010Q1 period	The log-differenced series seems to have a normal distribution and features high variance. The scenario is similar with four consecutive shocks of 1.5 standard deviation from sample mean. The quarterly decrease is slightly lower than the 7% quantile.
Interest rate shock: 6 p.p. increase. Gradual increase of 1.5 p.p. per quarter.	-6 p.p. increase observed in 2009Q1-2010Q1 period	The differenced series seems to have a non-normal distribution and features high variance. The scenario is similar with four consecutive shocks of 1.5 standard deviation from sample mean. The quarterly increase is slightly lower than the 95% quantile.

Table 8 Scenarios proposed for households' model

Adverse scenarios	Historical background	Comparison with usual probabilistic approach
Private consumption shock: decrease of -13.3% over a year (equally distributed over four quarters, -3.33% decrease/quarter)	-13.3% decrease observed in 2008Q3-2009Q3 period	The log-differenced series seems to follow a normal distribution. The scenario is similar with four consecutive shocks of almost 2 standard deviations from sample mean.
Sharp increase of interest payment service by 10.48 p.p. (from 37.5% to ~48%), for example due to RON depreciation and/or interest rate shocks, accompanied by a stagnation of private consumption (0% growth for 1 year) Gradual increase of interest payment service: 2.62 p.p./quarter	Hypothetical scenario – corresponds for example with a depreciation of 20% of the RON and an increase of 5 p.p. in RON interest rate (ceteris paribus). Largest annual historical increase was of 5.51 p.p. (2008:Q2 – 2009:Q1)	The differenced series seems to follow a normal distribution, with high standard deviation. The scenario is similar with four consecutive quarters shocks of 1 standard deviation from sample mean.

The adverse scenario involving a hypothetical shock of the interest payment service is designed to test the vulnerability of the household sector documented in the previous sections: high indebtedness due to increased interest rate cost and unhedged exposure to currency fluctuations. The scenario could be triggered for example by a 20% local currency depreciation (the 2008-2009 depreciation was of 16.92%), cumulated with a sudden reversal of the downward trend of interest rate for RON loans (sharp increase of 5 p.p., which entails interest rates at the high level registered in 2009).

The selected time horizon is 2 years for corporate sector and 3 years for household sector (given its lag structure), similar to the approach of central bank and longer than the horizon chosen in the independent research cited above. This scenarios horizon should assure a good balance between the specific dynamic environment (emerging market, accelerated and volatile credit risk dynamics) and the gradual accumulation of the effects of an adverse shock.

The shocks proposed in the scenario take place in the first year and the macroeconomic factors resume their auto-regressive pattern in the second year. Depending on the ARMA specification, this implies a prolongation of the negative trend in the second year for higher order / persistent ARMA's (slow mean reverting processes), a quicker return to long term average for lower term / non-persistent ARMA's or an immediate return to long term average for non-zero mean white noise specification.

4.7. Simulation results

The above proposed methodology includes usually a baseline scenario given by the forecasted values of the macroeconomic factors based on their autoregressive specifications, i.e. equations (16) (Chiriacescu, 2012; Virolainen, 2004; Boss, 2002), and consequently this approach is used also in this study.

The Monte Carlo simulation performed here is based on a large number of replications (50,000 replications for corporate models and 20,000 replication for household model), which ensures high simulation accuracy (low simulation standard errors). As noted by Flegal et al (2008) Monte Carlo standard error (MSCE) is an important accuracy measure, but it's not usually reported in studies using Monte Carlo techniques. This study will report the MCSE computed as proposed by Owen (2013):

$$MSCE = \frac{s}{\sqrt{n}} \qquad (20)$$

where is *s* is the standard error of the estimated variables (default rates in this case) and *n* is the number of replications.

The below table details the simulated values of the macroeconomic factors included in the models proposed in this study:

Table 9 Baseline scenario – current and simulated values (annual evolution)

Models \ Factors	Lag		Previous year value*	Last 4 quarters value*	1st year forecasted value	2nd year forecasted value
Corporate Models						
Real GDP growth	0	% growth		+4.07%	+3.73%	+2.94%
Consumer confidence indicator**	1	% change		-7.98%	+16.40%	+16.48
Construction activity	0	Ln-diff		-2.81%	+2.73%	+7.47%
Domestic stock market index	7	Ln-diff	+8.80%	+24.60%		
Interest rate for RON loans	5	First diff		-1.39 p.p.	-0.86 p.p.	
Exchange rate	7	Ln-diff	+5.10%	-0.85%		
Household Model						
Household consumption	4	Ln-diff		+1.22%	+3.22%	
Interest rate payment service	6	First-diff	-5.49 p.p.	-4.19 p.p.	-3.72 p.p.	
Interest rate for RON loans	8	First-diff	-0.82 p.p.	-0.69 p.p.		

** based on the last 4 quarters evolution (2012:Q4 – 2013Q3) and the previous 4 quarters for previous year value (2011:Q4 – 2012:Q3).*
Figures for previous year and for forecasted values are reported only if relevant for the simulation (depending on their lag in the model).
*** negative evolutions denotes improvement of consumer confidence*

The table below presents the results of the model simulation based on Monte Carlo method (normally distributed residuals; no artificial stress test scenario shock) under the baseline scenario over the 2 years simulation horizon. The expected and unexpected values of the defaults rate are reported for all models:

Table 10 Result of models simulation

		Corporate sector				Households sector	
		Model 1	MCSE	Model 2	MCSE	Main model	MSCE
1st year	Expected default rate	18.14%	0.01%	18.37%	0.01%	8.86%	<0.01%
	Unexpected default rate	22.37%		23.47%		9.16%	
2nd year	Expected default rate	23.11%	0.03%	22.63%	0.03%	10.04%	<0.01%
	Unexpected default rate	34.20%		34.01%		10.61%	
3rd year	Expected default rate	n/a	n/a	n/a	n/a	10.96%	<0.01%
	Unexpected default rate	n/a	n/a	n/a	n/a	11.78%	

The unexpected values take into consideration a 5% probability level of occurrence (95% quantile).

Current value (2013 Q3) for corporate default rate is 14.09% (up from 10.47% in 2012 Q3, and from 8.14% in 2011 Q3; Figure 2 below). The expected values indicated by the model simulation imply that the default rate increase will maintain its pace in spite of improved macroeconomic environment (as reflected by recent past values of macroeconomic variables and by the proposed baseline scenario described above, e.g. GDP growth, interest rates decrease). The Romanian central bank also expects an increase of NPL rates in the next period, but at a slower pace, citing improved macroeconomic conditions and decrease of probabilities of default (N.B.R., 2013a).

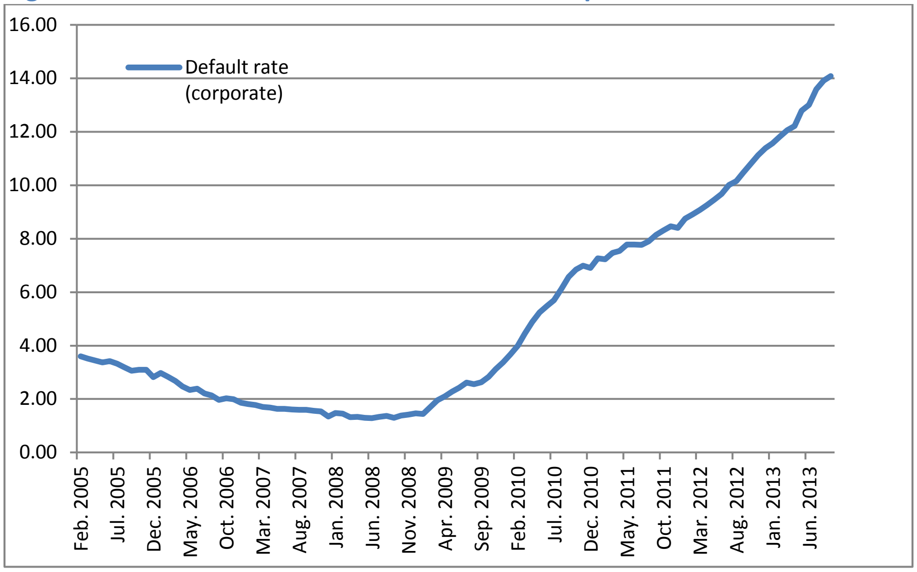
There are several factors that could explain the findings reported here:

- Due to data availability restriction, the dependent modeled here is a lagged indicator of probability of default (please see section 3.5. Credit Risk variable selection for a discussion); the current macroeconomic improvement has only recently taken place and it's still mixed (N.B.R. 2013a) and although PD have improved, their decrease doesn't seem to be reflected yet in default rates (and thus the model doesn't capture this dynamic);

- Some factors are included with distant lags and their improvement is only partially reflected over the chosen time horizon;
- The model assumes that banks will maintain the same current behavior of NPL build-up (downward trend of lending activity, i.e. decrease of total loan volumes, the denominator in default rates, and maintaining NPL on balance sheets for longer periods; please see section 4.1. Main recent evolution in credit risk)

At any rate, this study focuses on stress testing rather than on forecasting or expected values. The models are calibrated on a sample that includes also crisis and post-crisis period and since the stress testing framework involves the assumption of “extreme but plausible” adverse shocks (the alternative scenario) in the future, the potential failure of the model to fully capture the positive effect of recent macroeconomic improvement in the baseline scenario shouldn’t represent an issue. Specifically, in case the adverse shock will actually take place, the calibrated model should adequately estimate the default rate dynamics (since its initial calibration was done in a crisis affected environment and the assumption of NPL build-up should continue to hold).

Figure 2 Default rate historical evolution for corporate sector



The charts below (Figure 3 and 4) plot the distribution of the simulated default rate for Model 1 (Model 2 yields very similar plots); as expected, the non-linearity of the model is evident, the probability distribution being skewed to the right, with the median lower than the mean (similar with Chiriacescu, 2010 findings). A rough interpretation, in line with usual credit risk behavior, is that simulated default rates are below expected mean more often than above the mean, but the average magnitude of the positive deviations from mean (in case of unexpected shocks occurrences) is larger the average magnitude of negative deviation from the mean (small negative deviations are more likely, while above average default rates are less likely, but more extreme).

Figure 3 Default rate (corporate) probability distribution (first year simulation, Model 1)

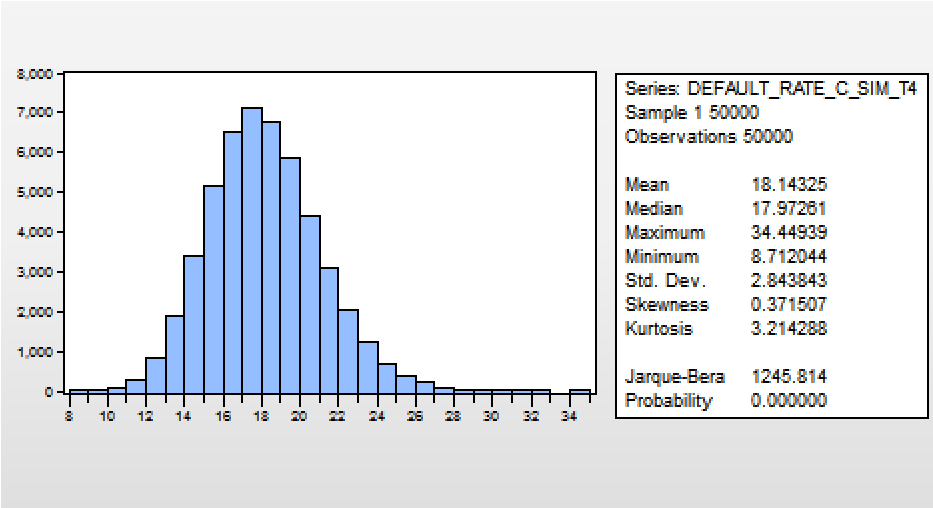
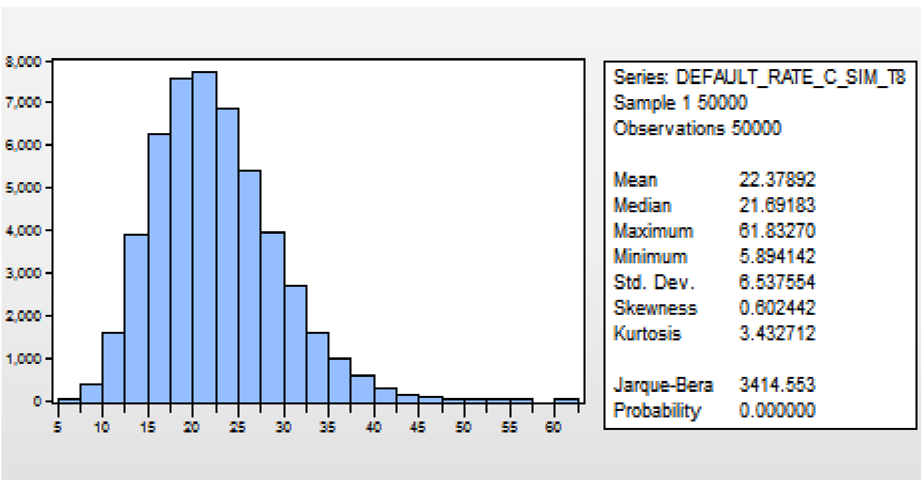
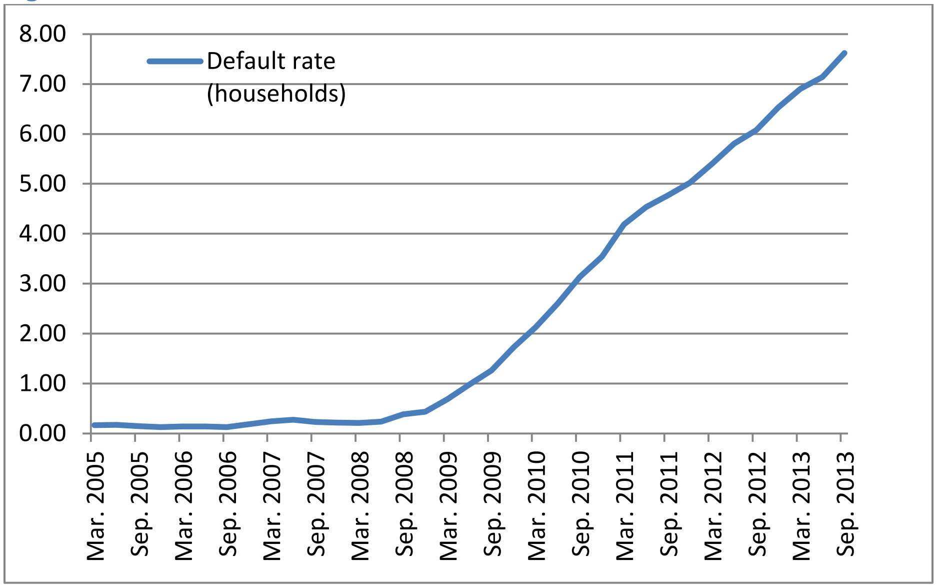


Figure 4 Default rate (corporate) probability distribution (second year simulation, Model 1)



Current value (2013 Q3) for household default rate is 7.62% (up from 6.07% in 2012 Q3, and from 4.77% in 2011 Q3, Figure 5 below). For this segment, the model simulation indeed forecasts a slower pace of default rate increases compared with recent years' evolution.

Figure 5 Default rate historical evolution for household sector



Since the household model is based on a linear specification, the distribution follows a normal distribution pattern (Figure 6 & 7 below), implying a symmetric response of credit risk to macroeconomic shocks.

Figure 6 Default rate (households) probability distribution (2nd year simulation)

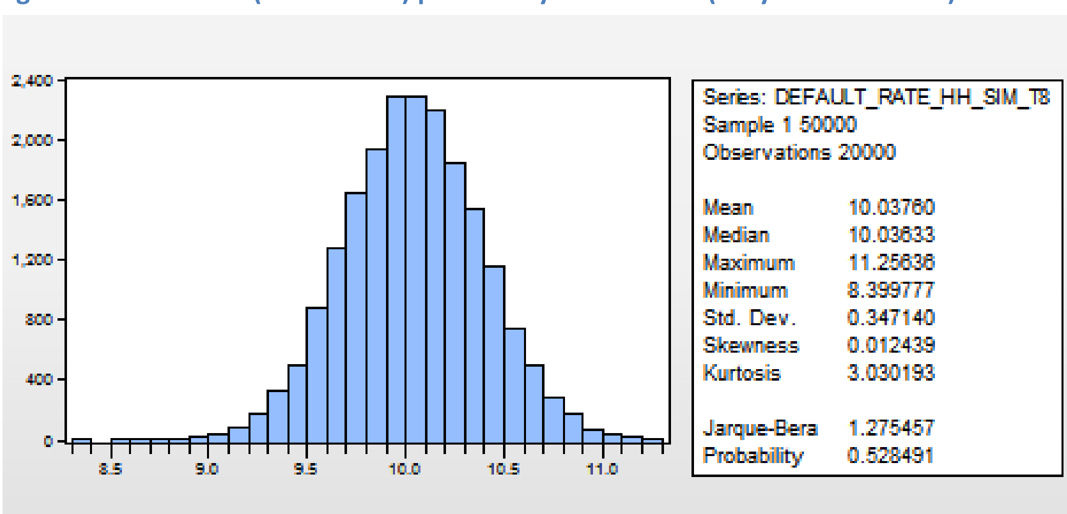
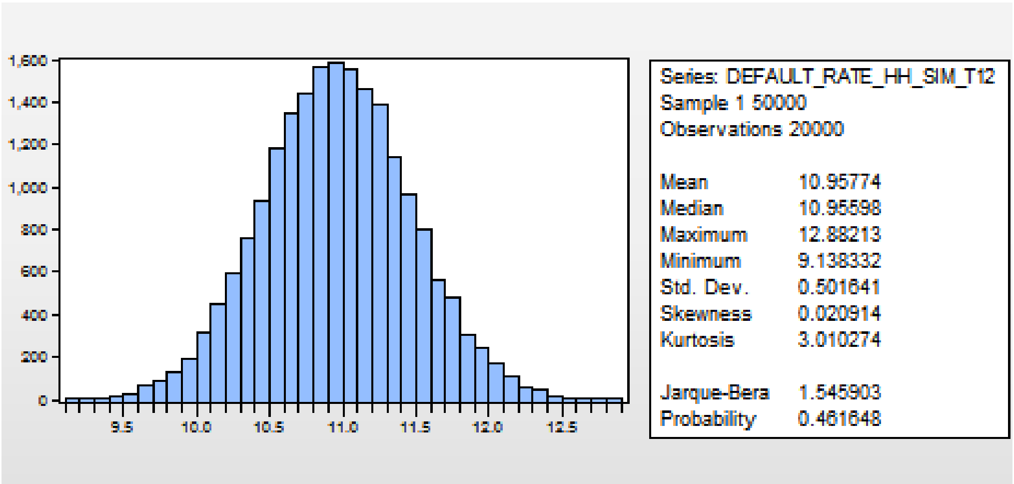


Figure 7 Default rate (households) probability distribution (3rd year simulation)



4.8. Stress testing results

The table below report the expected value of default rates under the stress test scenarios mentioned above.

