BANCA D'ITALIA
EUROSISTEMA

Questioni di Economia e Finanza

(Occasional Papers)

Assessing financial stability risks arising from the real estate market in Italy

by Federica Ciocchetta, Wanda Cornacchia, Roberto Felici and Michele Loberto

March 2016

Number 323

BANCA D'ITALIA
EUROSISTEMA

Questioni di Economia e Finanza

(Occasional papers)

Assessing financial stability risks arising from the real estate market in Italy

by Federica Ciocchetta, Wanda Cornacchia, Roberto Felici and Michele Loberto

Number 323 – March 2016

The series Occasional Papers *presents studies and documents on issues pertaining to the institutional tasks of the Bank of Italy and the Eurosystem. The* Occasional Papers *appear alongside the* Working Papers *series which are specifically aimed at providing original contributions to economic research.*

The Occasional Papers *include studies conducted within the Bank of Italy, sometimes in cooperation with the Eurosystem or other institutions. The views expressed in the studies are those of the authors and do not involve the responsibility of the institutions to which they belong.*

The series is available online at www.bancaditalia.it .

ISSN 1972-6627 (print)
ISSN 1972-6643 (online)

Printed by the Printing and Publishing Division of the Bank of Italy

ASSESSING FINANCIAL STABILITY RISKS ARISING FROM THE REAL ESTATE MARKET IN ITALY

by Federica Ciocchetta*, Wanda Cornacchia[+], Roberto Felici[+] and Michele Loberto[x]

Abstract

We provide an analytical framework for assessing financial stability risks arising from the real estate sector in Italy. This framework consists of two blocks: three complementary early warning models (EWMs) and a broad set of indicators related to the real estate market, to credit and to households. We focus separately on households and on firms engaged in construction, management and investment services in the real estate sector. Since in Italy there have been no real estate-related systemic banking crises, as vulnerability indicator we consider a continuous indicator represented by the ratio between the annual flow of bad debts related to the real estate sector and banks' capital and reserves.

We contribute to the recent literature on EWMs by implementing a Bayesian Model Averaging (BMA) based on linear regression models with a continuous dependent variable of vulnerability and an ordered logit model with a discrete dependent variable of vulnerability classes. Both models exhibit good predictive abilities. Based on the BMA projections for the period from the third quarter of 2015 to the second quarter of 2016, banking vulnerability related to the real estate sector is expected to gradually decline.

JEL Classification: C35, C52, E44, E58, G21, G28.
Keywords: real estate markets, early warning models, bayesian model averaging, banking crises, macroprudential policy.

Contents

* Bank of Italy, Regulations and Macroprudential Analysis Directorate, [+] Bank of Italy, Financial Stability Directorate, [x] Bank of Italy, Economic Outlook and Monetary Policy Directorate.

1. Introduction

Systemic risks stemming from overheating real estate markets have contributed significantly to financial instability both in the past, as for example in Denmark, Sweden and the United Kingdom in the early '90s, and in the recent financial crisis. Financial and economic busts preceded by an excessive real estate boom are particularly harmful from a financial stability perspective since they are longer and costlier than the average downturn (Claessens et al., 2008). Operationalizing macroprudential instruments aimed at real estate markets is a key issue for European authorities. Some practical country experience on addressing systemic concerns arising from the real estate sector is already available, including in EU member states (Ciani, Cornacchia and Garofalo, 2014).

Macroprudential policy strategies involve linking the ultimate objectives of macroprudential policy to instruments and indicators. Instruments such as risk weights for real estate exposures, limits to loan-to-value (LTV) and debt service-to-income (DSTI) ratios are considered important macroprudential tools for targeting real estate risks.

Their effectiveness, however, depends on their timeliness. Macroprudential measures seem to be more effective when they are timely[1], based on early warnings from monitoring appropriate indicators. The operationalization of real estate macroprudential tools therefore requires the identifying of sound leading indicators (and associated thresholds) signalling excesses in the real estate sector well in advance.

This work lays out an analytical framework to support the decisions that the Bank of Italy may take in the future on the use of macroprudential instruments to address financial stability risks arising from the real estate sector. It focuses primarily on risk assessment, by implementing different analytical tools to identify the build-up of system-wide risks that may warrant macroprudential action.

First of all, since Italy has not experienced any real estate-related systemic banking crises, we measure the systemic vulnerabilities stemming from the real estate sector through a continuous indicator based on the ratio of the annual flow of new bad debts related to the real estate sector and banks' capital and reserves. We focus separately on households on one side and business firms engaged in construction, management and investment services in real estate on the other, because of the different magnitude of the risks the two sectors pose to financial stability. In Italy, home ownership is widespread, households are leveraged at low levels and mortgage loans, which are full recourse[2], present a relatively low loan-to-value at origination compared with other countries. Business firms engaged in real estate activities, on the contrary, are typically more highly leveraged than in other sectors because they can offer properties as collateral.

With regard to the risk assessment framework, the work presents three complementary early warning models (EWMs) that can provide some guidance to the policymaker in the operationalization of macroprudential instruments for the real estate sector. As it is standard in the EWM literature and a widespread practice across European authorities, we implement a classic binary logit model (crisis vs. non crisis). However, since in Italy there have not been any identified real estate-related systemic banking crisis, we go beyond this approach. Therefore, we contribute to the recent literature on EWMs by implementing a Bayesian Model Averaging (BMA) based on linear regression models with a continuous dependent variable of vulnerability and an ordered logit model with a discrete dependent variable of vulnerability classes. This choice is mainly motivated

[11] See for example the Special Feature "A recent experience of European countries with macroprudential policy" in ECB Financial Stability Review, May 2014.

[2] As in other countries in continental Europe, borrowers in Italy must repay their debt in full, regardless of any change in the value of the property, and a creditor can in some cases attach other (present and future) assets of the debtor. See IMF Country Report (2013).

by the possibility to overcome the typical binary assumption (crisis/no crisis) and therefore to describe different levels of financial stress explicitly. In this respect, the BMA is preferable because there is no need to discretize the vulnerability indicators and no information is lost due to this procedure. At the same time, the two approaches are complementary and this explains why we use both of them: while the BMA provides point estimates and confidence intervals for the evolution of our vulnerability indicators, the ordered logit returns a probability distribution over different levels of financial stress.

The early warning models presented in this work are to be considered as complementary to the structural model of Nobili and Zollino (2012), which assesses the multiple interactions between housing and banking in Italy using a system of simultaneous equations. While structural models are suitable for assessing how exogenous drivers, such as an increase in interest rates or disposable income, can be transmitted to house prices and loans to firms and households (and therefore if there are imbalances in the housing market), the focus of EWM models is to anticipate potential vulnerabilities for the financial system related to the real estate sector.

According to BMA linear regression models, the best set of early warning indicators for banking vulnerability related to households comprises the household credit-to-GDP ratio, the value added of construction-to-GDP ratio, the gap of the number of house sales with respect to its long-term trend, the growth rate of nominal residential prices and the growth rate of the number of house sales. For construction and real estate firms, the best-performing set includes the long-term government bond yields, the gap of the value added of construction to GDP ratio with respect to its long-term trend, the price-to-income ratio, the growth rate of credit granted to construction and real estate firms and the growth rate of the number of house sales. Roughly the same set of variables is also selected by the ordered logit exercise.

Both the BMA linear regression and the ordered logit models exhibit good predictive abilities; they can jointly help to identify in advance financial stability risks arising from the real estate sector. In particular, the BMA linear regression models are capable of accurate predictions up to two years in advance. These models thus provide a useful analytical framework for supporting Bank of Italy's decisions on the possible use of macroprudential instruments to address such risks.

According to the projections of the Bayesian models from the third quarter of 2015 to the second quarter of 2016, banking vulnerability related to the real estate sector, though remaining at relatively high levels, should gradually decline. These results are consistent with the judgment that there currently is no need to activate macroprudential tools in order to counter risks arising from the real estate sector.

Besides implementing EWM models, this work gathers a broad set of indicators related to the real estate market, to credit and to households' financial situation, in order to periodically monitor and assess the financial stability risks related to the real estate sector. Some indicators are already used in the Bank of Italy's Financial Stability Report as well as in regular internal analyses of housing cycles, while several are new. The main insights provided by these indicators are, among others, that: i) the share of Italian municipalities recording a decline in house prices compared to the previous period decreased; ii) the riskiness of more recent borrowers is far below that of the borrowers that took out a loan before 2009.

The remainder of the work is organized as follows. Section 2 illustrates the nexus between the real estate market and financial stability in Italy. Section 3 discusses the evolution of EWM literature and how our approach is related to this literature. Section 4 describes the dataset used in our work. Section 5 presents the methodologies, the results of all the three EWM models implemented and the out-of-sample forecasting exercise. Section 6 illustrates a broad set of real estate-related indicators for monitoring financial stability risks in Italy. Finally, section 7 highlights the main conclusions of the work.

2. The real estate market and financial stability in Italy

The real estate sector plays a central role in the Italian economy, due to the contribution that it makes to production[3], the preponderance of real estate assets in households' wealth[4], and the links with the financial system. In particular, a significant share of bank lending is directed to this sector: in June 2015, 35% of total bank loans were granted to households for house purchase, to construction firms and real estate agencies (Figure 2.13 in Annex C).[5]

Direct effects on financial stability derive from the fact that real estate investments have very long time horizons and are usually financed by banks through collateralized loans; the collateral is generally represented by the same property that is financed. The real estate cycle is usually positively correlated with the credit cycle: a rise in real estate prices leads to an increase in the value of collateral, thereby improving access to credit and investment ability. Banks are willing to grant credit because the presence of collateral implies a more favourable treatment in terms of regulatory risk weights compared to uncollateralized loans. A real estate price decline, on the contrary, implies a fall in the value of collateral, thus reducing borrowing capacity. Moreover, as the profitability of several investments is reduced, the number of defaults increases, with negative consequences for banks in terms of non-performing loans.

The real estate sector also indirectly affects financial stability, through its impact on economic activity. Changes in property values affect gross fixed investments both in the construction industry, as they alter the industry's profitability, and in the rest of the economy, as the variations in the collateral value of real estate properties imply a tightening or an easing of firms' borrowing constraints. Moreover, changes in house prices can also influence home-owners' consumption via a wealth effect, especially if these changes are perceived by households as permanent.[6]

Although Italy has never experienced a real estate-related systemic banking crisis, real estate weakness during the mid-nineties and the great recession made a heavy impact on banks' balance sheets. According to Baldinelli, Gangeri and Leandri (1998), the sharp contraction in real estate prices in the years 1993-97 implied for the banking system a marked deterioration of credit quality, and a reduction in the value of both collaterals and owned properties. It led to a € 9 billion loss, mainly connected to exposures towards non-financial firms.

More recent difficulties in the real estate market, which began before the financial crisis, resulted in a sharp contraction in volumes (production, investment and transactions), while the effects on prices were weaker. Credit quality deteriorated sharply, although with significant differences between households and the real estate business sector. For households, credit deterioration was limited, also thanks to the selective policies adopted by credit institutions before the outbreak of the crisis (Gobbi and Zollino, 2013) and to the measures implemented afterwards in order to support households which had difficulties in meeting the debt service (such as for instance the debt moratoria, see Magri and Pico, 2012). Instead, loans to construction firms and real estate agencies experienced a

---

[3] In Italy the supply chain of the real estate sector, as the set of industrial activities and services connected with the construction industry, accounted for over one fifth of GDP in 2012 (see Fabrizi et al., 2015). Moreover, construction is one of the most important sectors in sustaining domestic activity, both for the variety of inputs involved in the production and the limited share of those purchased abroad.

[4] According to Istat (2015) data on non-financial assets by institutional sector, in 2013 residential and commercial properties accounted for about 88% of real assets in Italy (about 95% considering only the household sector).

[5] Loans to households for house purchase, to construction firms and real estate agencies constitute by far the largest part of banks direct exposures to real estate, representing around 17% of their total assets (Figure 2.5 in Annex C). The incidence of other direct exposures related to real estate (i.e. properties held by banks, bonds/securities issued by constructions firms and real estate agencies, mortgage backed securities) is below 1%.

[6] Bassanetti and Zollino (2008) find a long-run marginal propensity to consume of 2 cents out of each Euro increase in housing wealth for Italian households.

severe worsening in quality: from December 2007 to June 2015 the outstanding amount of non-performing loans increased by around € 90 billion and total loans decreased. The main factors behind this evolution were the drastic fall in property sales and the growing accumulation of unsold properties. The consequent fall in revenues reduced the ability of firms to repay the high debt they had contracted before the beginning of the economic recession (Bonaccorsi di Patti et al., 2014).

To sum up, in Italy bank vulnerabilities related to real estate market downturns mostly originated from the real estate business sector, characterized by high debt, and to a much lesser extent from the household sector, whose indebtedness level is limited, also compared with other countries.

3. Related literature on early warning models

The literature on Early Warning Models (EWMs) for the occurrence of crises has a long tradition (e.g., Eichengreen and Rose, 1998). The first studies concerned currency crises in emerging economies (e.g., Frankel and Rose, 1996) whereas more recent work has focused on identifying and possibly preventing banking crises (e.g., Betz et al., 2013; Alessi et al., 2014).

In this research field, it is common to express crisis events with a binary dummy variable, which assumes the value 1 if a crisis has occurred, 0 otherwise. From a methodological point of view, in the case of a binary representation of crises, EWMs are classified into three different categories:

1) (univariate and multivariate) signalling approach: the behaviour of leading indicators is analysed and a signal is issued whenever one or more indicators exceed their respective thresholds (e.g., Borio and Drehmann, 2009; Drehmann et al., 2010, 2011; Alessi and Detken, 2011; Drehmann and Juselius, 2013).
2) discrete choice (logit) regression models: the probability that a crisis occurs is described in terms of a set of explanatory variables. Instead of obtaining thresholds for each individual indicator, the discrete choice approach maps a number of indicators into a single metric, which expresses the predicted probability of a crisis occurring within a given time horizon (e.g., Babecky et al., 2012; Behn et al., 2013).
3) binary decision trees and random forest algorithms: a decision tree is a partitioning algorithm which recursively identifies the indicators and the respective thresholds able to best split the data into the relevant classes (crisis and tranquil periods). The output of the model is a tree structure in which each internal node represents a test on a relevant variable, the branches are the possible outcome of the test and each terminal node (leaf) represents a class label. Random forests are defined as an aggregation of decision trees (Alessi et al., 2014).

The main concerns about the implementation of these models are the definition of systemic crisis events and data availability. In the case of banking and currency crises, extensive work has been carried out in order to create databases of crisis events and related indicators (e.g., Babecky et al., 2012). Furthermore, crisis events are rare and modelling and forecasting them is challenging.

Applications of early warning models to banking crises related to developments in the real estate sector are relatively scarce and mainly focus on identifying the determinants of booms and busts in asset and/or real estate prices.[7] The first steps in this area have been undertaken under the aegis of

[7] In the literature, some indicators (mainly related to house prices) have been considered for defining limits on loan-to-value and loan-to-income ratios in order to prevent a credit boom from fuelling an asset price bubble (see e.g. Barrell et al. (2010), Borio and Drehmann (2009). Furthermore, potential early warning indicators for boom/busts, including interest rates and credit variables, have been analysed (e.g., Agnello and Schuknecht, 2011; Alessi and Detken, 2011; Borgy et al., 2011; Gerdesmeier et al., 2012). These papers confirm an evident and strong connection between credit and housing market cycles. Since 2008 the International Monetary Fund (IMF) and the Financial Stability Board (FSB)

the ESRB Instruments Working Group for the preparation of the ESRB Handbook on Operationalising Macroprudential Policy in the Banking Sector. Chapter 3 of the ESRB Handbook provides operational guidance on implementing real estate instruments for macroprudential purposes and presents a graphical analysis of potential early warning indicators for the build-up of vulnerabilities in the real estate sector.

Ferrari, Pirovano and Cornacchia (2015) build on the ESRB Handbook by adding a formal statistical evaluation approach. Performing indicators and models are estimated on a pooled set of 25 EU countries through both a non-parametric and a discrete choice (logit) approach.

Given that financial cycles and real estate markets are likely to be heterogeneous across countries, performing indicators and models estimated on pooled data are not necessarily well suited for individual countries. Ferrari, Pirovano and Cornacchia (2015) carry out a country level evaluation for both the best trivariate non-parametric combination of indicators and the best logit model. For Italy, however, this kind of analysis cannot be performed since no true positive rate (i.e. the share of correctly identified crisis episodes) can be calculated. Actually, according to the ESRB dataset on real estate banking crises[8], Italy has not experienced any real estate-related systemic banking crises and is considered among the non-crisis countries[9]. The classic binary models are also not appropriate for several other non-crisis countries.

Some alternative approaches to overcoming the problems related to a discrete representation of crises were implemented.. Some authors proposed multinomial models (Bussiere and Fratzscher, 2006), which generalize the discrete choice from two (yes/no) to more states (crisis, post-crisis, and tranquil periods). Recently, the literature has also been extended with the use of continuous indicators that allow the model to explain the actual scale of real costs or nominal movements (Rose and Spiegel 2011, Frankel and Saravelos 2012, Babeckey et al. 2012b).

Finally, another research stream is about ensemble methods (combinations of different models) and BMA models, which have been applied in order to account for the uncertainty about the correct set of variables that should be included in an EWM (Fernandez et al., 2001b). In Holopainen et al. 2015, the authors proposed various ensemble approaches to aggregate the information of different classes of EWMs (with a binary variable for crisis events), providing a robust measure for country-level vulnerabilities. A BMA approach was used in Babecky et al. (2012) to identify the most useful early warning indicators for currency, banking and debt crises from a list of 30 macroeconomic and financial potential variables. In this work the BMA was based on linear regression models where the dependent variable is a standard dummy variable for crisis and non-crisis events.

---

have been collaborating on regular Early Warning Exercises (EWEs); real estate vulnerabilities are summarized by an index that comprises estimates of price misalignment, potential impact on economic activity, household balance sheets, and mortgage market characteristics.

[8] The dataset builds on the ESCB Heads of Research (HoR) Group's banking crises database which defines a banking crisis by significant signs of financial distress in the banking system as evidenced by bank runs in relevant institutions or losses in the banking system (non-performing loans above 20% or bank closures of at least 20% of banking system assets), or significant public intervention in response to or with the aim of avoiding the realization of losses in the banking system. The HoR database has been narrowed down by the ESRB Expert Group on Countercyclical Capital Buffers (CCB) by (1) excluding crises that were not systemic, (2) excluding systemic banking crises that were not associated with a domestic credit/financial cycle, and (3) adding periods where domestic developments related to the credit/financial cycle could well have caused a systemic banking crisis had it not been for policy action or an external event that dampened the financial cycle. The resulting CCB database has finally been further adjusted on the basis of the ESRB IWG work stream members' judgments, in order to reflect only systemic banking crises stemming from the real estate sector.

[9] However, Baldinelli, Gangeri and Leandri (1998) offer a detailed analysis of the impact of the real estate crisis of the mid-90s on banks' balance sheets.

4. Data description

The statistical evaluation of potential early warning indicators for real estate-related banking crises requires two types of variables: a variable that identifies the banking crises stemming from excessive developments in real estate markets (left-hand-side variable) and one or more economic variables that signal the build-up of risks preceding the crises (early warning indicators).

Since Italy has not experienced any real estate-related systemic banking crises, the first step is to define an appropriate left-hand side variable. In order to identify systemic banking vulnerabilities stemming from the real estate sector we therefore construct the following ratio:

$$\frac{annual\ flow\ of\ new\ bad\ debts}{banks'capital\ and\ reserves^{10}}$$

We believe that this indicator, used for the first time, is able to measure the systemic vulnerability of the banking system better than the new bad debts rate[11] because it takes into account not only the evolution of real estate exposures' riskiness but also their impact on banks' balance sheets. Indeed one of the primary objectives of macroprudential policy must be to increase banks' resilience[12], which contributes to the reduction of systemic risk in the financial system.

The ratio is available since 1990Q1 for households[13] (i.e. the residential real estate sector, RRE) and constructions and real estate agencies (C&RE). In the ordered logit exercise we use the indicator to identify four classes of vulnerability according to the quartiles of its distribution: 1st quartile = class 1 (no vulnerability); 2nd quartile = class 2 (low vulnerability); 3rd quartile = class 3 (medium vulnerability); and 4th quartile = class 4 (high vulnerability).

According to Figure 1, households' systemic banking vulnerability indicator reached the highest levels in 1994, 1995Q4-1996Q1 and since 2010Q1 has been hovering around 1.8% (panels a and b). With regard to construction firms and real estate agencies, banking vulnerability recorded its highest levels in the period 1994Q1-1998Q2 and nowadays: in 2014Q3 the indicator stood at 5.7%.

[10] We use the aggregate of ECB MFI balance sheet statistics, including: (i) equity capital; (ii) non-distributed benefits or funds.

[11] Flows of adjusted bad debts in relation to the stock of loans at the end of the previous period, net of adjusted bad debts.

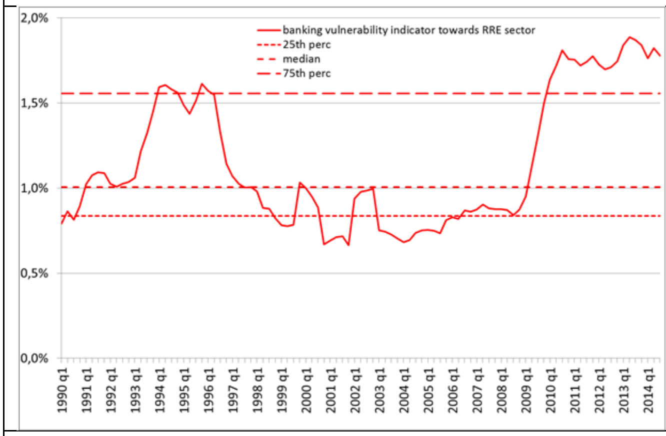
[12] The ultimate objective of macroprudential policy is to contribute to safeguarding the stability of the financial system as a whole, including by strengthening the resilience of the financial system and decreasing the build-up of systemic risks, thereby ensuring a sustainable contribution of the financial sector to economic growth (ESRB Recommendation of 4 April 2013 on intermediate objectives and instruments of macroprudential policy).

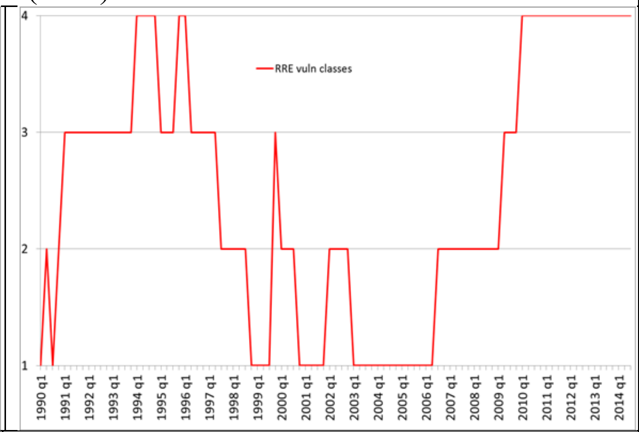
[13] The flows of new bad debts, coming from the Credit Register, refer to the total loans to households, which can be deemed as an approximation for loans to households for house purchases considering that: i) flows do not include borrowers whose total exposure toward a single lender is below 30,000 euros (75,000 euros before 2009); ii) financial institutions whose majority of loans is constituted by consumer credit are exempted from reporting to CR; iii) the majority of loans to households is represented by loans for house purchase (over 60% in December 2013). Caution in interpreting the outcome of the estimation is still needed, particularly when considering the variability in the incidence of bad debts across mortgages and consumer credit loans.

Figure 1 - Systemic banking vulnerability indicator

(a) *ratio of new bad debts to capital and reserves* *(quarterly data; per cent)*	(b) *Systemic banking vulnerability classes* *(quarterly data)*

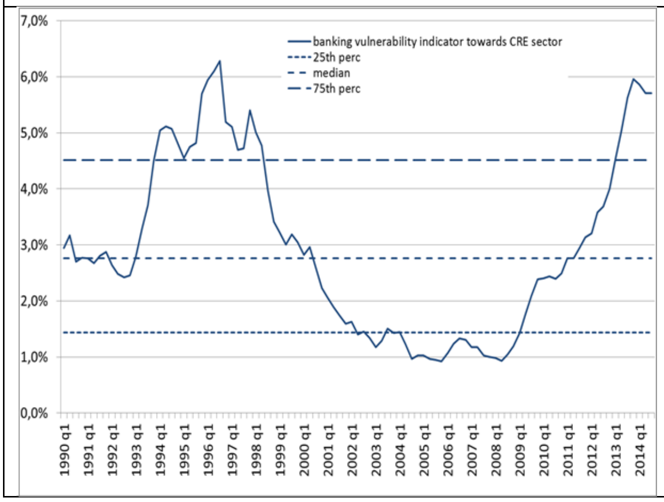
Households (RRE)

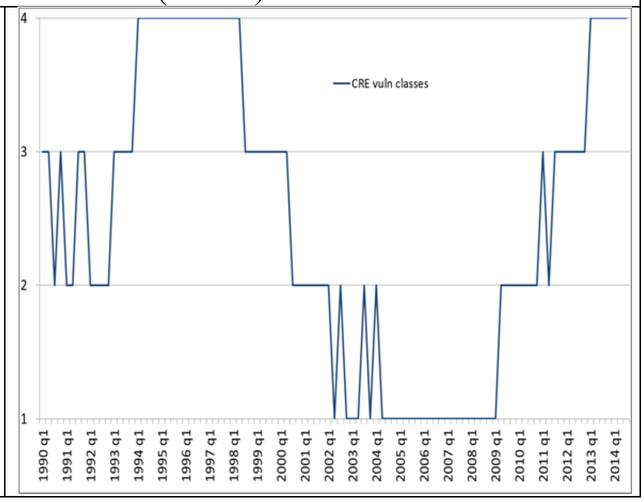




(a) *ratio of new bad debts to capital and reserves* *(quarterly data; per cent)*	(b) *Systemic banking vulnerability classes* *(quarterly data)*

Construction and real estate firms (C&RE)





Sources: elaborations based on Supervisory Reports and Central Credit Register data.

