Crisis, Credit and Resource Misallocation: Evidence from Europe during the Great Recession

1st Policy Research Conference of the European Central Banking Network

Edited by
Biswajit Banerjee and Fabrizio Coricelli

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- promotes the smooth operation of payment systems.

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Foreword

We know the source of the Global Crisis emanated in the United States, yet somehow Europe has suffered the most. The depth of recession, as well as a slow recovery, means that financial markets and banking sectors in Europe are still struggling to recover from the 2008 crisis. This has led to unresolved problems involving bank fragility and bad loans.

This chapters of this eBook are based on the findings from the 1st Policy Research Conference of the European Central Bank Network at the Bank of Slovenia in October 2015. At the conference, researchers from 19 European central banks, senior officials of other financial institutions and leading academics discussed the behaviour of bank credit in Europe during the Great Recession and afterwards during the recovery. A lack of availability of credit is thought to have been one of the many reasons for the modest recovery of growth in Europe. The contributions in this book discuss two main issues on how this related to the real performance of European economies: the determinants of bank credit; and the role of credit in the allocation, or misallocation, of resources before and after the Great Recession.

CEPR is grateful to Professors Biswajit Banerjee and Fabrizio Coricelli for their joint editorship of this eBook and to the Bank of Slovenia for hosting the conference from which the chapters of the eBook were collated. Our thanks also go to Simran Bola and Anil Shamdasani for the excellent and swift handling of its production. CEPR, which takes no institutional positions on economic policy matters, is delighted to provide a platform for an exchange of views on this crucially important topic.

Tessa Ogden
Chief Executive Officer, CEPR

February 2017

Misallocation in Europe during the global financial crisis: Some stylised facts

Biswajit Banerjee and Fabrizio Coricelli
Bank of Slovenia; Paris School of Economics and CEPR

Although the source of the global financial crisis of 2008 was the United States, Europe has suffered the most in terms of the depth of the recession and, more importantly, in terms of a slow recovery. Financial markets and the banking sectors in several European countries are still struggling to recover from the crisis, with many instances of unresolved problems involving bad loans and fragility of banks. The chapters in this book, resulting from the first conference of the European Central Banking Network (ECBN), held in Ljubljana in September 2015, focus on the role played by the financial sector in the allocation of resources across different firms and sectors of the economy. The papers presented at the conference discussed whether misallocation is magnified during credit booms and whether misallocation is reduced during the deleveraging process following a financial crisis. The conference provided a unique perspective, covering a broad sample of countries characterised by different levels of development of financial markets, different magnitudes of macroeconomic imbalances, and different policy responses.

In this introduction, we provide a broad overview of some main stylised facts for a large sample of European countries.[1]

We focus on the relationship between credit booms and busts and the potential misallocation of resources at the micro level. Some of the hardest hit countries in Europe experienced a pre-crisis credit boom followed by deleveraging and, in some cases, a creditless recovery. The key questions are:

- How did the credit boom affect the efficiency of the system in terms of resource allocation?
- How is the deleveraging affecting the efficiency of resource allocation?

When financial markets are imperfect, the allocation of resources may be inefficient. Furthermore, with financial imperfections, deleveraging may not lead to a more efficient allocation, even when the pre-crisis boom was highly inefficient. For instance, reliance on collateral implies that the allocation of credit follows a collateral criterion rather than efficiency/productivity of the borrowing firm. The possible inefficiencies of the credit boom preceding the Great Recession have often been associated with macro imbalances and sectoral imbalances. In Southern Europe and some Central and Eastern European countries, macro imbalances went hand-in-hand with sectoral imbalances. The

1 The empirical analysis summarised in this introduction draws from Coricelli and Frigerio (2016).

accumulation of huge current account deficits was associated with a boom in non-tradable sectors, especially real estate and construction, accompanied by shrinking shares of manufacturing output and employment. Less attention has been given to more micro measures of misallocation, which are however crucial for assessing the costs of the crisis and the prospects for recovery. This is crucial to determine whether the recession produced a shift to a lower potential output.

We use the Amadeus firm-level database to give a broad picture of the behaviour of misallocation of resources before and after the Great Recession. We look at both within-sector allocation and across-sectors allocation. Following Hsieh and Klenow (2009), as is done in many of the chapters in this book, we define misallocation as arising from two sources: different productivities across firms within the same sector, and inefficiency in the allocation of inputs across firms.

Because of frictions and policy distortions (taxes, financial frictions), a significant fraction of productive resources (inputs) are employed in low-productivity firms, instead of being employed in high-productivity firms. Misallocation of resources is thus detected by observing a distribution of firms within sectors with a large dispersion and fat tails. In the distribution chart, a fat left tail signals a large weight of low-productivity firms. The main question addressed in this book is whether inefficiencies in financial markets and financial cycles have an impact on the degree of misallocation of resources? As noted by Restuccia and Rogerson (2008), "[f]avoured establishments demand more capital and become larger than in the absence of the distortion".

Using the Amadeus database, we also compute misallocation separately for various clusters: industry, country, time period and macro-regions.[2]

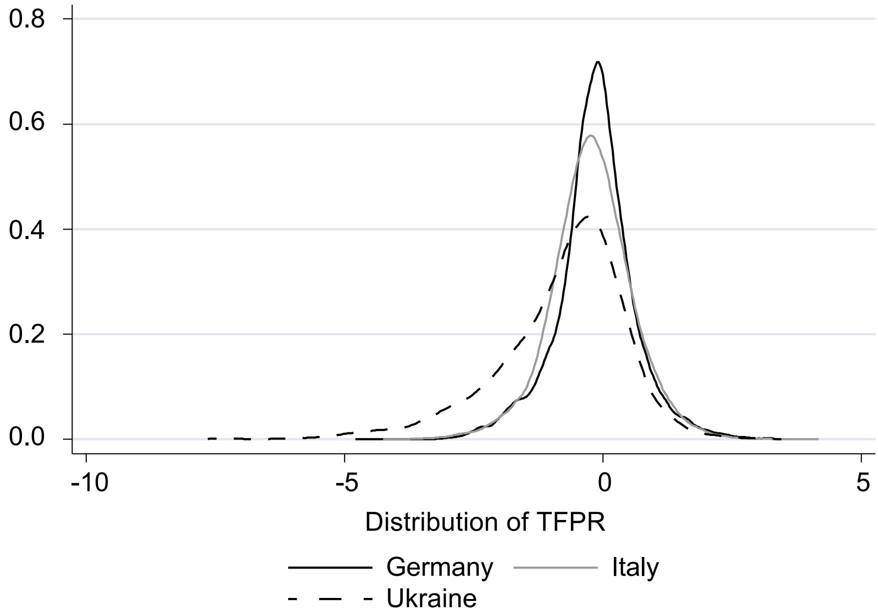
Misallocation can be visually summarised by looking at the distribution of total factor productivity in firms within finely defined sectors. The case of no misallocation would correspond to a distribution collapsing to a line at zero. Looking at macro regions, we find higher misallocation in Eastern Europe. In terms of sectors, there is higher misallocation in services, possibly reflecting a lower degree of competition here than in manufacturing. The dynamics over time indicate little change before the crisis, some change during the crisis and also some change after it.

Measuring misallocation at the country level, we find that misallocation plays a crucial quantitative role in explaining productivity differences across countries. Figure 1 reports as an example the distributions of total factor productivity (TFP) for Germany, Italy and Ukraine.[3] Italy, for instance, could increase its industrial TFP by 7.5% if its allocative efficiency were aligned to that of Germany.

2 Western Europe; Central Eastern Europe plus Turkey and Cyprus, which for simplicity we call “Eastern Europe”. Industry disaggregation is at the 4-digit level.

3 Our estimates for advanced EU countries are of the same order of magnitude of those estimated by Hsieh and Klenow (2009) for the United States.

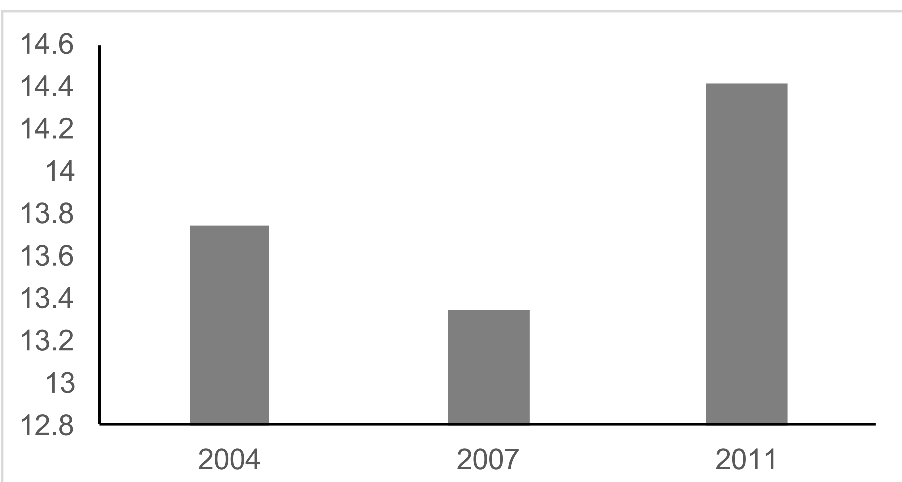
Figure 1 Distribution of TFP by country



Note: TFPR indicates revenue total factor productivity, which is real total factor productivity multiplied by output prices.

Addressing the role of the financial crisis, Figure 2 summarises the distributions for the period before 2008 and after it. We note that the change in misallocation during 2004-2007 corresponds to a TFP gain of 0.35%, while during the crisis period of 2007-2011 the increase in misallocation corresponds to a reduction in TFP of 0.9%.

Figure 2 Misallocation over time, whole sample (%)

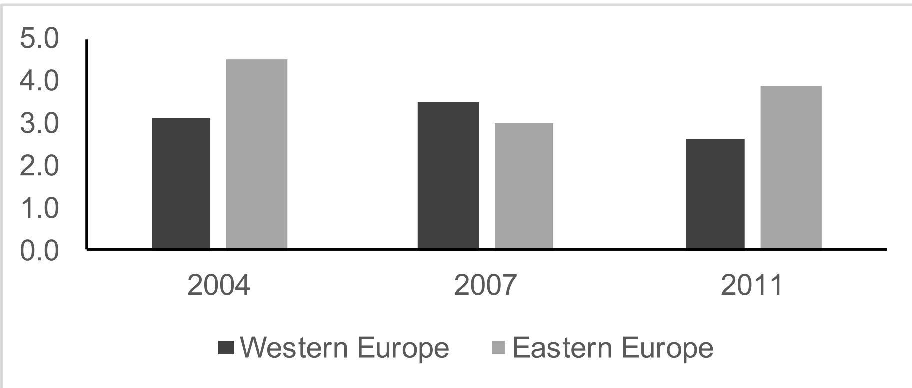


We then distinguish countries in terms of the dynamics of credit before the crisis.

We use the methodology from Gourinchas et al. (2001) to identify credit boom episodes by looking at deviations from trends.

For the two macro-regions Figure 3 reports the difference in the MIS index in credit boom countries versus no-credit boom countries. Results indicate that credit booms are associated with higher misallocation in Western Europe but not in Eastern Europe, while the crisis led to a closing of the gap in Western Europe and a widening in Eastern Europe.

Figure 3 Misallocation: Differences between credit booms vs non-credit booms



We analyse more deeply the role of credit booms by running a regression that allows us to control for 'excessive' debt exposure before the crisis (Table 1). We then interact this variable with the credit boom dummy, which allows us to better identify the effects of the credit boom, by controlling for the different excessive debt accumulation by sectors. Excess debt is computed as the ratio of debt to capital in a given sector/country relative to the average for the whole sample. Therefore, we try to capture the fact that credit booms disproportionally affected misallocation of resources in sectors that displayed the largest debt exposure, relative to the European mean.

Table 1 Misallocation, credit booms and "excess" debt

Fixed effects for both country and industry	Whole (1)	Western Europe (2)	Eastern Europe (3)	Credit boom (4)	Normal (5)
$ExtDep\_Excess_{c,s,y}$	-0.0295**	-0.0525**	-0.0155	-0.0444*	-0.0206
	[0.013]	[0.020]	[0.013]	[0.022]	[0.014]
N	5103	2957	2112	2051	2995
R-squared	0.49	0.60	0.49	0.52	0.55

Note: Standard errors in brackets. * p < 0.1, ** p < 0.05, *** p < 0.01. For each country-sector-year cluster, *ExtDep_Excess* indicates the deviation of Debt to Total Capital with respect to averages by sector (s) and country (c). The Debt to Total Capital is obtained as follows.

Results indicate that credit booms induced a significant increase in misallocation in Western Europe but not in Eastern Europe. One possible explanation is that in Eastern Europe, firms might still be far from an optimal level of indebtedness and thus there is still room for an increase in debt-to-capital ratios that reflects an equilibrium phenomenon rather than an inefficient 'excess'. Note that this does not contradict findings on misallocation across sectors, with an excessive accumulation of debt in non-tradable sectors in Eastern Europe.

In summary, credit booms seem to be associated with higher misallocation, even within sectors. This is particularly true for Western Europe, but less so for Eastern Europe.

Overall, the crisis has not brought any visible improvement in the allocation of resources. Therefore, there is no evidence that deleveraging has had, at least initially (up to 2011), any 'cleansing' effects. Improving the functioning of credit markets and their ability to improve the allocation of resources is crucial to lift Europe out of the phase of low growth that has followed the global financial crisis.

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Analysis of the bank lending survey results for Bulgaria (for the period 2003-2014)

Tania Karamisheva
Bulgarian National Bank

1 Introduction

Since the fourth quarter of 2003, the Bulgarian National Bank (BNB) has conducted a regular quarterly bank lending survey among commercial banks in Bulgaria. The aim of the survey is to obtain additional qualitative information about changes in banks' lending policies and in the demand for loans, as well as to identify factors affecting credit demand and banks' credit standards and terms. This additional information may be helpful to enhance understanding of the lending behaviour of banks and the role of credit in the economy. Credit developments may have different implications for macroeconomic policy decisions depending on whether their determinants are demand- or supply-side driven. The main contribution of the bank lending survey is in making a distinction between loan demand and loan supply factors, as definitive conclusions about the exact determinants of changes in lending to enterprises and households cannot be drawn from the available monetary statistics. Thus, the findings of the survey can be useful for a complementary interpretation of existing monetary and interest rate statistics. They can also help to improve the forecasting of credit growth and economic developments.

In this paper, I present the results from the bank lending survey and try to examine its information content for lending growth. I try to find a relationship between the survey results and other macroeconomic variables such as real GDP growth, loan growth, gross fixed capital formation and industrial confidence. We also undertake an empirical analysis, first on a macro level using aggregate data on lending. In a next step, I construct a panel by merging the individual banks' responses to the bank lending survey (BLS) questions with individual data on lending amounts for the surveyed banks.

The paper is organised as follows. Section 2 provides a summary of the main findings of different theoretical and empirical studies analysing bank lending survey results and their role in explaining credit developments or changes in leading macroeconomic indicators. Section 3 provides a short overview of the main banking system and credit developments in Bulgaria before and during the global financial and economic crisis, and the role of the Bulgarian National Bank (BNB) monetary policy. Section 4 follows with a discussion of the main bank lending survey results for Bulgaria and a comparison of BLS results with other macroeconomic and financial data. Section 5 provides an empirical analysis both on a macro level and by individual banks. Section 6 concludes with some final remarks.

2 Literature overview

Credit developments are an important determinant of economic developments, and conditions in credit markets may affect the way monetary policy impacts the economy. In this respect, it is important to be able to distinguish between factors affecting the credit supply and those altering the demand for credit, both of which influence the actual volume of credit. Available data from the monetary statistics on changes in bank lending provide information only on realised transaction volumes; they do not give an indication of whether and to what extent these changes are influenced by the supply side or the demand side. The objective of the bank lending survey is to contribute to filling this gap and to enhancing knowledge of developments in banks' lending policies. The qualitative results obtained from the survey should enable policymakers to assess credit developments more accurately. The survey also provides the banks' assessments of the factors determining their potential changes in the supply of loans and those influencing changes in credit demand. Thus, the findings of the survey can be useful for a complementary interpretation of existing monetary and interest rate statistics. They can also help to improve the forecasting of credit growth and economic developments.

Several studies have analysed the information content of bank lending surveys conducted in individual countries, in parts of the Eurozone, across the Eurozone as a whole, and in the United States for an explanation of changes in credit activity or some real variables such as GDP, consumption or investment. In some of these studies, only a descriptive analysis is used, based on the graphical comparison of data collected via the bank lending surveys and other macroeconomic data, with a focus on finding some similar trends in their performance. Berg et al. (2005), for example, present the first results of the bank lending survey for the Eurozone, conducted since January 2003, and compare them with information derived from other sources. They compare BLS data on credit standards and real GDP growth or monetary financial institution (MFI) loan growth, and also carry out a comparison of BLS data and industrial confidence, consumer confidence and gross fixed capital formation. Their graphical and descriptive analysis shows that even at this early stage of conducting the bank lending survey, it is possible to identify some systematic patterns in the results from the survey that prove to be in line with indicators obtained from other sources. Mottiar and Monks (2007) undertake an analysis of the bank lending survey results for Ireland and compare them with aggregate Eurozone results. By means of a graphical and descriptive analysis, they also conclude that it is possible to see some systematic patterns across the bank lending survey and other macro variables, in particular with regards to loan growth, gross fixed capital formation and consumer/industrial confidence.

Other studies focus on an empirical analysis, using different econometric techniques and methods. Using data obtained from the survey undertaken by the Federal Reserve, Lown et al. (2000) find that a strong correlation exists between the tightening of credit standards and slowdowns in commercial lending and output. They find that the economy seems to grow more slowly during periods in which banks tighten credit standards, and that four of the five past recessions were preceded by sharply tighter standards. The chain of events following a tightening of standards resembles a credit crunch: commercial loans at banks plummet immediately and continue to fall until lenders ease up, output falls, and the federal funds rate – which is identified with the stance of monetary policy – is lowered.

In a further study using VAR analysis, Lown and Morgan (2006) find that fluctuations in credit standards are highly significant in predicting commercial bank loans, real GDP and inventory investment in the trade sector. They conclude that credit standards are more informative about future lending than loan rates, which is consistent with the idea that some sort of friction in lending markets leads lenders to ration loans via changes in standards more than through changes in rates. They also find evidence of a feedback from loans to standards, suggesting a sort of credit cycle. Higher loan levels cause tightening standards, perhaps because lenders conclude (or are told by supervisors) that standards are too loose. Tighter standards are followed by lower spending and loan levels, which eventually lead to standards being eased and to higher spending, higher loan levels, and so on. Some of their negative findings are that shocks to the federal funds rate do not cause changes in standards, because lenders simply raise loan rates more or less in step with the funds rate.

In the January 2009 Monthly Report of the Deutsche Bundesbank, a simple regression analysis is undertaken to examine the explanatory content of BLS data on credit supply and demand for developments in lending to non-financial corporations in Germany. The regression analysis indicates the importance of demand for developments in long-term lending, while the BLS supply variable lacks significance. In the case of long-term loans to enterprises, the BLS demand is a robustly significant explanatory factor, which suggests that growth in long-term corporate lending in Germany has been determined in large part by demand-side factors.

De Bondt et al. (2010) examine empirically the information content of the Eurozone bank lending survey for aggregate credit and output growth. Using a panel regression analysis, they show that the responses of the lending survey, especially those related to loans to enterprises, are a significant leading indicator for Eurozone bank credit and real GDP growth. Their results support the existence of a bank lending, balance sheet and risk-taking channel of monetary policy. These findings imply that it is not only changes in the official interest rate and in loan demand that matter for credit and output, but also bank loan supply factors, the balance sheet position of borrowers, and the risk perception in the economy. Finally, the authors discuss the implications for the 2008-09 financial and economic crisis and come to the conclusion that the BLS responses provided an early and reliable signal of the deterioration of financing conditions and economic growth in the Eurozone. According to their panel estimates, the strong net tightening of credit standards and the increases in margins on average and in riskier loans to enterprises during the crisis resulted in around a one percentage point lower quarterly GDP growth in the Eurozone.

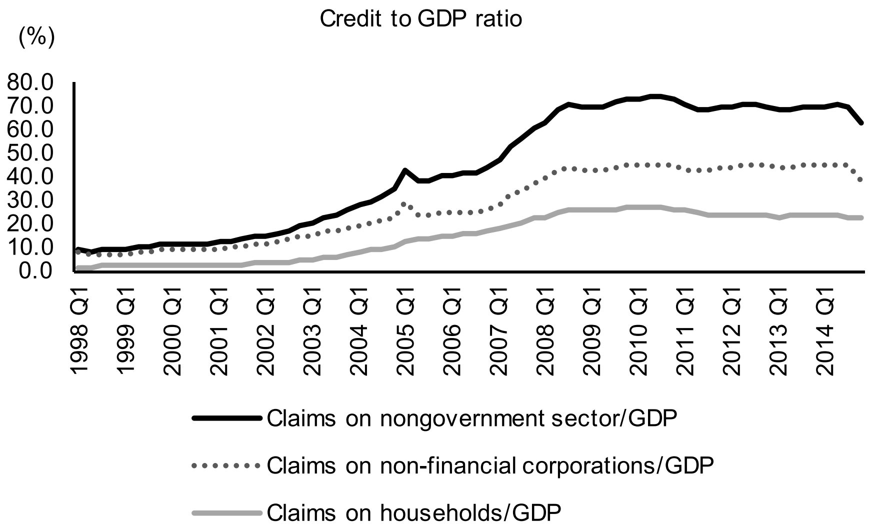
Blaes (2011) undertakes an analysis of the role of bank-related factors in explaining the slowdown in bank lending to non-financial corporations in Germany during the recent financial and economic crisis. For the econometric panel analysis, micro data on lending quantities and prices are used and are matched to individual banks' survey responses. The main finding of the paper is that BLS indicators have significant explanatory power with regards to bank lending in the period 2003-2010. Both bank-related supply and demand-side factors prove to be important in explaining the sharp slowdown in lending after the collapse of Lehman Brothers. The results indicate that the dampening impact of the bank-related supply factor on loan developments occurred with a time lag of several quarters, and was strongest from the third quarter of 2009 to the first quarter of 2010. During this period, more than one third of the explained negative loan development was due to the restrictive adjustments of purely bank-side determinants, such as banks' capital costs, market financing conditions and liquidity position.

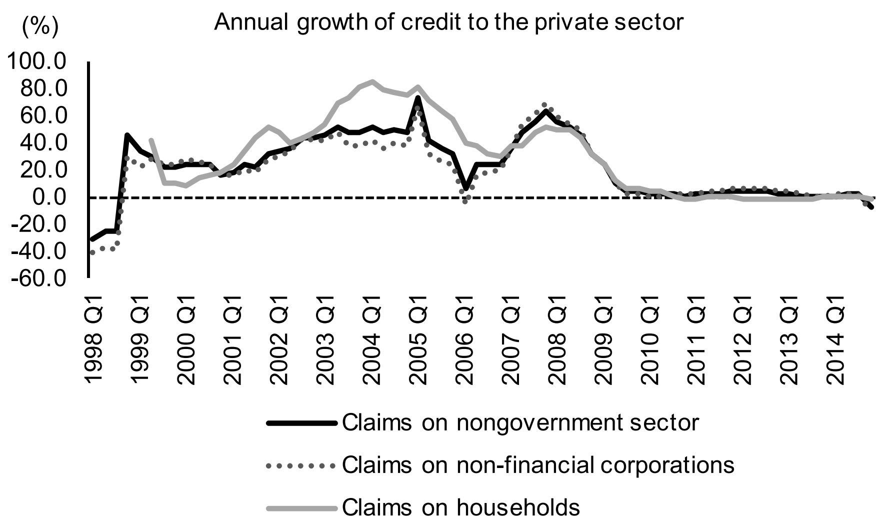
3 Banking system and credit developments in Bulgaria and the BNB's policy after the introduction of the currency board

In this section, we provide a short overview of the main banking system and credit developments in Bulgaria before and during the global financial and economic crisis, along with a description of the Bulgarian National Bank's policy over the period after the introduction of the currency board arrangement. The purpose for this is to set the context in which we will later present the main results from the bank lending survey.

After several inconclusive attempts to stabilise the Bulgarian economy between 1991 and 1996 and a major financial crisis which culminated in a short-lived hyperinflationary episode in December 1996 to February 1997, a currency board was introduced in Bulgaria with the new Law on the Bulgarian National Bank of 10 June 1997. In the first several years after the adoption of the currency board, credit growth in the country was moderate and the credit-to-GDP ratio was low, averaging 11% in the period 1998-2001. At that time, the banking system in Bulgaria was characterised by a comparatively high level of non-performing loans, low capitalisation and liquidity constraints. There were also structural factors that inhibited the expansion in bank lending associated with the fact that the majority of banks were state-owned and lacked the knowledge required for modern banking practices. Meanwhile, bank privatisation was an important factor which started the gradual process of the restructuring of the banking sector in Bulgaria.

Figure 1 Credit developments in Bulgaria after the introduction of the currency board in 1997





Source: BNB, NSI.

From 2002 onwards, a gradual credit expansion was observed and credit-to-GDP reached nearly 70% in late 2008. In the years before the collapse of Lehman Brothers, there were two periods of high growth of credit to the private sector in Bulgaria: the first one from 2003 until 2005, and the second one in 2007. Rapid credit growth in these years was driven on the one hand by high loan demand, which was stimulated by the favourable domestic and external macroeconomic environment and the global upswing in the credit cycle, high expected return on investment and positive income convergence expectations. On the other hand, banks actively expanded their operations. An important factor which contributed to the deepening of the financial intermediation over the period was the privatisation of many domestic banks by foreign financial institutions. Parent banks provided capital, liquidity and know-how to their subsidiary banks and their branches in Bulgaria, aiming to boost their market share in the region where return on capital was very high. These processes prompted strong competition among banks and a certain easing of lending standards was observed. Another factor pushing credit growth was the signing of the Treaty of Accession to the EU in 2005, which positively affected investor confidence in the development prospects of the country.

In this context – operating in a currency board and being unable to set interest rates – the Bulgarian National Bank pursued a consistent countercyclical policy, mostly with macroprudential and supervisory measures aimed at ensuring the stability of the banking system and at containing rapid credit growth. In the years of high economic growth before 2008, the BNB imposed very strict and conservative regulations for capital, liquidity, risk classifications and provisioning. Some of the macroprudential measures were related to the conduct of a more restrictive policy regarding banking license issuance, the extension of the deposit base on which minimum reserve requirements (MRR) are calculated, or the tightening of banking supervision through different prudential measures. In April 2005, the BNB introduced administrative credit limits (credit ceilings), which were effective until January 2007. Banks whose quarterly credit growth exceeded the reference values set by the BNB bank had to hold additional minimum reserves with the central bank. Following the introduction of the credit ceilings, there was an improvement in banks' balances and a reduction in the credit risk in the banking system; a certain moderation of credit growth was also observed. After the administrative measures were abolished in the beginning of 2007, credit growth started accelerating again and reached 62.5% at the end of the year. Continuing to conduct a consistent countercyclical policy, the BNB introduced an increase in the MRR ratio from 8% to 12% in September 2007.

Towards the end of 2008 and following the Lehman Brothers bankruptcy, banks' behaviour changed. Parent banks reduced the availability of funds provided for market expansion. Bulgarian banks tightened their credit standards and started to finance their activities mostly through domestic recourses. From the end of 2008, growth of lending to the private sector slowed down significantly, reflecting the intensification of the global financial and economic crisis. The Bulgarian economy was affected through increased uncertainty on the international financial markets, lower foreign capital inflows and declining external demand.

During the economic downturn, the BNB continued to conduct a countercyclical policy, taking a number of measures in late 2008 and 2009 aimed at providing greater liquidity management flexibility of commercial banks using liquidity buffers created in previous years. Some of the measures were related to the easing of regulations on minimum reserve requirements and included the recognition of 50% of cash balances as reserve assets and the reduction of the MRR rate from 12% to 10%, followed by a reduction of the MRR rate to 5% for funds attracted from non-residents and to 0% for government deposits collateralised with government securities. After 1 January 2009, the average effective minimum reserve requirement for the banking system fell to some 7%, and the overall effect of these BNB measures was a release of liquidity to banks. Other measures taken by the central bank as a response to the crisis concerned the easing of loan classifications and provisioning rules. These measures were aimed at easing credit institutions' negotiating of credit conditions and at converging with the international practices of the more conservative approach applied so far for loan classification and loan loss provisions. In this manner, more benevolent conditions were created for banks to be flexible with their viable customers who were experiencing temporary difficulties in a harsh economic situation.

4 Survey results for Bulgaria

Against the background of the banking system and credit developments before and during the financial crisis described in the previous chapter, in this section we provide an overview of the main results of the bank lending survey for Bulgaria. The questions in the survey concern either developments in credit standards or in demand for loans.[1] First, we present these developments for the period from 2003 Q4 to 2014 Q4. Furthermore, we discuss the contributing factors put forward by the banks surveyed in more detail. Finally, we compare the results of the bank lending survey with information collected from other sources. The analysis covers lending to enterprises as well as lending to private households. Lending to enterprises is further classified into lending for short-term purposes and lending for long-term purposes, while lending to households is classified into lending for house purchase and lending for consumer credit.

4.1 Lending to enterprises

As the time series concerning short-term loans and long-term loans to enterprises cover a longer period of time than those concerning total lending to firms, we will focus our analysis on the two types of loans separately.[2] This will enable us to include the recession years in the analysis in order to reach more comprehensive

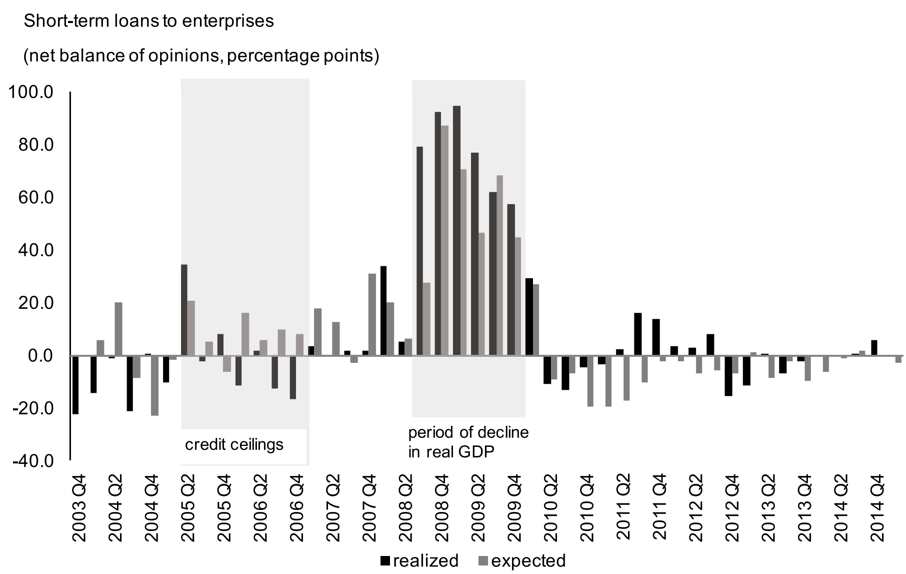
1 For details concerning the structure of the bank lending survey, see Annex I of this paper, "Structure and implementation of the BLS".

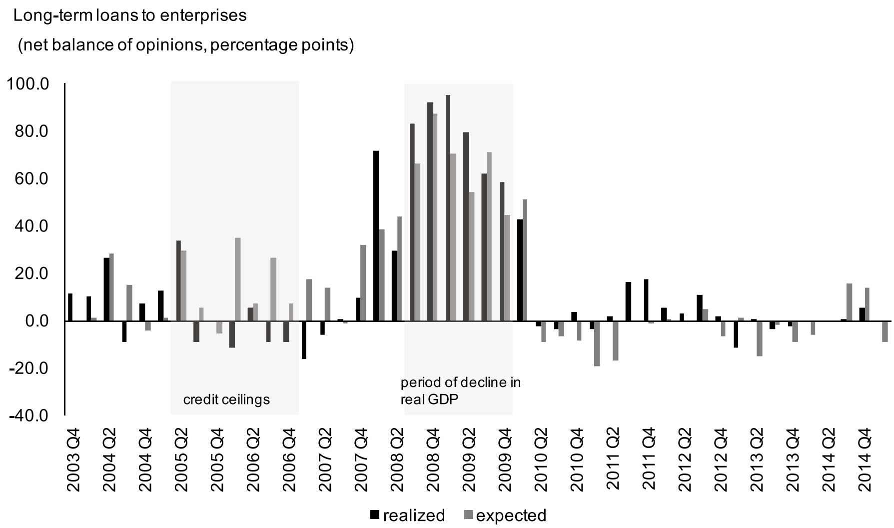
2 For the period from the fourth quarter of 2003 to the present day, the BLS included questions on demand and credit standards separately for short-term and long-term corporate loans. The BNB has included questions on demand and credit standards for total corporate loans and consumer and housing loans to households since the first quarter of 2010.

conclusions. For the purposes of the following analysis, we define the recession period as the period from the third quarter of 2008 until the fourth quarter of 2009, when, based on seasonally adjusted data on quarterly growth, Bulgaria's GDP decreased. By the post-recession period we mean the period from the first quarter of 2010 until the present. It is important to bear in mind that the above-defined recession period for Bulgaria is not identical to the period of the global financial and economic crisis from the point of view of other countries. The first signs of the crisis were present in the United States in late 2007 and early 2008, but they only showed in Bulgaria several quarters later. Bulgarian commercial banks did not have an exposure to securities tied to the US real estate market, which plummeted in 2007, damaging financial institutions globally. The crisis in Bulgaria was channelled through the real economy and was a consequence of increased uncertainty on global financial markets, which led to lower foreign capital inflows and declining external demand.

For the purposes of our analysis, in the figures below, which show developments in credit standards and in demand for loans to enterprises, we explicitly indicate the above-defined recession period for Bulgaria and the period in which the administrative credit limits (credit ceilings) were effective (see Section 3).

Figure 2 Changes in credit standards for loans to enterprises



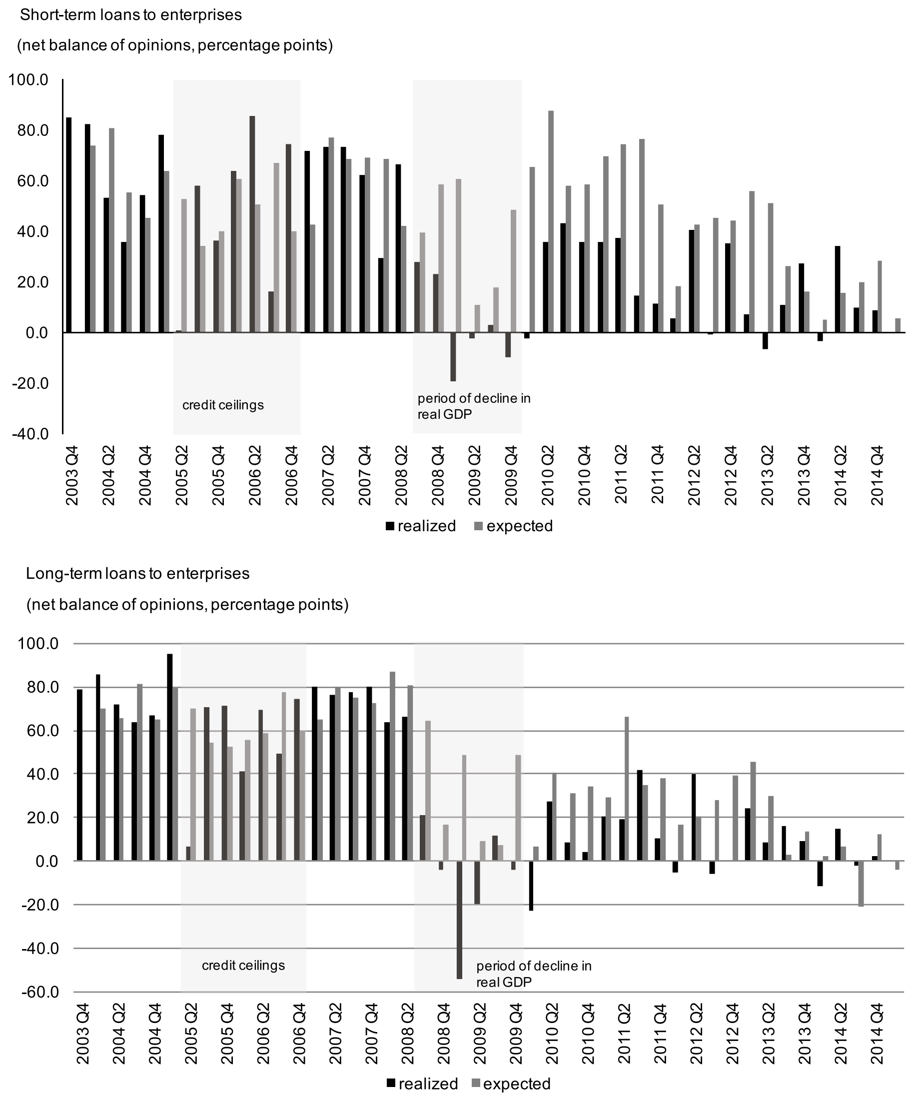


Note: The balance of opinions is defined as the difference in percentage points between the percentage of banks responding "tightened" (either "considerably" or "somewhat") and the percentage of banks responding "eased" (either "considerably" or "somewhat"). All bank responses are weighted by the bank's market share in lending to non-financial corporations for the relevant quarter. "Realised" values refer to the period in which the survey was conducted. "Expected" values are the net percentages calculated from the responses given by the banks in the previous survey.

Source: BNB Bank Lending Survey.

Figure 2 shows how credit standards applied to the approval of loans to enterprises changed in the period from 2003Q4 until 2014Q4. In the years before the global financial and economic crisis, a general net easing of credit standards was observed with respect to short-term loans to enterprises. Concerning long-term loans, a net tightening of standards was reported in the first several rounds of the bank lending survey, and a net easing afterwards. From the third quarter of 2008 until the first quarter of 2010, banks strongly tightened credit standards applied to the approval of short-term as well as long-term loans to enterprises. In the post-crisis years, banks did not undertake any serious easing of standards. An easing of credit standards was observed only with respect to loan interest rates and, to a lesser extent, with respect to fees and commissions, which can be explained by the high competition from other banks. Concerning the maximum size of loans, the premium on riskier loans and collateral requirements, standards remained tighter (see Figure 12 in Annex II). Expectations of banks concerning developments in their lending policy were generally in line with the actual outcomes in most of the period under consideration.

Figure 3 Changes in demand for loans to enterprises



Note: The balance of opinions is defined as the difference in percentage points between the percentage of banks responding "increased" (either "considerably" or "somewhat"), and the percentage of banks responding "decreased" (either "considerably" or "somewhat"). All bank responses are weighted by the bank's market share in lending to non-financial corporations for the relevant quarter. "Realised" values refer to the period in which the survey was conducted. "Expected" values are the net percentages calculated from the responses given by the banks in the previous survey.

Source: BNB Bank Lending Survey.

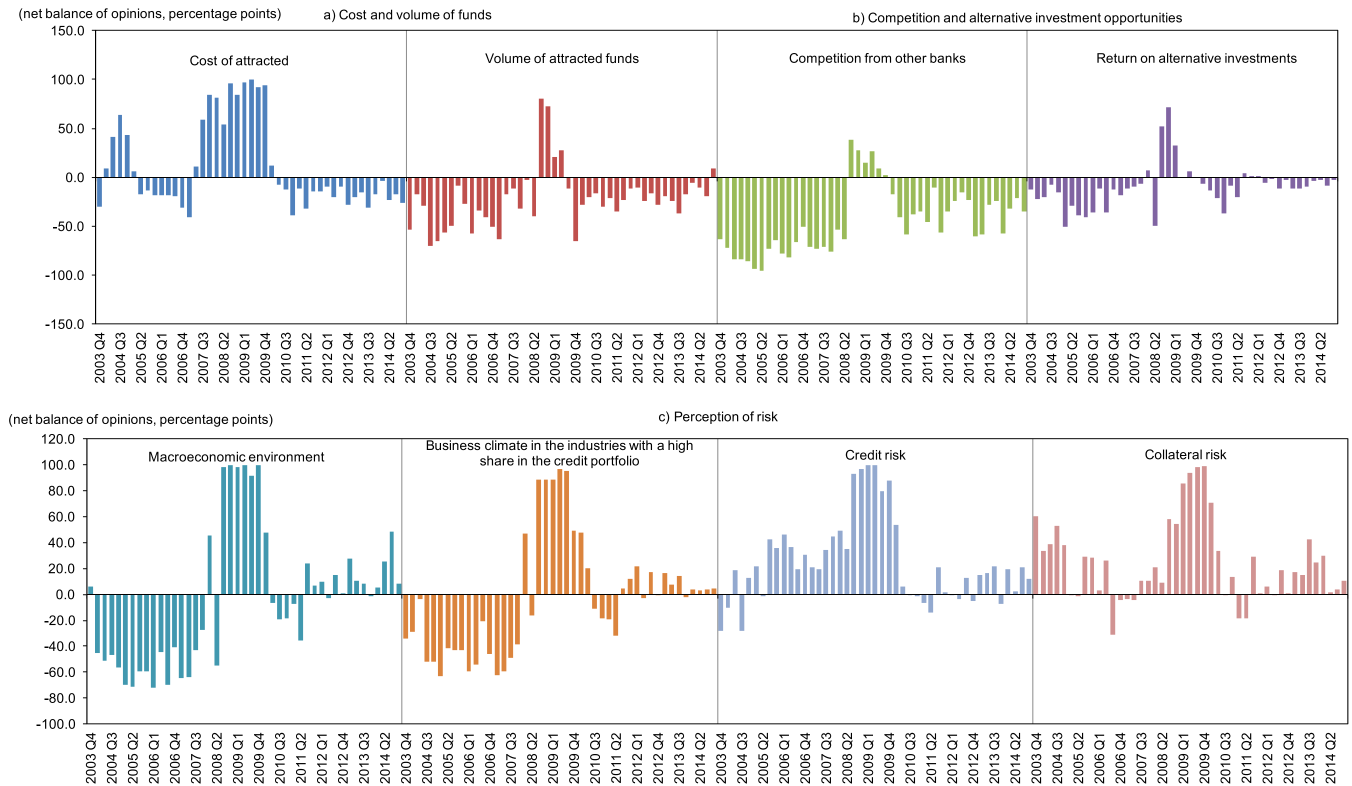
Concerning banks' responses on changes in demand for loans, a net increase of loan demand from enterprises was observed until the end of 2008, followed by a net decrease in 2009 and the first quarter of 2010 (see Figure 3).[3] In the post-recession period, loan demand started growing again (with growth more pronounced for short-term loans), but growth was slow compared to the pre-crisis years. The certain recovery of loan demand from enterprises and the lack of considerable easing of banks' credit standards in the post-crisis years may lead to the conclusion that low credit growth from 2010 till 2014 was supply-side driven.[4] However, it should be borne in mind that growth of lending to enterprises concerns the stock of loans, including maturing loans. When looking at volumes of new loans extended to enterprises, they have returned to close to their pre-crisis levels.[5] Expectations regarding the development of credit demand were generally in line with the actual outcomes except during the recession period, when banks did not expect demand for loans to decrease as it in fact did.

Turing to the reasons behind the tightening or easing of credit standards, Figure 4 shows the factors affecting credit standards for approving loans to enterprises. In the pre-crisis years, almost all the factors included in the bank lending survey contributed to the easing of credit standards, with the exception of credit risk and collateral risk. During the recession years, the main reasons behind the tightening of credit standards were linked to the increasing cost of attracted funds and the perception of risk. Against the background of heightened uncertainty related to the general economic situation, banks started competing to attract funds from residents, which resulted in higher costs of financing. In the post-recession period, the factors contributing most to the easing of credit standards were related to stronger competition from other banks and the increased volume and declining cost of attracted funds, as banks had already accumulated enough liquidity. Perception of risk continued to play a negative role in the background of economic uncertainty.

Concerning the factors affecting demand for loans to enterprises, during the whole period under consideration demand for loans due to financing needs of inventories and working capital was increasing, but at a decelerating pace. Before the crisis, firms demanded loans for investment purposes, while during the recession years fixed investment was subdued and consequently credit demand decreased. In the post-recession period, loan demand for investment purposes recovered slightly, but was far from its pre-crisis levels. A factor which made a positive contribution to the demand for loans to enterprises during the recession was the limited access of firms to alternative sources of finance, such as internal financing or loans from non-banking institutions.

3 By net increase/decrease in demand for loans, we mean a positive/negative value for the net percentage of banks reporting an increase in loan demand.
4 The average annual growth of claims to non-financial corporations in the period 2010-2014 came to 2.8%, compared to an average of 38.6% for the period 2003-2008.
5 See Figure 14 in Annex II.

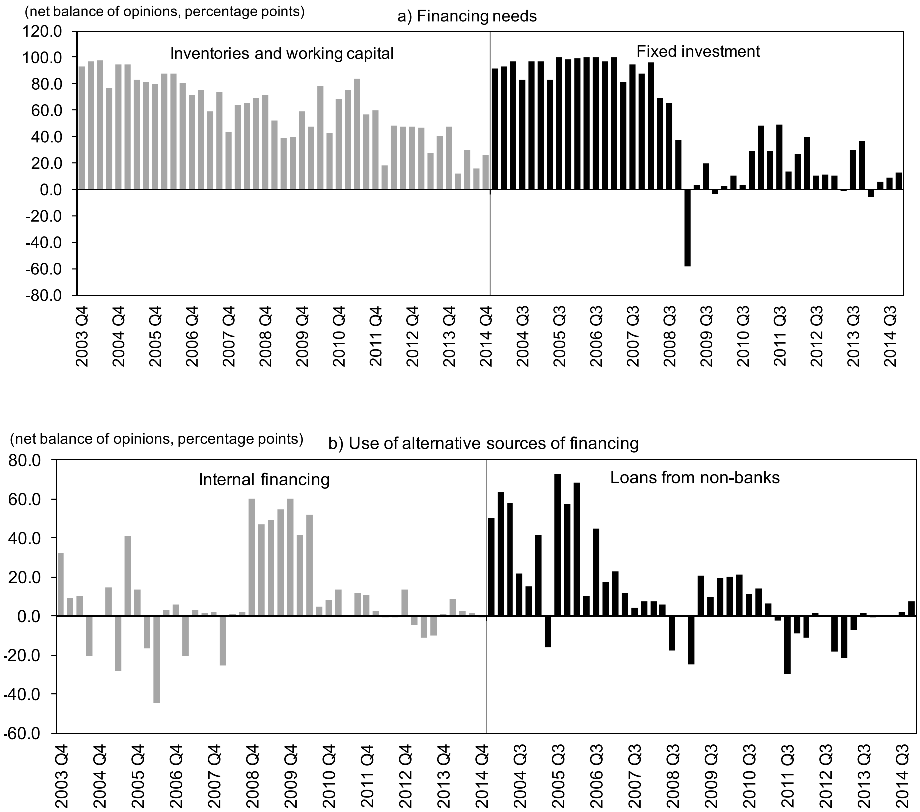
Figure 4 Factors contributing to changes in banks' lending policies



Note: The balance of opinions in responses about factors of credit standards is defined as the difference between the percentage of banks' responses for "has contributed to tightening" (either "considerably" or "somewhat") and the percentage of banks' responses for "has contributed to easing" (either "considerably" or "somewhat").

Source: BNB Bank Lending Survey.

Figure 5 Factors contributing to changes in demand for loans to enterprises



Note: The balance of opinions in responses about factors of loan demand is defined as the difference between the percentage of banks' responses for "has contributed to growth" (either "considerably" or "somewhat") and the percentage of banks' responses for "has contributed to a decrease" (either "considerably" or "somewhat").

Source: BNB Bank Lending Survey.

4.2 Lending to households

Questions concerning lending to households have been included in the bank lending survey since the first quarter of 2010.[6] Consequently, conclusions about developments in lending for consumer credit and for house purchase during the recession years cannot be drawn from the survey results. In the years after the crisis, survey results show that credit standards for approving loans to households generally eased, and that this was more pronounced for loans for house purchases (see Figure 6). Banks' expectations about their lending policy were generally in line with actual outcomes. Despite the easing of credit standards, demand for housing loans decreased from the last quarter of 2011 until the third quarter

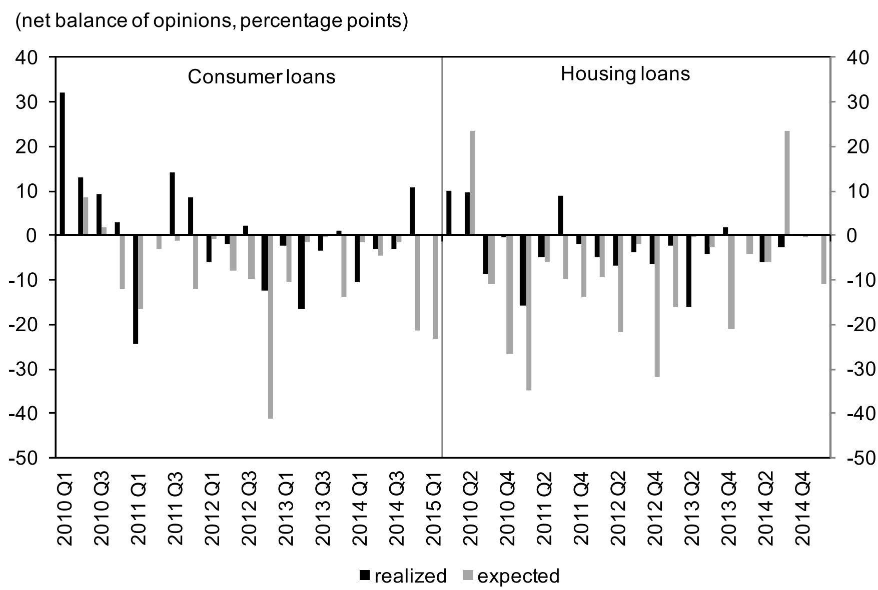
6 For more detailed description of the structure of the bank lending survey see Annex I to this paper, "Structure and implementation of the Bank Lending Survey".

of 2012. In the quarters before and after that, changes in demand for loans for house purchases generally moved in the opposite direction to changes in credit standards. Demand for consumer loans was increasing during most of the period under consideration, but these developments were not always stimulated by banks' lending policy. Concurrently, banks' expectations about developments in credit demand were not always realised.

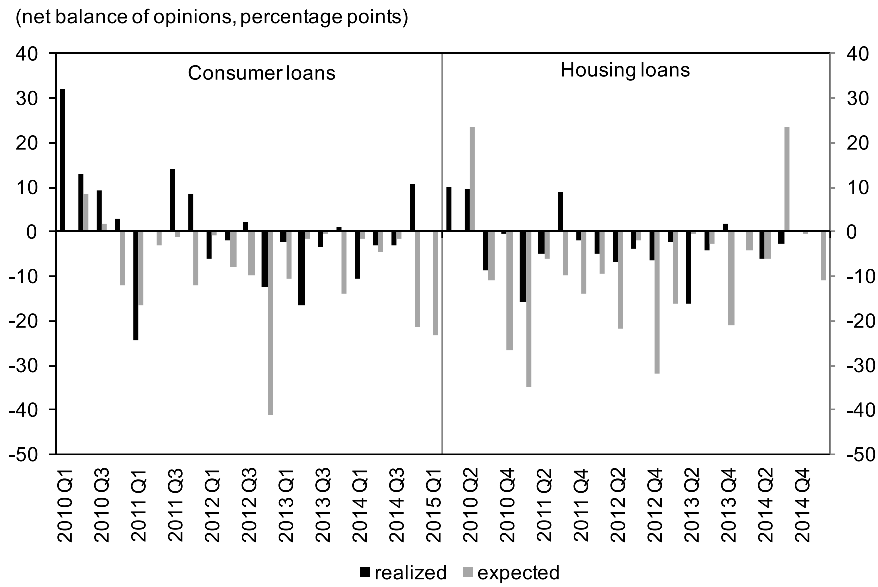
With regards to conditions and terms for approving loans to households, during the period under consideration banks eased their lending policy mostly with respect to loan interest rates, the interest spread and the fees and commissions for approving and managing loans (see Figure 13 in Annex II). Furthermore, from the first quarter of 2012 banks eased credit standards with respect to the maximum size of loans for consumer credit. Standards were tightened concerning the premium on riskier loans and collateral requirements.

Figure 6 Credit standards and demand for loans for consumer credit and house purchase

a) Changes in credit standards



b) Changes in demand for loans



Note: The balance of opinions is defined as the difference in percentage points between the percentage of banks responding "tightened/increased" (either "considerably" or "somewhat") and the percentage of banks responding "eased/decreased" (either "considerably" or "somewhat"). All bank responses are weighted by the bank's market share in lending to households for the relevant quarter. "Realised" values refer to the period in which the survey was conducted. "Expected" values are the net percentages calculated from the responses given by the banks in the previous survey.

Source: BNB Bank Lending Survey.

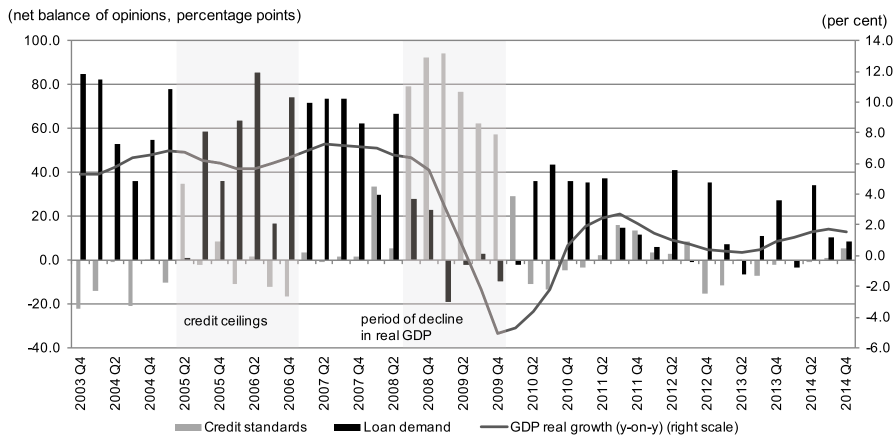
4.3 Comparison of bank lending survey data with other indicators

This section aims at comparing some of the reported variables in the survey with information from other sources (real GDP growth, loan growth, gross fixed capital formation and industrial confidence). The purpose of this analysis is to assess the information content of the BLS results in relation to other macroeconomic and financial data.