As discussed earlier, selecting a certain degree of severity of the scenarios in the context of near post-crisis period is complicated. The scenarios chosen here usually replicate the recent 2008-2009 shocks, which seems to be a very low probability event since the macroeconomic environment seems to be on a recovery path and the replicated shock has recently taken place (e.g. in terms of GDP shocks, the central bank's scenarios are milder than the ones implied by replication of 2008-2009 shocks), and thus one may considered them too severe and implausible. On the other hand, replicating 2008-2009 shocks is a standard approach in current practice (e.g. in I.M.F.'s F.S.A.P., Jobst et al. 2013) and the historical background itself should ensure plausibility, while comprising on severity could underestimate the losses.

Table 11 Stress test results – corporate sector

Scenarios	Year	Model 1		MCSE	Model 2		MCSE
		Stressed value	vs expected*		Stressed value	vs expected*	
GDP shock	1st year	23.65%	5.51	0.01%	24.99%	6.85	0.01%
	2nd year	32.12%	9.01	0.03%	33.67%	10.56	0.03%
Consumer confidence shock	1st year	18.98%	0.84	0.01%	n/a	n/a	n/a
	2nd year	24.47%	1.36	0.03%	n/a	n/a	n/a
Construction activity shock	1st year	21.02%	2.88	0.01%	19.82%	1.68	0.01%
	2nd year	31.13%	8.02	0.03%	30.35%	7.24	0.03%
Interest rate shock	1st year	n/a	n/a	n/a	n/a	n/a	n/a
	2nd year	27.22%	4.11	0.03%	28.42%	5.31	0.03%

** stressed value difference versus expected value under the baseline scenario*

The results reveal a substantial increase of default rates (the current level of default rate in corporate sector is 14.09% as of 2013 Q3) in the case of severe GDP and construction activity shocks. The stressed default rates are substantially higher than the excepted values reported above under the baseline scenario.

Consumer confidence shock, although severe as well, implies only a relatively small increase of default rates versus baseline scenarios expected value (1.36 p.p. over two years).

Interest rate shock is related also with an important increase of default rates (due to its lag in the model, the effect of the shock is registered only in the second year), with increases versus baseline scenario of 4 p.p. in Model 1 and 5.31 p.p. in Model 2.

Table 12 Stress test results - household sector

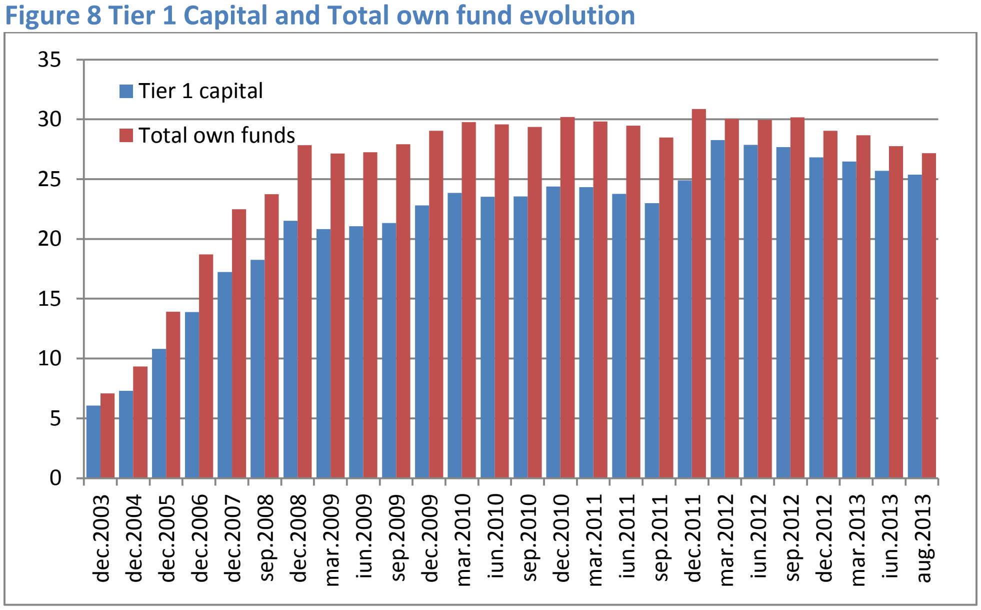
Scenarios	Year	Expected value	vs expected value	MSCE
Private consumption shock	2nd year	10.74%	0.70	<0.01%
	3rd year	11.86%	0.90	<0.01%
Interest payment service shock	2nd year	10.24%	0.20	<0.01%
	3rd year	11.37%	0.41	<0.01%

As expected the households sector is considerably more resilient to adverse macroeconomic evolutions. The private consumption shock is related to an increase default rates of 0.9 p.p. versus expected value under the baseline scenario. In spite of existing vulnerability in the sector, an interest payment service (a proxy for indebtedness) doesn't generate an important increase of default rates versus their expected value (0.41 p.p. over two years horizon).

Given the contribution of the corporate sector in total loans to private sector at banking level system (66%), the finding of the stress testing exercise show that the banks' profitability and capital adequacy can be substantially affected in case of occurrence of the adverse shocks considered in the stress test scenarios.

For example, the central bank (N.B.R., 2013a) documents that in 2012 the domestic banking sector has incurred losses of RON 2.3 billion mostly due to increased NPL volumes and collateral revaluation. These losses, amounting to around 8.1% of the RON 28.27 billion Tier 1 capital registered at system level as of March 2012, have substantially affected the own funds of banks. The own fund decrease trend continued also in 2013 (-9.5% as of August 2013, chart below).

Figure 8 Tier 1 Capital and Total own fund evolution



Nevertheless, the report shows that the banks maintain very good provisioning coverage of NPL volumes, and a comfortable solvency ratio of 14.7% as of June 2013 (substantially more than the minimum regulatory value of 8% and mostly assured by Tier 1 permanent capital, which account for 93% of total own funds). The N.B.R. maintains also substantial temporary prudential filters for computing own funds and regulatory prudential indicators (downward adjustment of Tier 2 funds) that imply a *de facto* higher solvency ratio (4 p.p. higher than reported levels). These filters are to be gradually released in 2014-2018 period in line with Basel III additional capital requirements.

While, due to data availability restriction, this report doesn't compute an estimation of overall losses, it's worth mentioning that in 2012 the default rate for corporate sector has increased by 2.98 p.p. (from 8.4% to 11.38%), while the household loan portfolio registered an increase 1.13 p.p. (from 5.4% to 6.53%). The most severe evolutions estimated under the adverse scenarios analyzed here imply an increase of 8-9 p.p. per year of corporate default rates (versus current level) and an increase of around 2 p.p. per year for households default rates, both dynamics being substantially more adverse than the evolution registered in 2012.

Consequently, under these scenarios the banks' overall losses can increase correspondently.

The estimations of stressed default rates reported in this study offer an indication of the potential evolution of default rates (and thus NPL and credit risk losses) in the banking sector in case of adverse extreme but plausible macroeconomic events.

4.9. Limitations

In spite of employing a consistent and documented framework for all components of the models, coupled with robust testing procedures, the study has several limitations:

- The models don't expressly incorporate second round effects from financial sector to real economy and related spiral effect, thus potentially missing relevant dynamics. While the reduced form models use here may partially incorporate such effects (since the sample includes the 2008-2009 shock and its effects on the real economy), the implicit assumption is that the feedback spiral simply follows historical pattern.

  As documented in the literature review section, research on incorporating macro feedback in stress testing procedure setting is still at incipient stage.
- Given the data availability restriction, the study models default rates (measured in volumes), an indicator that includes the effect of probability of default (PD) but also the effect of loss given default (LGD). While default rates contain useful information (they are a usual proxy for NPL) and have direct impact on bank loan losses, they remain a lagged indicator versus PD.

5. Conclusions

Macro stress testing is an important tool within the macro-prudential and crisis management framework of central banks and international institutions around the globe, including Romania.

In spite of their relevance in assessing the health of financial systems and addressing financial crisis effects, applications of macro stress testing for the Romanian financial system are scarce, especially as independent applications research (stress tests not conducted by the central bank and/other international financial institutions within supervision frameworks).

Credit risk remains the dominant risk challenging domestic financial stability, and thus this report assesses the potential impact of macroeconomic adverse shocks scenarios on credit risk variables.

The literature review, focusing on methodology approaches, documents the rich practical and theoretical research on macro stress testing. Impressive amount of research and substantial progress notwithstanding, the review explains that except for a rough consensus on the model structure, the proposed methodology is diverse and heterogeneous and the process involves high degree of complexity, still unsolved difficulties and limitations and sometimes conflicting objectives.

A main strand of macro stress testing research is based on Wilson (1997a, 1997b and 1998) proposed methodology involving modelling of default probabilities as a non-linear function of macro-economic variables. Typically, the framework comprises a reduced form multi-factor model for estimating industry-specific probability of default, a dynamic specification for forecasting the evolution macroeconomic factors, followed by Monte Carlo simulations in benchmark and stressed scenarios. The methodology has been extended and applied to various contexts of credit risk analysis and macro stress testing.

Using a specific model derived from this methodological framework, this study analyses default rates (an important credit risk variable and a proxy for non-performing loan ratio) for corporate and household sectors.

The econometric models and their calibration are also informed by the findings of a qualitative assessment of credit risk in the domestic banking system. Taking into consideration these qualitative findings, as well as the practices and results of previous similar research, an extended list of macroeconomic variables are tested in order to identify the relevant macroeconomic – credit risk links.

The results of the quantitative estimations generally confirm the influence of macroeconomic variables on credit risk as documented in previous research including applications for Romania; the proposed multi-factor models specifications include the following explanatory macroeconomic variables: real GDP growth, interest rate for RON loans and exchange rate evolution for corporate sector and private consumption, indebtedness degree and interest rates for RON loans for household sector.

The estimations however convey also specific and novel findings, such as inclusion of construction activity level for corporate credit risk models and the specification of an alternative model for corporate risk that includes two forward looking variables, i.e. consumer confidence and the domestic stock exchange index.

In accordance with international practices on stress scenarios design and underpinned by the broader modelling approach, an extended list of relevant scenarios are specified. Given the limited sample size, historical based scenarios are preferred over probabilistic specifications, but a comparison of the magnitude of the proposed shock with the usual probabilistic specification is also included in order to ensure comparability. Generally, the severe shock proposed within the stress scenarios replicate the 2008-2009 shocks in line with current practice in scenario design.

A qualitative hypothetical adverse scenario is specified for assessing a specific vulnerability in household portfolio credit risk (high indebtedness); the qualitative specification avoids the inherent limitation of the historical approach in this case.

As usually undertaken within the proposed methodology, Monte Carlo techniques are employed to perform both model simulation under a baseline scenario and to simulate the dynamic of stressed default rates under the specified adverse shock scenarios.

The results of stress testing procedure show that under the adverse shock scenarios, corporate default rates can increase substantially more than the expected evolution under the baseline scenario in case of GDP shock, construction activity shock or interest rate shocks and to a lesser extent following a consumer confidence shock. Under the assumptions of the adverse scenarios, given also the large share of corporate loans in the banks' balance sheet, the default rates evolution could have a substantial impact on banks' loan losses.

The households sector stress testing simulation show that this sector is more resilient to macroeconomic adverse evolutions, with stressed default rates higher than expected values under baseline scenario, but with substantially lower deviations.

The proposed macro-perspective model and its findings can be incorporated by private banks in their micro-level portfolio risk management tools. Additionally, supplementing the authorities' stress tests with independent approaches could positively contribute to increasing the credibility of such financial stability assessment.

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Annex A Macroeconomic variables

Macroeconomic variable	Unit	Sample	Source	Observations
Cyclical Indicators				
GDP (2000 fixed prices)	Mil RON	Q4 2003–Q3 2013	National Institute of Statistic database	Seasonally adjusted series
Real GDP growth		Q1 2004–Q3 2013	Own computation	Percentage change of GDP fixed prices
GDP current prices	Mil RON	Q4 2003–Q3 2013	National Institute of Statistic database	Seasonally adjusted series
Nominal GDP growth		Q1 2004–Q3 2013	Own computation	Percentage change of nominal GDP
GDP gap	Mil RON	Q1 2004–Q3 2013	Own computation using HP filter*	Applied to both GDP series
Industrial production	Mil RON	Q4 2003–Q3 2013	National Institute of Statistic database	Seasonally adjusted series, real & nominal terms
Total loans granted households	Mil RON	Q1 2005–Q3 2013	N.B.R. credit register database	
Total loans granted companies	Mil RON	Q1 2005–Q3 2013	N.B.R. credit register database, own computation	
Economic Sentiment Indicator	Points	Q4 2003–Q3 2013	ECFIN	Seasonally adjusted
Price stability indicators				
Inflation rate	%	Q4 2003–Q3 2013	National Institute of Statistic database	Based on Consumer Price Index (CPI)
Household indicators				
Household consumption	Mil RON	Q4 2003–Q3 2013	National Institute of Statistic database	Seasonally adjusted series, real and nominal terms
Net wage nominal	RON	Q4 2003–Q3 2013	National Institute of Statistic database, own computations	Own seasonal adjustment on monthly data (Census X12)
Net wage real terms	RON	Q4 2003–Q3 2013	National Institute of Statistic database, own computations	Own computation (based on net wage nominal seasonally adjusted and consumer price index).
Unemployment rate	%	Q1 2004–Q3 2013	National Institute of Statistic database	Seasonally adjusted series
Interest payment service	%	Q1 2005–Q3 2013	Own computations based on loan interest rates and total amounts, for RON and EUR separately. Percentage of nominal wage.	Proxy for indebtedness and disposable income.
Consumer confidence indicator	Points	Q4 2003–Q3 2013	ECFIN	Seasonally adjusted

**GDP gap (deviation from the long term trend) has been estimated using Hodrick Prescott filter (Hodrick and Prescott, 1997); similar procedure is undertaken by Chiriacescu (2010). Moinescu (2012) uses data from Ameco database, but they are available only for annual frequency.*

Macroeconomic variable	Unit	Sample	Source	Observations
Corporate indicators				
Gross fixed capital formation (GFCF)	Mil RON	Q4 2003–Q3 2013	National Institute of Statistic database	Seasonally adjusted series, real and nominal terms
Indebtedness	%	Q1 2005–Q3 2013	Own computation	Proxy computed as ratio of Total corporate loans to Total nominal gross value added (Virolainen, 2006).
Construction activity level	Mil RON	Q4 2003–Q3 2013	National Institute of Statistic database	Seasonally adjusted series, real and nominal terms
Stock Market Indicators				
Bucharest Exchange Trading (BET)	Index points	Q4 2003–Q3 2013	Bucharest Stock Exchange database	Closing price
EURO STOXX 500	EUR price	Q4 2003–Q3 2013	Stoxx Ltd (www.stoxx.com)	Closing price
Interest rate indicators				
ROBOR 3M	%	Q4 2003–Q3 2013	N.B.R. database	Money market indicator relevant for Romania domestic currency loans (used also in Moinescu, 2012 and Chiriacescu, 2010)
EURIBOR 3M	%	Q4 2003–Q3 2013	Deutsche Bundesbank time series (http://www.bundesbank.de)	Money market indicator relevant for Romania foreign currency loans (used also in Moinescu, 2012 and Chiriacescu, 2010)
Banks interest rates for RON loans	%	Q4 2003–Q3 2013	N.B.R. database and reports	Distinct series for household and corporate loans.
Banks interest rates for EUR loans	%	Q4 2003–Q3 2013	N.B.R. database and reports	Distinct series for household and corporate loans.
Real interest rates for RON loans	%	Q4 2003–Q3 2013	Own computation – *ex-post* interest rates computed as *[(1+interest rate)/(1+inflation rate)-1]*	Distinct series for household and corporate loans. GDP deflator used for corporate loans (Virolainen, 2004) and CPI for household loans.
Interest rates spreads	%	Q4 2003–Q3 2013	Computed as difference between total interest charge and money market interest rates	Distinct series for household and corporate loans.
External variables				
RON/EUR Exchange rate	RON/EUR	Q4 2003–Q3 2013	N.B.R. database and reports	
Total exports	Mil RON	Q4 2003–Q3 2013	National Institute of Statistic database	
Net exports	Mil RON	Q4 2003–Q3 2013	National Institute of Statistic database	
Oil price	EUR equivalent / barrel	Q4 2003–Q3 2013	National Institute of Statistic database	Crude Oil (petroleum), simple average of three spot prices; Dated Brent, West Texas Intermediate, and the Dubai Fateh.