As can be seen from Figure 2, risks for banking stability come mainly from loans to construction and real estate firms, while mortgage loans to households seem to pose relatively fewer risks to banks: the median level of the indicator for firms (2.8%) was well above the historical peak (1.9%) reached by the indicator for households. Moreover, among bank loans to households, loans for house purchase are characterized by a lower incidence of bad debts on outstanding bank loans compared to consumer credit loans (Figure 2.9 in Annex C). On the contrary, the riskiness of loans to construction firms and real estate agencies (measured by the ratio of the annual flow of new bad debts to performing loans) is well above the level for those to other companies (Figure 2.8 in Annex C). Indeed, before the crisis mortgage loans were granted mainly to financially solid households (Gobbi and Zollino, 2013); therefore, the impact of the economic crisis on the riskiness of loans to households was small. With regard to construction and real estate firms the vulnerability is mainly due to the level of indebtedness, which was very high even before the crisis (see Section 2).

Historically banking vulnerability indicators for households and for construction and real estate firms started to rise almost simultaneously, but that of firms reached its peak several quarters after that of households (Figure 2). In addition, firms' vulnerability exhibit higher volatility. Figure 3 shows the correlation between the households' and the construction and real estate firms' systemic vulnerability indicator, time-shifted from one to twelve quarters[14]: correlation coefficients are generally high and increase from $C\&RE_t$ to $C\&RE_{t+8}$ (83%), indicating that the evolution of banking vulnerabilities related to construction and real estate firms has a similar trend to that for households with a lag of around 2 years.

Figure 2 – Households' (RRE) and construction and real estate firms' (C&RE) systemic banking vulnerability indicator
(quarterly data; per cent)

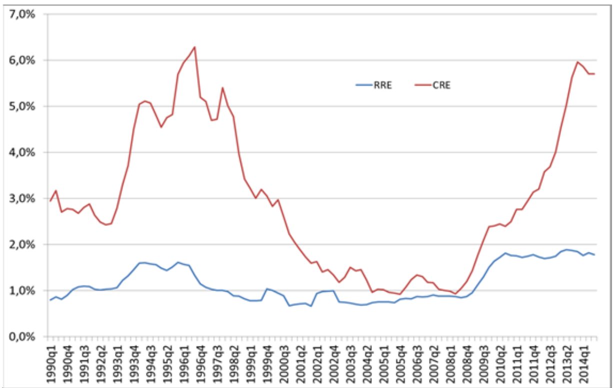
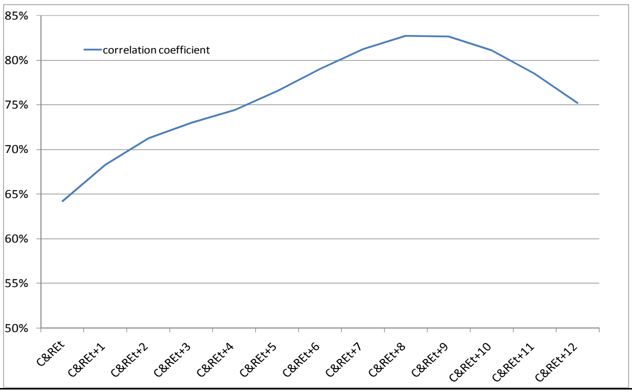


Figure 3 – Correlation between households' (RRE) and construction and real estate firms' (C&RE) systemic banking vulnerability indicator
(per cent)



Sources: elaborations based on Supervisory Reports and Central Credit Register data.

As for the data on potential early warning indicators, i.e. economic variables that can provide information on the build-up of risks in the run-up to a crisis, the following variables have been analysed: i) residential real estate prices, ii) price-to-income ratio, iii) price-to-rent ratio, iv) credit to the RRE and C&RE sectors, v) debt service-to-income ratio, vi) value added in the construction sector-to-GDP ratio, vii) residential transactions, viii) long-term government bond yields and ix) some macroeconomic variables (real GDP, disposable income and so on). Both levels, annual growth rates and deviations from the long-term trends ("gaps")[15] have been considered (see Table 1).

Apart from the 'value added in the construction sector-to-GDP ratio' and 'credit to C&RE sector', all the other potential early warning indicators refer to households.

Finally, since many variables represent similar concepts, the dataset is characterized by a high correlation between variables. In particular, Table A.1 in Annex A shows that pairwise correlations over the period 1987Q1-2014Q2 can sometimes be higher than 80%. These correlations will be accounted for in the variable selection procedures.

[14] The correlation between RRE and $C\&RE_{t+4}$ is calculated between the RRE data from 1990q1 to 2013q3 and C&RE data from 1991q1 and 2014q3.
[15] The long-term trend has been calculated with a one-sided Hodrick-Prescott filter with lambda equal to 400,000.

Table 1

Overview of potential early warning indicators

Cyclical price variables	Cyclical credit variables
RRE price growth (nominal, real) RRE price gap (nominal, real) RRE price to rent growth RRE price to rent gap RRE price to income growth RRE price to income gap	RRE credit growth C&RE credit growth RRE credit to GDP gap C&RE credit to GDP gap
Structural price variables	**Structural credit variables**
RRE price to rent (level) RRE price to income (level)	RRE credit to GDP (level) C&RE credit to GDP (level) debt service ratio (level)
Other variables	
Value added construction to GDP (current, chain-linked) Value added construction to GDP gap (current, chain-linked) Long term gov't. bond yield	Residential transactions (level) Residential transactions growth Residential transactions gap Real GDP Industrial production Disposable income (growth) Output gap

5. Risk assessment framework: early warning models for Italy

In this work three complementary types of early warning models have been considered.

The first is a Bayesian Model Averaging (BMA) based on linear regression models. This choice is motivated by several reasons:

1) BMA is a widely-used technique that can be used both for the selection of the most relevant variables and model estimation;
2) It takes into account model uncertainty by considering combinations of models and thus has the advantage of minimizing subjective judgment in determining the optimal set of early warning indicators;
3) The choice of linear regression models allows us to have our vulnerability indicator as a continuous left-hand-side variable and therefore to extract all the information available from the data.

The other two models are a binary logit and an ordered logit model. In the binary logit the crisis event is defined as the case in which the vulnerability indicator is above the median value of its historical time series. The most relevant variables selected by the binary logit models are also used in the ordered logit exercise, where four classes of vulnerability are considered in order to take into account different levels of financial stress.

Among the possible models with a binary dependent variable, we chose logit models because they are well-known and represent a widely-used family of techniques in the early warning literature. Furthermore, logit models are more robust than decision tree algorithms (the structure of the tree and the selection of the significant variables are very sensitive to the available data) and explicitly consider the evolution of the variables over time. Finally, with the ordered logit we have the possibility to overcome the classic binary assumption (crisis vs. non crisis) and therefore to explicitly analyse different degrees of vulnerability.

5.1 Linear regression models through Bayesian Model Averaging

A Bayesian Model Averaging (BMA) based on linear regression models has been implemented. In order to avoid multicollinearity and select the variables with the best forecasting power, a feature selection procedure has been applied to the initial set of all our variables[16]. Finally, an out-of-sample estimation has been made with the aim of generalizing the results and of not overfitting in-sample data.

After a brief introduction to BMA, we present the methodology used and its application to our data.

5.1.1 An introduction to Bayesian Model Averaging (BMA)

BMA tackles the problem of model and variable selection by estimating models for all possible combinations of variables and constructing a weighted average over all the models[17]. If there are *K* potential variables, 2^K variable combinations are available and therefore 2^K models are estimated. Generally it is assumed that models are linear regressions, but other model structures can also be taken into consideration.

Given the dependent variable y and the (nxK) matrix X of possible explanatory variables (where n is the number of observations), the model weighted posterior distribution for any statistic θ (for example the model coefficients) is:

$$p(\theta|y,X) = \sum_{\gamma=1}^{2^K} p(\theta|M_\gamma, y, X)p(M_\gamma|X,y) \qquad (1)$$

where the weight $p(M_\gamma|X,y)$ is the posterior model probability (PMP) derived from Bayes' theorem:

$$p(M\gamma|y,X) = \frac{p(y|M\gamma,X)p(M\gamma)}{p(y|X)} \qquad (2)$$

and the model $M\gamma$ is assumed to have the standard structure $y = \alpha_\gamma + X_\gamma\beta_\gamma + \varepsilon$, where ε is a normal IID error term with variance σ^2. In equation (2), $p(y|X)$ is the integrated likelihood (constant over all models), $p(y|M\gamma,X)$ is the marginal likelihood of the model (i.e. the probability of the data given the model $M\gamma$) and $p(M\gamma)$ is the prior model probability (i.e. how probable the model $M\gamma$ is before looking at the data). A uniform prior probability for each model $p(M\gamma)$ is usually assumed (i.e. lack of prior knowledge).

$P(\theta|M_\gamma, y, X)$ in equation (1) depends on the chosen estimation framework; a standard approach is to use a Bayesian regression linear model with a specific prior structure called Zellner's g prior[18]. Indeed, the need to obtain posterior distributions means specifying the priors of the model

[16] We consider all our variables to be lagged by 8, 9,10,11 and 12 quarters.

[17] See Fernandez et al. (2001a) for the most prominent application of BMA. In particular the authors analyse the importance of 41 explanatory variables for long-term economic growth in 72 countries by means of BMA.

[18] On the basis of theoretical results and empirical simulations, this benchmark prior distribution is proved to have little influence on posterior inference and predictive results; it is therefore recommended when incorporating prior information is not possible or desirable. According to Zellner's hypothesis, for each regression model, it is assumed that the constant parameter α_γ and the error variance σ^2 are evenly distributed over their domain (non-informative distribution), whereas the (non-constant) regression coefficient parameters of the model are distributed according to a normal distribution with mean 0 (meaning lack of knowledge about them) and variance defined as $\sigma^2(\frac{1}{g}X_\gamma^i X_\gamma^i)^{-1}$ (meaning that their variance-covariance structure is broadly in line with that of the data X_γ).

parameters. The parameter *g* indicates the degree of prior uncertainty: a low g means a low parameter variance and then makes the prior coefficient distribution tight around a zero mean, while a large *g* implies large prior coefficient variance and therefore uncertainty that the coefficient is zero.

In the case of a large number of variables, the number of models to be estimated becomes computationally infeasible. In such a case, Monte Carlo Markov Chain (MCMC) samplers are adopted to solve the problem: MCMC samplers gather results on the most important part of the posterior model distribution and thus approximate it as closely as possible. BMA mostly relies on the Metropolis-Hastings algorithm, which moves in the model space as follows: at step *i,* the sampler stands at a model M_i, at step $i+1$ another model is proposed and the sampler switches from the model M_i to M_j with a probability p_{ij}. If the model M_j is rejected, another model M_k is proposed against M_i; in case M_j is accepted it becomes the current model and is compared to other models in the next steps. Different variants have been defined, according to the different ways to propose possible candidates. In our analysis we consider the birth-death sampler (*bd*): one of the K potential variables is randomly chosen; if it is already part of the current model, this variable is dropped in the new model, otherwise it is added.

By using the BMA, it is possible to associate each variable with a posterior inclusion probability, i.e. the sum of posterior model probabilities for all the models where a variable was included. This allows us to rank the indicators in terms of their importance in the BMA estimation.

We implement our model in R using the R library BMS[19]. The standard assumptions on prior model and parameter distributions are considered; in particular we follow Fernandez et al. (2001b) who propose a "benchmark" prior distribution $g = max(n,K^2)$[20].

5.1.2 Our approach

Our methodology is based on three main steps: 1) the selection of the optimal set of variables to be used in the BMA linear regression model (feature selection); 2) the estimation and the out-of-sample performance evaluation of the BMA model; 3) an out-of-sample forecasting exercise.

As in a standard out-of-sample-analysis, we divide the data into two subsets: a first set (called training period) from 1990 Q1 to 2005q4, where the model is estimated, and a second set (called test period) from 2007q1 to 2014q2, where the model is evaluated. We are interested in forecasting the vulnerability indicator one year after the end of the training period for 4 quarters in order to give time to the macroprudential authority and to banks for activating and implementing any macroprudential tool. Both for the selection of the best set of variables and for the out-of-sample analysis, we perform a quasi-real-time recursive exercise in order to evaluate the forecasting power of the model on the test period. This results in a new estimation every 4 quarters only using information available up to that point in time (i.e. the training period is extended by 4 quarters at each estimation) and enables us to test whether the use of our model would have allowed the prediction of possible vulnerabilities. We repeat the estimation at the end of each year until 2012Q4 and evaluate the model one year after for 4 quarters (for the last estimation the evaluation is made on 2 quarters).

We report below a brief description of the three steps.

1) Feature selection (section 5.1.3). First, the variables that are correlated with the dependent variable (i.e. our vulnerability indicator) and not highly correlated with each other (to avoid

[19] See Zeugner (2011).

[20] Note that in the reference paper by Fernandez et al. (2001) $g = 1/max(n,K^2)$, the inverse of the notation reported in the R documentation.

multicollinearity) in the training period are selected. Second, starting from these variables, we estimate BMA linear regression model on the training period and we keep the subset of variables that minimize the average prediction error, expressed in terms of the root mean squared error, for the test period. To do this we use a grid search algorithm and identify the variables with the best out-of-sample BMA performance, calculated using the recursive approach. This results in the optimal set of variables to be used in the following steps.

2) BMA model estimation and out-of-sample evaluation (Section 5.1.3). We estimate our BMA linear regression model on the training period using the optimal subset of variables selected at step 1) and we apply the recursive approach to evaluate the out-of-sample performance of the model.

3) Forecasting exercise (Section 5.3). We use our BMA model, estimated on the whole observed period (1990 Q1-2014Q2), to forecast the average value, together with the first and third quartile of the distribution, of the vulnerability indicator in the period 2015Q3-2016Q2.

5.1.3 Results

Out-of-sample forecasting exercise for households' systemic banking vulnerability indicator

We consider all the potential early warning indicators presented in Table 1, excluding those specifically related to credit granted to construction and real estate firms, lagged by 8, 9, 10, 11 and 12 quarters.

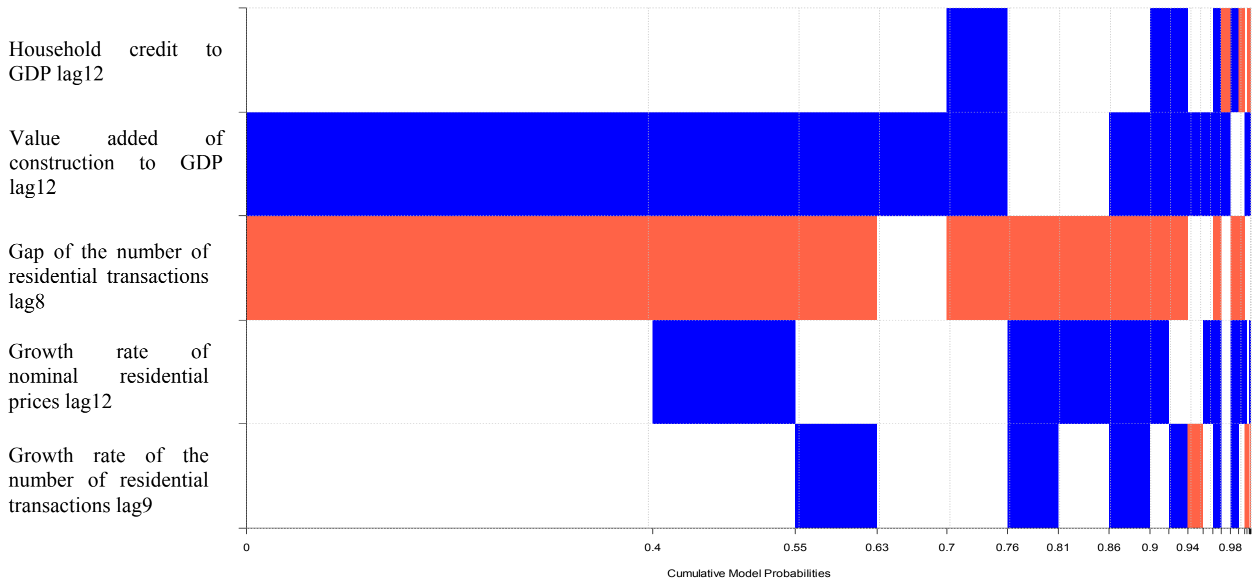
We then apply the feature selection procedure described above in order to reduce the number of candidate variables[21]. First, from the correlation analysis the number of variables is significantly reduced to 13[22]. In particular, by using our expert judgment, we have included two variables related to household credit to GDP (level and gap) among the 13 variables; these two variables were indeed initially excluded since they displayed a low correlation with our households' vulnerability indicator in the training period (1990Q1-2005Q4). However, the recent financial crisis and the literature on early warning indicators have demonstrated the importance of credit developments for real-estate related banking crises[23]. Second, from the recursive BMA function the set of optimal variables for our households' systemic banking vulnerability indicator (i.e. the ones that minimize the average prediction error on the test period) comprises the following 5 early warning indicators[24]: household credit to GDP lagged 12 quarters, value added of construction to GDP (current) lagged 12 quarters, gap of the number of residential transactions lagged 8 quarters, growth rate of nominal residential prices lagged 12 quarters and growth rate of the number of residential transactions lagged 9 quarters.

According to the estimates of our BMA linear regression models for the selected 5 early warning indicators, Figure 4 shows which models actually perform better, scaled by their posterior model probability (PMP). The best model, with 40% PMP, is the one that includes the value added of construction to GDP lagged 12 quarters and the residential transactions gap lagged 8 quarters; while the second model includes, in addition to these two variables, the growth rate of nominal residential prices lagged 12 quarters and has a PMP of 15%. We see that the value added of construction to GDP lagged 12 quarters and the transactions gap lagged 8 quarters are included in many models.

[21] We have dropped the variables that have a low correlation (lower than 30%) with the dependent variable and that are highly correlated (higher than 90%) with each other.
[22] See figure A.2 in Appendix A for the plot of the pairwise correlations between the 13 variables.
[23] Ferrari, Pirovano and Cornacchia (2015) find a superior signalling performance for a multivariate logit model featuring real total credit growth, bank credit-to-GDP, the price-to-rent ratio, the nominal 3-month money market rate and inflation as early warning indicators for EU countries.
[24] See figure A.3 in Appendix A for the plot of the correlations between the set of optimal variables.

Finally, we perform the out-of-sample forecasting exercise for the selected 5 early warning indicators. Figure 5 shows the systemic banking vulnerability indicator related to households (black line) and the out-of-sample (from 2007Q1 to 2014Q2) prediction of its average level (solid red line) together with the 10th and 90th percentile of its predictive density (dashed red lines). As we can see the average prediction fits the rise of our vulnerability indicator well, reaching a slightly lower level. For the last quarter of the test period a sharp increase was predicted.

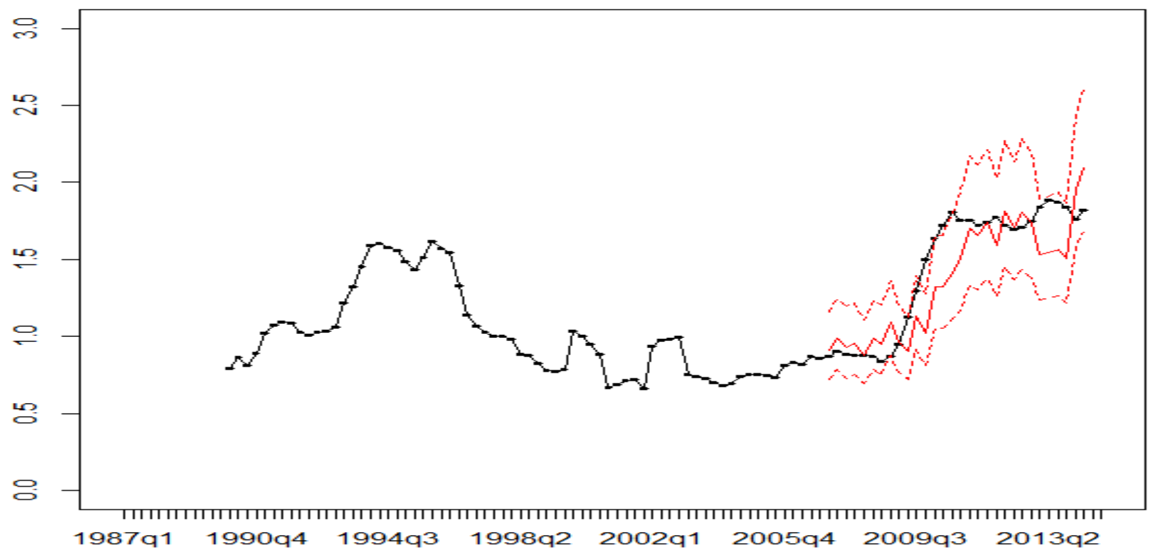
Figure 4 - Model inclusion based on the best 22 models (1)



Source: elaborations based on Supervisory Reports and Central Credit Register data.

(1) Blue corresponds to a positive coefficient, red to a negative coefficient and white to non-inclusion (zero coefficient).

Figure 5 – Out-of-sample prediction (from 2007Q1 to 2014Q2) of the best set of indicators for households' systemic banking vulnerability (1)



Source: elaborations based on Supervisory Reports and Central Credit Register data.

(1) The best set of indicators includes household credit to GDP lagged 12 quarters, value added of construction to GDP (current) lagged 12 quarters, residential transactions gap lagged 8 quarters, growth rate of nominal residential prices lagged 12 quarters and growth rate of residential transactions lagged 9 quarters. Out-of-sample prediction for households' systemic banking vulnerability average level (solid red line) together with the 10th and 90th percentile of the predictive density (dashed red lines).

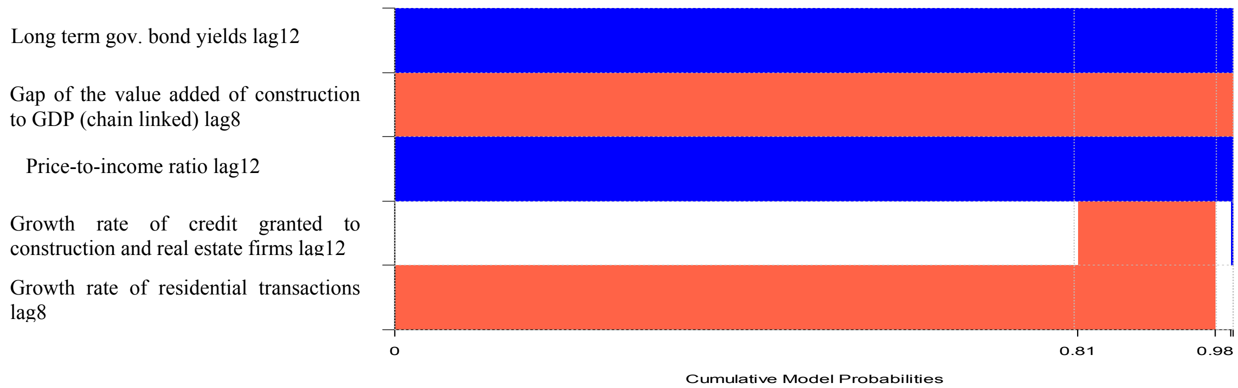
Out-of-sample forecasting exercise for construction and real estate firms' systemic banking vulnerability indicator

We consider all the potential early warning indicators presented in Table 1, excluding those related specifically to credit granted to households, also lagged by 8, 9, 10, 11 and 12 quarters.

We then reduce the number of candidate variables through the feature selection procedure described in Section 5.1.2[25]. First, from the correlation analysis the number of variables is significantly reduced to 13[26]. Secondly, from the recursive BMA function the set of optimal variables for our construction and real estate firms' systemic banking vulnerability indicator comprises the following 5 early warning indicators[27]: long-term government bond yields lagged 12 quarters, gap of the value added of construction to GDP (chain-linked) lagged 8 quarters, price-to-income ratio lagged 12 quarters, growth rate of credit granted to construction and real estate firms lagged 12 quarters and growth rate of the number of residential transactions lagged 8 quarters.

According to the estimates of our BMA linear regression models for the selected 5 early warning indicators (Figure 6), the best model, with 81% PMP, is the one that includes long-term government bond yields lagged 12 quarters, gap of the value added of construction to GDP (chain-linked) lagged 8 quarters, price-to-income ratio lagged 12 quarters and growth rate of residential transactions lagged 8 quarters; while the second model includes the growth rate of credit granted to construction and real estate firms lagged 12 quarters in addition and has a PMP of 17%.

Figure 6 - Model inclusion based on the best 4 models (1)



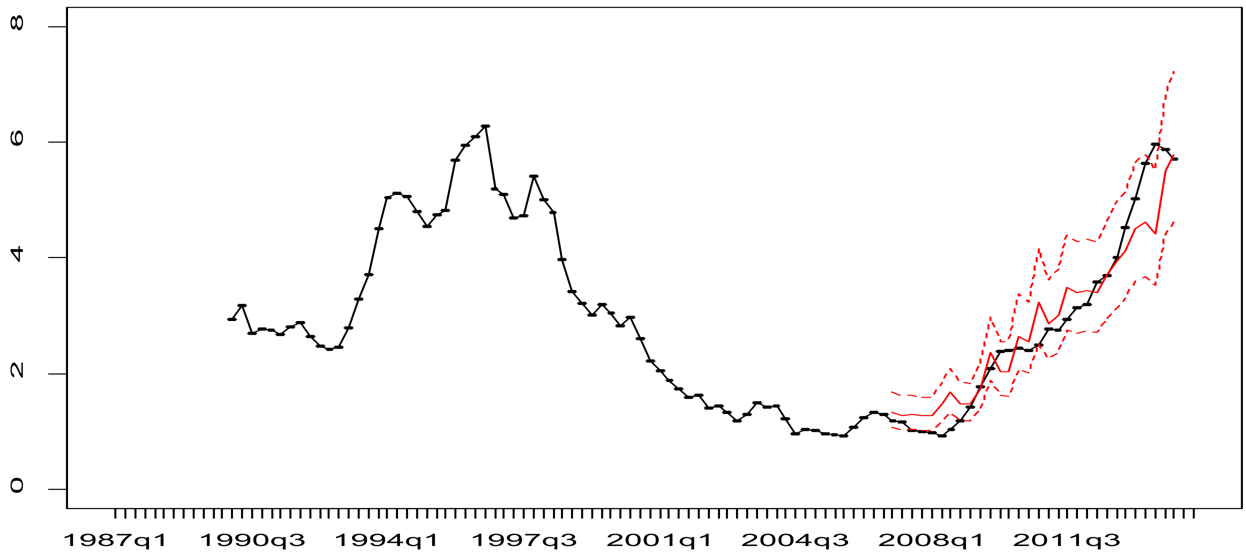
Source: elaborations based on Supervisory Reports and Central Credit Register data.
(1) Blue corresponds to a positive coefficient, red to a negative coefficient and white to non-inclusion (zero coefficient).