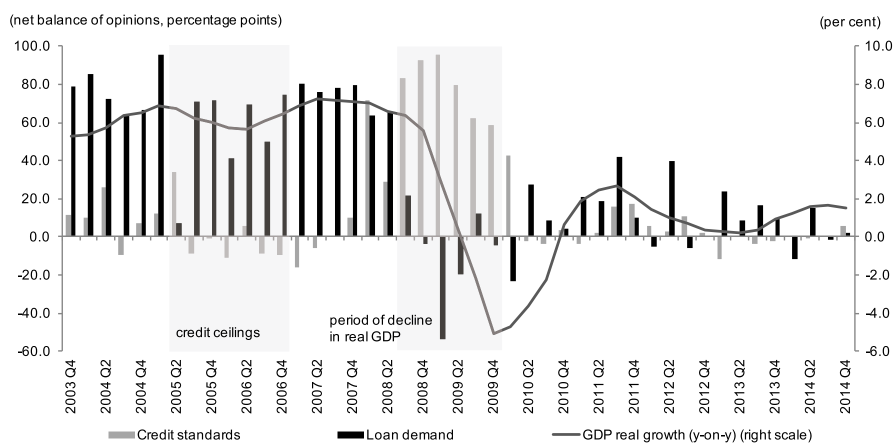
Credit standards – among other factors such as interest rates, exchange rates, consumer or business confidence – may be linked to economic activity. To the extent that credit availability depends on lenders' standards, a tightening of banks' lending policies should cause a decline in spending by firms and households that depend on banks for credit, and this in turn should lead to lower economic activity. Figure 7 presents developments in real activity alongside those in banks' credit standards and in demand for loans to enterprises.

Figure 7 Comparison of BLS data on credit standards and demand for loans to enterprises and real GDP growth

a) Short-term loans to enterprises



b) Long-term loans to enterprises



Source: BNB Bank Lending Survey, NSI.

In the years before the global financial crisis, a net easing of credit standards with respect to short-term loans to enterprises was generally observed. Concerning long-term loans to enterprises, a net tightening of banks' lending policies was reported in the period 2003Q4 to 2005Q2, and a net easing afterwards. Indeed, taking into account the very tight initial credit standards, the cumulative effect in this period was an easing of banks' lending policies towards enterprises, driven by supply factors and competition for market share. At that time, banks had easy access to foreign financing. Financial resources were provided by parent banks to their subsidiary banks and their branches in Bulgaria, with the aim of boosting their market share in the region because of the significant return on investment. At the same time, demand for short-term as well as long-term loans was increasing rapidly. In line with developments in credit standards and credit demand, real activity was strong, averaging 6.2% for the period 2003-2007. Banks started tightening their lending policies from the first quarter of 2008, shortly after the first signs of the global financial crisis had appeared, and demand for loans started declining several quarters later. A possible explanation for these developments is the fact that banks could react more rapidly to what was happening on international financial markets and change their lending policy accordingly. At the same time, a longer period of time was needed for a change in firms' behaviour to be seen. The first signs of a slight improvement in economic activity could be observed from the first quarter of 2010, and credit demand started growing again one quarter later. Banks also started easing their lending policies from the second quarter of 2010. During the post-recession period, demand for loans from enterprises has been increasing most of the time, while banks' lending policies have been not very consistent, with periods of easier as well as of tighter lending standards.

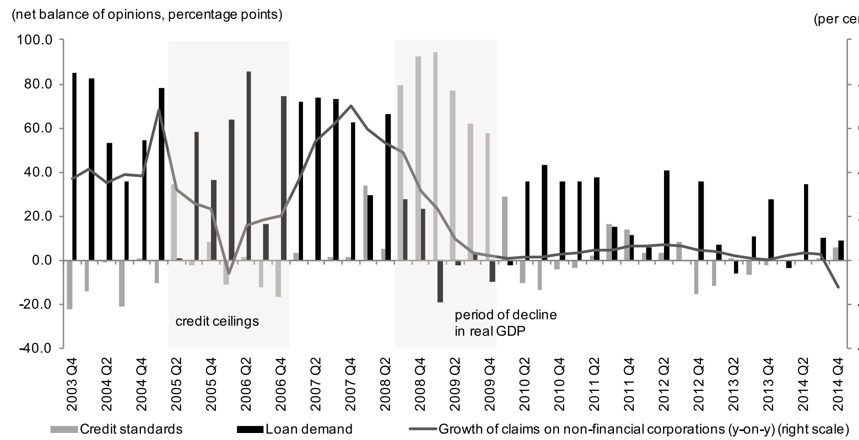
One of the objectives of the bank lending survey is to complement information retrieved from other sources, such as the monetary statistics. A high net percentage of tightening of credit standards can be expected to be associated with low (and sometimes even negative) lending growth.

In Figure 8, data from the bank lending survey are plotted together with data on the claims on non-financial corporations from the monetary statistics. In fact, in the period from the first quarter of 2008 until the first quarter of 2010, a considerable net tightening of credit standards was observed, while at the same time the year-on-year growth of lending to non-financial corporations was posting a significant deceleration (from a peak of 70.2% in 2007Q4, it fell to around 1% at the beginning of 2010). However, the results of the bank lending survey show that the inverse relationship between a tightening of credit standards and loan growth is not always apparent. For example, the net tightening of standards with regard to long-term loans to enterprises over the first several rounds of the survey was associated with a net increase in demand for such loans according to banks' answers, and the year-on-year growth of lending to non-financial corporations was not showing any signs of deceleration. A possible explanation for the increased loan demand from enterprises in this period are the optimistic expectations of firms for the medium-term economic outlook. With respect to short-term loans, the relationship is more intuitive for the first several survey rounds. In the post-recession years, there are also periods in which standards and credit growth were not moving in opposite directions. One possible reason for these results may be that banks' answers relate to short-term and long-term loans separately, while the growth of lending to non-financial corporations concerns total loans to enterprises. However, if we look at banks' answers concerning total loans to enterprises (for which we have data since the first quarter of 2010) and compare them with data on lending to non-financial corporations from the monetary statistics, the results do not show a very different picture. It is highly possible that in the post-crisis years, many other factors besides credit standards

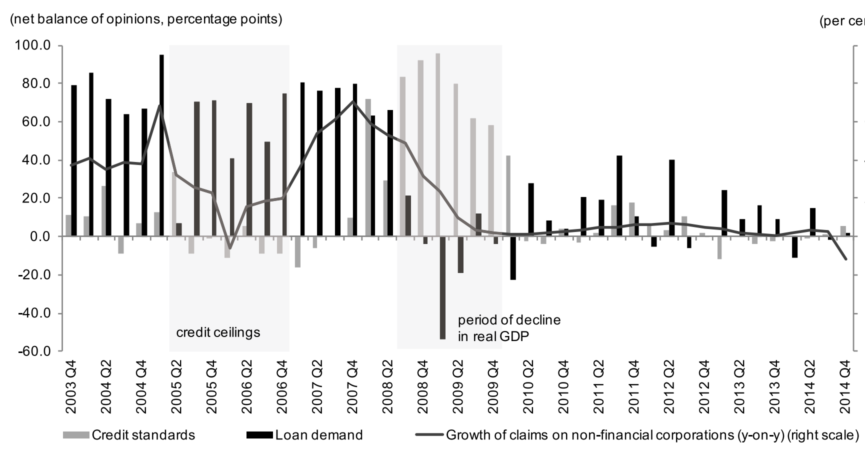
– such as the uncertain economic environment, postponed investment by firms or unwillingness of enterprises to run up more debts – have influenced credit growth.

Figure 8 Comparison of BLS data on credit standards and demand for loans to enterprises and growth of loans to non-financial corporations

a) Short-term loans to enterprises



b) Long-term loans to enterprises



Note: In the fourth quarter of 2014, the year-on-year decline in claims on non-financial corporations is driven by the exclusion of Corporate Commercial Bank as a reporting unit from monetary statistics since November 2014 after the banking license revocation.

Source: BNB Bank Lending Survey and Monetary Statistics.

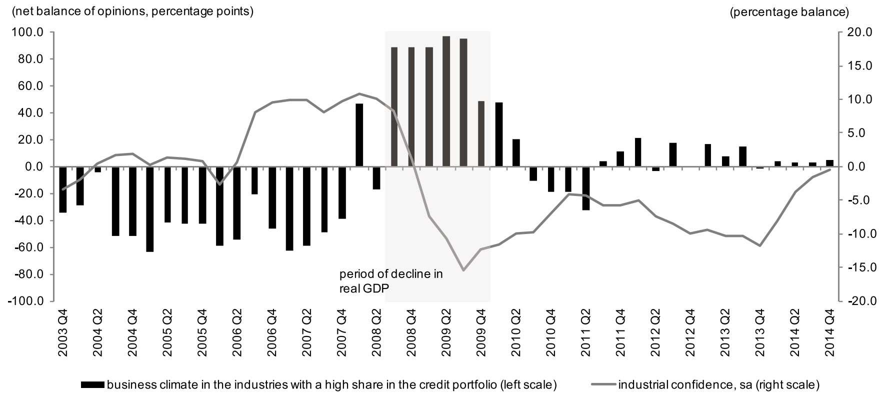
However, if we look at BLS data on demand for loans from enterprises and compare them with the growth of claims on non-financial corporations, there is much more systematic pattern to the directions in which they move. In the years before the global financial and economic crisis, demand for loans from enterprises was high, stimulated by the favourable macroeconomic environment and high expected return on investment. At the same time, rapid credit growth, as reported from the monetary statistics, was observed, with the exception of the period from 2005Q2 to 2006Q1. The significant deceleration of growth of loans to non-financial corporations in 2005 and the beginning of 2006 was most certainly strongly affected by the introduction of the credit ceilings by the BNB and was not driven by declining loan demand.[7] During the recession years, demand for loans started decreasing and credit growth was decelerating as well. In the post-recession period, loan demand from enterprises recovered somewhat, while the growth of claims on non-financial corporations remained weak (but was at least in positive territory), and both indicators moved in the same direction.

Turning to the factors affecting credit standards, one of the reasons reported for the tightening of credit standards for loans to enterprises is the risk perception related to the business climate among the industries with a high share in the credit portfolio. Figure 9 compares the net percentage reported by banks for the business climate with the industrial confidence indicator as reported by the European Commission's Business and Consumer Surveys.[8] In most of the period before the recession, industrial confidence was positive and banks also reported this factor as contributing to the easing of credit standards. From the third quarter of 2008, the industrial confidence indicator started declining and even turned negative in the beginning of 2009. Along with the enhancement of risk perception, banks reported a tightening of credit standards. In the post-crisis period, a general improvement in industrial confidence, i.e. a less negative value of the indicator, was associated with an easing of banks' lending policies, and a deterioration of the confidence indicator went along with tighter credit standards.

7 For details, see Section 3.

8 The industrial confidence indicator is the arithmetic average of the balances (in percentage points) of the answers to the questions on production expectations, order books and stocks of finished products. Balances are seasonally adjusted.

Figure 9 Comparison of BLS data and industrial confidence



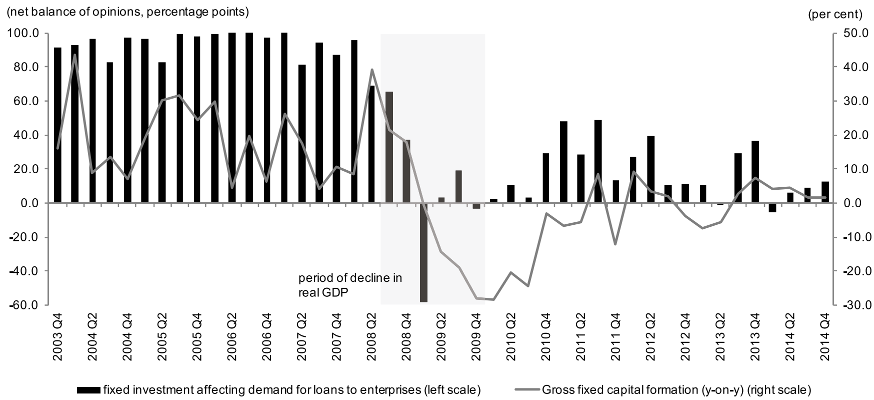
Note: The net percentage reported for the business climate in the industries with a high share in the credit portfolio is defined as the difference between the sum of "contributed considerably to tightening" and "contributed somewhat to tightening" and the sum of "contributed somewhat to easing" and "contributed considerably to easing".

Source: BNB Bank Lending Survey; European Commission.

Turning to the demand side, the bank lending survey provides information on the drivers of the demand for loans from both enterprises and households. In the pre-crisis period, almost all the banks participating in the bank lending survey reported that financing needs related to fixed investment contributed to a higher demand for loans from enterprises. During the recession, against the background of an uncertain macroeconomic environment, demand for bank loans for financing investment opportunities declined, but recovered to a certain degree in the period thereafter. Figure 10 compares this information from the bank lending survey with the growth rate of gross fixed capital formation, which is the GDP component that is mostly related to investment.

Figure 10 shows that both indicators move in the same direction. High demand for loans from enterprises for investment purposes before the crisis was associated with comparatively high growth in gross fixed capital formation. At the same time, lower credit demand for financing fixed investment, as reported in the bank lending survey, was accompanied by lower, or even negative, growth in gross fixed capital formation in the period from the fourth quarter of 2008 until the third quarter of 2010.

Figure 10 Comparison of BLS data and gross fixed capital formation



Note: The net percentage reported for fixed investment is defined as the difference between the sum of "contributed considerably to higher demand" and "contributed somewhat to higher demand" and the sum of "contributed somewhat to lower demand" and "contributed considerably to lower demand".

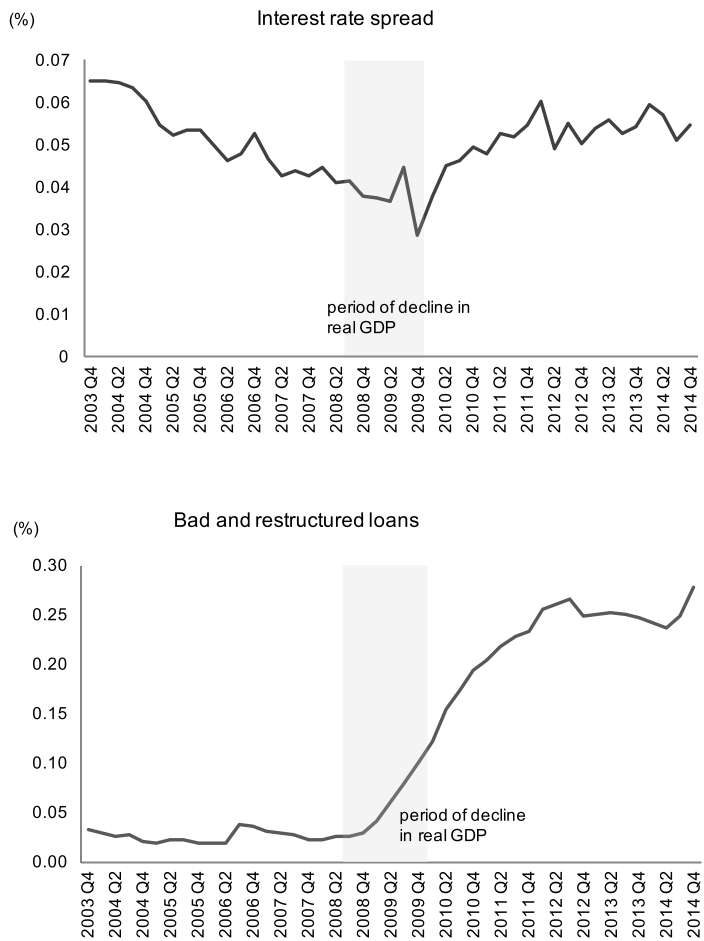
Source: BNB Bank Lending Survey, NSI.

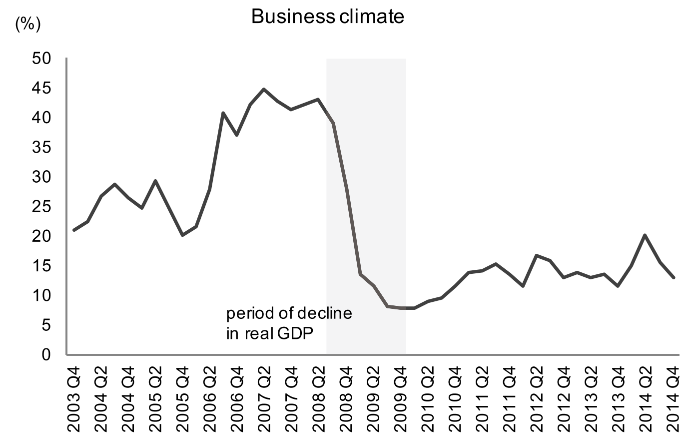
The inference from the graphical analysis above is that there is some comparability of data obtained from the bank lending survey with macroeconomic data collected from other sources like GDP growth, loan growth, investment or industrial confidence. In the next section, we will try to examine empirically the information content of the bank lending survey results by using them as explanatory variables for credit developments. Most certainly, credit growth cannot be entirely explained by survey results. Therefore, along with survey data, we include in the empirical analysis other variables such as real GDP growth, the spread between interest rates on loans and deposits of enterprises, the capital-to-asset ratio, bad and restructured loans as a share of total loans,[9] and the business climate. As can be seen from Figure 11, during the recession period when the business climate was starting to deteriorate sharply, there is evidence of an increasing share of bad and restructured loans and declining banks' profit margins. Banks tried to hedge against the uncertainty and the deteriorating economic environment by increasing their capital buffers. The decrease in banks' profit margins was partly due to the significant increase in interest rates that banks were ready to pay to attract more deposits from residents against a background of reduced access to international financial markets. In the post-recession period, the profit margins of commercial banks returned to certain levels as, faced with high accumulated liquidity, they started lowering deposit interest rates again. After reaching a capital-to-asset ratio of around 13%, banks kept the level of capitalisation close to this percentage. As a consequence of the worsened economic environment, firms started to experience difficulties in financing their investments and in repaying their obligations to banks, which

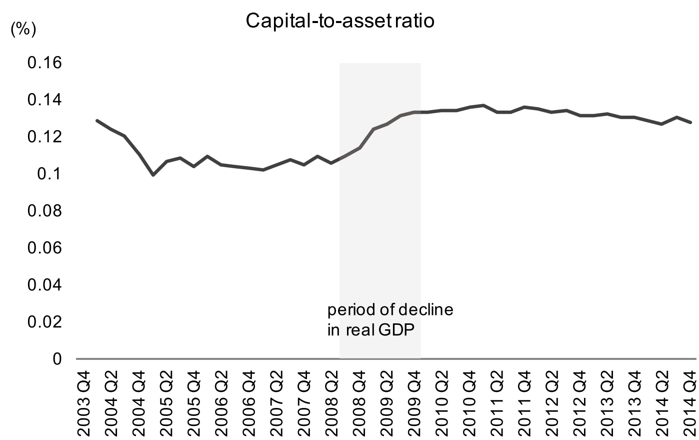
9 Data on bad and restructured loans are taken from the monetary statistics; see also footnote 13.

translated into an increasing share of bad and restructured loans, even after the crisis period.

Figure 11 Indicators used in the empirical analysis







Notes: The interest rate spread is defined as the spread between the average weighted interest rates on loans to non-financial corporations and the average weighted interest rates on deposits of non-financial corporations. Bad and restructured loans are defined as the share of loans to NFC with impaired performance past-due over 90 days and restructured loans in total loans to enterprises. Data on bad and restructured loan are provided by the monetary statistics. The business climate indicator is taken from the NSI tendency surveys. The capital-to-asset ratio is the ratio of bank capital to bank assets for the banking system as a whole.

Source: BNB; NSI.

Using data obtained from the bank lending survey and combining it with these additional variables, which could possibly explain changes in credit developments, we will try to examine the information content of the BLS results for growth of lending to enterprises. The analysis will be done first at the macro level, and subsequently at the micro level using data by individual banks.

5 Empirical evidence

5.1 Macro level

As mentioned above, definitive conclusions about the exact determinants of changes in bank lending cannot be drawn from the available statistics. Since there is only a limited possibility of making a clear-cut distinction between supply and demand variables using macroeconomic measurement variables, approximation values – such as GDP or investment for the demand side, and an interest spread to capture the supply factors – are typically used in in loan equations. In this respect, the bank lending survey can provide valuable information for a separate treatment of loan demand and loan supply as determinants in a loan equation. The net balances of banks' responses with respect to loan demand and credit standards for approving loans can be used as alternative indicators of a change in the supply of credit ($\Delta supply_t$), and of an adjustment in the demand for credit ($\Delta demand_t$), respectively.[10] In this section, using data on aggregate lending to enterprises (claims on non-financial corporations from the monetary statistics) and combining them with the results from the bank lending survey, we will try to make a distinction between loan supply-side and loan demand-side factors affecting the actual growth of credit. For the purposes of this analysis, we will use the following equations:

$$\Delta\ ln\ K_t = \beta_0 + \beta_1\ \Delta demand_t\_sh + \beta_2\ \Delta supply_t\_sh\ + \varepsilon_t \qquad (1)$$

$$\Delta\ ln\ K_t = \beta_0 + \beta_1\ \Delta demand_t\_lg + \beta_2\ \Delta supply_t\_lg + \varepsilon_t \qquad (2)$$

where the dependent variable $\Delta\ ln\ K_t$ is the growth rate of claims on non-financial corporations, $\Delta demand_t\_sh$ and $\Delta supply_t\_sh$ are the net balances of banks' responses to the BLS questions on the change in the demand and in credit standards with respect to short-term loans to enterprises, $\Delta demand_t\_lg$ and $\Delta supply_t\_lg$ are the net balances of banks' responses to the BLS questions on the change in the demand and in credit standards with respect to long-term loans to enterprises. The expected signs are positive for the coefficients β_1 and negative for the coefficients β_2. Cross-correlations between the above-defined BLS indicators and growth of claims on non-financial corporations at various lags (-) and leads (+) are presented in Table 4 in Annex II, and tests for stationarity are reported in Table 6 in Annex II. The regression equations are estimated using the ordinary least squares method. Initially, only survey results are included in the regression, and subsequently additional explanatory variables, such as quarter-on-quarter seasonally adjusted real GDP growth (Δ ln GDP), interest spreads defined as the difference between weighted average lending rates and weighted average deposit rates for non-financial corporations, the share of bad and restructured loans in the

10 Positive values for the net balances indicate an increase in demand for loans or a tightening of credit standards.

total amount of loans to non-financial corporations (Δ BRL),[11] business climate and the banking system capital-to-assets ratio. Cross-correlations between growth of claims on non-financial corporations and the additional explanatory variables at various lags (-) and leads (+) are presented in Table 5 in Annex II, and tests for stationarity in Table 6 in Annex II. To deal with problems of normal distribution of the residuals we include three dummies for 2005Q1, 2005Q2 and 2014Q4 in our specifications, and to deal with problems of serial correlation we include one lag of the dependent variable. The main results of the empirical macro analysis are presented in Table 1.

The empirical analysis outcomes show that the variable recording the change in demand for loans by corporations is statistically significant for the growth of claims for both short-term and long-term loans to corporations. These results remain unchanged when demand significance in the current or previous period is tested (i.e. when the first lag of explanatory variable is taken into account). The inclusion of additional explanatory variables in the specifications has no impact on the robustness of estimates. The coefficient in front of the variable recording the changes in demand for loans remains stable in the various specifications, moving within a range of 0.05 to 0.07, in other words, a one percentage point increase in demand for loans positively affects the growth of claims on non-financial corporations by 0.05–0.07 percentage points. Changes in credit standards have a statistically insignificant effect on corporate loans dynamics. Among the additional explanatory variables, statistical significance for the growth of claims is found regarding real GDP growth and the banking system capital-to-assets ratio. The coefficients in front of these variables have the expected positive signs and are relatively higher than those in front of the variables from the survey. The overall explanatory power of the equations is comparatively high: the explanatory variables explain between 80% and 90% of the variation of the dependent variable.

To test whether our conclusions up to now can change if we go down to the micro level, we will perform the analysis taking into account individual banks' answers to the bank lending survey and matching them to the individual volumes of loans granted by each bank.

11 The regression analysis is based on monetary statistics data on loans, which are restructured and with impaired performance past-due over 90 days, due to available data time series for the whole period under review (fourth quarter of 2003 to fourth quarter of 2014). It should be stated that in monetary statistics, banks provide aggregated data on these loans, because detailed data on the exposures according to their past-due periods are not collected for the purpose of these statistics. In accordance with the international practice, reporting of monetary statistics differs from supervisory reporting, including the reporting of loans which are restructured or with impaired performance. Therefore, the aggregated data on loans which are restructured and with impaired performance past-due over 90 days represent neither the total loans with impaired performance, nor the share of loans with impaired performance past-due over 90 days.

Table 1 Growth of claims on non-financial corporations (Δ ln K_t)

Explanatory Variables	Short-term loans to corporations		Long-term loans to corporations	
Constant	0.01 (0.01)	0.01 (0.01)	0.01* (0.01)	0.00 (0.01)
Δ credit demand (-1)	0.05** (0.02)	0.03 (0.03)	0.07*** (0.02)	0.07*** (0.03)
Δ credit supply (-1)	0.02 (0.03)	-0.01 (0.02)	0.01 (0.02)	-0.01 (0.02)
d_2005q1	0.20*** (0.03)	0.26*** (0.03)	0.20*** (0.03)	0.25*** (0.03)
d_2005q2	-0.32*** (0.04)	-0.27*** (0.04)	-0.31*** (0.04)	-0.26*** (0.04)
d_2014q4	-0.17*** (0.03)	-0.17*** (0.03)	-0.16*** (0.03)	-0.16*** (0.03)
Δ BRL (-1)		-0.55 (0.56)		-0.47 (0.52)
Δ ln GDP (-1)		1.20* (0.71)		0.34 (0.73)
Δ Business climate (-1)		0.00 (0.00)		0.00 (0.00)
Δ Capital/Assets (-1)		5.41*** (1.78)		5.46*** (1.64)
Δ Interest spread (-1)		0.58 (1.11)		0.98 (1.00)
Δ ln Kt (-1)	0.38*** (0.12)	0.43*** (0.11)	0.24** (0.12)	0.29** (0.12)
R^2	0.81	0.88	0.84	0.90
S.E. of regression	0.03	0.03	0.03	0.03
Jarque-Bera test	0.06	0.58	0.11	0.67
Breusch-Godfrey LM test	0.40	0.90	0.97	0.68
Durbin-Watson test	1.61	2.03	1.72	2.05
Breusch-Pagan-Godfrey test	0.04	0.01	0.56	0.25
Number of observations	45	42	45	42

Notes: *** indicates significance at the 1% level, ** at the 5% level,* at the 10% level, standard errors in parenthesis. Three dummies are included in the specifications: d_2005q1, d_2005q2 and d_2014q4 for the first and second quarters of 2005, and the fourth quarter of 2014. The results of the following test are presented in the table: the Jarque-Bera normality test for distribution of residuals with null hypothesis: normal distribution, p-value is presented; the Breusch-Godfrey LM test for serial correlation with null hypothesis: a lack of serial correlation in the residuals, p-value is presented; the Durbin-Watson test for serial correlation in the residuals with DW statistics presented; the Breusch-Pagan-Godfrey test for heteroscedasticity with null hypothesis: a lack of heteroscedasticity, p-value is presented. According to the Jarque-Bera criterion for normality of residuals, they are normally distributed. While the tests indicate that no serial correlation in the residuals is observed, the Breusch-Pagan-Godfrey test reveals problems with heteroscedasticity of residuals regarding short-term loans to corporations. When applying White's procedure to clear heteroscedasticity, the significance of coefficients in front of explanatory variables remained unchanged. Therefore, it may be concluded that it has no effect on empirical assessment conclusions.

Source: BNB.

5.2 Individual banks

When matching BLS responses to aggregate data on lending, potential mismatch errors and inaccurate interpretations of the results could arise. To deal with this problem, we construct a panel by merging the individual banks' responses to the BLS-questions with individual data on lending amounts for the surveyed banks. In doing so, we guarantee that the survey responses and loan data refer to the same panel of banks. Data on banks' lending amounts are drawn from the financial supervision reports and represent the end-of-quarter values of stocks. Complementary to the survey results, additional explanatory variables are added to the panel. These comprise specific factors for each individual bank – such as interest spreads between corporate loans and deposits by individual bank[12] and individual bank capital-to-assets ratios[13] – and variables that are common to all banks, such as real GDP growth (quarter-on-quarter seasonally adjusted), the business climate in Bulgaria and the share of bad and restructured loans in the total amount of loans to non-financial corporations.[14]

The panel econometric analysis is carried out for unbalanced data panel comprising the period between the fourth quarter of 2003 and the last quarter of 2014, applying panel estimation with cross-section fixed effects to account for the unobserved variation among the banks. To examine the determinants of banks' lending to non-financial corporations, we estimate an equation with the following form:[15]

$$\Delta ln\ K_{i,t} = \alpha_i + \beta\ (L)\ BLS_{i,t} + \gamma\ (L)\ X_{(i)t} + \varepsilon_{i,t} \tag{3}$$

where the dependent variable $\Delta ln\ K_{i,t}$ is the first difference of the logarithm of loans to enterprises for bank i in period t. $BLS_{i,t}$ denotes a set of BLS indicators for loan supply and loan demand for bank i in period t and $X_{(i)t}$ is a vector with the additional macro and micro control variables mentioned above. Since the information content of the BLS indicators is of a qualitative nature, they are included in our specifications as dummy variables. As regards loan demand and credit standards, two pairs of variables are designed for a decrease and an increase in loan demand by corporations and a tightening and an easing of credit standards, respectively. Thus, specification equation (3) can be rewritten as:

$$\Delta ln\ K_{i,t} = \alpha_i + \beta_1\ (L)\ Demand\ decreased_{i,t} + \beta_2\ (L)\ Demand\ decreased_{i,t} + \beta_3\ (L)\ Standards\ tightened_{i,t} + \beta_4\ (L)\ Standards\ eased_{i,t} + \gamma\ (L)\ X_{(i)t} + \varepsilon_{i,t} \tag{3}$$

where, for instance, the variable *demand decreased* takes the value 1 if bank i has reported a decrease in demand in period t (response categories "decreased considerably" or "decreased somewhat") and 0 otherwise. The variable *standards tightened* takes the value 1 if bank i has reported a tightening of credit standards in

12 Interest spreads between corporate loans and deposits by individual bank are implicitly calculated using the ratio of interest income on extended loans to average loans and the ratio of interest expenditure on attracted funds to the average amount of attracted funds.
13 Data of the Banking Supervision Department on capital and assets of individual banks.
14 Monetary statistics data; see also footnote 13 above.
15 The approach used in this section is similar to that used in Blaes (2011).

period *t* (response categories "tightened considerably" or "tightened somewhat") and 0 otherwise. The variables *demand increased* and *standards eased* are similarly designed. The expected signs are negative for the coefficients $ß_1$ and $ß_3$, and positive for $ß_2$ *and* $ß_4$. We estimate six alternative specifications. We first estimate the impact of only the BLS indicators on growth of lending to enterprises and then include, step by step, the additional control variables. In Annex II (Table 7) we report cross-correlations between loan growth and the additional macro and micro control variables at various lags (-) and leads (+). Tests for unit roots are presented in Table 8 in Annex II. The main results of the empirical micro analysis with respect to banks' answers concerning credit standards and demand for short-term loans are presented in Table 2, while those concerning credit standards and demand for long-term loans are shown in Table 3.

As can be seen from Table 2 concerning short-term loans to enterprises, the constructed variables for "demand decreased" and "standards tightened" have the expected negative sign, implying that lower credit demand or tighter bank lending policies negatively affect the growth of loans to enterprises, while the corresponding variables for "demand increased" and "standards eased" show the expected positive sign. However, the results show that the BLS indicators that are significant in explaining growth of lending to enterprises are those for "demand decreased" and "standards tightened". In fact, the BLS indicator "demand decreased" is significant in all six specifications, and the BLS indicator "standards tightened" is significant in two of them. The coefficients are broadly comparable among the different specifications used. In our baseline specification (1), the coefficient of "demand decreased", for example, indicates that a decrease in credit demand by one percentage point in period t-1 is associated with a decline of loan growth amounting to 0.09 percentage points in period t. The impact of this variable on lending remains robust when I include additional variables in the estimation. Regarding these additional control variables (the growth of real GDP, the interest spread by bank, the change in the capital-to-assets ratio or in bad and restructured loans), their estimated coefficients are highly significant in most specification variants. In particular, the coefficient of real GDP growth has the expected positive sign, implying that positive developments in economic activity translate into higher growth of lending. The sign of the capital-to-assets ratio, included as a further micro variable, is also positive, indicating that higher capitalisation of the banking system, and hence lower risk, is a factor stimulating loan growth from the supply side. Non-performing loans as a macroeconomic risk variable have the expected negative impact on bank lending growth. According to the panel estimation results, an increase of NPLs by one percentage point in period t-1 is associated with a decline in growth of loans to enterprises of around two percentage points in period t. The coefficient of the interest spread between corporate loans and deposits is positive, indicating that higher banking profits stimulate banks to increase the credit supply and thus translate into higher lending growth. The business climate, included as an explanation variable in the last specification, has the expected positive sign but the coefficient is low, implying that it does not explain much of the variance of credit growth to enterprises.

Table 2 Growth of loans to corporations (Δ ln K), unbalanced panel (OLS, cross-section fixed effects), short-term loans

Explanatory variables	Short-term loans to corporations					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.05*** (0.01)	-0.01 (0.02)	-0.02 (0.02)	-0.02 (0.02)	-0.01 (0.02)	-0.01 (0.02)
Δ credit demand (-1) (decrease)	-0.09*** (0.03)	-0.09*** (0.03)	-0.08*** (0.03)	-0.08*** (0.03)	-0.08*** (0.03)	-0.08*** (0.03)
Δ credit demand (-1) (increase)	0.02 (0.02)	0.02 (0.02)	0.02 (0.02)	0.02 (0.02)	0.02 (0.02)	0.01 (0.02)
Δ credit standards (-1) (tightening)	-0.04* (0.02)	-0.04** (0.02)	-0.01 (0.02)	-0.01 (0.02)	0.00 (0.02)	0.01 (0.02)
Δ credit standards (-1) (easing)	0.03 (0.03)	0.03 (0.03)	0.02 (0.03)	0.03 (0.03)	0.03 (0.03)	0.03 (0.03)
Interest spread by bank		1.26*** (0.39)	0.86** (0.39)	0.82** (0.39)	0.83** (0.39)	1.04*** (0.39)
Δ ln real GDP			4.09*** (0.67)	4.29*** (0.67)	3.79*** (0.69)	2.49*** (0.80)
Δ Capital to assets				0.75*** (0.21)	0.73*** (0.21)	0.72*** (0.21)
Δ BRL (-1)					-2.00*** (0.69)	-2.32*** (0.69)
Δ Business climate						0.01*** (0.00)
Δ ln K (-1)	-0.22*** (0.03)	-0.23*** (0.03)	-0.24*** (0.03)	-0.24*** (0.03)	-0.24*** (0.03)	-0.24*** (0.03)
Periods	43	43	43	43	43	43
Cross-sections	41	41	41	41	41	41
Number of observations	1303	1301	1301	1301	1301	1301
R^2	0.08	0.09	0.12	0.13	0.13	0.14
DW	2.12	2.14	2.12	2.09	2.09	2.08

Notes: *** indicates significance at the 1% level, ** at the 5% level,* at the 10% level, standard errors in parenthesis. The results of the following test are presented in the table: the Durbin Watson (DW) test for serial correlation is presented with DW statistics. The results of this test suggest that no serial correlation is observed in the residuals. The number of cross-sections is determined by the existence of restructuring in the banking sector over the review period related to mergers at banks or emergence of new banks. In the case of mergers, individual banks before the merger and the emerged new bank thereafter are treated as separate units in the panel.

Source: BNB.

Table 3 Growth of loans to corporations (Δ ln K), unbalanced panel (OLS, cross-Section fixed effects), long-term loans

Explanatory variables	Short-term loans to corporations					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.05*** (0.01)	-0.01 (0.02)	-0.02 (0.02)	-0.02 (0.02)	-0.01 (0.02)	-0.01 (0.02)
Δ credit demand (-1) (decrease)	-0.07*** (0.03)	-0.07*** (0.03)	-0.05** (0.03)	-0.05** (0.03)	-0.04* (0.03)	-0.05* (0.03)
Δ credit demand (-1) (increase)	0.03 (0.02)	0.02 (0.02)	0.01 (0.02)	0.01 (0.02)	0.01 (0.02)	0.01 (0.02)
Δ credit standards (-1) (tightening)	-0.02 (0.02)	-0.02 (0.02)	0.01 (0.02)	0.01 (0.02)	0.01 (0.02)	0.02 (0.02)
Δ credit standards (-1) (easing)	0.04 (0.03)	0.03 (0.03)	0.03 (0.03)	0.03 (0.03)	0.03 (0.03)	0.03 (0.03)
Interest spread by bank		1.15*** (0.39)	0.80** (0.39)	0.76** (0.39)	0.78 ** (0.39)	1.00*** (0.39)
Δ ln real GDP				4.30*** (0.67)	3.80*** (0.69)	2.38*** (0.80)
Δ Capital to assets				0.76*** (0.21)	0.73*** (0.21)	0.72*** (0.21)
Δ BRL (-1)					-2.02*** (0.69)	-2.35*** (0.69)
Δ Business climate						0.01*** (0.00)
Δ ln K (-1)	-0.22*** (0.03)	-0.23*** (0.03)	-0.24*** (0.03)	-0.24*** (0.03)	-0.24*** (0.03)	-0.24*** (0.03)
Periods	43	43	43	43	43	43
Cross-sections	41	41	41	41	41	41
Number of observations	1303	1301	1301	1301	1301	1301
R^2	0.08	0.09	0.11	0.12	0.13	0.14
DW	2.13	2.14	2.12	2.09	2.09	2.07

Notes: *** indicates significance at the 1% level, ** at the 5% level,* at the 10% level, standard errors in parenthesis. The results of the following test are presented in the table: the Durbin Watson (DW) test for serial correlation is presented with DW statistics. The results of this test suggest that no serial correlation is observed in the residuals. The number of cross-sections is determined by the existence of restructuring in the banking sector over the review period related to mergers at banks or emergence of new banks. In the case of mergers, individual banks before the merger and the emerged new bank thereafter are treated as separate units in the panel.

Source: BNB.

The panel estimation results with respect to banks' answers concerning long-term loans to enterprises (Table 3) show that the BLS indicators still have the expected signs, but the only variable which is statistically significant for the growth of corporate loans is the variable for "demand decreased". The coefficient in front of this BLS indicator remains broadly unchanged among the different specifications (varying between -0.05 and -0.07). Concerning the additional macro and micro control variables, their explanatory power for loan growth remains high. According to the estimation results, corporate loan dynamics are positively influenced by real GDP growth, the interest rate spread and the capital-to-asset ratio, and negatively by the share of bad and restructured loans in total loans extended to enterprises.

In conclusion, the results of the empirical micro analysis generally confirm those of the macro analysis. The variable recording the changes in demand for loans by corporations, particularly *demand decreased*, has the expected negative sign and is statistically significant for the growth of corporate loans in all tested specifications. The coefficient in front of it is stable, ranging between -0.04 and -0.09. Overall, changes in credit standards have a statistically insignificant effect on credit growth. These results are not affected by the inclusion of additional explanatory micro and macro variables. Besides the demand for loans by corporations, a statistical significance is found regarding real GDP growth and the share of bad and restructured loans in the total amount of loans to non-financial corporations, as well as for bank-specific factors, such as the interest spread between loans and deposits and individual banks' capital-to-assets ratios. The coefficients in front of these variables display the expected signs: positive for real GDP growth, the business climate indicator and individual banks' specific interest spreads and capital-to-assets ratios; and negative in front of the share of bad and restructured loans in the total amount of corporate loans. The coefficients in front of these variables are relatively higher than those in front of the variables derived from the survey.

6 Conclusions

The main goal of this paper was to shed additional light on the factors that influence credit growth on the demand as well as on the supply side in Bulgaria, with a focus on lending to non-financial corporations. Using data obtained from the regular quarterly bank lending survey conducted by the BNB among commercial banks in Bulgaria, and combining these with data from the monetary statistics, from the banking supervision, and with other macroeconomic variables like GDP growth or the business climate, I first undertook a descriptive analysis, followed by an empirical assessment on a macro level and at the level of individual banks.

The general conclusion of the descriptive analysis suggests broadly similar trends in the change of demand and credit standards based on the survey results on the one hand, and the growth dynamics of loans to non-financial corporations based on monetary statistics data on the other hand. A similar conclusion can be made comparing the survey results with other macroeconomic indicators such as real GDP growth, investment in fixed capital and confidence in the industry sector based on the business situation survey.

Empirical analyses carried out based on macro data and individual bank data for the period 2003 to 2014 show that changes in demand estimated by survey data have a statistically significant effect on corporate loans dynamics. The empirical research also reveals that important factors positively affecting corporate loans dynamics at both the macro level and the bank level are real GDP growth and banks' capital-to-assets ratios. The analysis at the individual bank level finds that statistically significant factors for the growth in corporate loans also include the improvement in the business climate in Bulgaria, the decrease in the share of bad and restructured loans in the total amount of loans, and bank-specific factors such as the interest spread between corporate loans and deposits.

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Tania Karamisheva is an expert at the Bulgarian National Bank. She graduated from the Julius-Maximilian's University of Wuerzburg, Germany in 2006. Since 2007 she has been working at the Economic Research and Forecasting Department of the Bulgarian National Bank. In her current position, she deals with monetary policy analysis and forecasting, research and econometric modeling, analysis and forecasting of money, credit and interest rates developments, analysis of financial markets and banking sector developments. She is involved in the preparation of the BNB macroeconomic projections. In her research she also deals with the implementation and testing of different econometric models for explaining the dynamics of monetary and credit aggregates, interest rates and the monetary transmission mechanism.

Annex I

Structure and implementation of the Bank Lending Survey

The current questionnaire used in the BNB's Bank Lending Survey is consistent with the survey conducted by the ECB. It consists of 12 regular questions and is divided into two subsections. The first subsection concerns loans to enterprises (short-term loans and long-term loans), and the second concerns lending to households (consumer and housing loans). Some of the questions are backward-looking and examine developments during the preceding three months. Changes in credit demand and the factors underlying these changes are covered by the survey. On the supply side, questions concern changes in credit standards and their determinants, and changes in credit terms and conditions. Furthermore, there is a forward-looking element in the survey whereby banks are asked to give an opinion on what changes they expect both in their own lending policy and in customer demand during the next three months. By answering questions concerning changes in demand for loans and in credit standards, banks have to choose between five options: 1 = "decreased/tightened considerably", 2 = "decreased/tightened somewhat", 3 = "remained basically unchanged", 4 = "increased/eased somewhat", 5 = "increased/eased considerably". Regarding the factors affecting demand for loans or credit standards and terms, banks are asked to attribute answers on a five-point scale ranging from "- -" to "++", or "NA".[16]

The bank lending survey is conducted in the first month of each quarter (i.e. January, April, July and October). In Bulgaria, the survey is addressed to contact persons set up by the individual banks, who answer the questionnaire electronically. All 30 commercial banks operating in Bulgaria at present have

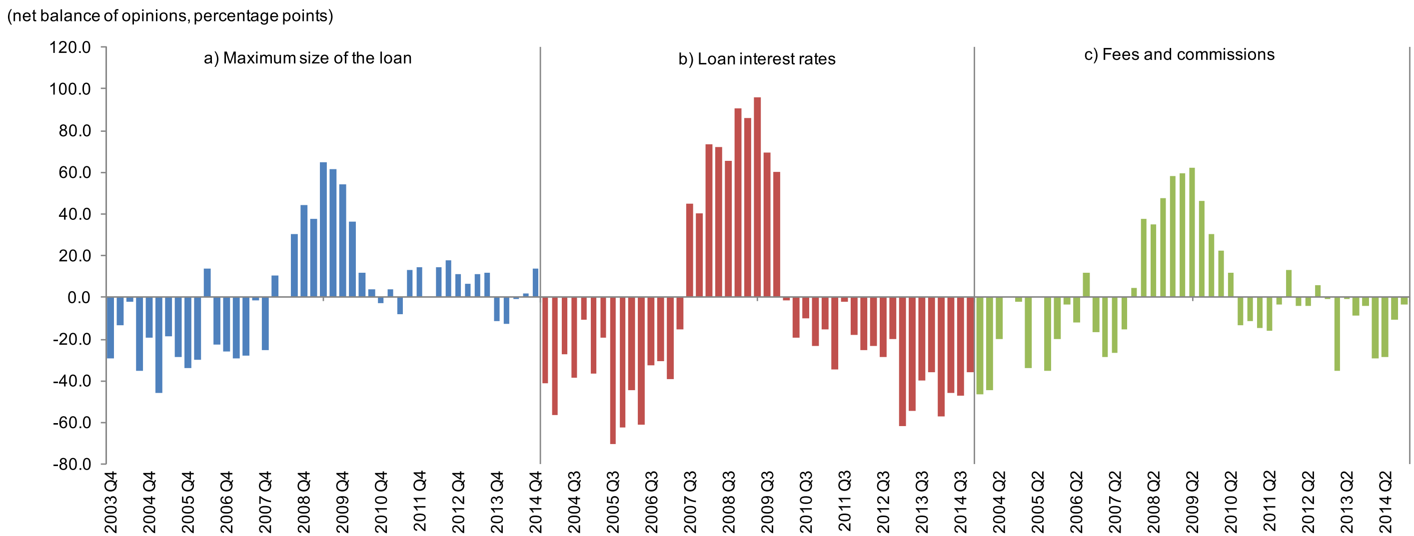
16 "- -" = "contributed considerably to lower demand/tightening of credit standards; "-" = "contributed somewhat to lower demand/tightening of credit standards"; "0" = "contributed to basically unchanged demand/credit standards"; "+" = "contributed somewhat to higher demand/easing of credit standards"; "+ +" = "contributed considerably to higher demand/easing of credit standards"; NA = "not applicable".

taken part in the survey. After all of the participating banks have passed on their answers to the BNB, the central bank undertakes an aggregation of the results on the basis of individual banks weights. These weights are calculated as a ratio of the amounts of loans to enterprises, consumer and housing loans allowed by each bank to the total amount of the respective loans allowed by the banking system as a whole. Each quarter, the results of the survey are sent back to the participating banks and are also published in the quarterly economic review of the BNB.

The bank lending survey in Bulgaria has been conducted since the fourth quarter of 2003, and hence the dataset covers a period of 45 quarters. However, it should be noted that the dataset covers the whole period from 2003 Q4 to 2014 Q4 only with respect to short-term and long-term loans to enterprises. Regarding total lending to firms, housing and consumer loans data are available only from 2010 Q1. When interpreting the survey findings, the qualitative nature of the results should be borne in mind. They are not objective, quantitative data such as precise figures on credit volume, but reflect tendency estimates recorded on a five-point scale. Furthermore, the survey is only concerned with identifying changes in respect to the previous quarter. As a result, information on levels (such as the degree of restriction imposed by a bank's current lending policy) cannot be automatically derived from the survey data. In order to be able to interpret and analyse the results, the net balance of responses in percentage terms is calculated. For questions related to the supply side of lending, this net percentage is the difference between the percentage share of responses in the restrictive range (i.e. reporting a tightening of credit standards) less the percentage share of responses in the expansionary range (i.e. reporting an easing of credit standards). This means that a positive value suggests a restrictive tendency, while a negative value indicates an expansionary tendency. Regarding loan demand, the net percentage is the difference between the percentages reporting an increase and a decrease in demand.

Annex II

Figure 12 Conditions and terms for approving loans to enterprises



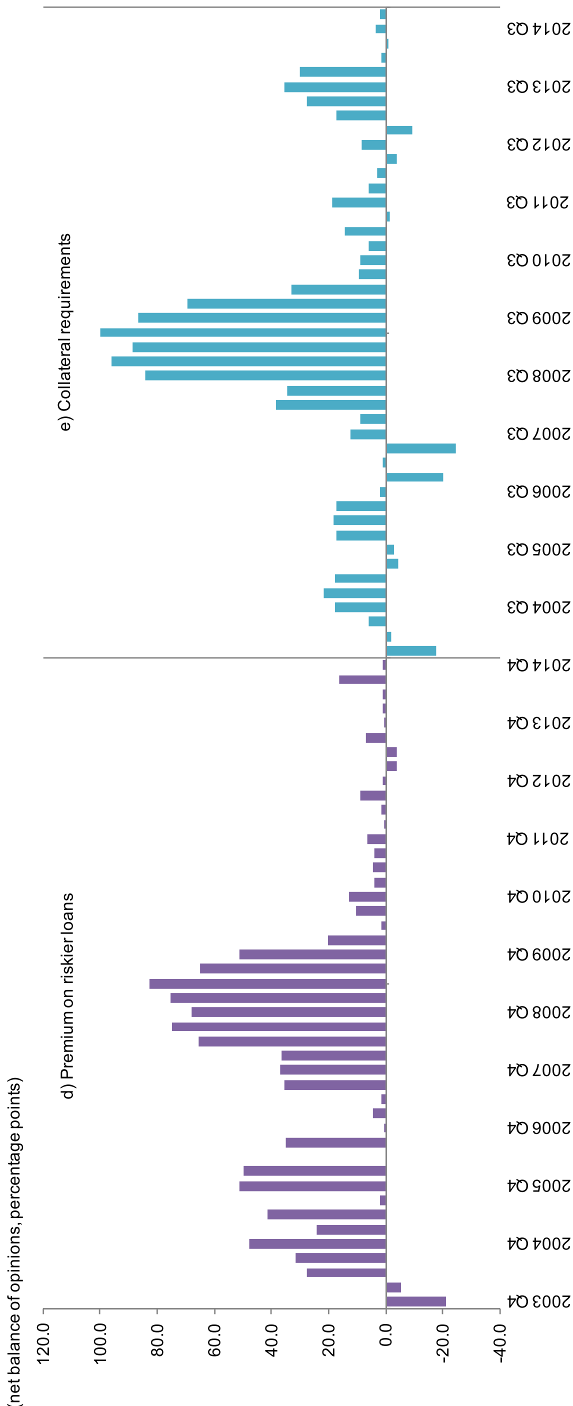
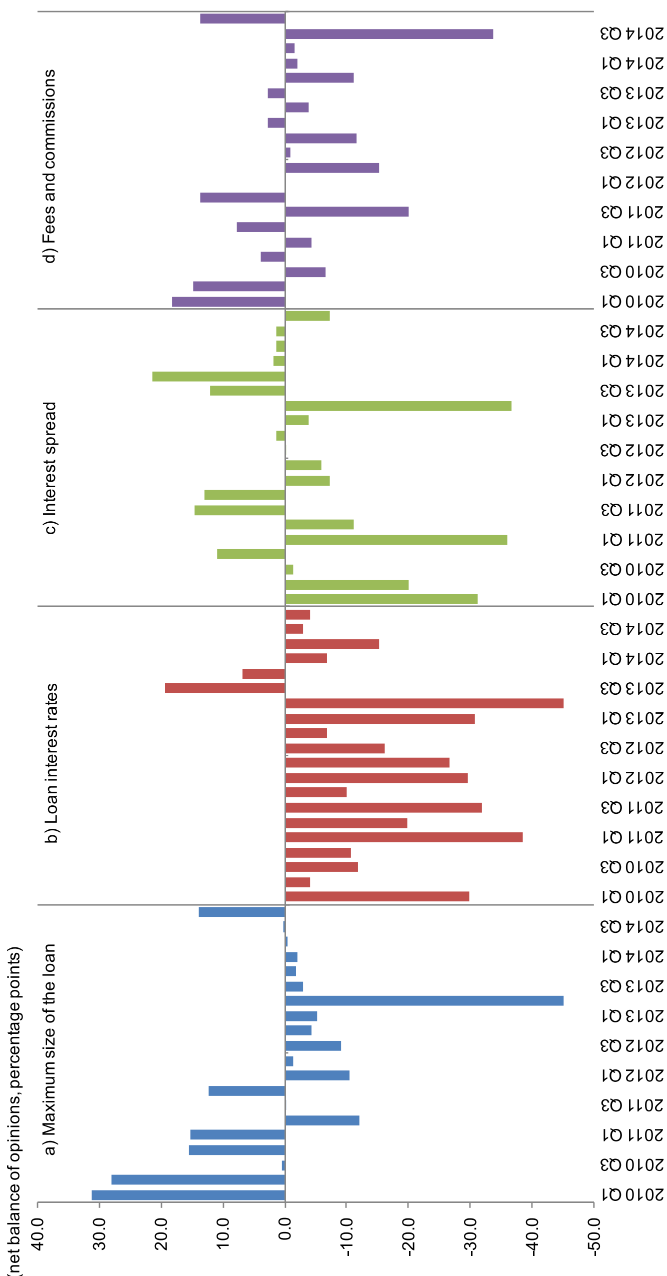
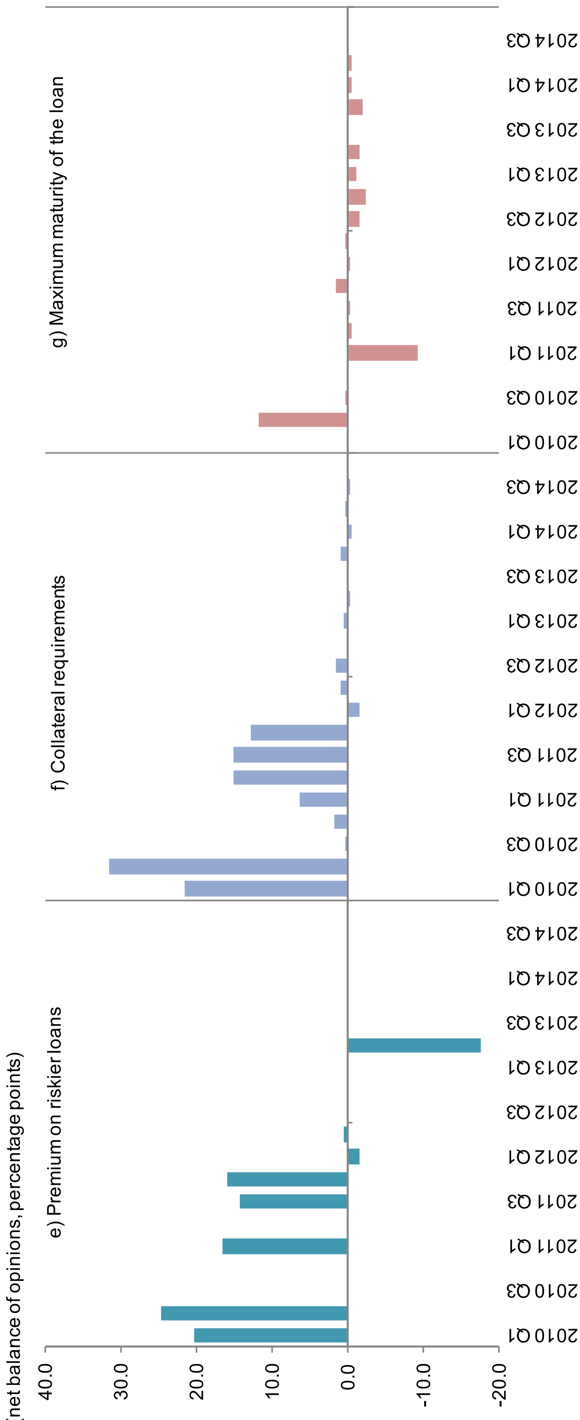

e) Collateral requirements
d) Premium on riskier loans
(net balance of opinions, percentage points)
120.0
100.0
80.0
60.0
40.0
20.0
0.0
-20.0
-40.0
2003 Q4
2004 Q4
2005 Q4
2006 Q4
2007 Q4
2008 Q4
2009 Q4
2010 Q4
2011 Q4
2012 Q4
2013 Q4
2014 Q4
2004 Q3
2005 Q3
2006 Q3
2007 Q3
2008 Q3
2009 Q3
2010 Q3
2011 Q3
2012 Q3
2013 Q3
2014 Q3

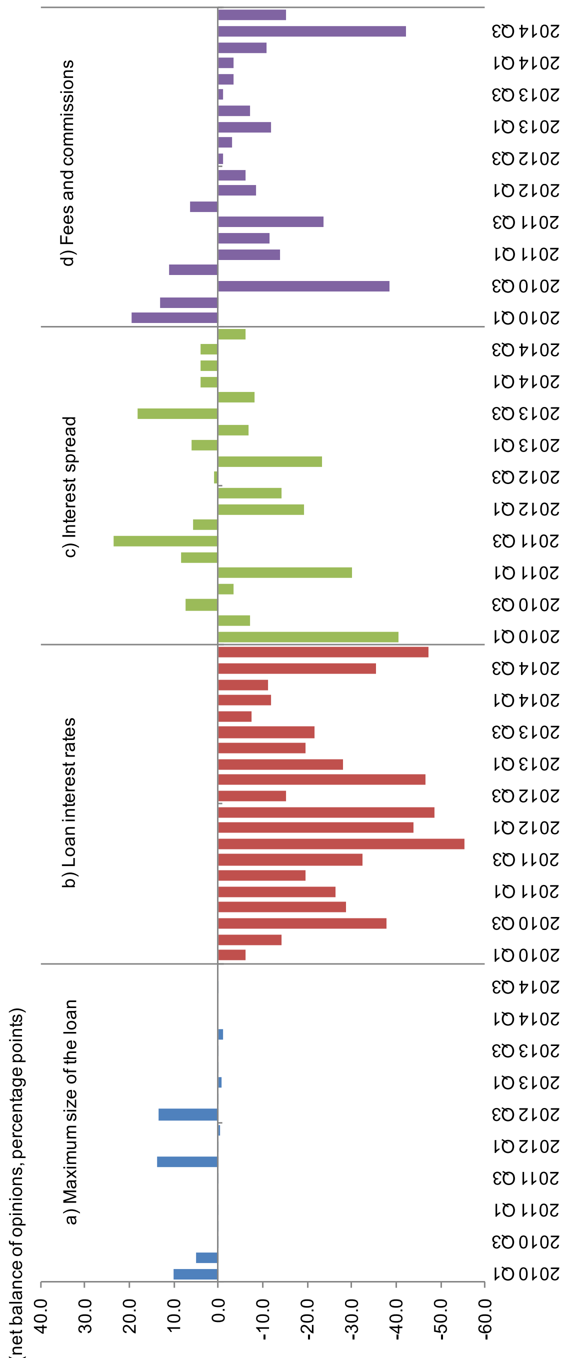
Figure 13 Conditions and terms for approving loans to households

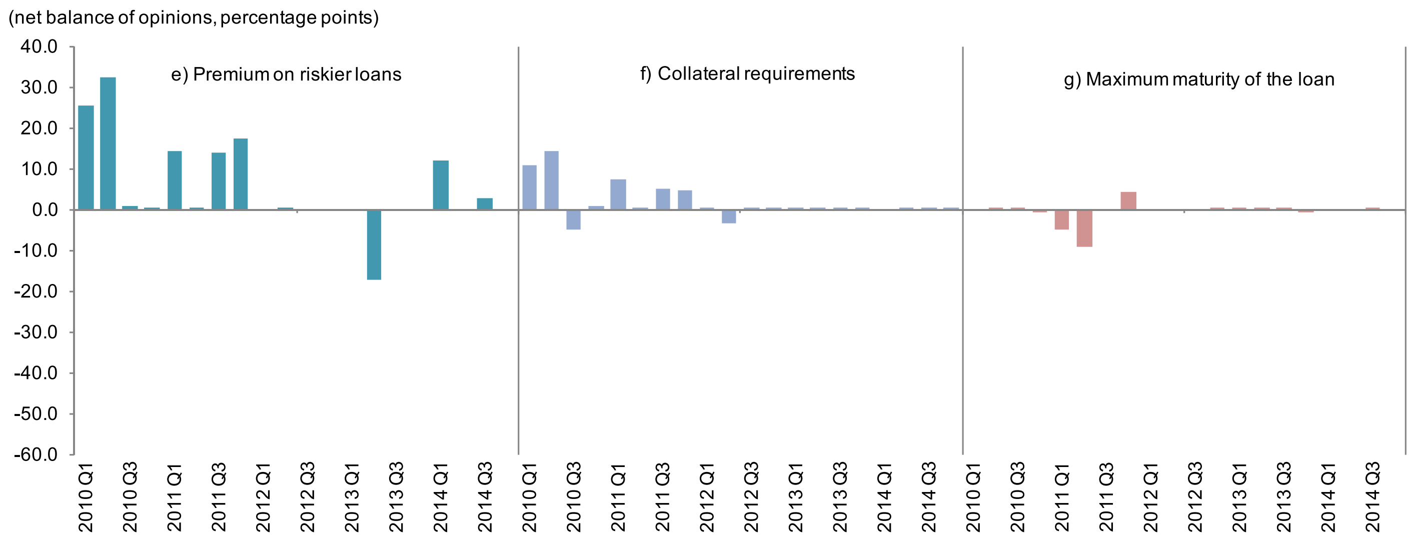
a) Loans for consumer credit




(net balance of opinions, percentage points)
e) Premium on riskier loans
f) Collateral requirements
g) Maximum maturity of the loan
40.0
30.0
20.0
10.0
0.0
-10.0
-20.0
2010 Q1
2010 Q3
2011 Q1
2011 Q3
2012 Q1
2012 Q3
2013 Q1
2013 Q3
2014 Q1
2014 Q3

b) Loans for house purchase

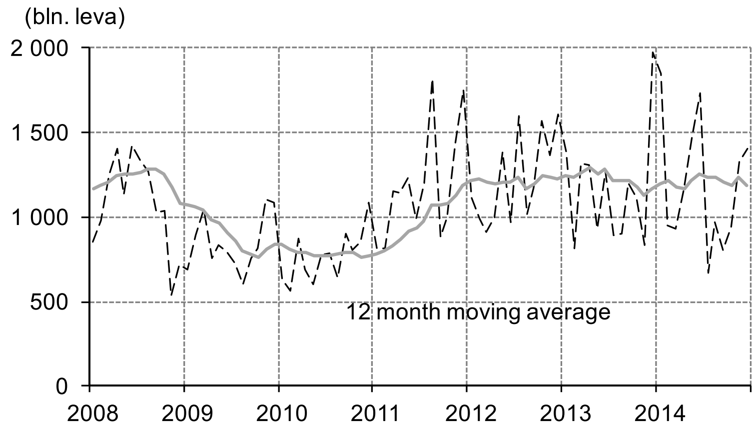




Note: The net percentage of opinions is defined as the difference between the sum of "tightened considerably" and "tightened somewhat" and the sum of "eased somewhat" and "eased considerably".