Annex B Expected sign, unit root tests results and transformations

Macroeconomic variable	Exp. sign	Transformation	ADF test (p-value for the null)	KPSS test result (@ confidence level)	Final result	Abbreviation	Model* (hh/c/ both)
Default rates							
Corporate default rate		Logit	87%	Null rejected @95%	Unit root	Def_c	C
		Logit diff	0%	Null cannot be rejected	Stationary	Ddef_c	C
Household default rate			99.7%	Null rejected @95%	Unit root	Def_hh	Hh
		First diff	47% (65% without a constant)	Null rejected @95%	PP test cannot reject null. Assumed stationary	Ddef_h	Hh
Cyclical Indicators							
GDP (2000 fixed prices)	-		30%	Null rejected @95%	Unit root	Gdp	Both
Real GDP growth	-		1%	Null rejected @90%	Inconclusive. PP rejects unit root null. Assumed stationary.	Gdp_g	Both
GDP current prices	-		49%	Null rejected @99%	Unit root	Gdp2	Both
Nominal GDP growth	-		1%	Null rejected @95%	Inconclusive. PP rejects unit root null. Assumed stationary.	Gdp_g2	Both
GDP gap (real)	-		13% (1% without constant)	Null cannot be rejected	Inconclusive. PP rejects unit root null @95%. Assumed stationary.	Gdp_gap	Both
GDP gap (nominal)	-		37% (6% without constant)	Null cannot be rejected	Inconclusive. PP rejects unit root null @95%. Assumed stationary.	Gdp_gap2	Both
Industrial production (real)	-		35%	Null rejected @95%	Unit root	ind	Both
		Ln-diff	0%	Null cannot be rejected	Stationary	Dind	Both
Industrial production (nominal)	-		98%	Null rejected @95%	Unit root	Ind2	Both
		Ln-diff	0%	Null cannot be rejected	Stationary	Dind2	Both
Economic Sentiment Indicator	-		53%	Null rejected @95%	Unit root	Esi	Both
		Ln-diff	0%	Null cannot be rejected	Stationary	Desi	Both

Macroeconomic variable	**Exp. sign**	**Transformat ion**	**ADF test (p-value for the null)**	**KPSS test result (@ confidence level)**	**Final result**	**Abbreviation**	**Model*** (hh/c/ both)
Price stability indicators							
Inflation rate			0% (5% without constant)	Null rejected @95%	Inconclusive. PP rejects null @99%. Tested in both forms.	Inf	Both
		First diff	0%	Null cannot be rejected	Stationary	Dinf	Both
Household indicators							
Household consumption (nominal)	**-**		24%	Null rejected @95%	Unit root	Cons	Both
		Ln-diff	0% (2% without constant)	Null rejected @95%	Inconclusive. PP rejects null. Assumed stationary.	Dcons	Both
Household consumption (real)	**-**		40%	Null rejected @95%	Unit root	Cons2	Both
		Ln-diff	0% (2% without constant)	Null rejected @90%	Inconclusive. PP rejects null. Assumed stationary.	Dcons2	Both
Net wage nominal	**-**		45%	Null rejected @99%	Unit root	Wage	Hh
		Ln-diff	0% (19% without constant)	Null rejected @99%	Inconclusive. PP rejects null. Assumed stationary.	Dwage	Hh
Net wage real terms	**-**		99%	Null rejected @99%	Unit root	Wage_r	Hh
		Ln-diff	0%	Null cannot be rejected	Stationary	Dwage_r	Hh
Unemployment rate	**+**		25% (61% without constant)	Null cannot be rejected	Inconclusive. PP cannot reject null. Tested as difference.	Unempl	Both
		first-diff	0%	Null cannot be rejected	Stationary	dunempl	Both
Interest payment service (proxy for disposable income)	**+**		53%	Null rejected @95%	Unit root	Ints	Both
		first-diff	0%	Null cannot be rejected	Stationary	Dints	Both
Consumer confidence index	**-**		54%	Null rejected @90%	Unit root	Cci	Both
		% change	0%	Null cannot be rejected	Stationary	Dcci	Both

Corporate indicators							
Gross fixed capital formation (GFCF) real	-		12% (67% without constant)	Null cannot be rejected	Inconclusive. PP cannot reject null. Tested as difference.	Gfcf	C
		Ln-diff	9% (1% without constant)	Null cannot be rejected	Stationary	Dgfcf	C
Gross fixed capital formation (GFCF) nominal	-		31%	Null rejected @95%	Unit root	Gfcf2	C
		Ln-diff	2% (0% without constant)	Null rejected @90%	Stationary	Dgfcf2	C
Indebtedness	+		12%	Null rejected @99%	Unit root	Debt	C
		First-diff	0%	Null cannot be rejected	Stationary	ddebt	C
Construction activity (real)	-		21%	Null rejected @95%	Unit root	Build	C
	-	Ln-diff	38% (9% without constant)	Null cannot be rejected	Inconclusive. PP rejects null @99%. Assumed stationary.	Dbuild	C
Total loans granted to companies (outstanding amounts)	-		9% (94% without constant)	Null rejected @95%	Unit root	Loans_c	C (PD)
	-	Ln-diff	31% (5% without constant)	Null rejected @95%	Inconclusive. PP rejects null @95%. Assumed stationary.	Dloans_c	C (PD)
Construction activity (nominal)	-		21%	Null rejected @95%	Unit root	Build2	C
		Ln-diff	38% (9% without constant)	Null rejected @90%	Inconclusive. PP rejects null @95%. Assumed stationary.	Dbuild2	C
Stock Market Indicators							
Bucharest Exchange Trading (BET)	-		26% (66% without constant)	Null cannot be rejected	Inconclusive. PP test cannot reject null. Tested as difference.	Bet	Both
		Ln-diff	0%	Null cannot be rejected	Stationary	Dbet	Both
EURO STOXX 500	-		59% (60% without constant)	Null cannot be rejected	Inconclusive. PP test cannot reject null. Tested as difference.	Stoxx	Both
		Ln-diff	0%	Null cannot be rejected	Stationary	Dstoxx	Both

Macroeconomic variable	Exp. sign	Transformation	ADF test (p-value for the null)	KPSS test result (@ confidence level)	Final result	Abbreviation	Model* (hh/c/ both)
Interest rate indicators - money market							
ROBOR 3M	+		15%	Null rejected @95%	Unit root	Rbor	Both
		First diff	0%	Null cannot be rejected	Stationary	Drbor	Both
EURIBOR 3M	+		44%	Null rejected @90%	Unit root	Ebor	Both
		First diff	3%	Null cannot be rejected	Stationary	Debor	Both
Interest rate indicators - corporate							
Banks interest rates for RON loans	+		10% (4% without constant)	Null rejected @99%	Inconclusive. PP rejects null. Tested as difference.	Ron_irc	C
		First diff	1%	Null cannot be rejected	Stationary	Dron_irc	C
Banks interest rates for EUR loans	+		79%	Null rejected @95%	Unit root	Eur_irc	C
		First diff	0%	Null cannot be rejected	Stationary	Deur_irc	C
Real interest rates for RON loans	+		5% (10% without constant)	Null rejected @90%	Inconclusive. PP cannot reject null. Tested as difference	Ron_rirc	C
		First diff	0%	Null rejected @95%	Inconclusive. PP rejects null. Assumed stationary.	Dronrirc	C
Interest rate spread RON	+		7% (42% without constant)	Null cannot be rejected.	Inconclusive. PP test cannot reject null. Tested as difference.	Spr_ronc	C
		First diff	0%	Null cannot be rejected.	Stationary	Dsprronc	C
Interest rate spread EUR	+		23% (50% without constant)	Null cannot be rejected	Inconclusive. PP test cannot reject null. Tested as difference.	Spr_eurc	C
		First diff	0%	Null cannot be rejected	Stationary	Dspreurc	C

Macroeconomic variable	**Exp. sign**	**Transformation**	**ADF test (p-value for the null)**	**KPSS test result (@ confidence level)**	**Final result**	**Abbreviation**	**Model*** (hh/c/ both)
Interest rate indicators - household							
Banks interest rates for RON loans	+		0% (2% without constant)	Null rejected @95%	Inconclusive. PP rejects null. Tested in both forms	Ron_irhh	Hh
		First diff	13% (4% without constant)	Null cannot be rejected	PP rejects null. Stationary.	Dron_irhh	Hh
Banks interest rates for EUR loans	+		99%	Null rejected @99%	Unit root	Eur_irhh	Hh
		First diff	0%	Null cannot be rejected	Stationary	Deurirhh	Hh
Real interest rates for RON loans	+		36%	Null rejected @95%	Unit root	ron_rirhh	Hh
		First diff	0%	Null cannot be rejected	Stationary	Drorirhh	Hh
Interest rate spread RON	+		24% (52% without constant)	Null cannot be rejected	Inconclusive. PP cannot reject null. Tested as difference.	Spr_ronhh	Hh
		First diff	0%	Null cannot be rejected	Stationary	Dsprohh	Hh
Interest rate spread EUR	+		17% (35% without constant)	Null cannot be rejected	PP cannot reject null. Inconclusive. Tested as difference.	Spr_eurhh	Hh
		First diff	1%	Null cannot be rejected	Stationary	Dspeurhh	Hh
External variables							
Exchange rate	+	Ln-diff	84%	Null rejected @95%	Unit root		Both
			0%	Null cannot be rejected	Stationary		Both
Total exports, real terms	-		93%	Null rejected @99%	Unit root	Expo	C
		Ln-diff	0%	Null cannot be rejected	stationary	Dexpo	C
Net exports, real terms	-		17% (60% without constant)	Null cannot be rejected	Inconclusive. PP cannot reject null. Tested as difference.	Nexp	C
		First-difference	4% (0% without constant)	Null cannot be rejected	Stationary	Dnexp	C
Total exports, nominal terms	-		99%	Null rejected @99%	Unit root	Expo2	C
		Ln-diff	0%	Null cannot be rejected	Stationary	Dexpo2	C

Macroeconomic variable	Exp. sign	Transformation	ADF test (p-value for the null)	KPSS test result (@ confidence level)	Final result	Abbreviation	Model* (hh/c/ both)
External variables (continued)							
Net exports, nominal terms	-		79% (39% without constant)	Null cannot be rejected.	Inconclusive. Tested as difference.	Nexp2	C
		First-difference	0%	Null cannot be rejected	Stationary	Dnexp2	C
Oil price	+						
		Ln-diff	31%	Null rejected @99%	Unit root	Oil	Both
			0%	Null cannot be rejected	Stationary	Doil	Both

**Hh – households model; C – corporate model; Both – both models*

Notes on unit root test results:

- Given the small samples size unit roots test may discriminate poorly between hypotheses (Brooks, 2008). KPSS test use can be problematic in highly auto-correlated series (over-rejection for slowly mean reverting) (Muller, 2005);
- All tests have been performed with a constant in the regression/test (less restrictive test than without a constant, Sjö (2008)); trend possibility (the least restrictive configuration) was excluded since trend-stationarity would require additional computation (de-trending) and for some series this results in negative values (default rates in the first part of the series when low absolute values are recorded);
- In case of inconclusive results, tests have been rerun without a constant (results are mentioned in parenthesis). Phillips Perron (without constant) is performed as well for this cases and results reported. For the other cases, test results are not sensitive to the option regarding the constant;
- Unit root rejection for series in levels was performed on a cautionary manner to avoid spurious regression as the dependent variables are slowly mean reverting (Sjö, 2008);
- When result are inconclusive for the first order / log / percentage change diff, series are assumed to be I(1), as the explosive data series hypothesis seems unlikely (e.g. the case of default rate for households, which after a sharp increase has started to decrease in the last period).

Tests:

ADF test – Augumented Dickey Fuller test (null hypothesis of a unit root)

KPSS test – Kviatkowski Phillips Schimdt Shin test (stationary series null hyphotesis, tested for confidence levels of 1%, 5% and 10%)

PP test – Phillips Perron test (null hypothesis of a unit root)

Annex C Uni-variate regressions results - corporate model

Macroeconomic variable	Expected sign	Coefficient	Lag	p-value	R-squared adjusted	Observations
Default rates						
Corporate default rate						
Cyclical indicators						
Real GDP growth	-	-5.0797	0	0%	49%	
Nominal GDP growth	-	-3.0047	0	0%	43%	
GDP gap (real)	-	+0.0001	7	0%	38%	Wrong sign
GDP gap (nominal)	-	+0.0001	5	0%	38%	Wrong sign
Industrial production (real)	-	-2.1640	3	4%	10%	
Industrial production (nom)	-	-2.4825	6	0%	13%	
Economic Sentiment Indicator	-	-0.7392	4	14%	9%	Not significant
Price stability indicators						
Inflation rate – series in levels		-0.0336	7	6%	8%	
Inflation rate – series in diff		+0.1960	6	5%	4%	
Household indicators						
Household consumption (real)	-	-4.2162	1	0%	58%	
Household consumption (nom)	-	-1.9439	1	0%	27%	
Unemployment rate	+	+0.1588	3	4%	16%	
Interest payment service (proxy for disposable income)	+	+1.9282	5	1%	18%	
Consumer confidence index (negative values)	+	+0.1487	1	0%	17%	
Corporate indicators						
Gross fixed capital formation (GFCF) real	-	-1.2509	0	0%	49%	
Gross fixed capital formation (GFCF) nominal	-	-1.7520	0	0%	53%	
Indebtedness	+	-0.8669	2	2%	10%	Wrong sign
Construction activity (real)	-	-2.2994	0	0%	56%	
Construction activity (nominal)	-	-1.7526	0	0%	61%	
Stock Market Indicators						
Bucharest Exchange Trading (BET)	-	-0.3123	7	0%	25%	
EURO STOXX 500	-	-0.5663	5	2%	21%	

Macroeconomic variable	Expected sign	Coefficient	Lag	p-value	R-squared adjusted	Observations
Interest rate indicators - money market						
ROBOR 3M	+	+0.0261	6	2%	18%	
EURIBOR 3M	+	-0.1623	1	0%	40%	Wrong sign
Interest rate indicators - corporate						
Banks interest rates for RON loans	+	+0.0605	5	0%	36%	
Banks interest rates for EUR loans	+	-0.2619	0	0%	35%	Wrong sign
Real interest rates for RON loans	+	+0.0677	1	5%	6%	
Interest rate spread RON	+	+0.0348	0	3%	12%	
Interest rate spread EUR	+	+0.2671	1	0	37%	
External variables						
Exchange rate	+	+1.9455	4	0%	30%	
Total exports, real terms	-	-0.7599	7	8%	5%	
Net exports, real terms	-	+0.0001	0/3	0%	30-31%	Wrong sign
Total exports, nominal terms	-	-0.6167	0	24%	5%	Not significant
Net exports, nominal terms	-	-0.1236	7	5%	4%	
Oil price	+	-0.2020	1	1%	9%	Wrong sign

Note: Newey-West heteroskedasticity and autocorrelation consistent covariance matrix estimator for the parameters is used in order to accommodate any expected residuals heteroskedasticity and/or autocorrelation of unknown order.

Annex D.1 Corporate model multi-variate regression diagnostic tests. Model 1

Table 1 – model specification and estimation

Dependent Variable: DDEF_C
Method: Least Squares
Date: 01/21/14 Time: 23:12
Sample (adjusted): 2005Q4 2013Q3
Included observations: 32 after adjustments

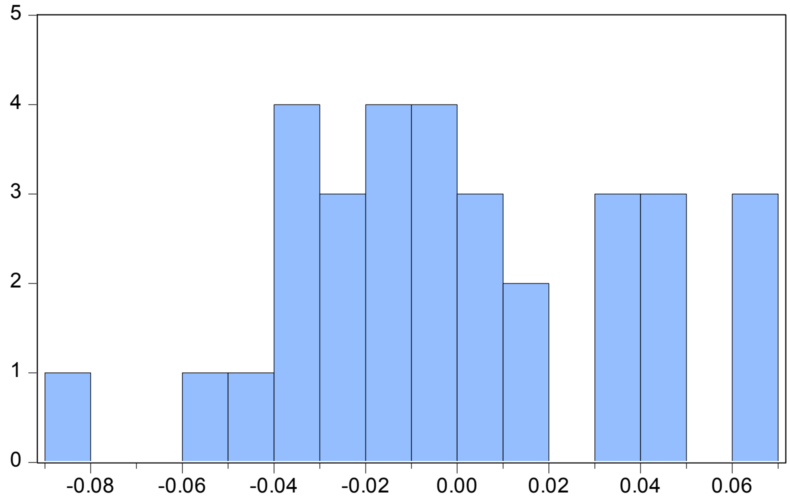
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.103671	0.008562	12.10844	0.0000
GDP_G	-1.826404	0.649547	-2.811812	0.0092
DCCI(-1)	0.066711	0.028277	2.359206	0.0261
DBUILD2	-0.876286	0.190611	-4.597252	0.0001
DBET(-7)	-0.130456	0.040163	-3.248144	0.0032
DRON_IRC(-5)	0.033769	0.006316	5.346770	0.0000
R-squared	0.913047	Mean dependent var		0.051390
Adjusted R-squared	0.896325	S.D. dependent var		0.124737
S.E. of regression	0.040163	Akaike info criterion		-3.424357
Sum squared resid	0.041941	Schwarz criterion		-3.149532
Log likelihood	60.78971	Hannan-Quinn criter.		-3.333260
F-statistic	54.60233	Durbin-Watson stat		1.987063
Prob(F-statistic)	0.000000			

Table 2 Residuals auto and partial correlations

Date: 01/21/14 Time: 23:36
Sample: 2005Q4 2013Q3
Included observations: 32

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.005	-0.005	0.0008	0.977
		2	0.106	0.106	0.4113	0.814
		3	0.154	0.157	1.3067	0.728
		4	-0.175	-0.189	2.4899	0.646
		5	0.288	0.271	5.8252	0.324
		6	-0.124	-0.142	6.4658	0.373
		7	-0.029	-0.015	6.5031	0.482
		8	-0.123	-0.249	7.1944	0.516
		9	-0.078	0.120	7.4787	0.587
		10	-0.042	-0.195	7.5675	0.671
		11	-0.244	-0.108	10.640	0.474
		12	0.070	0.032	10.910	0.537
		13	-0.066	0.110	11.162	0.597
		14	0.137	0.132	12.293	0.583
		15	-0.057	-0.174	12.500	0.641
		16	-0.119	-0.008	13.460	0.639

Table 3 Jarque-Bera normality test for residuals



Series: Residuals
Sample 2005Q4 2013Q3
Observations 32

Mean	2.60e-18
Median	-0.003377
Maximum	0.067845
Minimum	-0.085724
Std. Dev.	0.036782
Skewness	0.104512
Kurtosis	2.569017
Jarque-Bera	0.305917
Probability	0.858165

Test result: the null hypothesis of normal distribution cannot be rejected.

Table 4 Breusch-Godfrey Serial Correlation LM Test

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.165347	Prob. F(2,24)	0.8486
Obs*R-squared	0.434933	Prob. Chi-Square(2)	0.8046

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 01/21/14 Time: 23:41
Sample: 2005Q4 2013Q3
Included observations: 32
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000330	0.008893	-0.037075	0.9707
GDP_G	-0.084771	0.701881	-0.120776	0.9049
DCCI(-1)	0.000305	0.029389	0.010373	0.9918
DBUILD2	0.036324	0.209337	0.173519	0.8637
DBET(-7)	-0.003893	0.042110	-0.092456	0.9271
DRON_IRC(-5)	0.000250	0.006914	0.036102	0.9715
RESID(-1)	-0.004487	0.230184	-0.019493	0.9846
RESID(-2)	0.127558	0.222062	0.574428	0.5710

R-squared	0.013592	Mean dependent var	2.60E-18
Adjusted R-squared	-0.274111	S.D. dependent var	0.036782
S.E. of regression	0.041518	Akaike info criterion	-3.313042
Sum squared resid	0.041371	Schwarz criterion	-2.946608
Log likelihood	61.00867	Hannan-Quinn criter.	-3.191579
F-statistic	0.047242	Durbin-Watson stat	1.987209
Prob(F-statistic)	0.999812		

Test result: the null hypothesis of no residual auto-correlation cannot be rejected. Similar results are found when testing with 1 lag and 3 lags.