We see that the long-term government bond yields lagged 12 quarters, the gap of the value added of construction to GDP (chain-linked) lagged 8 quarters and the price-to-income ratio lagged 12 quarters are included in all four best models.

Finally, we perform the out-of-sample forecasting exercise for the selected 5 early warning indicators. Figure 7 shows the systemic banking vulnerability indicator related to construction and real estate firms (black line) and the out-of-sample (from 2007Q1 to 2014Q2) prediction of its average level (solid red line) together with the 10th and 90th percentile of its predictive density (dashed red lines). As we can see, the average prediction fits the rise of the vulnerability indicator very well, reaching exactly the same level at the end of the test period. The sharp rise of the vulnerability indicator in the first half of 2014 is attributable to the significant drop in residential transactions in the first half of 2012.

[25] We have dropped the variables that have a low correlation (lower than 35%) with the dependent variable and that are highly correlated (higher than 90%) with each other.
[26] See figure A.4 in Appendix A for the plot of the correlations between the 13 variables.
[27] See figure A.5 in Appendix A for the plot of the correlations between the set of optimal variables.

Figure 7 – Out-of-sample prediction (from 2007Q1 to 2014Q2) of the best set of indicators for construction and real estate firms' systemic banking vulnerability (1)



Source: elaborations based on Supervisory Reports and Central Credit Register data.
(1) The best set of indicators includes long-term government bond yields lagged 12 quarters, gap of the value added of construction to GDP (chain-linked) lagged 8 quarters, price-to-income ratio lagged 12 quarters, growth rate of credit granted to construction and real estate firms lagged 12 quarters and growth rate of residential transactions lagged 8 quarters. Out-of-sample prediction for construction and real estate firms' systemic banking vulnerability average level (solid red line) together with the 10th and 90th percentile of the predictive density (dashed red lines).

5.2 Binary logit and ordered logit models

5.2.1 Evaluation methodology

In this section we illustrate both a widely used evaluation methodology for binary logit EWMs and a similar new methodology that we have elaborated for ordered logit models.

In the binary logit regression model, the left-hand side variable indicates the probability p that vulnerability starts (i.e. vulnerability classes 3 or 4) within the assumed prediction horizon. Using a threshold τ it is possible to transform the probability into a binary variable such that a signal is issued if the probability exceeds τ:

$$\begin{cases} \textit{signal issued} & \textit{if } p \geq \tau \\ \textit{signal not issued} & \textit{if } p < \tau \end{cases}$$

The choice of the optimal threshold (and consequently of the best performing model) is based on its ability to correctly predict upcoming vulnerability and at the same time to not issue too many false alarms. For each possible model M the optimal threshold is chosen among N=1,000 different values, from the minimum to the maximum model's predicted probabilities in the sample through a grid search algorithm. For each of these 1,000 values a 'Confusion Matrix' is calculated (Table 2) in order to compare the predictions of model M with the actual outcomes. In particular, the model outcome is classified as correct if a vulnerability state follows within the relevant horizon (true positives, TP), whereas if a vulnerability state does not follow, then the signal results in a false alarm (false positives, FP). A non-issued signal is correct when a vulnerability state does not follow (true negatives, TN) whereas it is incorrect when a vulnerability state occurs (false negatives, FN).

Table 2

Confusion Matrix *(M, τ)*

	Crisis	No crisis
Signal issued	TP	FP
Signal not issued	FN	TN

Based on the 'Confusion Matrix', a number of key ratios can be calculated:

1) the true positive rate ($\mathrm{TPR}(\tau) = \frac{TP}{\mathrm{TP+FN}}$), i.e. the fraction of correctly predicted vulnerability states;
2) the type I error rate ($1-\mathrm{TPR}(\tau) = \frac{FN}{\mathrm{TP+FN}}$), i.e. the fraction of missed vulnerability states;
3) the type II error rate, noise or false positive ratio ($\mathrm{FPR}(\tau) = \frac{FP}{\mathrm{FP+TN}}$), i.e. the fraction of false alarms;
4) the accuracy ratio ($\mathrm{ACC} = \frac{TP+TN}{\mathrm{TP+TN+FP+FN}}$); i.e. the correctly predicted states over total observations. On the other hand, 1-ACC ratio is the fraction of wrongly (misclassified) predicted states over total observations.

The 'Confusion Matrix', and the associated evaluation metrics require a predefined evaluation horizon. The prediction horizon needs to be chosen long enough, so that the policymaker still has time to take preventive action. On the other hand, the evaluation horizon should not be too long either, as this may blur the indicators' signalling power. In our analysis we consider a prediction horizon of 5 to 12 quarters as is generally used in the literature for this kind of analysis. The objective of our EWM is not to predict the exact timing of the vulnerability, but to predict whether the vulnerability will occur within a specific time horizon. Observations included in windows of 5 to 12 quarters before the vulnerability occurs (i.e., the indicator enters vulnerability classes 3 or 4) determine the sample on which TPR and Type I errors are computed. Observations outside these windows serve as a basis for the calculation of Type II errors and the fraction of periods where signals were not correctly issued.[28]

The predictive power of a model can be assessed through different metrics, such as the noise to signal ratio $\left(\frac{\mathrm{FPR}(\tau)}{\mathrm{TPR}(\tau)}\right)$ and the policymaker's loss function $L(\tau,\theta) = \theta^* (1-\mathrm{TPR}(\tau)) + (1-\theta)^* \mathrm{FPR}(\tau)$, where the parameter θ represents the policymaker's relative preference for missing vulnerability states versus issuing false alarms. Finally, the relative usefulness (RU) expresses the policymaker's gain from using the model for predicting vulnerability states compared to disregarding the model and always issuing a signal or never issuing a signal; it is defined as $\mathrm{RU}(\tau,\theta) = \frac{\min[\theta,(1-\theta)] - L(\tau,\theta)]\,)}{\min[\theta,(1-\theta)]}$.

In recent early warning applications the predictive power of models is also expressed in terms of the ROC (Receiver Operating Characteristic) curve and the AUROC (Area Under the ROC).[29] The ROC plots the model's TPR against the FPR for every possible value of threshold τ. The area under the ROC-curve ranges from 0 (the model is not informative at all) to 1 (fully informative model). The AUROC is a robust evaluation criterion, as it assesses the model for all possible thresholds, but in order to provide some guidance for policymakers' decisions it is necessary to calculate the optimal threshold for each model, so that an assessment on the signalling can be made.

[28] Observations in windows of 1 to 4 quarters before a vulnerability state starts and observations during such vulnerability were dropped from the sample.
[29] See Drehman and Juselius (2013).

In order to consider the model as well-performing, we first select models whose AUROC is greater than 0.5. For each of these models, the optimal threshold value is defined by maximising the relative usefulness, with the preference parameter θ=2/3.[30] Finally the models are ranked according to their relative usefulness.

The evaluation methodology and the relative metrics illustrated above assume a two-class problem and cannot easily be extended to the evaluation of the ordered logit model based on *n* (with *n* greater than 2) classes. In particular, not one but *n-1* optimal thresholds should be defined.

In order to evaluate ordered logit models it is therefore crucial to: 1) find appropriate metrics that allow to extend the definition of TP, TN, FP, FN, ACC, the associated ratios, the loss function and the relative usefulness to the *n*-class problem; 2) implement an algorithm to calculate the *n-1* optimal thresholds.

With regard to the former point, the following measures can be considered for describing the "goodness" of the ordered logit model:

a) Accuracy ACC (and 1-ACC), as described above. This is a standard measure, but it does not allow us to consider the various misclassification episodes differently (i.e. the error of a class '4' predicted as class '1' as the same weight as an error of a class '4' predicted as '3');

b) Weighted false positives (WFP) and weighted false negatives (WFN): the misclassification errors are weighted in terms of the distance between the true class and the predicted one.
In order to define these weighted measures, the difference between the true and the predicted class is calculated. In the case of *n=4* we obtain the following matrix of possible differences:

	Class 1	Class 2	Class 3	Class 4
Pred 1	0	1	2	3
Pred 2	-1	0	1	2
Pred 3	-2	-1	0	1
Pred 4	-3	-2	-1	0

The weighted false positives are calculated as the sum of the absolute values of all the negative differences (lower triangular matrix) divided by 3 (the maximum possible difference), whereas the weighted false negatives are calculated as the sum of all the positive differences (upper triangular matrix) divided by 3. This results in weighting a small prediction error of one class by 1/3, a medium error of two classes by 2/3 and a big error of three classes by 1. In order to obtain error indices equivalent to type I and type II error rates, the weighted false negatives and false positives (WFN and WFP) are used as numerator, whereas the denominator is calculated by using the total number of observations. Finally, an assessment of the magnitude of the errors can be made by comparing 1-ACC with its corresponding weighted measure (weighted(1-ACC)= $\frac{WFP+WFN}{\mathrm{TP+TN+FP+FN}}$). The loss function and the relative usefulness for a multiple class problem are then defined by replacing TPR and FPR with the corresponding weighted forms.

As far as the computation of the *n-1* optimal thresholds is concerned, an algorithm has been implemented in order to deal with the multiclass problem. Specifically:

[30] After the recent financial crisis we assume that policy makers are now more cautious, preferring to give more weight in their loss function to missed vulnerability states than to false alarms. See Appendix B for some robustness checks on theta sensitivity.

1) the single threshold in the binary case is replaced by a triplet of thresholds (τ_1,τ_2,τ_3), with $\tau_1<\tau_2<\tau_3$;
2) for a given triplet, the thresholds are applied to the latent variable (or score value $X\beta$, where X is the matrix of predictors). The ordered logit predictions are therefore defined in terms of the triplet, as they can be described by the following probabilities:

$$P(X\beta + \mu < \tau_1) = F(X\beta - \tau_1);$$
$$P(\tau_1 < X\beta + \mu < \tau_2) = F(X\beta - \tau_2) - F(X\beta - \tau_1);$$
$$P(\tau_2 < X\beta + \mu < \tau_3) = F(X\beta - \tau_3) - F(X\beta - \tau_2);$$
$$P(X\beta + \mu > \tau_3) = 1 - F(X\beta - \tau_3)$$

   where $F(z) = (1 + e^{-z})^{-1}$ is the logistic cumulative density function.

   Each observation is assigned to the class with the maximum probability. Varying the thresholds induces a change in the probabilities of a single observation of being in each class and therefore the predicted class;
3) a three-dimension grid search algorithm is used to identify the possible triplets and the optimal thresholds are obtained by maximizing their relative usefulness.

As for the binary logit, the models and the associated thresholds are ranked according to their maximum relative usefulness.

Finally, it is also useful to define the AUROC for each ordered model. The standard definition of the AUROC is based on the binary classification, but in the literature there are different extensions for handling multi-class problems. Here we refer to the version based on the paper by Hand and Till (2001), implemented in MATLAB by means of the function *colAUC*. The algorithm is based on two steps: the calculation of the AUROC for each couple of classes and the definition of the total AUROC as a mean of the single AUROCs. In the case of 2 classes, this corresponds to the standard AUROC.

5.2.2 Estimation and results

<u>Binary logit model</u>
The following binary logit model is estimated:

$$\Pr\ (y_t = 1 \mid X_{kt}) = F\ (X_{kt}\, \beta_k)$$

where:

- y_t is the observed binary dependent variable, coded as 1 if vulnerability starts within the prediction horizon (for observations 5 to 12 quarters before vulnerability classes 3 or 4 starts) and 0 otherwise;
- the matrix X_{kt} collects the potential early warning indicators, including a constant term;
- the vector β_k collects the regression coefficients;
- F represents the logistic cumulative density function of the form $F(z) = (1 + e^{-z})^{-1}$, which maps the indicators into the predicted vulnerability probability.

In particular, we estimate and statistically evaluate the early warning performance of binary logit models for all possible uni- and bivariate indicator combinations for the systemic banking vulnerability related to households and to construction and real estate firms, respectively:

- out of the 28 univariate logit models[31], 19 and 13 models present significant coefficients[32] for the predicted probabilities of banking vulnerability related to households mortgage loans and to loans to construction firms and real estate agencies, respectively;
- out of the 378 bivariate logit models, 302 and 277 models present acceptable correlations between indicators[33] and significant coefficients for the predicted probabilities of banking vulnerability related to households' mortgage loans and to loans to construction firms and real estate agencies, respectively.

The resulting models have then been ranked according to their early warning performance evaluated in terms of relative usefulness (see Section 5.2.1). Tables 3 and 4 show the estimation results of the three best performing uni- and bivariate logit models for the predicted probabilities of the banking vulnerability indicator related to households and to construction and real estate firms.

As we said before, risks coming from households were relatively small, both recently and in the early nineties. However, the econometric exercise can identify variables that can anticipate an increase in the vulnerability indicator above the historical median level.

According to Tables 3 and 4, the best individual early warning indicators have a relatively good performance, since they have never missed a 'vulnerability' state. Nevertheless, the best pairs of early warning indicators are even better able to anticipate an increase in vulnerability than individual indicators, as they also generate fewer false alarms. With regard to households, the best pair of indicators comprises the price-to-rent ratio gap and the value added of construction to GDP gap (chain-linked); while for construction and real estate firms, the best pair includes the C&RE credit–to-GDP ratio and long-term government bond yields[34].

We have taken into account the evolution of the economic outlook by considering the unemployment rate, the growth rate of disposable income and the output gap. However, these variables (individually or in pairs) show a limited predictive power for households' and construction and real estate firms' banking vulnerability; they rarely lie among the top three best early warning indicators, except for the output gap. Similarly, Ferrari, Pirovano and Cornacchia's (2015) panel logit analysis for EU countries shows a limited predictive power for macroeconomic variables related to the business cycle (e.g., GDP growth and unemployment).

Overall, all the early warning indicators for systemic banking vulnerability related to households and to construction and real estate firms, as reported in Tables 3 and 4, are highly significant and have the expected signs.

Finally, as the banking vulnerability indicator of construction and real estate firms presents high volatility, levels below the median may also be worthy of attention for policy makers. In order to overcome this issue, we propose a discretization of the indicator based on the quartiles of its distribution (ordered logit) so as not to lose too much information[35].

---

[31] Table 1 shows the 28 potential early warning indicators analysed.

[32] The p-value of a likelihood ratio (LR) chi-squared for the test of the null hypothesis, that all the coefficients associated with the independent variables are simultaneously equal to 0, is rejected at 10% significance level.

[33] As highlighted in section 4, pairwise correlation exceeds 80% between a certain number of variables. These variables have been excluded from the possible pairs of indicators.

[34] In Annex B an in-sample forecasting exercise has been implemented for both best pairs of indicators.

[35] Binary logit models are designed to detect the accumulation of financial stability risks arising from the real estate sector for the possible activation of macroprudential tools. In a situation of evident banking vulnerability those models are useless by definition. With ordered logit models, but especially with linear models using BMA we managed to estimate a continuous level of vulnerability in order to take into account also a possible release of macroprudential tools.

Table 3

Best univariate and bivariate binary logit regressions for banking vulnerability related to households

(prediction horizon of 5 to 12 quarters)

	Univariate 1	*Univariate 2*	*Univariate 3*	*Bivariate 1*	*Bivariate 2*	*Bivariate 3*
Price to rent gap	0.87 (***)			4.48 (***)	1.77 (**)	
VA construction to GDP (current)		7.8 (***)				
Output gap			2.18 (***)			
VA construction to GDP gap (chain-linked)				24.3 (****)		
Real RRE price growth					2.25(**)	
Long-term gov't bond yields						2.95 (***)
Price to income						0.68(***)
Constant	-0.37	-41.01 (***)	-4.14 (***)	-10.47 (***)	-5.45 (***)	-77.42 (***)
Type 1 error	0.00	0.00	0.00	0.00	0.00	0.00
Type 2 error	0.11	0.21	0.24	0.03	0.03	0.03
Relative usefulness	0.89	0.79	0.76	0.97	0.97	0.97
AUROC	0.97	0.85	0.95	1.00	0.99	0.99
Accuracy	0.93	0.85	0.83	0.98	0.98	0.96
1-ACC	0.07	0.15	0.17	0.02	0.02	0.04
N. observations	54	54	54	54	54	54

* Significant at 10%. ** Significant at 5%. *** Significant at 1%.

Table 4

Best univariate and bivariate binary logit regressions for banking vulnerability related to construction and real estate firms

(prediction horizon of 5 to 12 quarters)

	Univariate 1	*Univariate 2*	*Univariate 3*	*Bivariate 1*	*Bivariate 2*	*Bivariate 3*
Price to rent	0.34 (***)					
Price to income		0.11 (***)				
Residential transactions			-0.03 (***)			
C&RE credit to GDP				0.98 (***)		
Long-term gov't bond yields				3.02 (***)		
Real RRE price gap					0.35 (***)	
Residential transactions gap					-0.61 (***)	-0.51 (***)
Price to income gap						0.15 (***)
Constant	-34.74 (***)	-10.44 (***)	2.08 (*)	-60.65 (***)	2.41 (**)	1.47 (**)
Type 1 error	0.00	0.00	0.00	0.00	0.00	0.00
Type 2 error	0.41	0.43	0.45	0.02	0.09	0.11
Relative usefulness	0.59	0.57	0.55	0.95	0.91	0.89
AUROC	0.82	0.78	0.68	0.99	0.95	0.94
Accuracy	0.70	0.68	0.67	0.97	0.93	0.92
1-ACC	0.30	0.32	0.33	0.03	0.07	0.08
N. observations	60	60	60	60	60	60

* Significant at 10%. ** Significant at 5%. *** Significant at 1%.

Ordered logit model

The following logit model with 4 ordinal vulnerability classes is estimated:

Pr $(y_t = 1 \mid X_{k,t-l}) = F\left(\tau_1 - X_{k,t-l}\,\beta_{k,t-l}\right)$ for l = lags 5 to 12 quarters
Pr $(y_t = m \mid X_{k,t-l}) = F\left(\tau_m - X_{k,t-l}\,\beta_{k,t-l}\right) - F\left(\tau_{m-1} - X_{k,t-l}\,\beta_{k,t-l}\right)$ for m = classes 2 to 3 and for l = lags 5 to 12 quarters
Pr $(y_t = 4 \mid X_{k,t-l}) = 1 - F\left(\tau_3 - X_{k,t-l}\,\beta_{k,t-l}\right)$ for l = lags 5 to 12 quarters

where:

- y_t is the observed dependent variable, coded as 1 for no vulnerability, 2 for low vulnerability, 3 for medium vulnerability and 4 for high vulnerability;
- the matrix $X_{k,t-l}$ collects the potential early warning indicators with 12 to 5 quarter lags;
- the vector $\beta_{k,t-l}$ collects the regression coefficients;
- τ_1, τ_2 and τ_3 are the cut-points of the latent variable (when the latent y_t^* crosses a cut-point, the observed class changes);
- F represents the logistic cumulative density function of the form $F(z) = (1 + e^{-z})^{-1}$, which maps the indicators into the predicted vulnerability probability.

In particular, out of the 28 potential early warning indicators we have restricted our analysis to a subset of best univariate and bivariate indicators according to the binary logit model with 5 to 12 quarter lags, for households (RRE) and construction and real estate firms (C&RE) respectively.

We estimate and statistically evaluate the early warning performance of ordered logit models for all possible uni- and bivariate indicator combinations for RRE- and C&RE-related systemic banking vulnerability:

- out of the 48 and 40 univariate ordered models, 31 and 32 models present significant coefficients[36] for the predicted probabilities of banking vulnerability classes related, respectively, to households' mortgage loans and to loans to construction firms and real estate agencies;
- out of the 1,128 bivariate ordered models, 906 and 847 models respectively present acceptable correlations between indicators[37] and significant coefficients for the predicted probabilities of banking vulnerability classes related to households' mortgage loans and to loans to construction firms and real estate agencies.

The resulting models have then been ranked according to their relative usefulness, calculated in terms of the weighted false positive and false negative (see Section 5.2.1). Tables 5 and 6 show the estimation results of the three best performing uni- and bivariate ordered logit models for systemic banking vulnerability related to households and to construction and real estate firms. Various combinations of variables are optimal in terms of usefulness. By comparing 1-ACC with its corresponding weighted measure it is possible to conclude that ordered logit models make relatively small prediction errors, as for each model weighted (1-ACC) is much lower than (1-ACC). With regard to households, the best pair of indicators comprises long-term government bond yields lagged 6 quarters and the debt service ratio lagged 12 quarters (in addition to a high usefulness, it has also the highest accuracy and AUROC); while for construction and real estate firms, the best pair includes long-term government bond yields lagged 7 quarters and residential transactions gap lagged 12 quarters[38].

[36] The p-value of a likelihood ratio (LR) chi-squared for the test of the null hypothesis, that all the coefficients associated with the independent variables are simultaneously equal to 0, is rejected at 10% significance level.
[37] As highlighted in section 4, pairwise correlation exceeds 80% between a certain number of variables. These variables have been excluded from the possible pairs of indicators.
[38] In Annex B an in-sample forecasting exercise has been implemented for both best pairs of indicators.

Table 5

Best univariate and bivariate ordered logit regressions for banking vulnerability related to households
(prediction horizon of 5 to 12 quarters)

	Univariate 1	*Univariate 2*	*Univariate 3*	*Bivariate 1*	*Bivariate 2*	*Bivariate 3*
Price to rent gap lag 11	0.20 (***)					
Price to rent gap lag 10		0.19 (***)				
VA construction to GDP lag 12 (current)			3.9 (***)			
Long-term gov't bond yields lag 6				0.78 (***)		
Debt service ratio lag 12				128.64(***)		
VA construction to GDP gap lag 12 (chain-linked)					-11.31 (***)	-12.24 (***)
Price to income lag 8					0.35(***)	
Price to income lag 7						0.36 (***)
Type 1 error (weighted)	0.02	0.02	0.05	0.05	0.03	0.03
Type 2 error (weighted)	0.19	0.20	0.15	0.04	0.07	0.08
Weighted relative usefulness	0.76	0.75	0.75	0.86	0.86	0.86
AUROC (multiclass)	0.79	0.78	0.82	0.91	0.90	0.89
Accuracy	0.52	0.50	0.44	0.75	0.70	0.68
Weighted 1-ACC	0.22	0.23	0.20	0.09	0.10	0.11
N. observations	99	99	99	99	99	99

* significant at 10%. ** significant at 5%. *** significant at 1%

Table 6

Best univariate and bivariate ordered logit regressions for banking vulnerability related to construction and real estate firms

(prediction horizon of 5 to 12 quarters)

	Univariate 1	*Univariate 2*	*Univariate 3*	*Bivariate 1*	*Bivariate 2*	*Bivariate 3*
Residential transactions lag 5	-0.16 (***)					
Residential transactions lag 6		-0.14(***)				
Residential transactions lag 7			-0.12 (***)			
Residential transactions gap lag 12				-0.20(***)	-0.20(***)	
Long-term gov't bond yields lag 7				0.45(***)		
Long-term gov't bond yields lag 8					0.46(***)	
Long-term gov't bond yields lag 6						0.46(***)
Price to income gap lag 5						-0.28(***)
Type 1 error (weighted)	0.03	0.04	0.05	0.00	0.01	0.01
Type 2 error (weighted)	0.09	0.10	0.11	0.15	0.13	0.13
Weighted relative usefulness	0.86	0.83	0.80	0.86	0.85	0.85
AUROC (multiclass)	0.89	0.88	0.85	0.86	0.86	0.88
Accuracy	0.68	0.63	0.59	0.62	0.65	0.63
Weighted 1-ACC	0.12	0.14	0.15	0.15	0.14	0.14
N. observations	99	99	99	99	99	99

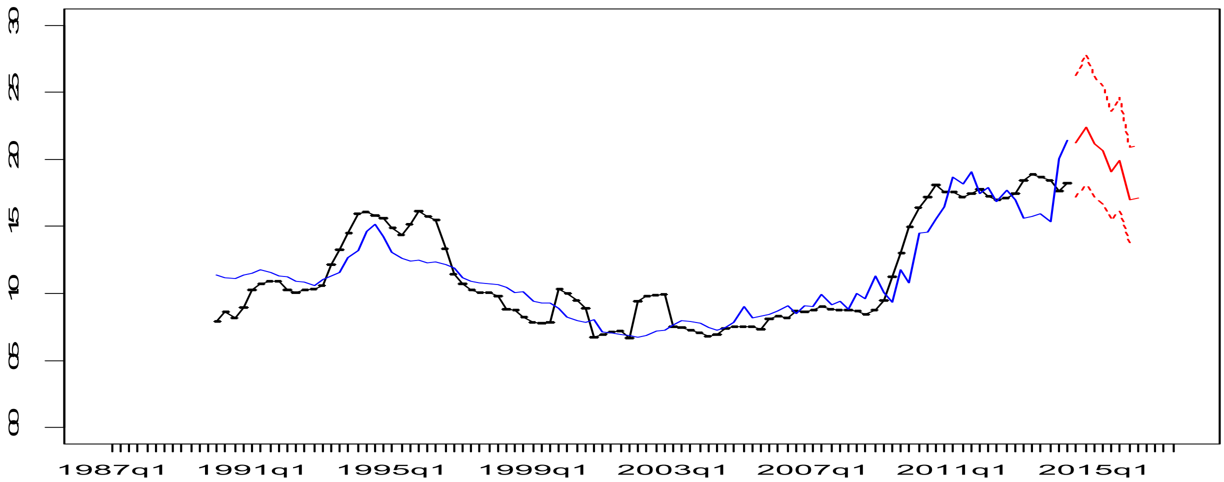
* significant at 10%. ** significant at 5%. *** significant at 1%

5.3 A projection exercise

<u>BMA</u>

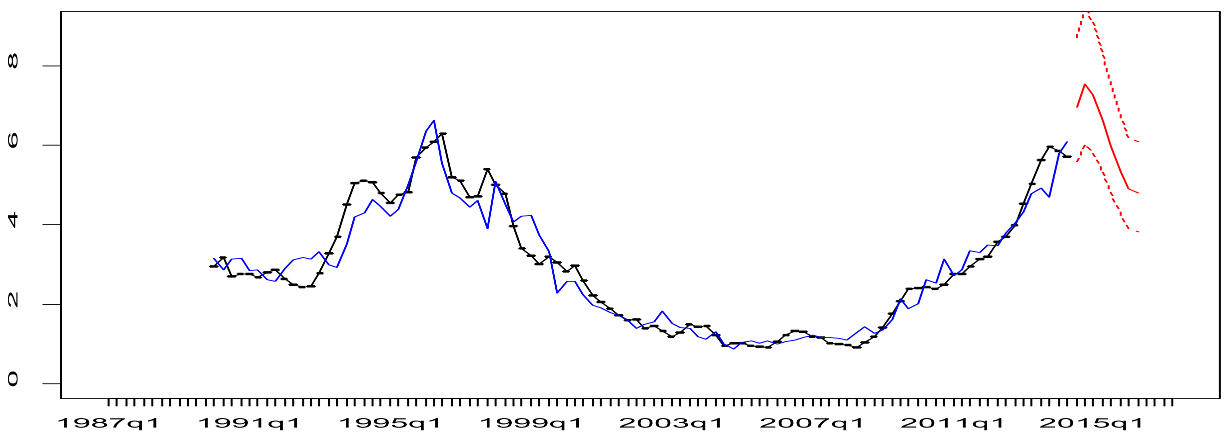
In Figures 8 and 9 we have considered 1990Q1-2014Q2 as training period (i.e. the BMA model is estimated over the full sample for the selected best set of indicators; blue line) and we have made projections for 2015Q3-2016Q2 (red lines). According to the BMA linear regression models, the average systemic banking vulnerability related to households and to construction and real estate firms, though remaining at relatively high levels, should gradually decline.