Source: BNB Bank Lending Survey.

Figure 14 Volume of new business loans to non-financial corporations



Source: BNB.

Table 4 Cross correlations between growth of claims on non-financial corporations (in period t=0) and BLS indicators at various lags (t-k) and leads (t+k), k=1…4. Macro-level.

Δ ln Kt	Δ demand_sh	Δ supply_sh	Δ demand_lg	Δ supply_lg
-4	0.44**	-0.03	0.39**	-0.02
-3	0.49**	0.09	0.48**	0.19
-2	0.30**	-0.08	0.41**	-0.07
-1	0.39**	0.13	0.46**	0.08
0	0.66**	-0.10	0.70**	0.04
1	0.21	0.49**	0.28	0.45**
2	0.34**	-0.03	0.32**	-0.04
3	0.05	0.27	0.27	0.23
4	0.09	-0.02	0.12	0.02

Note: ** indicates significance at the 5 % level

Table 5 Cross correlations between growth of claims on non-financial corporations (in period t=0) and additional explanatory variables at various lags (t-k) and leads (t+k), k=1…4. Macro-level

Δ ln Kt	Δ ln realGDP	Δ Interest spread	Δ BRL	Δ Business climate	Δ Capital/ Assets
-4	0.29	-0.08	-0.13	0.15	0.03
-3	0.40**	-0.16	-0.15	0.23	-0.14
-2	0.47**	-0.01	-0.08	0.21	0.06
-1	0.35**	0.05	-0.27	0.19	-0.13

Δ ln Kt	Δ ln realGDP	Δ Interest spread	Δ BRL	Δ Business climate	Δ Capital/ Assets
0	0.35**	-0.23	-0.45**	0.03	-0.44**
1	0.33**	-0.16	-0.26	0.14	0.13
2	0.17	-0.13	-0.23	-0.1	0.06
3	0.12	-0.03	-0.18	-0.22	-0.08
4	-0.03	-0.07	-0.15	-0.30	0.34**

Note: ** indicates significance at the 5 % level.

Table 6 Unit-root tests

H0: Variable has a Unit Root	ADF Test t-statistics			Phillips-Perron Test t-statistics		
	Level	First difference	First difference of the log	Level	First difference	First difference of the log
Claims on non-financial corporations	-1.82	-2.63*	-4.85***	-1.80	-2.52	-5.24***
Demand for loans (BLS): short-term loans	-4.30***			-4.65***		
Credit standards (BLS):short-term loans	-2.39	-8.60***		-2.42	-8.45***	
Demand for loans (BLS): long-term loans	-3.06**			-3.21**		
Credit standards (BLS): long-term loans	-2.35	-9.05***		-2.38	-8.80***	
BRL	0.27	-2.96**		0.20	-2.62*	
Real GDP_sa	-2.47	-2.92**	-2.93**	-2.64*	-2.96**	-2.94**
Business climate	-1.68	-4.74***		-1.49	-4.76***	
Capital to asset ratio	-1.06	-5.60***		-1.32	-5.62***	
Interest rate spread	-2.50	-9.36***		-2.58	-9.48***	

Note: *** indicates significance at the 1 % level; ** at the 5% level;* at the 10% level

Table 7 Cross correlations between growth of loans to corporations (in period t=0) and additional explanatory variables at various lags (t-k) and leads (t+k), k=1…4. Micro-level

Growth of loans to corporations	Δ ln of realGDP	Interest spread by bank	Δ Capital/ Assets	Δ BRL	Δ Business climate
-4	0.10 **	0.00	0.05**	-0.06**	0.07**
-3	0.13 **	0.01	0.09**	-0.02	0.16**
-2	0.12 **	0.09 **	0.00	-0.04	0.06**
-1	0.05 **	0.08 **	-0.07**	-0.11**	-0.06**
0	0.17 **	0.07 **	0.08**	-0.07**	0.13**
1	0.06 **	0.05	0.01	-0.04	0.07**
2	0.07 **	0.10 **	-0.15**	-0.09**	-0.1**
3	-0.03	0.13 **	0.05**	-0.05	-0.17**
4	0.02	0.07 **	0.04	-0.19**	-0.19**

Note: ** indicates significance at the 5 % level.

Table 8 Panel unit-root tests

H0: Variable has a Unit Root	Im, Pesaran and Shin W-statistics		
	Level	First difference	First difference of the log
Loans to corporations	0.65	-15.69***	-18.58***
Real GDP_sa	-1.14	-2.73***	-2.25***
Interest rate spread by individual banks	-2.62***		
Capital to asset ratio	-3.96***		
BRL	11.57	-3.69***	
Business climate	-0.90	-17.46***	

Note: *** indicates significance at the 1 % level; ** at the 5% level;* at the 10% level.

A forensic analysis of credit activity in Croatia

Mirna Dumičić and Igor Ljubaj[1]
European Central Bank; Croatian National Bank

Introduction

After the escalation of the global financial crisis, credit activity in Croatia slowed down considerably compared to the pre-crisis period. The results of the detailed analysis of the Croatian credit market based on the data available up to the mid-2015 imply that the postponed recovery and weak growth prospects, combined with the inefficient legal environment, are the most significant factors influencing sluggish credit developments in Croatia. Such developments weaken the scope of monetary policy measures aimed at stimulating a credit recovery.

The main goal of this research is to summarise the most relevant empirical, descriptive and anecdotal findings related to the potential determinants of credit demand and credit supply of households and corporates in Croatia. For that purpose, the results of the credit market disequilibrium model are combined with the information obtained from the bank lending survey (BLS) which has been conducted by the Croatian National Bank (CNB) since 2012 and the available information related to the domestic legal environment. The research ends with concluding considerations presented from the perspective of the scope of monetary policy to influence the revival of credit activity in the current phase of the economic cycle.

Recent credit developments in Croatia

Despite the above-average increase in corporate loans in 2010 and 2011 in Croatia compared to the majority of the Central and Eastern European (CEE) countries, the deleveraging of this sector intensified in 2014 and at the beginning of 2015. If this process continues, it might jeopardise the fragile recovery of the economy, which is an additional motivation for the analysis of the determinants of credit supply and demand for this sector.

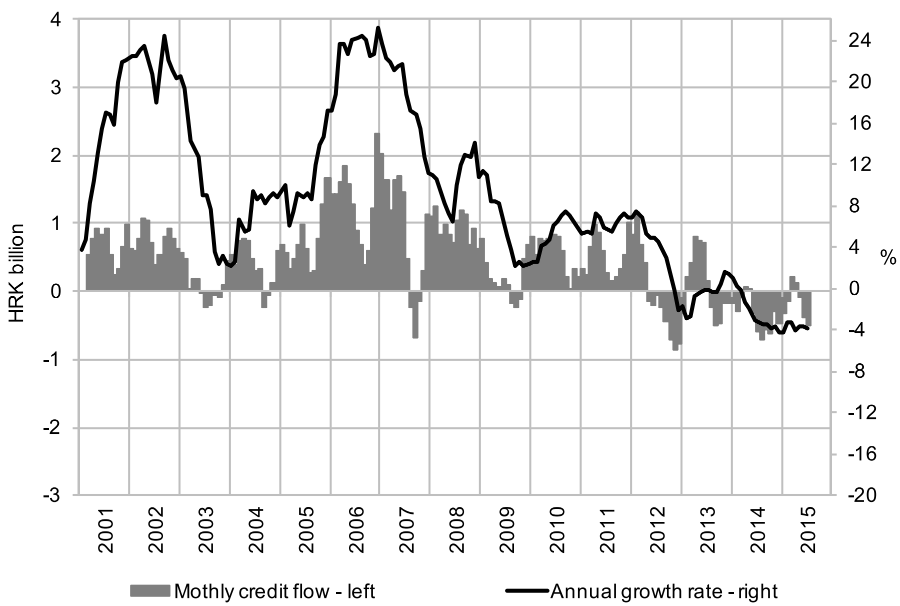
Credit to households has been falling year on year since 2009 (Figure 2), but despite the continuous deleveraging in the past few years, the latest analysis

1 Views presented in this paper are the views of the authors and do not necessarily express views of the Croatian National Bank or the European Central Bank.

points to the need for a further short-term reduction in the debt burden (CNB, 2014b), which suggests that only the intensification of economic activity and increased consumer confidence will open up the possibility for this sector to take on further debt.

Notwithstanding the fact that this paper is focused on loans to the private sector, to understand their determinants it is necessary to take at least a brief look at government loans. In the recent period, government loans have exhibited different dynamics to private sector loans and have grown almost continuously (Figure 3). The rise in the spread between implicit interest rates on loans and deposits adjusted for charges for value adjustments confirms the increased relative attractiveness of the government as debtor (Figure 4). If banks use released liquidity for financing government in the form of loans or bonds, or hold it at central banks, measures affecting liquidity might not be sufficient to encourage credit activity (Catao, 1997). In line with this, Baek (2002) qualifies increased holdings of government bonds or granting primarily government loans as one of potential symptoms of restricted loan supply to the private sector. All of these described developments reveal deep structural problems in the Croatian economy and a lack of credible fiscal consolidation, which cannot be solved purely by increased system liquidity.

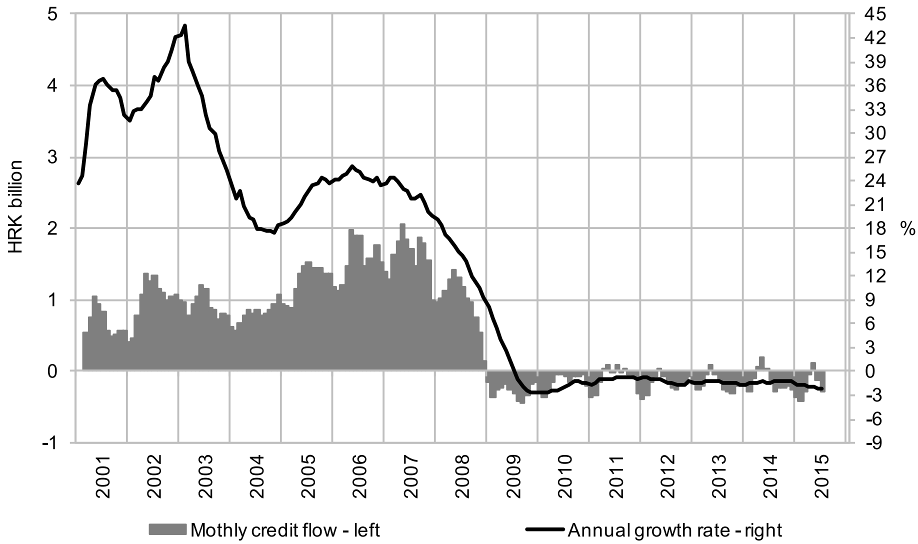
Figure 1 Placements to the corporate sector in Croatia



Note: Data are adjusted for exchange rate movements and one-off effects, including loan sales, bank bankruptcies, methodological changes and the government assumption of the shipyards' debt. Data for monthly credit flows are three-month moving averages.

Source: Croatian National Bank.

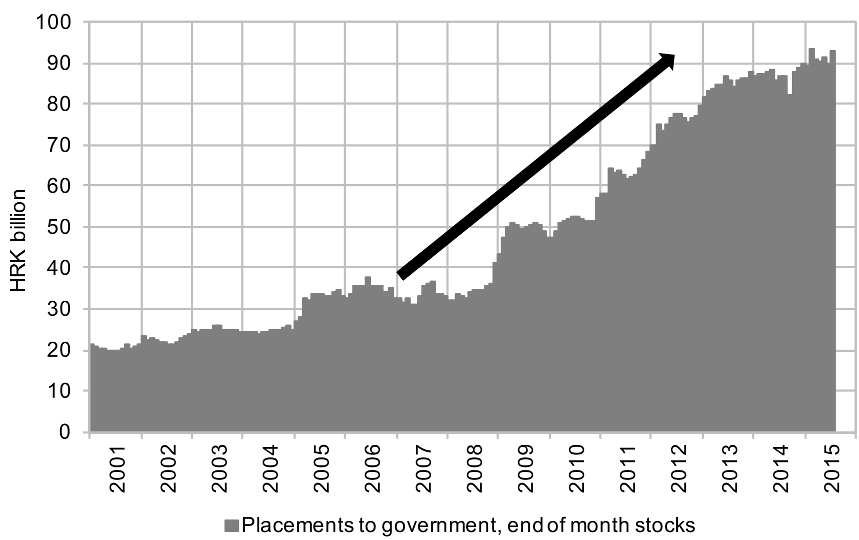
Figure 2 Placements to the household sector in Croatia



Note: Data are adjusted for exchange rate movements and one-off effects, including loan sales, bank bankruptcies and methodological changes. Data for monthly credit flows are three-month moving averages.

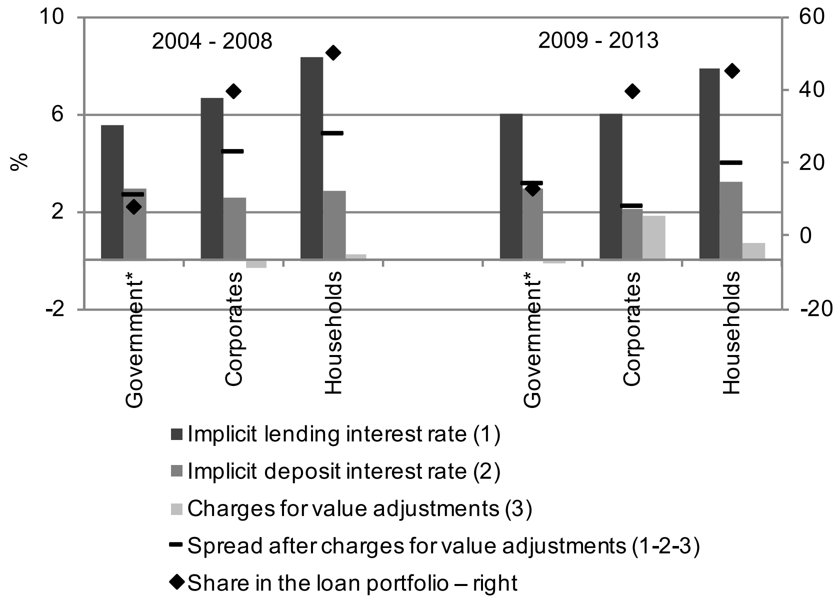
Source: Croatian National Bank.

Figure 3 Placements to government



Source: Croatian National Bank.

Figure 4 Change in bank profitability in various segments of financing in the period of crisis

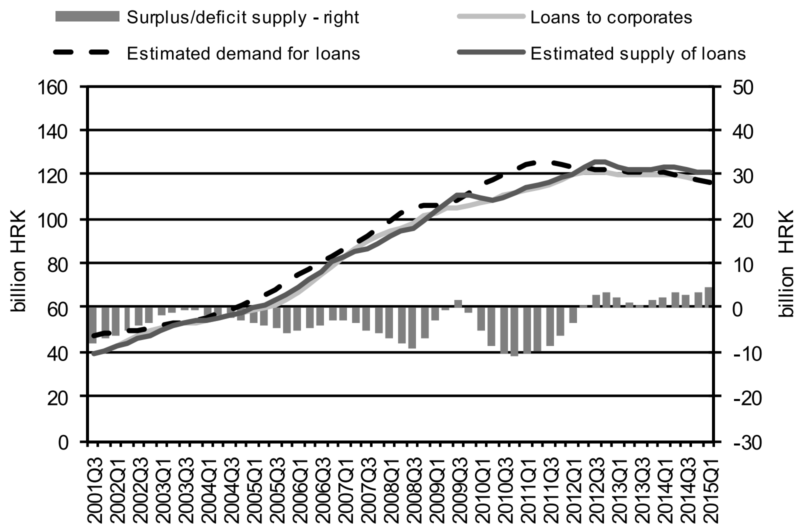


Source: CNB Financial Stability Report No. 14.

Determinants of credit supply and demand for corporate sector

According to the results of our credit market disequilibrium model for the corporate sector (Dumičić and Ljubaj, 2017), the period from 2012 onwards was marked by a surplus of supply of loans over demand, while credit demand has mostly been declining because of the low level of economic activity, negative future expectations and, to a certain extent, the stabilisation in the international financial markets and easier access to foreign capital. Nevertheless, the BLS results show that up to 2015, lending standards for corporate loans were almost continuously being tightened, primarily encouraged by negative expectations of general economic developments, a pessimistic outlook for industry or specific corporates, and risks related to collateral (Figure 6). At the same time, favourable liquidity of the banking system, competition from other banks and eased financing conditions contributed to an easing of standards in the second half of 2014 and first half of 2015. This implies that positive conditions for bank financing encouraged by the expansive monetary policy are a supporting factor behind the credit supply. But, as stressed by Allain and Oulidi (2009), high liquidity of the banking system accompanied by non-negligible credit demand implies the existence of some kind of credit rationing.

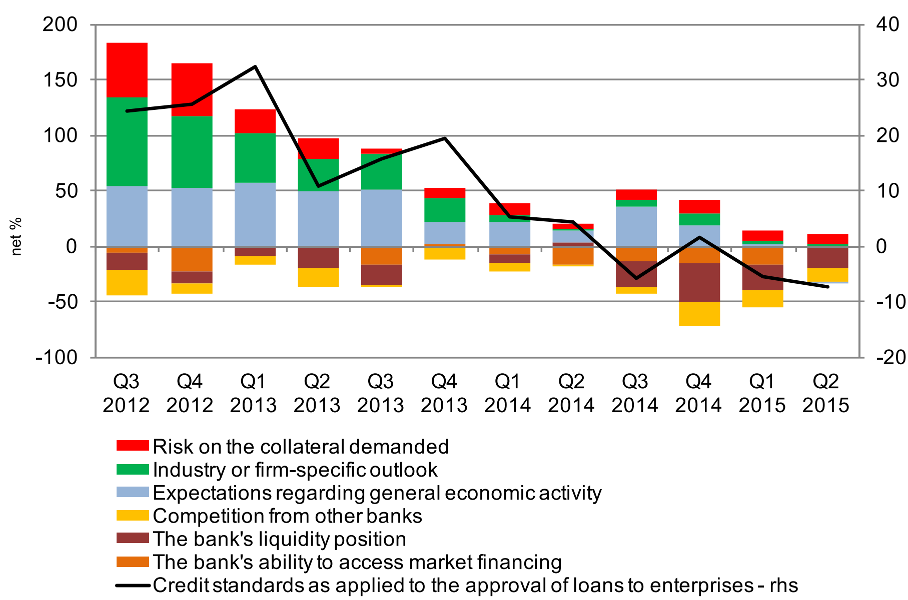
Figure 5 Estimated supply and demand for corporate loans



Source: Authors' calculation.

Note: Moving average of last four quarters.

Figure 6 Factors affecting credit standards as applied to the approval of loans to the corporate sector

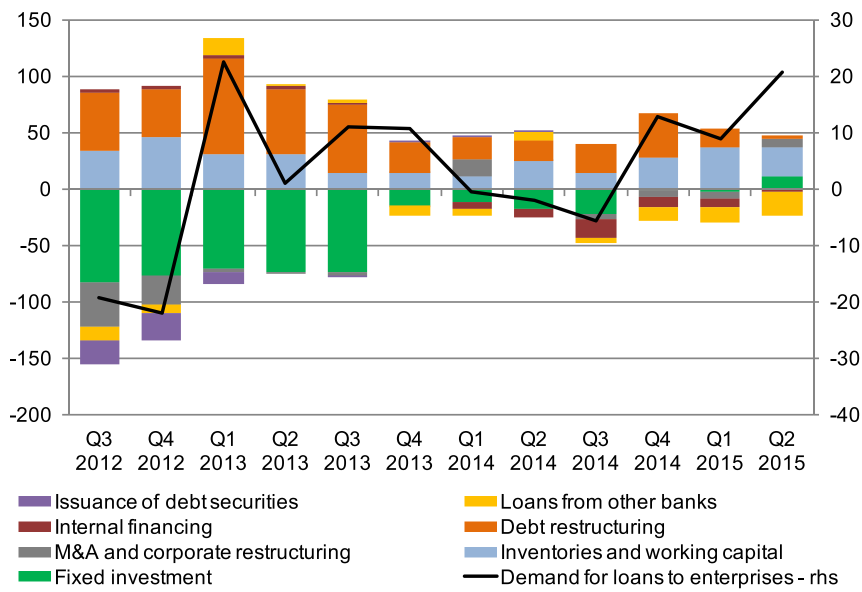


Note: The positive value shows that the factor contributes to standard tightening and the negative that it contributes to standard easing.

Source: CNB Bank Lending Survey.

In view of the constraints caused by the long-term recession, high debt levels and poor capitalisation of corporates, demand from corporates for domestic loans was subdued. This was especially true new loans, with the increased loan demand primarily being driven by the need for debt restructuring and the financing of working capital (Figure 7). On the other hand, lack of investments negatively affects the demand for loans. It could be concluded that the demand determinants from the BLS and the model estimation confirm that the delayed recovery of the Croatian economy limits the recovery of corporate credit demand.

Figure 7 Factors affecting the demand for loans to the corporate sector



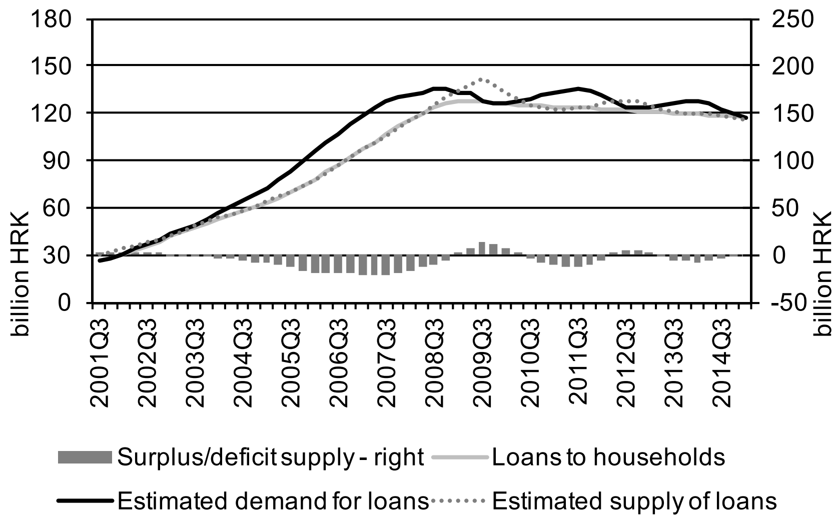
Note: The positive value shows that the factor contributes to higher demand and the negative that it contributes to lower demand.

Source: CNB Bank Lending Survey.

Determinants of credit supply and demand for households

The results of the market disequilibrium model show that over the recent period, both supply and demand for household loans have been declining, which resulted in continuous deleveraging of this sector. The BLS confirms these results, as it points to the tightening of lending standards for housing loans granted during most of the observed period (Figure 9). At the same time, for consumer and other loans, banks reported an almost continuous easing of lending standards. The main factor contributing to the tightening of lending standards for both groups of household loans is the negative expectations for general economic trends, which is also confirmed by the disequilibrium model for households. The negative perspective of the real estate market for home loans and the credit capacity of clients for consumer loans are also emphasised as factors that restrict loan supply. In contrast, banking competition, funding costs and balance sheet restrictions contribute to the easing of lending standards.

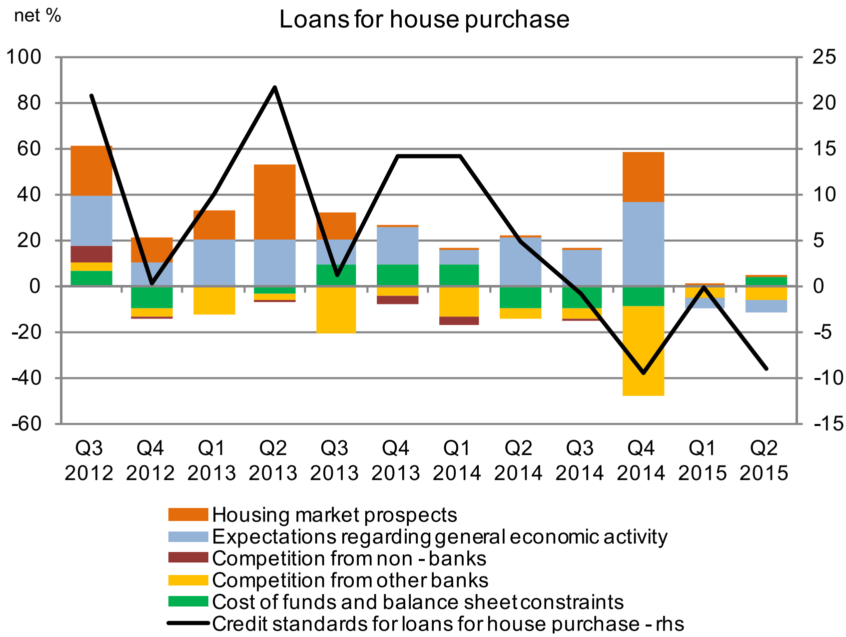
Figure 8 Estimated supply and demand for household loans

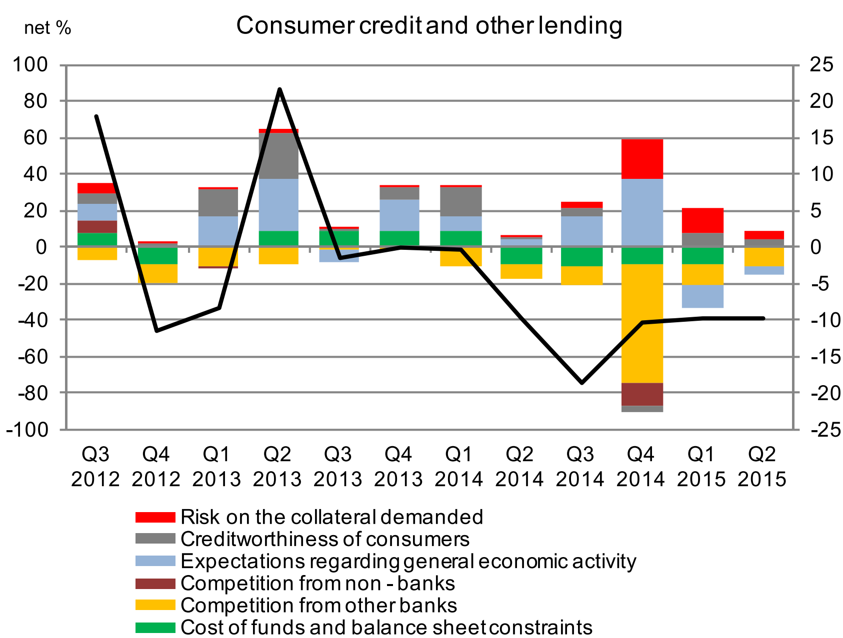


Source: Authors' calculation
Note: Moving average of last four quarters.

From 2012 to the end of 2014 household demand for loans mostly decreased according to the BLS, particularly for housing loans, but also for consumer loans (Figure 10). In general, demand has been unfavourably affected by decreased consumer confidence, household consumption, the perspectives of the real estate market and housing savings (Figure 10). This also confirms the importance of economic recovery for the revival of credit demand.

Figure 9 Factors affecting credit standards as applied to the approval of loans to households

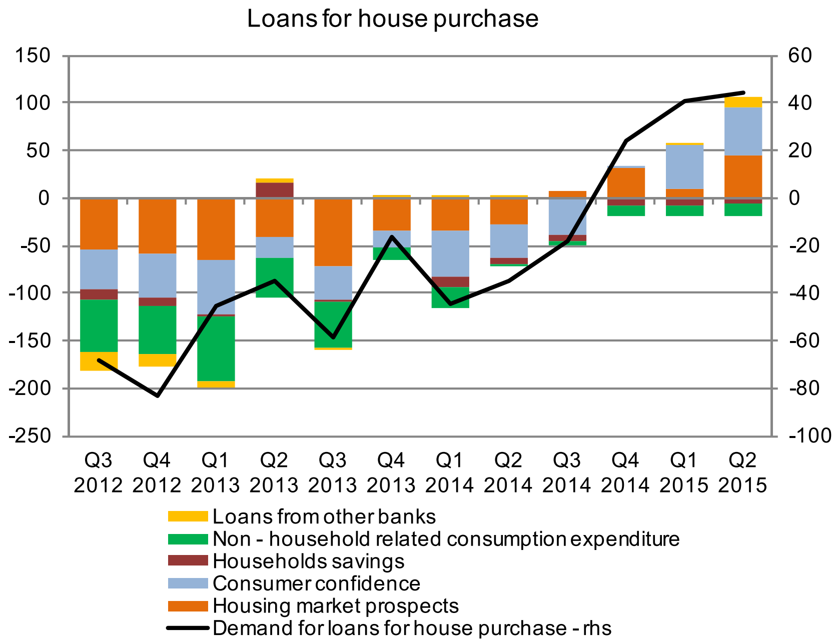


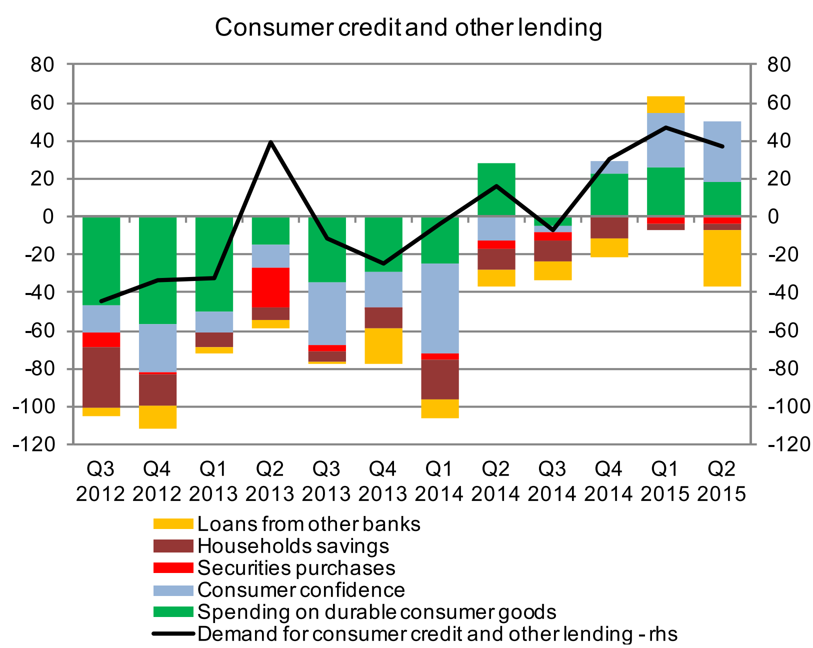


Note: The positive value shows that the factor contributes to standard tightening and the negative that it contributes to standard easing.

Source: CNB Bank Lending Survey.

Figure 10 Factors affecting demand for loans to households





Note: The positive value shows that the factor contributes to higher demand and the negative that it contributes to lower demand.

Source: CNB Lending Survey.

Brief analysis of domestic legal environment

Due to a lack of appropriate data on the legal environment, it is not possible to include it in the model. However, due to its immense impact on both loan demand and loan supply, it has been taken into consideration when drawing the conclusion about the credit activity. For the analysis of the efficiency of the domestic legal system, we used findings obtained from the CNB Bank Surveys, the special CNB survey on the repayment of collateralised corporate loans, findings reported by commercial banks and the Croatian Employers' Association, as well as the World Bank's Doing Business indicators.

As no major reforms to the legal system have been carried out since the latest CNB Bank Survey, these findings present relevant indicators of general creditors' perception of the functioning of the legal system. Some of the main problems underlined by banks referred to the bureaucratisation and inefficiency of courts resulting in long court proceedings, making it almost impossible to collect claims. The need to speed up the procedures related to public auctions, especially for the corporate sector, is also emphasised, as well as the inability to write off debts in case of bankruptcy until the end of the procedure, which usually lasts for many years (Banjad, 2015; Pavlović, 2015). There is also a strong perception that debtors are usually favoured over creditors in courts, as the social element prevails over the legal facts. These problems are ascribed in part to poor regulation, but also to the inadequate implementation of 'good' regulation and the lack of standardised legal practice (Table 1). In that sense, weak creditor protection rights in Croatia and difficulty in seizing collateral represent serious obstacles to disposing of non-performing loans (NPLs) (Vujčić, 2015). This has been confirmed by the data obtained from the CNB survey on the efficiency of seizure of collateral for loans to the corporate sector, which shows that the 'success rate' has been very low and 'success' achieved on rather unfavourable terms, which means that repayment from commercial real estate is very slow and inefficient.

Table 1 Main results of the CNB survey on collateral seizure for corporate loans

Number of attempted real estate enforcements	3,579
Number of successful real estate enforcements	618 (17%)
Ratio of realised price and estimated value of the real estate when enforcement has been successful	55%
The percentage of successful real estate enforcements when real estate remained in banks' balance sheets	52%

Source: CNB

The effect of the inefficient legal framework on the behaviour of households and corporates should also be taken into consideration. According to the Croatian Employers' Association, the length and cost of the processes related to enforcement are perceived as factors that discourage economic activity and that directly and indirectly affect both the supply and demand for loans. The

World Bank's Doing Business indicators also suggest there is plenty of space for improvement in the area of legal rights related to obtaining credit.

Frequent changes of regulation that increase legal uncertainty are also an important factor that affect both real and credit activity. The recent period has seen many changes in regulations directly or indirectly related to credit activity (interest rates, exchange rates, etc.). Some of these have been implemented retroactively, which additionally increases the risks of granting loans and (indirectly) the price of borrowing. All of these problems are compounded by the lack of public awareness regarding the importance of an efficient legal system for lending conditions.

It can be concluded that an inefficient legal system inevitably has a negative impact not only on the supply of loans but also the demand for loans, as it is a prerequisite for a successful corporate sector and, consequently, for better a financial position of households through positive developments in the labour market.

Conclusion

An understanding of the determinants and the evolution of credit supply and demand is crucial for an analysis of the scope of monetary policy measures aimed at influencing credit activity. A disequilibrium model expanded by the findings from the Croatian National Bank's bank lending surveys shows that the main determinants of corporate and household credit demand are greatly influenced by the domestic macroeconomic environment. Over the recent period, the demand for corporate loans has fallen and is not in a healthy state (corporates are seeking loans for the refinancing old debts, but not for the investment), while lending conditions have been tightened despite supply exceeding demand. In the case of households, there are problems on the both supply and demand side, which has resulted in the long-lasting deleveraging of this sector. The attractiveness of government loans, which are perceived as non-risky assets with relatively high returns in an uncertain macroeconomic environment, and a heavily indebted private sector with structural balance sheet problems additionally weaken the scope of monetary policy measures aimed at stimulating credit recovery.

Although the interrelations of the various factors affecting credit demand and supply are sometimes confusing, it seems that the delayed recovery and weak growth prospects, combined with the inefficient legal environment, are the most significant factors influencing sluggish credit developments in Croatia. Nevertheless, despite the puzzling evidence on credit dynamics, there is no doubt that a balance sheet clean-up for all sectors is needed.

As shown by Baek (2002), uncertainty in the credit market is also closely related to delays in overall economic reforms. The reversal of negative economic developments and reforms aimed at creating a stimulative business environment would definitively have a positive effect on the inclination of credit institutions to offer loans, which, combined with the current low interest rates, might result in favourable non-price-related financing conditions. There is also room for other policy actions which would reduce supply and demand constraints, such as a more efficient NPL resolution framework, credit guarantee schemes or tax incentives, corporate debt restructuring and better absorption of EU co-financing instruments.

A special challenge is to create a more efficient legal framework. Catao (1997) confirms that limitations to the seizure of collateral property, coupled with long and expensive legal processes, increase the costs of borrowing and indirectly affect the speed of economic recovery and/or growth.

Until such changes take place, despite the stability and high liquidity of the domestic banking sector supported by an expansive monetary policy, the effectiveness of the Croatian central bank's efforts to boost the credit recovery will be limited.

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Igor Ljubaj is an economist at the Croatian National Bank. He graduated from the Faculty of Economics, University of Zagreb, in the field of macroeconomics. He also received Master's degree at the University of Zagreb, field Statistical methods in economic analysis and forecasting, where he defended thesis on the impact of monetary policy on credit activity in Croatia. Mr Ljubaj works for the Croatian National Bank more than ten years, of which last six as a Head of Monetary Analysis Division within Research Area. Besides his usual tasks which include assessing monetary policy issues and developments in analysis and projections within the central bank, his research interests are focussed on the macroeconomics and monetary economics. This is especially related to the influence of monetary policy instruments on credit activity, and interrelations between economic activity and credit developments.

Discussion of "Analysis of the bank lending survey results for Bulgaria" and "A forensic analysis of credit activity in Croatia"

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University of Ljubljana and Bank of Slovenia

The papers in this book by Dumičić and Ljubljaj and by Karamisheva present analyses of bank lending dynamics in Croatia and Bulgaria, respectively, before and after the global financial crisis of 2008. The two countries exhibited quite similar credit cycles in the period 2000-2015: the pre-crisis period was marked by high credit growth, followed by a sharp decline in lending activity towards the end of 2008 and muted credit dynamics in the post-crisis period.

Both papers present analyses of the factors operating on the supply of credit and demand for credit by exploiting the information from bank lending surveys (BLS) in separating the supply and demand side factors of bank lending. The surveys provide data on banks' perceptions of demand conditions and various factors determining their supply of credit. For policymakers, such information is key to understanding how the business cycle and monetary policy measures (the emphasis is on macroprudential measures) affect lending activity. Given that the pre-crisis period was marked by excessive credit growth that fuelled an economic boom with a subsequent significant deterioration of the quality of credit portfolios and a credit-less recovery, understanding what factors influenced the process is of immense importance. This is where I see the most important contribution and policy value of these papers.

The way BLS information is included in the analysis differs in the two papers. While the BLS data span a long time in the case of Bulgarian (2003-2014), the Croatian BLS data only begin in 2012. This data-availability constraint leads Dumičić and Ljubaj to combine an econometric and narrative approach to their analysis. They estimate a disequilibrium model of the credit market for the period 2001Q1 to 2015Q1 and explain the results for the post-2012 period through the lens of the BLS data.

Although they address a common question, the two papers take different econometric approaches. Dumičić and Ljubaj build a disequilibrium model of the credit market. Such a model sees the quantity of credit extended on the market as the minimum of either supply or demand. Under the assumption of normally distributed errors of supply and demand schedules, the model is estimated by maximum likelihood. Model structure and selection is motivated by conventional economic wisdom and statistical testing. Besides standard macroeconomic variables that are likely to affect credit activity, it is important that the authors also include an indicator capturing the monetary policy stance. Estimation is separated into the credit market for corporate loans and loans extended to households.

The methodological approach by Karamisheva differs to some extent, as she considers two levels of data aggregation: the macroeconomic level and the individual bank level. On macroeconomic level, she estimates an autoregressive distributed lag (ARDL) model of growth of credit in which she controls for macroeconomic factors such as GDP growth, interest rates, economic outlook and quality of bank assets, but the key element of the model is the inclusion of BLS data. Moreover, the effect of BLS indicators is separated into phases of an improvement in and a worsening of supply and demand conditions. Given that using BLS indicators averaged across responding banks might mask important heterogeneity, Karamisheva additionally employs a panel data analysis controlling for bank-specific effects. At both levels of analysis, her results indicate that only a decrease in the credit demand indicator results in a significantly negative effect on the growth of credit to non-financial corporations. In a finding that is to some extent surprising, supply-side factors did not seem to have a significant effect on credit activity in Bulgaria.

Both papers offer some common findings. They indicate that the most important factor behind the excessive credit expansion prior to the crisis was strong demand for credit. This follows both from the BLS data and the model estimates. Macroprudential measures employed by the respective central banks did curb fast credit expansion to some extent, but were insufficient to prevent credit imbalances accumulating. More restrictive lending standards on the supply side have become relatively more important after the crisis, but across the board no factor seems to stand out as dominating the sluggish credit activity observed in both countries in recent years. In this respect, the Croatian study points to increased lending to the government as an indicator of reluctance to lend to the private sector despite generally favourable liquidity conditions.

Another important finding of both studies concerns the effect of the quality of bank portfolios. The burden of non-performing loans (NPLs) appears to be a significant factor preventing the transmission of abundant liquidity in the banking system into a higher supply of credit. In both countries, as in many others in the region, the pre-crisis lending boom left a high share of NPLs which, despite some economic recovery, is decreasing only slowly. Difficulties with the disposal of bad loans appear to be rooted in weak legal frameworks and insufficient enforcement of the rule of law.

Overall, I think both papers add significantly to our understanding of what factors determine credit cycles in southeast Europe. As such, they provide useful guidelines for future calibration and deployment of macroprudential instruments. In addition, the studies indicate how BLS information can be used to monitor credit dynamics.

Housing and mortgage dynamics in the Netherlands: Some evidence from household survey data

David-Jan Jansen[1]
De Nederlandsche Bank

1 Introduction

In the wake of the financial crisis, the housing market in the Netherlands has been characterised, as in many countries, by a marked slowdown. From their peak in mid-2008, house prices have declined by close to 25%, before starting a slow recovery over the course of 2014. The decline in the number of sales was even stronger; at its lowest, the number of sales was halved compared to pre-crisis levels. Simultaneously, there was a slowdown of credit growth.

To capture the processes that govern aggregate credit and housing dynamics, one could embody a set of estimated equations in an estimated structural macroeconometric model (e.g. DNB, 2011). In addition to macroeconomic approaches, recent research uses microeconomic data to study the links between credit and housing. An important contribution of household surveys is the possibility to study various dimensions of heterogeneity across households. A second contribution is more refined data that can be used in macroeconomic analyses of various macroprudential policies.

This paper discusses these developments and provides an empirical example from the Netherlands using data from the De Nederlandsche Bank Household Survey (DHS).[2] First, it introduces two examples of how microeconomic data can inform research and policy (Section 2). Section 3 discusses how household survey data can be used to gather time-series data on actual loan-to-value (LTV) ratios. Section 4 further explores the heterogeneity in LTV ratios, and finds it can be explained by various housing characteristics and demographic variables. Concluding comments are provided in Section 5.

1 Views expressed in this paper are personal and do not necessarily coincide with those of de Nederlandsche Bank or the Eurosystem.
2 For a description of these data, see Teppa and Vis (2012).

2 Mortgage type and house price dynamics

A first example of the added value of micro data is provided by Galati et al. (2011). Their paper estimates a dynamic panel data model using data from the DNB Household Survey on house prices and mortgages with the aim of investigating heterogeneity across different segments of the Dutch housing markets. The key perspective in their paper is the speed of convergence of house prices to fundamentals. Indeed, they find evidence of heterogeneity in this speed of convergence along many important dimensions, including the geographic region, the age of the house, and the type of the house.

The panel estimations of Galati et al. (2011) also reveal that the type of mortgage financing plays an important role. The dynamics for houses with annuity mortgages differ substantially from those with interest-only mortgages. The key difference is the degree of mean reversion to the fundamental value of the house. As it turns out, houses that are financed with interest-only mortgages show a much lower degree of mean reversion. The authors argue that an important implication of this finding is that the proportion of interest-only mortgages can have an important influence on aggregate house price dynamics.

A second example of how the use of micro data can uncover important housing and mortgage dynamics concerns the role of house price perceptions. Van der Cruijsen et al. (2017) use DHS data to understand how households value their own home. One of their approaches is to combine survey questions with actual data on house price developments per Dutch province. The survey questions provide evidence on the year in which the house was bought and the amount for which the property was purchased. By assuming that the house price developed in line with provincial price developments, the authors are able to estimate the current value of the home. The perceived home value is taken from a question in the DHS that asks: "Around how much do you expect to get for your home if you sold it today?".

The evidence in Van der Cruijsen et al. (2017) suggests that bias in valuing one's house is usually positive, can be quite substantial, and occurs in quite a few of the cases. The question then is to what extent rationality can be assumed in the context of housing and mortgage decisions. A further relevant issue concerns the implications of the rose-tinted spectacles of homeowners, and whether policy can and should address them. One apparent solution would be to address the bias either through information or a form of nudging. Another approach would be to make households more shockproof through policy measures concerning loan-to-income or loan-to-value measures.

3 Constructing data on LTV ratios

A key question in the literature on macroprudential policy is how various policy measures could mitigate risks concerning the housing market. A first approach in the literature is to use cross-country variation. The findings are suggestive, but perhaps not conclusive, partly because data availability may be an issue. Almeida et al. (2006) find that both house prices and new mortgage borrowings are more sensitive to income shocks when LTV ratios are high. In related work, Lamont and Stein (1999) find that house prices react more to city-specific shocks when homeowners are more leveraged. However, using information on macroprudential policies in over 100 countries, Cerutti et al. (2015) find that limiting the maximum LTV ratio affects credit growth but has no effect on house prices.

One challenge here is that cross-country estimations are often constrained to using variation in the regulatory LTV ratio, rather than the actual LTVs for first-time buyers. An analysis of micro data can further inform policy decisions. For instance, Igan and Kang (2011), who analyse data for the Korean housing market, find that a tightening of LTV limits pushes down price expectations and lowers the demand for homes.

Recent work using the DHS has, therefore, turned to constructing data on LTV ratios in the Netherlands. This has been implemented by posing additional question to members of the DHS panel to determine the moment when the house was bought, the amount for which it was purchased, and the mortgage that was taken out (Timmermans, 2012; Verbruggen et al., 2015; De Jong and De Veirman, 2015).

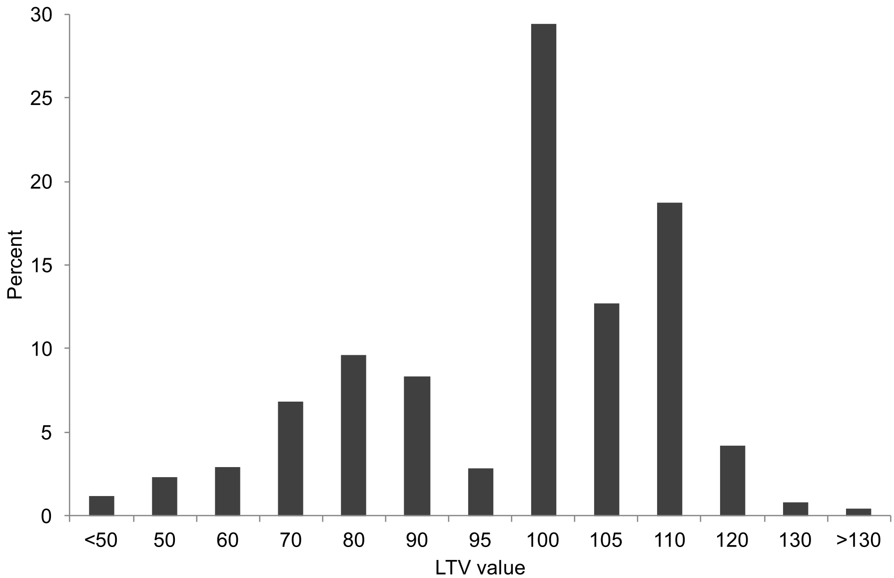
Regarding the development of the LTV, Verbruggen et al. (2015) find a clear increase in the average LTV for first-time buyers in the 1990s. More recently, the upward trend in the LTV ratio has disappeared, in line with recent policy measures aiming to bring back the maximum LTV to 100% in 2018. Simulations in Verbruggen et al. (2015) and De Jong and De Veirman (2015) indicate that a restriction to 90% would lead to a long-run decline in house prices of around 10% and a decline in the level of consumption of a little over a percentage point.

4 Heterogeneity in LTV ratios for first-time buyers

We now perform an exploratory analysis of heterogeneity in the LTV ratios for first-time buyers described in Verbruggen et al. (2015). Based on the survey responses, we construct a series that measures loan-to-value ratios on an ordered scale that lies between 1 (LTV ratios of less than 50%) and 13 (LTV ratios of 130% or more). The distribution of this variable is shown in Figure 1. Around 30% of the respondents report an LTV ratio of 100%, while around a third report ratios of higher than 100%. Around 15% of respondents report ratios of 70% or less.

The heterogeneity in loan-to-value ratios can be explained by various housing characteristics and demographic variables. Table 1 reports selected marginal effects for an ordered logit regression, where we use the LTV ratio as the dependent variable. As expected, a house that was bought more recently is more likely to have a higher LTV ratio. A higher purchase price, interestingly, does not have a significant relationship to the LTV ratio. In terms of demographics, we find that the young and those who live in urban environment are more likely to own houses with high LTV ratios.

Figure 1 Distribution of LTV ratios for first-time buyers in the Netherlands



Notes: Data are constructed using the DNB Household Survey. The horizontal axis shows categories for LTV ratios, ranging between "less than 50%" and "more than 130%". The vertical axis shows the percentage of respondents in each category. N = 1,900.