Table 5 White heteroskedasticity test (with cross-products)

Heteroskedasticity Test: White

F-statistic	1.717387	Prob. F(20,11)	0.1789
Obs*R-squared	24.23776	Prob. Chi-Square(20)	0.2322
Scaled explained SS	12.55269	Prob. Chi-Square(20)	0.8957

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 01/21/14 Time: 23:48
Sample: 2005Q4 2013Q3
Included observations: 32

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.001546	0.000889	1.738205	0.1100
GDP_G	-0.044302	0.055751	-0.794648	0.4436
GDP_G^2	-0.324722	2.477385	-0.131075	0.8981
GDP_G*DCCI(-1)	-0.295143	0.249737	-1.181813	0.2622
GDP_G*DBUILD2	1.500561	1.285738	1.167082	0.2679
GDP_G*DBET(-7)	0.411785	0.238543	1.726248	0.1122
GDP_G*DRON_IRC(-5)	-0.041242	0.063037	-0.654255	0.5264
DCCI(-1)	0.001809	0.002757	0.656385	0.5251
DCCI(-1)^2	-0.012011	0.009360	-1.283264	0.2258
DCCI(-1)*DBUILD2	-0.011309	0.081433	-0.138877	0.8921
DCCI(-1)*DBET(-7)	0.000799	0.016703	0.047858	0.9627
DCCI(-1)*DRON_IRC(-5)	0.001705	0.003005	0.567192	0.5820
DBUILD2	0.018676	0.020316	0.919251	0.3777
DBUILD2^2	-0.283081	0.252411	-1.121509	0.2860
DBUILD2*DBET(-7)	-0.060511	0.060705	-0.996803	0.3403
DBUILD2*DRON_IRC(-5)	0.013975	0.013956	1.001323	0.3382
DBET(-7)	0.001574	0.002414	0.651917	0.5278
DBET(-7)^2	0.004507	0.009607	0.469156	0.6481
DBET(-7)*DRON_IRC(-5)	0.002114	0.002250	0.939558	0.3676
DRON_IRC(-5)	0.000552	0.000415	1.329695	0.2105
DRON_IRC(-5)^2	0.000182	0.000297	0.611985	0.5530

R-squared	0.757430	Mean dependent var	0.001311
Adjusted R-squared	0.316394	S.D. dependent var	0.001668
S.E. of regression	0.001379	Akaike info criterion	-10.09011
Sum squared resid	2.09E-05	Schwarz criterion	-9.128218
Log likelihood	182.4417	Hannan-Quinn criter.	-9.771268
F-statistic	1.717387	Durbin-Watson stat	2.224927
Prob(F-statistic)	0.178865		

Test result: no indication of common variance of squared residual and squared exogenous or their cross-products. The null hypothesis of no heteroskedasticity cannot be rejected.

Table 6 White heteroskedasticity test (no cross-products)

Heteroskedasticity Test: White

F-statistic	2.532651	Prob. F(5,26)	0.0538
Obs*R-squared	10.48086	Prob. Chi-Square(5)	0.0627
Scaled explained SS	5.428017	Prob. Chi-Square(5)	0.3659

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/02/14 Time: 16:11
Sample: 2005Q4 2013Q3
Included observations: 32

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000478	0.000506	0.945761	0.3530
GDP_G^2	2.792700	0.975985	2.861417	0.0082
DCCI(-1)^2	-0.003378	0.001216	-2.778257	0.0100
DBUILD2^2	-0.005059	0.072834	-0.069465	0.9452
DRON_IRC(-5)^2	-7.33E-05	0.000104	-0.707228	0.4857
DBET(-7)^2	0.009947	0.005670	1.754529	0.0911

R-squared	0.327527	Mean dependent var	0.001311
Adjusted R-squared	0.198205	S.D. dependent var	0.001668
S.E. of regression	0.001494	Akaike info criterion	-10.00794
Sum squared resid	5.80E-05	Schwarz criterion	-9.733110
Log likelihood	166.1270	Hannan-Quinn criter.	-9.916838
F-statistic	2.532651	Durbin-Watson stat	2.247717
Prob(F-statistic)	0.053821		

Test result: the result indicate a potential common variance of squared residual and squared exogenous series GDP growth. The null hypothesis of no heteroskedasticity can be rejected @ 90% confidence level, but not on 90% confidence level.

Given this finding, following Gujarati (2004) guidelines, a weighted least square regression (WLS) with weighting based on GDP growth series[1] was run to address the potential relation between residual variance and squared GDP growth. However, the procedure resulted in worsening the heteroskedasticity problem, with the null being rejected at 95% confidence level (White test, no cross-products).

Consequently, the initial model was preserved in the report based on the following arguments:

- using HAC Newey-West autocorrelation and heteroskedasticity consistent White coefficient covariance matrix estimators doesn't change substantially the results of this model (Table 7 below); the coefficientsmaintain the same significance levels;
- additionally, comparison of the coefficient error variance (squared standard error) from the OLS standard regression with the ones of the WLS regression, shows that there are no important differences (the largest OLS error variance is around 1.5 times larger than the smallest variance, while the rule of thumb maximum ratio proposed by Gujarati (2004) is 10);
- the report already includes an alternative model for corporate (Model 2) for which there is no indication of heteroskedasticity;

[1] In Eviews options terminology, "weight series" was given by the inverse of GDP growth series and "weight type" was set to "inverse standard deviation" (full result are available at request).

Table 7 Model 1 Newey West HAC standard errors & covariance and White heteroskedasticity consistent standard errors & covariance

Dependent Variable: DDEF_C
Method: Least Squares
Date: 03/02/14 Time: 16:34
Sample (adjusted): 2005Q4 2013Q3
Included observations: 32 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.103671	0.007969	13.00944	0.0000
GDP_G	-1.826404	0.499335	-3.657673	0.0011
DCCI(-1)	0.066711	0.017467	3.819375	0.0007
DBUILD2	-0.876286	0.186261	-4.704606	0.0001
DRON_IRC(-5)	0.033769	0.004583	7.368041	0.0000
DBET(-7)	-0.130456	0.050062	-2.605870	0.0150

R-squared	0.913047	Mean dependent var	0.051390
Adjusted R-squared	0.896325	S.D. dependent var	0.124737
S.E. of regression	0.040163	Akaike info criterion	-3.424357
Sum squared resid	0.041941	Schwarz criterion	-3.149532
Log likelihood	60.78971	Hannan-Quinn criter.	-3.333260
F-statistic	54.60233	Durbin-Watson stat	1.987063
Prob(F-statistic)	0.000000		

Dependent Variable: DDEF_C
Method: Least Squares
Date: 03/02/14 Time: 16:35
Sample (adjusted): 2005Q4 2013Q3
Included observations: 32 after adjustments
White heteroskedasticity-consistent standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.103671	0.006830	15.17850	0.0000
GDP_G	-1.826404	0.547161	-3.337966	0.0026
DCCI(-1)	0.066711	0.019101	3.492527	0.0017
DBUILD2	-0.876286	0.164902	-5.313987	0.0000
DRON_IRC(-5)	0.033769	0.006092	5.543604	0.0000
DBET(-7)	-0.130456	0.043353	-3.009160	0.0058

R-squared	0.913047	Mean dependent var	0.051390
Adjusted R-squared	0.896325	S.D. dependent var	0.124737
S.E. of regression	0.040163	Akaike info criterion	-3.424357
Sum squared resid	0.041941	Schwarz criterion	-3.149532
Log likelihood	60.78971	Hannan-Quinn criter.	-3.333260
F-statistic	54.60233	Durbin-Watson stat	1.987063
Prob(F-statistic)	0.000000		

Test result: coefficients maintain approximately the same level of statistical significance also when using Newey West HAC estimator and White heteroskedasticity consistent estimator for the coefficient covariance matrix.

Table 7 Parameters stability tests Chow forecast test for last 4 observations

Chow Forecast Test
Equation: DDEF_C_MAIN
Specification: DDEF_C C GDP_G DCCI(-1) DBUILD2 DBET(-7) DRON_IRC(-5)
Test predictions for observations from 2012Q3 to 2013Q3

	Value	df	Probability
F-statistic	0.403942	(5, 21)	0.8406
Likelihood ratio	2.938507	5	0.7095

F-test summary:

	Sum of Sq.	df	Mean Squares
Test SSR	0.003680	5	0.000736
Restricted SSR	0.041941	26	0.001613
Unrestricted SSR	0.038261	21	0.001822
Unrestricted SSR	0.038261	21	0.001822

LR test summary:

	Value	df
Restricted LogL	60.78971	26
Unrestricted LogL	62.25897	21

Unrestricted log likelihood adjusts test equation results to account for observations in forecast sample

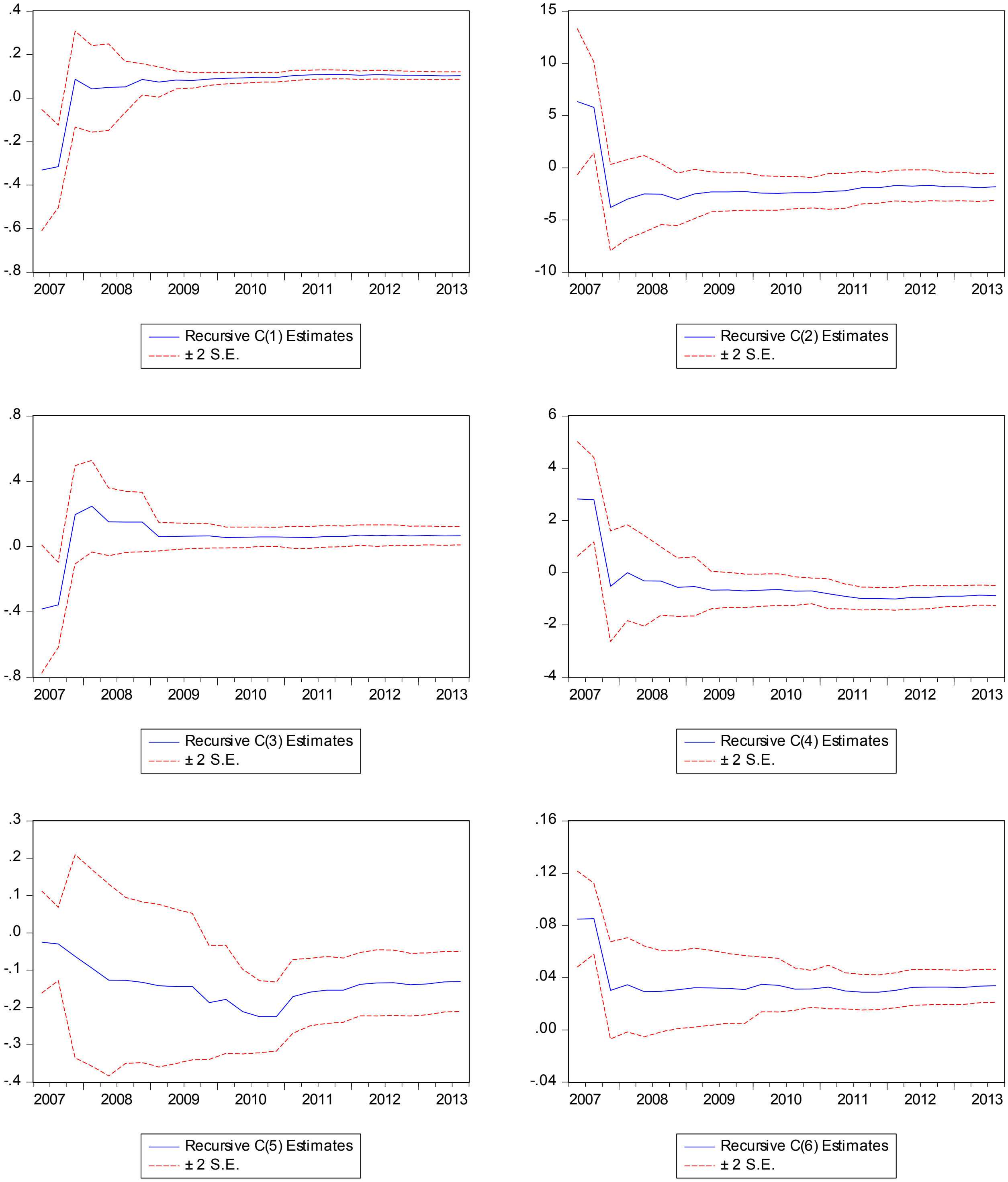
Unrestricted Test Equation:
Dependent Variable: DDEF_C
Method: Least Squares
Date: 01/21/14 Time: 23:56
Sample: 2005Q4 2012Q2
Included observations: 27

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.107588	0.010239	10.50767	0.0000
GDP_G	-1.752603	0.772308	-2.269306	0.0339
DCCI(-1)	0.066238	0.033075	2.002633	0.0583
DBUILD2	-0.948279	0.224593	-4.222213	0.0004
DBET(-7)	-0.134227	0.044485	-3.017338	0.0066
DRON_IRC(-5)	0.032519	0.006889	4.720355	0.0001

R-squared	0.919451	Mean dependent var	0.045106
Adjusted R-squared	0.900273	S.D. dependent var	0.135164
S.E. of regression	0.042684	Akaike info criterion	-3.276842
Sum squared resid	0.038261	Schwarz criterion	-2.988878
Log likelihood	50.23737	Hannan-Quinn criter.	-3.191215
F-statistic	47.94241	Durbin-Watson stat	2.006666
Prob(F-statistic)	0.000000		

Test result: null hypothesis of stable coefficient in the sub-samples cannot be rejected; no predictive failure.

Table 8 Parameters stability test: recursive coefficients estimation



Test results: coefficients stabilize quickly and maintain within confidence level intervals. The coefficient for stock market index (BET) displays larger fluctuations in 2009-2010 period.

Table 9 Parameters stability tests

Quandt-Andrews unknown breakpoint test
Null Hypothesis: No breakpoints within 20% trimmed data
Varying regressors: All equation variables
Equation Sample: 2005Q4 2013Q3
Test Sample: 2007Q3 2012Q1
Number of breaks compared: 19

Statistic	Value	Prob.
Maximum LR F-statistic (2010Q4)	3.586053	0.0248
Maximum Wald F-statistic (2010Q4)	21.51632	0.0248
Exp LR F-statistic	0.872138	0.1690
Exp Wald F-statistic	8.524224	0.0134
Ave LR F-statistic	1.562294	0.0910
Ave Wald F-statistic	9.373766	0.0910

Note: probabilities calculated using Hansen's (1997) method

Test result: there is indication that parameters stability is broken on 2010Q4. However the already small sample had to be trimmed considerably (20%) to avoid near singular matrix error, and thus the number of observation included in the test is low and may not ensure asymptotic properties.

Table 10 Functional form test: Ramsey RESET

Ramsey RESET Test
Equation: DDEF_C_MAIN
Specification: DDEF_C C GDP_G DCCI(-1) DBUILD2 DBET(-7) DRON_IRC(-5)
Omitted Variables: Squares of fitted values

	Value	df	Probability
t-statistic	0.818015	25	0.4211
F-statistic	0.669149	(1, 25)	0.4211
Likelihood ratio	0.845248	1	0.3579

F-test summary:

	Sum of Sq.	df	Mean Squares
Test SSR	0.001093	1	0.001093
Restricted SSR	0.041941	26	0.001613
Unrestricted SSR	0.040847	25	0.001634
Unrestricted SSR	0.040847	25	0.001634

LR test summary:

	Value	df
Restricted LogL	60.78971	26
Unrestricted LogL	61.21234	25

Unrestricted Test Equation:
Dependent Variable: DDEF_C
Method: Least Squares
Date: 01/22/14 Time: 00:20
Sample: 2005Q4 2013Q3
Included observations: 32

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.112783	0.014083	8.008389	0.0000
GDP_G	-2.008236	0.690478	-2.908472	0.0075
DCCI(-1)	0.077137	0.031182	2.473746	0.0205
DBUILD2	-0.895153	0.193217	-4.632894	0.0001
DBET(-7)	-0.133479	0.040590	-3.288485	0.0030
DRON_IRC(-5)	0.036162	0.006997	5.168126	0.0000
FITTED^2	-0.410264	0.501536	-0.818015	0.4211

R-squared	0.915314	Mean dependent var	0.051390
Adjusted R-squared	0.894989	S.D. dependent var	0.124737
S.E. of regression	0.040421	Akaike info criterion	-3.388271
Sum squared resid	0.040847	Schwarz criterion	-3.067641
Log likelihood	61.21234	Hannan-Quinn criter.	-3.281991
F-statistic	45.03445	Durbin-Watson stat	1.928133
Prob(F-statistic)	0.000000		

Test results: the null of correct functional form cannot be rejected.

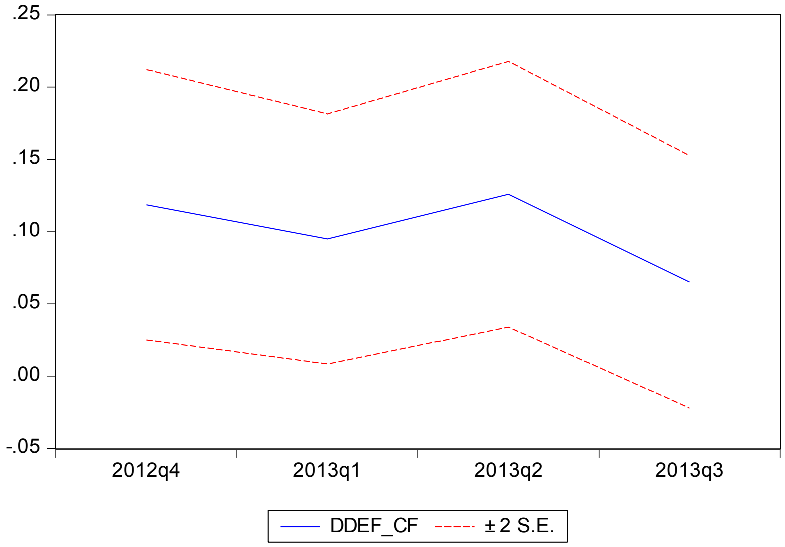
Table 11 Out-of-sample forecast evaluation – re-estimation of the equation

Dependent Variable: DDEF_C
Method: Least Squares
Date: 01/22/14 Time: 00:41
Sample (adjusted): 2005Q4 2012Q3
Included observations: 28 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.106184	0.009568	11.09773	0.0000
GDP_G	-1.685512	0.743743	-2.266257	0.0336
DCCI(-1)	0.070257	0.031250	2.248193	0.0349
DBUILD2	-0.943342	0.220209	-4.283857	0.0003
DBET(-7)	-0.133925	0.043664	-3.067142	0.0056
DRON_IRC(-5)	0.032721	0.006748	4.848706	0.0001

R-squared	0.918990	Mean dependent var	0.046652
Adjusted R-squared	0.900579	S.D. dependent var	0.132889
S.E. of regression	0.041902	Akaike info criterion	-3.319579
Sum squared resid	0.038626	Schwarz criterion	-3.034107
Log likelihood	52.47411	Hannan-Quinn criter.	-3.232307
F-statistic	49.91441	Durbin-Watson stat	2.141607
Prob(F-statistic)	0.000000		

Table 12 Out-of-sample forecast evaluation – forecast evaluation



Forecast: DDEF_CF	
Actual: DDEF_C	
Forecast sample: 2012Q4 2013Q3	
Included observations: 4	
Root Mean Squared Error	0.030573
Mean Absolute Error	0.030086
Mean Abs. Percent Error	36.38283
Theil Inequality Coefficient	0.161681
Bias Proportion	0.291409
Variance Proportion	0.168607
Covariance Proportion	0.539984

Evaluation results: Mean absolute percent error shows reasonable values. Theil inequality coefficient is close to 0 indicating good fit. Some forecasted value mean bias is present but the number of observation is low.