Figure 8 – Projections (2015Q3-2016Q2) for the banking vulnerability indicator related to households (1)



Source: elaborations based on Supervisory Reports and Central Credit Register data.
(1) The projections are based on the best set of indicators, which includes household credit to GDP lagged 12 quarters, value added of construction to GDP lagged 12 quarters, residential transactions gap lagged 8 quarters, growth rate of nominal residential prices lagged 12 quarters and growth rate of residential transactions lagged 9 quarters. Projections for households' systemic banking vulnerability average level (solid red line) together with the 10th and 90th percentile of the predictive density (dashed red lines).

Figure 9 – Projections (2015Q3-2016Q2) for the banking vulnerability indicator related to construction and real estate firms (1)



Source: elaborations based on Supervisory Reports and Central Credit Register data.
(1) The projections are based on the best set of indicators, which includes long-term government bond yields lagged 12 quarters, gap of the value added of construction to GDP (chain-linked) lagged 8 quarters, price-to-income ratio lagged 12 quarters, growth rate of credit granted to construction and real estate firms lagged 12 quarters and growth rate of residential transactions lagged 8 quarters. Projections for construction and real estate firms' systemic banking vulnerability average level (solid red line) together with the 10th and 90th percentile of the predictive density (dashed red lines).

Ordered logit

According to the latest projections in Figures B.3 and B.5 (Appendix B), for 2015 our best bivariate ordered logit models forecast that systemic banking vulnerability for households and for construction and real estate firms will remain above the 75th percentile.

6. Risk assessment framework: the main real estate-related indicators for monitoring financial stability risks in Italy

In this section we assess real estate-related financial stability risks in Italy through the monitoring of a restricted number of indicators related to the real estate market, to bank and credit and to households' financial situation. Some of these indicators are already used in the Bank of Italy's Financial Stability Report, while several others are new. Annex C provides an exhaustive set of indicators.

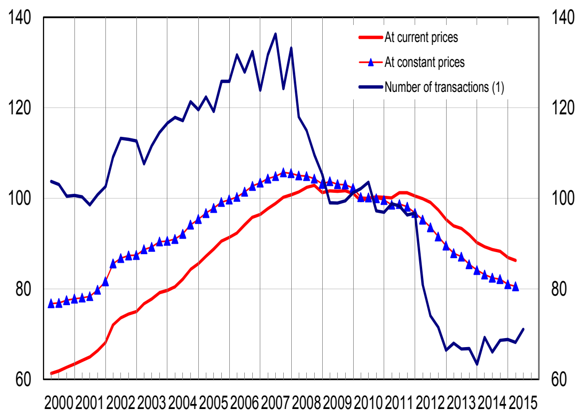
While econometric models can provide an initial warning, an exhaustive risk assessment cannot avoid considering the cyclical and structural characteristics of the real estate, bank and credit and household sectors that are analysed in this section.

Real estate market indicators

The real estate market indicators we monitor can be divided into three main categories:
1. Sales and prices in residential and commercial estate markets
2. Supply and demand in the housing market
3. Supply in the construction sector

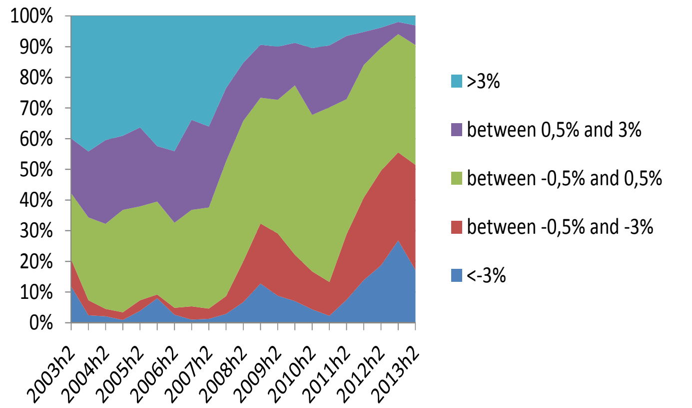
The main indicators in the first category are residential property prices (both nominal and real) and house sales at national level (Figure 10).

Figure 10 – House sales and residential property prices in Italy
(quarterly data; indices 2010=100)



Source: Agenzia delle Entrate, Banca d'Italia, Istat and Il Consulente Immobiliare. - (1) Seasonally and working-day adjusted.

Figure 11– Share of municipalities according to house prices variations
(biannual data; percentage values)

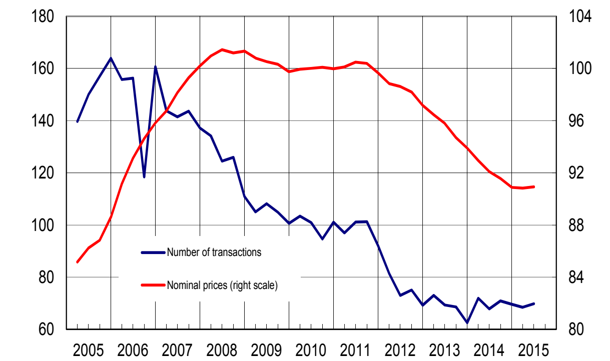


Source: Banca d'Italia, Agenzia delle Entrate, Il Consulente Immobiliare. Percentage variations of house prices compared to the previous semester for about 1,200 municipalities with a population greater than 10,000 inhabitants. The aggregation method is described in L. Cannari and I. Faiella, "House prices and housing wealth in Italy" in "Household Wealth in Italy", Banca d'Italia, 2008.

Looking initially at the price indicators is important both when prices increase, to check if at first glance there are risks of bubbles, and when they fall, to assess the effects on the value of houses as collateral. The analysis of the evolution of house sales, together with prices, makes possible a more comprehensive assessment of the health of the housing market. Looking at house sales helps in

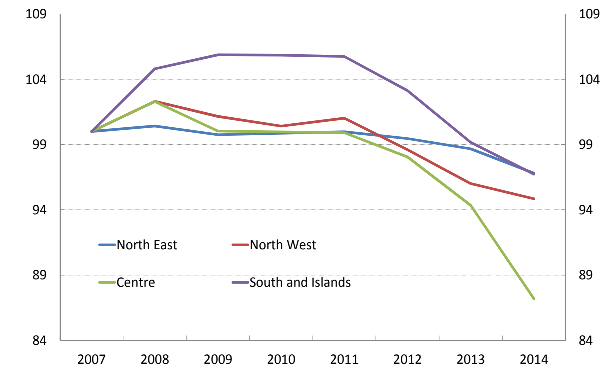
assessing the conditions of demand. Moreover, since the frictions that characterize the housing market result in a positive correlation between prices and quantities exchanged[39], the evolution of house sales gives insights into the future path of prices, which may initially be more sticky.
This analysis can be conducted in Italy not only at national level, but also with a more detailed geographical focus. This is important because macroprudential measures could also be designed with a view to targeting developments at the level of a specific geographic area[40]. The indicators we present in this paper are calculated for four geographical areas, the North West, the North East, the Centre and the South and Islands (NUTS 1 level). For these four geographical areas we have data on nominal prices (Figure 1.3 in Annex C), constructed using the methodology proposed by Cannari and Faiella (2008)[41], and house sales (Figure 1.4 in Annex C). Moreover, in order to verify if an increase (or a decrease) in house prices at national level is broad based across regions, or concentrated in a specific area or in the main cities, we consider a synthetic indicator based on house price evolution at municipality level[42] (Figure 11).

Figure 12 – Commercial property prices and sales in Italy (1)
(quarterly data; indices 2010=100)



Souce: Bank of Italy calculations based on Agenzia del Territorio, Istat, Nomisma and Scenari Immobiliari data. (1) Property sales are seasonally and working day adjusted.

Figure 13 – Commercial property prices in Italy
(annual data; indices 2007=100)



Source: Agenzia delle Entrate.

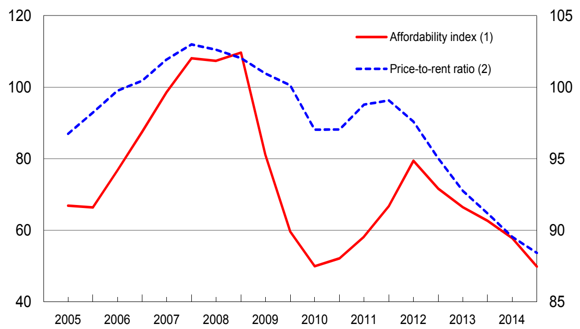
However, financial stability can be threatened not only by mispricing in the residential segment of the real estate market but also in the commercial segment. For this reason, we monitor the evolution of commercial property prices using an experimental indicator developed by the Bank of Italy (Figure 12); we also consider the evolutions of transactions. Both these indicators are also available at the NUTS 1 level (Figure 13; Figure 1.8 in Annex C).

A more in-depth analysis of the dynamics of the housing markets is provided by further indicators. Among them, considerable attention is devoted to the housing affordability index and the ratio of house prices to rents (price-to-rent; Figure 14)[43]. These indicators are useful in order to detect risks of house price misalignment, but they can be subject to specification and measurement issues. With regard to the price-to-rent ratio, we need to test carefully for the quality of statistics on rents. In particular in Italy and in other European countries the HICP rental index (used for example by

[39] The main frictions considered in the literature are: (i) credit market imperfections (Stein, 1994); (ii) matching frictions (Weathon, 1990).
[40] According to art. 124 CRR risks weights can be applied at a regional level.
[41] L. Cannari and I. Faiella, 2008.
[42] We computed the house price percentage variations compared with the previous period for about 1,200 municipalities. Then, according to house price variations, we computed the shares of municipalities in each of the following intervals: (i) greater than 3%; (ii) between 0.5% and 3%; (iii) between 0.5% and -0.5%; (iv) between -0.5% and -3%; (v) lower than -3%.
[43] The housing affordability index is a measure of the ability of households to buy a home. Affordable housing generally refers to housing units that are affordable by households whose income is below the median household income.

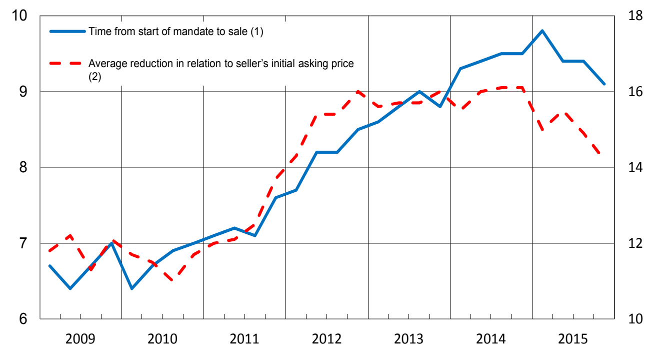
many international institutions) seems to underestimate the real trends in market rents. We believe that more reliable indications come from either the deflator of rent expenditure in the National accounts or *Il Consulente Immobiliare*, a private research institute that provides us with data on new rental contracts. Accordingly, the trend in the price-to-rent index we compile is significantly different from the trend in the HICP based index, and we believe it is more informative about misalignment risks in house prices. Compared with the affordability ratio, instead, the standard indicator only considers house prices and households' disposable income, ruling out the role of credit for housing affordability. Conversely, due to sound evidence that house prices are closely (and inversely) related to the cost of credit, we include the average mortgage rate in our indicator. As a result, the price to rent and affordability index we present here are much more reliable than those provided for example by the OECD and generally used for the early warning models.

Figure 14 – Housing affordability index and ratio of house prices to rents in Italy
(biannual data; indices 1992-2013 average=100)



Sources: Based on Bank of Italy, Istat, Agenzia delle Entrate and Consulente immobiliare data.
(1) The indicator is given by the ratio of debt service on new mortage loans – proxied by the product of house prices and interest rates – to household disposable income; a decrease indicates that housing is more affordable. – (2) Right-hand scale. With respect to new rental contracts.

Figure 15 – Time-on-market and average reduction on asking price in Italy



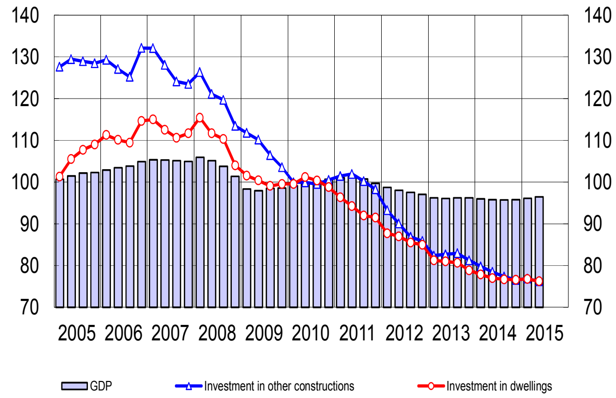
Source: Quarterly data from the survey conducted by the Bank of Italy, Agenzia delle Entrate and Tecnoborsa.
(1) Left-hand scale, months. (2) Right-hand scale, percentage points.

An additional source of information on the evolution of the housing market is the quarterly survey of real estate agents (Italian Housing Market Survey), jointly conducted by the Bank of Italy, Tecnoborsa and Agenzia delle Entrate. This survey provides information not only on the current situation but also on expectations. From the answers to the questions about the numbers of homes still registered with an agent at the end of a quarter and the numbers of homes newly registered during the quarter it is possible to get insights into the evolution of housing supply (Figure 1.16 in Annex C). Information about housing demand, instead, is derived from the answers to the question about the number of potential buyers, namely the number of people seeing at least one house for sale during the quarter. Further consideration on the tightness (ratio of number of buyers over the number of sellers) of the housing market can be made by looking at the evolution of the time-on-market (time between the start of the mandate to sell and the sale of the property) and the average margin for reductions on the selling price in relation to the seller's initial asking price (Figure 15). Finally, the survey provides estate agents' short-term expectations for prices, mandates to sell, the outlook of the own market and the general situation of the national market (Figure 1.18 in Annex C). All these variables are also available at NUTS 1 level.

Understanding the evolution of the housing market also requires a consideration of the dynamic of the housing stock. For this reason we monitor gross fixed investments in dwellings (Figure 16) and, from a medium-to-long-term perspective, building permits. An excessive expansion of the housing stock, not justified by a corresponding increase in the number of households, can put downward pressure on house prices in the medium term. More generally, the evolution of the construction sector, assessed through the gross value added (Figure 17; Figure 1.3 in Annex C), has to be monitored because of the close dependence of this sector on the banking sector.

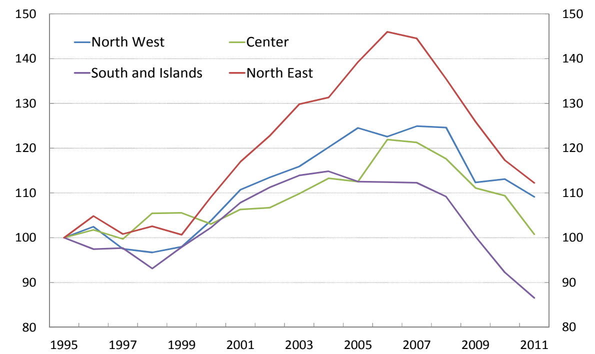
Finally, among other factors not explicitly considered by the indicators, particular attention is devoted to housing taxation (see FSR no.2/2014), which can have a marked effect on the housing market due to its effects on households' tenure choice.

Figure 16 – GDP and gross fixed investments in construction in Italy
(quarterly data; indices 2010=100)



Source: Istat.

Figure 17 – Gross value added of the construction sector in Italy
(annual data; indices 1995=100)



Source: Istat.

Bank and credit indicators

The recent financial crisis has shown that financial stability risks may originate from an excessive credit growth. In particular, the faster bank credit expands, the higher the risk of an asset bubble. As regards the real estate sector, large increases in bank loans to households for house purchase and to firms operating in that market may correspond to an overheating of house prices and a marked easing of credit standards[44] implying risks of a self-reinforcing feedback loop in which a flow of new borrowers with access to easy credit fuels an excessive surge in house prices. This surge then encourages lenders to ease credit further on the assumption that house prices will continue to rise[45].

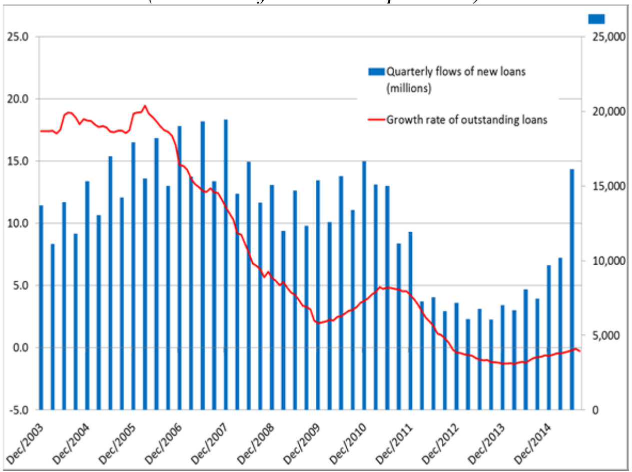
On the other hand, a strong reduction in credit growth caused by supply restrictions could have an adverse impact on sectors characterized by the presence of a sizeable share of small firms, such as in construction, for which the recourse to alternative funding is more difficult in the short term. Since credit restriction increases the likelihood of borrowers' distress, the real economy could be affected adversely, in turn weighing on banks' vulnerability.

Bearing in mind that loans to households for house purchase, to construction firms and real estate agencies constitute a large share of Italian banks' total credit to customers, the growth rate of loans to the real estate market represents an important indicator that needs monitoring.

Figures 18 and 19 show respectively the evolution of bank credit to households for house purchase and to construction and real estate firms in the last 10 years.

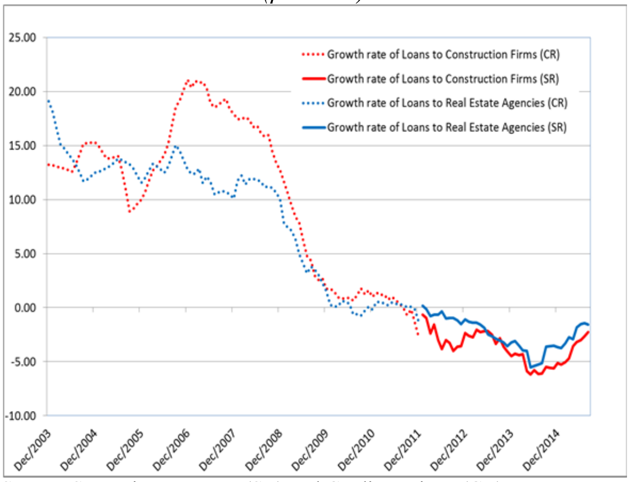
[44] Dell'Ariccia, G., Igan, D. and Laeven, L. (2012).
[45] U.S. Financial Crisis Inquiry Commission (2011).

Figure 18 – Loans to households for house purchase
(millions of euros and per cent)



Source: Supervisory reports.

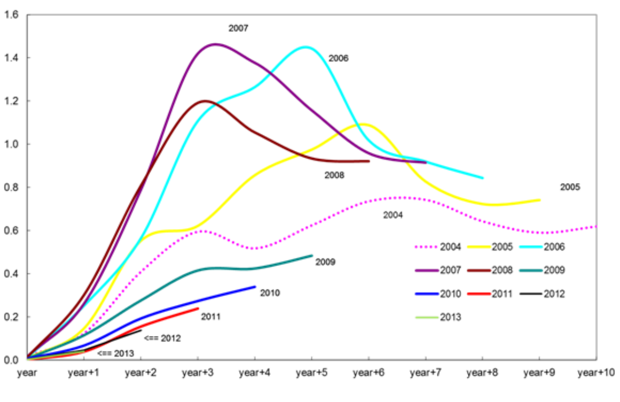
Figure 19 – Loans to construction and real estate
(per cent)



Source: Supervisory reports (SR) and Credit Register (CR).

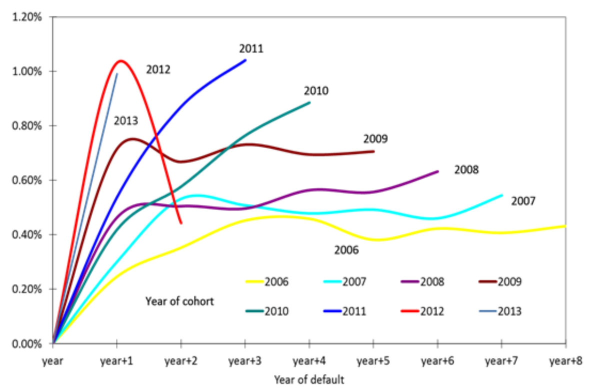
As mentioned above, rapid increases in credit could be associated with a relaxation of lending standards. Analysing default rates of loans from different cohorts may help to monitor this aspect, as higher default rates of borrowers belonging to the same vintage could occur as a consequence of banks loosening their lending standards, leading to a decrease in the ex-ante creditworthiness of debtors. In addition to changes in the borrowers' composition, the pattern of cohort default rates could reflect other factors, such as price declines, changes in mortgage product characteristics and hikes in interest rates. Figures 20 and 21 report the ratio between new bad loans and outstanding loans to households and construction firms, calculated at borrower level and by year of disbursement.

Figure 20-New bad loans to households for house purchase by year of disbursement
(per cent of the number of contracts)



Source: Analytical survey of interest rates and Credit Register.

Figure 21– Default rates of construction firms by cohort of borrowers
(per cent of the number of firms)



Source: Credit Register.

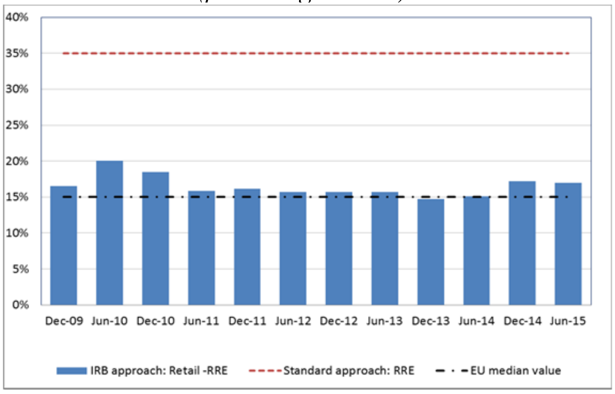
Finally we analyse some loan characteristics: their risk weights (RWs) and loan-to-value (LTV) ratio. RWs can be useful to describe how the potential risks associated with mortgage loans were taken into account in calculating the minimum capital requirements for credit and how floors to RWs can be applied as a macroprudential measure in order to handle risks associated with the real estate sector.

Figure 22 reports the average RWs of non-defaulted exposures relative to real estate for the Italian banks adopting the internal ratings-based (IRB) approach[46]. The IRB portfolio considered is the one concerning the real estate secured exposures to households (retail-residential mortgages). The RW values are about 15%, corresponding to the median value for a sample of 43 European banks (as reported in the third interim report on the consistency of risk-weighted assets by the EBA, the black dotted line in the Figure 22). In the case of the standard approach, the RW value for the residential real estate is 35% (red dotted line).

As regards the LTV ratio on new loans to households for house purchase, it has decreased by 10 percentage points in the last 8 years, reaching an average level of 58% in 2013 (Figure 2.17 in Annex C). AQR banks[47], in particular, show lower LTV ratios on average than non-AQR banks (Figure 2.17a, 2.17b in Annex C), but the share of loans with LTV > 80% has been increasing rapidly in recent years (Figure 23).

Figure 22- Risk weights of real estate secured exposures

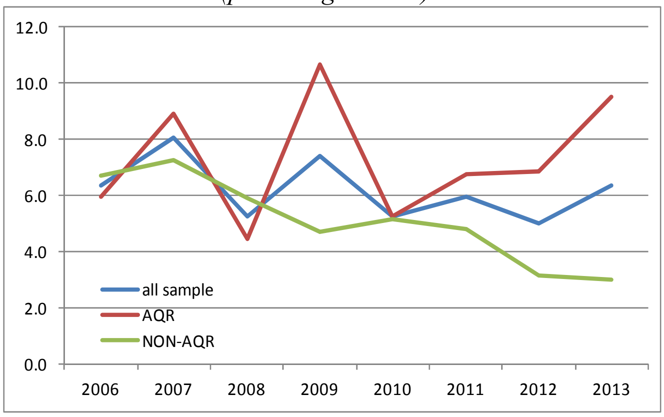
(percentage values)



Source: Supervisory reports.

Figure 23– Share of new loans for house purchase with LTV > 80%

(percentage values)



Source: RBLS.

Household' indicators

Excessive levels of household indebtedness may pose threats to financial stability. On the one hand, decreases in income and rises in interest rates - reflecting increasing costs of variable-rate mortgages - may cause financial distress to highly indebted households, directly affecting banks' balance sheets. On the other hand, some households might react to shocks by reducing consumption in order to continue to service their debts, which could lead to a weakening of the real economy.