Table 1 Covariates of LTV categories

	LTV category				
	90	95	100	105	110
House characteristics					
Bought prior to 1990	0.014***	0.003***	0.001	-0.017***	-0.056***
Bought after 1999	-0.021***	-0.005***	-0.001	0.026***	0.083***
Demographic factors					
Aged between 25 and 34	-0.011*	-0.003*	-0.001	0.014*	0.047*
Aged between 35 and 44	-0.015***	-0.003***	-0.001	0.018***	0.059***
Urbanisation	-0.003***	-0.001**	-0.000	0.004***	0.013***

Notes: Average marginal effects based on ordered logit estimations where loan-to-value ratios are dependent variables. The regressions use a wide range of covariates. Only selected effects are shown. N = 1,755. * / ** / *** denotes p < 0.1 / 0.05 / 0.01.

5 Conclusions

This paper discusses the recent body of work that uses data from the DNB Household Survey to inform ongoing research and policy discussions regarding housing and credit dynamics in the Netherlands. An important contribution of household survey data is the ability to further understand the role of heterogeneity across households. One promising avenue seems to be using survey data to improve the quality of data on loan-to-value ratios (De Jong and De Veirman, 2015). Such information may then be used to provide a balanced assessment of the effectiveness of various macroprudential policies. For example, this information can be useful in understanding which sections of the general public would most likely be affected by various types of macroprudential regulation.

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Discussion of "Housing and mortgage dynamics in the Netherlands: Some Evidence from household survey data"

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The paper by David-Jan Jansen nicely connects the developments in the Dutch housing market with literature on loan-to-value (LTV) ratios based on micro data from De Nederlandsche Bank (DNB) Household Survey. Central banks usually deal with balance sheet information, and increasingly in the recent period also with the loan level credit register data. However, this paper points to the importance of collection of the data that characterise the borrower side of the credit relationship. A literature review is upgraded with the author's research focusing on an explanation of LTV ratios heterogeneity by housing and demographic variables. The results point to the importance of micro data for the analysis of financial stability and calibration of borrower directed macroprudential measures. The data available in the DNB Household Survey could be useful to the policymaker when designing macroprudential instruments, especially since they are very socially sensitive. Similarly, *ex post* analysis of the effects of the measures could be conducted using these data.

The paper employs an ordered logit regression and tries to identify the determinants of LTV ratios obtained from a household survey. LTV ratios are divided into 13 brackets (LTVs are presented on an ordered scale) and regressed on year of purchase, house price, demographic factors such as sex, age, income, education, marital status and religion, household size and urbanisation. The results show that LTVs are higher for recently bought houses, for younger buyers, for buyers with higher levels of income and for people living in urban environments. LTVs are lower for singles and religious people.

The analysis is limited to first-time buyers; however, it would be interesting to also see the results for others (i.e. non-first-time buyers), especially because macroprudential measures often differentiate between these two groups of buyers based either on the presumed ability to repay the loan[2] or on social considerations. The latter characteristics are exactly those that are considered when designing macroprudential measures. Although the findings tend to be logical, it would be beneficial to see a more evolved explanation of the results. Additionally, it

1 The views expressed are those of the author, not necessarily those of the Bank of Slovenia.

2 Hypotheses differ – some claim that first-time buyers in a full-recourse mortgage system are riskier since they possess lower collateral, while on the other hand they can be less risky since their purchase is normally not speculative, as in the case of second- or third-time buyers.

would also be interesting to see how the impact of different determinants evolves over time. One of the preferences expressed in the call for papers was the use of the micro-economic databases. This paper fulfils this requirement and manages to offer very interesting research in the field of financial stability analysis and macroprudential policy that at the same time brings important takeaways for policymakers.

About the author

Graduated from the Faculty of Law, University of Ljubljana, **Meta Ahtik** continued with PhD studies at the Faculty of Economics, University of Ljubljana (completed in 2010) while working as a researcher at the Faculty of Law, where she has held a title of an assistant professor of Law and Economics since 2011. Her research interests spread from law and economics to monetary economics and banking. She worked at the European Central Bank between 2012 and 2014. Currently she is the Head of Implementation of Macroprudential Policy Section at the Bank of Slovenia and Researcher at the Institute for Comparative Law, University of Ljubljana.

The quantity of corporate credit rationing with matched bank-firm data

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Bank of Italy

1 Introduction

Is there a cut in lending to the corporate sector? And if so, how relevant are banks' balance sheet conditions? What about the role of borrowers' creditworthiness? These questions are not only key for macroeconomics in general but also for policymakers and regulators that are still managing the legacy of the financial crisis.

Quantifying the relevance of restrictions to credit availability is well known to be a difficult task. The identification problem is not only that the supply of credit needs to be disentangled from its demand. The key challenge is to understand whether a supply restriction takes place through an increase in the cost of credit, which in turn transmits to loan quantities via the elasticity of loan demand to lending rates, or through non-price allocation of credit, that is, a condition of excess demand over supply.

Policymakers usually look at qualitative information provided by surveys among banks or firms, which include questions on the terms and conditions of access to credit. In the case of Italy, both the Bank Lending Survey and the Istat survey among manufacturing firms provide evidence of quantitative restrictions on business loans occurred during the crisis (see Figure 1). Survey-based methods are timely and ready-to-use, but may be biased due to self-reporting.[2] It is therefore

1 The views expressed do not necessarily reflect those of the Bank of Italy. This work was started during Lorenzo Burlon's research fellowship at the Bank of Italy. We would like to thank Piergiorgio Alessandri, Ginette Eramo, Alberto Locarno, Francesco Manaresi, Stefano Neri, Giacomo Rodano, Alfonso Rosolia, Paolo Sestito, Enrico Sette, Luigi Federico Signorini, Stefano Siviero, and participants at seminars at the Banco de Portugal, at the II IAAE conference in Thessaloniki, at the 3rd MBF Workshop in Pavia, at the 1st ECBN conference in Ljubljana, and at the Joint BOE-ECB-CEPR-CFM conference in London. All remaining errors are ours.

2 One strand of the empirical literature focused on the effects of credit supply restrictions on the intensive margin using matched bank-specific information on lending with survey data, as in Del Giovane et al. (2011) and Bassett et al. (2014). Interestingly, Del Giovane et al. (2013) find that, among the various replies to the Bank Lending Survey, Italian banks' assessment on their capital position is the indicator capturing non-price allocation of credit.

useful to cross-check survey-based indicators with measures of credit rationing computed from 'hard' information on balance sheets and compulsory reports. However, related evidence based on 'hard' data is scant. A major complication is that several economic theories and concepts are consistent with the notion of quantitative credit restrictions. Broadly speaking, credit rationing occurs when, at a given level of the interest rate, the demand for loans exceeds the supply and lenders do not provide additional credit even if the borrowers are willing to pay higher rates.[3]

The theory behind the existence of credit rationing relies primarily on the existence of severe informational asymmetries between the actors of the credit market. This strand of literature stems from the seminal work by Stiglitz and Weiss (1981), in which credit rationing occurs in equilibrium because banks do not raise lending rates above a certain level to avoid financing more risky borrowers (adverse selection) or to discourage firms to take more risk (moral hazard).[4] A different route of empirical research emphasises the role of banks' capital constraints in determining quantitative restrictions in lending, and sometimes uses the expression 'credit crunch' as an alternative to 'credit rationing'. Bernanke and Lown (1991), for instance, define a bank credit crunch as "a significant leftward shift in the supply curve for bank loans, holding constant both the safe real interest rate and the quality of potential borrowers", and argue that there is "no necessary connection between a credit crunch and credit rationing in a strict sense". Schreft and Owens (1991) define a credit crunch as "a period of sharply increased non-price rationing" that "may (but need not) be independent of any change in borrowers' risk profile". Notwithstanding the semantic aspects, there is wide consensus that well-capitalised banks are less likely to generate strong procyclical changes in credit supply conditions through rationing.

In this paper, we propose an approach that uses bank-firm information to compute credit rationing at the aggregate level while imposing as little structure on the data as possible. We provide an extensive application of this method to the case of Italian market for bank term loans to the non-financial corporate sector, with a unique dataset based on more than five million observations. To this end, for each bank-firm relationship we match high-quality information on both the quantity and the cost of credit, which are available from two different sections of the Italian Credit Register. The identification of loan supply and demand curves and the measurement of the quantitative restrictions are obtained by merging the credit variables with bank- and firm-specific variables taken from other sources of micro data, namely the confidential supervisory reports of the Bank of Italy and the Company Accounts Data Service managed by the Cerved Group.

We adopt maximum likelihood (ML) methods à la Fair and Jaffee (1972), which have been developed to estimate mismatches between demand and supply for various markets and to evaluate the presence of credit rationing at the

3 Typical references for credit rationing are the seminal works by Jaffee and Modigliani (1969), Jaffee and Russell (1976) and Stiglitz and Weiss (1981). For a review of the motivations and definitions of credit rationing, see Jaffee and Stiglitz (1990). See also Bellier et al. (2012) for a recent survey.

4 Previous theoretical approaches stemming from the availability theory of Roosa (1951) treat credit rationing as a temporary misalignment of credit supply and demand which drives the credit market out of equilibrium.

macroeconomic level.[5] We estimate a system that consists of a demand equation, a supply equation, and a 'short-side rule' for which the observed quantity of credit is the minimum between the demand and supplied quantities. Several recent studies use this approach to identify the presence of credit rationing using firm-level panel data from a number of countries.[6] Its main advantage is that it introduces a minimal structure to the data while remaining quite neutral on its theoretical underpinnings. To the best of our knowledge, ours is the first paper that applies this methodology to bank-firm data, which is particularly desirable in this framework for a number of reasons.

First, we can circumvent potential aggregation bias problems stemming from the use of macroeconomic information or firm- or bank-level data. The 'short-side' rule (i.e., the minimum condition) that characterises models à la Fair and Jaffee (1972) may indeed hold at the level of the single bank-firm transaction and not necessarily in the aggregate. The averaging process stemming from the use of more aggregate data may signal no credit rationing, while in reality some firms are de facto rationed.[7]

Second, the estimation of supply and demand curves in a unified framework allows us to endogenously identify whether any bank-firm transaction is credit rationed or not, without relying on a priori exogenous classifications used in previous studies based on micro data.[8] Ogawa and Suzuki (2000) and Atanasova and Wilson (2004) point out the need for an endogenous classification of rationed firms. The structure of our matched bank-firm data allows us to distinguish across different cases. In a specific time period, a firm may be rationed in the access to credit with certain banks but not with others. At the same time, a bank may ration credit to part of its pool of borrowers but not to the others. Finally, the borrowers may switch between the groups of rationed and not rationed over time also as a result of their own internal decisions, as they may substitute bank credit with alternative and less costly sources of financing.

An important advantage of our dataset is that we can control for the interest rate at the bank-firm level, which is not available or hardly matched with loan quantities in other credit registers and is crucial to identify non-price allocations of credit. Since for each bank-firm contract the loan interest rate may be the result of a bargaining between the lender and the borrower, it is endogenous in the model, thus providing inconsistent estimates of the supply and demand curve. We carefully address the endogeneity of the loan interest rate by using a two-stage approach. In the first stage the loan interest rate is regressed on the whole set of demand and supply variables, while in the second stage we estimate the system using the predicted value of the cost of credit. Previous papers have

5 See, among many others, Amemiya (1974), Fair and Kelejian (1974), Maddala and Nelson (1974) and Goldfelfd and Quandt (1975). Laffont and Garcia (1977) and Sealey, Jr (1979) estimate demand and supply functions of commercial bank loans in the United States. Ito and Ueda (1981) test the equilibrium versus disequilibrium hypothesis in the US and Japanese business loan markets.

6 See Ogawa and Suzuki (2000), Atanasova and Wilson (2004), Carbó-Valverde et al. (2009), Shikimi (2013), Kremp and Sevestre (2013) and Farinha and Félix (2015).

7 See Perez (1998) for an early mention of the aggregation bias problem in the study of credit markets.

8 On the use of micro data on credit rationing as exogenous variables in macro studies, see, for example, Fazzari et al. (1987), Berger and Udell (1992), Hoshi et al. (1993), Petersen and Rajan (1994), Gilchrist and Zakrajšek (1995), Gertler and Gilchrist (1994) and Harhoff and Körting (1998).

usually assumed that the loan interest rate does not enter the loan supply curve, thus assuming that banks first decide on the amount they are willing to lend and then negotiate the interest rate with firms. Our model allows the cost and the amount of credit to be jointly determined by the two parties involved in the contract, and our estimates provide robust evidence that the interest rate enters significantly into the supply equation.

Our paper clearly relates to previous studies that provide estimates of the effects of a supply restriction on the intensive margin of lending using high-quality micro data, such as Khwaja and Mian (2008) and Jiménez et al. (2012), among others. Differently from our paper, these studies focus on general definitions of credit supply restrictions and not necessarily on the identification of credit rationing episodes. In this regard, our matching of the amount and the cost of credit for each bank-firm relationship is crucial to discriminate situations in which supply restrictions take place through an increase in the cost of credit from those stemming from a decline in the availability of loan quantities (i.e., a condition of excess demand).

Since it is particularly important for policy purposes to provide reliable measures of credit rationing that can span an extended period of time and cover as much of the cross-section of banks and firms as possible, we depart from other compelling approaches. In particular, we do not rely on natural experiments that create an easily identifiable supply shock (e.g. Peek and Rosengren, 2005; Khwaja and Mian, 2008) but are feasible only in specific episodes.[9] Moreover, we do not need to narrow the data to the subsample of firms that have multiple lenders so as to control for demand conditions with firm or firm-time fixed effects.[10]

In our sample, firm-time fixed effects are highly correlated with firm-specific variables, of which some are supply factors. There is inevitably a trade-off between the need to impose the most restrictive controls for demand conditions and deriving a comprehensive measure of aggregate credit rationing. Apart from the sample coverage issue, there may be additional challenges related to the identification of fixed effects with matched bank-firm data, similarly to what happens with the use of matched employer-employee data since the seminal contribution of Abowd et al. (1999). For example, the inclusion of two-way fixed-effects imposes additivity between firm-time and bank-time fixed effects. Thus, it rules out any heterogeneity in firm-specific credit terms across banks or in bank-specific credit terms across firms, as well as any complementarity between banks and firms, which makes them also incompatible with theoretical models of sorting between banks and firms.[11]

When interpreting our results, it is important to remark that our dataset allows us to identify 'weak' credit rationing, which occurs when borrowers are willing to

9 Gan (2007) and Iyer et al. (2014) explored this issue using credit register data for a number of countries, while Albertazzi and Marchetti (2010), Bonaccorsi di Patti and Sette (2012) and Bofondi et al. (2013) used the Italian Credit Register.

10 See Albertazzi and Bottero (2013), Cingano et al. (2013), Bottero et al. (2015) and Rodano et al. (2015) for recent applications of this method using Italian Credit Register data.

11 Amiti and Weinstein (2013) provide a methodology to solve the first of these limitations. See Bonhomme et al. (2015) for a recent discussion of these issues for the case of matched employer-employee data.

pay the prevailing interest rate but receive a loan amount which is smaller than what they apply for. Following the definition of Jaffee and Stiglitz (1990), weak credit rationing differs from 'pure' (strong) credit rationing, which occurs when the borrowers face the rejection of the entire loan amount they applied for. In this regard, our analysis on the intensive margin of lending may be considered complementary to empirical studies on the extensive margin of lending, such as Puri et al. (2011), Jiménez et al. (2012, 2014) and Albertazzi et al. (2015).[12]

Our study suggests that the amount of credit rationing mostly depends on banks' level of non-performing loans and firms' ability to provide collateral against bank loans. Ex ante credit risk as captured by firm-specific ratings also contributes to a lesser extent to the dynamics of our aggregate credit-rationing measures. We also provide evidence of significant aggregation biases stemming from the use of firm- or bank-level information as opposed to bank-firm match-specific data.

The structure of the paper is as follows. In Section 2 we present the model and the methodology. In Section 3 we describe the high-quality dataset used in the empirical analysis and the demand and supply factors used to reach identification. In Section 4 we comment on the benchmark estimates. In Section 5 we develop some indicators of credit rationing that can be used for policy analysis and compare them to those available from survey data conducted among banks and firms. In Section 6 we present a battery of robustness checks. Section 7 offers some concluding remarks.

2 A model for the estimation of credit rationing

We are interested in the intensive margin of credit rationing in the market of term loans to the non-financial corporate sector in Italy over time. With transaction-level data, this corresponds to assessing how much of the financing needs of the firms involved in the observed transactions is covered by the supply of credit provided by the banks involved in the same transactions. Since we do not investigate the extensive margin of lending, our estimates of the credit rationing should be considered a lower bound of the overall credit rationing. We are not only interested into the determinants of the demand and supply of credit but also in their evolution over time. Hence, we need to impose some structure to the data in order to extract the information in which we are interested.

2.1 Theoretical set-up

We observe the universe of realised transactions between firms and banks in the market of term loans. Since our analysis focuses on this specific market, it necessarily reflects a partial-equilibrium perspective. The market for lending to

12 Studies on the extensive margin of credit are based on information from the credit register on loan rejection rates and usually estimate the effects of a supply restriction on the probability that the application for a new loan is rejected. Jiménez et al. (2014) propose a two-stage approach aiming at evaluating both the extensive and the intensive margin of lending.

firms is decentralised and bipartite, where each bilateral transaction depends on the realisation of the pairwise matches between one bank and one firm. Moreover, the two sides of the market face relevant informational asymmetries and the banks operate in a context that is far from perfect competition. In the absence of a central auctioneer, the market does not necessarily clear, so the equilibria that arise in it are possibly non-Walrasian. There may be systematic mismatches between the credit demand and credit supply within each bank-firm match and at the aggregate level, thus giving rise to situations of persistent excess demand or excess supply. We are interested in quantifying the excess demand for credit at the aggregate level in the market for term loans.

We define a match *bft* as the association of a bank *b* and a firm *f* at time *t*. An equilibrium credit contract is a match-specific pair (l_{bft}, r_{bft}) of terms, where l_{bft} is the quantity of credit that the firm *f* borrows from the bank *b* at time *t* and r_{bft} is the interest rate at which firm *f* borrows that amount from bank *b* at time *t*. Independently from how the match between the bank and the firm is realised in the first place, this contract is the result of a bargaining between the two agents. Hence, its terms depend on firm characteristics X_{ft}, bank characteristics X_{bt}, as well as other match-specific characteristics X_{bft} at time *t*, that is,

$$(l_{bft}, r_{bft}) = F(X_{ft}, X_{bt}, X_{bft}),$$

where F is the reduced-form equilibrium mapping between characteristics $(X_{ft}, X_{bt}, X_{bft}) \in \mathbb{R}^P$ of the agents into the pair $(l_{bft}, r_{bft}) \in \mathbb{R}^2$, where P is the sum of the dimensions of X_{ft}, X_{bt}, and X_{bft}. We do not impose any restrictions on how the interest rate may depend on these characteristics, that is, the equilibrium interest rate is a reduced-form generic function f^r of all characteristics,

$$r_{bft} = f^r\,(X_{ft}, X_{bt}, X_{bft}).$$

However, we need to impose some structure on the data in order to define and quantify the credit rationing. We assume that the loan contracts are incomplete, that is, the value of the contract to any trader who accepts it is not determined entirely by the terms of the contract. Since the equilibrium is non-Walrasian and contracts are incomplete, there may be systematic misalignments of the quantity demanded and the quantity supplied within each match. Firms may prefer to borrow a quantity l^d_{bft} at the observed interest rate r_{bft} that is higher than the quantity l_{bft} that appears in the contract. Similarly, banks may prefer to lend a quantity l^s_{bft} at the observed interest rate that is higher than the observed quantity l_{bft}. However, we suppose that there is no situation in which both the firm and the bank would prefer l_{bft} to be higher for the interest rate r_{bft}. We define a demand function f^d and a supply function f^s as two correspondences between firm, bank, and match-specific characteristics and the amounts l^d_{bft} and l^s_{bft} of credit that the firm *f* prefers to borrow from bank b and that the bank *b* prefers to lend to firm *f* at time *t*, respectively. In other words,

$$l^i_{bft} = f^i\,(X_{ft}, X_{bt}, X_{bft}),$$

where $i \in \{d, s\}$ indexes the demand and the supply, and X_{ft}, X_{bt}, and X_{bft} are firm-specific, bank-specific and match-specific determinants of the demand and supply of credit at time t. Note that we abstract from how the equilibrium is determined. Hence, the functions f^d and f^s are simply a characterisation of the reduced-form dependence between exogenous variables and equilibrium objects, they are not the structural demand function and the structural supply function. The characteristics can influence the demand and the supply of credit both directly or through their impact on the bargained interest rate. In other words,

$$\frac{\mathrm{d}l^i_{bft}}{\mathrm{d}x} = \frac{\partial l^i_{bft}}{\partial x} + \frac{\partial l^i_{bft}}{\partial r_{bft}} \frac{\partial r_{bft}}{\partial x},$$

where x can be any element of X_{ft}, X_{bt} or X_{bft}, for $i \in \{d, s\}$. We suppose that the quantity l_{bft} that ends up written in the contract is the minimum between the quantity demanded and the quantity supplied, that is,

$$l_{bft} = \min\{l^d_{bft}, l^s_{bft}\} \tag{1}$$

Equation (1) describes the characterisation of the reduced-form mapping F for the quantity. There are two identifying differences between the demand and the supply functions. First, each characteristic influences the quantity either through the interest rate alone or directly as well. The derivative $\partial l^d_{bft}/\partial x$ of the demand function is nil for some characteristic x, the derivative $\partial l^s_{bft}/\partial x'$ of the supply function is nil for some other characteristic x', and all the characteristics influence the demand only, the supply only, or both. Second, the sign of the impact of the interest rate on the quantity is different between the demand and the supply. In the demand function, $\partial l^d_{bft}/\partial r_{bft}$ is negative. In the supply function, $\partial l^s_{bft}/\partial r_{bft}$ is positive.

2.2 Methodology

In this section we briefly describe our empirical strategy. We suppose that the functions f^r, f^d, and f^s are linear in X_{ft}, X_{bt} and X_{bft} and propose a two-stage estimation approach.

In the first stage, we estimate the interest rate equation by simply regressing our measure of the cost of credit on the entire set of observable and unobservable variables, that is,

$$r_{bft} = \beta^r \, [X_{ft}, X_{bt}, X_{bft}]' + \varepsilon^r_{bft}, \tag{2}$$

where β^r is the vector of the OLS estimated coefficients and ε^r_{bft} is a normally distributed error term. We therefore remain agnostic regarding the interest rate dynamics, but recognise that changes in this variable may reflect the confluence of demand and supply factors. Recognising this endogeneity problem is particularly important for the identification of the supply curve because we are interested in distinguishing quantitative restrictions from those arising from the interest rate channel. Banks may act as price-takers but set their loan rates taking into account the demand for loans and deposits. Practical considerations also suggest that the interest rate charged on any loan may also depend on the bank cost of retail and wholesale funding, a risk premium charged to compensate the bank for the probability of default risk inherent in the loan request, as well as a profit margin on each loan that provides the bank with an adequate return on the use of capital. Our specification essentially aims at capturing all these features.

In the second stage, we use the predicted values of (2) as a regressor. We can write the demand function f^d and the supply function f^s as

$$l^i_{bft} = \rho^i \bar{r}_{bft} + \beta^i \, [X_{ft}, X_{bt}, X_{bft}]' + \varepsilon^i_{bft}, \tag{3}$$

where $i \in \{d, s\}$ and $\bar{r}_{bft} = \beta^r \, [X_{ft}, X_{bt}, X_{bft}]$. Thus, β^i is a vector of coefficients that represent the direct impact of each explanatory variable on the loan quantity l^i_{bft}, while ρ^i captures the corresponding impact of the interest rate in the quantity demanded and supplied. Hence, the total derivative of l^i_{bft} with respect to the xth element of $[X_{ft}, X_{bt}, X_{bft}]$ is $\beta^i_x + \rho^i_x \beta^r_x$, where β^i_x represents the direct impact and $\rho^i_x \beta^r_x$ is the indirect impact through the interest rate channel. In (3) we implicitly suppose that the list of determinants of the interest rate in (2) is exhaustive enough to include all the observables that contribute to the determination of the quantity demanded and supplied, so that ε^r_{bft} does not need to be included in (3).

As ε^r_{bft} is not correlated with ε^i_{bft}, we can estimate (2) separately, derive its predicted value $\hat{r}_{bft} = \hat{\beta}^r \, [X_{ft}, X_{bt}, X_{bft}]$, and plug it in (3) instead of $\bar{r}_{bft}$. In this way, we are left with a system of three equations, that is, a demand equation

$$l^d_{bft} = \rho^d \hat{r}_{bft} + \beta^d \, [X_{ft}, X_{bt}, X_{bft}]' + \varepsilon^d_{bft},$$

a supply equation

$$l^s_{bft} = \rho^s \hat{r}_{bft} + \beta^s \, [X_{ft}, X_{bt}, X_{bft}]' + \varepsilon^s_{bft},$$

and the measurement equation (1).

In order to identify the system, we need to impose exclusion restrictions, namely to distinguish some variables that enter only the demand equation from those that enter only into the supply equation. It may be difficult to identify whether some variables are demand or supply factors, thus they enter both equations.

Hence, we define subsets X^d_{ft}, X^s_{ft}, and X^{ds}_{ft} that are a partition of X_{ft}, X^d_{bt}, X^s_{bt}, X^{ds}_{bt} that is a partition of X_{bt}, and X^d_{bft}, X^s_{bft}, and X^{ds}_{bft} that are a partition of X_{bft}. Hence, the first two equations of the system become

$$l^d_{bft} = \rho^d \hat{r}_{bft} + \beta^d X^d_t + \varepsilon^d_{bft} \tag{4}$$

where $X^d_t = [X^d_{ft}, X^d_{bt}, X^d_{bft}, X^{ds}_{ft}, X^{ds}_{bt}, X^{ds}_{bft}]'$ and

$$l^s_{bft} = \rho^s \hat{r}_{bft} + \beta^s X^s_t + \varepsilon^s_{bft}, \tag{5}$$

where $X_t^s = [X_{ft}^s, X_{bt}^s, X_{bft}^s, X_{ft}^{ds}, X_{bt}^{ds}, X_{bft}^{ds}]'$. As long as $X_i^d \neq \emptyset$ for at least an i in $\{ft, bt, bft\}$ and $X_i^s \neq \emptyset$ for at least an i in $\{ft, bt, bft\}$, the system is identified. The size of β^d and β^s depends on the number of observables included in each specification. The system of equations (4), (5), and (1) can be estimated through full-information maximum likelihood methods, as in Maddala and Nelson (1974).[13]

3 Data and specification

For the empirical analysis we use a unique dataset containing information at the bank-firm level on both terms of the credit contracts, that is, quantities l_{bft} and prices r_{bft}, and other match-specific information X_{bft}. The unique identifiers of banks and firms allow us to merge the bank-firm information with a number of bank- and firm-specific characteristics (X_{bt} and X_{ft}, respectively), which are used to better disentangle the supply from the demand for loans. Data are collected over the period 2006Q1 to 2015Q2. This allows us to characterise (2), (4), and (5).

3.1 The data

The data on loan quantities and interest rates come from the Italian Credit Register and covers the universe of loans from a large representative sample of intermediaries operating in Italy (about 200 banks).[14] We consider the end-of-quarter outstanding granted amounts and corresponding interest rates of term loans to firms operating in the industry sector (i.e., manufacturing and construction), which represents more than 60% of total granted term loans to non-financial firms.[15] In Figure 2 we report the total amount of term loans granted in our sample as opposed to harmonised aggregate statistics for the industry sector, which certifies that our panel of firms is highly representative of the whole industry sector. As a measure of the interest rate we use the loan margin, which is the difference between the annual percentage rate and the Eonia rate. We do this to filter out ex ante any changes in the monetary policy stance and knowing that in practice, the Eonia plays for intermediaries the role of a floor over which to set the interest rates on loans to non-financial firms.[16] For each single transaction we also observe other characteristics, namely collateralisation and maturity.

The firm-level data X_{ft} come from the Company Accounts Data Service (CADS) managed by the Cerved Group, which is one of the largest sources of balance-sheet data on Italian firms. The bank-level data X_{bt} come from the supervisory reports on banks' balance sheets submitted by each individual bank to the Bank

13 See our working paper for details about the estimation procedure (Burlon et al., 2016).
14 We provide more details about the dataset in the appendix.
15 Term loans are more related to firms' investment decisions in the medium term. They differ considerably from revolving credit lines, which are instead managed day-by-day by firms depending on their liquidity needs. We use granted amounts because drawn credit may be more relevant in empirical analysis of credit lines, where it is a temporary indicator of firm demand.
16 Results are unaffected if we use the interest rate applied on the loan or take its deviations from the MRO rate, as all aggregate effects are captured by time fixed effects in the various specifications.

of Italy. We use consolidated balance sheet items. Business strategies are usually decided by the holding of the banking group rather than by the single bank. In addition, regulatory requirements must be computed on consolidated balance sheets and banks belonging to the same group usually exchange funds on the interbank market among themselves, meaning that funding difficulties are better assessed at the banking-group level. For simplicity, we refer to banking groups simply as banks henceforth.

The data are at the bank-firm match level. If a firm has more than one distinct term loan granted by the same bank, we compute the total exposure of that firm towards the bank. We compute the weighted averages at the bank-firm level for all the other transaction-level observables, where the weights are the transaction-level amounts. The index *bft* refers therefore to the uniquely identified bank *b*-firm *f* relationship at time *t,* although from now on we refer interchangeably to the match as a transaction. Our final database consists of over 5.2 million observations from almost 468,000 bank-firm matches for 38 quarters, which involve 120 banking groups and almost 166,000 firms. Table 1 reports some summary statistics of the variables contained in the database.

3.2 Demand factors

Bank lending is just one of multiple sources of funding for firms, which can potentially rely on internal funds, as well as alternative external sources. For example, firms can rely on their internal revenue or on commercial paper, as well as on trade credit or the deep pockets of the business groups they are part of. We include two variables for internal and external substitutes of bank lending, respectively. The ratio of firms' cash flow to total sales is a measure of firms' ability to generate internal funds, while the ratio of trade debt to total assets is a measure of firms' reliance to financing from their trade partners by delaying the payment of input purchases. In order to avoid endogeneity, we use the one-year lag of each firm-specific variable.

An important aspect of the demand for credit of a firm is its maturity needs. Moreover, due to the presence of re-issuance costs or roll-over risks, firms may prefer higher maturities, other things equal.[17] The bank may alter its supply decisions depending on the average maturity of its overall portfolio, but it is unlikely to take these decisions on the basis of the single transaction. Hence, we assign the maturity variable to the credit demand. For each transaction we have some information on the loan maturity. In the credit register, this variable is recorded only according to two modalities, namely up to and over 12 months (up to and over 18 months before 2009). Since we have aggregated the transaction-level data at the bank-firm level, our maturity variable for each bank-firm pair is the percentage of credit that is flagged to have maturity below 12 months.

17 See Altinkiliç and Hansen (2000) or Bruche and Segura (2015) for the effect of re-issuance costs on maturity, and He and Xiong (2012a and 2012b) for the effect of roll-over risks.

3.3 Supply factors

The credit-rationing literature emphasises the importance of borrowers' characteristics. In the case of imperfect and asymmetric information in the credit market, adverse selection and adverse incentive effects are likely to occur. In these cases, as Stiglitz and Weiss (1981) point out, the interest rate does not allow the lender to discriminate between different types of borrower, and it is important to screen and monitor borrowers to reduce the probability that firms fail to repay the loans. In the hypothetical case of perfect screening and monitoring, no firm should be rationed and each borrower should pay the right price to get the loan. However, distinguishing safe from risky firms may be virtually impossible or very costly, and credit rationing may be the outcome. For the purpose of our analysis, we consider the Z-score to be an overall measure of the ex ante risk of firms' default. This score is computed annually by the CADS on balance sheet information.[18] The Z-score takes values ranging from 1 to 9 where firms with assigned values between 1 and 3 are considered a 'low risk', firms with values between 4 and 6 are considered a 'medium risk', and firms with values between 7 and 9 are considered a 'high risk'. The latter firms are more likely to default within the next two years. As the Z-score is an ex ante measure of credit risk, it may have different information content with respect to the bank loan quality indicators, which are a measure of the ex post credit risk. Ex ante credit-risk indicators reduce the information asymmetry between borrowers and lenders and are expected to have a positive effect on credit availability. To avoid collinearity problems, we include in the system two time-varying dummies, corresponding to 'medium risk' and 'high risk'. The estimated coefficients reflect the premium (or the discount) paid by these firms with respect to those that are considered a 'low risk'. In order to stress the nature of ex ante credit risk, we use the one-year lag of all firm-level variables.

In the existing literature, the key bank balance-sheet variables used to identify a supply restriction are the bank liquidity position and the bank capital ratio as a measure of the bank's net worth.[19] As for the former, there is large empirical evidence that banks reduce their supply of loans when hit by liquidity shocks, as predicted by the bank lending channel.[20] Kapan and Minoiu (2013) show that during the 2007-2008 crisis, the intensity of the credit supply restriction was related to the degree of banks' reliance on interbank funding. Jiménez et al. (2012) stress the role played by the liquidity ratio, namely the ratio of liquid assets held by the bank (i.e., cash and deposits with central banks and public debt with a maturity up to one year) and the total assets of the bank.

In the case of Italy, the shocks to banks' funding occurred in two distinct phases of the financial crisis and originated from different components of banks' liabilities. During the global crisis of 2007-2008, the financial shocks originated abroad and hit the Italian banking system through a dramatic liquidity drought

18 The methodology is described by Altman (1968) and Altman et al. (1994).
19 See, for example, Holmstrom and Tirole (1997), Bernanke (2007), and Diamond and Rajan (2011).
20 See, for example, Stein and Kashyap (2000) and Khwaja and Mian (2008).

in interbank markets.[21] As a result, the reliance of banks on interbank funding, as captured by the interbank-to-assets ratio, represents an important source of variation in banks' exposure to liquidity shocks (Bonaccorsi di Patti and Sette, 2012) and may then be a valid instrument for assessing the effects of a credit supply tightening on the real economy (Cingano et al., 2013).[22] During the sovereign debt crisis, the financial shocks stemmed from the increase in the sovereign risk, which transmitted rapidly to the banking sector. Identifying this effect is challenging, since banking and sovereign crises are closely intertwined through several channels, reinforcing each other through strong feedback effects. However, between November 2011 and February 2012 Italian banks' funding was hit by a dramatic fall in non-residents' deposits (Banca d'Italia, 2012), which comprise mainly interbank funds raised abroad, owing to the heightened perception of country risk from foreign lenders. As a result, a drop in non-residents' deposits may be also considered as a source of liquidity shock.[23] In light of these considerations, we consider a single interbank funding variable that comprises the interbank exposure of the banking group with both domestic and foreign intermediaries.[24] In the benchmark model we do not consider the liquidity obtained by the Eurosystem through the ordinary and the exceptional long-term refinancing operations. Since banks have used this liquidity to substitute for the decline in the wholesale funding, we explore the role played by the funding obtained from the Eurosystem in the robustness check section.

As for banks' capital position, conclusive evidence of a capital-related contraction of credit supply is still unresolved in the existing literature.[25] In the case of Italy the evidence is mixed as well, albeit confined to event studies for the global crisis of 2007-2008.[26] In this study we consider the bank capital position as measured by the Tier 1 capital ratio over risk-adjusted assets.

We also consider the credit quality in banks' balance sheets, measured by the ratio of non-performing loans to total loans standing in each bank's consolidated balance sheet. As already discussed, this is an ex post measure of the average credit risk. In addition, the impairment in the quality of bank assets induces a drop in bank profitability, which in turn leads to capital losses and deleveraging

21 See Angelini et al. (2011) and Affinito (2013) for a focus on the Italian banking system in the aftermath of the global financial crisis.

22 For banks belonging to groups, the use of consolidated balance sheet items allows us to exclude interbank transactions made by banks belonging to the same banking group, which cannot be considered genuine interbank funding.

23 An alternative measure of a liquidity shock is the funding gap indicator (i.e., the fraction of loans to the private sector not financed by customers' deposits). When included in the estimated regressions, the funding gap turns out to not be statistically significant, meaning that this variable has no marginal information content beyond the already mentioned indicators for the bank liquidity position.

24 In order to rule out intra-group domestic interbank exposures, we use the bank-to-bank liabilities from the supervisory reports and the list of mergers and acquisitions across banks in our sample. Thus, we know which bank belongs to which group in each period, and we can exclude the liabilities towards domestic members of the same banking group for each bank. We then aggregate the domestic extra-group liabilities across banks of the same banking group to create a consolidated measure together with the liabilities towards foreign entities.

25 See, for example, Rosengren and Peek (2000), Puri et al. (2011), Jiménez et al. (2012) and Udell (2009).

26 See Bonaccorsi di Patti and Sette (2012) and Albertazzi and Marchetti (2010).

needs. This has been considered one the most relevant factors affecting both the cost and the availability of credit during the recent financial crisis.[27]

The existence of collateral is expected to increase credit availability, since it mitigates the ex ante problems of adverse selection and moral hazard. Hence, we allow the supply to depend on the percentage of collateralised loans, that is, the percentage of credit that is flagged as guaranteed in the credit register.

3.4 Other control variables

We consider a number of variables that cannot be uniquely classified as demand or supply factors. These are not used to reach the identification of demand and supply curves by means of the exclusion restrictions, but are included in both equations as relevant control variables for observed and unobserved factors.

Firm size, which is measured by the logarithm of total assets, may affect the demand for loans to the extent that the financing needs of firms depend on their size for a standard scale effect. Larger firms face larger operating costs and larger need of external financing in absolute terms. Firm size may also help to explain the supply of credit. Large firms are usually considered less risky than smaller ones. Petersen and Rajan (1994) show that credit constraints become more severe as firm size decreases because the effects of adverse selection and moral hazards are larger when the company is smaller. Using data from a national survey of small businesses, Levenson and Willard (2000) find that the smallest firms in the United States are both more discouraged and more rationed than other firms. By comparing large firms with SMEs in the Capitalia surveys on Italian manufacturing firms, Agostino et al. (2008) also find that larger firms are less credit rationed than small firms.

The system specification also includes a number of fixed effects. We include a series of time-invariant, 2-digit subsector dummies to capture sectoral differences in demand and supply conditions. We also include a series of time-invariant geographical dummies that correspond to firms' 'macroareas'[28] to control for spatial differences in supply and demand conditions. Finally, we consider an appropriate set of time-specific and bank-specific fixed effects to control, respectively, for macro variables and unobservable bank characteristics.

We do not include firm fixed effects for two reasons. The first is that by including firm fixed effects, we would limit our sample to multiple-lender firms, which may be the least likely to experience rationing of their demand for credit. The second reason is technical and refers to the nature of our ML estimation procedure. For a successful estimation of the model, each single value of categorical variables like firm-specific dummies or bank-ID dummies needs to have a sufficient amount of valued observations. Otherwise, the ML estimation assigns a disproportionate weight to that observation on the demand or the supply side, leading to exploding magnitudes of the estimated coefficients

27 See Banca d'Italia (2013).

28 Under the NUTS1 classification, there are five 'macroareas' in Italy: North West, North East, Centre, South, Islands (https://en.wikipedia.org/wiki/First-level_NUTS_of_the_European_Union).

corresponding to the variable. This limitation relates to a well-known problem of corner solutions in the estimation of models à la Fair and Jaffee (1972).[29] Our simulations suggest that, to avoid corner solutions, we would need at least 1,000 observations for each firm ID. Since a firm ID can reach at most a few hundred observations, we would end up dropping almost all our sample. This is not the case for bank fixed effects or sector-specific fixed effects, as the number of observations for each bank or sector ID is high enough.30 We give an idea of the amount of information we lose without firm fixed effects in Subsection 4.2, where we evaluate the empirical correlation between firm-time fixed effects and the firm-level variables we include in the specification.

3.5 The benchmark specification

We allocate observables between the demand function and the supply function depending on whether that observable is likely to be a demand shifter, a supply shifter, or both. On the basis of what we discuss in Subsections 3.2 and 3.3, our benchmark system of equations is

$$\begin{aligned} l^d_{bft} = \rho^d \hat{r}_{bft} + \beta^d\, [&\mathit{Cash\text{-}flow/Sales}_{ft}, \mathit{Trade\ debt/Assets}_{ft}, \\ &\mathit{Short\ maturity}_{bft}, \\ &\mathit{Firm\ assets}_{ft}, \\ &\mathit{Sector}_f, \mathit{Macroarea}_f, \mathit{Bank}_b, \mathit{Quarter}_t]' + \varepsilon^d_{bft}, \end{aligned} \tag{6}$$

for the demand and

$$\begin{aligned} l^s_{bft} = \rho^s \hat{r}_{bft} + \beta^s\, [&\mathit{Average\ rating}_{ft}, \mathit{Bad\ rating}_{ft}, \\ &\mathit{Bad\ loans/Loans}_{bt}, \mathit{Tier\ 1\ capital}_{bt}, \\ &\mathit{Interbank/Assets}_{bt}, \\ &\mathit{Collateralisation}_{bft}, \\ &\mathit{Firm\ assets}_{ft}, \\ &\mathit{Sector}_f, \mathit{Macroarea}_f, \mathit{Bank}_b, \mathit{Quarter}_t]' + \varepsilon^s_{bft}, \end{aligned} \tag{7}$$

for the supply. Hence, our identification scheme is as follows. First, the demand is identified by X^d_{ft} = [*Cash-flow/Sales*$_{ft}$, *Trade debt/Assets*$_{ft}$] and by X^d_{bft} = [*Short maturity*$_{bft}$]. Second, the supply is identified by X^s_{ft} = [*Average rating*$_{ft}$, *Sector*$_f$, *Macroarea*$_f$], by X^s_{ft} = [*Interbank/Assets*$_{bt}$, *Tier 1 capital*$_{bt}$, *Bad Loans/Loans*$_{bt}$] and by X^s_{bft} = [*Collateralization*$_{bft}$]. There are covariates that serve only as controls and not for identification. For example, X^{ds}_{ft} = [*Firm assets*$_{ft}$, *Sector*$_f$, *Macroarea*$_f$], X^{ds}_{bt} = [*Bank*$_b$]. Moreover, the time dummies *Quarter*$_t$ appear on both sides as well.[31]

Lastly, the specification (2) of the interest rate comprises all covariates of demand and supply, that is,

29 See Maddala (1986) for further details.

30 In the benchmark model, we solve this limitation by dropping from our sample sectors with fewer than 50,000 observations and bank-IDs with fewer than 1,000 observations. This leads to an overall loss of around 90,000 observations out of a sample of more than 5.2 million observations.

31 As mentioned before, we use the one-year lag of all firm-level variables in X^d_{ft}, X^s_{ft}, and X^{ds}_{ft}.

$$\begin{aligned} r_{bft} = \beta\ [&\textit{Cash-flow/Sales}_{ft}, \textit{Trade debt/Assets}_{ft}, \\ &\textit{Average rating}_{ft}, \textit{Bad rating}_{ft}, \\ &\textit{Bad loans/Loans}_{bt}, \textit{Tier 1 capital}_{bt}, \\ &\textit{Interbank/Assets}_{bt}, \\ &\textit{Short maturity}_{bft}, \textit{Collateralisation}_{bft}, \\ &\textit{Firm assets}_{ft}, \\ &\textit{Sector}_f, \textit{Macroarea}_f, \textit{Bank}_b, \textit{Quarter}_t]' + \varepsilon^r_{bft}, \end{aligned} \tag{8}$$

4 Estimation results

In Table 2 we present the estimation results for the benchmark model. We compute standard errors in all estimated equations by a two-way clustering at the firm-sector and bank-category level. We assign banks to five categories: first five groups, large groups, medium groups, small groups and minor groups. The structure of our data is complex and characterised by several dimensions, so that many clustering schemes are possible. We offer a robustness check about the statistical significance of the coefficients based on alternative clustering schemes in Section 6.6.

The first column of Table 2 reports the estimated coefficients of the loan margin equation. Demand factors are in general weakly correlated with the loan margin, while supply factors are highly significant. The cost of credit indeed declines with the borrowers' creditworthiness. The dummies for averagely and badly rated firms enter with a positive sign, meaning that these firms pay a premium with respect to the best rated firms (about 30 and 70 basis points, on average, respectively). The loan margin is also lower for larger firms, which are usually considered less risky than smaller ones. Firm size has therefore marginal predictive content beyond the rating, which should capture all relevant characteristics related to firms' riskiness.

All the considered bank-specific variables are significant. Lower interest rate margins are associated with banks with a higher capital ratio and with a better credit quality in their loan portfolios. The cost of credit is also lower for banks with access to the interbank market.[32] Finally, the charge for collateralised loans is, on average, about 30 basis points less than for unsecured loans. Long-term loans are cheaper than short-term by about 70 basis points, on average.

In the second column of Table 2, we report the estimation result of demand equation. The predicted loan margin from the first-stage equation has a negative coefficient, thus identifying a downward-sloping demand curve. An increase of one percentage point in the interest rate corresponds to a 30% decrease in credit

32 Our estimates suggest large heterogeneity with respect to previous studies for Italy. Gambacorta (2008) uses bank-level data and finds that higher interest rates are associated with lower asset quality (a higher bad loan-to-total loan ratio) and bank efficiency (as measured by the cost-to-total asset ratio). The results also suggest a positive correlation with a number of macroeconomic variables, such as inflation, permanent income, and money market rate volatility, which in our model might be captured by the time dummies. However, this study focuses on a different sample period that was not characterised by a financial crisis.

demand. The two substitutes to bank lending that we consider – namely, the ratio of cash-flow over sales and the ratio of trade debt over assets – enter with the expected sign. The elasticity of substitution is higher for external financing, perhaps capturing payment delays by the customers of the firm that the latter transmits to the providers. The negative coefficient on the duration dummy suggests a preference for long-term debt. This outcome is consistent with re-issuance costs, as in Altinkiliç and Hansen (2000) and Bruche and Segura (2015), or roll-over risks as in He and Xiong (2012a). Firm size captures scale effects and the large estimated coefficient is the outcome of the level-specification of the model.[33]

In the third column, we report the estimated coefficients of the supply equation. The predicted loan margin enters with a positive sign, thus describing an upward-sloping supply curve. This outcome suggests that studies that typically assume a flat supply curve may not be consistent with the data. Interestingly, the credit supply seems to be more elastic to changes in the cost of credit than the credit demand. This result is a novelty in the literature that uses models à la Fair and Jaffee (1972), since previous contributions either do not have match-specific data on the cost of credit or include it only in the demand equation. We explore the relevance of this assumption for our estimates in Section 4.1 in addition to other econometric issues related to the identification of the supply equation.

Borrowers' characteristics are pivotal in explaining the supply of credit, thus providing empirical support to standard theoretical models of asymmetric information à la Stiglitz and Weiss (1981). Compared to the best-rated firms, the reduction in credit supply to firms with an average and bad rating is, on average, 19% and 31% larger.

However, banks' balance-sheet composition plays an important role. A decrease of one percentage point in the Tier 1 capital ratio may force the bank to reduce its loans to the corporate sector by almost 1% in order to comply with the regulatory requirements. Later we present some evidence on the non-linear effects that these requirements may have on banks' behaviour. Moreover, an increase of one percentage point in the ratio of bad loans over total loans leads to a 2.7% decrease in credit supply, as banks tighten their supply when they become too exposed to defaults. Considering that on average this ratio rose from 3% before the crisis to over 13% at the end of our sample, we can estimate a decrease in aggregate credit supply of around 30% due to the rapid accumulation of bad loans in banks' balance sheets. Banks' access to cheap funding is relevant as well, although the statistical significance is less strong and the magnitude is relatively small. A reduction of one percentage point in an intermediary's exposure to the interbank market leads to a 0.4% decrease in its supply of credit.

The size of the firm has a positive impact on credit supply, which may again capture a simple scale effect. However, there is a difference of 0.3 percentage points in the increase of credit supply relative to the increase of credit demand that corresponds to an increase of 1% in firm size. This may reflect the fact that the size of a firm's balance sheet may be among the characteristics that the bank

33 Atanasova and Wilson (2004), normalise loan quantity by firms' assets to filter out scale effects, so that the estimated coefficient can be interpreted as a true size effect.

takes into account when evaluating the risk profile of a borrower beyond its credit rating. Finally, posting collateral in the transaction reduces informational asymmetries and the credit supply triples with respect to transactions with no collateral.

4.1 The treatment of the loan margin

The inclusion of a transaction-level interest rate in our estimation deserves an in-depth discussion, as it raises relevant econometric issues.

First, recent contributions that use models à la Fair and Jaffee (1972) to study the credit market, such as Kremp and Sevestre (2013) or Farinha and Félix (2015), include the interest rate only on the demand function. Hence, column 1 of Table 3 reports the estimation of an alternative model where we assume that the supply curve is not affected by the interest rates.[34] The estimates for the coefficients of the demand equation do not change significantly in magnitude except for the short-term maturity dummy, which loses statistical significance and exhibits a wrong sign. The supply equation instead is significantly affected. The estimated effects of all covariates decline in magnitude to the reduced-form coefficients, which can be computed by a back-of-the-envelope calculation on the basis of Table 2 as the values that sum up the direct effect on the supply and the indirect effect through the interest rate. In particular, the interbank exposure now enters with a negative sign. This result points to the crucial role that imposing a structure on the data may have in the study of the market for term loans. Access to funding from the interbank market may appear to be associated with a lower credit supply to the corporate sector in reduced form, but that may be the result of its effect on the cost of funding, and in turn on loan interest rates, rather than a factor affecting credit availability.

The second issue is related to the endogeneity problem. Column 2 of Table 3 reports the results of an alternative experiment in which we estimate the model by replacing the predicted loan margin with its actual value. Therefore, we do not estimate the first-stage regression and evaluate the effects of considering r_{bft} endogenous in the model. The semi-elasticity of the demand curve to the loan margin is less than one quarter of that obtained with the benchmark estimate, while the semi-elasticity of the supply curve becomes negative, raising concerns about the identification of the supply function. Hence, addressing the endogeneity of interest rate is crucial for the identification of the system.[35]

4.2 Decomposition of the data

The use of bank-firm data for the cost and the amount of credit and their matching with bank-specific and firm-specific characteristics represent the major

34 For the sake of brevity, we report only the coefficients associated with the variables of main interest. The other estimated coefficients are available upon request.

35 Results are similar if we include the endogenous version of the loan margin only on the demand side. In this case, however, the semi-elasticity on the demand curve doubles in magnitude. These results are also available upon request.

novelty of this paper with respect to previous studies that relied on an approach à la Fair and Jaffee (1972) to identify credit rationing. In this regard, what is the relative importance of observable and unobservable firm-specific and bank-specific characteristics in explaining our endogenous variables?

To answer this question, we first decompose the overall variance in loan quantities and prices into its fundamental components, namely, bank-time fixed effects and firm-time fixed effects.[36] We then compare how much of each component of variability is explained by the observables we include in our model. We regress bank-time fixed effects on the observable bank-level variables, and firm-time fixed effects on the observable firm-level variables. As a measure of their ability to capture their respective dimension of variability, we look at the R-squared of these regressions. This exercise also informs us about the amount of information we lose by not considering firm fixed effects in the benchmark specification.

A regression of the observable credit quantities on bank-time and firm-time fixed effects leads to the dropping of 1.8 million singleton observations, which correspond mostly to single-lender firms at a given time. The R-squared on the remaining 3.5 million observations is 69%, of which bank-time fixed effects explain 2% of the variation in credit quantities, whereas firm-time fixed effects explain the remaining 67%. This asymmetry lies at the heart of the reduced-form evidence on the predominance of borrowers' characteristics as drivers of loan quantities.

Under the assumption that bank-time fixed effects capture all the variation of credit quantity that is due to bank characteristics, we want to understand how much of this variation we capture with the variables we include in our benchmark model. We find that our time-varying bank-level covariates, together with the bank fixed effects, time fixed effects, and the dummies for firms' sectors and geographical location, explain 93% of bank-time fixed effects. We do the same for firm-time fixed effects and firm-level characteristics included in our benchmark specification, and obtain an R-squared of 67%. We can therefore conclude that our specification accounts for a sufficiently high share of overall bank-time and firm-time variation.

We perform the same analysis for the cost of credit. We obtain that bank-time and firm-time fixed effects explain 21% and 39% of overall variance of the interest rates, respectively, for a total of 60%. Our bank-level variables explain 93% of bank-time fixed effects, and our firm-level variables explain 15% of firm-time fixed effects. Hence, it seems that interest rate developments are explained more by bank-level variables than by firm-level variables.

Among the explanatory variables we include in the model, particular attention should be paid to the bank-firm-time variables, namely, the maturity and the level of collateralisation of the loan contracts. Interestingly, these observables add 7 percentage points to the overall variance of loan quantities and 2 percentage points of the overall variance of the loan prices.

36 We do not consider bank-firm fixed effects because the matches themselves are not stable over time, so the variation in their number and distribution would capture important time-varying effects. We leave the exploration of this dimension to future research.

Overall, our analysis suggests some important considerations. First, there may be a relevant loss of information when analysing the loan markets with a dataset that does not comprise both firm- and bank-specific variables. Second, the identification of the effects of a supply restriction on lending dynamics by including firm-time fixed effects to control for demand conditions is powerful, but may be too conservative. We showed that firm-time fixed effects are not independent from firm characteristics, of which some are supply factors. Similar considerations may apply when bank-time fixed effects are included in the regression which relies on multiple-borrower banks, although that may be less of an issue empirically.[37]

There are additional challenges related to the identification with matched bank-firm data, as it has been recognised in the literature on matched employer-employee data since the seminal contribution of Abowd et al. (1999). For example, the inclusion of two-way fixed-effects imposes additivity between firm- and bank-specific fixed effects. Thus, it rules out any heterogeneity in firm-specific credit terms across banks or in bank-specific credit terms across firms, as well as any complementarity between banks and firms, which makes them also incompatible with theoretical models of sorting between banks and firms.[38]

4.3 Explaining aggregate demand and supply

We now compute aggregate demand and supply and decompose their evolution into their time-varying observable and unobservable determinants. We are particularly interested in evaluating the contributions of the variables that directly affected the loan supply while condensing together those affecting the loan market through the interest rate channel.

We use the benchmark estimates for (6) and (7) to compute the predicted demand and predicted supply at the level of the single transaction. Then, we sum the predicted demand and the predicted supply across all bank-firm matches within each quarter. Figure 4 reports the two time series. Aggregate demand grew from the beginning of the sample to 2009Q2 when the global financial crisis drove the economy into recession. It fell into a persistent decline during the sovereign debt crisis. Aggregate supply instead grew until the first quarter of 2008, when the financial turmoil in the interbank market and the Lehman collapse led to a supply contraction. Then, loan supply increased until the breakout of the sovereign debt crisis.

Given the estimated coefficients and the time variation of the explanatory variables, in Figures 5 and 6 we report the cumulative contribution of demand and supply factors at each point in time. The most striking result is that non-performing loans are the main driver of the fall in the supply factor during the sovereign debt crisis. The collateral also provided a negative contribution in the last part of the sample period, reflecting the decline in its availability. The deterioration of the borrowers' creditworthiness played a minor role. The positive contribution of the firm rating during the crisis reflect a change in

37 Bank-firm fixed effects would rely on the existence of the same match in at least two quarters.
38 See Bonhomme et al. (2015) for a recent discussion of these issues in the case of the labour market.

the borrowers' composition with banks that switched their supply of funds in favour of firms with a higher creditworthiness. Interestingly, bank capital did not contribute to the fall in loan supply, suggesting that banks' recapitalisation that occurred during the crisis did not have perverse effects on loan supply. As for the reduction of aggregate demand, this is mostly explained by the unobservable characteristics of the model. Time dummies play a dominant role in this regard, perhaps capturing the effects of the aggregate business cycle on the demand for loans.