Table 13 Multi-collinearity evaluation – Variance Inflation Factors Analysis

Variance Inflation Factors
Date: 03/02/14 Time: 16:54
Sample: 2003Q4 2013Q3
Included observations: 32

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	7.33E-05	1.454207	NA
GDP_G	0.421912	2.912323	2.576614
DCCI(-1)	0.000800	1.766847	1.729913
DBUILD2	0.036333	2.872908	2.275338
DRON_IRC(-5)	3.99E-05	1.413294	1.238264
DBET(-7)	0.001613	1.248191	1.233245

Analysis results: The highest VIF is 2.9 , indicating that there are no multi-collinearity issues (Gujarati, 2004 proposes as rule of thumb a ratio of minimum 10 as indication of excessive multi-collinearity)

Annex D.2 Corporate model multi-variate regression diagnostic tests. Model 2

Table 1 – model specification and estimation

Dependent Variable: DDEF_C
Method: Least Squares
Date: 01/22/14 Time: 00:50
Sample (adjusted): 2005Q4 2013Q3
Included observations: 32 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.108627	0.009923	10.94717	0.0000
GDP_G	-2.894943	0.623082	-4.646168	0.0001
DBUILD2	-0.733675	0.222176	-3.302219	0.0027
DRON_IRC(-5)	0.040000	0.007380	5.420042	0.0000
DFX(-7)	0.516016	0.266499	1.936276	0.0634

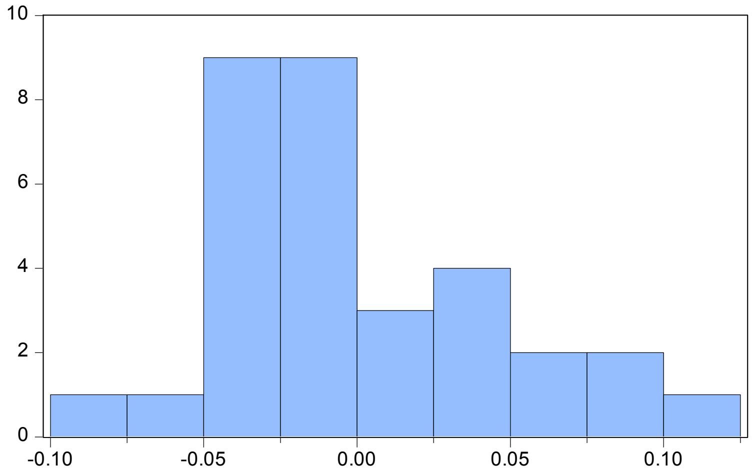
R-squared	0.870910	Mean dependent var	0.051390
Adjusted R-squared	0.851786	S.D. dependent var	0.124737
S.E. of regression	0.048022	Akaike info criterion	-3.091720
Sum squared resid	0.062265	Schwarz criterion	-2.862699
Log likelihood	54.46752	Hannan-Quinn criter.	-3.015806
F-statistic	45.53929	Durbin-Watson stat	2.020000
Prob(F-statistic)	0.000000		

Table 2 Residuals auto and partial correlations

Date: 01/22/14 Time: 00:50
Sample: 2005Q4 2013Q3
Included observations: 32

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.023	-0.023	0.0190	0.890
		2	-0.057	-0.058	0.1389	0.933
		3	-0.028	-0.031	0.1680	0.983
		4	-0.155	-0.160	1.0960	0.895
		5	0.242	0.236	3.4491	0.631
		6	-0.189	-0.222	4.9430	0.551
		7	0.056	0.103	5.0771	0.651
		8	-0.070	-0.145	5.3019	0.725
		9	0.079	0.213	5.5985	0.779
		10	0.000	-0.225	5.5986	0.848
		11	-0.366	-0.204	12.543	0.324
		12	0.070	-0.041	12.813	0.383
		13	0.035	0.139	12.883	0.457
		14	0.239	0.131	16.339	0.293
		15	-0.015	-0.069	16.354	0.359
		16	-0.170	-0.038	18.327	0.305

Table 3 Jarque-Bera normality test for residuals



Series: Residuals	
Sample 2005Q4 2013Q3	
Observations 32	
Mean	6.51e-18
Median	-0.011174
Maximum	0.106608
Minimum	-0.079835
Std. Dev.	0.044817
Skewness	0.625403
Kurtosis	2.785793
Jarque-Bera	2.147203
Probability	0.341775

Test result: the null hypothesis of normal distribution cannot be rejected.

Table 4 Breusch-Godfrey Serial Correlation LM Test

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.059366	Prob. F(2,25)	0.9425
Obs*R-squared	0.151257	Prob. Chi-Square(2)	0.9272

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 01/22/14 Time: 00:52
Sample: 2005Q4 2013Q3
Included observations: 32
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000143	0.010297	-0.013932	0.9890
GDP_G	0.003638	0.660705	0.005507	0.9956
DBUILD2	-0.014875	0.234429	-0.063450	0.9499
DRON_IRC(-5)	-0.000822	0.008129	-0.101135	0.9202
DFX(-7)	0.017325	0.284843	0.060822	0.9520
RESID(-1)	-0.036552	0.222197	-0.164504	0.8707
RESID(-2)	-0.067433	0.211026	-0.319547	0.7520

R-squared	0.004727	Mean dependent var	6.51E-18
Adjusted R-squared	-0.234139	S.D. dependent var	0.044817
S.E. of regression	0.049788	Akaike info criterion	-2.971458
Sum squared resid	0.061970	Schwarz criterion	-2.650828
Log likelihood	54.54333	Hannan-Quinn criter.	-2.865179
F-statistic	0.019789	Durbin-Watson stat	1.987610
Prob(F-statistic)	0.999959		

Test result: the null hypothesis of no residual auto-correlation cannot be rejected. Similar results are found when testing with 1 lag and 3 lags.

Table 5 White heteroskedasticity test

Heteroskedasticity Test: White

F-statistic	0.877243	Prob. F(14,17)	0.5930
Obs*R-squared	13.42165	Prob. Chi-Square(14)	0.4936
Scaled explained SS	8.531682	Prob. Chi-Square(14)	0.8598

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 01/22/14 Time: 00:52
Sample: 2005Q4 2013Q3
Included observations: 32

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.001888	0.001086	1.738520	0.1002
GDP_G	-0.050769	0.076019	-0.667841	0.5132
GDP_G^2	1.310454	2.362004	0.554806	0.5863
GDP_G*DBUILD2	0.637421	1.934187	0.329555	0.7458
GDP_G*DRON_IRC(-5)	-0.048465	0.096500	-0.502233	0.6219
GDP_G*DFX(-7)	-3.509064	1.858807	-1.887805	0.0762
DBUILD2	0.036755	0.027410	1.340924	0.1976
DBUILD2^2	-0.404937	0.352153	-1.149887	0.2661
DBUILD2*DRON_IRC(-5)	0.014048	0.017509	0.802376	0.4334
DBUILD2*DFX(-7)	0.181772	0.632091	0.287573	0.7772
DRON_IRC(-5)	0.000897	0.000637	1.408882	0.1769
DRON_IRC(-5)^2	0.000163	0.000374	0.436897	0.6677
DRON_IRC(-5)*DFX(-7)	0.006138	0.014477	0.423965	0.6769
DFX(-7)	0.023993	0.030910	0.776235	0.4483
DFX(-7)^2	0.277688	0.500772	0.554520	0.5864

R-squared	0.419427	Mean dependent var	0.001946
Adjusted R-squared	-0.058693	S.D. dependent var	0.002642
S.E. of regression	0.002718	Akaike info criterion	-8.672694
Sum squared resid	0.000126	Schwarz criterion	-7.985630
Log likelihood	153.7631	Hannan-Quinn criter.	-8.444952
F-statistic	0.877243	Durbin-Watson stat	2.012596
Prob(F-statistic)	0.592997		

Test result: no indication of common variance of squared residual and squared exogenous or their cross-products. The null hypothesis of no heteroskedasticity cannot be rejected. The result maintains on running the test without cross-products.

Table 6 Parameters stability tests Chow forecast test for last 4 observations

Chow Forecast Test
Equation: DDEF_C_MAIN_ALT
Specification: DDEF_C C GDP_G DBUILD2 DRON_IRC(-5) DFX(-7)
Test predictions for observations from 2012Q4 to 2013Q3

	Value	df	Probability
F-statistic	0.208300	(4, 23)	0.9312
Likelihood ratio	1.138732	4	0.8881

F-test summary:

	Sum of Sq.	df	Mean Squares
Test SSR	0.002177	4	0.000544
Restricted SSR	0.062265	27	0.002306
Unrestricted SSR	0.060088	23	0.002613
Unrestricted SSR	0.060088	23	0.002613

LR test summary:

	Value	df
Restricted LogL	54.46752	27
Unrestricted LogL	55.03689	23

Unrestricted log likelihood adjusts test equation results to account for observations in forecast sample

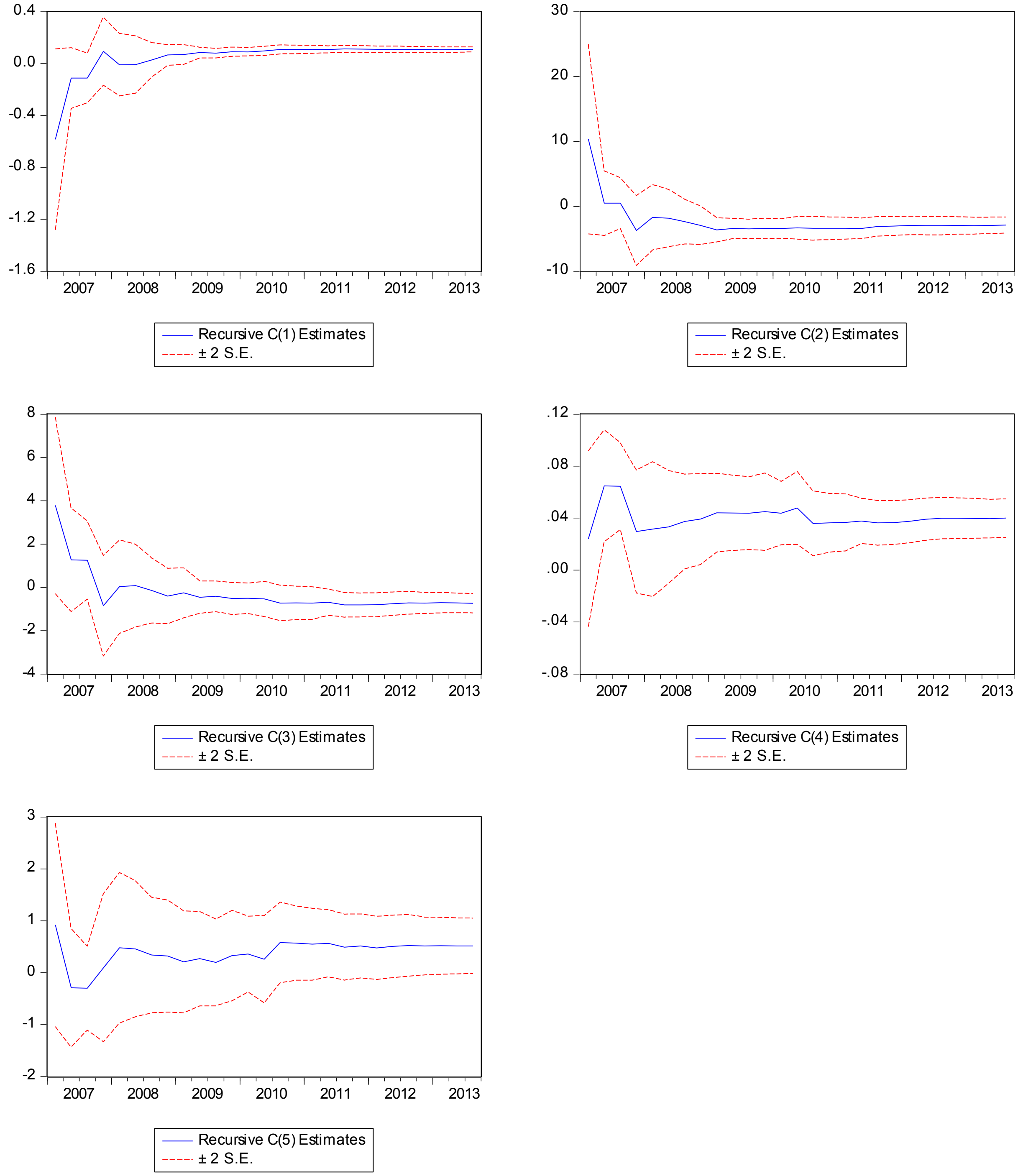
Unrestricted Test Equation:
Dependent Variable: DDEF_C
Method: Least Squares
Date: 01/22/14 Time: 00:53
Sample: 2005Q4 2012Q3
Included observations: 28

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.107755	0.011854	9.089968	0.0000
GDP_G	-2.978371	0.709076	-4.200356	0.0003
DBUILD2	-0.712640	0.262496	-2.714860	0.0124
DRON_IRC(-5)	0.039916	0.007993	4.993615	0.0000
DFX(-7)	0.524689	0.297952	1.760985	0.0915

R-squared	0.873979	Mean dependent var	0.046652
Adjusted R-squared	0.852063	S.D. dependent var	0.132889
S.E. of regression	0.051113	Akaike info criterion	-2.949131
Sum squared resid	0.060088	Schwarz criterion	-2.711238
Log likelihood	46.28784	Hannan-Quinn criter.	-2.876405
F-statistic	39.87742	Durbin-Watson stat	1.999251
Prob(F-statistic)	0.000000		

Test result: null hypothesis of stable coefficient in the sub-samples cannot be rejected; no predictive failure.

Table 7 Parameters stability test: recursive coefficients estimation



Test results: coefficients stabilize quickly and maintain within confidence level intervals.

Table 8 Parameters stability tests

Quandt-Andrews unknown breakpoint test
Null Hypothesis: No breakpoints within 20% trimmed data
Varying regressors: All equation variables
Equation Sample: 2005Q4 2013Q3
Test Sample: 2007Q3 2012Q1
Number of breaks compared: 19

Statistic	Value	Prob.
Maximum LR F-statistic (2009Q4)	1.953286	0.5059
Maximum Wald F-statistic (2009Q4)	9.766428	0.5059
Exp LR F-statistic	0.504630	0.6018
Exp Wald F-statistic	2.891051	0.4903
Ave LR F-statistic	0.984189	0.4379
Ave Wald F-statistic	4.920947	0.4379

Note: probabilities calculated using Hansen's (1997) method

Test result: the null of no breakpoints within 20% trimmed data cannot be rejected.
Note: the already small sample had to be trimmed considerably (20%) to avoid near singular matrix error, and thus the number of observation included in the test is low and may not ensure asymptotic properties.

Table 9 Functional form test: Ramsey RESET

Ramsey RESET Test
Equation: DDEF_C_MAIN_ALT
Specification: DDEF_C C GDP_G DBUILD2 DRON_IRC(-5) DFX(-7)
Omitted Variables: Squares of fitted values

	Value	df	Probability
t-statistic	0.159424	26	0.8746
F-statistic	0.025416	(1, 26)	0.8746
Likelihood ratio	0.031266	1	0.8596

F-test summary:

	Sum of Sq.	df	Mean Squares
Test SSR	6.08E-05	1	6.08E-05
Restricted SSR	0.062265	27	0.002306
Unrestricted SSR	0.062204	26	0.002392
Unrestricted SSR	0.062204	26	0.002392

LR test summary:

	Value	df
Restricted LogL	54.46752	27
Unrestricted LogL	54.48316	26

Unrestricted Test Equation:
Dependent Variable: DDEF_C

Method: Least Squares
Date: 01/22/14 Time: 00:57
Sample: 2005Q4 2013Q3
Included observations: 32

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.110883	0.017385	6.377956	0.0000
GDP_G	-2.941460	0.698504	-4.211083	0.0003
DBUILD2	-0.740095	0.229854	-3.219853	0.0034
DRON_IRC(-5)	0.040652	0.008556	4.751106	0.0001
DFX(-7)	0.506701	0.277660	1.824900	0.0795
FITTED^2	-0.091990	0.577017	-0.159424	0.8746

R-squared	0.871037	Mean dependent var	0.051390
Adjusted R-squared	0.846236	S.D. dependent var	0.124737
S.E. of regression	0.048913	Akaike info criterion	-3.030197
Sum squared resid	0.062204	Schwarz criterion	-2.755372
Log likelihood	54.48316	Hannan-Quinn criter.	-2.939100
F-statistic	35.12150	Durbin-Watson stat	2.007332
Prob(F-statistic)	0.000000		

Test results: the null of correct functional form cannot be rejected.