The debt service-to-income ratio may help to identify excessive levels of indebtedness. It is defined as the share of service payments (principal plus interest) on total loans to income. Data from the Survey on Household Income and Wealth allow us to extend the analysis by splitting households into quantiles of income distribution (Figure 24). This is relevant as low-income households, i.e. with an income below the median, are most at risk in adverse economic scenarios. Identifying those households can provide some evidence for evaluating the real consequences for banking

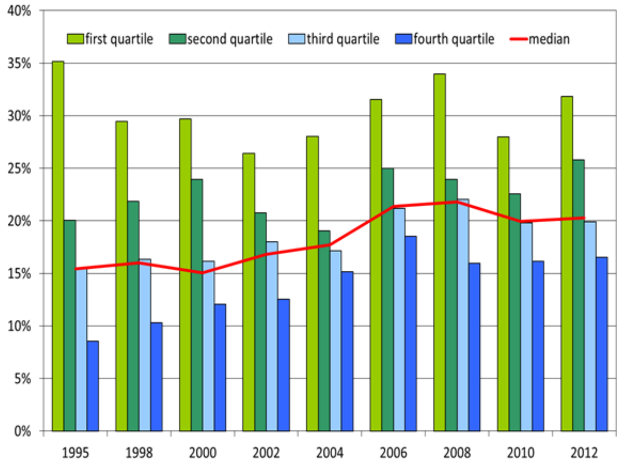
[46] Broadly speaking, the internal risk approach consists of a set of credit risk measurement techniques proposed under the Basel II capital adequacy rules for banking institutions and are also present in Basel III and CRR/CRD IV. The approach allows banks to assess their credit risk using their own models. In the case of the advanced IRB approach, banks are supposed to use their own quantitative models to estimate the PD (probability of default), EAD (exposure at default), LGD (loss given default) and other parameters required for calculating the RWA (risk-weighted asset), whereas the foundation IRB approach only calculates the PD.

[47] According to the SSM list of significant supervised entities as of June 24th 2014, AQR banks are: Banca Carige, Banca Monte dei Paschi, Banco Popolare, Banco Popolare dell'Emilia Romagna, Banco Popolare di Milano, Banco Popolare di Sondrio, Banco Popolare di Vicenza, Barclays Bank, Iccrea Holding, Intesa San Paolo, Mediobanca, Unicredit, UBI and Veneto Banca.

intermediaries, associated with new non-performing loans in the household sector. In addition, both in policy and academic debates, households with debt service above 30 per cent of income are considered more vulnerable to interest rate or income variations[48] (Figure 25).

Figure 24– Service of debt to income

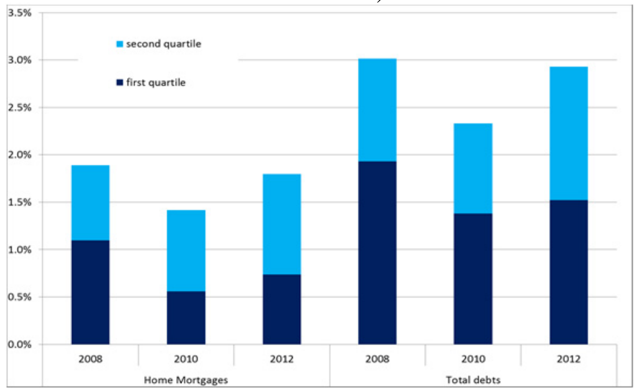
(per cent; quartiles of income distribution)



Source: Survey on Household Income and Wealth.

Figure 25 – Households with debt service exceeding 30% of income and income below the median

(per cent of total households; quartiles of income distribution)



Source: Survey on Household Income and Wealth

7. Conclusions

This work identifies a number of relevant findings:

- In 2014Q3 the ratio of households' new bad debts to banks' capital and reserves stood at 1.8%, well above the previous peak of the mid-nineties (1.6%). The same ratio for construction and real estate firms stood at 5.7%, a value equal to the 94th percentile of its distribution and just below the historical peak of 1996Q3 (6.3%).
- Risks for financial stability come mainly from loans to construction and real estate firms, while mortgage loans pose fewer concerns: the median level of the indicator for firms (2.8%) was well above the historical peak (1.9%) reached by the indicator for households in the entire period analysed. Moreover, among bank loans to households, loans for house purchase are characterized by a lower incidence of bad debts on outstanding bank loans compared to consumer credit loans. On the contrary, the riskiness of loans to construction firms and real estate agencies (measured by the ratio of the annual flow of new bad debts to performing loans) is well above the level of other companies.
- Historically, the systemic banking vulnerability indicator of construction and real estate firms has displayed a high correlation with household' indicators, with a lag of about two years, and a higher volatility.
- According to BMA linear regression models, which allow us to forecast a continuous level of financial stress, the best set of early warning indicators for banking vulnerability related to households comprises: (i) household credit-to-GDP ratio, (ii) value added of construction-to-GDP ratio, (iii) gap (deviation from long-term trend) of the number of residential transactions, (iv) growth rate of nominal residential prices, and (v) growth rate of the number of residential transactions. For the vulnerability related to construction and real estate firms, the best set includes: (i) long-term government bond yields, (ii) gap (deviation

[48] See Michelangeli and Pietrunti (2014).

from long-term trend) of the value added of construction-to-GDP ratio, (iii) price-to-income ratio, (iv) growth rate of credit granted to construction and real estate firms, and (v) growth rate of the number of residential transactions. Roughly the same set of variables is also selected in the ordered logit models.

- Both the BMA linear regression and the ordered logit models exhibit good predictive abilities; they can help to identify in advance financial stability risks arising from the real estate sector. In particular, the BMA linear regression models are capable of accurate predictions up to two years in advance. These models thus provide a useful analytical framework for supporting Bank of Italy's decisions on the possible use of macroprudential instruments to address such risks.
- According to the projections of the Bayesian models from the third quarter of 2015 to the second quarter of 2016, banking vulnerability related to the real estate sector, though remaining at relatively high levels, should gradually decline. These results are consistent with the judgment that there currently is no need to activate macroprudential tools in order to counter risks arising from the real estate sector.
- The econometric analysis is complemented with a set of real estate-related indicators, some of which are new, developed to monitor financial stability risks in Italy. The results provided by these indicators are, among others, that: i) the share of Italian municipalities that recorded a decline in house prices on a cyclical basis decreased; ii) the riskiness of more recent borrowers is far below that of the borrowers that took out a loan before 2009.

ANNEX A – Correlations

Table A.1

Pairwise correlation between potential early warning indicators

(reference period: 1987Q1-2014Q2; quarterly data)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
1. RRE price growth (nominal)	1.00																											
2. RRE price growth (real)	0.97	1.00																										
3. RRE price gap (nominal)	0.65	0.65	1.00																									
4. RRE price gap (real)	0.61	0.64	0.96	1.00																								
5. price-to-rent (growth rate)	0.70	0.63	0.56	0.54	1.00																							
6. price-to-rent gap	0.47	0.35	0.46	0.37	0.72	1.00																						
7. price-to-income (growth rate)	0.65	0.69	0.31	0.35	0.46	0.14	1.00																					
8. price-to-income gap	0.45	0.52	0.71	0.85	0.48	0.26	0.53	1.00																				
9. price-to-rent (level)	-0.16	-0.20	0.30	0.36	0.11	0.04	-0.44	0.18	1.00																			
10. price-to-income (level)	-0.15	-0.10	0.15	0.32	0.16	0.35	0.07	0.63	0.17	1.00																		
11. value added construction to GDP (current)	0.46	0.41	0.60	0.58	0.54	0.83	0.27	0.55	-0.11	0.56	1.00																	
12. value added construction to GDP (chain-linked)	0.80	0.73	0.80	0.66	0.59	0.62	0.42	0.38	-0.14	-0.14	0.68	1.00																
13. value added construction to GDP gap (current)	0.49	0.60	0.71	0.79	0.36	0.13	0.53	0.88	-0.05	0.41	0.53	0.48	1.00															
14. value added construction to GDP gap (chain-linked)	0.63	0.72	0.72	0.73	0.33	-0.03	0.56	0.69	-0.06	-0.02	0.26	0.59	0.87	1.00														
15. long-term govt bond yield (nominal)	0.58	0.39	0.37	0.24	0.58	0.64	0.07	-0.08	0.12	-0.32	0.35	0.66	-0.19	-0.03	1.00													
16. RRE credit growth (nominal)	0.63	0.66	0.37	0.37	0.34	-0.01	0.66	0.36	-0.40	-0.20	0.15	0.49	0.41	0.53	0.18	1.00												
17. C&RE credit growth (nominal)	0.57	0.55	0.86	0.81	0.44	0.41	0.26	0.61	0.06	0.14	0.63	0.78	0.66	0.66	0.36	0.36	1.00											
18. RRE credit to GDP gap	-0.25	-0.13	-0.03	0.11	-0.03	-0.02	0.15	0.49	-0.14	0.79	0.27	-0.30	0.45	0.09	-0.67	0.03	0.00	1.00										
19. C&RE credit to GDP gap	-0.08	-0.05	0.47	0.47	0.17	0.44	-0.06	0.49	0.25	0.68	0.63	0.21	0.41	0.10	-0.12	-0.19	0.48	0.49	1.00									
20. RRE credit to GDP (level)	-0.56	-0.47	-0.45	-0.28	-0.28	-0.08	-0.14	0.13	-0.08	0.77	0.08	-0.64	0.03	-0.35	-0.69	-0.39	-0.38	0.83	0.34	1.00								
21. C&RE credit to GDP (level)	-0.63	-0.56	-0.35	-0.22	-0.29	-0.01	-0.28	0.11	0.11	0.78	0.12	-0.60	-0.02	-0.42	-0.62	-0.52	-0.30	0.76	0.56	0.94	1.00							
22. debt service ratio (level)	-0.45	-0.37	-0.26	-0.11	-0.15	0.06	-0.08	0.29	-0.03	0.86	0.25	-0.49	0.17	-0.24	-0.61	-0.36	-0.18	0.85	0.52	0.96	0.94	1.00						
23. residential transactions (level)	-0.03	0.15	0.29	0.39	-0.03	-0.27	0.29	0.61	-0.04	0.42	0.07	-0.07	0.71	0.58	-0.70	0.22	0.24	0.72	0.40	0.38	0.34	0.45	1.00					
24. residential transactions (growth rate)	0.27	0.32	0.23	0.19	0.04	-0.25	0.17	0.03	-0.04	-0.45	-0.26	0.22	0.11	0.36	0.03	0.45	0.04	-0.27	-0.29	-0.48	-0.51	-0.51	0.23	1.00				
25. residential transactions gap	0.47	0.52	0.53	0.45	0.18	-0.27	0.35	0.25	-0.01	-0.51	-0.19	0.45	0.42	0.73	0.07	0.60	0.40	-0.26	-0.23	-0.66	-0.71	-0.63	0.39	0.76	1.00			
26. unemployment (level)	-0.33	-0.42	-0.61	-0.66	-0.33	-0.31	-0.39	-0.78	0.06	-0.63	-0.64	-0.38	-0.82	-0.59	0.25	-0.30	-0.61	-0.67	-0.69	-0.29	-0.30	-0.46	-0.75	0.05	-0.17	1.00		
27. disposible income (growth rate)	0.69	0.57	0.43	0.29	0.61	0.48	0.26	0.06	-0.11	-0.36	0.29	0.69	0.12	0.33	0.68	0.43	0.40	-0.42	-0.21	-0.63	-0.67	-0.56	-0.24	0.26	0.41	-0.04	1.00	
28. output gap	0.69	0.70	0.59	0.53	0.60	0.25	0.58	0.45	-0.10	-0.12	0.24	0.59	0.54	0.68	0.20	0.60	0.51	0.02	0.02	-0.39	-0.46	-0.26	0.40	0.33	0.66	-0.52	0.61	1.00

Figure A.2 - Households' banking vulnerability indicator: correlations between the intermediate set of 13 variables

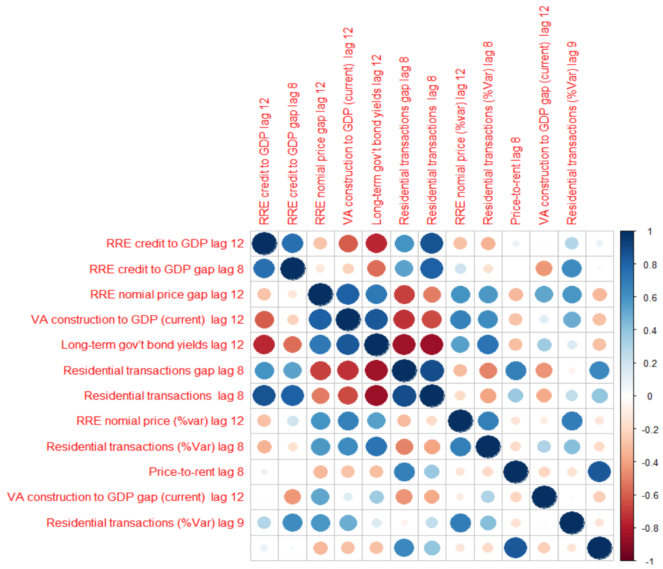


Figure A.3 - Households' banking vulnerability indicator: correlations between the optimal set of 5 variables

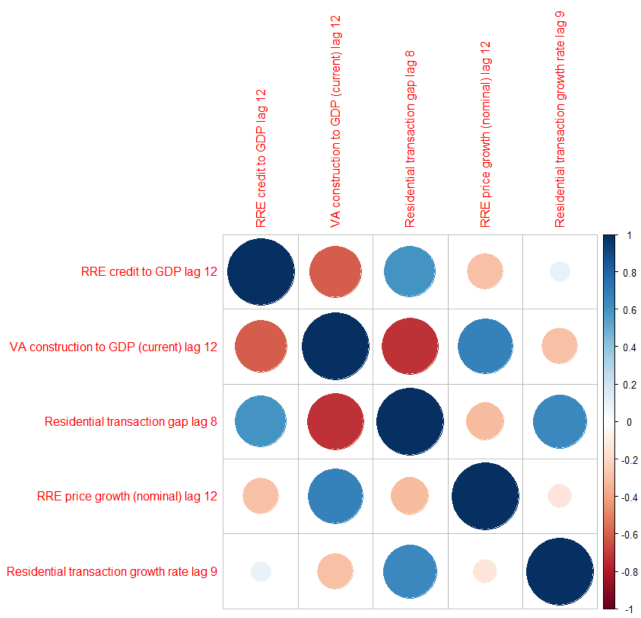


Figure A.4 – Construction and real estate firms' banking vulnerability indicator: correlations between the intermediate set of 13 variables

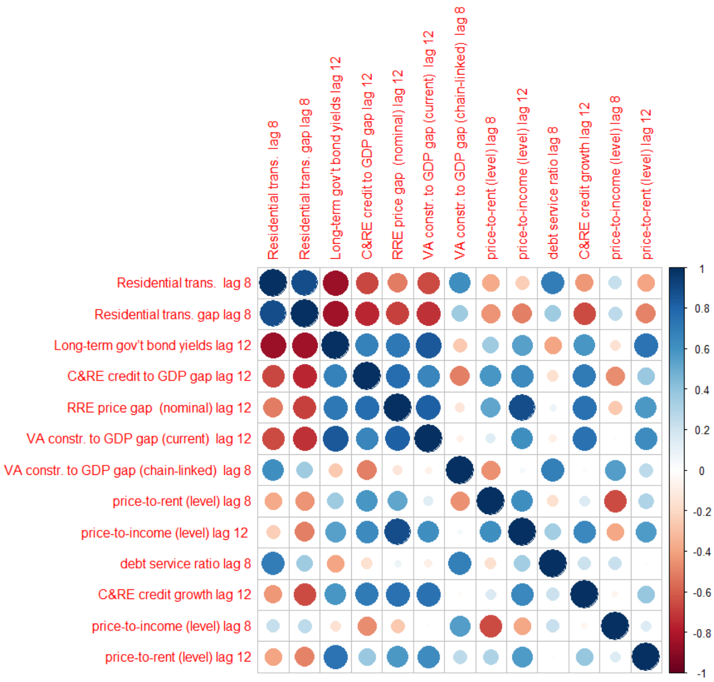
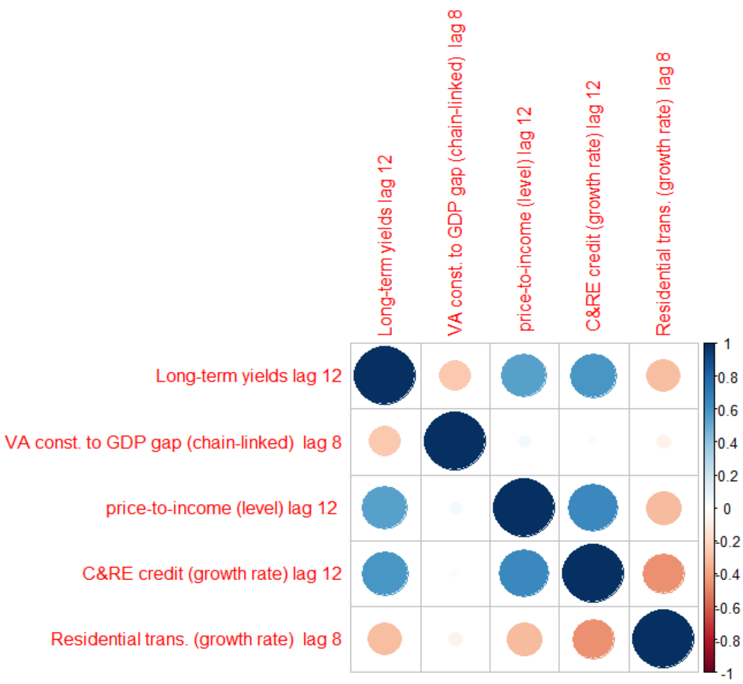


Figure A.5 - Construction and real estate firms' banking vulnerability indicator: correlations between the optimal set of 5 variables



ANNEX B - Logit models: in-sample forecasting exercise and robustness checks

In-sample forecasting exercise

Binary logit

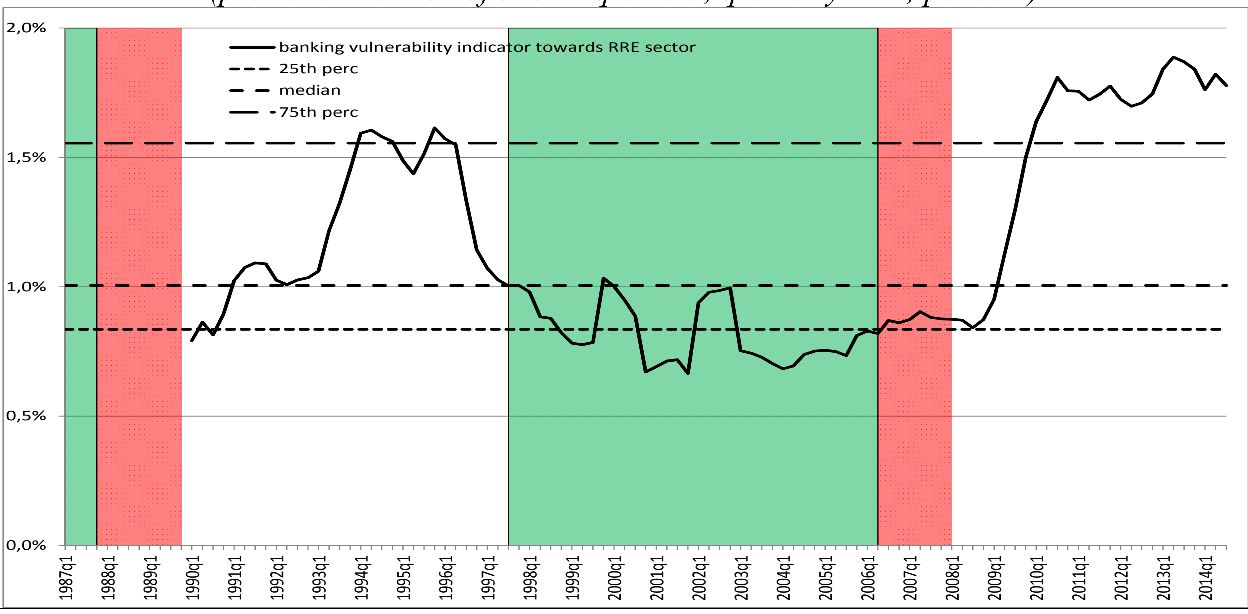
Using binary logit regressions, we can assess whether some warning signals would have been issued ahead of vulnerability states (i.e. vulnerability indicator above its median level) by comparing the predicted values of the best pair of early warning indicators for the systemic banking vulnerability related to households and to construction and real estate firms with the relative optimal threshold.

Figure B.1 shows the households' systemic banking vulnerability indicator, presented in section 4, and the signals issued by the best bivariate binary logit model (the price to rent ratio gap and the value added construction to GDP gap (chain-linked): the red shaded area marks the periods during which a warning signal would have been issued, the green shaded area shows tranquil periods, whereas the remaining periods are characterized by a vulnerability state (indicator above its median level)[49]. In particular, a warning signal would have been issued since 2006Q1, well ahead the last households' systemic banking vulnerability state started in 2009Q2.

Similarly, Figure B.2 shows the construction and real estate firms' systemic banking vulnerability indicator, presented in section 2.2, and the signals issued by the best bivariate binary logit model (the C&RE credit to GDP and long-term government bond yields). In this case, a warning signal would have been issued since 2008Q3 when the vulnerability indicator was below the 25th percentile, so well ahead the last construction and real estate firms' systemic banking vulnerability state started in 2011Q3.

Figure B.1 – Binary logit regression: warning signals of the best pair of indicators for households' systemic banking vulnerability (1)

(prediction horizon of 5 to 12 quarters; quarterly data; per cent)



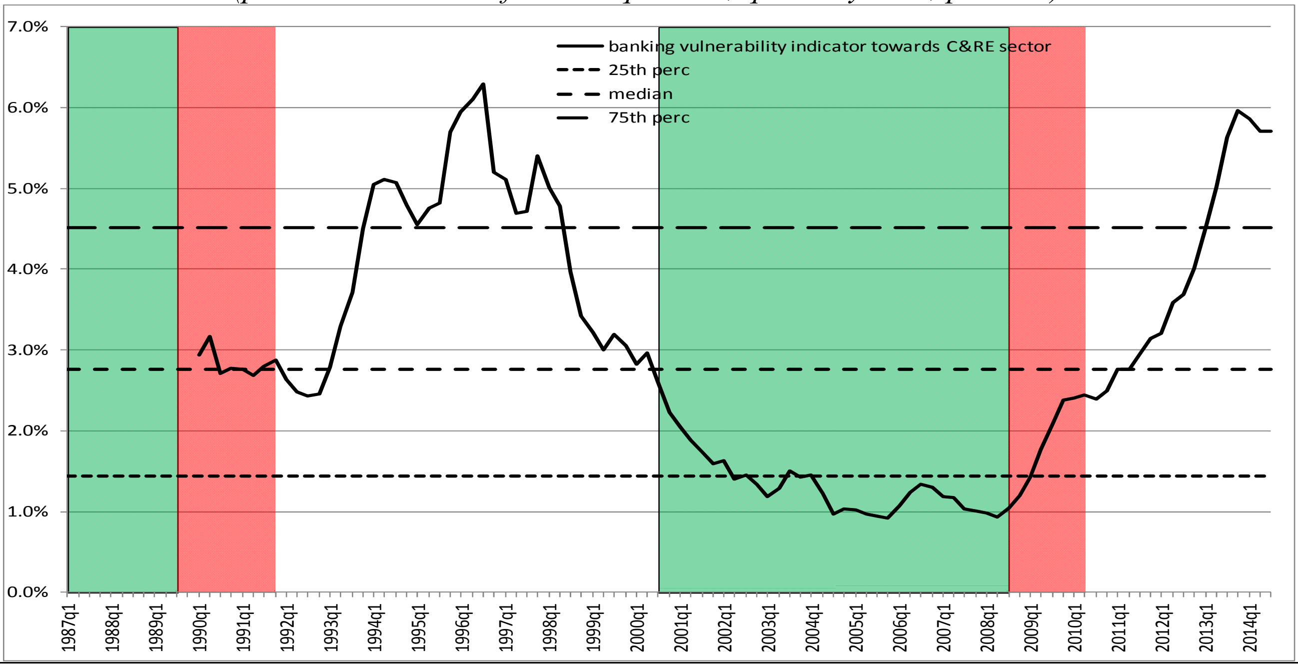
Source: elaborations based on Supervisory Reports and Central Credit Register data.

(1) The best pair of indicators comprises the price to rent ratio gap and the value added construction to GDP gap (chain-linked).

---

[49] Observations in windows of 1 to 4 quarters before a vulnerability state starts, as well as observations during such vulnerability were dropped from the sample.