5 Indicators of credit rationing

In this section, we describe some credit rationing indicators that can be used for policy analysis.

The maximum likelihood estimation of the system (6)-(7)-(1) provides us the predicted demand,

$$\hat{l}^d_{bft} = \hat{\rho}^d \hat{r}_{bft} + \hat{\beta}^d X^d_t,$$

and the predicted supply,

$$\hat{l}^s_{bft} = \hat{\rho}^s \hat{r}_{bft} + \hat{\beta}^s X^s_t,$$

for each bank-firm relationship. We can also compute the estimated probability that each bank-firm match is credit rationed as an analogue $\hat{\pi}_{bft}$ of the actual probability π_{fbt}, that is,

$$\begin{aligned}\hat{\pi}_{bft} &= Pr\left(\hat{\rho}^d \hat{r}_{bft} + \hat{\beta}^d X^d_t - \left(\hat{\rho}^s \hat{r}_{bft} + \hat{\beta}^s X^s_t\right) > \varepsilon^s_{bft} - \varepsilon^d_{bft}\right), \\ &= Pr\left(\hat{l}^d_{bft} - \hat{l}^s_{bft} > \varepsilon^s_{bft} - \varepsilon^d_{bft}\right),\end{aligned}$$

which, under the assumption of independently and normally distributed errors, implies that

$$\hat{\pi}_{bft} = \Phi\left[\frac{\hat{l}^d_{bft} - \hat{l}^s_{bft}}{\sqrt{(\hat{\sigma}^d)^2 + (\hat{\sigma}^s)^2}}\right],$$

where Φ is the normal cumulative distribution function and $(\hat{\sigma}^d)^2$ and $(\hat{\sigma}^s)^2$ are the realised variances of the residuals of the demand and the supply equations, respectively.

Once we have $\hat{\pi}_{bft}$, we can analyse its distribution over time and across firms and banks. For example, Figure 3 reports the distribution of $\hat{\pi}_{bft}$ in different years. A credit rationing probability close to 1 ($\hat{\pi}_{bft} \approx 1$) means that the predicted demand for that particular transaction is considerably higher than the predicted supply, while a credit rationing probability close to 0 ($\hat{\pi}_{bft} \approx 0$) means that the predicted demand is considerably lower than supply. The situation of equality between demand and supply corresponds to a probability of 50%, represented by the vertical bar at the $\hat{\pi}_{bft}$ = 50% level. The distribution seems to tilt slightly towards the right, especially when the sovereign debt crisis hit the Italian economy in 2011. This evidence is consistent with the identification of 'weak' credit rationing during the financial crisis.

5.1 Head counts of transactions and weighted measure

We propose two macroeconomic indicators of credit rationing. The first measure simply counts the number of observations that, for each period t, have a credit rationing probability $\hat{\pi}_{bft}$ above a threshold. In order to be conservative, we fix this threshold at 80%, so that in case $\hat{\pi}_{bft} > 0.80$ we are far away from the situation of perfect equality between demand and supply. The indicator can be computed as follows:

$$I_t^1 = \%\text{ observations with } \pi_{bft} > 80\%_t \equiv \frac{\sum_{bf \in N_t} \mathbb{1}\left(\hat{\pi}_{bft} > 0.80\right)}{\#(N_t)}, \tag{9}$$

where $\mathbb{1}(\hat{\pi}_{bft} > 0.80)$ is an indicator function that takes value 1 if $\hat{\pi}_{bft} > 0.80$, N_t is the set of transactions at time t, and $\#(N_t)$ is the number of transactions at time t. This indicator is similar in spirit to the indicators of supply conditions that can be drawn from survey data among firms or banks, where 'net percentages' essentially reflect head counts.

A second indicator can be based on the quantity of rationed credit, namely, on the percentage of credit demand that is satisfied by the supply at each point in time. Precisely, this measure weighs the excess demand at the bank-firm level with the probability that the same bank-firm match is rationed. This indicator has the advantage of not relying on any arbitrary threshold for the selection of the rationed bank-firm relationships and provides a different perspective with respect to head counts-based measures. The indicator can be computed as follows:

$$I_t^2 = \text{Weighted credit rationing ratio}_t \equiv \frac{\sum_{bf \in N_t} \left(\hat{l}_{bft}^d - \hat{l}_{bft}^s\right) \hat{\pi}_{bft}}{\sum_{bf \in N_t} \hat{l}_{bft}^d}. \tag{10}$$

In Figure 7 we compare the two credit-rationing indicators. Not surprisingly, both measures reach their maximum values in the most acute phases of the global and the sovereign debt crises. The credit rationing measures jump from an average of 10% before the crisis (involving around 6% of the granted loans) to about 20% (10% by head count) in the global financial crisis, and to about 17% (8% by head count) at the peak of the sovereign debt crisis.[39] Note that the two measures may exhibit different levels and dynamics since they are related to different aspects of credit rationing. For example, there may be several small bank-firm transactions

39 The pre-crisis level accounts also for 'equilibrium' credit rationing due to informational frictions.

that are not rationed and a few large transactions that are rationed, which would result in a low level for I_t^1 but a high level for I_t^2.

5.2 Comparison with survey-based measures of credit rationing

We can construct measures of credit rationing that help the comparison with sources of soft information such as surveys across banks or firms. The main difference is that our measures are based on hard information and are not self-reported.

We first compute the percentage of firms that result to be rationed according to the definition of I_t^1. Since we can derive the firm-level probability of credit rationing as

$$\hat{\pi}_{ft} \equiv \frac{1}{\#(B_t(f))} \sum_{b \in B_t(f)} l_{bft} \hat{\pi}_{bft},$$

where $B_t(f)$ is the set of banks that lend to firm f at time t, the size of the set Bt(f), the firm-level version of indicator $I^1{}_t$ and $\#B_t(f)$ is given by

$$I_t^{1F} = \text{\% observations with } \hat{\pi}_{ft} > 80\%_t \equiv \frac{\sum_{f \in F_t} \mathbb{1}\,(\hat{\pi}_{ft} > 0.80)}{\#(F_t)},$$

where $\mathbb{1}\,(\hat{\pi}_{ft} > 0.80)$ is an indicator function that takes value 1 if $\mathbb{1}\,(\hat{\pi}_{ft} > 0.80)$, F_t is the set of firms in period t, and $\#(F_t)$ is the number of firms at period t. The indicator I_t^{1F} counts the firms that resulted to be rationed according to our estimates. Hence, it is comparable in nature with survey-based indicators based on the number of firms that declare themselves as rationed.

Similarly, we can define the bank-level probability that a single bank rations its pool of borrowers as

$$\hat{\pi}_{bt} \equiv \frac{1}{\#(F_t(b))} \sum_{f \in F_t(b)} l_{bft} \hat{\pi}_{bft},$$

and, therefore, the bank-level version of indicator I_t^1 is given by

$$I_t^{1B} = \text{\% observations with } \hat{\pi}_{bt} > 80\%_t \equiv \frac{\sum_{b \in B_t} \mathbb{1}\,(\hat{\pi}_{bt} > 0.80)}{\#(B_t)},$$

where $F_t(b)$ is the set of firms that borrow from bank b at time t, $\#(F_t(b))$ is the number of the firms in $F_t(b)$, B_t is the set of banks in period t, and $\#(B_t)$ is the number of banks in period t. The indicator I_t^{1B} counts the banks whose average transactions were rationed (according to the 80% threshold). Hence, it is comparable in nature with survey-based indicators based on the number of banks that declare themselves as having tightened their credit standards via quantitative restrictions.

In Figure 8 we report both the firm- and bank-level head count-based indicators of credit rationing and compare them with our indicator based on bank-firm level information. This allows us to give an assessment of the bias stemming from data aggregation.

Figure 9 compares our measure with the indicator stemming from the Istat survey, which is available only since 2010. The dynamics of the two indicators are quite correlated during the sovereign debt crisis, albeit with differences arising in the first part of the sample period. Istat's survey reports a peak of credit rationing in 2012, when the number of rationed firms reached 3.6%; the level of our measure in that year is 3.3%.

The percentage of rationing banks increases throughout the sample, but reaches 1.1% only towards the end of the sample. This coincides with the evidence from the Bank Lending Survey for Italian banks, which reports a steady increase of credit rationing throughout the sample, with two accelerations in the most acute phases of the financial crisis. Figure 10 reports the comparison between our measure and that of the Bank Lending Survey, whose evolution is similar.

6 Robustness

6.1 Alternative estimation techniques

Table 4 reports the estimated coefficients of the benchmark model obtained with alternative econometric techniques. In column 1 we report the OLS estimates of demand and supply functions. The simple OLS regressions are able to capture qualitatively the correlations in the demand function, but miss on identifying the supply function. The semi-elasticity on the supply for the OLS regression is positive, which is a clear signal of misspecification.

In column 2 we report the same estimates using separate IV regressions, where the first-stage equation consists of the estimation of the interest rate equation. The semi-elasticity on the demand curve to the interest rate is three times that of the benchmark model. The semi-elasticity of the supply curve is positive but not significantly different from zero. The interbank exposure and the Tier 1 capital ratio coe cients are not significant either. The use of IV regressions therefore leads to the conclusion that the loan supply does not depend on either the interest rate or bank-specific variables, and is mostly related to borrowers' characteristics. The difference between the IV and ML estimates is due precisely to potential non-price allocations of credit. Suppose that for certain transactions the demand is high and the supply is low, which means that the observed quantity is the result of supply determinants. The IV assigns the same weight to these observations in the estimation of the supply function that it assigns to observations that are most likely driven by demand determinants. Our model instead assigns more weight to these observations than to those driven by demand determinants. The IV estimates a supply equation treating observations that are structurally driven by demand factors in the same way as observations that are structurally driven by supply factors, thus mixing up direct effects on the supply with effects that pass through the interest rate.

6.2 Alternative specifications of the supply

We explore the role played by other variables that the recent empirical literature points out as important drivers of the credit supply. Table 5 summarises the results.

First, we include the ratio of government bonds over total assets in both the interest rate equation and the supply equation. In a recent contribution, Bottero et al. (2015) show that Italian banks' exposure to sovereign debt significantly affected the supply of loans to non-financial firms. Moreover, government bonds may simply substitute corporate lending in banks' investment strategies. Banks' exposure to sovereign risk significantly affected both the cost and the availability of credit. An increase of one percentage point in the ratio of government bonds over total assets leads to a 1.5% decrease in the credit supply. This decrease is still as high as 1.2% when we also take into account its effect through the interest rate, as a government bond ratio that is one percentage point higher is associated with a fall in the loan margin of 0.7 basis points. However, its inclusion does not significantly affect our measures of non-price allocations of credit.

Second, we control for the role played by the Eurosystem refinancing operations. There is no doubt that these operations offset the liquidity risk in the most acute phases of the financial crisis and have been used by banks to substitute the drop in the wholesale funding. In the cross-section, we find a high and negative correlation between banks' interbank exposure and their reliance on Eurosystem liquidity, which tend to offset one another when included simultaneously in our model. If we included the ratio of Eurosystem funding over banks' total assets in the supply function, we would not identify the effect of unconventional monetary policy. Given their complementarity, we include in the model the sum of banks' interbank exposure and their use of Eurosystem funding. Interestingly, this variable has no significant effect on credit supply, suggesting no role for banks' funding conditions in the evolution of credit rationing.[40]

Third, we check the role played by banks' profitability. We consider the ratio of bank profits over total assets. The profitability of banks seems to negatively affect the supply of credit, which may be a consequence of tighter and more selective lending standards. This interpretation is confirmed by the fact that higher profitability is also associated with higher rates, which makes it a standard supply shifter. The rest of the covariates are broadly unaffected except for access to interbank funding, which becomes not statistically significant.

40 It may be interesting to disentangle domestic and foreign components of banks' interbank exposure. Domestic net exposure has a negative effect on supply, while non-residents' deposits do not have a significant impact on either the credit supply or the interest rate. We do not report these results for the sake of brevity.

6.3 Alternative specifications of the demand

Our demand curve does not include a measure of firms' ex ante investment decisions, which may be important in explaining the dynamics of term loans but are not observed. We can consider firms' realised investments as captured by the change in fixed assets, which is, however, an ex post measure of investment decisions. This raises a relevant problem of endogeneity, since firms' investment depends on their access to bank lending.[41] The use of the one-year lag that characterises our firm-level information may help, but does not guarantee pure exogeneity. It is useful nonetheless to assess the robustness of the results by including in the demand curve investments as measured by the ratio of gross variation of fixed assets over total assets. The first column of Table 6 shows that investments enter significantly and with the expected sign but do not alter the rest of the coefficients in a relevant way. Moreover, the evolution of the credit rationing indicators is the same.

Our estimation relies on the joint determination of both terms of a credit contract, that is, quantity and price. However, we also stress how crucial it is for our procedure to focus on the market for a single credit product such as the term loans to non-financial corporations by bank entities. Hence, it is important to check that our benchmark specification is effective even within a subsample of relevant characteristics that may describe a further segmentation of the market. Column 2 of Table 6 presents the same estimation within the subsample of uncollateralised short-term financing. In order to construct this subsample, we consider only transactions with a percentage of short-term amount above 50% but with a percentage of collateralised amount below 50%. In this way, we separate around half of the benchmark sample. Within this subsample, the estimated coefficients do not differ from the benchmark in a relevant manner, despite the absence by construction of two key determinants of demand and supply, namely, maturity and the level of collateralisation.

Another potential determinant of the demand for credit is credit availability from other lenders. Firms that do not rely solely on one intermediary may be less rationed than single-lender firms, and their demand for credit from a given intermediary could depend negatively on the number of additional counterparts. Hence, we include in the demand function the number of banks that each firm borrows from at each point in time and report the estimation results in the third column of Table 6. The transaction-specific demand for credit depends negatively on the number of additional lenders that a firm may have. The benchmark estimation and the indicators of credit rationing, however, are robust to the inclusion of this variable.

In Figure 11 we compare the credit rationing indicator for single-lender firms with that for multiple-lender firms. The intensity of credit rationing is persistently stronger for single-lender firms than for multiple-lender peers over the considered sample period. This finding points to the importance of including single-lender firms in our sample to obtain a more comprehensive estimation of credit rationing at the aggregate level. It also suggests that estimates based on the

41 See Cingano et al. (2013) for an event study on the effect of bank-lending shock on investment in Italy.

subsample of multiple-lender firms may provide a lower bound. It is important to note, however, that the credit rationing indicators are all based on the estimated coefficients of the benchmark model. In this regard, column 4 of Table 6 shows that estimated coefficients using only the subsample of multiple-lender firms are not very different from the benchmark, with the exception of the semi-elasticity of supply to the interest rate.

6.4 Structural breaks

In the benchmark estimation, we do not consider potential breaks in the estimated relationships over time. Hence, we re-estimate the model by augmenting our benchmark specification with interaction terms between all demand and supply factors and year-specific dummies. The time-varying estimates highlight some intertemporal differences in the magnitudes for certain variables, but qualitatively the benchmark model remains valid. In particular, the coefficient of interbank exposure remains statistically significant only up until 2008. The global financial crisis seems to favour initially a pooling of clientele with respect to their credit rating, with the difference between firms with an average rating and firms with a bad rating narrowing in 2009. However, averagely and badly rated firms diverge from firms with a good rating from that point on, reaching their joint maximum distance from zero at the end of the sample. Finally, the indicators of credit rationing using the time-varying estimates do not change in a relevant manner, and their evolution over time is virtually identical.

6.5 Bootstrap evidence

Our estimation imposes as little structure on the data as we deem necessary for the purpose of estimating a measure of credit rationing. Hence, our estimates are conditional upon our sample, and in particular upon the distribution of characteristics across observations in our sample. Thus, we try to control for the biases that the composition of our sample may entail by considering a bootstrap procedure. In particular, we set up a bootstrap for the maximum-likelihood estimation of our system of equations. The bootstrap estimates coincide in magnitude with our benchmark, and the statistical significance is substantially higher. Our benchmark estimation thus appears to be robust to variations in the composition of our sample, at least to the extent that such variations are random.

6.6 Clustering schemes

The richness of our dataset implies that there are several potential dimensions of correlation in the estimated residuals. Hence, we make sure that the significance of our estimated coefficients does not depend on the clustering structure we adopt in the benchmark specification. In particular, we check clusters by firm sector, by bank type, by time, and three-way clustering by firm sector, bank type and time. Finally, we also check the case of no clustering. The statistical significance of the estimated coefficients is robust to the adoption of the clustering scheme.

7 Conclusion

Largely due to the use of reduced-form specifications, empirical models of the credit market do not discriminate situations in which the supply restriction takes place through an increase in the cost of credit from situations of credit rationing, that is, a condition characterised by excess demand over supply. Episodes of credit rationing may be due to higher risk aversion of banks, severe asymmetric information problems between lenders and borrowers, as well as significant bank balance-sheet constraints.

Our contribution to the literature lies in meeting this identification challenge and in providing estimates of the non-price allocation of credit. We use an unexplored, high-quality dataset comprising about five million observations by merging bank-firm information about the quantity and the cost of credit, available in the Italian Credit Register. We use maximum likelihood methods to estimate a model for the market of term loans, in which we control for a number of bank- and firm-specific characteristics. Our model endogenously identifies all the rationed bank-firm relationships and provides measures of credit rationing at the aggregate level.

We find some important results regarding the dynamics of the market of term loans. Credit rationing is mostly explained by lenders' exposure to increasing non-performing loans and borrowers' ability to provide collateral against bank loans. Other characteristics, such as the ex ante credit risk, contribute to the evolution of credit rationing, thus confirming the major role played by information asymmetries among banks and firms. Moreover, banks switched their supply of funds in favour of firms with a higher creditworthiness after the breakout of the sovereign debt crisis. Banks' funding conditions deteriorated significantly in the most acute phases of the financial crisis, but do not seem to have induced strong restrictions in the availability of lending.

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Appendix: Data

The data on loan quantities are monthly and come from the Italian Credit Register, which covers the universe of all banks operating in Italy. We consider the amounts of term loans granted to firms operating in the industry sector (i.e., manufacturing and construction), which represent more than 60% of total granted term loans to non-financial firms. There exists a reporting thresholds at €75,000 (€30,000 from 2009) for the quantity of credit in the credit register. However, this threshold does not impact the sample as much as we may expect. In fact, this threshold refers to the overall exposition of a borrower towards an intermediary. Hence, if a firm has two loans of €20,000 each with the same bank, that firm appears in our sample with the two loans. We can find almost 1.3 million observations below the €75,000 threshold and 0.5 million observations below the €30,000 threshold, with no noticeable change of this sample over time and specifically not around the change in threshold for the credit register data between 2008 and 2009. Moreover, there is no bunching of observations around the threshold, which lies in the far-left tail of the observed distribution in any period of time.

The data on loan interest rates come from the TAXIA database, which is a sub-sample of the credit register, reported at quarterly frequency, for a large representative sample of intermediaries (about 200 Italian banks and ten branches and subsidiaries of foreign banks). We compute the annual percentage rate of interest for each loan on the basis of the actual interests paid by firms. For consistency with the credit quantity variable, we consider the observed interest rates net of fees and commissions, since these may be at least partly charged on the actual drawn amounts. To merge loan interest rate and quantities, we consider the end-of-quarter outstanding amounts from the monthly credit register database.

The firm-level data X_{ft} come from the Company Accounts Data Service (CADS) managed by the Cerved Group, which is one of the largest sources of balance sheet data on Italian firms and covers about 700,000 firms per year, of which over 160,000 operate in the industry sector. The bank-level data X_{bt} come from the supervisory reports on banks' balance sheets submitted by each individual bank to the Bank of Italy. In order to construct banks' consolidated balance sheets, we carefully manage merges and acquisitions among banks. The two banks involved in each merge operation are considered as separate entities until the effective date of the operation and as a new single one afterwards. At the same time, if a firm has a relationship with a specific bank and this bank disappears from the database because of a merger or an acquisition by another intermediary, we can track whether there is a new relationship with the newly formed bank or with the acquirer. In this case, we consider the relationship as a new one since both the characteristics of the 'new' bank and its business model can be very different from the previous ones. Hence, we collapse all bank-firm matches at the banking group level.

Appendix: Tables

Table 1 Variable description and summary statistics.

Variable	Unit	Definition	Mean	Std. Dev.	Min.	Max.
Loan quantity$_{bft}$	log(EUR)	Log of granted credit	12.291	1.625	0	20.834
Loan margin$_{bft}$	%	Spread between loan rate and EONA rate	2.921	1.896	-4.253	25.100
Firm assets$_{ft}$	log(000 EUR)	Log of firm's total assets	8.184	1.443	4.927	11.546
Cash-flow/Sales$_{ft}$	%	Firm's ratio of cash-flow over total sales	2.438	20.673	-326.923	56.944
Trade debt/Assets$_{ft}$	%	Firm's ratio of trade debt to total assets	23.235	16.979	0	80.088
Average rating$_{ft}$	0/1	1 if firm's rating is between 4 and 6	0.598	0.490	0	1
Bad rating$_{ft}$	0/1	1 if firm's rating is between 7 and 9	0.303	0.460	0	1
Sector$_f$	Cat.	Firm's sector	-	-	1	22
Macroarea$_f$	Cat.	Firm's macroarea	-	-	1	3
Bad loans/Loans$_{bt}$	%	Bank's ratio of bad loans over total loans	5.642	3.846	0.369	41.080
Interbank/Assets$_{bt}$	%	Bank's ratio of interbank exposure to total assets	8.144	7.372	0	57.926
Tier 1 capita$_{bt}$	%	Bank's Tier 1 capital ratio	13.566	4.927	0	61.567
Collateralization$_{bft}$	%	Percentage of loan which is collateralized	28.274	43.340	0	100
Short maturity$_{bft}$	%	Percentage of loan with maturity less than 12 months	22.291	37.984	0	100
Bank$_b$	Cat.	Bank's ID	-	-	1	120
Quarter$_t$	Cat.	Quarter	-	-	2006Q1	2015Q2

Notes: All variables have 5231134 non-missing observations. The firm index f ranges from 1 to 165878. The bank index b ranges from 1 to 120. The time index t ranges from 2006Q1 to 2015Q2 for a total of 38 quarters.

Table 2 Benchmark model

	Interest rate equation (1)	Demand equation (2)	Supply equation (3)
Dependent variable	Loan margin	Loan quantity	Loan quantity
Loan margin		-0.290 ***	0.478***
		(0.043)	(0.091)
Cash-flow/Sales	0.000	-0.003 ***	
	(0.000)	(0.000)	
Trade debt/Assets	0.002**	-0.010 ***	
	(0.001)	(0.001)	
Average rating	0.327***		-0.187 ***
	(0.013)		(0.025)
Bad rating	0.678***		-0.515 ***
	(0.026)		(0.051)
Bad loans/Loans	0.024***		-0.027 ***
	(0.005)		(0.003)
Interbank/Assets	-0.017 ***		0.004*
	(0.003)		(0.002)
Tier 1 capital	-0.013 ***		0.010***
	(0.003)		(0.002)
Collateralization	-0.003 ***		0.024***
	(0.000)		(0.001)
Short maturity	0.007***	-0.001	
	(0.000)	(0.001)	
Firm assets	-0.246 ***	0.711 ***	0.749***
	(0.008)	(0.020)	(0.030)
Pseudo R-squared	0.275		
Log-likelihood		-7848774.3	-7848774.3
Observations	5,231,134	5,231,134	5,231,134

Notes: All estimated equations include time dummies, firm sector-specific fixed effects, geographical area-specific fixed effects, bank-specific fixed effects. *, ** and *** denote statistical significance at 5, 1 and 0.1 per cent, respectively. Standard errors are two-way clustered at the firm sector-banks type level.

Table 3 Alternative treatment of the loan margin

	Excluded from supply equation (1)	Endogenous loan margin (2)
Demand equation		
Loan margin	-0.262 ***	-0.070 ***
	(0.039)	(0.009)
Cash-flow/Sales	-0.003 ***	-0.003 ***
	(0.000)	(0.000)
Trade debt/Assets	-0.010 ***	-0.010 ***
	(0.001)	(0.001)
Short maturity	0.001	0.000
	(0.001)	(0.000)
Firm assets	0.717 ***	0.764 ***
	(0.020)	(0.017)
Supply equation		
Loan margin		-0.118 ***
		(0.006)
Average rating	-0.033	-0.033
	(0.028)	(0.031)
Bad rating	-0.199 ***	-0.197 ***
	(0.039)	(0.045)
Bad loans/Loans	-0.016 ***	-0.015 ***
	(0.003)	(0.004)
Interbank/Assets	-0.003 **	-0.003 *
	(0.001)	(0.001)
Collateralization	0.022 ***	0.022 ***
	(0.001)	(0.001)
Tier 1 capital	0.004	0.004 *
	(0.002)	(0.002)
Firm assets	0.642 ***	0.618 ***
	(0.023)	(0.022)
Log-likelihood	-7852057	-7799702.9
Observations	5,231,134	5,231,134

Notes: All estimated equations include time dummies, firm sector-specific fixed effects, geographical area-specific fixed effects, bank-specific fixed effects. *, ** and *** denote statistical significance at 5, 1 and 0.1 per cent, respectively. Standard errors are two-way clustered at the firm sector-banks type level.

Table 4 Benchmark model: alternative estimation techniques

	OLS estimation		IV estimation	
	Demand equation	Supply equation	Demand equation	Supply equation
	(1)		(2)	
Loan margin	-0.119 ***	-0.100 ***	-0.935 ***	0.004
	(0.004)	(0.005)	(0.066)	(0.052)
Cash-flow/Sales	-0.002 ***		-0.004 ***	
	(0.000)		(0.001)	
Trade debt/Assets	-0.009 ***		-0.006 ***	
	(0.001)		(0.001)	
Average rating		-0.016		-0.054 *
		(0.015)		(0.024)
Bad rating		-0.111 ***		-0.186 ***
		(0.019)		(0.033)
Bad loans/Loans		-0.008 ***		-0.011 ***
		(0.002)		(0.003)
Interbank/Assets		-0.001 *		0.000
		(0.001)		(0.001)
Tier 1 capital		0.002 *		0.004
		(0.001)		(0.003)
Collateralization		0.011 ***		0.012 ***
		(0.000)		(0.001)
Short maturity	-0.002 ***		0.004 ***	
	(0.000)		(0.001)	
Firm assets	0.684 ***	0.677 ***	0.473 ***	0.701 ***
	(0.013)	(0.013)	(0.024)	(0.036)
Observations	5,231,134	5,231,134	5,231,134	5,231,134

Notes: All estimated equations include time dummies, firm sector-specific fixed effects, geographical area-specific fixed effects, bank-specific fixed effects. *, ** and *** denote statistical significance at 5, 1 and 0.1 per cent, respectively. Standard errors are two-way clustered at the firm sector-banks type level.

Table 5 Robustness. Alternative specification of the supply

	Government bonds (1)	Eurosystem liquidity (2)	Bank profits (2)
Demand equation			
Loan margin	-0.295 ***	-0.294 ***	-0.308 ***
	(0.044)	(0.044)	(0.046)
Cash-flow/Sales	-0.003 ***	-0.003 ***	-0.003 ***
	(0.000)	(0.000)	(0.000)
Trade debt/Assets	-0.010 ***	-0.010 ***	-0.010 ***
	(0.001)	(0.001)	(0.001)
Short maturity	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Firm assets	0.710 ***	0.710 ***	0.708 ***
	(0.020)	(0.020)	(0.020)
Supply equation			
Loan margin	0.479 ***	0.479 ***	0.474 ***
	(0.091)	(0.092)	(0.092)
Average rating	-0.185 ***	-0.186 ***	-0.183 ***
	(0.025)	(0.025)	(0.025)
Bad rating	-0.513 ***	-0.514 ***	-0.510 ***
	(0.051)	(0.051)	(0.051)
Bad loans/Loans	-0.024 ***	-0.028 ***	-0.025 ***
	(0.003)	(0.003)	(0.004)
Interbank/Assets	0.005 *		0.000
	(0.002)		(0.002)
Interbank+Eurosystem/Assets		0.000	
		(0.002)	
Bank profits/Assets			-0.041 *
			(0.018)
Tier 1 capital	0.009 ***	0.009 ***	0.007 ***
	(0.002)	(0.002)	(0.002)
Government bonds/Assets	-0.016 ***		
	(0.002)		
Collateralization	0.024 ***	0.024 ***	0.024 ***
	(0.001)	(0.001)	(0.001)
Firm assets	0.750 ***	0.749 ***	0.758 ***
	(0.030)	(0.030)	(0.030)
Log-likelihood	-7848026.5	-7848814.7	-7593123.6
Observations	5,231,134	5,231,134	5,063,414

Notes: All estimated equations include time dummies, firm sector-specific fixed effects, geographical area-specific fixed effects, bank-specific fixed effects. *, ** and *** denote statistical significance at 5, 1 and 0.1 per cent, respectively. Standard errors are two-way clustered at the firm sector-banks type level.

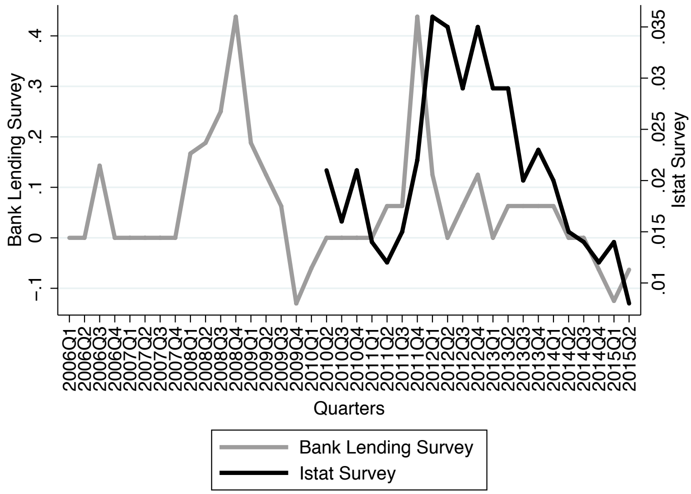
Table 6 Robustness. Alternative specifications of the demand

	Fixed investment (1)	Short term uncollateralized (2)	# lenders (3)	Multiple lender data (4)
Demand				
Loan margin	-0.314***	-0.234***	-0.221***	-0.397***
	(0.038)	(0.037)	(0.043)	(0.038)
Cash-flow/Sales	-0.003***	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Trade debt/Assets	-0.009***	-0.010***	-0.010***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
Investment/Assets	0.391***			
	(0.093)			
# bank counterparts			-0.086***	-0.058***
			(0.012)	(0.007)
Short maturity	-0.001		-0.002*	-0.003***
	(0.001)		(0.001)	(0.001)
Firm assets	0.709***	0.575***	0.800***	0.796***
	(0.019)	(0.024)	(0.023)	(0.016)
Supply				
Loan margin	0.484***	0.472*	0.510***	0.913***
	(0.094)	(0.187)	(0.088)	(0.133)
Average rating	-0.189***	-0.229***	-0.140***	-0.362***
	(0.025)	(0.057)	(0.027)	(0.046)
Bad rating	-0.534***	-0.439***	-0.500***	-0.888***
	(0.052)	(0.110)	(0.053)	(0.087)
Bad loans/Loans	-0.027***	-0.027***	-0.029***	-0.036***
	(0.003)	(0.006)	(0.003)	(0.004)
Interbank/Assets	0.004*	0.012*	0.006**	0.010***
	(0.002)	(0.005)	(0.002)	(0.002)
Tier 1 capital	0.009***	0.013**	0.024***	0.015***
	(0.002)	(0.005)	(0.001)	(0.002)
Collateralization	0.024***	0.011***	0.023***	***
	(0.001)	(0.002)	(0.001)	
Firm assets	0.760***	0.937***	0.761***	0.929***
	(0.030)	(0.051)	(0.031)	(0.039)
Log-likelihood	-7557150.9	-4039593.7	-7825697.9	-5010810.3
Observations	5042664	2629670	5231134	3359951

Notes: All estimated equations include time dummies, firm sector-specific fixed effects, geographical area-specific fixed effects, bank-specific fixed effects. *, ** and *** denote statistical significance at 5, 1 and 0.1 per cent, respectively. Standard errors are two-way clustered at the firm sector-banks type level.

Appendix: Figures

Figure 1 Indicators on weak credit rationing in Italy: evidence from business and bank surveys.



Notes: The Istat's survey is the "Business confidence survey conducted in the manufacturing sector." The indicator refers to the net percentage of firms that reported to have received a lower-than-asked amount of credit. The Bank Lending Survey is conducted among banking groups. The indicator refers to the net percentage of banks that reported a tightening/easing of their terms and conditions via a change in the 'size of the loan or credit line' with respect to the previous quarters.

Figure 2 Representativeness of the sample: evolution of aggregate granted credit (in billions of euros)

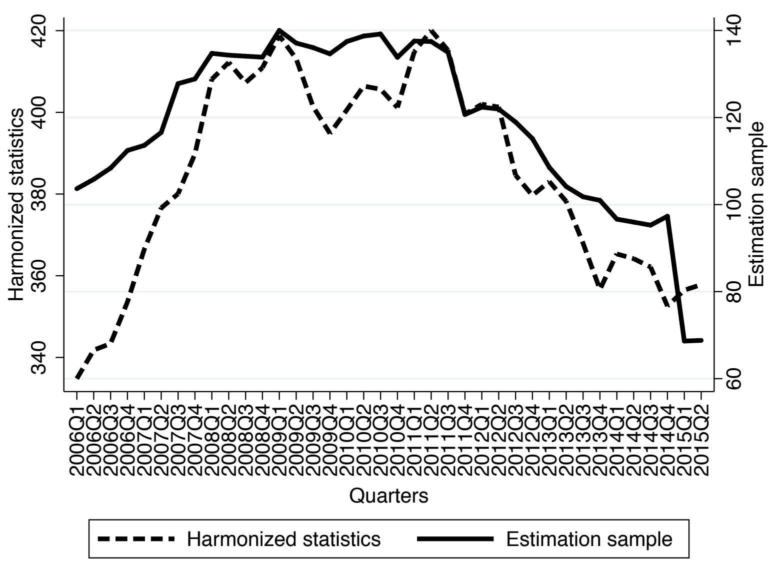
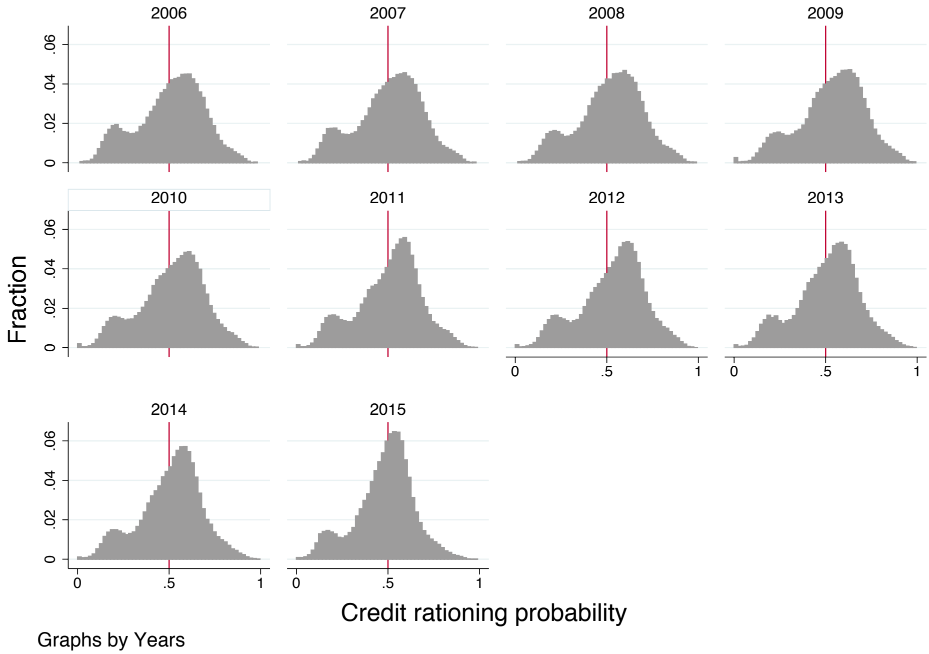


Figure 3 Distribution of match-level credit rationing probability $\hat{\pi}_{fbt}$ over time.



Notes: We report the distribution conditional on the first quarter of each year. The vertical line corresponds to $\hat{\pi}_{fbt}$ = 50%.

Figure 4 Evolution of aggregate predicted demand and aggregate predicted supply

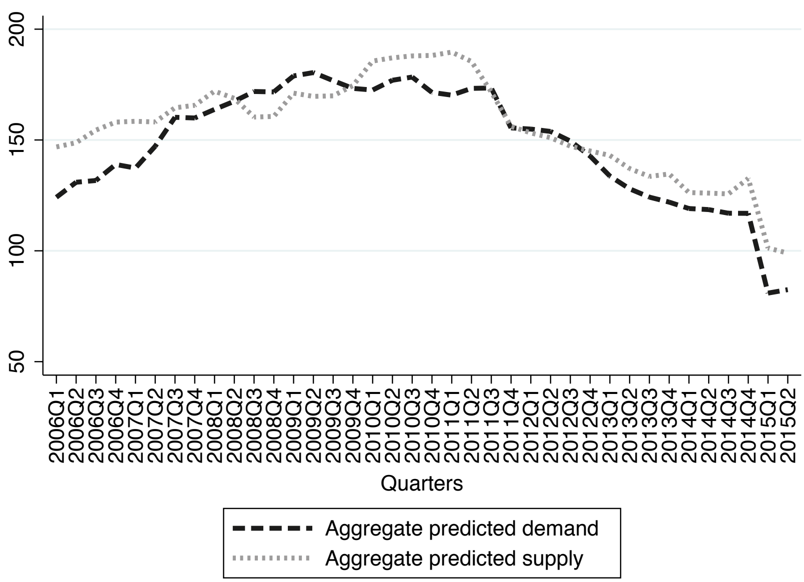
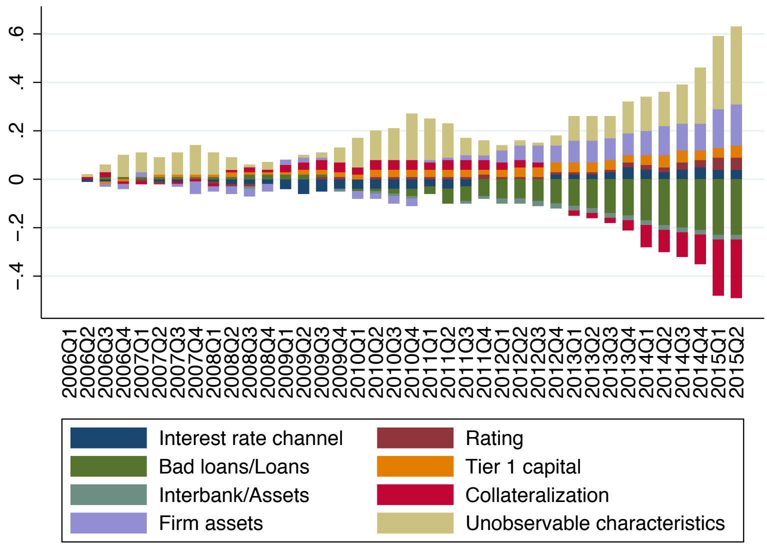
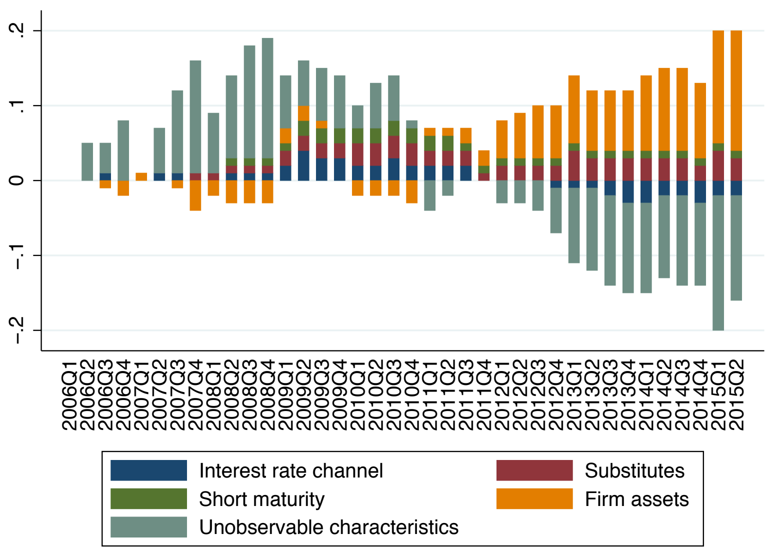


Figure 5 Decomposition of aggregate predicted supply.



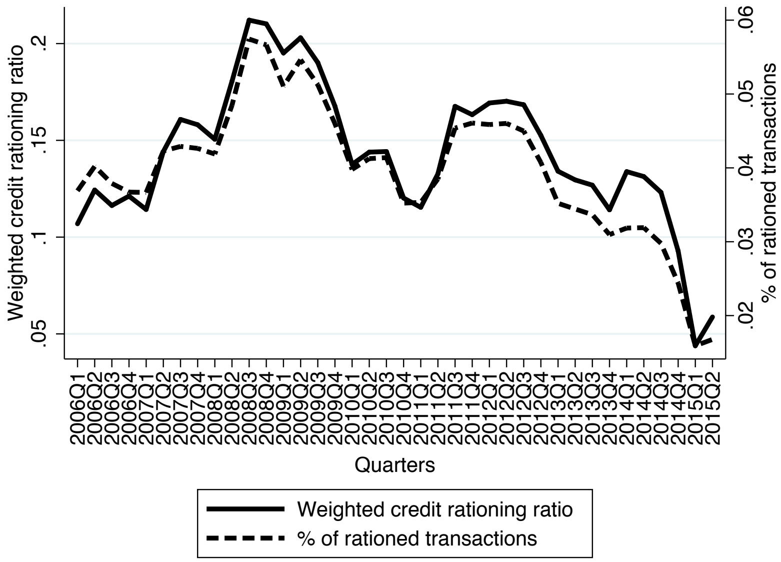
Notes: We report the estimated contribution of our observable and unobservable variables to the dynamics of the estimated aggregate supply. The "interest rate channel" includes the estimated effects of all observable variables that enter the loan margin equation. The 'unobservable characteristics' comprise the effects of all specific fixed effects included in the model.

Figure 6 Decomposition of aggregate predicted demand.



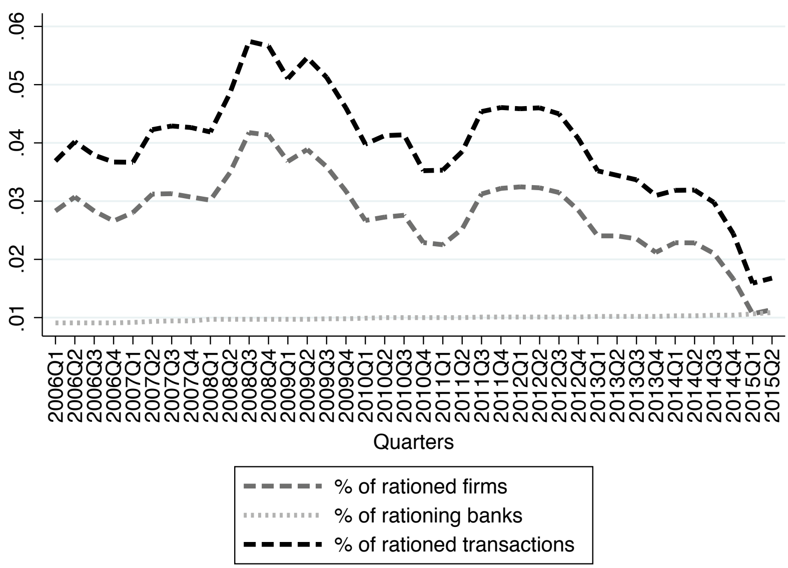
Notes: We report the estimated contribution of our observable and unobservable variables to the dynamics of the estimated aggregate demand. The 'interest rate channel' includes the estimated effects of all observable variables that enter the loan margin equation. The 'unobservable characteristics' comprise the effects of all specific fixed effects included in the model. The 'substitutes' comprise the effects of the firm-specific variables that are substitutes for bank lending, namely the ratio of cash-flow over total sales and the ratio of trade debt to total assets.

Figure 7 Evolution of the credit rationing indicators



Notes: We report on the left axis the indicator I_t^1, which measures the percentage of transactions in each period that have a predicted probability $\hat{\pi}_{bft}$ of being rationed above 80%. We report on the right axis the indicator I_t^2, which measures the amount of credit rationing as a percentage of aggregate demand. In the latter case each transaction-level excess demand, $\hat{l}^d_{bft} - \hat{l}^s_{bft}$, is weighted according to the predicted probability of being rationed.

Figure 8 Evolution of alternative credit rationing indicators.

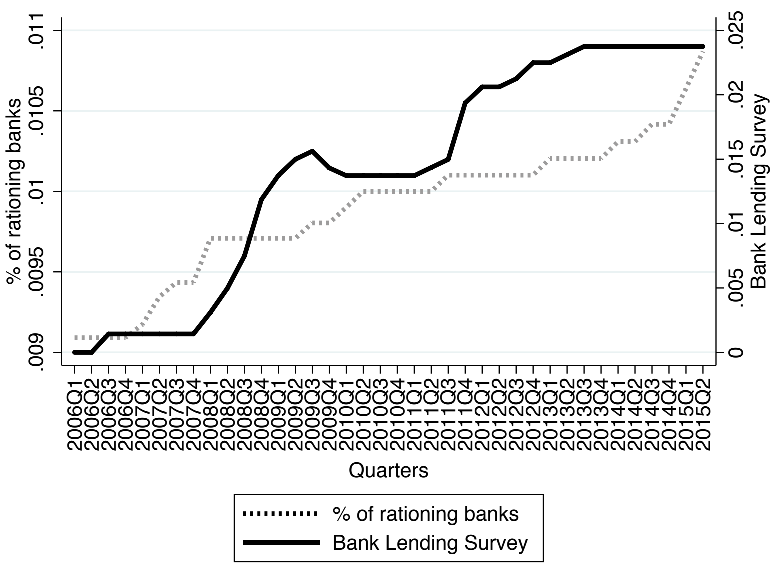


Notes: We report the percentage I_t^1 of rationed transactions (dashed black), the percentage I_t^{1F} of rationed firms (dashed blue), and the percentage I_t^{1B} of rationing banks (short-dashed red). We classify a firm as rationed if the weighted average across all its transactions of the probability $\hat{\pi}_{bft}$ of credit rationing is above 80%. We classify a bank as rationing in the same way.

Figure 9 Comparison between our firm-level credit rationing, $I_{t}^{1,F}$, and Istat's survey.

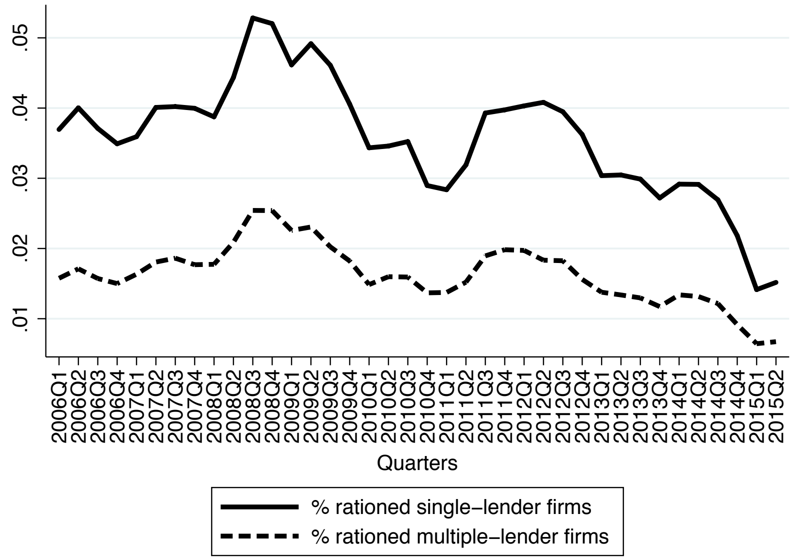
Notes: The Istat's survey is the "Business confidence survey conducted in the manufacturing sector." The indicator refers to the net percentage of firms that reported to have received a lower-than-asked amount of credit.

Figure 10 Comparison between our measure $I_{t}^{1,F}$ of bank-level credit rationing and the Bank Lending Survey



Notes: The Bank Lending Survey provides the net percentage of banks that report a tightening or easing of their terms and conditions by a change in the 'size of the loan or credit line' with respect to the previous quarters. For comparison purposes with our indicator in levels we take 2006Q1 as the base quarter and cumulate the net percentages.

Figure 11 Credit rationing indicators: single- versus multiple-lender firms



Notes: We report the percentage I_t^{1F} of rationed firms for the subsamples of single-lender and multiple-lender firms. Estimates are based on the benchmark model.

Discussion of "The quantity of corporate credit rationing with matched bank-firm data"

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The paper by Lorenzo Burlon, Davide Fantino, Andrea Nobili and Gabriele Sene is a well-crafted microeconometric study of potential disequilibria – in the form of credit rationing – in the Italian market for firm credit. It brings together a large matched bank-firm data set and classical econometric methods for disequilibrium analysis. These econometric methods have had their (first) heydays in the 1970s, with early contributions including Amemiya (1974), Fair and Jaffee (1972), Fair et al. (1974) and Maddala and Nelson (1974) (see also the discussions in Maddala, 1983, 1984).[1] This, of course, is not a coincidence. Prior to the period starting with the financial crisis in 2007 and lasting up to now, the 1970s were probably the last period were there was not only public and political but also *academic debate* of potentially large imbalances and (the importance of) disequilibria. It was the period of oil price shocks and stagflation then, and it is a period of unresolved financial sector issues, low growth and (too) low inflation now. In other words, even in econometrics, history repeats itself, but never twice in exactly the same way.[2] One aspect that is of course different today than in the 1970s is the availability of large and detailed data sets, as well as the software and hardware to estimate potentially complicated models with these large data sets.

The questions that the authors address are: Did Italian firms experience credit rationing in the period 2006 to 2015? And if so, to what extent did this credit rationing occur, and what were the factors behind it? The data to analyse these question comprise around five million observations stemming from the Italian Credit Register, the (confidential) supervisory reports of the Bank of Italy, and firm-level accounting information. The object of interest is the credit relationship between a bank and a firm characterised by credit-specific attributes, including, of course, quantity (the amount granted) and price/interest rate (the so-called 'loan margin'). The underlying data are at the transaction level and have been aggregated to the bank-firm relationship level and, with respect to the bank side, to the banking group level. Bank- and firm-specific characteristics are available, which are indispensable for identifying demand and supply separately.

1 A closely related strand of the literature focusing very much on the switching aspect of the disequilibrium problem is associated mainly with the name of Richard E. Quandt (e.g., Quandt, 1982).
2 In the words of Lord Byron, "History, with all her volumes vast, hath but one page".

The main bank (loan supply) characteristics include, among others, banks' liquidity positions as well as their capital ratios. The main firm (loan demand) characteristics are the ratio of cash flow to sales, the ratio of trade debt to total assets, a variable capturing the maturity structure of outstanding debt, and the firms' ratings. In addition to these core variables, a variety of other firm-, bank- and firm-bank-specific variables (such as collateralisation) are also included in the analysis, as are sectoral and regional dummies as well as certain fixed effects (which, as expected, capture a lot of the variation in the data). The authors take considerable care in thinking about their data and the potential problems.

An econometric analysis of disequilibrium situations is much more involved than an analysis of equilibrium situations, that is, situations where throughout the sample observed demand equals observed supply. When explicitly allowing for disequilibrium, *it is necessary to determine* for each observation whether it corresponds to supply or demand (with the typical assumption in the literature, as in this paper, that the observed quantity equals the minimum of supply and demand). Considering the minimum of two random quantities of course has a 'binary choice' flavour (Maddala and Nelson, 1974). The observations in both subsamples will in general have non-zero mean errors and regressors that are correlated with the errors, an effect that is very well-known from other situations in econometrics with truncation. Thus, even if one were to know which observations belong to which regime, least squares estimation on the subsamples would not be consistent. The literature provides ML estimation techniques for this type of problem.[3] As in standard discrete choice analysis, the probability that an observation corresponds to either demand or supply can be estimated by the econometric analysis, which in the present context allows for a probabilistic assessment of the likelihood, and thus the relevance, of credit rationing. For the Maddala and Nelson (1974) approach, one has to think carefully about how to include the endogenous price variable – in the current study, the interest rate – in the equation system. Burlon et al. try to avoid having to think too much about the endogeneity of the price by replacing the price variable in the demand and supply equations with the fitted values of regressing actual prices on all explanatory variables. It is not entirely clear to this reviewer why this is necessarily solving all the endogeneity problems associated with the simultaneous system. This is also an important aspect given that including the interest rate itself as regressor leads to both quantitatively as well as qualitatively different findings. It is also not clear exactly what is meant by the OLS and IV estimation of the demand and supply equations as discussed in the robustness section of the paper. But, of course, this is not an econometric theory paper but a paper on credit rationing, for which the authors – conditional upon the econometric analysis being sound – present interesting and relevant findings.[4]

3 For an early contribution, see Maddala and Nelson (1974), whose approach is briefly recapped in Appendix A of the paper.

4 The paper also contains a variety of robustness checks including different specifications, as well as different forms of so-called cluster-robust standard errors. Furthermore, the variation in the data is decomposed along several (dummy-variable) dimensions to gauge the importance of different mechanisms and channels (e.g., analysing separately firms that have multiple lenders and firms dependent upon a single lender).

So, what are the findings? First, the estimated supply and demand equations have coefficients with the expected signs according to theory. The interest rate elasticity of credit demand is quite large, with a one percentage point increase in the (predicted) interest rate reducing credit demand by about 30%. With the predicted interest rate variable, the supply curve is upward sloping. Section 5 of the paper addresses the question of how relevant a phenomenon credit rationing is. The fitted bank-firm specific probabilities that demand is larger than supply are calculated and, based on these probabilities, two indicators of credit rationing are defined. During the height of the financial crisis, it appears that about 5% of the credit transaction volume (and about 4% of firms) was subject to rationing, with a second peak occurring during the sovereign debt crisis around 2011. Since then, financing conditions have, by this yardstick, improved considerably. Thus, credit rationing appears to have been a relevant aspect during the financial crises over the last few years in Italy.

Applying appropriate econometric methodology to the increasingly available "universes of financial data" (here all credit transactions matched with other sources of information) that are collected by either central banks or financial supervisory authorities – as is done in this paper – allows for a deeper and more detailed understanding of the functioning of financial (here more specifically, credit) markets. This increased understanding in turn helps in assessing the effectiveness of the (different) channels of monetary policy. Understanding the differences of these mechanisms across Eurozone countries will help to better understand the effectiveness of monetary policy across the region. The new European Central Banking Network, with its conferences and publications, has become a key generator of this important knowledge.