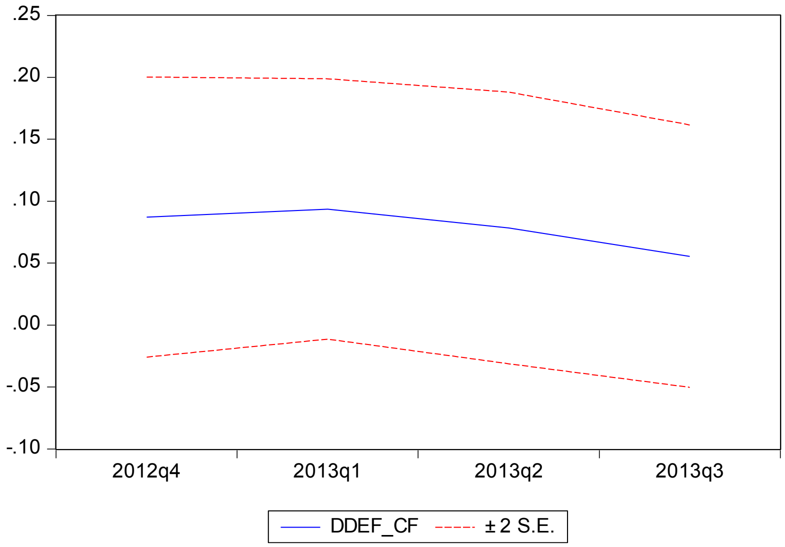
Table 10 Out-of-sample forecast evaluation – re-estimation of the equation

Dependent Variable: DDEF_C
Method: Least Squares
Date: 01/22/14 Time: 00:57
Sample (adjusted): 2005Q4 2012Q3
Included observations: 28 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.107755	0.011854	9.089968	0.0000
GDP_G	-2.978371	0.709076	-4.200356	0.0003
DBUILD2	-0.712640	0.262496	-2.714860	0.0124
DRON_IRC(-5)	0.039916	0.007993	4.993615	0.0000
DFX(-7)	0.524689	0.297952	1.760985	0.0915

R-squared	0.873979	Mean dependent var	0.046652
Adjusted R-squared	0.852063	S.D. dependent var	0.132889
S.E. of regression	0.051113	Akaike info criterion	-2.949131
Sum squared resid	0.060088	Schwarz criterion	-2.711238
Log likelihood	46.28784	Hannan-Quinn criter.	-2.876405
F-statistic	39.87742	Durbin-Watson stat	1.999251
Prob(F-statistic)	0.000000		

Table 11 Out-of-sample forecast evaluation – forecast evaluation



Forecast: DDEF_CF	
Actual: DDEF_C	
Forecast sample: 2012Q4 2013Q3	
Included observations: 4	
Root Mean Squared Error	0.023653
Mean Absolute Error	0.019850
Mean Abs. Percent Error	24.68803
Theil Inequality Coefficient	0.143133
Bias Proportion	0.062347
Variance Proportion	0.018931
Covariance Proportion	0.918722

Evaluation results: Mean absolute percent error shows a good value (25). Theil inequality coefficient is close to 0 indicating good fit. The mean squared forecast error decomposition shows that the errors are mainly unsystematic with limited bias and variance proportion.

Table 12 Multi-collinearity evaluation – Variance Inflation Factors Analysis

Variance Inflation Factors
Date: 03/02/14 Time: 17:08
Sample: 2003Q4 2013Q3
Included observations: 32

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	9.85E-05	1.366304	NA
GDP_G	0.388231	1.874533	1.658451
DBUILD2	0.049362	2.730275	2.162373
DRON_IRC(-5)	5.45E-05	1.349859	1.182685
DFX(-7)	0.071022	1.274049	1.270084

*Analysis results**:** The highest VIF is 2.73**,** indicating that there are no multi-collinearity issues (Gujarati, 2004 proposes as rule of thumb a ratio of minimum 10 as indication of excessive multi-collinearity)*

Annex E Uni-variate regressions results - Households model

Macroeconomic variable	Expected sign	Coefficient	Lag	p-value	R-squared	Observations
Default rates						
Household default rate						
Cyclical Indicators						
Real GDP growth	-	-6.6504	4	0%	36%	
Nominal GDP growth	-	-4.6519	3	0%	42%	
GDP gap (real)	-	-0.0001	0	2%	19%	
GDP gap (nominal)	-	+0.0001	8	1%	26%	Wrong sign
Industrial production (real)	-	-5.1358	7	0%	22%	
Industrial production (nominal)	-	-2.9622	6	0%	19%	
Economic Sentiment Indicator	-	+1.0459	0	9%	6%	Wrong sign
Price stability indicators						
Inflation rate – series in levels		-0.0722	3	3%	11%	
Inflation rate – series as diff		-0.0213	3	12%	2%	Not significant
Household indicators						
Household consumption (real)	-	-6.0364	4	0%	50%	
Household consumption (nominal)	-	-3.0355	3	0%	27%	
Net wage nominal	-	-4.1534	2	0%	28%	
Net wage real terms	-	-1.2203	2	1%	4%	
Unemployment rate	+	+0.2195	4	4%	12%	
Interest payment service (proxy for disposable income)	+	+2.6815	6	1%	15%	
Consumer confidence index	-	+0.1517	4	1%	7%	Wrong sign
Stock Market Indicators						
Bucharest Exchange Trading (BET)	-	-0.5105	8	0%	27%	
EURO STOXX 500	-	-1.0306	8	0%	29%	
Interest rate indicators - money market						
ROBOR 3M	+	-0.0300	0	9%	6%	Wrong sign
EURIBOR 3M	+	-0.2030	4	0%	24%	Wrong sign

Macroeconomic variable	Expected sign	Coefficient	Lag	p-value	R-squared	Observations
Interest rate indicators – household						
Banks interest rates for RON loans – series in levels	**+**	-0.0253	8	0%	39%	Wrong sing
Banks interest rates for RON loans – series as diff	**+**	+0.1253	8	0%	35%	
Banks interest rates for EUR loans	**+**	-0.02885	3	6%	8%	Wrong sign
Real interest rates for RON loans	**+**	-0.0353	3	4%	10%	
Interest rate spread RON	**+**	-0.0361	0	3%	9%	
Interest rate spread EUR	**+**	+0.1698	6	0%	18%	
External variables						
Exchange rate	**+**	+2.5209	6	0%	20%	
Oil price	**+**	-0.1556	6	10%	2%	Wrong sign

Note: Newey-West heteroskedasticity and autocorrelation consistent covariance matrix estimator for the parameters is used in order to accommodate any expected residuals heteroskedasticity and/or autocorrelation of unknown order.

Annex F Households multi-variate regression diagnostic tests.

Table 1 – model specification and estimation

Dependent Variable: DDEF_H
Method: Least Squares
Date: 01/22/14 Time: 03:35
Sample (adjusted): 2006Q4 2013Q3
Included observations: 28 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.355519	0.025395	13.99974	0.0000
DCONS(-4)	-3.635916	1.074828	-3.382789	0.0025
DINTS(-6)	1.120832	0.471816	2.375571	0.0259
DRONIRHH(-8)	0.099010	0.021504	4.604219	0.0001

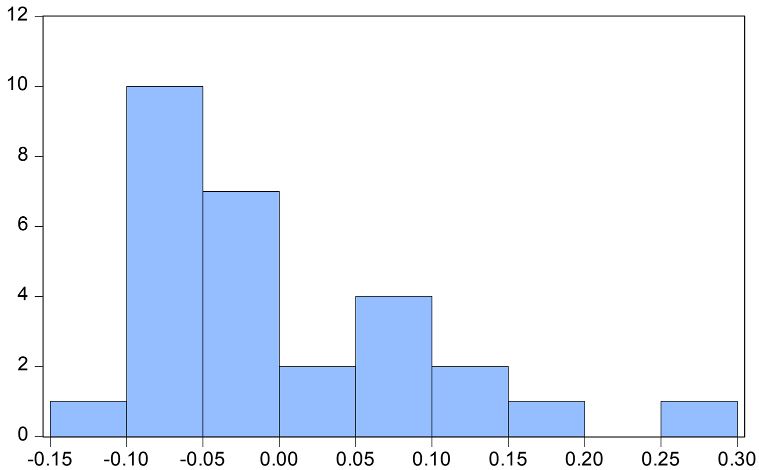
R-squared	0.760760	Mean dependent var	0.267500
Adjusted R-squared	0.730855	S.D. dependent var	0.190275
S.E. of regression	0.098713	Akaike info criterion	-1.661634
Sum squared resid	0.233863	Schwarz criterion	-1.471319
Log likelihood	27.26288	Hannan-Quinn criter.	-1.603453
F-statistic	25.43927	Durbin-Watson stat	1.720864
Prob(F-statistic)	0.000000		

Table 2 Residuals auto and partial correlations

Date: 01/23/14 Time: 07:16
Sample: 2006Q4 2013Q3
Included observations: 28

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.095	0.095	0.2822	0.595
		2	0.169	0.161	1.2046	0.548
		3	0.037	0.009	1.2514	0.741
		4	-0.100	-0.136	1.6038	0.808
		5	0.245	0.271	3.8044	0.578
		6	0.085	0.087	4.0797	0.666
		7	0.209	0.121	5.8221	0.561
		8	0.102	0.027	6.2622	0.618
		9	-0.250	-0.292	9.0154	0.436
		10	0.018	0.000	9.0310	0.529
		11	-0.185	-0.113	10.725	0.467
		12	-0.133	-0.220	11.650	0.474

Table 3 Jarque-Bera normality test for residuals



Series: Residuals
Sample 2006Q4 2013Q3
Observations 28

Mean	2.08e-17
Median	-0.028211
Maximum	0.277434
Minimum	-0.135441
Std. Dev.	0.093068
Skewness	1.181255
Kurtosis	4.116003
Jarque-Bera	7.964733
Probability	0.018641

Test result: null hypothesis of normal distribution is rejected @95% confidence level. Statistics should follow the assumed distribution asymptotically.

Table 4 Breusch-Godfrey Serial Correlation LM Test

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.500491	Prob. F(2,22)	0.6130
Obs*R-squared	1.218535	Prob. Chi-Square(2)	0.5437

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 01/23/14 Time: 07:22
Sample: 2006Q4 2013Q3
Included observations: 28
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.003011	0.022181	0.135757	0.8932
DCONS(-4)	0.039038	0.895793	0.043580	0.9656
DINTS(-6)	0.315969	0.831562	0.379971	0.7076
DRONIRHH(-8)	-0.000489	0.023808	-0.020554	0.9838
RESID(-1)	0.069772	0.221326	0.315245	0.7555
RESID(-2)	0.218230	0.248179	0.879322	0.3887

R-squared	0.043519	Mean dependent var	2.08E-17
Adjusted R-squared	-0.173863	S.D. dependent var	0.093068
S.E. of regression	0.100834	Akaike info criterion	-1.563271
Sum squared resid	0.223685	Schwarz criterion	-1.277799
Log likelihood	27.88580	Hannan-Quinn criter.	-1.476000
F-statistic	0.200196	Durbin-Watson stat	1.936543
Prob(F-statistic)	0.958963		

Test result: the null hypothesis of no residual auto-correlation cannot be rejected. Similar results are found when testing with 1 lag and 3 lags.

Table 5 White heteroskedasticity test

Heteroskedasticity Test: White

F-statistic	0.620114	Prob. F(9,18)	0.7652
Obs*R-squared	6.626884	Prob. Chi-Square(9)	0.6759
Scaled explained SS	7.585490	Prob. Chi-Square(9)	0.5764

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 01/23/14 Time: 07:24
Sample: 2006Q4 2013Q3
Included observations: 28

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.012204	0.005256	2.322116	0.0322
DCONS(-4)	-0.170216	0.177323	-0.959923	0.3498
DCONS(-4)^2	-2.168595	4.011267	-0.540626	0.5954
DCONS(-4)*DINTS(-6)	-7.054012	8.788969	-0.802598	0.4327
DCONS(-4)*DRONIRHH(-8)	0.213774	0.412510	0.518227	0.6106
DINTS(-6)	-0.267801	0.193704	-1.382526	0.1837
DINTS(-6)^2	-2.801518	4.494265	-0.623354	0.5409
DINTS(-6)*DRONIRHH(-8)	-0.281591	0.205853	-1.367922	0.1882
DRONIRHH(-8)	-0.000770	0.007799	-0.098685	0.9225
DRONIRHH(-8)^2	0.002959	0.005152	0.574355	0.5728

R-squared	0.236674	Mean dependent var	0.008352
Adjusted R-squared	-0.144988	S.D. dependent var	0.015014
S.E. of regression	0.016066	Akaike info criterion	-5.151807
Sum squared resid	0.004646	Schwarz criterion	-4.676020
Log likelihood	82.12530	Hannan-Quinn criter.	-5.006355
F-statistic	0.620114	Durbin-Watson stat	2.760032
Prob(F-statistic)	0.765180		

Test result: no indication of common variance of squared residual and squared exogenous or their cross-products. The null hypothesis of no heteroskedasticity cannot be rejected. The result maintains on running the test without cross-products.

Table 6 Parameters stability tests Chow forecast test for last 4 observations

Chow Forecast Test
Equation: DDEF_H_MODEL_MAIN
Specification: DDEF_H C DCONS(-4) DINTS(-6) DRONIRHH(-8)
Test predictions for observations from 2012Q3 to 2013Q3

	Value	df	Probability
F-statistic	0.934939	(5, 19)	0.4807
Likelihood ratio	6.159100	5	0.2910

F-test summary:

	Sum of Sq.	df	Mean Squares
Test SSR	0.046177	5	0.009235
Restricted SSR	0.233863	24	0.009744
Unrestricted SSR	0.187685	19	0.009878
Unrestricted SSR	0.187685	19	0.009878

LR test summary:

	Value	df
Restricted LogL	27.26288	24
Unrestricted LogL	30.34243	19

Unrestricted log likelihood adjusts test equation results to account for observations in forecast sample

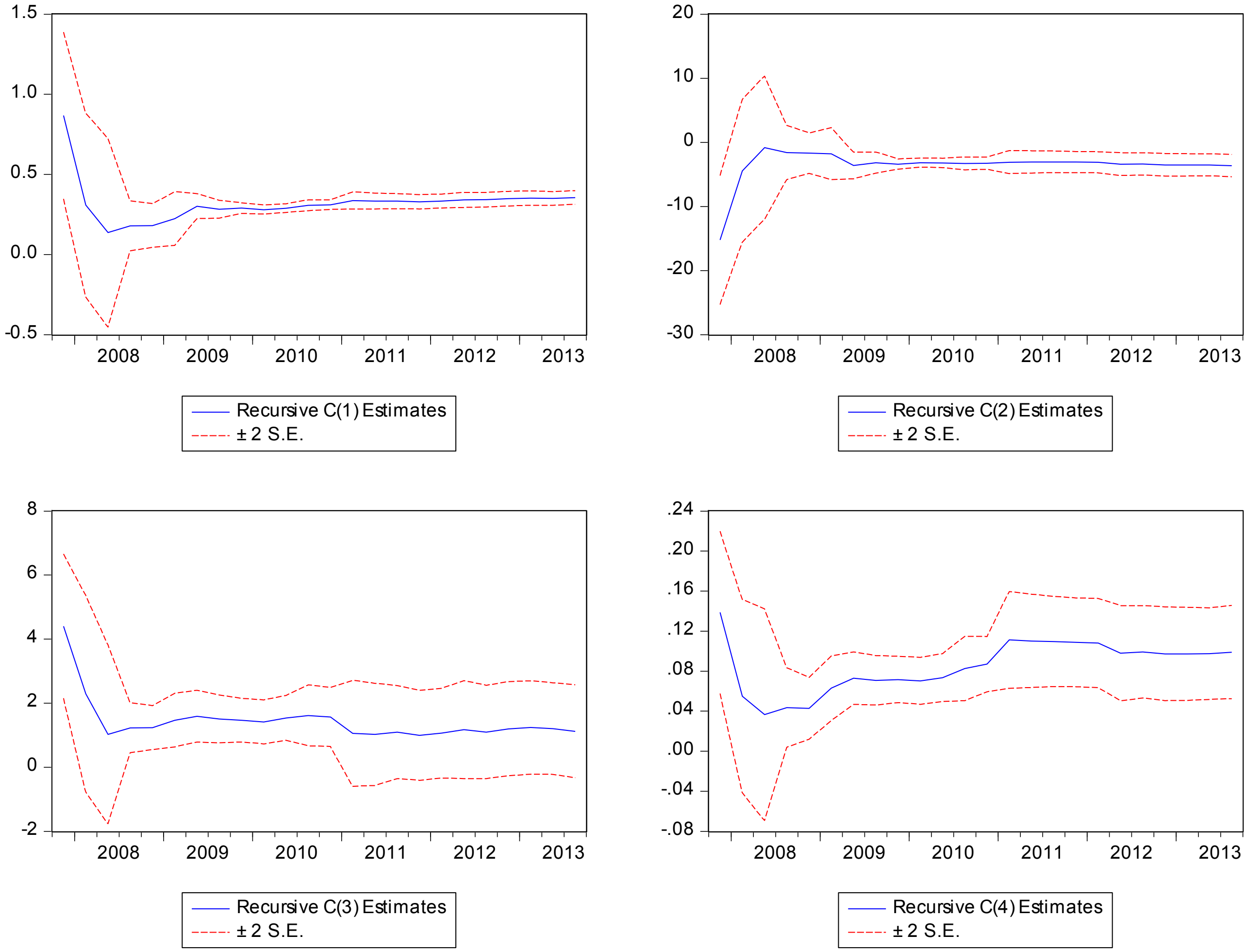
Unrestricted Test Equation:
Dependent Variable: DDEF_H
Method: Least Squares
Date: 01/23/14 Time: 07:25
Sample: 2006Q4 2012Q2
Included observations: 23
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 3.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.340455	0.026904	12.65437	0.0000
DCONS(-4)	-3.417163	0.889142	-3.843215	0.0011
DINTS(-6)	1.174306	0.501687	2.340712	0.0303
DRONIRHH(-8)	0.097824	0.025649	3.813989	0.0012

R-squared	0.785328	Mean dependent var	0.246957
Adjusted R-squared	0.751432	S.D. dependent var	0.199350
S.E. of regression	0.099389	Akaike info criterion	-1.622780
Sum squared resid	0.187685	Schwarz criterion	-1.425302
Log likelihood	22.66197	Hannan-Quinn criter.	-1.573115
F-statistic	23.16898	Durbin-Watson stat	1.691846
Prob(F-statistic)	0.000001		

Test result: null hypothesis of stable coefficient in the sub-samples cannot be rejected; no predictive failure.

Table 7 Parameters stability test: recursive coefficients estimation



Test results: coefficients stabilize quickly and maintain within confidence level intervals. The coefficient for interest service payment and RON interest rates (C4) display relatively larger fluctuations in 2010.

Table 8 Parameters stability tests

Quandt-Andrews unknown breakpoint test

Null Hypothesis: No breakpoints within 15% trimmed data

Equation Sample: 2006Q4 2013Q3

Test Sample: 2008Q1 2012Q3

Number of breaks compared: 19

Statistic	Value	Prob.
Maximum LR F-statistic (2010Q3)	3.003684	0.2112
Exp LR F-statistic	0.971106	0.1510
Ave LR F-statistic	1.773130	0.0670

Note: probabilities calculated using Hansen's (1997) method

Test result: two tests out of three cannot reject parameters stability null.