Figure B.2 – Binary logit regression: warning signals of the best pair of indicators for construction and real estate firms' systemic banking vulnerability (1)
(prediction horizon of 5 to 12 quarters; quarterly data; per cent)



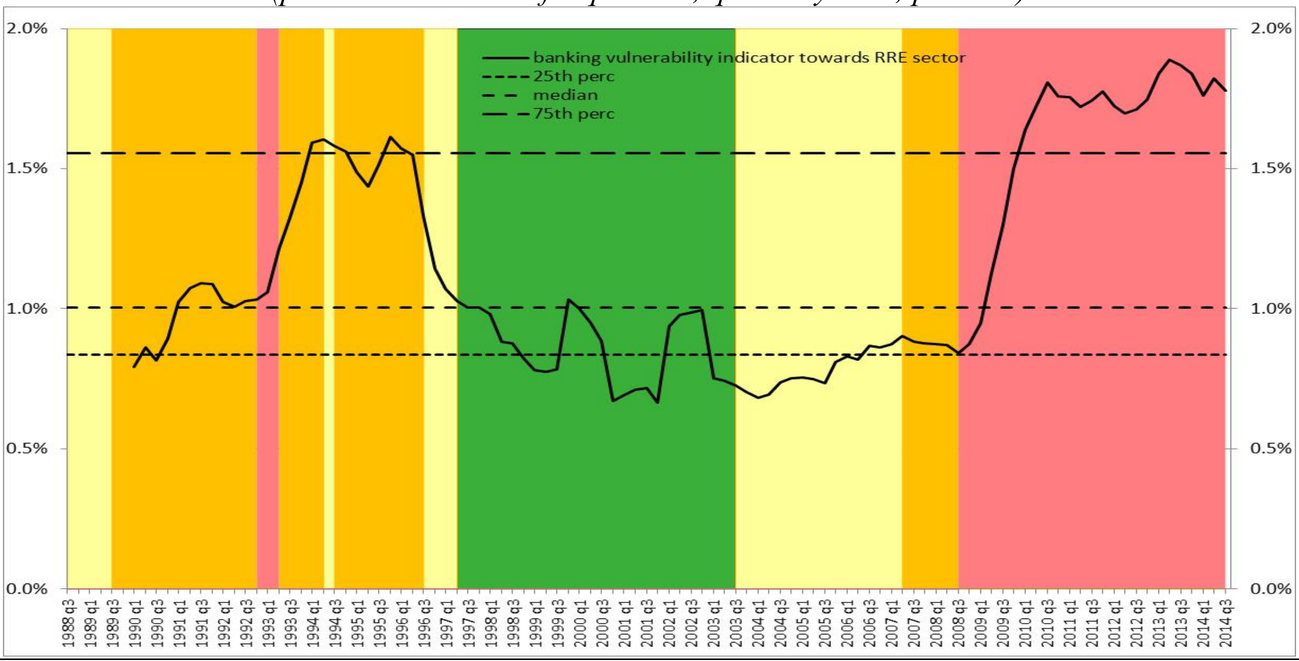
Source: elaborations based on Supervisory Reports and Central Credit Register data.
(1) The best pair of indicators includes the C&RE credit to GDP ratio and long-term government bond yields.

Ordered logit

By using the ordered logit regressions we are able to forecast the level of vulnerability to come several quarters ahead (depending on the lags of the early warning indicators). Figure B.3 shows the systemic banking vulnerability indicator related to households, presented in section 4, and the levels of vulnerability anticipated by the best RRE binary ordered logit model (long-term government bond yields lagged 6 quarters and the debt service ratio lagged 12 quarters). The shaded area marks the periods during which the model predicts, 6 quarters in advance, a level of vulnerability respectively below the 25th percentile (green), between the 25th percentile and the median (yellow), between the median and the 75th percentile (orange), above the 75th percentile (red). In particular, since 2008Q3 when the households' vulnerability indicator was just at the 25th percentile, the model already predicted a high level of vulnerability (above the 75th percentile): this result is driven by the debt service ratio lagged 12 quarters that has accelerated its growth since then (Figure B.4).

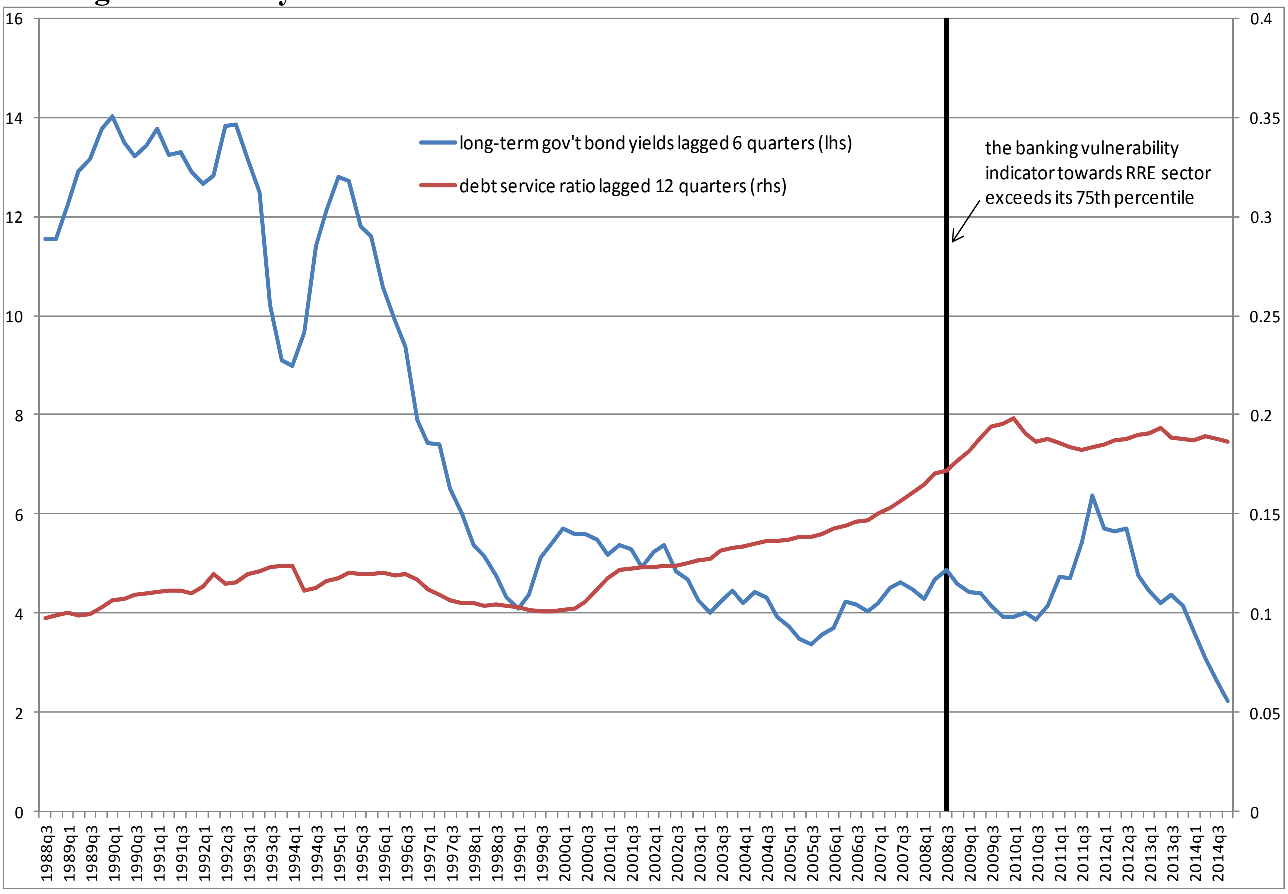
Similarly, Figure B.5 shows construction and real estate firms' systemic banking vulnerability indicator, presented in section 4, and the levels of vulnerability anticipated by the best C&RE binary ordered logit model (long term government bond yields lagged 7 quarters and residential transactions gap lagged 12 quarters). The shaded area marks the periods during which the model predicts, 7 quarters in advance, a negligible (green), low (yellow), medium (orange) and high (red) level of vulnerability. In particular, since 2009Q4 when the construction and real estate firms' vulnerability indicator was below the median level, the model already predicted a high level of vulnerability (above the 75th percentile): this result is driven by the residential transactions gap lagged 12 quarters that was shrinking significantly at that time (Figure B.6).

Figure B.3 – Ordered logit regression: warning signals of the best pair of indicators for households' systemic banking vulnerability (1)
(prediction horizon of 6 quarters; quarterly data; per cent)



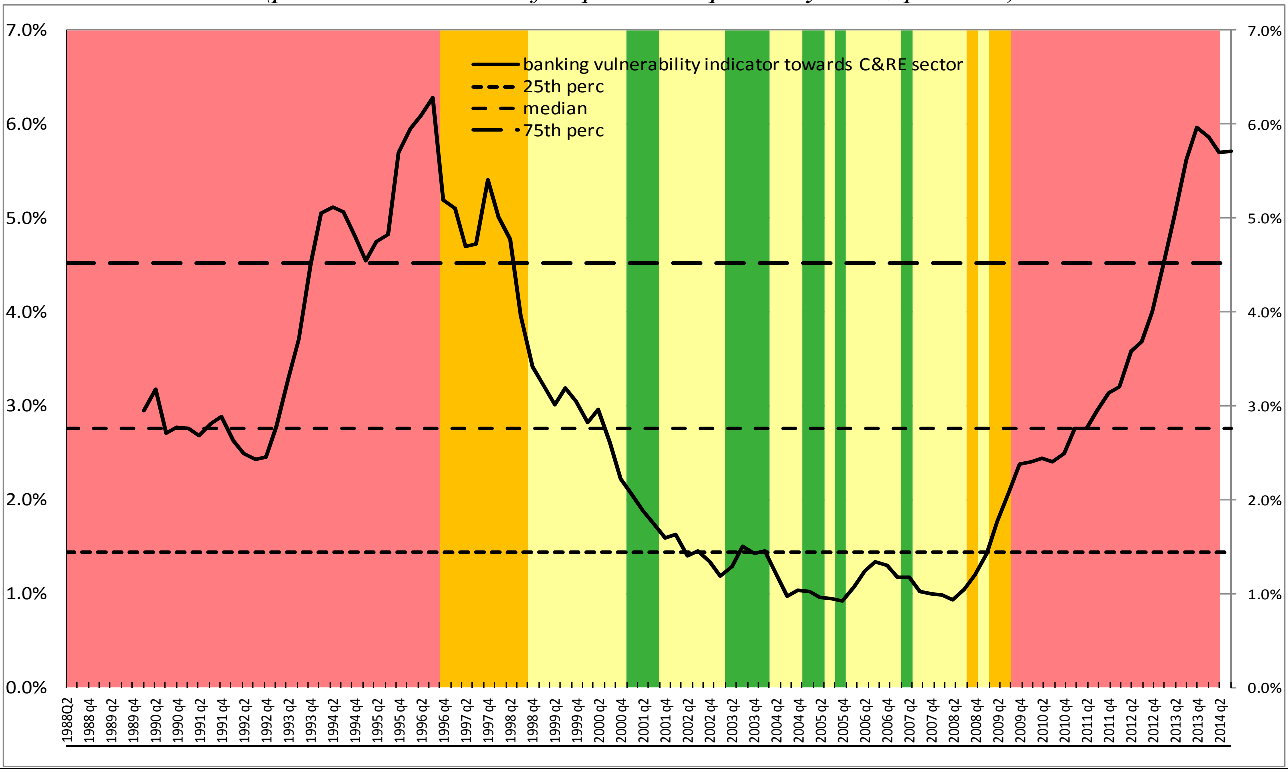
Source: elaborations based on Supervisory Reports and Central Credit Register data.
(1) The best pair of indicators includes long-term government bond yields lagged 6 quarters and the debt service ratio lagged 12 quarters.

Figure B.4 - Evolution of the best pair of early warning indicators for the RRE systemic banking vulnerability



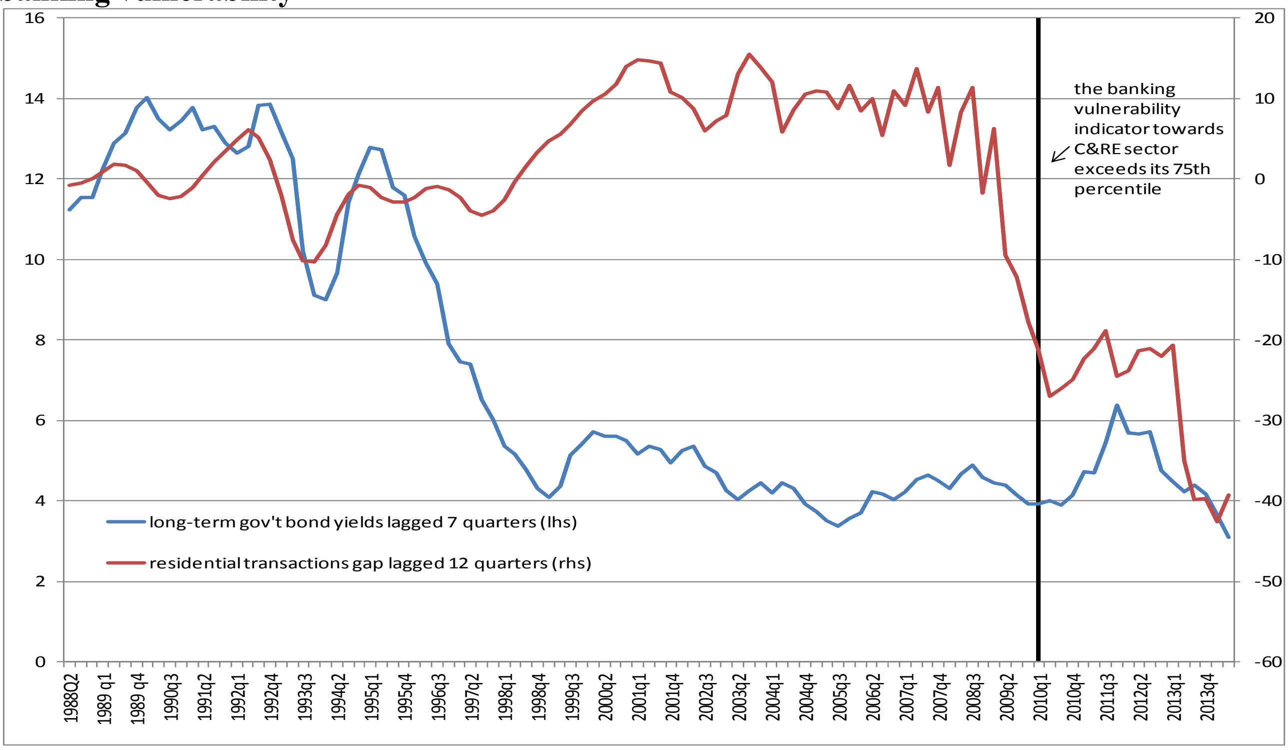
FigureB.5 – Ordered logit regression: warning signals of the best pair of indicators for construction and real estate agencies' systemic banking vulnerability (1)

(prediction horizon of 7 quarters; quarterly data; per cent)



Source: elaborations based on Supervisory Reports and Central Credit Register data.
(1) The best pair of indicators includes long-term government bond yields lagged 7 quarters and residential transactions gap lagged 12 quarters.

Figure B.6: Evolution of the best pair of early warning indicators for the C&RE systemic banking vulnerability



Robustness checks

Theta sensitivity

The selection of the optimal threshold and the optimal model depends on the parameter θ, i.e. a policymaker's relative preference for missing vulnerability states versus issuing false alarms. In our analysis we chose θ =2/3[50] and the previous results reported in Section 5.2.2 refer to this assumption.

In order to evaluate the robustness of the model to changes in the parameter θ, we apply the evaluation methodology for θ = 0.4, 0.5, 0.66 and 0.8. Table B.1 reports the results in the case of a univariate ordered logit model for households. Similar results can be obtained with the other models.

First of all, varying θ not only affects the selection of the optimal thresholds, but also the ranking of models. For all the parameter values considered, the first models are the ones relative to the variables 'VA construction to GDP (current)' and 'price-to-rent-gap', with different lags. These models are robust to changes in the parameter θ. The model 'VA construction to GDP (current) lag 12' is ranked first for three out of the four cases considered and third for θ=0.66. In this latter case the best model is 'price-to-rent gap lag11'.

Table B.1

Univariate ordered logit (households): the effect of varying θ on the selection of the optimal model/threshold

price-to-rent gap lag11	**RU**	**th1**	**th2**	**th3**	**wFN**	**wFP**	**w(1-ACC)**	**rank**
theta = 0.40	0,76	-1,02	-0,84	1,64	0,14	0,07	0,20	7
theta = 0.5	0,81	-2,09	-0,49	1,64	0,10	0,09	0,19	5
theta = 0.66	**0,76**	**-2,44**	**-0,84**	**0,04**	**0,02**	**0,19**	**0,22**	**1**
theta = 0.80	0,73	-2,44	-0,84	-0,13	0,02	0,20	0,22	2

price-to-rent gap lag10	**RU**	**th1**	**th2**	**th3**	**wFN**	**wFP**	**w(1-ACC)**	**rank**
theta = 0.40	0,77	-1,15	-0,81	1,58	0,13	0,07	0,20	5
theta = 0.5	0,80	-2,17	-0,64	1,24	0,09	0,11	0,20	6
theta = 0.66	0,75	-2,17	-0,47	-0,30	0,02	0,20	0,23	2
theta = 0.80	0,71	-2,17	-0,47	-0,30	0,02	0,20	0,23	5

VA construction to GDP (current) lag 12	**RU**	**th1**	**th2**	**th3**	**wFN**	**wFP**	**w(1-ACC)**	**rank**
theta 0.40	**0,81**	**18,76**	**20,15**	**22,13**	**0,12**	**0,05**	**0,17**	**1**
theta 0.50	**0,83**	**18,76**	**20,15**	**22,13**	**0,12**	**0,05**	**0,17**	**1**
theta 0.66	0,75	16,78	19,36	21,33	0,05	0,15	0,20	3
theta 0.80	**0,73**	**16,39**	**19,55**	**19,75**	**0,00**	**0,25**	**0,26**	**1**

[50] See note 28 for an explanation of this assumption.

VA construction to GDP (current) lag 11	RU	th1	th2	th3	wFN	wFP	w(1-ACC)	rank
theta 0.40	0,81	17,53	18,64	20,67	0,11	0,06	0,17	2
theta 0.50	0,83	17,53	18,64	20,67	0,11	0,06	0,17	2
theta 0.66	0,75	15,68	18,08	19,93	0,05	0,15	0,20	5
theta 0.80	0,70	15,31	17,71	19,01	0,01	0,25	0,26	6

VA construction to GDP (current) lag 10	RU	th1	th2	th3	wFN	wFP	w(1-ACC)	rank
theta 0.40	0,81	17,53	18,64	20,67	0,11	0,06	0,17	3
theta 0.50	0,82	15,93	16,43	18,60	0,12	0,06	0,18	3
theta 0.66	0,79	15,93	16,43	18,60	0,12	0,06	0,18	11
theta 0.80	0,67	13,77	15,93	17,10	0,02	0,26	0,27	11

price-to-rent gap lag 7	RU	th1	th2	th3	wFN	wFP	w(1-ACC)	rank
theta 0.40	0,74	-0,97	-0,82	1,33	0,13	0,09	0,21	10
theta 0.50	0,79	-1,11	-0,97	1,33	0,11	0,09	0,21	10
theta 0.66	0,75	-1,83	-0,54	0,32	0,04	0,18	0,22	6
theta 0.80	0,72	-2,83	-0,54	-0,39	0,01	0,25	0,26	3

Model selection: relative usefulness vs. Bayesian Information Criterion (BIC)

The best performing early warning indicators presented in section 5.2.2 are selected based on the maximization of relative usefulness. To check for the robustness of their ranking we also calculate the Bayesian Information Criterion (BIC). Like adjusted R^2 the BIC places a premium on achieving a given fit with a smaller number of parameters per observation, but with its heavier penalty for degrees of freedom lost the BIC will lean towards a simpler model. As a result the model with the lowest BIC is preferred.

Taking into consideration ordered logit models for banking vulnerability related to households, Table B.2 compares the best three individual and pairs of early warning indicators resulting from the maximization of the relative usefulness with those that present the lowest BIC. Both model selection methods broadly select the same individual and pair of early warning indicators, since the models selected according to one methodology are also relatively good predictors according to the other. Indeed, the gap of the price to rent ratio lagged 11 quarters, which is the 1st early warning indicator according to RU, ranks fourth according to BIC; similarly the value added construction to GDP (current) ratio lagged 12 quarters is confirmed as being very robust. With regard to the pairs of indicators, 'long-term government bond yields lagged 6 quarters and debt service ratio lagged 12 quarters' ranks 1st based on RU and among the first twenty models (over 906 models) according to BIC; similarly, 'VA construction to GDP gap and price to income' with several different lags is confirmed as a robust early warning pair of indicators.

Table B. 2

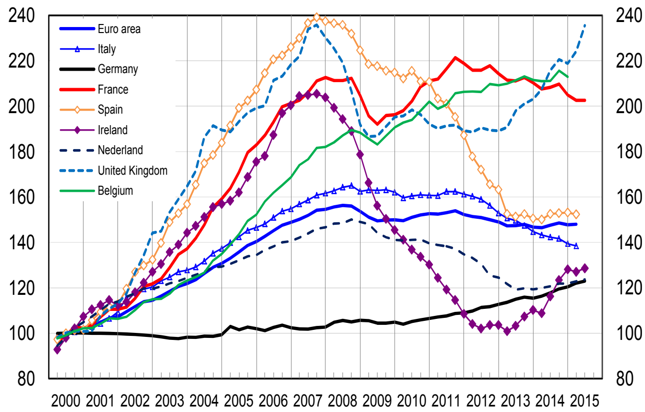
Ordered logit model selection (households): relative usefulness vs. BIC

	RU	BIC
Univariate	Price to rent gap lag 11	VA construction to GDP lag 12 (current)
	Price to rent gap lag 10	VA construction to GDP lag 11 (current)
	VA construction to GDP lag 12 (current)	Price to rent gap lag12
Bivariate	Long-term gov't bond yields lag 6 & Debt service ratio lag 12	VA construction to GDP gap lag 7 (chain-linked) & Price to income lag 7
	VA construction to GDP gap lag 12 (chain-linked) & Price to income lag 8	VA construction to GDP gap lag 7 (chain-linked) & Price to income lag 6
	VA construction to GDP gap lag 12 (chain-linked) & Price to income lag 7	VA construction to GDP gap lag 10 (chain-linked) & Price to income lag 7

ANNEX C – Real estate-related indicators

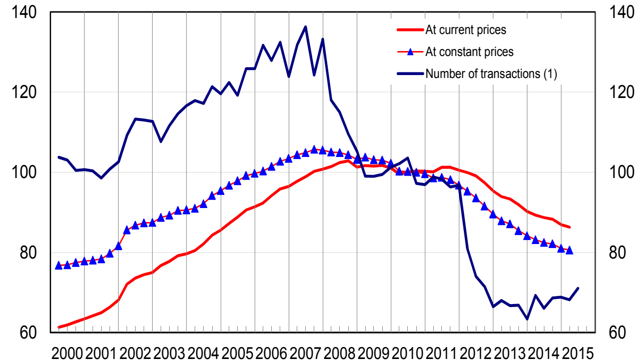
C.1 Real estate indicators

Figure 1.1 – Residential property prices in Europe
(quarterly data; indices 2000=100)



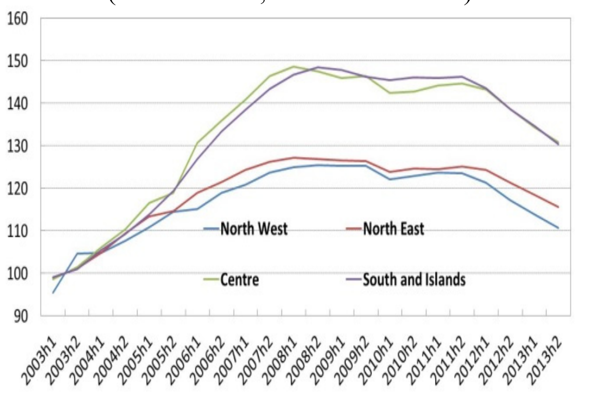
Source: ECB and Banca d'Italia.

Figure 1.2 – House sales and residential property prices in Italy
(quarterly data; indices 2010=100)



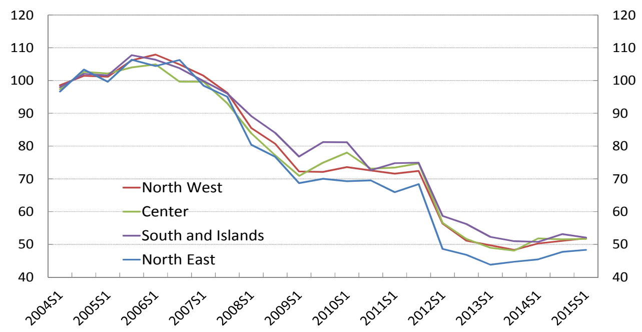
Source: Agenzia delle Entrate, Banca d'Italia, Istat and Il Consulente Immobiliare. - (1) Seasonally and working days adjusted.

Figure 1.3 – Residential property prices in Italy
(biannual data; indices 2003=100)



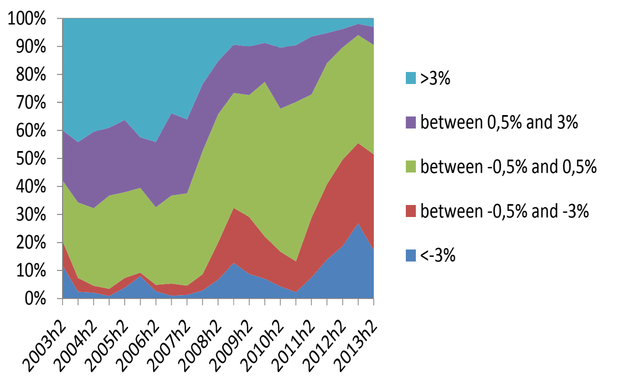
Source: Agenzia delle Entrate, Banca d'Italia, Istat and Il Consulente Immobiliare.

Figure 1.4 – House sales in Italy
(biannual data; indices 2003=100)



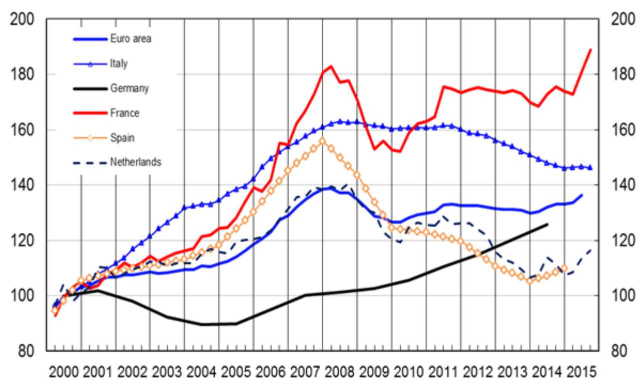
Source: Agenzia delle Entrate.

Figure 1.5 – House prices variations in major Italian municipalities
(biannual data; percentage values)



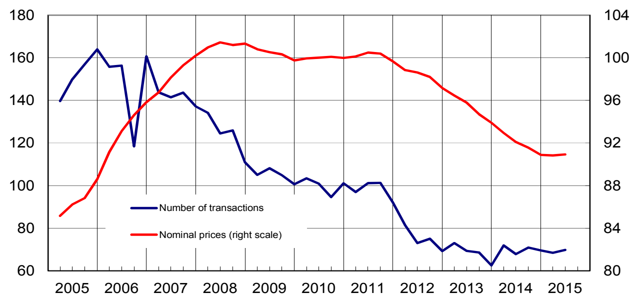
Source: Banca d'Italia, Agenzia delle Entrate, Il Consulente Immobiliare. Percentage variations of house prices compared to the previous semester for about 1.200 municipalities with a population greater than 10,000 inhabitants. The aggregation method is described in L. Cannari and I. Faiella, "House prices and housing wealth in Italy" in "Household Wealth in Italy", Banca d'Italia, 2008.