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Credit misallocation before and after the crisis: A microeconometric analysis for Slovenia

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1 Introduction

The efficient allocation of credit is crucial for a normal functioning of the economy and for stable long-run output growth. This is especially important for bank-dependent economies such as Slovenia, where banking loans are the main source of financing for firms and a possible misallocation can therefore have severe negative macroeconomic consequences.

Financing less productive firms results in lower aggregate output and can also create problems in banks' balance sheets, which in turn, through limited supply of loans in times of financial distress, additionally amplifies the negative effect of inefficient credit allocation. Banks thus have an important role in selecting borrowers whose projects are valuable and contribute most to aggregate output. Optimal credit allocation is of course not possible, since banks cannot perfectly predict future profitability and productivity of each firm. In addition, given a limited supply of funds, they cannot reallocate assets to other more productive firms until a loan is repaid. Banks' decisions in selecting borrowers might, however, not always follow objective criteria such as profitability, productivity, indebtedness or collateral. State-owned banks might have an incentive to finance firms with political influence even when they have low productivity (Khwaja and Mian, 2005). The presence of foreign banks, on the other hand, is shown to improve credit allocation, since their decisions are not affected by ownership relations (Giannetti and Ongena, 2009; Taboada, 2011).

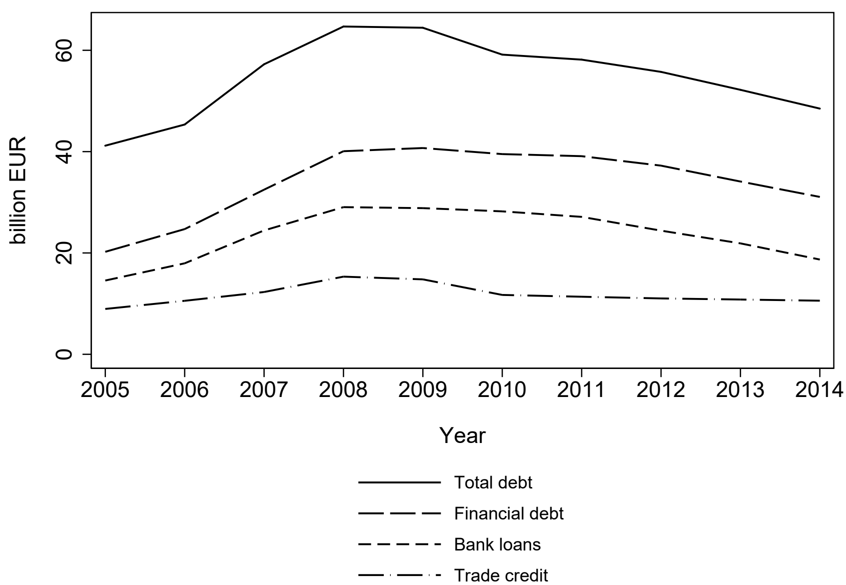
Slovenia is one of the European economies that suffered the most during the last crisis. After a deep recession with a 7.8% decline in real GDP in 2009 and a modest recovery in the following two years, the Slovenian economy entered a double dip recession in 2012. The prolonged effect of the financial crisis can be at least partially attributed to banks' inability to provide funds to the economy. Faced with huge credit losses that put pressure on their capital, banks severely tightened their credit standards and limited the supply of credit to the economy. This process was intensified by limited access to fresh funding and rising capital

1 The views expressed in this paper are the sole responsibility of the authors and should not be interpreted as reflecting the views of the Bank of Slovenia.

requirements due to an increasing share of non-performing loans (NPLs). For the corporate sector, which accounts for the large majority of all NPLs, the share of loans more than 90 days overdue exceeded 25% at its peak in 2013. There were, however, large differences across different groups of banks. Whereas the share of NPLs of state-owned banks reached 35% in 2013, it was only 13% for foreign-owned banks. Such a severe deterioration in banks' credit portfolios and differences between state- and foreign-owned banks can be largely attributed to adverse selection in the allocation of loans in the pre-crisis period.

These developments were heavily conditioned by the dynamics of credit before and after the crisis. Figure 1 shows that firms' debt increased by 57% (from €41 billion in 2005 to almost €65 billion in 2008) during the boom phase, and declined by 25% during recession (to €48 billion). Figure 1 also reveals that the main driver of the debt cycle was bank credit. For example, between 2005 and 2008 total financial liabilities increased from €20 billion to €40 billion, while bank loans increased from €14.5 billion to €29 billion. Furthermore, during the crisis total financial debt declined by €9 billion to €31 billion, while bank loans declined by €10 billion. Trade credit also exhibits cyclical behaviour, but accounts for much smaller part of total liabilities.

Figure 1 Aggregate dynamics of debt in Slovenian firms, 2005–2014

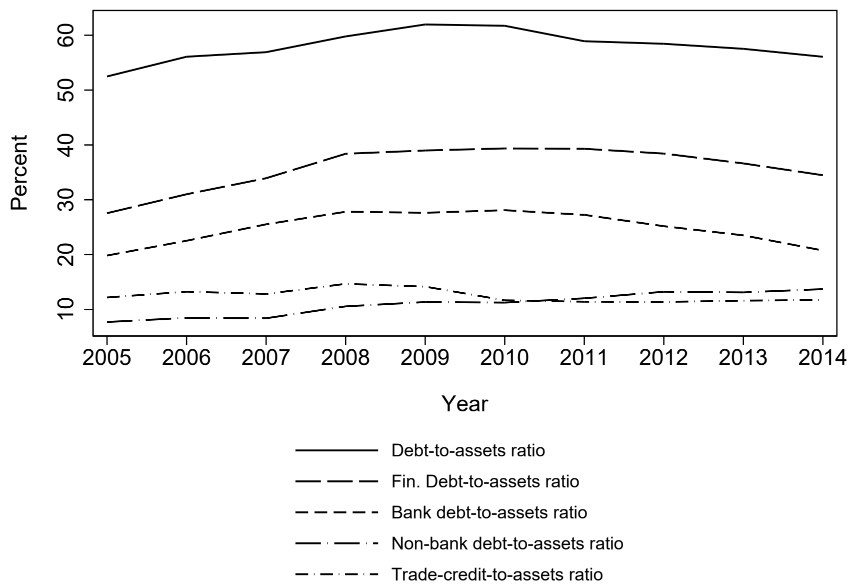


Note: Figure depicts ratio of total liabilities aggregate values of total assets, equity and total liabilities in current euros.

Source: AJPES and own calculations.

Rapid credit expansion was also reflected in the structure of firm financing. As seen in Figure 2, the process resulted in a marked increase in the share of debt in total assets before the crisis. After the outbreak of the crisis the process reversed, leaving trade credit as the only stable source of external finance after 2010. Finally, it is worth noting the maturity of debt as a very problematic feature of the Slovenian credit cycle – the share of short-term bank credit exceeded 50% of total bank credit outstanding in 2008. In the bust phase, short-term credit was quickly withdrawn and its share shrank by 15 percentage points by 2011.

Figure 2 Aggregate debt-to-assets ratios in Slovenian firms, 2005–2014



Notes: The ratios are calculated as specific categories of debt relative to total assets. Total debt consists of financial debt, trade credit and other types of debt. Financial debt comprises bank and non-bank debt.
Source: AJPES and own calculations.

In this paper, we study the quality of allocation of bank loans in Slovenia during the boom and bust phase of the economic cycle. Given the large amount of non-performing loans in banks' balance sheets, we can safely presume that credit allocation in the pre-crisis period was inefficient. Our main focus, therefore, is on whether the allocation of loans improved after the crisis. Our analysis consists of two parts. First, we evaluate misallocation of assets and loans using a static Olley-Pakes decomposition applied to return on assets (ROA). This gives us an insight into the differences in credit allocation over time as well as between groups of banks. Second, we perform an econometric analysis in which we model the participation decision to borrow/lend and the decision on loan amount. Our basic analysis is performed at the level of individual firms, which gives an answer about the responsiveness of both the probability of being granted a loan and of the loan amount itself to key firm characteristics, such as profitability and indebtedness. In addition, we exploit the data from the credit registry provided by the Bank of Slovenia to perform the analysis at a more disaggregated firm-bank level. The main advantage of this is that it allows us to study the effects of bank characteristics, such as capitalisation and the quality of credit portfolio, on loan-granting policy.

Our results confirm that credit allocation in the pre-crisis period was indeed inefficient. More surprisingly, we find that it may have become even more inefficient in the time of financial distress. The aggregate static decomposition returns negative covariance values for banking loans for all years in our sample (2006-2014). This is an indication that credit allocation was not efficient. In addition, we find that the allocation of banking loans was less efficient than the allocation of other assets. The econometric analysis shows very low responsiveness of probability of having a loan and log loan amount to firm-level measures. These effects dropped further during the crisis period, which signals that the allocation of loans might have deteriorated. The firm-bank level analysis shows that bank characteristics – among which we include capital adequacy, share of non-performing loans and ROA – do not play a significant role in loan allocation. We find some differences, however, between the credit allocation of foreign-owned and state-owned banks. The latter seem to grant loans least selectively, as the models estimated only on this group of banks show no responsiveness to some key performance measures such as ROA. This result is confirmed by aggregate decomposition, which shows the lowest covariance for loans granted by state-owned banks in all periods.

The financial crisis is in general expected to lead the economy towards a more sustainable path with lower risk appetite and moral hazard. Our results, however, show quite the opposite. Once the crisis hit, the aggregate amount of loans to firms in Slovenia began to contract rapidly and persistently. Our analysis shows that this contraction was selective in a negative way – it was done on better-performing borrowers. Looking from the bank perspective, this indeed might be the case as they could not contract loans to borrowers that did not repay their debt. Being exposed to large amounts of bad loans, as is the case in Slovenia, banks are stuck with these non-performing loans unless they write them off. To a large extent, therefore, the deleveraging can only take place on performing borrowers, and consequently the credit allocation worsens. Our analysis, by focusing only on surviving firms, excludes a large majority of firms that are shown to be non-performing in banks' portfolios. We still find, however, that the allocation deteriorated in the crisis period. We also find that it deteriorated for newly granted loans, which are not influenced by pre-crisis lending decisions by banks.

The rest of the paper is organised as follows. In Section 2 we review the literature most relevant to our paper. Section 3 presents some aggregate statistics and results of aggregate covariance decomposition, while Section 4 shows the results of the firm- and firm-bank-level econometric analysis. Finally, Section 5 concludes.

2 Literature review

The motivation for our comparative study of credit allocation before and during the financial crisis is rooted in the existing literature, which shows that the behaviour of banks changes when they are affected by a crisis. One of the reasons for changed lending behaviour might be increased macroeconomic uncertainty. Quagliariello (2009) shows that banks reduce their investments in loans relative to risk-free assets during such periods, which also leads to a reduction of funds available to bank-dependent borrowers. Similarly, Dell'Ariccia et al. (2008) show that the sectors that are more dependent on external financing perform significantly worse during a banking crisis, when compared to the sectors that are less dependent on credit. Also, Chava and Purnanadam (2011) find firms that primarily rely on bank financing to be significantly more affected by a negative credit supply shock. Fernandez et al. (2013) show there are two negative effects of a banking crisis on economic growth. In addition to lower credit supply, they also find an important contribution stemming from the asset allocation effect, which results in lower investment in intangible assets. Finally, Coricelli and Frigerio (2015) find that in creditless recoveries, there is a significant reallocation of resources away from sectors that are more dependent on credit. They conclude that creditless recoveries do not just reflect the deleveraging process, but can also result in misallocation of resources as credit-dependent firms might also be the more productive firms. This negative effect is somewhat softened in sectors that have access to alternative sources of funding, such as trade credit, or have larger amounts of collateral, which allows them easier access to funding. Summarising this literature, we can conclude that it is not surprising that during banking crises, output losses tend to be larger and take more time to recover (Babecky et al., 2014; Claessens et al., 2009).

During a banking crisis, some reallocation of credit would be desirable from a macroeconomic perspective as it could result in a higher aggregate output. However, as discussed by Herrera et al. (2011), the reallocation of financial resources might be significantly hindered by credit market frictions. Hovakimian (2011) provides evidence that in response to frictions in external capital markets, firms improve the efficiency in allocation of internal funds by investing them in more productive segments of production. Although firms are forced to cancel some possibly profitable investment projects due to unavailability of external financing, the financing constraint has a positive effect by improving the allocation of internal funds. A better allocation of internal funds relative to loans is also what emerges from our analysis. In a related study, Gerlach-Kristen et al. (2015) analyse the effects of credit constraints on employment on a sample of small and medium-sized enterprises. Distinguishing between credit rationing of banks and discouragement of borrowers, the authors find that the latter is the main driver of the overall negative effect. Firms' unwillingness to apply for a loan thus has a significant negative effect on employment. Moreover, Han et al. (2009) show that discouragement is an efficient self-rationing mechanism, as riskier borrowers tend to be more discouraged from applying for a loan. A similar result is found by Brown et al. (2011), who show that small and financially opaque firms are less likely to apply for a loan.

Another strand of literature focuses on incentives of banks to extend credit to firms in a poor financial condition. Peek and Rosengren (2005) study perverse incentives of Japanese banks in allocating credit. They find that firms are more likely to receive credit if they are in a poor financial condition. By refinancing financially weak borrowers, banks avoid recognising losses in their balance sheets. Cutting the financing would likely make these firms unable to regularly repay their credit obligation or even go bankrupt, which would require banks to cover the losses. The authors find this effect to be significantly more pronounced among banks with lower capital adequacy. Similarly, Brezigar-Masten et al. (2015) report that in the case of Slovenia during the recent crisis, banks with lower capital and a higher burden of non-performing loans applied systematically laxer standards in credit-risk assessment. This process, however, is not possible without the allowance of government and the regulators . Peek and Rosengren (2005) discuss how government might have the same incentive and may even encourage banks to continue their forbearance policy in order to avoid massive firm, and possibly even bank, failures. Brown and Dinc (2011) show that regulatory forbearance policy is usually applied when the banking sector is weak, and especially for larger banks whose failure would have larger negative consequences. Evidence of banks' adverse selection is also provided by Iosifidi and Kokas (2015), who find banks with a higher level of credit risk and lower capital adequacy to be associated with riskier firms.

More generally, efficiency of government ownership of banks has been the focus of many studies. These typically show that both allocation of credit and performance of such banks are worse than that of non-government-owned banks. Analysing political influence in state-owned banks, Dinc (2005) finds that these banks increase lending in election years relative to private banks. Sapienza (2004) finds that state-owned banks charge lower interest rates in areas where the leading political party has stronger power. Similarly, Khwaja and Mian (2005) show that government-owned banks exhibit preferential treatment of firms with political influence even though they have a significantly higher default rate, while Ying and Yuande (2013) find political connections to be a violation factor in the debt market, since loans are not allocated based on firms' performance. In spite of such poor performance of government-owned banks, Taboada (2011) finds even worse allocation of credit by the banks owned by domestic blockholders. These banks were shown to allocate a large portion of loans to private firms that are also controlled by the same blockholders, even though they are less productive and inefficient. In contrast to domestic ownership, foreign ownership of banks is shown to result in more efficient credit allocation. Giannetti and Ongena (2009) show that foreign bank ownership stimulates growth in firm sales and assets and results in more efficient capital allocation. In contrast to domestically owned banks, foreign-owned banks are more inclined to find profitable projects since their decisions are not influenced by political or other ownership relations. Taboada (2011) also finds that the presence of foreign owned banks increases lending to more productive industries. Brown et al. (2011) provide evidence that foreign banks are more likely to reject loans to small and government-owned firms.

3 Aggregate allocation of bank loans in Slovenia

As described above, Slovenia experienced a classic boom-bust credit cycle in the 2004-2013 period. In this section, we take a closer look at the allocation of bank credit in the process.

In a classical mean-variance framework, optimal allocation of assets should be made according to expected returns and the variance-covariance structure of these returns. In contrast to this more general approach, we focus here on drivers of dynamic returns and leave aside uncertainty, which implicitly assumes that the objective function pursued by allocators of assets considers only expected returns.

From the point of view of the economy as a whole, we can define the aggregate return on assets in analogy to the definition of portfolio return – as a weighted average of individual firms' returns:

$$r_t = \sum_{i=1}^{N_t} r_{it} \frac{A_{it}}{A_t} = \sum_{i=1}^{N_t} r_{it}\, \omega_{it} \tag{1}$$

where A_{it} and A_t denote the firm and aggregate values of assets invested at the beginning of period *t*, respectively. ω_{it} is thus the share of assets invested in firm *i* and r_{it} is its return on total assets generated during the entire period *t*. N_t denotes the number of all active firms in period *t*, which we restrict to those with positive value of assets and non-missing values for operating income in that year.[2] Following Olley and Pakes (1996), who use this decomposition for analysis of aggregate productivity dynamics, we can split the aggregate rate of return on assets into the unweighted average return on assets and the covariance between shares of asset values and rates of return:

$$r_t = \frac{1}{N_t}\sum_{i=1}^{N_t} r_{it} + \sum_{i=1}^{N_t}\left(\omega_{it} - \frac{1}{N_t}\right)\left(r_{it} - \frac{1}{N_t}\sum_{i=1}^{N_t} r_{it}\right) = \bar{r}_t + cov_t \tag{2}$$

Note that subtraction of the mean share does not change the expression and can be omitted. Also note that the definition of covariance between rates of return and share of allocated assets does not entail division by the number of firms, as this is already done in the calculation of asset shares. From this decomposition it is evident that higher covariance between firm-level asset shares and rates of return also implies a higher aggregate rate of return. In this static setting, the optimal allocation of assets is such that it maximises the aggregate rate of return, which for a given marginal distribution of rates of return can be achieved by allocating assets in a way that maximises the covariance term.[3]

The covariance depends on the allocation of different sources of capital, among which the most important ones are debt (bank loans, bonds, trade credit) and equity. Our main interest lies in understanding allocation of bank loans, which represent an important part of aggregate assets. Hence we shall distinguish between bank loans and all other assets, although this decomposition can be applied for an arbitrary number of sources of financing (or capital). The share of assets allocated to firm *i* can thus be expressed as a weighted average of source-specific shares with aggregate shares of assets as weights:

$$\omega_{it}^{L} = \frac{L_{it}}{L_t} \tag{3}$$

2 Note that alternatively we could define the aggregate operating income, which would simply yield the product of aggregate assets and weighted average ROA. The key expressions for static decompositions for aggregate operating income will be valid if we simply pre-multiply the decompositions for ROAs by the aggregate value of assets.

3 This and the ensuing decompositions take the marginal rates of return of firms as given. For a given distribution of returns the optimal allocation would have all the assets allocated to the most profitable firm(s). However, the optimal allocation of assets should take into account varying rates of return with the amount of assets engaged in firms' operations. As these typically decline with the amount of assets due, for example, to declining demand with prices or declining marginal productivity of capital, the optimal allocation should equate the marginal rates of return, in which case it would appear that the covariance term is equal to zero after all inter-firm reallocations of assets take place. Nevertheless, assets would be allocated according to differences in parameters that relate rates of return to the amount of assets. Specifically, if firms were to differ in one parameter such as productivity, but otherwise share the diminishing returns to scale technology, assets would be proportional to productivity after all reallocations take place.

where $\omega_{it}^{L} = \frac{L_{it}}{L_t}$ and $\omega_{it}^{O} = \frac{A_{it}-L_{it}}{A_t-L_t}$

denote the shares of loans and other sources of assets received by a firm, respectively, and d_t is the aggregate share of bank loans in total assets. Using this relationship, we can rewrite the expression for aggregate ROA given in (2) as:

$$cov_t^L = \sum_{i=1}^{B_t} \omega_t^b \, cov_t^b = \overline{cov}_t^{ba} + \tag{4}$$

Thus the aggregate ROA is a sum of the unweighted ROA and the weighted average of covariance terms for the two sources of capital, with corresponding weights equal to the shares of specific sources of capital.[4] We can also split the covariance for loans analogously to distinguish between allocation of credit by different banks:

$$cov_t^L = \sum_{i=1}^{B_t} \omega_t^b \, cov_t^b = \overline{cov}_t^{ba} + cov_t^{ba} \tag{5}$$

where ω_t^b is the share of loans provided by bank b in aggregate loans granted by all banks and cov_t^b is a bank-specific covariance term and B_t denotes the number of active banks in the period. This weighted sum is split into two terms:

$$cov_t^{ba} = \sum_{b=1}^{B_t} (\omega_t^b - 1/B_t)(cov_t^b - \overline{cov}_t^{ba}) \, ,$$

which is the unweighted average of bank-level covariance terms, and

$$cov_t^{ba} = \sum_{b=1}^{B_t} (\omega_t^b - 1/B_t)(cov_t^b - \overline{cov}_t^{ba}) \, ,$$

which captures the covariance term for allocation of credit by different banks. Allocation can thus be improved by increasing the unweighted covariance and by increasing the covariance between shares of loans given by banks and their intra-bank covariances between loan shares and the ROA of firms.

Let us now turn to results of the decomposition of aggregate ROA for all active Slovenian firms.[5] In the empirical analysis we combine three datasets. The first source of data is the Agency of the Republic of Slovenia for Public Legal Records and Related Services (AJPES), to which firms report balance sheet and income statement data on an annual basis. This is our primary source of data on bank loans, as the amounts include both domestic and foreign sources of credit and it is not subject to censoring. From this source we also extract information on firms' annual sales from main operations, costs of materials and services, operating income, revenues from financial operations, depreciation and write-offs for both

4 Note that allocating more resources to firms in the form of bank loans increases the aggregate rate of return only if the covariance between firm-level bank-loan shares and rates of return is higher than the covariance between shares for all other assets.

5 Some differences may also arise following the transfer of a portion of non-performing loans to the Bank Assets Management Company (BAMC) from four banks, which was carried out at the end of 2013 and in the second half of 2014. After the date of transfer, these loans are no longer recorded in the credit registry but are still present in firms' balance sheets. However, given that a large majority of transferred loans were to firms in bankruptcy that typically do not report their balance sheet data to AJPES, and that we additionally limit the sample of firms, the difference arising from this source is rather small.

physical capital and other real and financial investments, and revenues and costs not generated in main and financial operations, total assets, total debt, and value of pledgeable assets.

The second source of data is the credit registry of the Bank of Slovenia. This registry contains additional information on bank loans. Whereas the AJPES data include all banking loans from domestic as well as foreign banks, the credit registry is in general intended for supervisory purposes and thus includes only loans granted by domestic banks. Additionally, unlike the AJPES data, it excludes all loans below €1,000, which is the threshold for reporting data to the credit register. The third source of data is the Bank of Slovenia, which provided the data on bank characteristics (capital adequacy ratios, non-performing loans and bank ROA).

As firms in many industries engaged in various financial activities that generated incomes or financial losses, including industries that traditionally focus on operations such as manufacturing and retail trade, we use a definition of net income that includes not only net operating income, but also revenues from financing such as dividends for ownership shares and interest from loans given to other businesses, write-offs of financial assets, and net irregular revenues.[6] The denominator for calculation of rate of return is the unweighted average of assets at the beginning and end of the period *t* for which we calculate ROA.

Table 1 shows the components of the static Olley-Pakes decomposition (equation 1) for a sample of Slovenian firms that are used in the subsequent empirical analysis. The sample of firms is restricted in order to be able to calculate the rate of return on assets. We require that a firm has positive assets and value added and does not have an absolute value of ROA greater than 0.5, an EBITDA-to-debt ratio lower than 100, or a debt-to-asset ratio lower than 1.2. These restrictions are important to avoid the results in estimation of behavioural equation being driven by outliers.[7] As described above, the static Olley-Pakes decomposition splits the weighted average (column 1) into the unweighted average ROA (column 2) and the covariance between shares of assets and ROAs (column 3). The unweighted ROA exceeds the weighted ROA in most years, which results in a negative covariance term. However, in the pre-crisis period (2006–2007) and the period 2012–2014 the covariance term was significantly lower. This suggests that allocation of resources was less efficient in those periods. The last two columns of Table 1 contain the covariance between bank-loan shares and ROAs (column 4) and the share of bank loans in total assets (column 5). The covariance term for bank loans was significantly lower than that for all assets, which suggests that bank loan allocation was less efficient than allocation of other assets. This finding holds for all years of our sample. During the period 2012–2014 the covariance term is more negative again, which suggests a worsening of bank-loan allocation efficiency.

6 We exclude government subsidies from this measure of net income; the inclusion of government/EU subsidies in net income does not change our qualitative results.

7 Note that these restrictions affect the observed components of decompositions. We observe a general pattern of the covariance terms tending to be lower if the lower bound for firm activity is increased – if we focus only on firms with sufficiently high value added, the covariance term will generally be negative. However, the qualitative features of observed patterns over time and across banks are not sensitive to the definition of an active firm.

Table 1 Static Olley-Pakes (1996) decomposition of aggregate ROA, 2006-2014

Year	Number of firms	All assets			Bank loans	
		(1) = (2) + (3)	(2)	(3)	(4)	(5)
		Weighted (r_t)	Unweighted ($\bar{r}_t$)	Covariance (cov_t)	Covariance (cov_t^L)	Share (d_t)
2006	24,969	6.33	7.54	-1.21	-2.43	20.68
2007	26,328	7.37	10.36	-2.99	-3.93	21.82
2008	27,099	6.06	7.86	-1.81	-2.27	24.68
2009	28,061	3.32	3.54	-0.22	-1.34	27.19
2010	29,397	3.47	4.19	-0.72	-1.67	27.14
2011	29,847	3.70	3.08	0.62	-0.36	28.06
2012	30,305	3.37	4.51	-1.14	-2.62	26.98
2013	30,997	2.57	4.84	-2.27	-4.71	25.00
2014	32,129	3.99	6.04	-2.04	-5.15	23.06

Notes: The ratios are calculated as specific categories of debt relative to total assets. Total debt consists of financial debt, trade credit and other types of debt. Financial debt comprises bank and non-bank debt.

Source: AJPES and own calculations.

Next we look at the quality of allocation of loans using disaggregated data on bank loans. These allow us to differentiate according to bank ownership and bank size. In particular, we compare the covariance terms for state-owned and privately-owned banks, foreign-owned and domestically owned banks, and banks of different size (based on market share of total bank loans to firms). The criterion for a large bank is at least 5% market share in this market segment. We report only covariance terms for one of these three pairs of banks, as we can infer whether the covariances for the omitted groups are higher or lower than those for the reported groups by comparison to the overall covariance Cov_t^L. From Table 2 we can see that the dynamics of the covariance terms are similar for all groups of banks, but with important differences across the different groups of banks. The covariance terms for state-owned banks tend to be lower than those for private banks, which suggests that the former performed significantly worse in allocating resources. Significantly better allocation of resources is also observed for foreign banks in comparison to their domestic counterparts. The differences between large and small banks seem to be rather small. Note that Table 2 also reports the shares of bank loans for selected groups of banks. These show that the market shares of bank loans from state-owned, large and domestic banks declined non-monotonically over time, which led to an improvement in the covariance between shares of loans of banks and covariances (column 9). This suggests that increasing the share of foreign banks and reducing the number of state-owned banks leads to an improvement in the allocation of bank loans.

Table 2 Bank-level decomposition of covariance for domestic bank loans, 2006-2014

	Group of banks								
	State-owned		Foreign-owned		Large		All domestic	Bank-level decomposition	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year	Cov_t	Share	Cov_t	Share	Cov_t	Share	Cov_t^L	$\overline{Cov}_t^{ba}$	Cov_t^{ba}
2007	-2.10	61.01	-1.77	34.23	-2.01	71.04	-2.00	-1.59	-0.41
2008	-2.41	58.68	-1.27	35.86	-2.13	68.75	-1.98	-1.75	-0.24
2009	-1.03	57.48	-0.67	38.09	-0.98	65.03	-0.89	-0.76	-0.12
2010	-1.62	58.78	-0.12	36.45	-1.31	63.27	-1.18	-0.75	-0.41
2011	-1.53	59.35	-0.02	34.57	-1.31	63.02	-1.19	-0.75	-0.45
2012	-2.68	58.68	-0.95	34.81	-2.20	62.74	-2.23	-1.96	-0.28
2013	-5.05	57.94	-2.15	34.76	-3.95	61.28	-4.31	-3.92	-0.44
2014	-2.52	54.64	-1.73	38.29	-2.26	58.14	-2.42	-2.45	-0.06

Notes: The sample of firms consists of all those with positive assets in periods *t*-1, positive value added in period *t*, an absolute value of ROA lower than 50%, and a debt-to-assets ratio in period *t*-1 lower than 1.2. ROA is defined as the ratio between operating income and the unweighted mean of firms' assets in periods *t*-1. Operating income is the sum of operating profit, revenues from financing and irregular revenues, and subtracting financial write-offs and irregular expenses.

Source: AJPES and own calculations.

4 Econometric analysis of credit allocation

The decomposition of the aggregate return on assets in the previous section reveals that the allocation of bank loans contributed negatively to the return on assets before the crisis. Moreover, after an initial improvement at the onset of the crisis, the subsequent crisis years witnessed a further deterioration of the allocative efficiency of bank loans. State-owned banks contributed disproportionately to these dynamics. This section investigates the loan allocation process by means of an econometric analysis.

In order to test whether granting policies of banks did in fact change after the onset of crisis, we estimate two sets of empirical models. The first set of estimations is made at the level of individual firms, where we do not discriminate between loans granted by different banks, whereas the second set of estimations is done at the bank-firm level. The empirical models at the firm level allow us to compare whether banks changed their responsiveness in granting loans to a set of measures of return, risk and collateral after the onset of financial crisis in 2009. The empirical models at the firm-bank level allow us to investigate whether, in addition to firm-level characteristics, bank characteristics also had some influence on loan-granting policies during the crisis in comparison to the pre-crisis period.

4.1 Summary statistics

Before we turn to the empirical analysis, we provide some key summary statistics for the sets of dependent and explanatory variables for the firm- and bank-level analysis.

At the firm level, we model two decisions made jointly by the banks and firms: (i) the participation decision (whether to lend/borrow), and (ii) the decision on the amount of the loan. The dependent variable for the loan participation decision is an indicator variable that assumes a value of 1 if firm *i* had a positive value of bank loans at the end of period *t* and 0 otherwise. The dependent variable for the decision on the amount of loan is the log transformed value of total loans given in current euro prices. Thus, for the participation decision we model the conditional probability that firm *i* has a banking loan in period *t* ($\Pr[\mathrm{Loan}_{it} > 0|x]$), while for the decision on the amount of loan we model conditional expectation ($E[\mathrm{Log\ Loan}_{it} \mid \mathrm{Log\ Loan}_{i,t-1} > 0, x_{i,t-1}]$). In the empirical modelling, we relate these two dependent variables to a set of variables (denoted $x_{i,t-1}$ in the above expressions) that banks should/might use in order to select between firms with different returns and risks. Our measure of profitability is the rate of return on assets, which is calculated as the ratio between pre-tax net operating income in period *t* and total assets at the beginning of that period. Our definition of net operating income includes not only net income from main operations, but also revenues and losses generated from financial investments and net incomes from irregular events. This definition allows us to appropriately capture total returns and risks related to firms' operations.[8] We also include a measure of risk, the

8 Our sample eliminates many companies without positive value added that were involved in takeovers of large corporations, as we are unable to calculate rates of return (and other variables) for the periods before granting loans. These takeovers represent a significant part of non-performing loans that were reflected in write offs of financial investments. At the peak in 2008 loans to companies with non-positive value added amounted to almost €4.32 billion (out of total €29.02 billion) and excluding such companies might reduce observed improvement in bank lending policies.

standard deviation of ROA, which is calculated using the last five observations.[9] In addition to this measure, we use the Sharpe ratio, which is calculated as the ratio between the mean ROA over the last five periods and the standard deviation. In addition to these measures of risk and return, our empirical model also includes lagged loans for dynamic specification for continuing borrowers; lagged value of assets and sales as measures of firm size; the ratio of pledgeable assets to total assets (collateral); the EBITDA-to-debt ratio, which reflects the ability of firm to service debt; and the debt-to-assets ratio, a measure of total indebtedness that includes not only bank loans but also other types of loans such as trade credit.

Let us now focus on the summary statistics for these variables (reported in Table 3) and compare them in the pre-crisis and crisis periods, and also separately for firms with and without prior bank loans. Evidently, both the likelihood of having a bank loan and the loan value declined significantly for firms without prior loans, but only modestly for firms with prior loans. In particular, the share of firms with bank loans declined from 11.6% in the pre-crisis period to roughly 8%, whereas the measure of persistence of loans remained at 88% in both periods. Similarly, the average total value of bank loans declined by almost 75% for firms without prior bank loans, but by only 7% for firms with prior loans. At the same time, we also observe that indicators of firm performance change significantly. Average ROA declined and its standard deviation increased during the crisis for both groups of firms, although firms without prior loans experienced smaller absolute changes. The average Sharpe ratio was higher for firms without prior bank loans than for those with prior bank loans, which suggests that the latter have higher returns for a given risk. During the crisis both groups of firms exhibited comparable increases in this ratio.[10] At the same time, the values of assets for both groups of firms increased, while sales increased only for firms without prior bank loans. The share of pledgeable assets was significantly higher for firms with prior loans and increased further for these firms, whereas for prior non-borrowers this ratio decreased. The EBITDA-to-debt and debt-to-assets ratios were significantly lower for firms without prior debt, but appear to have improved for both groups of firms.

9 This restriction reduces the sample of firms to those surviving at least 6 years to be included in the sample.

10 Note that calculation of the Sharpe ratio requires at least six consequtive data points (current and five lags), which reduces the sample significantly in favour of better-performing firms.

Table 3 Summary statistics for firm-level analysis, 2006-2014

	Sample of firms							
	$Loans_{i,t-1} = 0$				$Loans_{i,t-1} > 0$			
	Pre-crisis		Crisis		Pre-crisis		Crisis	
Variable	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.
D [$Loans_{it}$>0]	11.61	32.03	7.96	27.07	88.49	31.91	88.35	32.08
Log $Loans_{it}$	9.91	2.24	9.16	2.71	11.47	2.18	11.40	2.24
$ROA_{i,t-1}$	9.58	11.02	8.06	10.41	8.80	8.91	6.51	7.71
Std. dev. $(ROA)_{i,t-1}$	15.86	265.56	25.86	761.66	16.36	344.72	31.51	1504.01
Sharpe $ratio_{i,t-1}$	1.42	1.17	1.62	1.43	1.88	1.50	2.12	1.83
Log $Loans_{i,t-1}$					11.13	2.24	11.21	2.35
Log $Assets_{i,t-1}$	11.44	1.62	11.58	1.64	13.12	1.72	13.16	1.72
Log $Sales_{i,t-1}$	11.68	1.70	11.74	1.71	13.19	1.72	13.09	1.72
$Collateral_{i,t-1}$	29.06	27.42	26.88	27.8	43.49	27.04	44.37	28.53
EBITDA-to-debt $ratio_{i,t-1}$	0.71	3.64	0.65	3.53	0.25	0.64	0.21	0.99
Debt-to-assets $ratio_{i,t-1}$	52.64	49.93	49.44	50.00	78.42	41.14	75.27	43.14

Notes: D[Loans>0] denotes an indicator variable that assumes value 1 if firm has loan at the end of period t and 0 otherwise. Collateral is defined as the share of pledgeable assets (physical capital, real and financial investments) in total assets. EBITDA-to-debt ratio is defined as the ratio between earnings before interest, taxes and depreciation and total debt of firm. The variables D[Loans>0], ROA, Std. dev. (ROA), Collateral and Debt-to-assets ratio are given in percent. The values of loans, assets and sales are given in current-price euros. All explanatory variables are predetermined (calculated for the period *t*-1).

Source: AJPES and own calculations.

As mentioned above, the second part of our empirical analysis relies on disaggregated firm-bank-level data. These data allow us to answer the following two questions: Do bank ownership and size have any influence on the probability of getting a loan and on the loan amount? And do bank performance measures affect credit allocation? To address the first question, we follow the prior analysis and compare the credit allocation patterns between state-, private- and foreign-owned banks and banks of different size. To address the second question, we use a measure of capital adequacy, which signals banks' incentives for taking risk. We use a leverage ratio defined as the share of capital in total assets. The second measure is the share of non-performing loans, which is used in many empirical studies as a determinant of loan allocation (e.g., Iosifidi and Kokas, 2015). For this measure, we use a combined share of C-, D- and E-rated borrowers as the standard measure, based on the value of loans that are 90-days overdue (only available from 2007 onwards). The third measure that we include is profitability, measured by ROA.

The summary statistics at the level of firm-bank observation are given in Table 4. It is evident that during the crisis the shares pertaining to ownership remained unchanged. More interestingly, the capital adequacy ratio deteriorated only marginally across the entire banking system. This is partly due to large recapitalisations of banks in 2013 and 2014, which significantly increased capital ratios in the otherwise poorly performing state-owned banks. The share of non-performing loans (NPLs) surged from around 3% in the pre-crisis period to more than 8% during the crisis period. These high levels of NPLs are reflected in the deterioration of profitability of banks during the crisis. The last two variables in the table are the dependent variables at the firm-bank level. The average share of firm-bank pairs with positive bank loans while having had no bank loans in the prior period declined from 0.48% to 0.32%, whereas the average share for the prior borrowers increased from 5.2% to 5.4%. This confirms the differential patterns of bank granting policy between prior bank borrowers and non-borrowers. Similar dynamics are observed for the average value of loans of firms to individual banks.

Table 4 Summary statistics for firm-bank-level analysis, 2006-2014

	Sample of observations							
	$Loans_{i,t\text{-}1} = 0$				$Loans_{i,t\text{-}1} > 0$			
	Pre-crisis		Crisis		Pre-crisis		Crisis	
Variable	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.
Foreign own. [%]	41.67	49.30	41.67	49.30	41.67	49.30	41.67	49.30
State own. [%]	25.00	43.30	25.00	43.30	25.00	43.30	25.00	43.30
Large [%]	25.00	43.30	25.00	43.30	25.00	43.30	25.00	43.30
Capital adequacy lev. [%]	7.86	4.39	7.30	3.46	7.86	4.38	7.33	3.45
Credit rating NPL [%]	3.25	2.14	8.75	10.44	3.24	2.14	8.25	9.82
Bank ROA [%]	0.86	1.46	-0.95	4.95	0.87	1.44	-0.73	4.60
D [$Loan_{bit}$>0] [%]	0.48	6.88	0.32	5.64	5.20	22.21	5.35	22.50
Log $Loan_{bit}$ [€]	0.05	0.71	0.03	0.56	0.60	2.61	0.61	2.60

Notes: The means and standard deviations are calculated at the level of firm-bank observations. The statistics for log of bank loans are calculated for those firm-bank relations with positive values. All measures of bank characteristics are predetermined (calculated for the period *t*-1).

Source: AJPES and own calculations.

4.2 Firm-level analysis

Table 5 shows the results of the firm-level linear probability model (LPM). Given that the effects on newly granted loans and continuing/refinancing loans can be different, especially in a crisis period, the model is estimated separately for the group of firms that had no banking loans in *t*–1 ($Loan_{i,t-1} = 0$) and firms that were already indebted to banks in the previous year ($Loan_{i,t-1} > 0$). The results for the latter group are further divided between firms that had a loan in period *t* Pr ($Loan_{i,t} > 0$), irrespective of its change, and the probability that the loan amount increased from period *t*–1 to *t* Pr ($Loan_{i.1} - Loan_{i,t-1} > 0$).

Column 1 shows the results for the probability that a firm is granted a loan in period *t* under the condition that it did not have bank loan in period *t*–1. Firms' total assets seem not to matter for the likelihood of obtaining new loans in the pre-crisis period – the coefficient is, as expected, positive but statistically insignificant. The interaction with the crisis dummy displays a negative coefficient. Note also that the overall effect in the crisis period is negative (0.00251-0.00553). This suggests that in the crisis period, banks granted loans on average to firms with lower values of total assets. In other words, the larger the firm (measured by total assets), the lower the probability that it received a loan from a bank in the crisis period. This result might be driven by the fact that larger firms tend to seek larger amounts of credit. In the crisis period, however, banks might have been unwilling to take on large loan exposures due to pressing capital requirements.

As expected, firms with higher sales revenues are more likely to receive credit from a bank. In the crisis period this effect declined, which implies that banks discriminate among their clients to a smaller extent based on their market performance. A similar adjustment is observed for collateral and ROA – both have a positive and highly statistically significant effect in the pre-crisis period. It is expected that firms with more pledgeable assets and higher profitability have a greater probability of receiving a loan. In crisis period, however, this positive elasticity declined, which is a signal of worse credit allocation in times of financial distress. This result might be partially driven by bank distress in the face of mounting NPL pressure. Due to problems in their balance sheets, banks significantly tightened their credit standards in the crisis period and were in general less willing to grant loans even to better performing firms. Consequently, the correlation between the probability of receiving a loan and firm performance measures declined. The EBITDA-to-debt ratio displays a negative and statistically insignificant coefficient for both the pre-crisis and crisis periods. One would expect a positive effect since firms with a higher debt-servicing capacity are in general less risky. This is another indication of adverse selection in the allocation of loans. Even more surprisingly, banks seem to be more willing to finance firms with higher indebtedness, as indicated by the positive and highly statistically coefficient for the debt-to-asset ratio. This effect somewhat declined in the crisis period but remained positive, which is another indication of poor credit allocation.

In column 2 we present the results for a specification that is augmented with additional measures of risk. As discussed above, we consider two measures – the standard deviation of ROA, denoted SD(ROA), and the Sharp ratio, denoted SR(ROA) – which are calculated at each point in time using the observations from the previous five years. For this reason, the number of observations is considerably lower than in column 1. In line with prior expectations, SD(ROA) displays a negative coefficient, whereas SR(ROA) has a positive effect on the probability that a loan is granted. Both are insignificant, however, and show that banks did not take into account any of these measures of risk in allocating loans. Moreover, although insignificant, the adjustment in the crisis was in an undesirable direction.

Columns 3 and 4 of Table 5 display the results of the LPM for having a loan in year *t* conditional on having loan in year *t*–1. As indicated by the coefficient for the lagged (log) value of loans, firms with a greater loan amount in the prior year had a higher probability of having a loan in the current year. This result is as expected, as higher loan values are more likely to have a longer duration. The positive and highly statistically significant interaction with the crisis dummy reveals that in times of financial distress, firms with greater loan amounts had an even higher probability of loan continuation. There are three potential reasons for this result. First, banks might favour firms with large exposures, since these are typically larger, less opaque and in general less risky. Second, during the crisis period banks reprogrammed a large number of loans. They might have a greater incentive to do this for larger loan exposures, as these can cause greater problems in their balance sheets in case of default. Third, in case of loan default and firm survival, the loan is refinanced with a probability of one. The signs of the effects for other variables are similar to those for newly granted loans (columns 1 and 2), and in most cases indicate a worsening of credit allocation in the crisis period.

Column 5 in Table 5 shows the estimated effects on the probability of a loan increase between two consecutive years. In contrast to the higher probability of loan continuation (columns 3 and 4), we find that firms with a larger loan amount have, on average, a lower probability of a loan increase. This effect became even more negative in the crisis period as banks tightened their credit standards and significantly limited credit supply in order to meet capital requirements. Similarly to the other four estimated models, we observe a shift towards poorer credit allocation during the crisis for most of the indicators. The only two positive changes are those for the effect of sales revenue and collateral. Note, however, that the latter had a negative effect in the pre-crisis period and, despite an adjustment in the desired direction, its effect remained negative for the crisis period.

Table 5 Linear probability model for bank loans: Firm-level analysis

	Group of firms				
	$Loan_{i,t\text{-}1} = 0$		$Loan_{i,t\text{-}1} > 0$		
	Pr [$Loan_{it} > 0$]		Pr [$Loan_{it} > 0$]		Pr [$\Delta Loan_{it} > 0$]
Variable	(1)	(2)	(3)	(4)	(5)
Log $Loan_{i,t\text{-}1}$			0.0715***	0.0738***	-0.0130***
			(0.00196)	(0.00223)	(0.00255)
Log $Loans_{i,t\text{-}1} \times Crisis_t$			0.00644***	0.00787***	-0.0131***
			(0.00232)	(0.00266)	(0.00293)
Log $Assets_{i,t\text{-}1}$	0.00251	0.000943	-0.0512***	-0.0563***	0.0183***
	(0.00167)	(0.0019)	(0.00337)	(0.00375)	(0.00506)
Log $Assets_{i,t\text{-}1} \times Crisis_t$	-0.00553***	-0.00480**	-0.00602	-0.00631	-0.0204***
	(0.0018)	(0.00203)	(0.00386)	(0.00431)	(0.00564)
Log $Sales_{i,t\text{-}1}$	0.0239***	0.0241***	0.00892***	0.00876***	0.0439***
	(0.00156)	(0.00176)	(0.00242)	(0.00272)	(0.00414)
Log $Sales_{i,t\text{-}1} \times Crisis_t$	-0.00632***	-0.00664***	-0.00509*	-0.00560*	0.00863*
	(0.00169)	(0.0019)	(0.00268)	(0.00298)	(0.00453)
$Collateral_{i,t\text{-}1}$	0.0730***	0.0700***	0.0423***	0.0387***	-0.0717***
	(0.00593)	(0.00669)	(0.0075)	(0.00841)	(0.0129)
$Collateral_{i,t\text{-}1} \times Crisis_t$	-0.0249***	-0.0242***	-0.0034	-0.00508	0.0276*
	(0.00658)	(0.00737)	(0.0085)	(0.00942)	(0.0142)
$ROA_{i,t\text{-}1}$	0.117***	0.0917***	0.0442**	0.0221	0.161***
	(0.0149)	(0.0177)	(0.0215)	(0.0257)	(0.0394)
$ROA_{i,t\text{-}1} \times Crisis_t$	-0.0521***	-0.0512**	-0.0204	-0.0298	-0.0612
	(0.0171)	(0.0203)	(0.0275)	(0.0327)	(0.0478)
EBITDA-to-$debt_{i,t\text{-}1}$	-0.000399	-0.000920***	-0.00178	-0.00839**	-0.0112*
	(0.000276)	(0.00025)	(0.00291)	(0.00427)	(0.00625)
E-to-$D_{i,t\text{-}1} \times Crisis_t$	-0.000206	0.0000842	0.00181	0.00723	0.00755
	(0.000318)	(0.000262)	(0.0033)	(0.00453)	(0.00647)

	Group of firms				
	$Loan_{i,t\text{-}1} = 0$		$Loan_{i,t\text{-}1} > 0$		
	Pr [$Loan_{it} > 0$]		Pr [$Loan_{it} > 0$]		Pr [$\Delta Loan_{it} > 0$]
Variable	(1)	(2)	(3)	(4)	(5)
Debt-to-assets ratio$_{i,t\text{-}1}$	0.0489***	0.0457***	0.0346***	0.0295***	0.0619***
	(0.0031)	(0.00358)	(0.00493)	(0.00522)	(0.00752)
D-to-A ratio$_{i,t\text{-}1}$ × Crisis$_t$	-0.0214***	-0.0223***	-0.0131**	-0.0134**	-0.0266***
	(0.00348)	(0.004)	(0.00569)	(0.006)	(0.00856)
SD(ROA)$_{i,t\text{-}1}$		-0.000269		(0.000249)	0.000763
		(0.000419)		-0.000209	-0.000702
SD(ROA)$_{i,t\text{-}1}$ × Crisis$_t$		0.000378		-0.000292	-0.000732
		(0.000433)		(0.000211)	(0.000705)
SR(ROA)$_{i,t\text{-}1}$		0.00194		0.00394***	0.0109***
		(0.00164)		(0.00113)	(0.00212)
SR(ROA)$_{i,t\text{-}1}$ × Crisis$_t$		-0.0028		-0.00075	-0.00556**
		(0.00174)		(0.00125)	(0.00231)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Firm age fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	151299	109034	109203	88927	88927
R2 Adj.	0.0327	0.0296	0.146	0.148	0.0589

Notes: Crisis denotes an indicator variable, which assumes a value of 1 if period t is during the crisis (2009-2014) and 0 otherwise. Loans comprises all bank loans that a firm receives. Collateral is a share of pledgeable assets (tangible capital, structures in a form of inventories, financial assets) in total assets. Industry-fixed effects are introduced at NACE 2-digit level (Rev. 2008). Firm cluster-robust standard errors are given in parentheses. *, ** and *** denote statistical significance at p<0.10, p<0.05 and p<0.01, respectively.

Source: AJPES and own calculations.

We now turn to the results of log-linear regressions, where we model the total agreed amounts of loans. Again, we model loan amounts for the group of firms with no prior loans ($\text{Loan}_{i,t-1} = 0$) and firms that were already indebted to banks in previous year ($\text{Loan}_{i,t-1} > 0$) separately. Let us first comment on the results of the autoregressive components in columns 3 to 6 in Table 6. As expected, the values of loans are positively autocorrelated. During the crisis this persistence increased, which can be attributed to a higher number of reprogramed loans, a higher number of defaults (which are refinanced in full) and possibly also to greater affection from banks towards larger firms. The autoregressive coefficients for the growth rate of loans is negative for both periods of interest, which we mainly attribute to the lumpiness of financed investment projects – periods of above-average capital growth rates are often followed by periods of below-average growth rates. However, during the crisis this autoregressive coefficient increased (decreased in absolute terms), which may be attributed to an increased share of firms in default, which exhibited low growth rates that are not correlated with lagged growth rates.

As can be seen in Table 6, the signs of coefficients for other variables (and their changes) are in many cases similar to those in Table 5. There are, however, some indications of better loan allocation relative to the results of the linear probability models. Loan amount seems to respond positively to total assets and sales revenues. More importantly, for the latter we observe a positive change for the crisis period, which suggests that increases in loans or new loans were allocated to firms that generated higher sales. Although insignificant, a similar positive change on newly granted loans is also found for collateral and ROA. In addition, for firms with no prior loans, the debt-to-assets ratio does not have a positive coefficient. Improvement can also be noted for the Sharp ratio, which has a positive coefficient and standard deviation of ROA, which shifted to a negative value during the crisis period.

In contrast to newly granted loans, existing loans – which represent a large majority of the total credit amount – still seem to be allocated quite poorly. During the crisis period the responsiveness to ROA weakened for both the amount of loans and its change. As before, we also observe that larger amounts of loans are held by more indebted firms. In the crisis period this effect changed towards more efficient allocation, but nevertheless the effect remained positive. The EBITDA-to-debt seems to be an important factor in explaining changes in loan amounts (columns 5 and 6 in Table 6). Its effect decreased considerably in crisis period, however, which is another indication of deteriorating credit allocation after 2009.

Table 6 Linear model for amount of bank loans: Firm-level analysis

	Group of firms					
	$Loan_{i,t-1} = 0$		$Loan_{i,t-1} > 0$			
	Log $Loan_{it}$		Log $Loan_{it}$		ΔLog $Loan_{it}$	
Variable	(1)	(2)	(3)	(4)	(5)	
Log $Loans_{i,t-1}$			0.700***	0.706***		
			(0.0121)	(0.0139)		
Log $Loans_{i,t-1} \times Crisis_t$			0.103***	0.117***		
			(0.0138)	(0.0156)		
ΔLog $Loans_{i,t-1}$					-0.200***	-0.209***
					(0.0162)	(0.0184)
ΔLog $Loans_{i,t-1} \times Crisis_t$					0.0915***	0.0909***
					(0.0179)	(0.0203)
Log $Assets_{i,t-1}$	0.482***	0.535***	0.291***	0.289***	0.00493	0.00863
	(0.0460)	(0.0575)	(0.0162)	(0.0182)	(0.00958)	(0.0101)
Log $Assets_{i,t-1} \times Crisis_t$	-0.0493	-0.0997	-0.103***	-0.122***	-0.0196*	-0.0224**
	(0.0582)	(0.0723)	(0.0182)	(0.0202)	(0.0103)	(0.0110)
Log $Sales_{i,t-1}$	0.364***	0.309***	0.0398***	0.0402***	0.0379***	0.0355***
	(0.0459)	(0.0563)	(0.00840)	(0.00938)	(0.00922)	(0.00984)
Log $Sales_{i,t-1} \times Crisis_t$	0.153***	0.197***	-0.00172	0.000545	0.00343	0.00626
	(0.0587)	(0.0713)	(0.00896)	(0.0100)	(0.00990)	(0.0107)
$Collateral_{i,t-1}$	0.494***	0.472***	0.0565**	0.0692**	-0.168***	-0.164***
	(0.121)	(0.143)	(0.0244)	(0.0269)	(0.0303)	(0.0333)
$Collateral_{i,t-1} \times Crisis_t$	0.165	0.121	0.0291	0.00812	0.141***	0.132***
	(0.159)	(0.188)	(0.0271)	(0.0297)	(0.0330)	(0.0361)
$ROA_{i,t-1}$	1.002***	1.269***	0.712***	0.530***	0.502***	0.448***
	(0.230)	(0.297)	(0.0728)	(0.0887)	(0.130)	(0.147)
$ROA_{i,t-1} \times Crisis_t$	0.524	0.144	-0.182**	-0.200*	-0.00887	-0.180
	(0.345)	(0.466)	(0.0909)	(0.109)	(0.146)	(0.165)

	Group of firms					
	$Loan_{i,t-1} = 0$		$Loan_{i,t-1} > 0$			
	Log $Loan_{it}$		Log $Loan_{it}$		ΔLog $Loan_{it}$	
Variable	(1)	(2)	(3)	(4)	(5)	
EBITDA-to-$debt_{i,t-1}$	0.0196	0.0771**	0.00177	0.00610	0.198***	0.172***
	(0.0167)	(0.0363)	(0.00764)	(0.0119)	(0.0430)	(0.0460)
E-to-$D_{i,t-1}$ × $Crisis_t$	0.0117	-0.113**	0.00119	-0.00521	-0.180***	-0.118**
	(0.0225)	(0.0449)	(0.00952)	(0.0129)	(0.0460)	(0.0515)
Debt-to-assets $ratio_{i,t-1}$	0.00401	-0.00345	0.225***	0.205***	0.116***	0.0883***
	(0.0565)	(0.0679)	(0.0165)	(0.0176)	(0.0208)	(0.0215)
D-to-A $ratio_{i,t-1}$ × $Crisis_t$	-0.0903	-0.128	-0.0432**	-0.0430**	-0.0547**	-0.0223
	(0.0751)	(0.0904)	(0.0188)	(0.0199)	(0.0227)	(0.0234)
$SD(ROA)_{i,t-1}$		0.0406***		0.00239**		0.000873
		(0.00718)		(0.00114)		(0.000792)
$SD(ROA)_{i,t-1}$ × $Crisis_t$		-0.0476***		-0.00216*		-0.000831
		(0.00770)		(0.00115)		(0.000799)
$SR(ROA)_{i,t-1}$		0.0461**		0.00914***		0.00316
		(0.0216)		(0.00342)		(0.00462)
$SR(ROA)_{i,t-1}$ × $Crisis_t$		-0.00497		-0.00245		0.00157
		(0.0314)		(0.00376)		(0.00494)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm age fixed effects	No	No	No	No	No	No
Observations	13696	9005	96532	79189	76891	65191
R2 Adj.	0.323	0.340	0.850	0.858	0.0413	0.0430

Notes: Crisis denotes an indicator variable, which assumes a value of 1 if period *t* is during the crisis (2009-2014) and 0 otherwise. Loans comprise all bank loans that a firm receives. Collateral is a share of pledgeable assets (tangible capital, structures in a form of inventories, financial assets) in total assets. Industry-fixed effects are introduced at NACE 2-digit level (Rev. 2008). Firm cluster-robust standard errors are given in parentheses. *, ** and *** denote statistical significance at p<0.10, p<0.05 and p<0.01, respectively.