Table 9 Functional form test: Ramsey RESET

Ramsey RESET Test
Equation: DDEF_H_MODEL_MAIN
Specification: DDEF_H C DCONS(-4) DINTS(-6) DRONIRHH(-8)
Omitted Variables: Squares of fitted values

	Value	df	Probability
t-statistic	1.617658	23	0.1194
F-statistic	2.616816	(1, 23)	0.1194
Likelihood ratio	3.017134	1	0.0824

F-test summary:

	Sum of Sq.	df	Mean Squares
Test SSR	0.023890	1	0.023890
Restricted SSR	0.233863	24	0.009744
Unrestricted SSR	0.209973	23	0.009129
Unrestricted SSR	0.209973	23	0.009129

LR test summary:

	Value	df
Restricted LogL	27.26288	24
Unrestricted LogL	28.77144	23

Unrestricted Test Equation:

Dependent Variable: DDEF_H
Method: Least Squares
Date: 01/23/14 Time: 07:29
Sample: 2006Q4 2013Q3
Included observations: 28
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.533725	0.094637	5.639700	0.0000
DCONS(-4)	-6.692536	1.813224	-3.690959	0.0012
DINTS(-6)	1.760214	0.632179	2.784358	0.0105
DRONIRHH(-8)	0.144608	0.030612	4.723906	0.0001
FITTED^2	-1.278676	0.643777	-1.986210	0.0591

R-squared	0.785199	Mean dependent var	0.267500
Adjusted R-squared	0.747843	S.D. dependent var	0.190275
S.E. of regression	0.095547	Akaike info criterion	-1.697960
Sum squared resid	0.209973	Schwarz criterion	-1.460067
Log likelihood	28.77144	Hannan-Quinn criter.	-1.625234
F-statistic	21.01899	Durbin-Watson stat	1.765608
Prob(F-statistic)	0.000000		

Test results: generally, the null of correct functional form rejected cannot be rejected. Likelihood ratio however test rejects the null @90% confidence level (the alternative logistic regression setting was taken into consideration but yielded poor result due to dependent low absolute values in the first part of the series, combined with logit-difference transformation; see section 3.4 "Specific model" for a discussion)

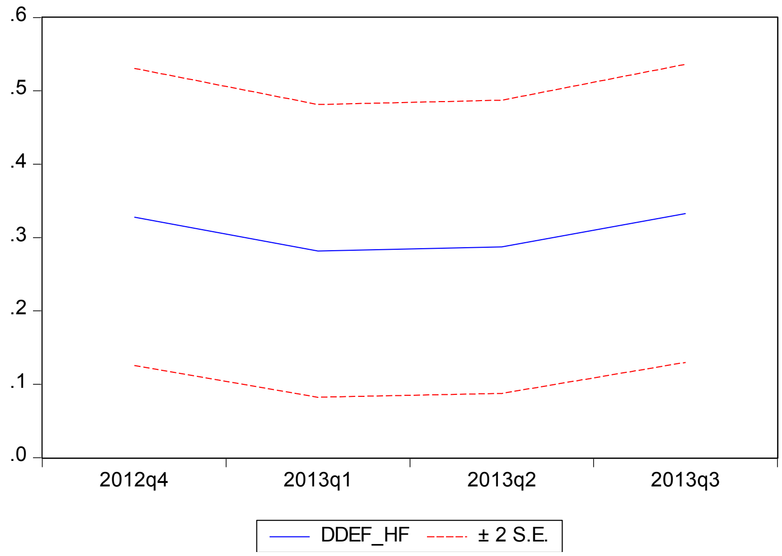
Table 10 Out-of-sample forecast evaluation – re-estimation of the equation

Dependent Variable: DDEF_H
Method: Least Squares
Date: 01/23/14 Time: 07:34
Sample (adjusted): 2006Q4 2012Q3
Included observations: 24 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 3.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.342025	0.025944	13.18311	0.0000
DCONS(-4)	-3.390972	0.894446	-3.791143	0.0011
DINTS(-6)	1.098009	0.443844	2.473863	0.0225
DRONIRHH(-8)	0.099247	0.024056	4.125614	0.0005

R-squared	0.783400	Mean dependent var	0.247500
Adjusted R-squared	0.750910	S.D. dependent var	0.194986
S.E. of regression	0.097315	Akaike info criterion	-1.670708
Sum squared resid	0.189406	Schwarz criterion	-1.474365
Log likelihood	24.04849	Hannan-Quinn criter.	-1.618618
F-statistic	24.11207	Durbin-Watson stat	1.786512
Prob(F-statistic)	0.000001		

Table 11 Out-of-sample forecast evaluation – forecast evaluation



Forecast: DDEF_HF
Actual: DDEF_H
Forecast sample: 2012Q4 2013Q3
Included observations: 4

Root Mean Squared Error	0.110805
Mean Absolute Error	0.103673
Mean Abs. Percent Error	25.72332
Theil Inequality Coefficient	0.156681
Bias Proportion	0.522209
Variance Proportion	0.417241
Covariance Proportion	0.060550

Evaluation results: Mean absolute percent error shows reasonable values. Theil inequality coefficient is relatively close to 0 indicating good fit. Forecasted value mean bias is present but the number of observation is low.

Table 12 Multi-collinearity evaluation – Variance Inflation Factors Analysis

Variance Inflation Factors
Date: 03/02/14 Time: 17:06
Sample: 2003Q4 2013Q3
Included observations: 28

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	0.000645	1.741933	NA
DCONS(-4)	1.155255	2.475789	1.455330
DINTS(-6)	0.222610	1.607568	1.603086
DRONIRHH(-8)	0.000462	2.758766	2.166041

*Analysis results**:** The highest VIF is 2.76**,** indicating that there are no multi-collinearity issues (Gujarati, 2004 proposes as rule of thumb a ratio of minimum 10 as indication of excessive multi-collinearity)*

Annex G Estimation of macroeconomic variables equations (ARMA)

I. CORPORATE MODELS VARIABLES

1. Real GDP Growth (*gdp_g*)

Table 1 Information Criteria (IC) values

ARMA order	Akaike	Schwarz	Hannan-Quinn
0,0	-5.233	-5.19	-5.218
0,1	-5.446	##-5.3607	##-5.415
0,2	-5.395	-5.267	-5.349
0,3	-5.422	-5.251	-5.361
0,4	-5.376	-5.163	-5.3
1,0	##-5.455	*-5.369	*-5.424
1,1	-5.403	-5.274	-5.357
1,2	n/a	n/a	n/a
1,3	n/a	n/a	n/a
1,4	n/a	n/a	n/a
2,0	-5.374	-5.243	-5.328
2,1	n/a	n/a	n/a
2,2	-5.39	-5.172	-5.313
2,3	n/a	n/a	n/a
2,4	-5.367	-5.062	-5.259
3,0	-5.338	-5.162	-5.276
3,1	-5.308	-5.088	-5.231
3,2	-5.396	-5.132	-5.304
3,3	-5.388	-5.081	-5.281
3,4	*-5.458	-5.107	-5.336
4,0	-5.303	-5.08	-5.226
4,1	-5.286	-5.019	-5.194
4,2	n/a	n/a	n/a
4,3	-5.424	-5.068	-5.301
4,4	-5.376	-4.977	-5.238

* indicates the lowest IC value
indicates the 2nd lowest IC value
Note: n/a in the IC table indicates non-invertible roots / non-stationarity issues

Table 2 Correlogram

Date: 05/10/14 Time: 19:50
Sample: 2003Q4 2014Q3
Included observations: 39

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.462	0.462	8.9666	0.003
		2	0.188	-0.031	10.501	0.005
		3	0.094	0.024	10.892	0.012
		4	-0.114	-0.206	11.485	0.022
		5	0.080	0.281	11.787	0.038
		6	0.176	0.065	13.291	0.039
		7	0.079	-0.055	13.603	0.059
		8	0.121	0.040	14.363	0.073
		9	-0.018	-0.081	14.379	0.109
		10	-0.080	0.006	14.734	0.142
		11	-0.045	-0.063	14.851	0.189
		12	-0.093	-0.037	15.358	0.222
		13	-0.069	-0.049	15.649	0.269
		14	0.067	0.148	15.937	0.317
		15	0.057	0.003	16.156	0.372
		16	0.002	-0.080	16.156	0.442

Table 3 Potential specifications and residual diagnostics results

ARMA(3,4)	no significant residual auto-correlation
AR(1)	**no significant residual auto-correlation – selected (parsimonious model and having minimum value for two IC)**
MA(1)	no significant residual auto-correlation

Table 4 Final model specification and diagnostic – AR(1)

Dependent Variable: GDP_G
Method: Least Squares
Date: 03/15/14 Time: 22:29
Sample (adjusted): 2004Q2 2013Q3
Included observations: 38 after adjustments
Convergence achieved after 3 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.007254	0.004669	1.553556	0.1290
AR(1)	0.463768	0.143697	3.227394	0.0027

R-squared	0.224407	Mean dependent var	0.007598
Adjusted R-squared	0.202862	S.D. dependent var	0.017272
S.E. of regression	0.015421	Akaike info criterion	-5.454994
Sum squared resid	0.008561	Schwarz criterion	-5.368805
Log likelihood	105.6449	Hannan-Quinn criter.	-5.424328
F-statistic	10.41607	Durbin-Watson stat	1.975310
Prob(F-statistic)	0.002663		

Inverted AR Roots .46

Date: 05/10/14 Time: 20:27
Sample: 2004Q2 2013Q3
Included observations: 38
Q-statistic probabilities adjusted for 1 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.007	0.007	0.0022	
		2	-0.091	-0.091	0.3482	0.555
		3	0.119	0.122	0.9662	0.617
		4	-0.247	-0.264	3.6832	0.298
		5	0.059	0.108	3.8411	0.428
		6	0.178	0.111	5.3530	0.374
		7	-0.085	-0.025	5.7080	0.457
		8	0.099	0.059	6.2084	0.516
		9	-0.047	-0.072	6.3221	0.611
		10	-0.110	-0.008	6.9806	0.639
		11	-0.001	-0.082	6.9806	0.727
		12	-0.070	-0.044	7.2665	0.777
		13	-0.108	-0.133	7.9782	0.787
		14	0.120	0.099	8.8898	0.781
		15	-0.031	-0.044	8.9516	0.834
		16	0.007	0.049	8.9552	0.880

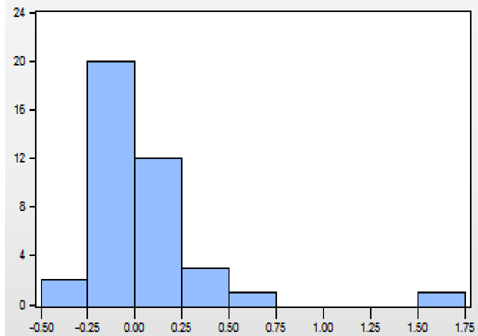
2. Consumer confidence (first difference – *dcci*)

Table 5 Correlogram

Date: 05/10/14 Time: 20:33
Sample: 2003Q4 2014Q3
Included observations: 39

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.011	0.011	0.0049	0.944
		2	-0.059	-0.059	0.1571	0.924
		3	0.133	0.135	0.9443	0.815
		4	-0.081	-0.091	1.2440	0.871
		5	-0.043	-0.023	1.3312	0.932
		6	0.094	0.069	1.7580	0.941
		7	-0.187	-0.180	3.5106	0.834
		8	-0.157	-0.142	4.7878	0.780
		9	-0.023	-0.067	4.8154	0.850
		10	-0.140	-0.111	5.8964	0.824
		11	-0.021	-0.013	5.9218	0.879
		12	0.060	0.014	6.1316	0.909
		13	-0.070	-0.039	6.4329	0.929
		14	-0.090	-0.122	6.9476	0.937
		15	0.308	0.268	13.285	0.580
		16	-0.132	-0.195	14.490	0.562

Table 6 Descriptive statistics



Series: DCCI
Sample 2003Q4 2014Q3
Observations 39

Mean	0.038441
Median	-0.018223
Maximum	1.645161
Minimum	-0.367589
Std. Dev.	0.329635
Skewness	3.162472
Kurtosis	15.74581
Jarque-Bera	328.9985
Probability	0.000000

Result: the series is a non-zero mean white noise process (the expected value is the sample mean).

3. Construction activity, nominal (log-difference – *dbuild2*)

Table 7 Information Criteria values

ARMA order	Akaike	Schwarz	Hannan-Quinn
0,0	-2.987	-2.944	-2.972
0,1	-3.195	-3.110	-3.165
0,2	-3.894	-3.766	-3.848
0,3	-3.926	-3.755	-3.865
0,4	n/a	n/a	n/a
1,0	-3.394	-3.307	-3.363
1,1	-3.515	-3.386	-3.469
1,2	-3.972	-3.800	-3.911
1,3	-4.035	-3.819	-3.958
1,4	n/a	n/a	n/a
2,0	-3.576	-3.445	-3.530
2,1	-3.533	-3.359	-3.471
2,2	-4.006	-3.789	-3.930
2,3	-3.662	-3.401	-3.570
2,4	-4.133	##-3.828	-4.025
3,0	-3.538	-3.362	-3.477
3,1	-3.812	-3.592	-3.735
3,2	##-4.136	*-3.872	*-4.044
3,3	-3.995	-3.687	-3.887
3,4	*-4.156	-3.804	##-4.033
4,0	-3.765	-3.542	-3.688
4,1	-3.779	-3.512	-3.687
4,2	-4.122	-3.811	-4.015
4,3	-4.071	-3.715	-3.948
4,4	-4.039	-3.639	-3.900

* indicates the lowest IC value
indicates the 2nd lowest IC value
Note: n/a in the IC table indicates non-invertible roots / non-stationarity issues

Table 8 Correlogram

Date: 05/10/14 Time: 20:46
Sample: 2003Q4 2014Q3
Included observations: 39

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.606	0.606	15.458	0.000
		2	0.654	0.453	33.935	0.000
		3	0.576	0.169	48.674	0.000
		4	0.270	-0.489	52.001	0.000
		5	0.430	0.276	60.680	0.000
		6	0.219	0.050	63.010	0.000
		7	0.097	-0.333	63.479	0.000
		8	0.140	-0.117	64.491	0.000
		9	-0.040	0.311	64.577	0.000
		10	-0.022	-0.064	64.603	0.000
		11	0.004	-0.163	64.604	0.000
		12	-0.156	-0.109	66.050	0.000
		13	-0.066	0.219	66.317	0.000
		14	-0.138	-0.080	67.542	0.000
		15	-0.114	0.097	68.406	0.000
		16	-0.100	-0.305	69.103	0.000

Table 9 Potential specification and residuals diagnostic results

ARMA(3,2)	significant residual auto-correlation
ARMA (2,4)	significant residual auto-correlation
ARMA(3,4)	significant residual auto-correlation
ARMA (1,3)	significant residual auto-correlation
ARMA (4,2)	**no significant residual auto-correlation –selected (lowest IC values model with no residuals correlation; other more parsimonious models don't eliminate auto-correlation)**

Table 10 Final model specification and diagnostic

Dependent Variable: DBUILD2
Method: Least Squares
Date: 03/30/14 Time: 14:41
Sample (adjusted): 2005Q1 2013Q3
Included observations: 35 after adjustments
Convergence achieved after 19 iterations
MA Backcast: 2004Q3 2004Q4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.024042	0.029168	0.824240	0.4168
AR(1)	-0.130315	0.184927	-0.704685	0.4868
AR(2)	0.336826	0.133107	2.530489	0.0173
AR(3)	0.644811	0.116526	5.533601	0.0000
AR(4)	-0.234959	0.176021	-1.334836	0.1927
MA(1)	0.684506	0.105272	6.502290	0.0000
MA(2)	0.999951	0.066794	14.97067	0.0000

R-squared	0.789553	Mean dependent var	0.031570
Adjusted R-squared	0.744457	S.D. dependent var	0.055792
S.E. of regression	0.028203	Akaike info criterion	-4.121897
Sum squared resid	0.022272	Schwarz criterion	-3.810828
Log likelihood	79.13320	Hannan-Quinn criter.	-4.014516
F-statistic	17.50837	Durbin-Watson stat	1.799288
Prob(F-statistic)	0.000000		

Inverted AR Roots	.82	.33	-.64-.67i	-.64+.67i
Inverted MA Roots	-.34+.94i	-.34-.94i		

Date: 05/10/14 Time: 21:06
Sample: 2005Q1 2013Q3
Included observations: 35
Q-statistic probabilities adjusted for 6 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.074	0.074	0.2110	
		2	-0.073	-0.079	0.4190	
		3	-0.022	-0.010	0.4386	
		4	-0.082	-0.086	0.7196	
		5	0.125	0.139	1.3964	
		6	0.186	0.156	2.9373	
		7	-0.036	-0.046	2.9957	0.083
		8	-0.190	-0.176	4.7226	0.094
		9	-0.161	-0.129	6.0086	0.111
		10	0.062	0.083	6.2072	0.184
		11	0.229	0.187	9.0458	0.107
		12	-0.192	-0.294	11.121	0.085
		13	-0.100	-0.049	11.712	0.110
		14	-0.167	-0.086	13.429	0.098
		15	0.099	0.258	14.065	0.120
		16	0.099	-0.100	14.738	0.142

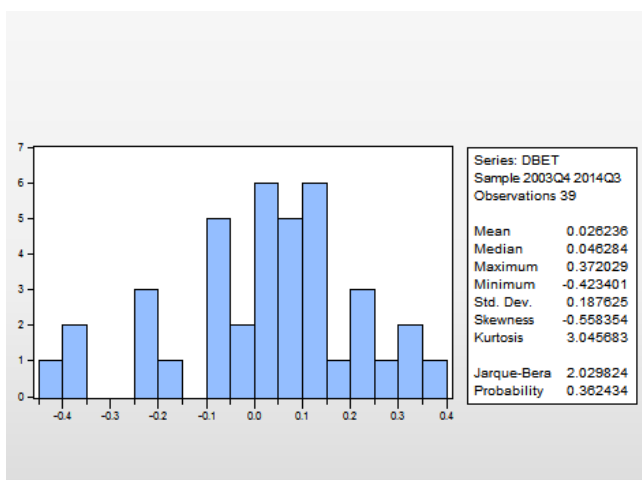
4. Domestic stock market (log-difference – *dbet*)

Table 11 Correlogram

Date: 05/10/14 Time: 23:17
Sample: 2003Q4 2014Q3
Included observations: 39

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.190	0.190	1.5260	0.217
		2	0.145	0.113	2.4404	0.295
		3	0.029	-0.018	2.4778	0.479
		4	-0.006	-0.026	2.4796	0.648
		5	-0.182	-0.187	4.0424	0.543
		6	-0.104	-0.042	4.5701	0.600
		7	0.025	0.106	4.6018	0.708
		8	-0.117	-0.123	5.3035	0.725
		9	-0.036	-0.015	5.3720	0.801
		10	-0.003	0.002	5.3724	0.865
		11	0.149	0.146	6.6357	0.828
		12	-0.118	-0.163	7.4582	0.826
		13	-0.087	-0.129	7.9287	0.848
		14	0.060	0.122	8.1607	0.881
		15	-0.035	-0.017	8.2441	0.914
		16	-0.224	-0.239	11.717	0.763

Table 12 Descriptive statistics



Result: the series is a non-zero mean white noise process (the expected value is the sample mean).