Figure 1.6 – Commercial property prices in Europe (1)
(quarterly data (2); indices 2005=100)



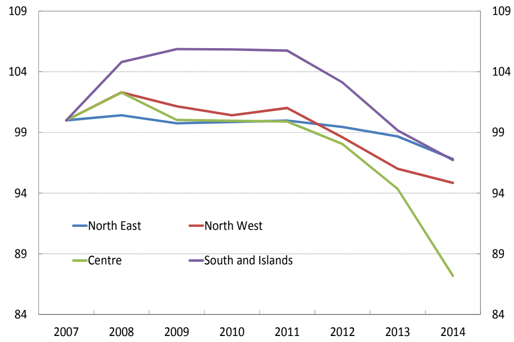
(1) These indicators are experimental and are based on different methodologies: transaction-based for Italy (Source: Banca d'Italia); valuation-based for Spain (Source MSCI); transaction hybrid for euro area (Source ECB), Germany (Source Bulweingesa), France (Source: MSCI), Netherlands (Source: MSCI). - (2) For Germany annual values.

Figure 1.7 – Commercial property prices and sales in Italy (1)
(quarterly data; indices 2010=100)



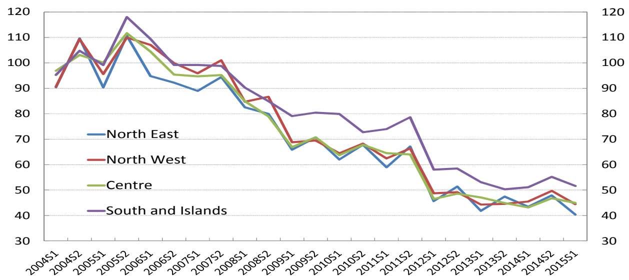
Source: Bank of Italy calculations based on Agenzia del Territorio, Istat Nomisma and Scenari Immobiliari data. (1) Property sales are seasonally and working-day adjusted.

Figure 1.8 – Commercial property prices in Italy
(annual data; indices 2007=100)



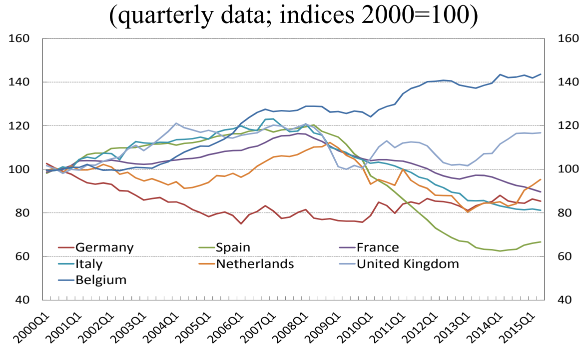
Source: Banca d'Italia calculations based on Agenzia delle Entrate data.

Figure 1.9 – Commercial property sales in Italy
(biannual data; indices 2004=100)



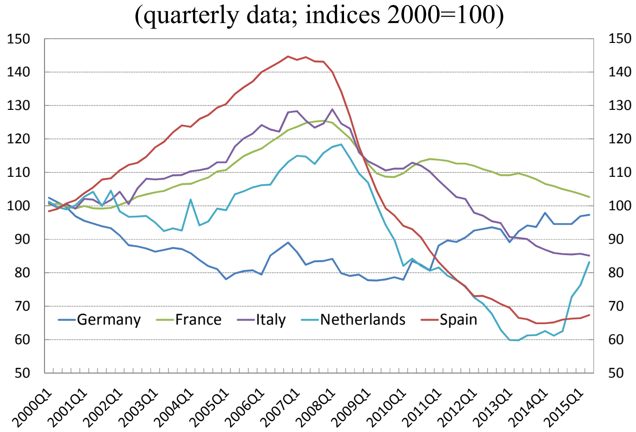
Source: Agenzia delle Entrate.

Figure 1.10 – Gross value added of the construction sector in Europe
(quarterly data; indices 2000=100)



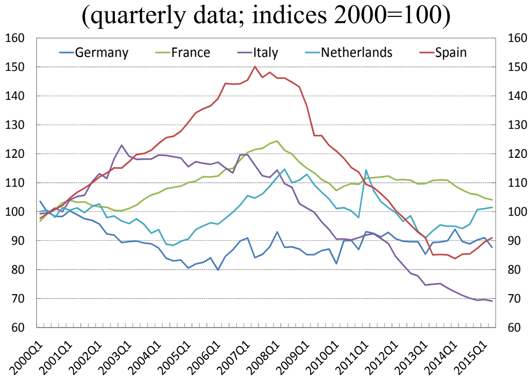
Source: Eurostat.

Figure 1.11 – Gross fixed investments in dwellings
(quarterly data; indices 2000=100)



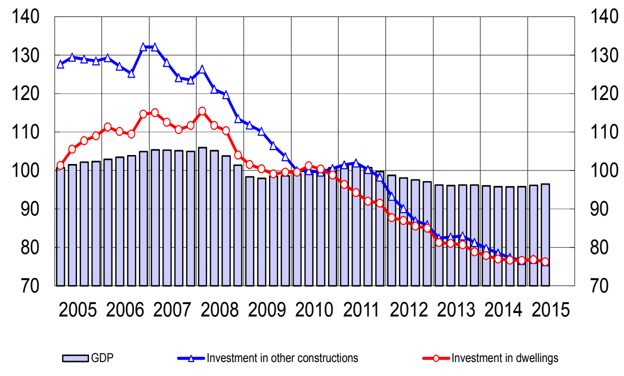
Source: Eurostat.

Figure 1.12 – Gross fixed investments in other buildings and structures
(quarterly data; indices 2000=100)



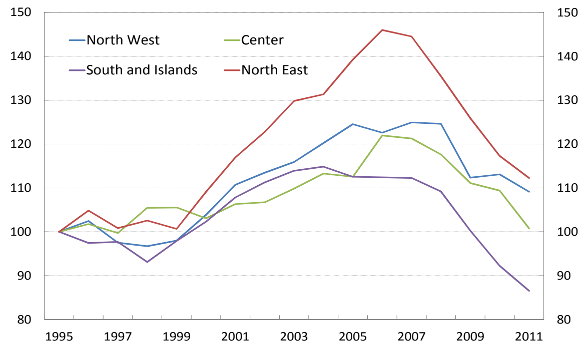
Source: Eurostat.

Figure 1.13 – GDP and gross fixed investments in constructions in Italy
(quarterly data; indices 2010=100)



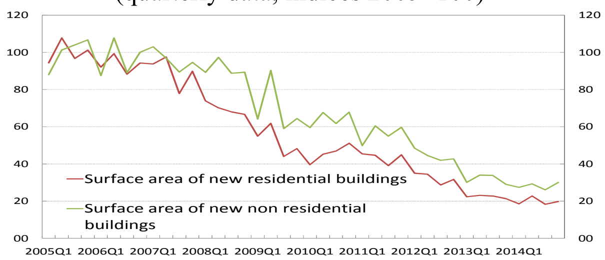
Source: Istat.

Figure 1.14 – Gross value added of the construction sector in Italy
(annual data; indices 1995=100)



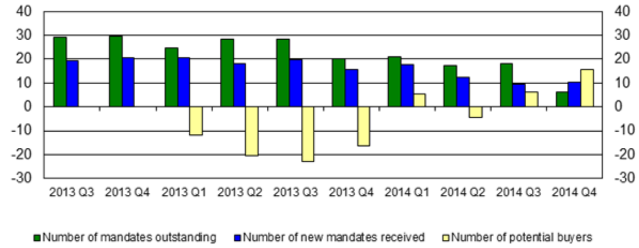
Source: Istat.

Figure 1.15 – Building permits in Italy
(quarterly data; indices 2005=100)



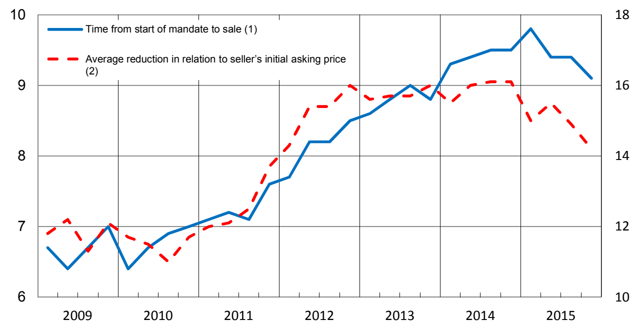
Source: Istat.

Figure 1.16 – Housing demand and supply according to estate agents (1)



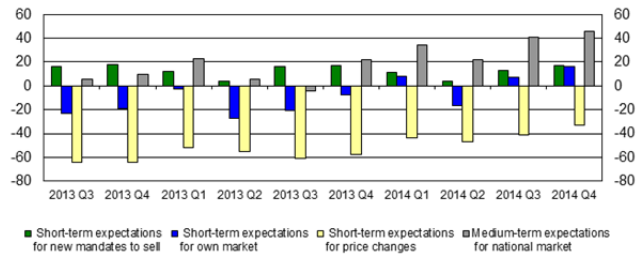
Source: Quarterly data from the survey conducted by the Bank of Italy, Tecnoborsa and OMI. (1) Balances between the percentages of replies indicating an increase or a decrease.

Figure 1.17 – Time-on-market and average reduction on asking price in Italy



Source: Quarterly data from the survey conducted by the Bank of Italy, Agenzia delle Entrate and Tecnoborsa. (1) Left-hand scale, months. (2) Right-hand scale, percentage points.

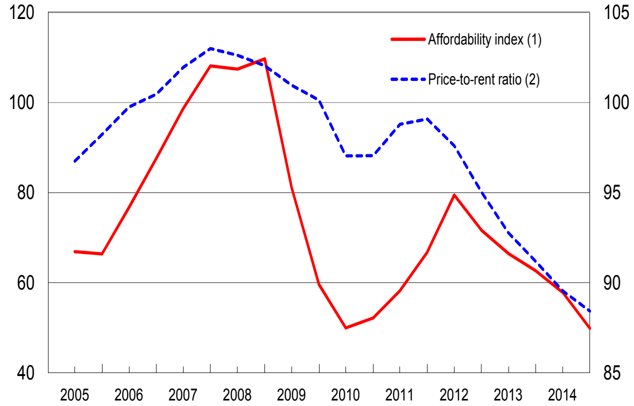
Figure 1.18 – Estate agents' expectations in Italy (1)



Sources: Quarterly data from the survey conducted by the Bank of Italy, Tecnoborsa and OMI. (1) Balances between the percentages of replies indicating a situation that is improving or worsening. Short-term expectations refer to the quarter following the one indicated; medium-term expectations refer to a 2-year horizon.

Figure 1.19 – Housing affordability index and ratio of house prices to rents in Italy

(biannual data; indices 1992-2013 average=100)

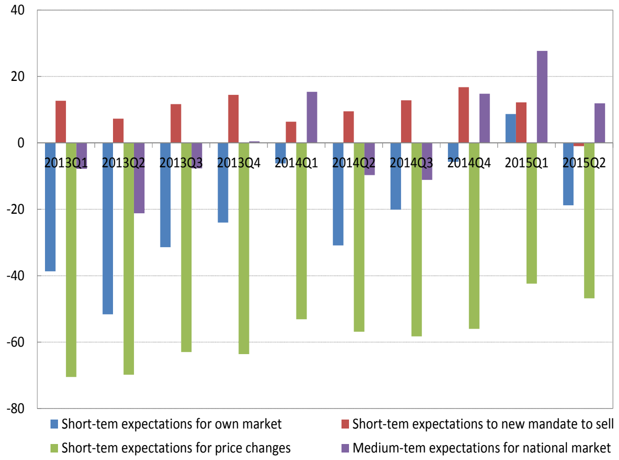


Sources: Based on Bank of Italy, Istat, Agenzia delle Entrate and Consulente immobiliare data. (1) The indicator is given by the ratio of debt service on new mortgage loans – proxied by the product of house prices and interest rates – to households' disposable income; a decrease indicates that housing is more affordable. – (2) Right-hand scale. With respect to new rental contracts.

Figure 1.20a – Estate agents' expectations in North West (1)

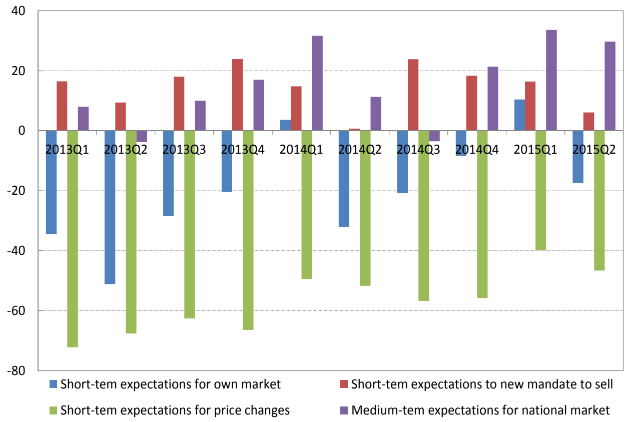
Sources: Quarterly data from the survey conducted by the Bank of Italy, Tecnoborsa and OMI. (1) Balances between the percentages of replies indicating a situation that is improving or worsening. Short-term expectations refer to the quarter following the one indicated; medium-term expectations refer to a 2-year horizon.

Figure 1.20b – Estate agents' expectations in North East (1)



Sources: Quarterly data from the survey conducted by the Bank of Italy, Tecnoborsa and OMI. (1) Balances between the percentages of replies indicating a situation that is improving or worsening. Short-term expectations refer to the quarter following the one indicated; medium-term expectations refer to a 2-year horizon.

Figure 1.20c – Estate agents' expectations in the Centre(1)



Sources: Quarterly data from the survey conducted by the Bank of Italy, Tecnoborsa and OMI. (1) Balances between the percentages of replies indicating a situation that is improving or worsening. Short-term expectations refer to the quarter following the one indicated; medium-term expectations refer to a 2-year horizon.

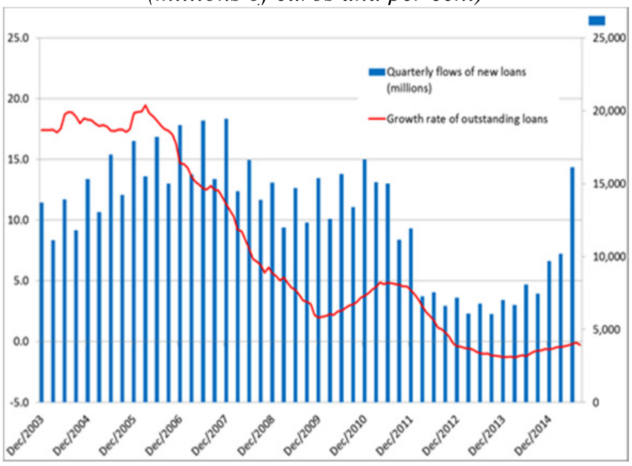
Figure 1.20d – Estate agents' expectations in the South and Islands(1)

Sources: Quarterly data from the survey conducted by the Bank of Italy, Tecnoborsa and OMI. (1) Balances between the percentages of replies indicating a situation that is improving or worsening. Short-term expectations refer to the quarter following the one indicated; medium-term expectations refer to a 2-year horizon.

C. 2. Banks and credit indicators

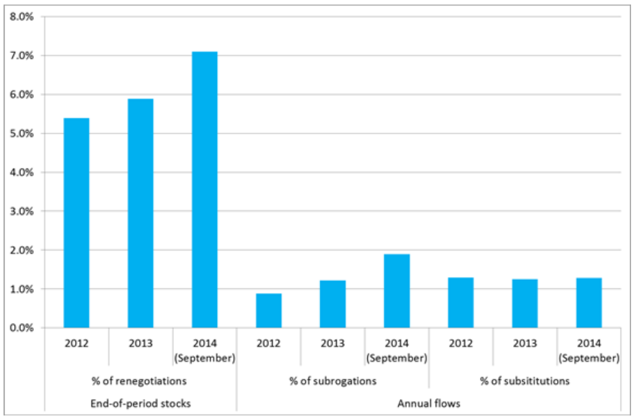
Recent developments in RE-loans

Figure 2.1 – Loans to households for house purchase
(millions of euros and per cent)



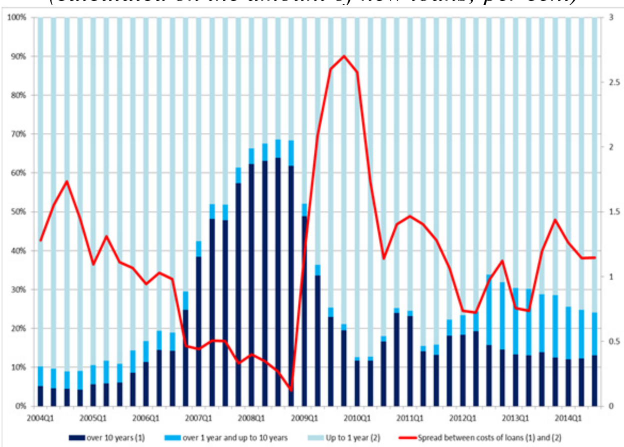
Source: Supervisory reports

Figure 2.2 – Loans renegotiations
(per cent of total loans)



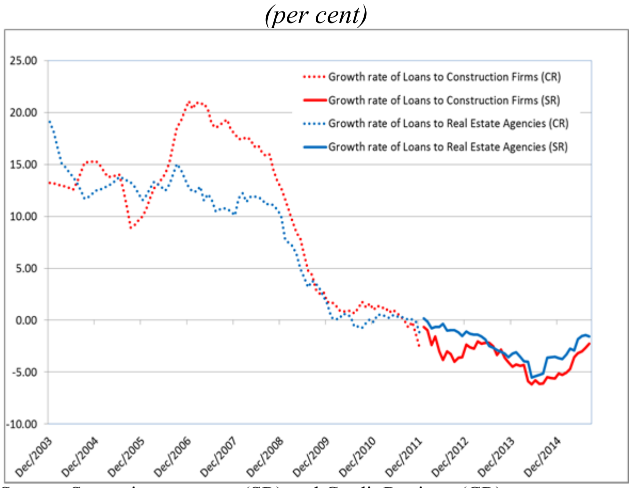
Source: Supervisory reports.

Figure 2.3 – Composition of loans for house purchase by rate fixation period
(calculated on the amount of new loans; per cent)



Source: Analytical survey of interest rates..

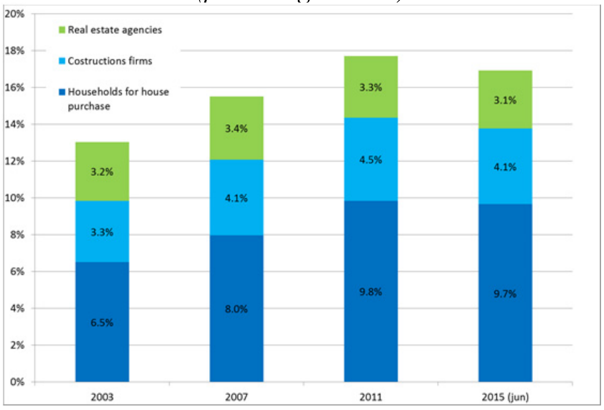
Figure 2.4 – Loans to construction and real estate
(per cent)



Source: Supervisory reports (SR) and Credit Register (CR).

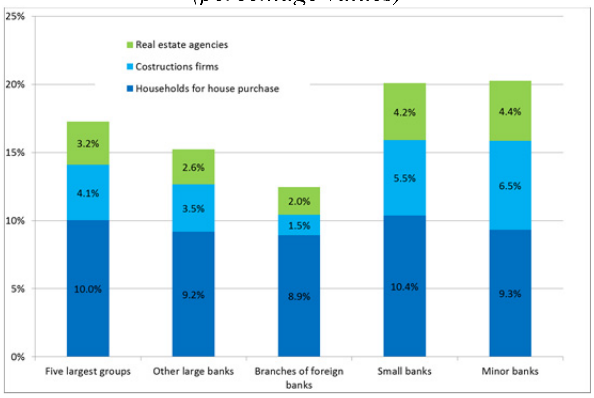
RE-loans share of total assets

Figure 2.5 – Ratio between RE- loans and total assets
(percentage values)



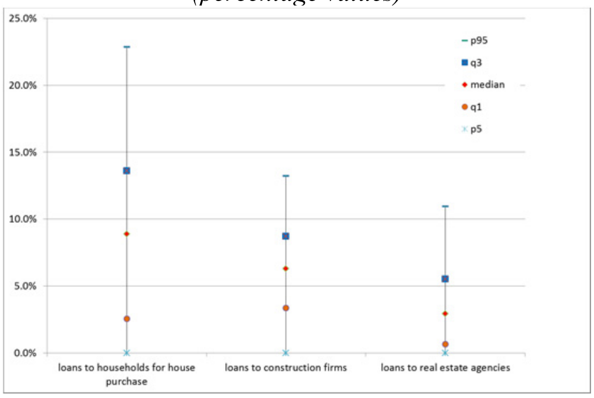
Source: Supervisory reports and Credit Register.

Figure 2.6 – Ratio between RE- loans and total assets by size and class of bank as of June 2015
(percentage values)



Source: Supervisory reports.

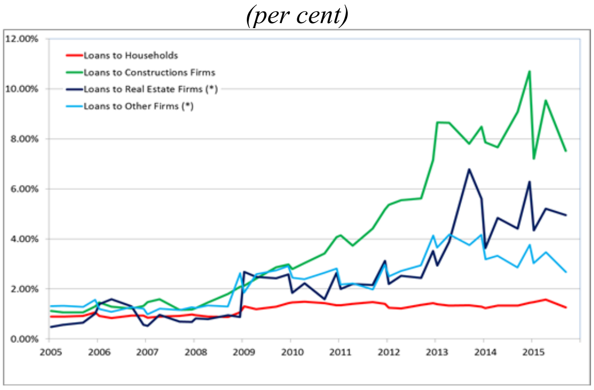
Figure 2.7 - Distribution of the ratio between RE loans and total assets by bank as of June 2015
(percentage values)



Source: Supervisory reports.

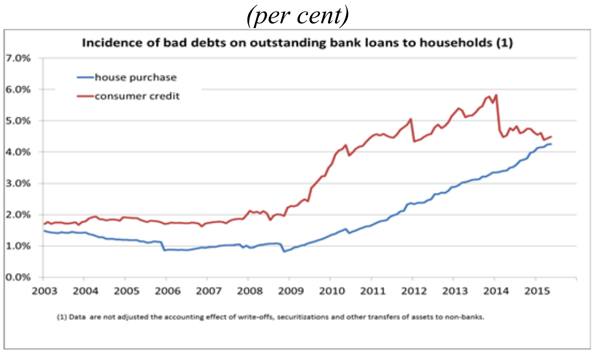
RE-loan quality

Figure 2.8– Ratio of new bad debts to outstanding loans above 30,000 euros
(per cent)



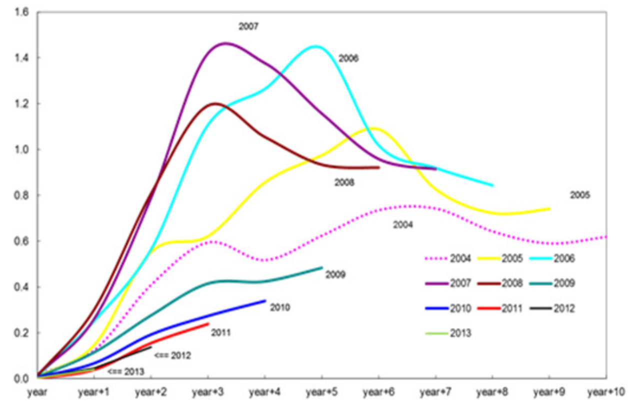
Source: Credit Register. (*) Not seasonally adjusted.

Figure 2.9 – Incidence of bad debts on outstanding bank loans to households (1)
(per cent)



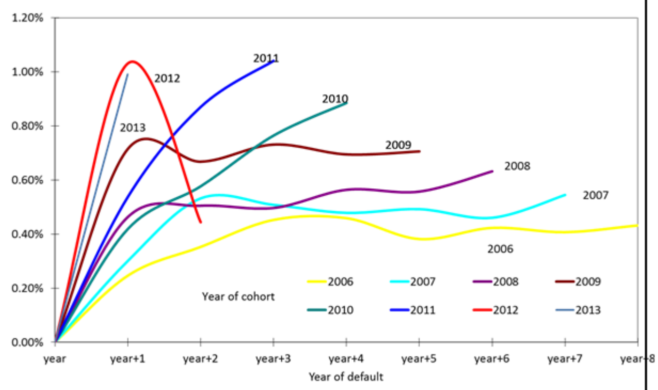
Source: Supervisory reports. (1) Data not adjusted for the accounting effect of write-offs, securitizations and other transfers of assets to non-banks.

Figure 2.10 – New bad loans to households for house purchase by year of disbursement
(per cent of the number of contracts)



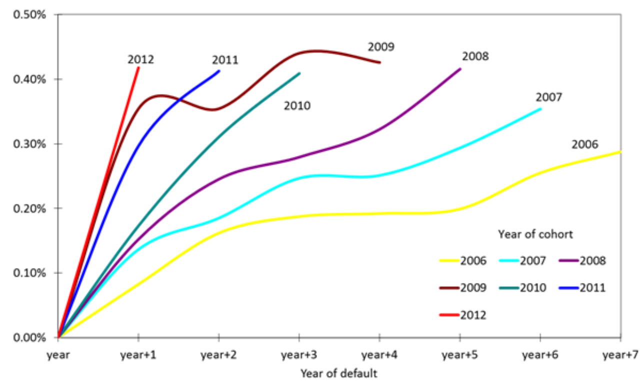
Source: Analytical survey of interest rates and Credit Register.