Source: AJPES and own calculations.

We now summarise our main results of the firm-level analysis. We find, irrespective of the left-hand variable, that loan allocation in general deteriorated during the crisis period. Credit allocation was already very poorly allocated before the crisis, which is reflected in very low values of some coefficients and the unresponsiveness of credit measures to key variables such as the EBITDA-to-debt ratio and both riskiness measure (SD(ROA) and SR(ROA)). Nevertheless, adverse selection in loan allocation in the pre-crisis period can be clearly seen in the huge amount of non-performing loans in banks' balance sheets. Therefore, a shift towards even poorer allocation during the crisis period is even more worrying. The overall amount of loans to firms contracted during the crisis period, and it seems that this contraction was not selective and that it mainly affected better-performing borrowers. This is not surprising, as banks cannot easily reduce loans that are not performing. However, our analysis is performed only on a sample of operating firms and additionally excludes firms with incomplete data and outliers. A large majority of NPLs that are still in banks' balance sheets are thus dropped and do not influence the results. In addition, we find a similar result when we look only at newly granted loans, which clearly are new decisions taken by banks to grant loans. Our finding of general decreasing marginal effects in the crisis period could, however, also be a consequence of other effects. The negative adjustment could also be the result of higher distress among banks once the crisis hit. Being heavily burdened with non-performing loans and with limited access to fresh capital, banks were unwilling to lend even to better-performing firms, which would result, as we observe, in lower responsiveness of credit-related measures to firm performance.

4.3 Firm-bank level analysis

In this subsection, we present the results of the linear probability model for the decision on borrowing/lending and log-linear model for the decision on loan amount at the firm-bank level. In our discussion, we focus mainly on the characteristics of banks. We estimate the models for all banks, state-owned banks, foreign-owned banks and large banks separately, and add bank-specific variables that could have an important effect on credit allocation. More specifically, we include the level of bank capitalisation, which is measured by the leverage ratio (share of capital in total assets) and the share of non-performing loans, which is defined as loans to C-, D- or E-rated borrowers.[11] Lower bank capitalisation and a higher NPL burden is expected to negatively affect credit supply. In addition, as has been found in many studies, these indicators might also signal perverse incentives of banks (Peek and Rosengren, 2005; Iosifidi and Kokas, 2015). The third measure that we include is bank profitability measured by ROA.

Table 7 presents the estimation results for the probability that firm i is granted *a new loan* by bank b for a sample of firms without any prior bank loans. Column 1 shows the results for all banks excluding firm-level riskiness measures SD(ROA) and SR(ROA). As can be seen in column 2, the inclusion of these measures seems to affect the estimated coefficients only marginally and changes the sign only for an indicator variable for the state-owned banks. We therefore discuss only the results in columns 2 to 5, which reflect the bank-specific characteristics. The

11 We rely on credit ratings that are assigned by banks to their borrowers to define the share of NPLs, since a standard measure of non-performing loans, which is based on 90-days past due, is only available from 2007. This would restrict the pre-crisis estimates to only two periods.

first coefficient in column 2 shows that firms have a higher probability of being granted a new loan by state-owned banks. This effect declined during crisis, although it remained positive. A similar pattern is observed for large banks, but resulted in negative overall coefficient during the crisis. The effect for foreign-owned banks was negative in both the pre-crisis and crisis periods. However, during the crisis period the coefficient increased, which shows that these banks were relatively more willing to grant new loans in times of financial distress than in the pre-crisis period. This might be due to the fact that foreign-owned banks weathered the crisis considerably better - they had higher capital adequacy and were exposed to a considerably lower amount of non-performing loans.

Contrary to prior expectations, we find a negative effect of capital adequacy on the probability that a loan is granted. However, this negative overall effect is driven only by the state-owned banks, as can be seen in column 4. This implies that less-capitalised state-owned banks were more aggressive in the market. For foreign banks, on the other hand, the coefficient is positive, which means that as expected, better-capitalised banks lent more aggressively in the pre-crisis period. This effect is expected to decline in a crisis, which is exactly what we find on average for the whole sample of banks. This decline in the estimated coefficient is most pronounced for foreign-owned banks, which reflects an aggressive tightening of credit supply. The adjustment for state-owned banks is positive, but nevertheless remained negative.

A larger burden of non-performing loans has a negative effect on granting loans. Although this effect remained negative for the crisis period, the adjustment was positive, which is somewhat surprising since it could lead us to conclude that NPLs were a less constraining factor during the crisis. That being the case and knowing that allocation actually worsened during the crisis, one could conclude that this inefficiency in loan allocation was led by the worst-performing banks. We believe, however, that the reason behind this result could be different. Banks, especially state-owned banks, were heavily burdened by non-performing loans in the times of financial distress. They continued to grant loans, however, albeit to a lesser extent. The reason for this positive adjustment could therefore be that in the crisis period, NPLs increased relatively more than newly granted loans declined. The loan granting of foreign banks seems not to be affected by the share of NPLs. These banks had a significantly lower share of non-performing loans and also, being part of multinational banking groups, were not constrained in accessing capital to cover losses. Therefore, NPLs did not substantially affect their credit supply.

More profitable banks, measured by ROA, seem on average to be less inclined to grant loans. This effect is positive for the group of state-owned and large banks. A positive relationship makes much more sense since it is expected that banks that generate more income will be more willing to lend. Higher profitability can, however, also signal higher riskiness of credit portfolios. Interaction with the crisis dummy is non-estimable due to insufficient variability, and is therefore not shown in Table 7.

Table 7 Linear probability model for the sample of firms without prior bank loans: Bank-firm-level analysis

	Sample of observations				
	All		5-year survivors		
	All banks		Foreign banks	State banks	Large banks
Variable	(1)	(2)	(3)	(4)	(5)
State owned$_{b,t\text{-}1}$	-0.00113**	0.00997***	.	.	0.00420***
	(0.000492)	(0.000728)	.	.	(0.00151)
State owned$_{b,t\text{-}1}$ × Crisis$_t$	-0.00360***	-0.00297***	.	.	0.00151
	(0.000337)	(0.000386)	.	.	(0.00148)
Foreign owned$_{b,t\text{-}1}$	-0.00288***	-0.00362***		.	-0.0285***
	(0.000473)	(0.000535)		.	(0.00204)
Foreign owned$_{b,t\text{-}1}$ × Crisis$_t$	0.00134***	0.00159***		.	0.0171***
	(0.000253)	(0.000281)		.	(0.00207)
Large$_{b,t\text{-}1}$	0.0126***	0.0124***	0.000262	0.0108***	.
	(0.000505)	(0.000589)	(0.000482)	(0.000822)	.
Large$_{b,t\text{-}1}$ × Crisis$_t$	-0.00396***	-0.00387***	-0.000390	-0.00704***	.
	(0.000339)	(0.000388)	(0.000515)	(0.000827)	.
Cap. adeq. lev.$_{b,t\text{-}1}$	-0.000143***	-0.000127***	0.000220***	-0.00209***	-0.000618
	(0.0000350)	(0.0000393)	(0.0000831)	(0.000249)	(0.000376)
Cap. adeq. lev.$_{b,t\text{-}1}$1 × Crisist	-0.000225***	-0.000190***	-0.000277***	0.00165***	0.000240
	(0.0000316)	(0.0000358)	(0.000103)	(0.000269)	(0.000397)
Cred. Ratings NPL$_{b,t\text{-}1}$	-0.000566***	-0.000567***	0.0000614	-0.00274***	-0.00289***
	(0.0000670)	(0.0000765)	(0.000193)	(0.000274)	(0.000309)
Cred. Rat.$_{b,t\text{-}1}$ × Crisis$_t$	0.000482***	0.000474***	-0.0000865	0.00253***	0.00274***
	(0.0000644)	(0.0000735)	(0.000192)	(0.000278)	(0.000310)

	Sample of observations				
	All		5-year survivors		
	All banks		Foreign banks	State banks	Large banks
Variable	(1)	(2)	(3)	(4)	(5)
Bank ROA$_{b,t-1}$	-0.000575***	-0.000526***	-0.000128	0.00710***	0.00409***
	(0.000150)		(0.000168)		(0.000377)
Log Assets$_{i,t-1}$	0.000296**		0.000291**		0.000528***
	(0.000128)		(0.000148)		(0.000176)
Log Assets$_{i,t-1}$ Crisis$_t$	-0.000222		-0.000220		-0.000304
	(0.000141)		(0.000167)		(0.000192)
Log Sales$_{i,t-1}$	0.00152***		0.00150***		0.000707***
	(0.000114)		(0.000127)		(0.000165)
Log Sales$_{i,t-1}$ × Crisis$_t$	-0.000276**		-0.000273**		0.000113
	(0.000120)		(0.000136)		(0.000175)
Collateral$_{i,t-1}$	0.00339***		0.00304***		0.00273***
	(0.000410)		(0.000465)		(0.000634)
Collateral$_{i,t-1}$ × Crisis$_t$	-0.00139***		-0.00116**		-0.00111**
	(0.000434)		(0.000493)		(0.000673)
ROA$_{i,t-1}$	0.00540***		0.00285**		0.00533***
	(0.000991)		(0.00114)		(0.00168)
ROA$_{i,t-1}$ × Crisis$_t$	-0.00304***		-0.00189		-0.00212
	(0.00108)		(0.00127)		(0.00185)
EBITDA-to-debt$_{i,t-1}$	-0.0000127		-0.00000442	-0.0000117	-0.00000611
	(0.0000150)	(0.0000192)	(0.0000148)	(0.0000523)	(0.0000540)
E-to-D$_{i,t-1}$ × Crisis$_t$	0.0000169		-0.00000502	-0.0000108	0.0000131

	Sample of observations				
	All		5-year survivors		
	All banks		Foreign banks	State banks	Large banks
Variable	(1)	(2)	(3)	(4)	(5)
	(0.0000215)	(0.0000297)	(0.0000171)	(0.0000723)	(0.0000802)
Debt-to-assets ratio$_{i,t-1}$	0.00246***		0.00217***		0.00175***
	(0.000214)		(0.000252)		(0.000342)
D-to-A ratio$_{i,t-1}$ × Crisis$_t$	-0.00144***		-0.00125***		-0.000614**
	(0.000232)		(0.000272)		(0.000368)
SD(ROA)$_{i,t-1}$			0.0000154		0.0000417
			(0.0000532)	(0.0000917)	(0.0000232)
SD(ROA)$_{i,t-1}$ × Crisis$_t$			-0.0000165		-0.0000370
			(0.0000525)	(0.0000907)	(0.0000236)
SR(ROA)$_{i,t-1}$			0.000154		0.000133
			(0.000116)		(0.000192)
SR(ROA)$_{i,t-1}$ × Crisis$_t$			-0.0000394		-0.0000954
			(0.000125)		(0.000195)
Observations	2,962,529		2,127,249		765,353
R2 Adj.	0.00902		0.00934		0.00336

Notes: Crisis denotes an indicator variable, which assumes a value of 1 if period t is during the crisis (2009-2014) and 0 otherwise. State, foreign owned and large denote indicator variables that assume a value of 1 if the bank is state-owned, foreign-owned or large (at least 5% market share in bank loans), respectively. Loans comprise all bank loans that a firm receives above €1,000 limit. Collateral is a share of pledgeable assets (tangible capital, structures in a form of inventories, financial assets) in total assets. All equations are estimated with firm-age, year, industry (NACE 2-digit), bank fixed effects. Firm cluster-robust standard errors are given in parentheses. **, ** and *** denote statistical significance at p<0.10, p<0.05 and p<0.01, respectively.

Source: AJPES, Bank of Slovenia and own calculations.

Firm-level variables in Table 7 display similar effects as in the firm-level analysis (Tables 5 and 6). The effects of most declined during the crisis. These adjustments seem to be smaller and less significant for the group of foreign banks, which can be interpreted as indicating better allocation relative to other groups of banks, especially state-owned banks. The allocation of the latter group is unresponsive to firm profitability (ROA) in both the pre-crisis and crisis periods, which is another indication of poorer allocation. A similar observation applies to large banks, among which state-owned banks represent the majority.

Next, we provide estimates of the probability model for firms having a loan from a specific bank, conditional on a prior bank loan being given by any bank. The estimates are presented in Table 8. Column 2 shows the regression coefficients for all banks and for firms that have at least a five-year history, which enables the inclusion of additional measures of risk. The signs of the coefficients for the banking-group dummies are somewhat different from those for the case of newly granted loans in Table 7. In contrast to state-owned banks, foreign-owned and large banks were more likely to continue a credit relationship with firms. The crisis led to a negative adjustment as expected, but this was insignificant for foreign-owned banks. These banks seem to operate a similar lending policy as in the pre-crisis period, which might be due to better capitalisation and lower exposure to NPLs.

The share of NPLs seem not to have any significant effect on the probability of loan continuation. The former is marginally statistically significant for all banks, but its value is very low and economically insignificant. The estimated coefficients for bank ROA show that in the pre-crisis period, firms had a lower probability of being granted a loan by a more profitable bank. The crisis led to positive adjustment, however, such that the overall effect of ROA in the crisis period became positive. This holds across all groups of banks, but it is not significant for large banks. No such improvement in response to the capital adequacy ratio is observed in the crisis period.

The results show that firms have a lower probability of obtaining a loan from bank *b* if they had not already borrowed from this bank in the previous period (indicated by a negative coefficient for *No loan bank*$_{ib,t\text{-}1}$). This negative effect declined somewhat in the crisis period across all groups of banks. In line with the firm-level analysis, we find a statistically significant effect of the previous period's loan amount. This holds for both overall firm indebtedness towards banks (Log *All loans*$_{i,t\text{-}1}$) and loan amount granted by bank *b* (Log *Loans bank*$_{ib,t\text{-}1}$), indicating the importance of relational banking in credit supply.

The responsiveness of firm characteristics is again found to be very low. Many effects became stronger in the crisis period, including the effects of log sales, collateral and ROA. This does not allow us to conclude that allocation improved, however, since all of the coefficients are economically insignificant and many are also statistically insignificant. Moreover, the only banking group that took into consideration ROA in their lending decisions seems to be foreign-owned banks. For all other groups, the effect of ROA is insignificant.

Table 8 Linear probability model for the sample of firms with prior bank loans: Firm-bank-level analysis

	Sample of observations				
	All		5-year survivors		
	All banks		Foreign banks	State banks	Large banks
Variable	(1)	(2)	(3)	(4)	(5)
Foreign owned$_{b,t\text{-}1}$	0.00760	0.00721	.	.	-0.0188
	(0.000650)	(0.000692)	.	.	(0.00334)
Foreign owned$_{b,t\text{-}1}$ × Crisis$_t$	-0.000873	-0.000360	.	.	0.00180
	(0.000534)	(0.000574)	.	.	(0.00349)
State owned$_{b,t\text{-}1}$	0.00556	-0.00566	.	.	-0.00858
	(0.000778)	(0.00124)	.	.	(0.00244)
State owned$_{b,t\text{-}1}$ × Crisis$_t$	-0.00212	-0.00153	.	.	-0.00347
	(0.000647)	(0.000702)	.	.	(0.00267)
Large$_{b,t\text{-}1}$	0.0251	0.0261	0.000372	0.00719	.
	(0.00102)	(0.00111)	(0.00113)	(0.00142)	.
Large$_{b,t\text{-}1}$ × Crisis$_t$	-0.00264	-0.00304	-0.00563	-0.00416	.
	(0.000625)	(0.000678)	(0.00120)	(0.00140)	.
Cap. adeq. lev.$_{b,t\text{-}1}$	-0.000170	-0.000151	0.000194	0.000107	0.000847
	(0.0000833)	(0.0000895)	(0.000197)	(0.000423)	(0.000678)
Cap. adeq. lev.$_{b,t\text{-}1}$1 × Crisist	-0.000114	-0.000127	-0.000554	0.000336	-0.000180
	(0.0000753)	(0.0000812)	(0.000233)	(0.000497)	(0.000732)
Cred. Ratings NPL$_{b,t\text{-}1}$	0.0000477	0.0000156	0.000326	0.00000871	-0.000986
	(0.000134)	(0.000145)	(0.000440)	(0.000440)	(0.000509)
Cred. Rat.$_{b,t\text{-}1}$ × Crisis$_t$	0.0000860	-0.000148	-0.000542	-0.000454	0.000817
	(0.000126)	(0.000137)	(0.000437)	(0.000458)	(0.000519)

	Sample of observations				
	All		5-year survivors		
	All banks		Foreign banks	State banks	Large banks
Variable	(1)	(2)	(3)	(4)	(5)
Bank ROA$_{b,t\text{-}1}$	-0.000596	-0.000744	-0.00205	-0.00872	-0.00299
	(0.000335)	(0.000360)	(0.000860)	(0.00213)	(0.00266)
Bank ROA$_{b,t\text{-}1}$ × Crisis$_t$	0.000843	0.000996	0.00471	0.0107	0.00312
	(0.000330)	(0.000355)	(0.000891)	(0.00212)	(0.00264)
No loan bank ROA$_{ib,t\text{-}1}$	-0.333	-0.335	-0.392	-0.312	-0.333
	(0.0141)	(0.0154)	(0.0316)	(0.0187)	(0.0170)
No loan bank ROA$_{ib,t\text{-}1}$ × Crisis$_t$	0.0413	0.0366	0.0497	0.0423	0.0663
	(0.0151)	(0.0165)	(0.0337)	(0.0209)	(0.0188)
Log loan bank ROA$_{ib,t\text{-}1}$	0.0442	0.0438	0.0383	0.0463	0.0444
	(0.00119)	(0.00129)	(0.00261)	(0.00153)	(0.00141)
Log loan bank ROA$_{ib,t\text{-}1}$ × Crisis$_t$	0.00383	0.00338	0.00517	0.00333	0.00569
	(0.00125)	(0.00136)	(0.00276)	(0.00169)	(0.00155)
Log All loans$_{i,t\text{-}1}$	0.00131	0.00145	0.00120	0.00295	0.00294
	(0.000176)	(0.000196)	(0.000285)	(0.000485)	(0.000521)
Log All loans$_{i,t\text{-}1}$ × Crisis$_t$	0.000345	0.000358	0.000231	0.0000454	0.00156
	(0.000190)	(0.000212)	(0.000309)	(0.000519)	(0.000573)
Log Assets$_{i,t\text{-}1}$	-0.00132	-0.00124	0.000589	-0.00436	-0.00509
	(0.000381)	(0.000427)	(0.000678)	(0.000916)	(0.00101)
Log Assets$_{i,t\text{-}1}$ Crisis$_t$	-0.00210	-0.00241	-0.00318	-0.00158	-0.00512
	(0.000411)	(0.000462)	(0.000727)	(0.000990)	(0.00110)
Log Sales$_{i,t\text{-}1}$	0.00119	0.00101	0.000321	0.00213	0.00288

	Sample of observations				
	All		5-year survivors		
	All banks		Foreign banks	State banks	Large banks
Variable	(1)	(2)	(3)	(4)	(5)
	(0.000300)	(0.000336)	(0.000548)	(0.000710)	(0.000792)
Log Sales$_{i,t\text{-}1}$ × Crisis$_t$	0.000644	0.000893	0.00112	0.000446	0.00146
	(0.000325)	(0.000364)	(0.000591)	(0.000764)	(0.000856)
Collateral$_{i,t\text{-}1}$	0.000789	-0.000103	0.00161	-0.000625	0.00104
	(0.000838)	(0.000915)	(0.00153)	(0.00210)	(0.00232)
Collateral$_{i,t\text{-}1}$ × Crisis$_t$	0.00223	0.00282	0.000892	0.00485	0.00589
	(0.000905)	(0.000990)	(0.00164)	(0.00228)	(0.00255)
ROA$_{i,t\text{-}1}$	0.00674	0.00311	0.0162	-0.00625	0.000996
	(0.00258)	(0.00292)	(0.00491)	(0.00669)	(0.00762)
ROA$_{i,t\text{-}1}$ × Crisis$_t$	0.00354	0.00379	-0.000795	0.00572	0.0135*
	(0.00296)	(0.00335)	(0.00561)	(0.00760)	(0.00900)
EBITDA-to-debt$_{i,t\text{-}1}$	0.0000415	-0.000179	0.000945	-0.00198	0.000110*
	(0.000374)	(0.000495)	(0.000924)	(0.000859)	(0.00126)
E-to-D$_{i,t\text{-}1}$ × Crisis$_t$	0.0000367	0.0000800	-0.00125	0.00215	-0.000150*
	(0.000386)	(0.000504)	(0.000936)	(0.000886)	(0.00128)
Debt-to-assets ratio$_{i,t\text{-}1}$	0.00321	0.00290	0.00269	0.00574	0.00892
	(0.000514)	(0.000548)	(0.000880)	(0.00130)	(0.00142)
D-to-A ratio$_{i,t\text{-}1}$ × Crisis$_t$	-0.000753	-0.000577	0.000263	-0.00333	-0.00496
	(0.000560)	(0.000596)	(0.000956)	(0.00141)	(0.00157)
SD(ROA)$_{i,t\text{-}1}$		0.000103	0.0000694	0.000269	0.000172
		(0.000137)	(0.000177)	(0.000240)	(0.000294)

	Sample of observations				
	All	5-year survivors			
	All banks		Foreign banks	State banks	Large banks
Variable	(1)	(2)	(3)	(4)	(5)
$SD(ROA)_{i,t\text{-}1} \times Crisis_t$		0.0000999	-0.0000548	-0.000273	-0.000168
		(0.000137)	(0.000177)	(0.000240)	(0.000295)
$SR(ROA)_{i,t\text{-}1}$		0.000489	0.000619	0.000600	0.000869
		(0.000162)	(0.000267)	(0.000362)	(0.000389)
$SR(ROA)_{i,t\text{-}1} \times Crisis_t$		0.0000816	-0.000239	0.000158	0.000127
		(0.000172)	(0.000287)	(0.000388)	(0.000418)
Observations	1,977,681	1,697,659	609,763	461,660	470,917
R2 Adj.	0.766	0.766	0.743	0.788	0.759

Notes: Crisis denotes an indicator variable, which assumes a value of 1 if period t is during the crisis (2009-2014) and 0 otherwise. State and foreign owned, and large bank denote indicator variables that assume a value of 1 if the bank is state owned, foreign owned or large (at least 5% market share in bank loans), respectively. No loan bank denotes a variable that assumes 1 if firm i had no loan from bank b and 0 otherwise. Loans comprise all bank loans that a firm receives above €1,000 limit. Collateral is a share of pledgeable assets (tangible capital, structures in a form of inventories, financial assets) in total assets. All equations are estimated with firm-age, year, industry (NACE 2-digit), bank fixed effects. Firm cluster-robust standard errors are given in parentheses. *,** and *** denote statistical significance at $p<0.10$, $p<0.05$ and $p<0.01$, respectively.

Source: AJPES, Bank of Slovenia and own calculations.

Tables 9 and 10 show the results of log-linear models for loan amounts at the firm-bank level. The results are shown separately for the group of firms with no prior loans (Table 9) and the group of firms that had prior bank loans (Table 10). The signs of the coefficients for both groups of firms are in line with the presented effects in the firm-bank linear probability models (Tables 7 and 8). The only notable difference is the effect of *No loan bank*$_{ib,t\text{-}1}$). This variable is equal to 1 if firm *i* had no loan from bank *b* and 0 otherwise. In Table 8 it displays a negative coefficient, which suggests that firm *i* is less likely to be granted a loan by bank *b* if it did not already have a credit relationship with bank *b* in year *t*–1. When we model the loan amount, however, this variable displays a positive and highly statistically significant coefficient (see Table 10). This allows us to conclude that although firms are less likely to access credit from banks that didn't finance them before, the amount they can obtain is on average larger.

To conclude, the firm-bank-level results confirm our prior finding that the allocation of loans was already inefficient in the pre-crisis period and has deteriorated further in the recent period. The worst allocation is found for state-owned banks, whose lending decisions seem not to respond to key firm performance debt-servicing measures such as ROA and the EBITDA-to-debt ratio. This is in line with the findings of Sapienza (2004), Khwaja and Mian (2005) and Dinc (2005). We have also shown that banks characteristics – such the level of capitalisation, quality of credit portfolio and profitability – have an effect on credit activity. In particular, our results indicate that banks with a weaker capital position have more aggressive lending policies. This effect became weaker on average during the crisis period.

Table 9 The amount of bank loan model for the sample of firms without prior bank loans: Bank-firm-level analysis

	Sample of observations				
	All		5-year survivors		
	All banks		Foreign banks	State banks	Large banks
Variable	(1)	(2)	(3)	(4)	(5)
Foreign owned$_{b,t\text{-}1}$	-0.0281***	-0.0370***		.	-0.286***
	(0.00481)	(0.00542)		.	(0.0206)
Foreign owned$_{b,t\text{-}1}$ × Crisis$_t$	0.0124***	0.0151***		.	0.176***
	(0.00262)	(0.00292)		.	(0.0209)
State owned$_{b,t\text{-}1}$	-0.0119**	0.0925***	.	.	0.0340**
	(0.00499)	(0.00717)	.	.	(0.0154)
State owned$_{b,t\text{-}1}$ × Crisis$_t$	-0.0366***	-0.0303***	.	.	0.0152
	(0.00345)	(0.00397)	.	.	(0.0152)
Large$_{b,t\text{-}1}$	0.123***	0.121***	0.00319	0.113***	.
	(0.00505)	(0.00592)	(0.00528)	(0.00843)	.
Large$_{b,t\text{-}1}$ × Crisis$_t$	-0.0438***	-0.0432***	-0.00658	-0.0744***	.
	(0.00347)	(0.00398)	(0.00564)	(0.00847)	.
Cap. adeq. lev.$_{b,t\text{-}1}$	0.00148***	-0.00136***	0.00194**	-0.0212***	-0.00522
	(0.000368)	(0.000416)	(0.000900)	(0.00253)	(0.00396)
Cap. adeq. lev.$_{b,t\text{-}1}$1 × Crisist	0.00228***	-0.00200***	-0.00298***	0.0167***	0.00123
	(0.000329)	(0.000376)	(0.00111)	(0.00271)	(0.00417)
Cred. Ratings NPL$_{b,t\text{-}1}$	0.00573***	-0.00574***	0.00140	-0.0284***	-0.0300***
	(0.000678)	(0.000777)	(0.00207)	(0.00275)	(0.00312)
Cred. Rat.$_{b,t\text{-}1}$ × Crisis$_t$	0.00482***	0.00473***	-0.00159	0.0260***	0.0283***
	(0.000653)	(0.000749)	(0.00206)	(0.00279)	(0.00313)

	Sample of observations				
	All		5-year survivors		
	All banks		Foreign banks	State banks	Large banks
Variable	(1)	(2)	(3)	(4)	(5)
Bank $ROA_{b,t\text{-}1}$	0.00564***	-0.00531***	-0.000417	0.0732***	0.0403***
	(0.00156)	(0.00176)	(0.00404)	(0.0122)	(0.0149)
Log $Assets_{i,t\text{-}1}$	0.00648***	0.00628***	0.00742***	0.00893**	0.00664
	(0.00149)	(0.00176)	(0.00210)	(0.00389)	(0.00425)
Log $Assets_{i,t\text{-}1}$ $Crisis_t$	0.00424***	-0.00412**	-0.00391**	-0.00699**	-0.00656
	(0.00164)	(0.00198)	(0.00227)	(0.00416)	(0.00470)
Log $Sales_{i,t\text{-}1}$	0.0153***	0.0151***	0.00807***	0.0309***	0.0436***
	(0.00127)	(0.00145)	(0.00188)	(0.00329)	(0.00362)
Log $Sales_{i,t\text{-}1} \times Crisis_t$	-0.00327**	-0.00324**	0.0000375	-0.0107***	-0.0105***
	(0.00134)	(0.00153)	(0.00197)	(0.00347)	(0.00387)
$Collateral_{i,t\text{-}1}$	0.0340***	0.0306***	0.0306***	0.0507***	0.0749***
	(0.00433)	(0.00497)	(0.00693)	(0.0121)	(0.0131)
$Collateral_{i,t\text{-}1} \times Crisis_t$	-0.0151***	-0.0127**	-0.0142**	-0.0225**	-0.0313**
	(0.00455)	(0.00522)	(0.00730)	(0.0126)	(0.0137)
$ROA_{i,t\text{-}1}$	0.0574***	0.0338***	0.0603***	0.0331	0.0617**
	(0.0104)	(0.0121)	(0.0186)	(0.0303)	(0.0319)
$ROA_{i,t\text{-}1} \times Crisis_t$	-0.0323***	-0.0210	-0.0246	-0.0480	-0.0508
	(0.0113)	(0.0134)	(0.0203)	(0.0323)	(0.0350)
EBITDA-to-$debt_{i,t\text{-}1}$	-0.0000455	0.0000975	-0.0000375	0.000300	0.000518
	(0.000147)	(0.000189)	(0.000168)	(0.000496)	(0.000521)
E-to-$D_{i,t\text{-}1} \times Crisis_t$	0.0000341	-0.000235	-0.000214	-0.000313	-0.000731

	Sample of observations				
	All	5-year survivors			
	All banks		Foreign banks	State banks	Large banks
Variable	(1)	(2)	(3)	(4)	(5)
	(0.000189)	(0.000256)	(0.000183)	(0.000632)	(0.000685)
Debt-to-assets ratio$_{i,t\text{-}1}$	0.0241***	0.0214***	0.0171***	0.0386***	0.0455***
	(0.00224)	(0.00265)	(0.00376)	(0.00654)	(0.00715)
D-to-A ratio$_{i,t\text{-}1}$ × Crisis$_t$	-0.0144***	-0.0122***	-0.00585	-0.0272***	-0.0311***
	(0.00240)	(0.00284)	(0.00401)	(0.00682)	(0.00764)
SD(ROA)$_{i,t\text{-}1}$		0.000188	0.000600	0.000489**	-0.000266
		(0.000579)	(0.00112)	(0.000228)	(0.000756)
SD(ROA)$_{i,t\text{-}1}$ × Crisis$_t$		-0.000209	-0.000587	0.000439**	0.0000944
		(0.000570)	(0.00111)	(0.000234)	(0.000739)
SR(ROA)$_{i,t\text{-}1}$		0.00148	0.00131	0.00512**	0.00552
		(0.00127)	(0.00224)	(0.00299)	(0.00359)
SR(ROA)$_{i,t\text{-}1}$ × Crisis$_t$		-0.000741	-0.00111	-0.00287	-0.00319
		(0.00134)	(0.00227)	(0.00312)	(0.00378)
Observations	2,962,529	2,127,249	765,353	577,376	588,390
R2 Adj.	0.00873	0.00896	0.00347	0.0135	0.0112

Notes: Crisis denotes an indicator variable, which assumes a value of 1 if period *t* is during the crisis (2009-2014) and 0 otherwise. State and foreign owned, and large denote indicator variables that assume a value of 1 if bank is state owned, foreign owned and large (at least 5% market share in bank loans), respectively. Loans comprise all bank loans that a firm receives above €1,000 limit. Collateral is a share of pledgeable assets (tangible capital, structures in a form of inventories, financial assets) in total assets. All equations are estimated with firm-age, year, industry (NACE 2-digit), bank fixed effects. Firm cluster-robust standard errors are given in parentheses. *, ** and *** denote statistical significance at $p<0.10$, $p<0.05$ and $p<0.01$, respectively.

Source: AJPES, Bank of Slovenia and own calculations.

Table 10 The amount of bank loan model for the sample of firms with prior bank loans: Bank-firm-level analysis

	Sample of observations				
	All		5-year survivors		
	All banks		Foreign banks	State banks	Large banks
Variable	(1)	(2)	(3)	(4)	(5)
Foreign owned$_{b,t\text{-}1}$	0.0952***	0.0922***		.	0.193***
	(0.00737)	(0.00791)		.	(0.0364)
Foreign owned$_{b,t\text{-}1}$ × Crisis$_t$	-0.0113**	-0.00586		.	0.0321
	(0.00600)	(0.00651)		.	(0.0380)
State owned$_{b,t\text{-}1}$	0.0685***	-0.0563***	.	.	0.0839***
	(0.00862)	(0.0130)	.	.	(0.0266)
State owned$_{b,t\text{-}1}$ × Crisis$_t$	-0.0158**	-0.00894	.	.	-0.00687
	(0.00711)	(0.00777)	.	.	(0.0292)
Large bank$_{b,t\text{-}1}$	0.270***	0.281***	0.00292	0.0911***	.
	(0.0110)	(0.0120)	(0.0135)	(0.0157)	.
Large$_{b,t\text{-}1}$ × Crisis$_t$	0.0416***	-0.0468***	-0.0720***	0.0573***	.
	(0.00698)	(0.00763)	(0.0143)	(0.0155)	.
Cap. adeq. lev.$_{b,t\text{-}1}$	-0.00228**	-0.00203**	0.00124	0.00296	0.00699
	(0.000948)	(0.00103)	(0.00228)	(0.00466)	(0.00751)
Cap. adeq. lev.$_{b,t\text{-}1}$1 × Crisist	-0.00192**	-0.00215**	-0.00800***	0.00162	-0.000181
	(0.000860)	(0.000937)	(0.00267)	(0.00539)	(0.00807)
Cred. Ratings NPL$_{b,t\text{-}1}$	-0.000533	0.000185	0.00721	0.00000488	-0.0116**
	(0.00148)	(0.00160)	(0.00515)	(0.00477)	(0.00557)
Cred. Rat.$_{b,t\text{-}1}$ × Crisis$_t$	-0.00179	-0.00263**	-0.00986**	-0.00721	0.00770
	(0.00139)	(0.00151)	(0.00510)	(0.00496)	(0.00566)

	Sample of observations				
	All	5-year survivors			
	All banks		Foreign banks	State banks	Large banks
Variable	(1)	(2)	(3)	(4)	(5)
Bank ROA$_{b,t\text{-}1}$	0.00985***	-0.0120***	-0.0204**	-0.123***	-0.0236
	(0.00378)	(0.00411)	(0.00985)	(0.0241)	(0.0290)
No loan bank ROA$_{ib,t\text{-}1}$	4.333***	4.415***	3.841***	4.651***	4.374***
	(0.142)	(0.155)	(0.346)	(0.184)	(0.168)
No loan bank ROA$_{ib,t\text{-}1}$ × Crisis$_t$	0.506***	0.394**	0.522	0.446**	0.535***
	(0.157)	(0.171)	(0.367)	(0.209)	(0.188)
Log loan bank ROA$_{ib,t\text{-}1}$	1.234***	1.239***	1.179***	1.267***	1.240***
	(0.0124)	(0.0135)	(0.0297)	(0.0155)	(0.0144)
Log loan bank ROA$_{ib,t\text{-}1}$ × Crisis$_t$	0.0358***	0.0256**	0.0468	0.0245	0.0333**
	(0.0137)	(0.0148)	(0.0315)	(0.0176)	(0.0162)
Log All loans$_{i,t\text{-}1}$	0.00757***	0.00944***	0.00944***	0.0170***	0.0143**
	(0.00204)	(0.00231)	(0.00345)	(0.00565)	(0.00597)
Log All loans$_{i,t\text{-}1}$ × Crisis$_t$	0.00574***	0.00599**	0.00389	0.00722	0.0224***
	(0.00218)	(0.00246)	(0.00368)	(0.00598)	(0.00643)
Log Assets$_{i,t\text{-}1}$	0.00832**	0.00900**	0.0291***	-0.00786	-0.00941
	(0.00471)	(0.00536)	(0.00865)	(0.0109)	(0.0119)
Log Assets$_{i,t\text{-}1}$ Crisis$_t$	0.0303***	-0.0339***	-0.0456***	0.0328***	0.0662***
	(0.00511)	(0.00583)	(0.00929)	(0.0118)	(0.0130)
Log Sales$_{i,t\text{-}1}$	0.0142***	0.0119***	0.00357	0.0255***	0.0371***
	(0.00374)	(0.00427)	(0.00697)	(0.00854)	(0.00937)
Log Sales$_{i,t\text{-}1}$ × Crisis$_t$	0.00731**	0.0105**	0.0140**	0.00612	0.0128

	Sample of observations				
	All		5-year survivors		
	All banks		Foreign banks	State banks	Large banks
Variable	(1)	(2)	(3)	(4)	(5)
	(0.00405)	(0.00462)	(0.00753)	(0.00917)	(0.0102)
$Collateral_{i,t\text{-}1}$	-0.00000297	-0.0107	0.0138	-0.0268	-0.00207
	(0.00963)	(0.0106)	(0.0180)	(0.0236)	(0.0257)
$Collateral_{i,t\text{-}1} \times Crisis_t$	0.0342***	0.0417***	0.0152	0.0759***	0.0806***
	(0.0103)	(0.0115)	(0.0192)	(0.0254)	(0.0282)
$ROA_{i,t\text{-}1}$	0.0779***	0.0360	0.193***	-0.0910	0.00778
	(0.0287)	(0.0330)	(0.0566)	(0.0739)	(0.0844)
$ROA_{i,t\text{-}1} \times Crisis_t$	0.0288	0.0309	-0.0240	0.0572	0.140
	(0.0324)	(0.0372)	(0.0637)	(0.0831)	(0.0978)
EBITDA-to-$debt_{i,t\text{-}1}$	0.000835	-0.00170	0.0111	-0.0198**	0.00124
	(0.00401)	(0.00561)	(0.0107)	(0.00945)	(0.0144)
E-to-$D_{i,t\text{-}1} \times Crisis_t$	-0.00106	0.000127	-0.0147	0.0204**	-0.00219
	(0.00410)	(0.00575)	(0.0109)	(0.00971)	(0.0147)
Debt-to-assets $ratio_{i,t\text{-}1}$	0.0351***	0.0327***	0.0275***	0.0693***	0.101***
	(0.00596)	(0.00643)	(0.0105)	(0.0144)	(0.0157)
D-to-A $ratio_{i,t\text{-}1} \times Crisis_t$	-0.00501	-0.00407	0.00760	-0.0356**	0.0471***
	(0.00640)	(0.00688)	(0.0113)	(0.0156)	(0.0171)
$SD(ROA)_{i,t\text{-}1}$		0.000501	0.000477	0.00112	0.00117
		(0.00120)	(0.00202)	(0.00214)	(0.00326)
$SD(ROA)_{i,t\text{-}1} \times Crisis_t$		-0.000454	-0.000257	-0.00117	-0.00102
		(0.00120)	(0.00203)	(0.00214)	(0.00327)

	Sample of observations				
	All		5-year survivors		
	All banks		Foreign banks	State banks	Large banks
Variable	(1)	(2)	(3)	(4)	(5)
$SR(ROA)_{i,t\text{-}1}$		0.00642***	0.00747**	0.00928**	0.0116***
		(0.00199)	(0.00339)	(0.00435)	(0.00449)
$SR(ROA)_{i,t\text{-}1} \times Crisis_t$		-0.00205	-0.00345	-0.000683	-0.000926
		(0.00208)	(0.00362)	(0.00459)	(0.00477)
Observations	1,977,681	1,697,659	609,763	461,660	470,917
R2 Adj.	0.795	0.795	0.765	0.822	0.798

Notes: Crisis denotes an indicator variable, which assumes a value of 1 if period *t* is during the crisis (2009-2014) and 0 otherwise. State and foreign owned, and large denote indicator variables that assume a value of 1 if the bank is state owned, foreign owned and large (at least 5% market share in bank loans), respectively. No loan bank denotes a variable that assumes 1 if firm i had no loan from bank b and 0 otherwise. with Loans comprise all bank loans that a firm receives above €1,000 limit. Collateral is a share of pledgeable assets (tangible capital, structures in a form of inventories, financial assets) in total assets. All equations are estimated with firm-age, year, industry (NACE 2-digit), bank fixed effects. Firm cluster-robust standard errors are given in parentheses. *, ** and *** denote statistical significance at $p<0.10$, $p<0.05$ and $p<0.01$, respectively.

Source: AJPES, Bank of Slovenia and own calculations.

5 Conclusion

Efficient credit allocation enables better performance of the economy and more sustainable growth. The recession in Slovenia was very severe and, albeit with some periods of modest GDP growth, lasted for more than five years. Both the depth and length of the crisis can be at least partially attributed to credit misallocation. If loans support a relatively lower-performing or riskier part of the economy, this can be expected to result in a deeper contraction once a crisis hits. Moreover, it is expected to also slow down the recovery, since a banking system that is burdened with huge amount of non-performing assets, like that of Slovenia, is unable to provide funds to the economy.

In this paper, we have studied credit allocation in Slovenia. We are especially interested in seeing whether the crisis led to an improvement in credit allocation. We find that in general, this is not the case. The effects of firm-level variables on the probability that a firm has a loan and on the loan amount were already low (and in most cases economically insignificant) in the pre-crisis period, and they fell further in the crisis period, signalling poorer allocation of loans. As we discuss, this result might be driven by a reduced correlation between firm performance measures and our credit-related variables in the crisis period. In addition, a certain influence may also stem from higher bank risk aversion and distress in the crisis period. Banks were also significantly less willing to lend to better-performing firms, which might be an additional reason behind the lower responsiveness in the crisis period.

A firm-bank-level analysis confirms our prior expectations and the results of the aggregate covariance decomposition, where we show that of the groups of banks that we study, state-owned banks exhibit the worst allocation. This is also clearly indicated by these banks having the largest share of non-performing loans. These banks also seem to respond differently to changes in their capital adequacy and shares of non-performing loans. It would be expected that banks with better capital position and lower share of NLPs are, on average, more willing to lend and that the crisis would have led to a negative correction for both indicators. For state-owned banks, however, we find that given their level of capital and share of non-performing loans, they seemed to be relatively more willing to lend in the crisis than in pre-crisis period. From this perspective their behaviour is countercyclical, but they still reduced their loan amount heavily during the crisis period. The effect of NPLs might have changed due to a significantly increased share of such loans among this group of banks in the crisis period.

Our finding that credit allocation is still worsening appears important for regulators and policy makers. As the Slovenian economy and banking system are still very vulnerable due to past misallocation, it is particularly problematic that additional funds are being allocated to the worst-performing firms. Our analysis reveals that increasing the share of foreign-owned banks and a reduction in the number of state-owned banks would lead to an improvement in the allocation of bank loans.

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The efficiency of banks' credit portfolio allocation: An application of kernel density estimation on a panel of Albanian banking system data

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Bank of Albania

1 Introduction

Financial intermediation and, in particular, credit growth are important factors for economic growth. They have played a significant supporting role for the Albanian economy since 2004, contributing to what became known as the absorption lead growth model. That model collapsed following the global 2008 financial crisis. The fast credit growth before 2009 'failed' to produce sustainable growth and employment. It did not even produce enough to sustain itself, leading to a sharp increase of non-performing loans (NPLs) from 4% to 25%. Credit and financial intermediation reduced sharply after 2009 following the global and domestic developments, and have been a hindrance to investment and growth from that point on. This reduction generated a symbiosis in the performance of NPLs and economic activity, leading to the deterioration of the balance sheets of the business and the banking system, and making it more and more difficult to support credit expansion and economic growth. Banks constrain new credit not only out of fear of new bad loans but also because NPLs deteriorate their financial soundness indicators, imposing capital and liquidity constraints on further credit expansion. Under these circumstances, it is important that credit growth is distributed efficiently to the most productive use.

This study focuses on the sectorial allocation of banks' credit portfolios of business loans in response to sector-specific economic and risk developments and bank-specific characteristics observed after 2008. Our focus is to investigate whether and how banks' business credit portfolios respond to changes in real economic activity, credit risk indicators and developments in the banking system itself as a measure of credit efficiency. We do so by analysing a panel of banks

1 The authors would like to emphasise that the ideas and comment expressed in this paper are the responsibility of the authors only and not those of the Bank of Albania.

using kernel estimation methodology and the cross-section method proposed by Tanku and Ceca (2013, 2014). One advantage of this method is that the analysis does not suffer from the endogeneity and autocorrelation problems that impair traditional panel data analysis. The adoption and application of the method itself to panel data sets is a second important objective of this research.

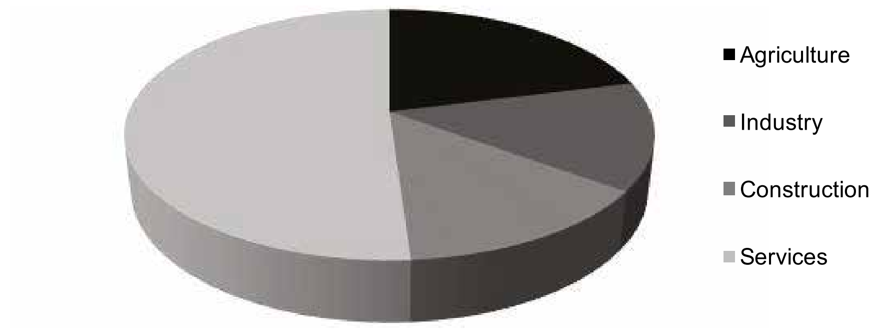
Stagnation of new credit in the Albanian economy is somewhat hard to explain for several reasons. First, the banking system is well capitalised and overall liquidity in the system is abundant. Second, the economy has been growing, albeit at a slow rate. At the same time, the composition of growth has changed in favour of tradable sectors. These sectors could benefit from new credit and contribute to faster growth and eventually to a reduction of NPLs. Third, credit is stagnating, in spite of several expansionary monetary policy and macroprudential measures taken by the central bank. Since 2008, the Bank of Albania has reduced its policy rate by 4.5%. This reduction of the monetary policy rate has been followed by a substantial reduction in credit interest rates; meanwhile, inflation is low and Albanian lek has been stable. Monetary policy has been supported by the introduction of macroprudential expansionary measures. Yet despite all this, credit has not recovered. Financial institutions have failed to respond to the significant decrease in interest rates or to stimulating macroprudential measures undertaken by the Bank of Albania. New credit has developed in favour of the domestic currency, but remains anaemic and has failed to produce significant growth. Most importantly, several important sectorial and macroeconomic imbalances that preceded the crisis are still present and there is no sign of significant adjustment in relative prices that would lead to their reduction. As a result, the transmission mechanism of monetary policy seems to be broken and the Albanian economy has remained stuck in low gear for more than five years. This is all documented in the Bank of Albania analyses and research discussed in its *Annual Monetary Policy and Financial Stability* reports published between 2008 and 2014. The reasons behind this prolonged severe underperformance is very important from the central bank's point of view.

Existing research indicates that such poor performance could relate to inefficient credit allocation. Peek and Rosengren (2003) observe that following periods of economic and financial stress, banks do not distribute credit to the most productive sectors in the economy. This is also confirmed by the works of Ahearne and Shinada (2005) and Caballero et al. (2006). They find that banks have short-term incentives to provide credit to underperforming sectors, insulating 'zombie firms' from market forces that would normally force the restructuring or bankruptcy of these otherwise insolvent firms. Banks tend to stick to their bad decisions of the past, and continue to support the same companies by restructuring or trading existing bad loans. This restricts investments and growth in the most productive sectors and affects the growth potential of the economy. This study investigates whether traces of this behaviour are currently present in the Albanian banking system by investigating the efficiency of credit allocation (in terms of business loans).

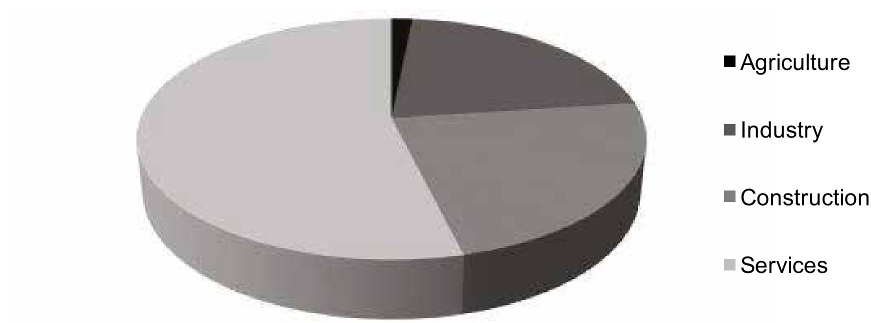
Albanian banking system data shows that the current distribution of outstanding stock of credit among sectors does not reflect the sectors' contribution to the economy (Figure 1). This composition reflects first and foremost the characteristics of the fast financial intermediation process and those of the absorption lead growth model that dominated economic activity prior to 2008.

Figure 1 Sector shares of value added, credit and non-performing loans

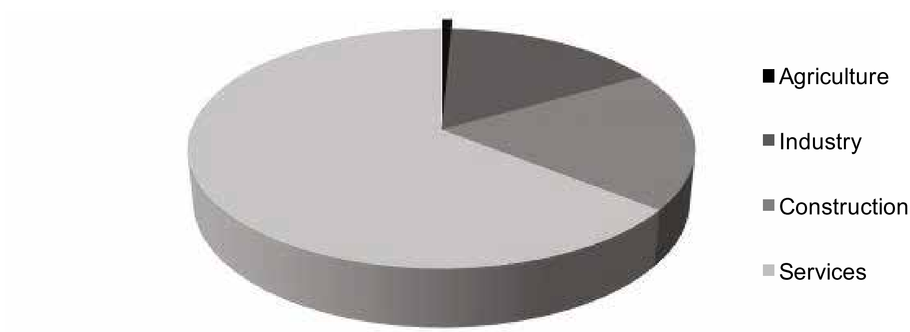
a) Value added



b) Credit



c) Non-performing loans



However, as mentioned above, credit expansion stopped after 2009, despite the fact that bank liabilities are mainly supported by domestic sources. Due to this anaemic growth, the composition of credit flows has not produced a significant change in the sectorial composition of the outstanding credit stock. The important question is whether the banks have adapted their behaviour to support the fastest growing sectors while simultaneously reflecting the risk proportionally? We also wish to investigate whether bank-specific factors have contributed to the speed and amount of the adjustment.

Using data on loans from individual banks for the period 2008-2014, we find evidence that banks do not respond appropriately to economic developments and changes in credit risk in all sectors. Not surprisingly, in some cases this response goes in both directions. We find evidence that banks tend to shield some sectors from negative developments and do not respond with the same intensity in supporting positive developments in other sectors. Capital ratios do not seem to play a significant role in credit allocation. In general, we find that banks behaviour is not unique across sectors or explanatory variables, confirming the hypothesis that credit allocation is not efficient.

The rest of this paper is organised as follows. The next section discusses the strategy of research. Sections 3 and 4 discuss the methodology, while Section 5 describes the variables, the dataset and its sources. The results are summarised in Section 6, which is followed by conclusions.

2 Plan and methodology of research

This paper investigates whether changes in outstanding credit stock to domestic sectors responds to developments in domestic sectorial growth and other financial and bank-based indicators.

The efficiency of credit allocation is an important issue and has been discussed previously in the literature. Mankiw (1986) defines a theoretic model for credit allocation which explains a bank's decision to lend based on two important elements: first, the expected return in the industry that is borrowing the money; and second, the firm's probability of default. These two characteristics of the firm are important to the bank in terms of the probability of repayment. They are, however, both unknown to the bank. Therefore, the bank must form a judgement or expectation based on indicators which serve as a proxy for these two elements. Assuming that the idiosyncratic return and risk preference are distributed normally amongst firms in the industry, with the mean equal to the industry average, allows researchers to use overall industry profitability and default figures. This leaves the bank, and us, with one problem: trying to work out the best figure for the profitability and risk of the industry relative to the rest of the economy. This direct relationship can be altered by three different and opposing forces.

First, the relationship between sectorial growth and sectorial credit allocation will be affected by the bank's past exposure to a particular industry, because more concentrated portfolios are less protected or incorporate higher risks.[2] Banks can control their risk exposure by reducing or containing new credit to this sector, discouraging new loans to the sector, or encouraging additional

2 Concentration measured as share of sector to total business loans.

loans to alternative sectors. The problem is even more evident once the sectorial breakdown of bad loans is taken into account. A larger exposure to a sector with a higher or rapidly increasing share of non-performing loans could force the bank to discourage new loans to this sector either by imposing growth targets or higher interest rate.

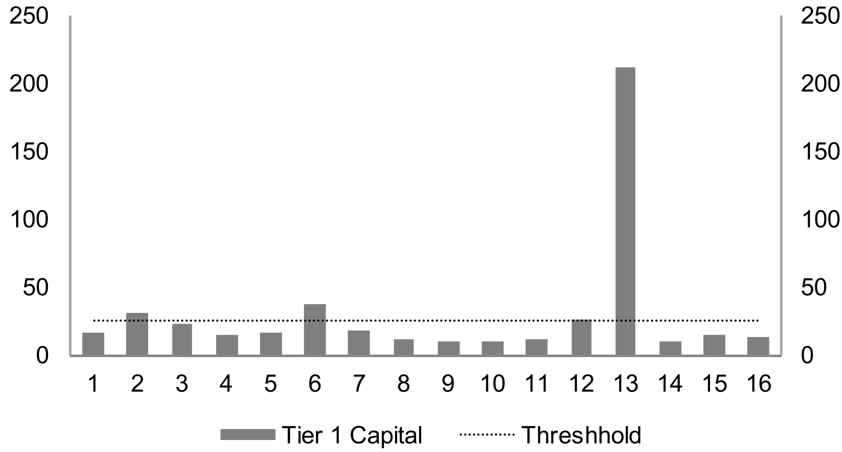
This adjustment might be altered by the 'legacy'-related costs associated with the outstanding stock of debt at the beginning of the period of study relative to the rest of the sectors. In this *second case,* inherited credit allocation becomes a burden for portfolio adjustment. As Peek and Rosengren (2003) found, once banks inherit a given distribution among industries, it might not be easy for them to adjust to new expanding sectors considering their commitment to the old ones. This is especially the case in times of difficulty when, due to hard economic conditions, banks restructure bad credit and support struggling client companies to contain the NPLs in their balance sheets. Therefore, when considering efficient credit risk allocation, it is important to account for bank exposure to the sector relative to the rest of the economy. As such, it would make sense to include some relative perspective in the sectorial credit allocation and NPLs, expressing both variables in terms of outstanding obligations.[3]

Third, the reorientation of credit toward new sectors would depend on the bank's ability or necessity to adjust its portfolio quickly. Kishan and Opiela (2000) find that the ability of banks to maintain loan growth depends on their individual characteristics, such as capital and asset size. It is common to assume that larger and better-capitalised institutions with larger networks and deposit bases are able to maintain their preferred portfolio allocation much easier than smaller and financially constrained institutions. This is acknowledged in other studies that have included individual bank characteristics in their regression equations. We intend to do the same by adopting the capital adequacy ratio in the analysis.

The capital adequacy ratio is an important indicator of bank behaviour in Albania. Figure 2 depicts the average capital adequacy ratios for the period of the study (2008–2014). Banking supervision regulation requires that banks maintain a capital adequacy ratio of 12%. However, the levels shown in the figure are substantially higher than this for several banks. The larger capital adequacy ratios, which correspond primary to smaller banks, indicate particular 'forced' episodes of compliance with banking regulation due to the injection of new capital or the sudden disappearance of large (relative to bank size) loans for particular sectors from a bank's credit portfolio. Their capital situation is important in banks' decision-making process, especially for the smaller institutions.