5. Interest rate for RON loans, corporate sector (first difference – *dron_irc*)

Table 13 Information criteria values

ARMA order	Akaike	Schwarz	Hannan-Quinn
0,0	3.191	3.234	3.207
0,1	2.952	3.037	2.983
0,2	2.999	3.127	3.045
0,3	2.933	3.103	2.994
0,4	n/a	n/a	n/a
1,0	2.940	3.027	2.971
1,1	2.991	3.121	3.037
1,2	3.042	3.215	3.104
1,3	2.978	3.193	3.054
1,4	3.015	3.273	3.107
2,0	3.005	3.136	3.051
2,1	## 2.837	## 3.011	## 2.898
2,2	3.021	3.239	3.098
2,3	2.961	3.223	3.053
2,4	2.996	3.301	3.104
3,0	3.068	3.244	3.129
3,1	3.082	3.302	3.158
3,2	3.116	3.380	3.208
3,3	2.960	3.268	3.067
3,4	2.877	3.229	3.000
4,0	3.077	3.299	3.153
4,1	* 2.740	* 3.006	* 2.832
4,2	3.152	3.463	3.260
4,3	3.014	3.370	3.137
4,4	3.070	3.470	3.208

* indicates the lowest IC value
indicates the 2nd lowest IC value
Note: n/a in the IC table indicates non-invertible roots / non-stationarity issues

Table 14 Correlogram

Date: 05/10/14 Time: 23:41
Sample: 2003Q4 2014Q3
Included observations: 39

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.507	0.507	10.829	0.001
		2	0.271	0.018	13.999	0.001
		3	0.243	0.133	16.619	0.001
		4	-0.017	-0.263	16.632	0.002
		5	-0.189	-0.152	18.310	0.003
		6	-0.245	-0.133	21.218	0.002
		7	-0.150	0.150	22.337	0.002
		8	-0.104	0.024	22.894	0.004
		9	-0.180	-0.157	24.627	0.003
		10	-0.191	-0.201	26.646	0.003
		11	-0.196	-0.151	28.841	0.002
		12	-0.259	-0.109	32.809	0.001
		13	-0.288	-0.078	37.900	0.000
		14	-0.243	-0.077	41.668	0.000
		15	-0.023	0.158	41.703	0.000
		16	0.158	0.158	43.447	0.000

Table 15 Potential specification and residuals diagnostic results

ARMA(4, 1)	no significant residual auto-correlation
ARMA (2,1)	**no significant residual auto-correlation –selected;** IC values are slightly higher than ARMA (4,1) but the model is selected due to parsimony considerations (residual auto-correlation maintains approx the same values as in ARMA(4,1) specification). More parsimonious increase more substantially IC values.

Table 16 Final model specification and diagnostic

Dependent Variable: DRON_IRC
Method: Least Squares
Date: 03/30/14 Time: 15:37
Sample (adjusted): 2004Q3 2013Q3
Included observations: 37 after adjustments
Failure to improve SSR after 9 iterations
MA Backcast: 2004Q2

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.240360	0.078949	-3.044511	0.0046
AR(1)	1.386124	0.140431	9.870503	0.0000
AR(2)	-0.536533	0.130396	-4.114644	0.0002
MA(1)	-0.999872	0.187117	-5.343569	0.0000

R-squared	0.420952	Mean dependent var	-0.437027
Adjusted R-squared	0.368311	S.D. dependent var	1.195087
S.E. of regression	0.949841	Akaike info criterion	2.836762
Sum squared resid	29.77254	Schwarz criterion	3.010915
Log likelihood	-48.48009	Hannan-Quinn criter.	2.898159
F-statistic	7.996703	Durbin-Watson stat	2.215000
Prob(F-statistic)	0.000384		

Inverted AR Roots	.69+.24i	.69-.24i
Inverted MA Roots	1.00	

Date: 05/11/14 Time: 00:34
Sample: 2004Q3 2013Q3
Included observations: 37
Q-statistic probabilities adjusted for 3 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.111	-0.111	0.4910	
		2	-0.116	-0.130	1.0449	
		3	0.195	0.171	2.6573	
		4	-0.028	-0.002	2.6914	0.101
		5	-0.057	-0.020	2.8381	0.242
		6	-0.173	-0.230	4.2256	0.238
		7	0.041	-0.003	4.3075	0.366
		8	0.036	0.017	4.3719	0.497
		9	-0.115	-0.031	5.0584	0.536
		10	-0.083	-0.129	5.4257	0.608
		11	-0.014	-0.093	5.4370	0.710
		12	-0.077	-0.130	5.7763	0.762
		13	-0.074	-0.069	6.1085	0.806
		14	-0.138	-0.193	7.2948	0.775
		15	0.053	-0.028	7.4758	0.825
		16	0.142	0.086	8.8519	0.784

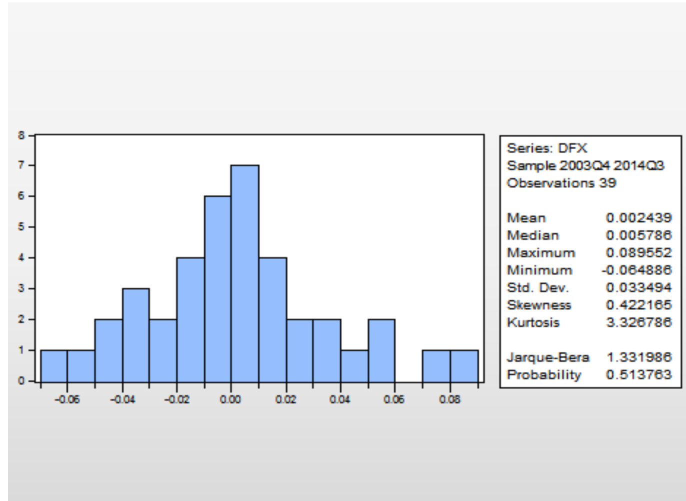
6. Exchange rate RON/EUR (log-difference – *dfx*)

Table 17 Correlogram

Date: 05/11/14 Time: 00:39
Sample: 2003Q4 2014Q3
Included observations: 39

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.171	0.171	1.2312	0.267
		2	-0.058	-0.090	1.3761	0.503
		3	-0.081	-0.057	1.6658	0.645
		4	0.096	0.120	2.0853	0.720
		5	0.224	0.186	4.4555	0.486
		6	0.005	-0.064	4.4568	0.615
		7	-0.018	0.031	4.4726	0.724
		8	-0.102	-0.092	5.0126	0.756
		9	-0.070	-0.087	5.2753	0.810
		10	0.021	0.003	5.2998	0.870
		11	-0.067	-0.087	5.5564	0.901
		12	-0.178	-0.168	7.4252	0.828
		13	0.048	0.173	7.5641	0.871
		14	-0.025	-0.075	7.6037	0.909
		15	-0.040	-0.043	7.7121	0.935
		16	-0.272	-0.218	12.849	0.684

Table 18 Descriptive statistics



Result: the series is a non-zero mean white noise process (the expected value is the sample mean).

II. HOUSEHOLD MODEL VARIABLES

1. Household consumption (log-difference – *dcons*)

Table 19 Information criteria values

ARMA order	Akaike	Schwarz	Hannan-Quinn
0,0	-4.662	-4.619	-4.647
0,1	-4.951	-4.866	-4.921
0,2	-5.613	-5.485	-5.567
0,3	-5.709	##-5.538	-5.648
0,4	-5.560	-5.347	-5.483
1,0	-5.224	-5.138	-5.194
1,1	-5.200	-5.070	-5.154
1,2	*-5.806	*-5.633	*-5.744
1,3	-5.716	-5.501	-5.640
1,4	-5.624	-5.365	-5.532
2,0	-5.224	-5.094	-5.178
2,1	-5.228	-5.054	-5.167
2,2	-5.748	-5.530	##-5.671
2,3	-5.739	-5.478	-5.647
2,4	-5.363	-5.058	-5.255
3,0	-5.275	-5.099	-5.214
3,1	-5.220	-5.000	-5.143
3,2	-5.688	-5.424	-5.595
3,3	-5.669	-5.361	-5.561
3,4	n/a	n/a	n/a
4,0	-5.266	-5.044	-5.189
4,1	-5.423	-5.156	-5.331
4,2	-5.696	-5.385	-5.588
4,3	-5.651	-5.295	-5.528
4,4	##-5.795	-5.395	-5.657

* indicates the lowest IC value
indicates the 2nd lowest IC value
Note: n/a in the IC values table indicates non-invertible roots / non-stationarity issues

Table 20 Correlogram

Date: 05/11/14 Time: 01:34
Sample: 2003Q4 2014Q3
Included observations: 39

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.627	0.627	16.538	0.000
		2	0.546	0.251	29.404	0.000
		3	0.277	-0.241	32.809	0.000
		4	0.081	-0.212	33.108	0.000
		5	0.160	0.394	34.305	0.000
		6	0.120	0.107	35.005	0.000
		7	0.177	-0.170	36.576	0.000
		8	0.086	-0.247	36.961	0.000
		9	0.076	0.258	37.266	0.000
		10	-0.067	-0.099	37.517	0.000
		11	-0.037	-0.050	37.594	0.000
		12	-0.060	-0.029	37.809	0.000
		13	-0.008	0.206	37.813	0.000
		14	0.044	-0.084	37.936	0.001
		15	-0.007	-0.167	37.939	0.001
		16	-0.029	-0.086	37.999	0.002

Table 21 Potential specification and residuals diagnostic results

ARMA(1,2)	no significant residual auto-correlation **– selected (lowest IC values, more parsimonious models increase substantially the IC values)**

Table 22 Final model specification and diagnostic

Dependent Variable: DCONS
Method: Least Squares
Date: 05/25/14 Time: 14:48
Sample (adjusted): 2004Q2 2013Q3
Included observations: 38 after adjustments
Convergence achieved after 15 iterations
MA Backcast: 2003Q4 2004Q1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.008467	0.005472	1.547288	0.1311
AR(1)	0.389856	0.156333	2.493751	0.0177
MA(1)	0.108905	0.133868	0.813525	0.4216
MA(2)	0.999946	0.044532	22.45472	0.0000

R-squared	0.712264	Mean dependent var	0.010070
Adjusted R-squared	0.686875	S.D. dependent var	0.022577
S.E. of regression	0.012634	Akaike info criterion	-5.805597
Sum squared resid	0.005427	Schwarz criterion	-5.633219
Log likelihood	114.3063	Hannan-Quinn criter.	-5.744266
F-statistic	28.05459	Durbin-Watson stat	1.854831
Prob(F-statistic)	0.000000		

Date: 05/25/14 Time: 14:49
Sample: 2004Q2 2013Q3
Included observations: 38
Q-statistic probabilities adjusted for 3 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.063	0.063	0.1617	
		2	-0.023	-0.027	0.1840	
		3	0.129	0.133	0.9035	
		4	-0.259	-0.283	3.9038	0.048
		5	0.037	0.102	3.9685	0.137
		6	0.162	0.121	5.2080	0.157
		7	-0.021	0.032	5.2287	0.265
		8	-0.060	-0.165	5.4115	0.368
		9	0.096	0.136	5.8993	0.435
		10	-0.150	-0.128	7.1187	0.417
		11	-0.080	-0.032	7.4804	0.486
		12	-0.095	-0.238	8.0047	0.534
		13	-0.048	0.145	8.1443	0.615
		14	0.049	-0.041	8.2947	0.687
		15	-0.095	-0.104	8.8949	0.712
		16	0.037	-0.019	8.9874	0.774

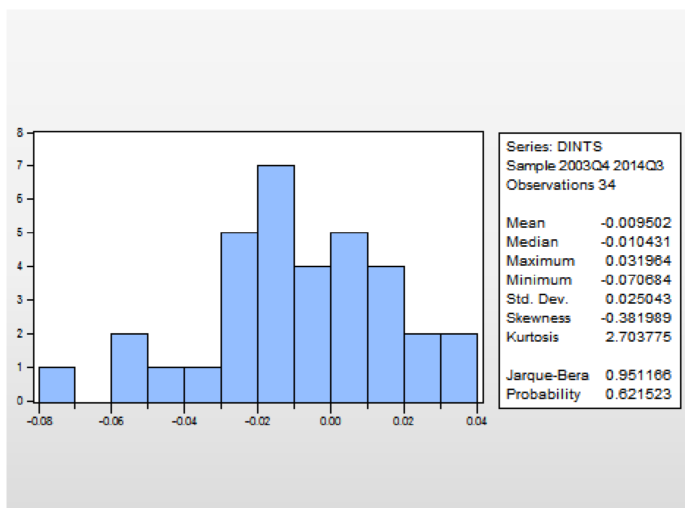
2. Interest payments service (first difference – *dints*)

Table 23 Correlogram

Date: 05/11/14 Time: 02:03
Sample: 2003Q4 2014Q3
Included observations: 34

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.125	-0.125	0.5822	0.445
		2	0.160	0.147	1.5612	0.458
		3	-0.039	-0.004	1.6225	0.654
		4	0.027	-0.001	1.6533	0.799
		5	-0.058	-0.051	1.7977	0.876
		6	-0.053	-0.071	1.9202	0.927
		7	0.104	0.113	2.4144	0.933
		8	-0.301	-0.277	6.6802	0.571
		9	-0.019	-0.117	6.6980	0.669
		10	-0.200	-0.146	8.7481	0.556
		11	0.187	0.176	10.606	0.477
		12	-0.188	-0.115	12.571	0.401
		13	0.166	0.077	14.175	0.362
		14	-0.067	-0.064	14.446	0.417
		15	-0.059	-0.075	14.672	0.475
		16	-0.004	-0.075	14.673	0.549

Table 24 Descriptive statistics



Result: the series is a non-zero mean white noise process (the expected value is the sample mean).

3. Interest rate for RON loans, household sector (log-difference – *dronirhh*)

Table 25 Information criteria values

ARMA order	Akaike	Schwarz	Hannan-Quinn
0,0	2.527	2.570	2.543
0,1	1.800	1.885	1.830
0,2	1.836	1.963	1.881
0,3	1.629	1.800	1.690
0,4	1.477	1.690	1.553
1,0	1.628	1.715	1.659
1,1	1.667	1.796	1.713
1,2	1.713	1.886	1.775
1,3	1.525	1.740	1.601
1,4	1.564	1.822	1.656
2,0	1.660	1.790	1.706
2,1	1.622	1.796	1.683
2,2	1.314	1.532	1.391
2,3	1.434	1.696	1.527
2,4	1.488	1.793	1.596
3,0	1.693	1.869	1.754
3,1	1.642	1.862	1.719
3,2	1.349	1.613	1.441
3,3	1.580	1.888	1.687
3,4	1.322	1.674	1.445
4,0	1.612	1.834	1.688
4,1	1.060	1.327	1.152
4,2	1.050	1.361	1.157
4,3	## 0.933	## 1.289	## 1.056
4,4	* 0.884	* 1.284	* 1.022

* indicates the lowest IC value
indicates the 2nd lowest IC value
Note: n/a in the IC values table indicates non-invertible roots / non-stationarity issues

Table 26 Correlogram

Date: 05/11/14 Time: 02:20
Sample: 2003Q4 2014Q3
Included observations: 39

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.749	0.749	23.578	0.000
		2	0.552	-0.019	36.745	0.000
		3	0.407	0.001	44.120	0.000
		4	0.155	-0.332	45.218	0.000
		5	0.002	0.005	45.218	0.000
		6	-0.122	-0.104	45.936	0.000
		7	-0.177	0.109	47.494	0.000
		8	-0.180	-0.026	49.161	0.000
		9	-0.202	-0.068	51.333	0.000
		10	-0.256	-0.239	54.948	0.000
		11	-0.227	0.094	57.898	0.000
		12	-0.232	-0.113	61.089	0.000
		13	-0.321	-0.189	67.443	0.000
		14	-0.273	0.078	72.194	0.000
		15	-0.172	0.163	74.160	0.000
		16	-0.073	0.102	74.532	0.000

Table 27 Potential specification and residuals diagnostic results

ARMA(4,4)	significant residual auto-correlations
ARMA(4,3)	significant residual auto-correlations
ARMA(4,2)	significant residual auto-correlations
ARMA(4,1)	significant residual auto-correlations
ARMA (2,2)	significant residual auto-correlations
ARMA (3,2)	significant residual auto-correlations
ARMA (3,4)	significant residual auto-correlations
ARMA (2,3)	significant residual auto-correlations
MA (4)	no significant residual auto-correlations
ARMA (2,4)	residual auto-correlations near significance limit at some lags
ARMA (1,3)	**no significant residual auto-correlations – selected;** low IC value, slightly higher than MA(4) but preferred for parsimony (less MA terms); lower IC values than AR(1) specification for 2 out of the 3 criteria;
AR (1)	no significant residual auto-correlations

Table 28 Final model specification and diagnostic

Dependent Variable: DRONIRHH
Method: Least Squares
Date: 05/04/14 Time: 23:44
Sample (adjusted): 2004Q2 2013Q3
Included observations: 38 after adjustments
Convergence achieved after 16 iterations
MA Backcast: 2003Q3 2004Q1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.537242	0.376200	-1.428075	0.1627
AR(1)	0.506127	0.162120	3.121918	0.0037
MA(1)	0.248388	0.078366	3.169599	0.0033
MA(2)	0.229835	0.073863	3.111646	0.0038
MA(3)	0.874573	0.068450	12.77677	0.0000

R-squared	0.691113	Mean dependent var	-0.431842
Adjusted R-squared	0.653672	S.D. dependent var	0.829024
S.E. of regression	0.487877	Akaike info criterion	1.524573
Sum squared resid	7.854796	Schwarz criterion	1.740045
Log likelihood	-23.96689	Hannan-Quinn criter.	1.601236
F-statistic	18.45882	Durbin-Watson stat	1.781928
Prob(F-statistic)	0.000000		

Inverted AR Roots	.51		
Inverted MA Roots	.36+.89i	.36-.89i	-.96

Date: 05/11/14 Time: 02:34
Sample: 2004Q2 2013Q3
Included observations: 38
Q-statistic probabilities adjusted for 4 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.080	0.080	0.2601	
		2	-0.074	-0.081	0.4927	
		3	-0.111	-0.099	1.0248	
		4	0.136	0.151	1.8544	
		5	0.156	0.122	2.9761	0.085
		6	-0.077	-0.099	3.2608	0.196
		7	0.026	0.092	3.2940	0.348
		8	-0.037	-0.048	3.3644	0.499
		9	-0.018	-0.070	3.3814	0.641
		10	-0.196	-0.188	5.4639	0.486
		11	0.059	0.101	5.6583	0.580
		12	0.055	-0.001	5.8344	0.666
		13	-0.097	-0.121	6.4035	0.699
		14	-0.201	-0.123	8.9659	0.535
		15	-0.054	0.018	9.1572	0.607
		16	0.000	-0.116	9.1572	0.689