Figure 2.11 – Default rates of construction firms by cohort of borrowers
(per cent of the number of firms)



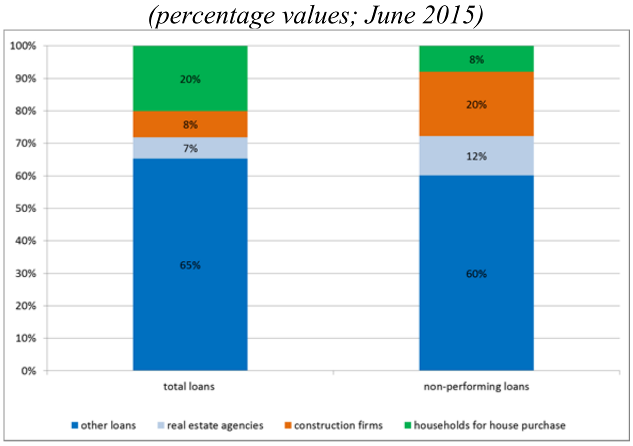
Source: Credit Register.

Figure 2.12 – Default rates of real estate agencies by cohort of borrowers
(per cent of the number of firms)



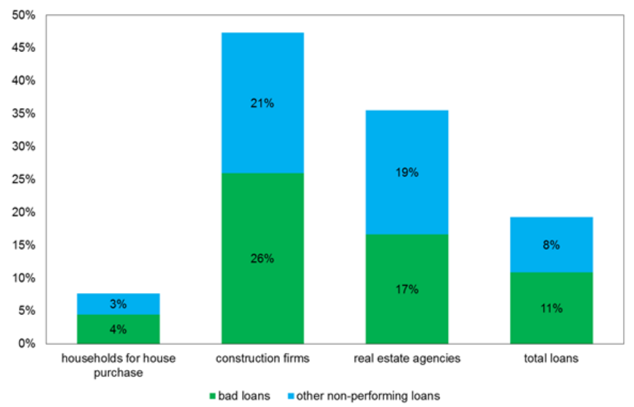
Source: Credit Register

Figure 2.13 - Loans composition
(percentage values; June 2015)



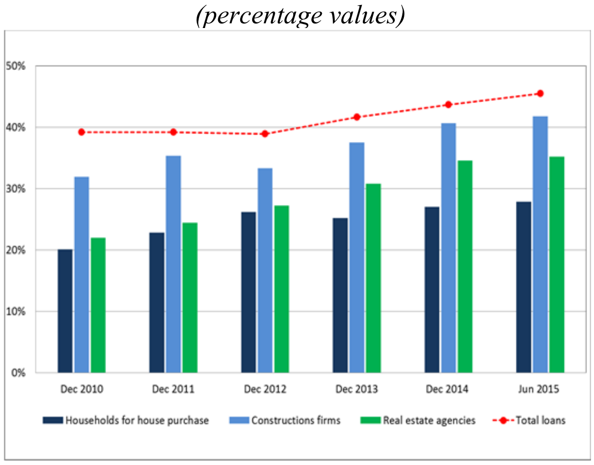
Source: Supervisory reports

Figure 2.14 - NPL on total loans
(percentage values; June 2015)



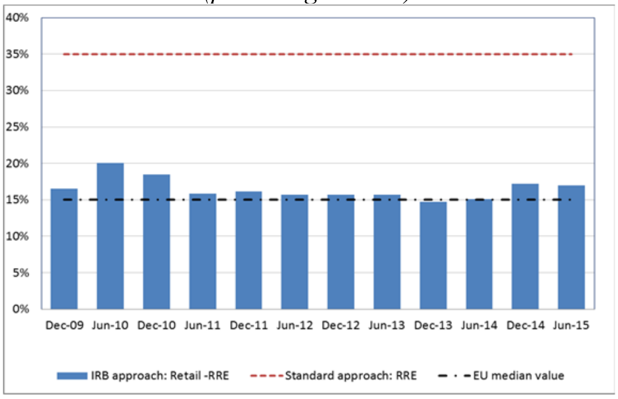
Source: Supervisory reports.

Figure 2.15 Coverage Ratio for NPL
(percentage values)



Source: Supervisory reports.

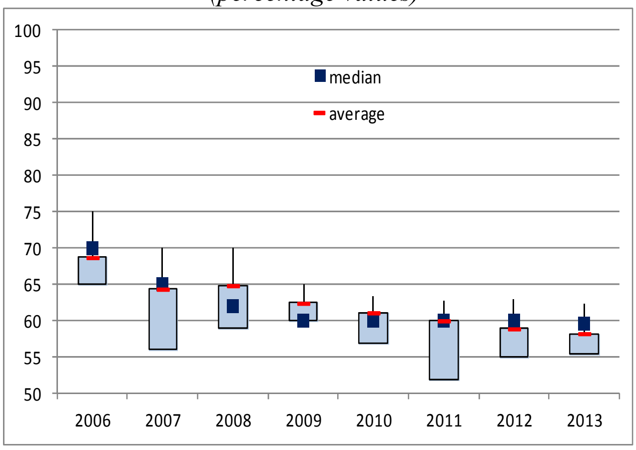
Figure 2.16 Risk weights of real estate secured exposures
(percentage values)



Source: Supervisory reports

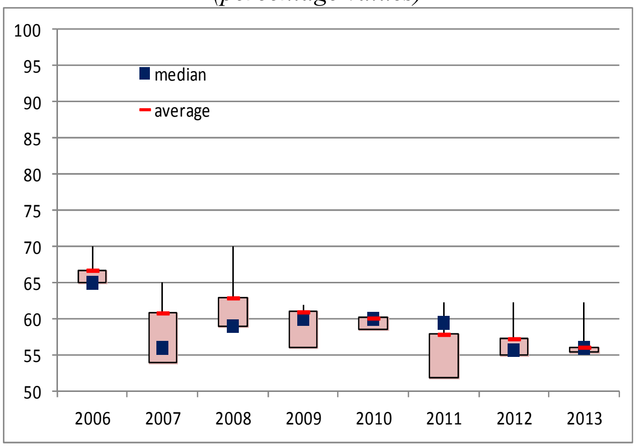
RE-new loan characteristics

Figure 2.17 Average LTV on new loans to households for house purchase
(percentage values)



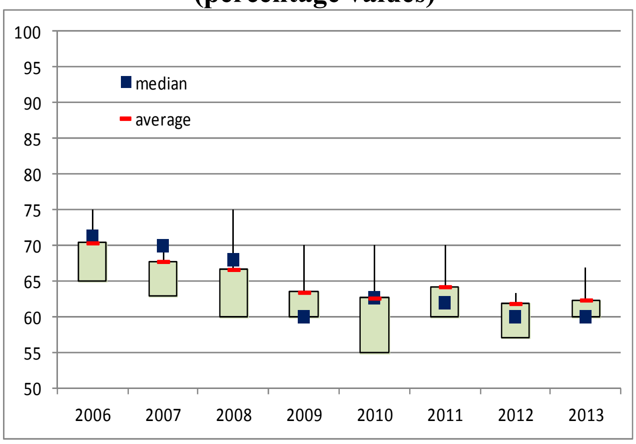
Source: RBLS.

Figure 2.17a Average LTV on new loans to households for house purchase – AQR banks
(percentage values)



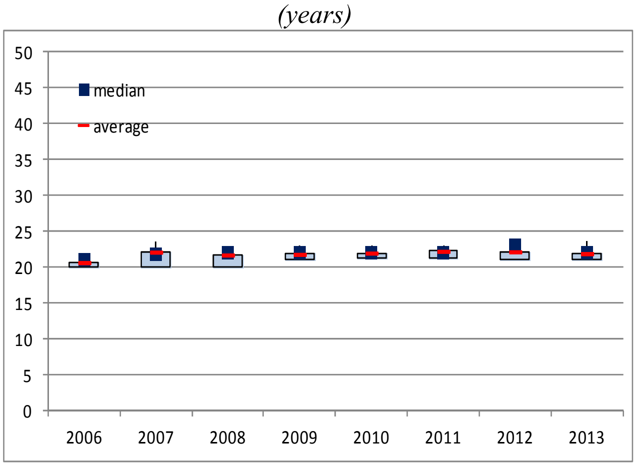
Source: RBLS.

Figure 2.17b Average LTV on new loans to households for house purchase – No AQR banks (percentage values)



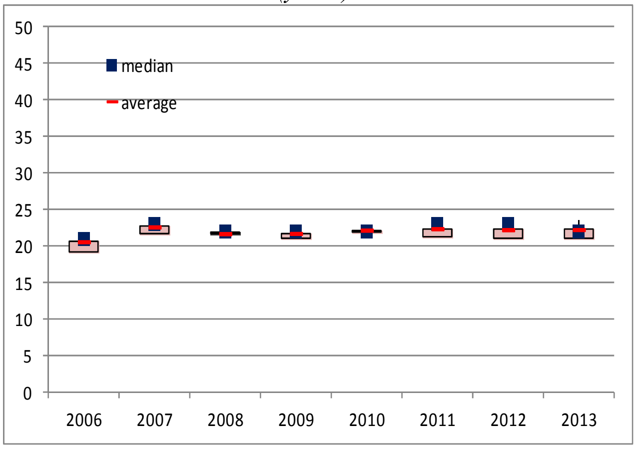
Source: RBLS.

Figure 2.18 Average duration of new loans to households for house purchase
(years)



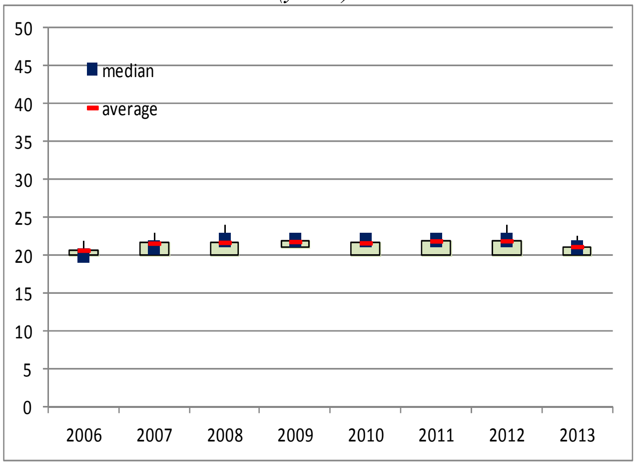
Source: RBLS.

Figure 2.18a Average duration of new loans to households for house purchase – AQR banks
(years)



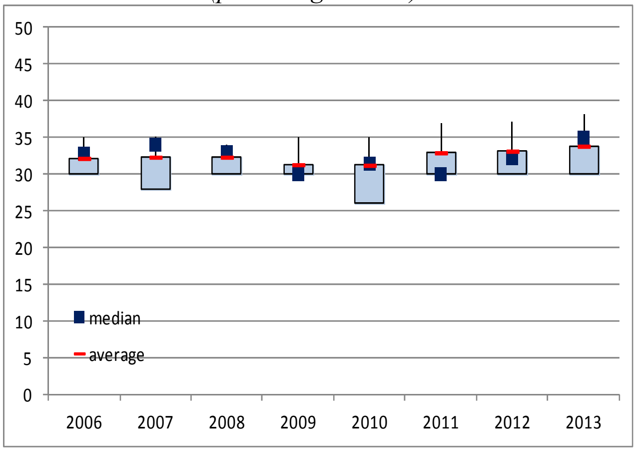
Source: RBLS.

Figure 2.18b Average duration of new loans to households for house purchase – No AQR banks
(years)



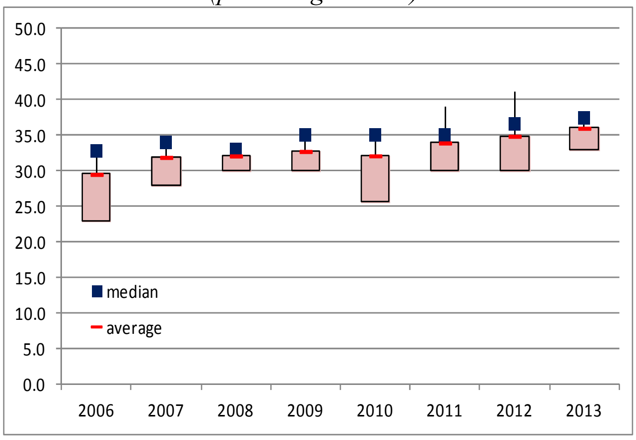
Source: RBLS.

Figure 2.19 Average debt service to income on new loans to households for house purchase
(percentage values)



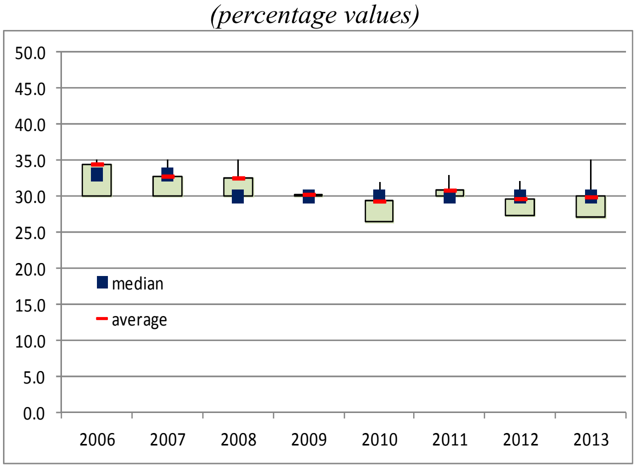
Source: RBLS.

Figure 2.19a Average debt service to income on new loans to households for house purchase – AQR banks
(percentage values)



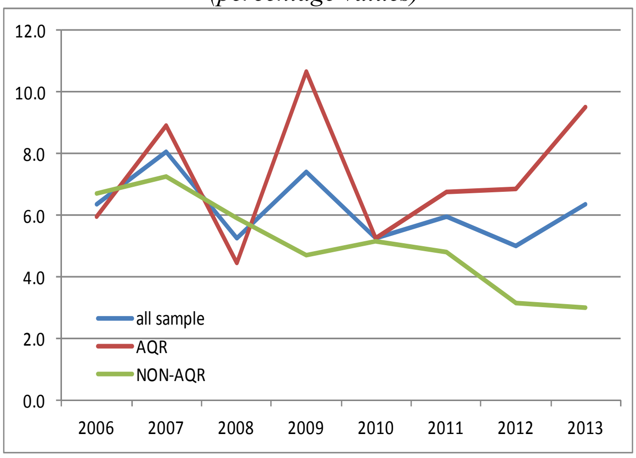
Source: RBLS.

Figure 2.19b Average debt service to income on new loans to households for house purchase – No AQR banks
(percentage values)



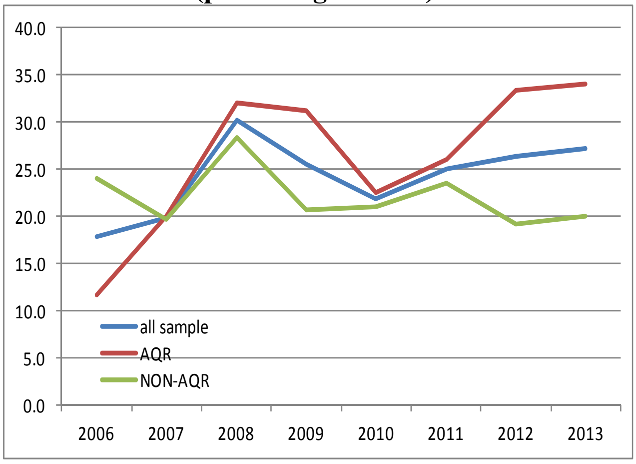
Source: RBLS.

Figure 2.20 Share of new loans for house purchase with LTV > 80%
(percentage values)



Source: RBLS.

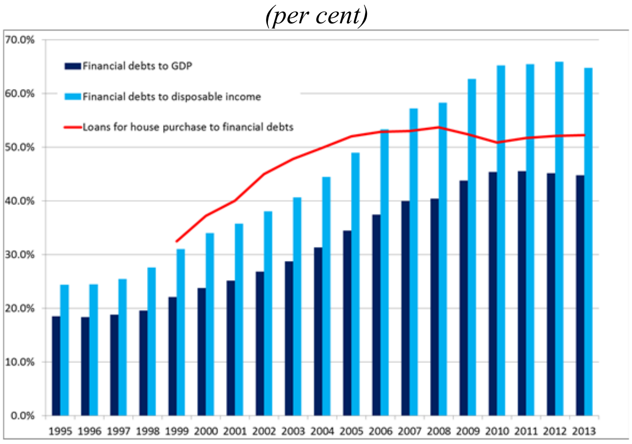
Figure 2.21 Share of new loans for house purchase with duration > 30 years (percentage values)



Source: RBLS.

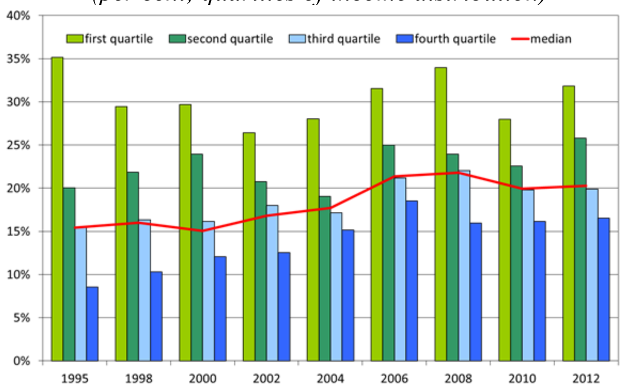
C. 3. Households' financial conditions

Figure 3.1 – Households financial debts
(per cent)



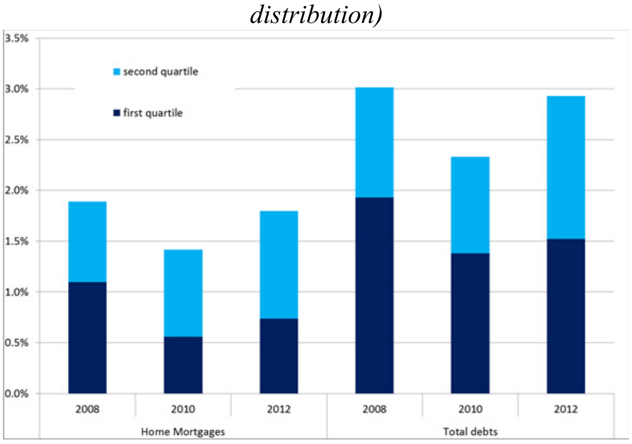
Source: Financial accounts.

Figure 3.2 – Service of debt to income
(per cent; quartiles of income distribution)



Source: Survey on Household Income and Wealth.

Figure 3.3 – Households with debt service exceeding 30% of income and income below the median
(per cent of total households; quartiles of income distribution)



Source: Survey on Household Income and Wealth.

References

Agnello, L. and L. Schuknecht (2011), “Booms and busts in housing markets: Determinants and implications”, Journal of Housing Economics 20(3): 171-190.

Alessi, L. and C. Detken (2011), “Quasi real time early warning indicators for costly asset price boom/bust cycles: A role for global liquidity”. European Journal of Political Economy, 27(3): 520-533.

Alessi, L. and C. Detken (2014), “Identifying excessive credit growth and leverage”, ECB, Working Paper Series, n. 1723.

Babecky, J., T. Havranek, J. Mateju, M. Rusnak, K. Smidkova and B. Vasicek (2012a), “Banking, debt and currency crises. Early warning indicators for developed countries”, ECB Working Paper Series n. 1485.

Babecky, J., T. Havranek,J. Mateju, M. Rusnak, K. Smidkova and B. Vasicek (2012b). “Leading indicators of crisis incidence evidence from developed countries”. ECB Working Paper Series n. 1486.

Baldinelli, C. Gangeri M., and F. Leandri (1998), “I riflessi sulle banche della crisi del mercato immobiliare”, Bancaria, Vol. 54(9), 2-12.

Barrell, R, E.P. Davis, D. Karim and I. Liadze (2009), “Bank regulation, property prices and early warning systems for banking crises in OECD countries”. NIESR Discussion Paper, n. 330.

Bassanetti A. and F. Zollino (2008), “The effects of housing and financial wealth on personal consumption: aggregate evidence for Italian households”, in “Household wealth in Italy”, Banca d’Italia.

Behn, M., Detken, C. , Peltonen, T. A. and W. Schudel (2013), “Setting Countercyclical Capital Buffers Based on Early Warning Models: Would it Work?”, ECB Working Paper, n. 1604.

Betz, F., Oprică, S., Peltonen, T.P. and P. Sarlin (2013), “Predicting Distress in European Banks”, ECB Working Paper Series, n. 1597.

Bonaccorsi di Patti E., D’Ignazio A., Gallo M. and G. Micucci (2014), “The role of leverage in firm solvency: evidence from bank loans”, Bank of Italy Occasional Paper n. 244.

Borio, C. and M. Drehmann (2009), “Towards an operational framework for financial stability: “fuzzy” measurement and its consequences”. BIS Working Paper n. 284.

Borgy, V., L. Clerc and J. Renne (2012), “Measuring aggregate risk: can we robustly identify asset-price boom-bust cycles?”, Banque de France, Mimeo.

Bussiere, M. and Fratzscher, M. (2006). “Towards a New Early Warning System of Financial Crises.” Journal of International Money and Finance, 25, 953–973.

Ciani D., Cornacchia W. and P. Garofalo (2014), “Le misure macroprudenziali adottate in Europa per il settore immobiliare”, Bank of Italy Occasional Paper n. 227.

Claessens S., Ayhan Kose M. and M.E. Terrones (2008), "What happens during recessions, crunches and busts?", IMF Working Paper n. 11/88.

Dell'Ariccia, G., Igan, D. and L. Laeven (2012), "Credit Booms and Lending Standards: Evidence from the Subprime Mortgage Market", Journal of Money, Credit and Banking, 44: 367–384.

Detken C., Weeken, O., Alessi, L., Bonfim, D., Boucinha, M., Castro, C., Frontczak, S., Giordana, G., Giese, J., Jahn, N., Kakes, J., Klaus, B., Lang, J., Puzanova, N. and P. Welz (2014), "Operationalizing the countercyclical capital buffer: indicator selection, threshold identification and calibration options", ESRB Occasional Paper Series n. 5/June.

Drehmann, M., Borio, C., Gambacorta, L., Jimenez, G., and C. Trucharte (2010), "Countercyclical capital buffers: exploring options", BIS Working Papers, 01/2010.

Drehmann, M., Borio, C. and K. Tsatsaronis (2011), "Anchoring countercyclical capital buffers: the role of credit aggregates", International Journal on Central Banking, Vol. 7(4), 189-240.

Drehmann M. and M. Juselius (2013), "Evaluating early warning indicators of banking crises: satisfying policy requirements", BIS Working Paper No. 421.

Eichengreen, B, and K. Rose (1998), "Staying Afloat When the Wind Shifts: External Factors and Emerging-Market Banking Crises", NBER Working Papers, no 6370.

ESRB Handbook on Operationalising Macro-prudential Policy in the Banking Sector (03/03/2014), https://www.esrb.europa.eu/pub/pdf/other/140303_esrb_handbook.pdf?e1d9ba0c39f025249fa986df68cd8b76

Fabrizi C., Pico R., Casolaro L., Graziano M., Manzoli E., Soncin S., Esposito L., Saporito G. and T. Sodano (2015), "Mercato immobiliare, imprese della filiera e credito: una valutazione degli effetti della lunga recessione", Bank of Italy Occasional Paper n.263.

Fernandez, C., Ley, E. and M. Steel (2001a), "Model Uncertainty in Cross-Country Growth Regressions", Journal of Applied Econometrics n. 16, 563-576.

Fernandez, C., Ley, E. and M. Steel (2001b), "Benchmark Priors for Bayesian Model Averaging", Journal of Econometrics n. 100, 381-427.

Ferrari S. and M. Pirovano (2014), "Evaluating early warning indicators for real estate related risks", National Bank of Belgium FSR.

Ferrari S., Pirovano M. and W. Cornacchia (2015), "Identifying early warning indicators for real estate banking crises", ESRB Occasional Paper n.8.

Frankel, J. and A. Rose (1996), Currency Crashes in Emerging Markets: An Empirical Treatment, Journal of International Economics 41(3–4): 351–366.

Frankel, J. A. and G. Saravelos (2012), "Can leading indicators of financial crisis assess country vulnerability? Evidence from the 2008–09 global crisis", Journal of International Economics, 87(2), 216-231.

Gobbi G. and F. Zollino (2013), "Tendenze recenti del mercato immobiliare e del credito" in "Le tendenze del mercato immobiliare: l'Italia e il confronto internazionale", Bank of Italy Workshops and Conferences series, n. 15.

Hand D.J. and R.J. Till (2001), "A Simple Generalisation of the Area Under the ROC curve for multiple Class Classification Problems", *Machine Learning* 45(2), 171-186.

Holopainen, M. and P. Sarlin (2015), "Toward robust early-warning models: A horse race, ensembles and model uncertainty", Bank of Finland, Research Paper 6/2015.

ISTAT (2015), "The stock of non-financial assets by institutional sector", May 27th. http://www.istat.it/en/archive/160852

IMF Country Report n.13/348 (2013), "Italy: technical note on the financial situation of Italian households and non-financial corporations and risks to the banking system", December. https://www.imf.org/external/pubs/ft/scr/2013/cr13348.pdf

Magri, S., and R. Pico (2012), "L'Indebitamento delle Famiglie Italiane Dopo la Crisi del 2008," Bank of Italy Occasional Paper, n.134.

Michelangeli V. and M. Pietrunti (2014), "A microsimulation model to evaluate Italian households' financial vulnerability", Bank of Italy Occasional Paper, n. 225.

Nobili A. and F. Zollino (2012), "A structural model for the housing and credit markets in Italy", Bank of Italy Working Papers, n.887.

Rose, A. K. and M. M. Spiegel (2011), "Cross-country causes and consequences of the 2008 crisis: an update", European Economic Review, 55(3), 309–324.

U.S. Financial Crisis Inquiry Commission 2011 Final Report on the Causes of the Financial and Economic Crisis in the United States, Pursuant to Public Law 111-2 (January).

Stein J. C. (1995), "Prices and Trading Volume in the Housing Market: A Model with Down-Payment Effects", The Quarterly Journal of Economics, 110(2):379–406.

Wheaton W. C. (1990), "Vacancy, Search, and Prices in a Housing Market Matching Model", Journal of Political Economy, 98(6):1270–92.

Zeugner S. (2011), "Bayesian Model Averaging with BMS - for BMS version 0.3.0", May 5th (bms.zeugner.eu/tutorials/bms.pdf).