3 This is discussed in more detail in the variable description and data construction section.

Figure 2 Average capital adequacy ratios, 2008–2014



Empirical studies on the topic, including Peek and Rosengren (2003), Buch et al. (2006), and Bebczuk and Galindo (2005), have relied on the general narrative above to investigate the efficiency of credit allocation. These studies are conducted on panel datasets of individual banks or enterprise records, and the empirical model is traditionally estimated by linear regression methods. Most of these studies have investigated credit allocation in response to sectoral growth, sectoral risk, institutional factors and bank-specific indicators. The model takes the form:

$$\Delta l = \alpha + \beta \Delta l_{t\text{-}1} + \theta X + \varepsilon \tag{1}$$

where l represents lending, X represents the vector of sector-specific or institutional and bank-specific explanatory variables, β and θ represent the vector of estimated elasticities that corresponds to the lagged value of lending and the set variables in X, and ε represents the errors of the estimated model

However, the implementation of this framework is not trouble-free, given the structure of the model and the endogeneity status of the variables. They have potential implications for the estimated coefficients, and therefore the conclusion. We try to deal with these problems by adapting an alternative methodology based on the kernel estimation technique, as discussed by Tanku and Ceca (2013, 2014). The following section discusses both methods.

3 General description of the estimation of the OLS and kernel estimation multidimensional density analysis

Economic developments have the characteristics of random events. The outcomes are generated and governed by the data-generating process (DGP), which is defined by Ericsson, Hendry and Mizon (1998) in the form of a probability space [Ω, *F*, *P*(.)]. *This DGP is in general unknown to the researcher*. Due to this limited knowledge, it is most likely that the choice of the variables involved in the empirical investigation process represent only a subspace of the true DGP, defined as the local data-generating process, or LDGP.

The focus of the empirical analysis is the identification of the functional form of this LDGP and the estimation of its unknown parameters. The estimation of parameters in pooled and panel data analysis is traditionally based on a linear regression methodology, or alternative techniques which build upon linear regression by dealing with potential violations of the general assumptions in OLS. The general representation of the random events can take the form below:

$$\{X_t^k\} = \begin{pmatrix} x_1^1 & \cdots & x_1^d \\ \vdots & \ddots & \vdots \\ x_T^1 & \cdots & x_T^d \end{pmatrix} \tag{1}$$

where t, $k \in N$ such that $t = 1, \ldots, T$ and $k = 1, \ldots, d$, represent the number of observations and the number of variables in the dataset, respectively.

Given any observed dataset specified in equation 1, the linear regression technique singles out one of the variables (let us call it the dependent or the response variable) and tries to express it as a function of the other d-1 variables (which we will call predictor variables or regressors). In general, linear regression assumes that the conditional mean of the response variable $\underline{X^\kappa}$ is a linear function of the predictor variables $X^{d\text{-}1}$, multiplied by a vector of unknown parameters β, formulated in equation 2:

$$E(\underline{X^\kappa}|\underline{X^{d\text{-}1}}, \beta) = E(\underline{\hat{X}^\kappa}|\underline{X^{d\text{-}1}}, \hat{\beta}) \tag{2}$$

where $\underline{X^\kappa}$ and $\underline{\hat{X}^\kappa}$ represent the observed and estimated $T \times 1$ vectors of response variable respectively, $\underline{X^{d\text{-}1}}$ represents d–1 vectors of predictor variables or alternatively a (d–1)×T matrix of repressors, and β and $\hat{\beta}$ represent the true and estimated coefficients, respectively.

In addition, linear regression assumes that the conditional variance of the error made in the prediction of the response variable (conditioned on $\hat{\beta}$ and $X^{d\text{-}1}$, defined as the error term of the model, has a known matrix variance Ω. This definition of linear regression is usually written in the form:

$$X^\kappa = X^{d\text{-}1}\hat{\beta} + \varepsilon \tag{3}$$

where $\underline{\varepsilon} = \underline{\hat{X}^d} - (\underline{X^{d\text{-}1}\hat{\beta}})$, and $E(\varepsilon|X^{d\text{-}1}) = \Omega$.

Equation 3 is one way to represent the LDGP (where LDGP $\in R^d$) as a linear combination of the reduced space R^{d-1} spanned by the vectors of the regressors.

It represents a projection of vector $\underline{X^{\kappa}}$ along the basis of $X^{d\text{-}1}$, with the vector of coefficients $\hat{\beta}$ being the factor that achieves this decomposition.[4] The estimation of this model is justified by a set of additional assumptions, including exogenous covariates $Cov(\varepsilon, X^{d\text{-}1}) = 0$ and uncorrelated errors $Cov(\varepsilon_t, \varepsilon_{t+m}) = 0$, which guarantee consistent, unbiased and efficient estimators.

This framework is adapted in the context of panel estimation leading to the following representation:

In a typical panel dataset, equation 1 transforms into:

$$\{X^{k}_{i,t}\} = \begin{pmatrix} x^{1}_{i,1} & \cdots & x^{d}_{i,1} \\ \vdots & \ddots & \vdots \\ x^{1}_{i,T} & \cdots & x^{d}_{i,T} \end{pmatrix} \tag{4}$$

where $i, t, k, \in N$ such that $i = 1, 2, \ldots, k$ represent the number of observed cross-sections in the dataset and t and p preserve the same definition as in (1) above, transforming equation 3 into the following form:

$$X^{\kappa}_{i} = X^{d\text{-}1}_{i}\,\hat{\beta} + \varepsilon_i \tag{5}$$

here, however, $\underline{\varepsilon_i} = u_i + \vartheta_{i,t}$, with $u_i + \vartheta_{i,t}$ representing the cross-section-specific unobserved variable and the residual, respectively; and $E(u_i \mid X^{d\text{-}1}_{i}) = 0$, $E(\vartheta_{i,t} \mid X^{d\text{-}1}_{i}) = 0$, $Var(\vartheta_{i,t} \mid X^{d\text{-}1}_{i}) = \Omega$, in addition $Cov(\vartheta_{i,t}, X^{d\text{-}1}_{i}) = 0$ for all i must be satisfied.

The problem with the panel estimation of linear regression models is the assumption regarding the nature of u_i, and the violation of the linear regression assumptions across cross-sectional or periods in the pooled data due to lack of knowledge of the true data-generating process.

The relationships between credit and growth, credit and risk, and credit and the capital adequacy ratio are typical examples of endogeneity and autocorrelation problems. The simultaneity of such events and/or potential loops of causality generate a symbiosis among credit growth and sectorial growth. These represent a significant problem in the empirical investigation analysis and the estimation of the coefficients. Any traditional econometric analysis textbook, such as Greene (2003), will provide a full discussion of the related problems; additional arguments are provided in Hendry and Johansen (2013).

The violation of the above-mentioned assumptions is problematic and must be addressed by the choice of the estimation methodology. Depending on the specific violation, the problem is solved by the adoption of alternative methods of linear regression (GMM, GLS, 2SLS, weighted OLS, non-linear OLS, etc.).

The solutions discussed above are not a panacea either. The 'tweaks', augmentations and substitutions of the error variance matrix represent arbitrary interventions which control and/or change the information to satisfy the assumption. The identification of instrumental variables is a problem in itself. Given the difficulty and subjectivity in the above-mentioned methods, several studies have resorted to the use of a panel VAR methodology. However, this too is subject to correct model identification. Erickson et al. (1998) describe the endogeneity problem in detail and identify the correct conditions under which the estimation of the conditional part of the 'empirical' model is justified. Therefore,

4 Vector $\hat{\beta}$ is estimated by means of minimising the sum of the squared residuals.

the correct inference on all these particular elements will have a significant impact on the results, and their interpretation. In general autocorrelation, endogeneity, linearity, normal distribution of errors, and so on are frequently present and hard to eliminate and justify in panel data. They remain important obstacles in the estimation of the econometric model.

Faced with these potential problems, we propose the density estimation technique as an alternative to linear regression estimation. We follow Tanku and Ceca (2013), based on the approximation of the joint density function using the kernel density estimation technique. Kernel density estimation allows the representation of the data-generating process in terms of the joint density function of any d-dimensional space spanned by the variables of interest, yielding the following general representation of the DGP:

$$D_{x^k}(X^k|f(.)) = D_{x^k}(x^k|\hat{f}(.)) \tag{7}$$

where D_{x^k} represents the density function of the LDGP, $k \in \{1, \dots, d\}$ represent the dimensions of the LDGP which density function is estimated (the variable or the set of variables of interest to the researcher, and $\hat{f}(.)$ represents the estimated d-dimensional joint density function.

Alternatively, the data-generating process could be expressed as a conditional probability of the joint density function of our d-dimensional space by the variables of interest in the following general form:

$$D_{x^k}(X^k|\, X^j, f(.)) = D_{x^k}(x^k|\, x^j, \hat{f}(.)) \tag{7.1}$$

where $j = (1, 2, \dots k - 1, k + 1, \dots, d)$ represent the conditioning dimensions' variables, and the rest of the notations preserve the same references as above.[5]

The focus of density estimation is the joint density of the LDGP rather than the vector β. The estimation of the density function given in equations 7 and 7.1 builds upon the density estimation technics discussed in Silverman (1986). Tanku and Ceca (2013) calculate and show the estimated densities of any d-dimensional space of economic variables using the Gaussian kernel, taking the form below:

$$\hat{f}(\underline{l}) = \frac{1}{Th^d(2\pi)^{d/2}} \cdot \sum_{t=1}^{T} exp\left\{-\frac{1}{2h^2}\left[(l_1 - x_t^1)^2 + (l_2 - x_t^2)^2 + \cdots + \left(l_d - x_t^d\right)^2\right]\right\}, \tag{8}$$

where $\underline{l} \in R^d$ is the variable of the estimated density $\hat{f}(\underline{l})$ and h is the smoothing parameter.

Equation 8 provides the model that defines and expresses the DGP in its alternative interpretation defined by equation 7 and 7.1. Tanku and Ceca (2013) point to the fact that this representation allows for the definition of economy as an expanding sequence of spaces in R^d leading to the interpretation of each m-dimensional LDGP as a projection of the original DGP in the R^m subspace (where $m < d$).

Density estimation provides several benefits compared to traditional linear regression methods. First, unlike linear regression methods, density estimation

5 The reader must not confuse the condition of equation 7.1 with the condition of equation 2. As will be explained below, condition in 2 defines the set of regressors, while the meaning of condition in equation 7.1 is for particular values or intervals along the variables in LDGP. The equivalent of condition in equation 2 will be presented in equation 9, in the following section.

provides a method to project DGP in itself, without loss of dimensions. At first glance, equations *7* and *8* seem to provide a 'similar' representation of the LDGP as equation *2*; however, there is a fundamental difference. Equation 8 expresses LDGP as a joint density function of LDGP in the R^d space as opposed to the R^{d-1} space spanned only by the vectors of the regressors in the case of linear regressions.

Second, under this alternative representation, the object of investigation shifts from the estimation of β to the estimation of the joint density function of the DGP. The focus of the investigation is the resulting density function D_x distribution, which contains the fullest information with regard to variable X. This provides a significant improvement upon equation 2, which focuses exclusively on the expected value of the dependent variable.

Third, there is no need to discuss the linear independence among regressors since the 'solution' is not found in the decomposition of the LDGP among the orthogonal bases of the subspace R^{d-1} spaned by the regressors. Therefore, the assumption of endogeneity becomes redundant, for it does not affect the calculation of equation 8. This is to say that the relationship among any two or more variables is given once and for all by their uniquely defined joint density. One must be careful, as the estimation indices simultaneity and might not exclude both variables reacting to a third and unknown cause. However, the important thing is that it does not affect the calculation of the density function.

Tanku and Ceca (2013) rely on the graphical representation of the estimated densities to interpret and analyse the information contained in the multidimensional density functions. In this respect, the analysis of estimated multi-dimensional densities is limited by our inability to perceive beyond three-dimensional spaces. This limitation constrains the analysis to the estimation of two-dimensional joint density functions. Therefore, the analysis of the LDGP is carried by the estimation of equation 8 and the interpretation of the resulting graphical presentations representing the projection of the LDGP onto R^2. This two-dimensional mapping has become a traditional approach in the study of density estimation and other forms of multi-dimensional data computation, analysis and visualisation methods. In addition, Tanku and Ceca[6] (2014, p. 5) introduce the 'cross-section method' to ease the readability, interpretation and comparison of the resulting *d*-dimensional estimated densities, based in the first moment and its standard deviation. This cross-section is defined as the generalized definition of conditional distribution of a continuous random variable – the case when the condition is a set to be a single value. The method estimates the continuous density function of the dependent variable for any potential value of the regressor, based on the expression given in equation 9:[7]

$$\hat{f}\left(\frac{l}{l_{k+1}, \dots, l_{k+m}}\right) = \frac{1}{h^{d\ \ m}(2\pi)^{\frac{d\ \ m}{2}}} \cdot \frac{\sum_{t=1}^{T} exp\left\{-\frac{1}{2h^2}\overbrace{\left[\left(l_1 - x_t^1\right)^2 + \dots + \left(l_d - x_t^d\right)^2\right]}^{d\ monomials}\right\}}{\sum_{t=1}^{T} exp\left\{-\frac{1}{2h^2}\underbrace{\left[\left(l_{k+1} - x_t^{k+1}\right)^2 + \dots + \left(l_{k+m} - x_t^{k+m}\right)^2\right]}_{m\ monomials}\right\}} \quad (9)$$

6 Forthcoming in Bank of Albania Working Paper Series, available from the authors on request.
7 The derivation is provided by Tanku and Ceca (2014), available from the authors on request.

where $\hat{f}(\underline{l}/l_{k+1},\ldots,l_{k+m})$ represents the conditional density estimates with m dimensional condition, for density estimates given as the ratio of the d-dimensional density estimates $\hat{f}(\underline{l})$ with the marginal ones $\hat{f}_{\{k+1,\ldots,k+m\}}(l_{k+1},\ldots,l_{k+m})$ using the Gaussian kernel. The rest of the notations follow the same interpretation as above.[8]

Equation 9 represents the analytical expression of the continuous density functions of the variable of interest for all potential values of other m 'explanatory' variables where $(m, d \in N | m < d)$. It simultaneously serves as the tool of investigation and as the metric of interpretation of the relationships among our variables of interest. The numeric characteristics of the resulting density can be used to describe and interpret the density function and provide comparison with the traditional linear regression method. In the exercise below, we calculate and show the continuous first moment as well as its standard deviation of the resulting two-dimensional densities for all potential values of the explanatory variable.

The shape and position of such 'maps' of estimated densities (equation 8) and conditional expectations (equation 9) contain and reveal information on the relationship between the variables in the graph.

4 Adaption of density estimate and multidimensional density analysis to panel data

Given the informative structure of panel data and the benefits of kernel density estimation with regard to endogeneity and autocorrelation problems, we wish to adopt density estimation as a tool of investigation for the panel data approach. The focus is the estimation of multidimensional density probabilities of DGP using the kernel density estimation technique. We start by rewriting DGP in its vector form as a process of dimensions along all cross-sections and time observations:

$$\begin{aligned} X^1 &= (x^1_{i,1}, x^1_{i,2}, \ldots, x^1_{i,T},)' \\ X^2 &= (x^2_{i,1}, x^2_{i,2}, \ldots, x^2_{i,T},)' \\ X^3 &= (x^3_{i,1}, x^3_{i,2}, \ldots, x^3_{i,T},)' \\ &\ldots \quad \ldots \quad \ldots \\ X^d &= (x^d_{i,1}, x^d_{i,2}, \ldots, x^d_{i,T},)' \end{aligned} \tag{10}$$

for $i = (1, 2, \ldots, p)$ where p represents the number of cross-sections in the panel.

The representation of panel data structure in the form of the joint density function of our d-dimensional space in the form of any d-dimensional density, using Gaussian Kernel requires rewriting equation 7:[9]

8 The expression of the calculated conditional density in the case of one and multidimensional conditions for the Gaussian and Epanechnikov kernels are available in Tanku and Ceca (2014).

9 Tanku and Ceca (2013) provide also the functional form of the estimated density in the case of Epanechnikov kernel.

$$\hat{f}(\underline{l}) = \frac{1}{(Tp)h^d(2\pi)^{d/2}} \cdot \sum_{t=1;i=1}^{T;p} exp\left\{-\frac{1}{2h^2}\left[\left(l_1 - x_{t,i}^1\right)^2 + \left(l_2 - x_{t,i}^2\right)^2 + \cdots + \left(l_d - x_{t,i}^d\right)^2\right]\right\} \quad (11)$$

where $\underline{l} \in R$ is the variable of the estimated density $\hat{f}(\underline{l})$ and h is the smoothing parameter.

This leads to the transformation of equation 9 into the following general representation:

$$\hat{f}\left(\frac{l}{l_{k+1}, \ldots, l_{k+m}}\right) = \frac{1}{h^{d\ \ m}(2\pi)^{\frac{d\ \ m}{2}}} \cdot \frac{\sum_{t=1;i=1}^{T;p} exp\left\{-\frac{1}{2h^2}\overbrace{\left[\left(l_1 - x_{t,i}^1\right)^2 + \ldots + \left(l_d - x_{t,i}^d\right)^2\right]}^{d\ monomials}\right\}}{\sum_{t=1;p=1}^{T;p} exp\left\{-\frac{1}{2h^2}\underbrace{\left[\left(l_{k+1} - x_{t,i}^{k+1}\right)^2 + \ldots + \left(l_{k+m} - x_{t,i}^{k+m}\right)^2\right]}_{m\ monomials}\right\}} \quad (12)$$

Equation 12 represents the estimated continuous density of the dependent variable for all potential values of the independent variable (preserving simultaneity across cross-sections and time period). So the evolution of density (or its numerical characteristics) provides all the information for the behaviour of the dependent variable in response to changes in the independent (regressor) variable.

The above-mentioned advantages of kernel density estimation methodology relative to linear regression transfer nicely to the study of panel data sets, freeing the estimation from potential implications of the cross-section-specific (in our case, bank-specific) errors and other endogeneity and autocorrelation problems. Therefore, there is no need to test and compensate for the presence of such problems in the data, or have prior knowledge of the true DGP. There is no miss-specification of the functional form as there is no need to assume a functional form for the DGP.

Our exercise has simply projected the expected value and its standard deviation. However, analysis can continue with the remaining numerical characteristics of the distribution. The variables and other characteristics of the database are discussed in the following section.

5 Variable description and data construction

The purpose of this study is to investigate whether credit allocation responds to sectorial developments in terms of growth and risk performance, and banks' individual financial situations. We plan to investigate this topic using kernel density estimation and the cross-section method, as proposed by Tanku and Ceca (2013, 2014). We use a panel of 16 banks and quarterly observations over the period of 2008Q4 to 2014Q4. Following theoretic models and previous empiric research, we will examine the behaviour of credit for four different sectors in response to value added by the sector, the behaviour of non-performing loans in the sector, and banks' financial situations. Specifically, we will use the value added by sector, non-performing loans by sector and capital adequacy ratios.

The dependent variable is represented by the first difference of each sector's share in the stock of outstanding credit to business at the end of each period. The share of credit for each sector represents the total outstanding debt allocated to the sector, expressed as a percentage of total outstanding stock allocated to business at the end of the reference period.

Following Buch et al. (2006), we will use sectorial value added as a proxy for return in the respective industry, and an explanatory variable for credit allocation among sectors. This is reasonable under the assumption that the fastest growing industries are also the most profitable ones. Therefore, banks' evaluations for the industry-specific allocation in our model will depend on their expectations of the value added by the industry relative to the rest of the economy.

Traditional studies have regressed change in loans on value added by sectors. However, this might not be an accurate measure in the case of sectors' contributions to DGP being substantially and persistently different. Faster growth in a relatively small sector would absorb a much smaller share of credit than a larger sector which is growing at a substantially slower peace. In this respect, it is necessary to introduce a sense of relativity in the sector value-added indicators. We subject the value-added variable to this effect by calculating, each sector's value added as the share (in percentage) of the total value added during the reference period. In addition, given the high seasonality of the value-added indicator, each sector's value added is represented in its annualised form (calculated as the rolling sum of four quarters). This indicator is lagged one quarter to account for the fact that the information can affect banks' decisions only after it becomes available.

The individual probability of default is also unknown to the bank, but can be approximated by the probability of the sector. Sectorial probability of default is not available either; therefore, we rely on the relative share of sectorial NPLs as a proxy indicator of the ability of the sector to repay back loans. This is based on the assumption that the idiosyncratic risk in the industry is distributed normally, with the mean equal to sector's NPLs. The non-performing loan indicator represents the first difference of sectors' outstanding stock of NPLs, expressed as a percentage of total outstanding stock of NPLs for each bank at the end of the reference period. As in the case of value added above, this indicator is lagged one quarter to account for the fact that the knowledge of the NPL situation at the end of a period can affect banks' decisions in the following period.

Banks' own indicators are defined by the capital adequacy ratio. This indicator varies substantially among cross-sections (and, for some particular banks, across the time dimension). Figure 2 shows the average capital adequacy ratio indicator for the period for each bank. The Albanian banking supervision regulation requires that the capital adequacy ratio equals 12%; however, Figure 2 shows that it has been substantially higher. While this is in itself a sign of financial inefficiency, it seems to be a rule rather than an exception in the Albanian banking system. The figure is extremely high for three particular banks. Not surprisingly, this corresponds to the banks that are very inactive in terms of credit activity. Their situation represents an exception rather than a reflection of their business strategies, so they are considered as outliers and are dropped from the sample, reducing the number of cross-sections to 13 from the original 16. In addition, four more observations are lost in each cross-section, three due to the calculation of the rolling sum, and one for the first difference in credit variable. After these adjustments are made, the number of observations in our balanced panel falls to a total of 286 from the original 400. Table 1 summarises the dataset and its sources.

Credit indicators and bank-specific data comes from the Bank of Albania's reporting system, and value added data come from INSTAT (Albania Institute of Statistics). More specific information is provided below.

Table 1 Data sources

Variable name*	Variable description	Source	Sector	Time period
AgriDk IndDk ConsDk ServDk	Credit variable: first difference of respective sector's outstanding credit calculated as %age of total outstanding credit to business. Expressed in basis points.	BoA	Agriculture Industry Construction Services	Q4,2008-Q4,2014
AgrirkDL1 IndrkDL1 ConsrkDL1 ServrkDL1	Credit risk variable: first difference of respective sector's NPL calculated as %age of total outstanding stock of NPL in economy.	BoA	Agriculture Industry Construction Services	Q4,2008-Q4,2014
AgrivaAL1 IndvaAL1 ConsvaAL1 ServvaAL1	Value added variable: annualized (rolling sum of last 4 quarters) of quarterly, not seasonally adjusted observations.	INSTAT	Agriculture Industry Construction Services	Q4,2008-Q4,2014
Tier 1	Capital adequacy ratio	BoA	Banks	Q4,2008-Q4,2014

Notes: */ D indicates the first difference, A indicates annualized data, and L1 indicates lagged 1 period.

6 Results

This section presents and discusses the results of our empiric investigation. Analysis is based in the interpretation of graphs (Figures 3.1 to 6.3), which represent the result of density estimation in R^2. The graphs depict the joint density and the conditional mean of the dependent variable (the change in credit for each sector) and each of the independent variables – value added, credit risk and capital adequacy ratio – separately. The discussion is focused on the shape and position of the isobars (of the density function resulting from equation 10) and the calculated conditional mean (of the density function resulting from equation 11). The analysis can easily be extended to include other moments or numerical characteristics for a more detailed discussion of the estimated conditional densities calculated by the cross-section method. The exercise is repeated for each sector.[10]

The graphs read as follows: the vertical axis shows the value of the dependent variable, and the horizontal one the value of the regressed. The colours of the

10 The resulting estimated density functions are subject to the choice of the smoothing parameter h in equations 10 and 11 controlling the smoothness of the density function. The choice of variable h is made so that we retrieve meaningful maps. In general, we have tried to keep the value of this parameter between 0.5 and 3. For further details on the selection of optimal h, see Tanku and Ceca (2013).

isobars depict the probability weight, with the scale shown on the right-hand side of the graph. In general, stronger red colours indicate events with high probability, and light blue colours indicate the opposite. The behaviour of the dependent variable is described by the shape and position of the isobars and the conditional mean in the graph, as the repressor's value moves from its minimum to its maximum value. As a general rule, estimating regular concentric circles and/or oval shaped isobars positioned perpendicularly to one of the axes in graph *a* would indicate independence of the response variable from the regressed. If this is the case, the resulting conditional mean in graph *b* will be horizontal, confirming that the expected value of the response variable does not respond to changes in the observed value of the regressed.

Alternatively, the estimation of a density function whose main axes are positioned at an angle to the main axes of the graph would indicate that the response variable reacts to changes in the observed value of the regressor, and the inclined position of the estimated conditional mean should confirm this, with the angle indicating the speed of response. Sections of graphs with higher elevation depict episodes with higher frequency, indicating that events in the corresponding range have a higher probability of occurrence. These deserve more attention in the interpretation of normal market developments. Events with lower elevation (those in the tails of the distribution) indicate rare events, and deserve more attention in the discussion and understanding of stress episodes. The following analysis discusses credit developments in each sector separately.

We start our discussion by analysing the behaviour of credit in the agriculture sector. In general, based on an economic interpretation, we would expect to observe a direct relationship between economic activity (value added) and sectorial developments in credit. The relationship between credit risk and credit could go in both directions, but a negative relationship would indicate that banks are behaving responsibly by reducing exposure to a sector when its credit risk increases. Finally, we would expect some reaction in credit as the capital adequacy ratio moves away from its required level of 12%. The size and direction would depend on the size of the bank and accessibility to funds. We look to identify these particular patterns in the density and cross-section graphs.

Figures 3.1a and 3.1b show the estimated densities and conditional mean of the credit to agriculture in response to value added, respectively. Figure 3.1a shows that credit to the agriculture sector is mainly located around zero, with two other frequent locations (dominant locations) located symmetrically on both sides of the main elevation at a distance of around 50 basis points. All three frequent locations on the graph are positioned horizontally, indicating that credit to the agriculture sector does not respond to changes in value added in this sector. This is also confirmed by the conditional mean in Figures 3.1b, which lies almost horizontal, responding only by a few basis points to the increase of value added in the agriculture sector vis-à-vis the rest of the economy.

Figure 3.1a

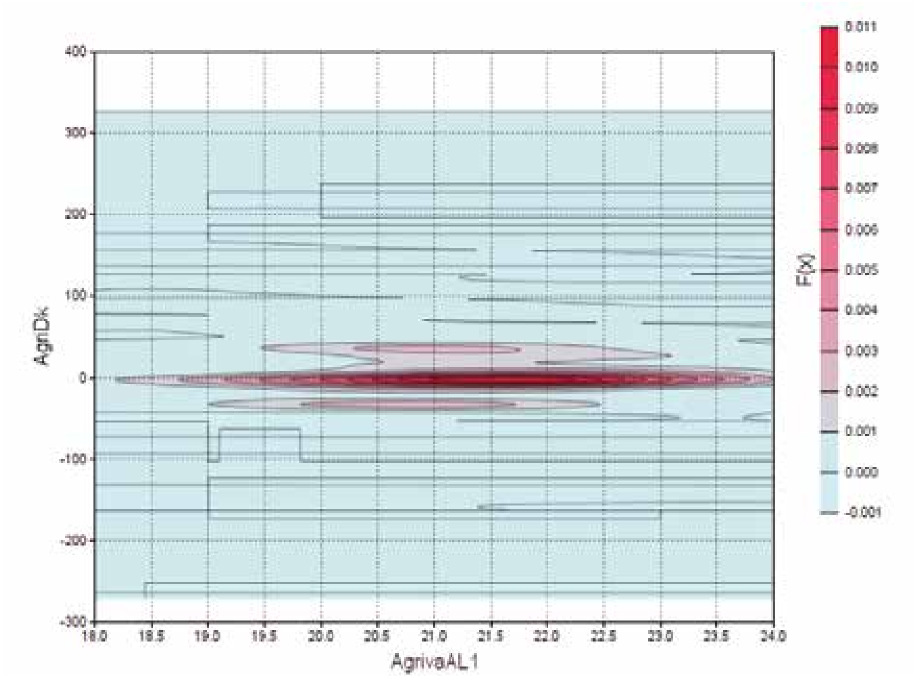


Figure 3.1b

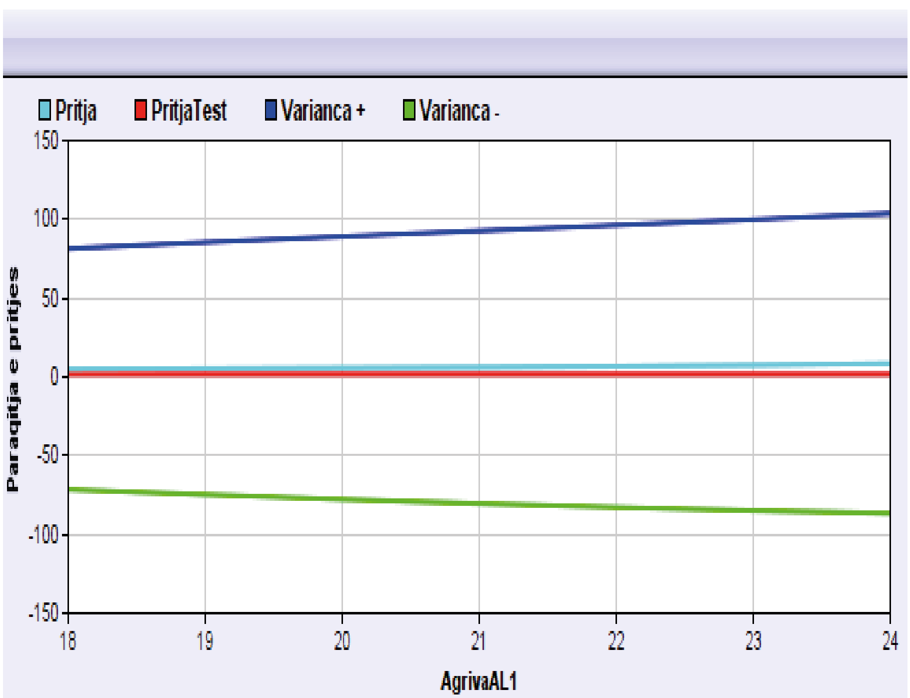


Figure 3.2 shows the response of credit to the agriculture sector to changes in credit risk. The estimated density depicted in Figure 3.2a shows that the density is dominated by a single rise, located horizontally around zero, with the tails extending in the direction of the main diagonal. We interpret this as an indication that an increase in credit risk is matched by an increase in credit growth. This is confirmed by the behaviour estimated conditional mean in Figure 3.2b, which shows that as the credit risk indicator increases from 24 to 36, credit increases by almost 20 basis points. In theory, this observation shows bank support for the sector while its credit risk increases, and indicates an inefficient allocation of credit. The effect is marginal, however, and credit growth is almost horizontal around zero in the majority of the observed credit risk interval. A marginal increase in the expected value of credit is also observed as the credit risk indicator decreases faster than 24 units, indicating that a drop in credit risk is accompanied by increased credit to the agriculture sector, as one would normally expect. In addition to its marginal effect, the observation is based on events with very low probability, and therefore might not be considered representative behaviour.

Finally, the density estimation of the credit growth and capital indicator in Figure 3.3a and the estimated conditional mean in Figure 3.3b indicate a marginal response of credit to changes in the capital adequacy ratio. Again, the density map is dominated by a single rise concentrated almost horizontally around zero, with few concentrated observations distributed above this. This is just enough to demonstrate a slight increase in credit as the capital adequacy ratio approaches 10-12% in Figure 3.3b The conditional expected value of credit to agriculture sector drops marginally in the capital adequacy ratio interval of 22-30%. This latter effect is almost twice as strong but is of a less importance due to the low probability of occurrence, as shown by the density map in panel a.

In summary, we observe a marginal response to credit risk and to capital situation developments. It seems that extreme values of relative credit risk influence credit in the opposite direction. Despite this, large changes in explanatory variables are met by only marginal increases in credit. We interpret this as a sign that credit to the agriculture sector develops independently of developments in real economic activity and the credit risk banking indicator.

Figure 3.2a

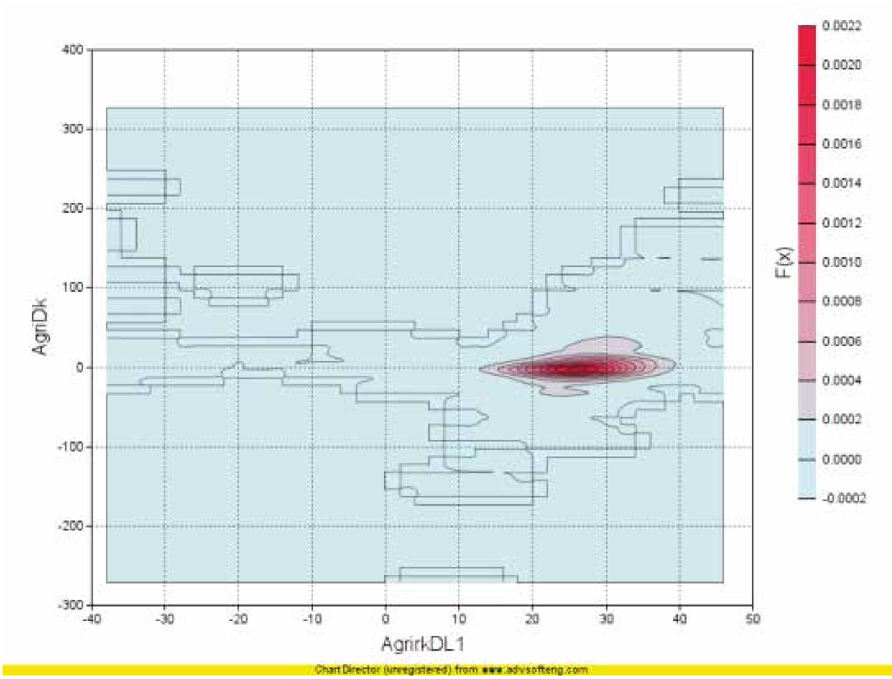


Figure 3.2b

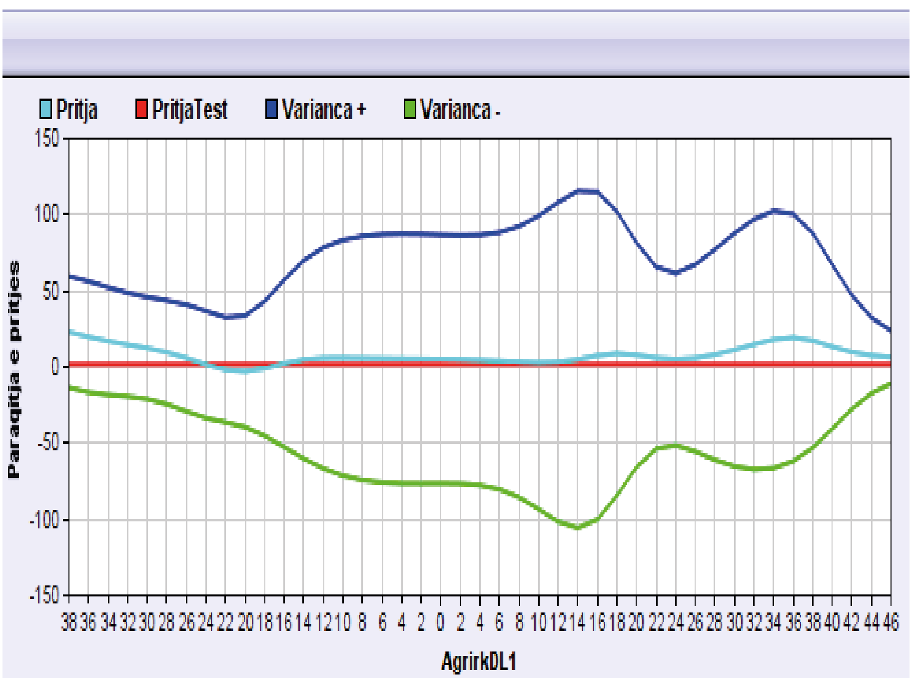


Figure 3.3a

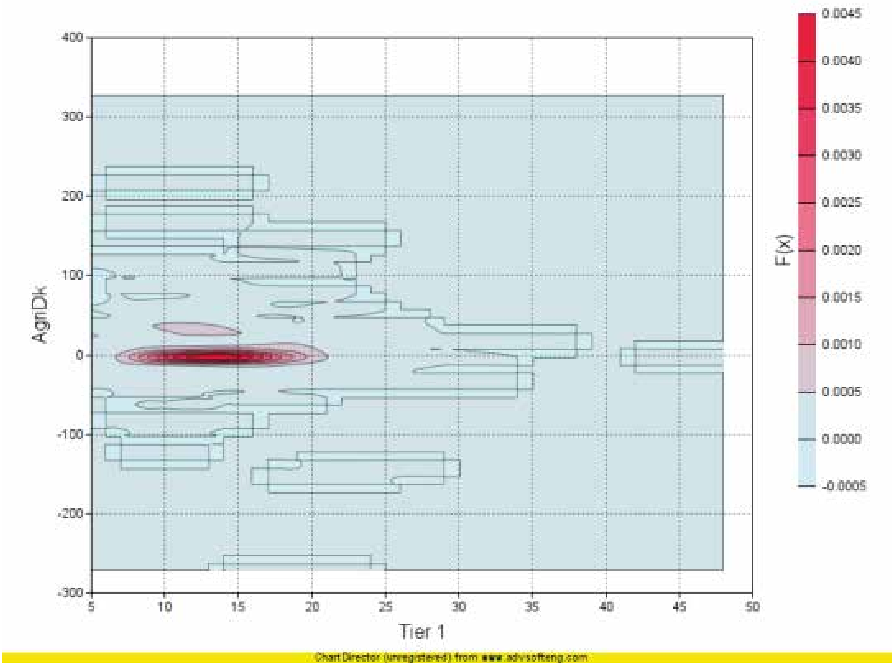
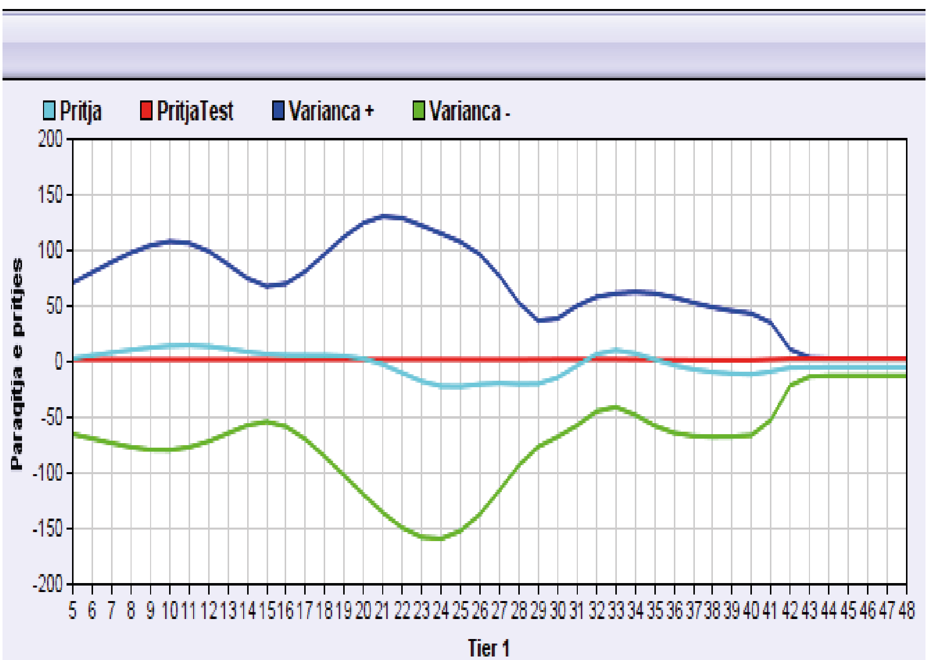


Figure 3.3b



Credit to the **industry** sector is depicted in Figures 4.1 to 4.3 In this case, the estimated densities are dominated by the presence of a larger number of bell-shaped rises, in particular in the case of development in value added and capital, all while being dominated by a single node in the case of credit risk.

The many nodes in the case of value added are spread out and positioned horizontally and parallel to each other. Even when considered together, they produce a trivial general upward trend, indicating a direct but trivial relationship between credit and value added. This is confirmed by the response of the estimated expected value of the conditional density in Figure 4.1b The graph shows that as the relative share of value added in construction increases from 10 to 14%, credit to this sector increases almost 50 basis points and becomes horizontal after that. This reaction is very small and indicates that banks are marginally more attentive to bad performance in the industry sector and in other sectors.

As in the case of value added, credit to the industry sector does not respond significantly to changes in relative credit risk (Figure 4.2). The density is dominated by a single oval bell, with its main axes seemingly parallel to the main axes in the graph. The most important observation here is that as the relative credit risk increases, we do not observe a strong adjustment in credit to this sector. The expected value of the conditional density in Figure 4.2b rises slightly by 100 basis points in response to changes in credit risk from -10 to 2. In principal, this indicates that a reduction in the relative share of NPLs of the industry sector compared with the rest of the economy is accompanied by a reduction of credit in this sector. Bank credit reduces significantly as the credit risk drops in the interval of -10 to -18. These developments are contrary our expectations and are difficult to explain. The expected value of credit increases only as the credit risk indicator falls below -18, which is what we would normally expect. However, both these changes are observed in events with low probability and do not indicate significant developments.

Finally, behaviour in response to banks' own capital is non-linear (Figure 4.3). The estimated density is dominated by the presence of many 'bells', which together produce a non-linear expected value for the conditional density. The response of credit to the industry sector to the capital adequacy ratio indicator is direct in the interval of 5-15%, indicating that a reduction of the capital adequacy ratio below the optimum level results in a reduction of credit to this sector. This credit drops significantly in the capital adequacy ratio interval of 21-31%, first falling and then rising again as the capital adequacy ratio increases beyond 27 %. We find these non-linear patterns difficult to interpret, but one can say that at as the capital adequacy ratio indicator reaches 21-31%, banks tend to allocate less credit to the industry sector.

In summary, credit to industry responds to developments in real economic activity and banks' individual indicators. As in the case of the agriculture sector, the relationship is direct but trivial in the most significant interval (i.e. the interval with high elevation in the Figure 4.2a). On the other hand, the relationship between the capital adequacy ratio and credit in the industry sector is not direct. In general, credit to industry drops as the capital adequacy ratio approaches its extreme values.

Figure 4.1a

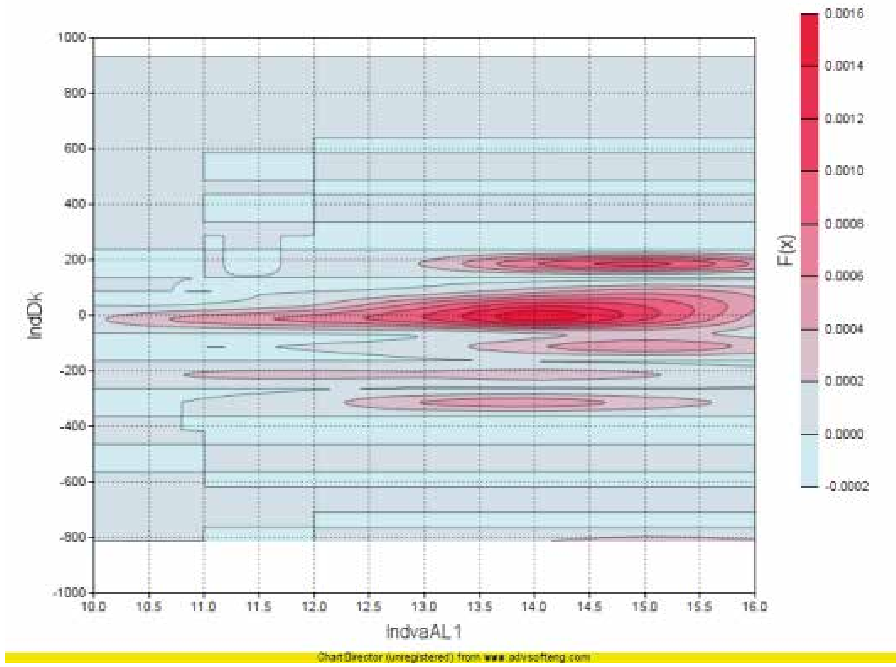


Figure 4.1b

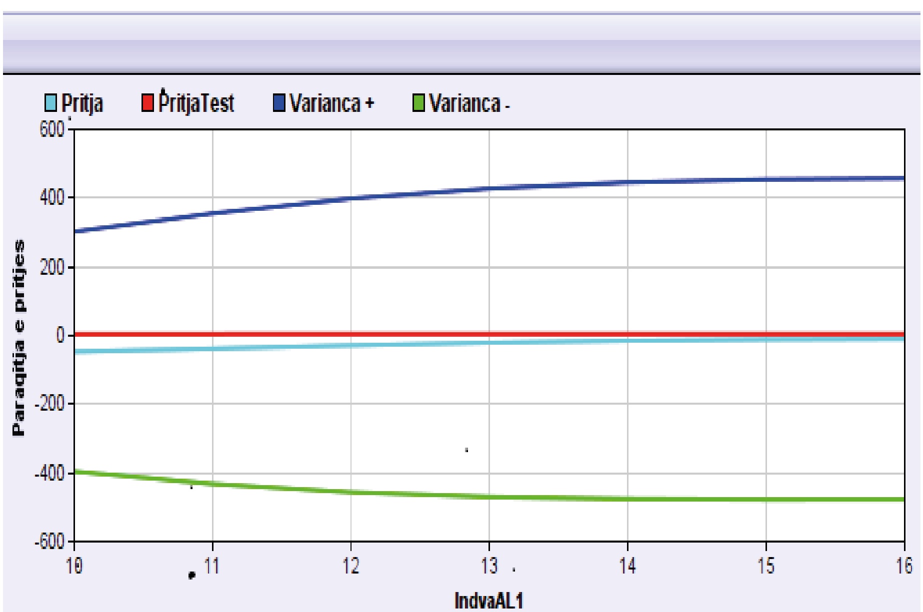


Figure 4.2a

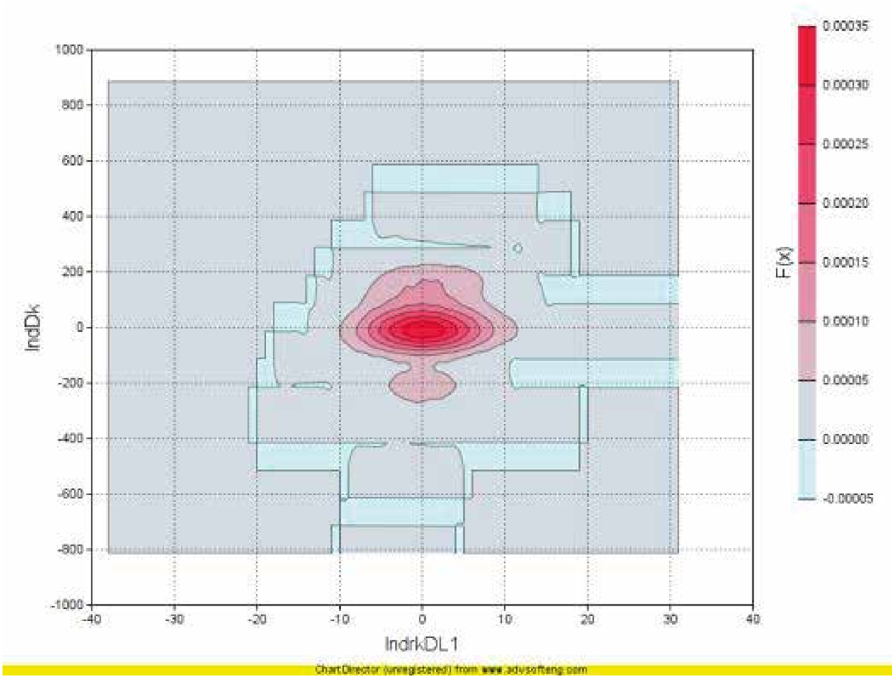


Figure 4.2b

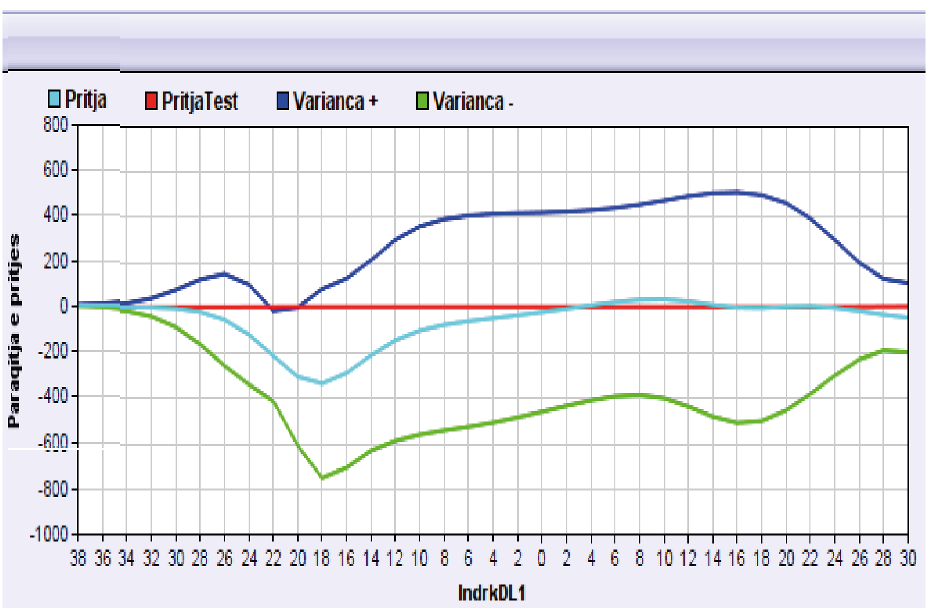


Figure 4.3a

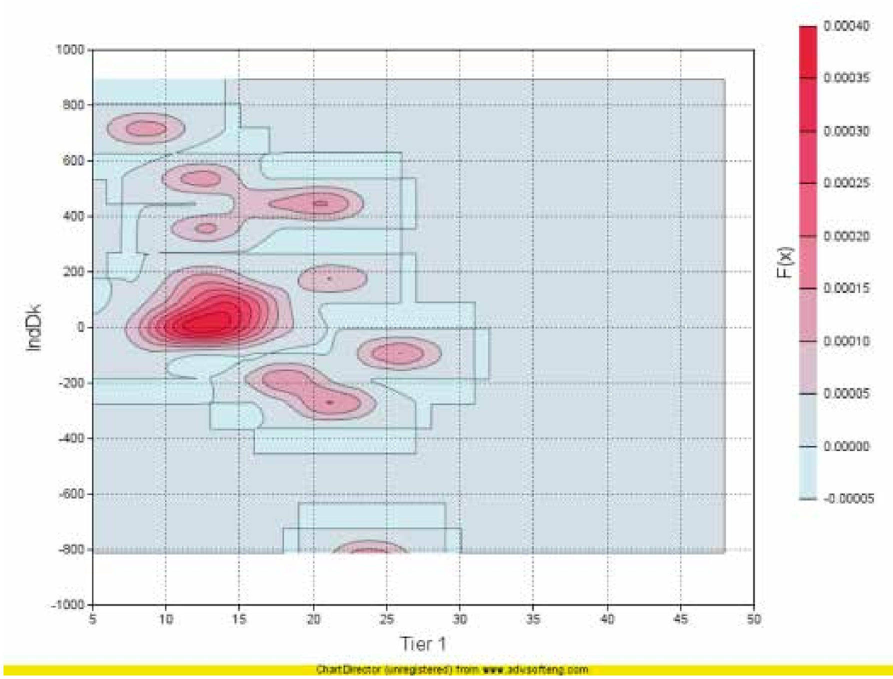
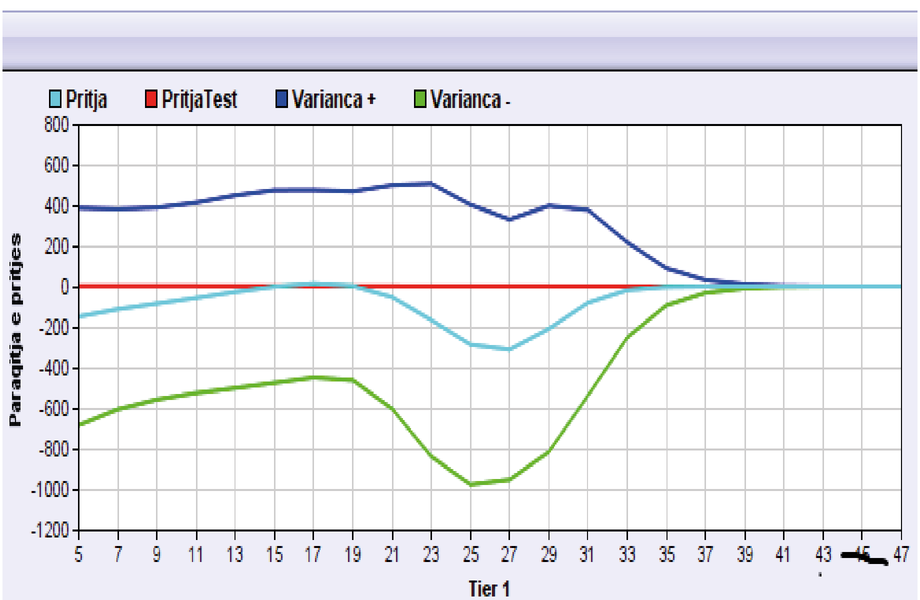


Figure 4.3b



Developments in the **construction** sector are of particular interest because this sector has suffered the most prominent loss in value added and increase in NPLs during the period of observation. As such, it would be interesting to see how banks have adjusted to these negative developments. The results of the analysis are reported in Figures 5.1 to 5.3.

We start with the discussion of value added. The graphs show that the estimated densities are dominated by the general presence of multimodal distributions which individually do not show much response to changes in explanatory variables. When considered together, however, they produce a general upward trend, indicating a direct relationship between increases in value added and increase in credit. This is confirmed by the response of the estimated expected value of the conditional density in Figure 5.1.b. The graph shows that as the relative share of value added in construction increases from 13 to 18%, credit to the sector increases almost 300 basis points. It is, however, interesting to observe that the reduction of the value added indicator below 13% does not coincide with the reduction of credit to the sector. Instead, the graph shows a marginal increase in the expected value of credit to construction below this point. We interpret this episode as a sign of 'unnatural selection', since banks continue to support this sector even when its value added underperforms relative to the rest of the economy.

Credit in the construction sector is almost independent of changes in credit risk for most of the credit risk range. However, it reduces by almost 300 basis points as the relative credit risk falls in the interval of 20 to 28%. The general explanation that emerges from the graph is that banks react by reducing credit to the construction industry only in response to extreme values of credit risk, precisely as the NPLs of this sector approaches almost one third of total NPLs. The relationship of credit indicator with the capital adequacy ratio is multimodal, dominated by several almost regular bell-shaped peaks which do not contribute in a significant reduction to the expected value of credit to this sector. Figure 5.3.b shows that credit to construction reduces to its minimal value as the capital adequacy ratio approaches 19%; however, this is a marginal effect, depicting an almost horizontal relationship.

We conclude that the banking system has responded to the reduction of construction share in economic activity. Banks, however, seem to have adopted protective behaviour towards the sector, shielding it from large reductions of value added and responding only to extreme values of NPLs in the sector relative to the rest of the economy.

Figure 5.1a

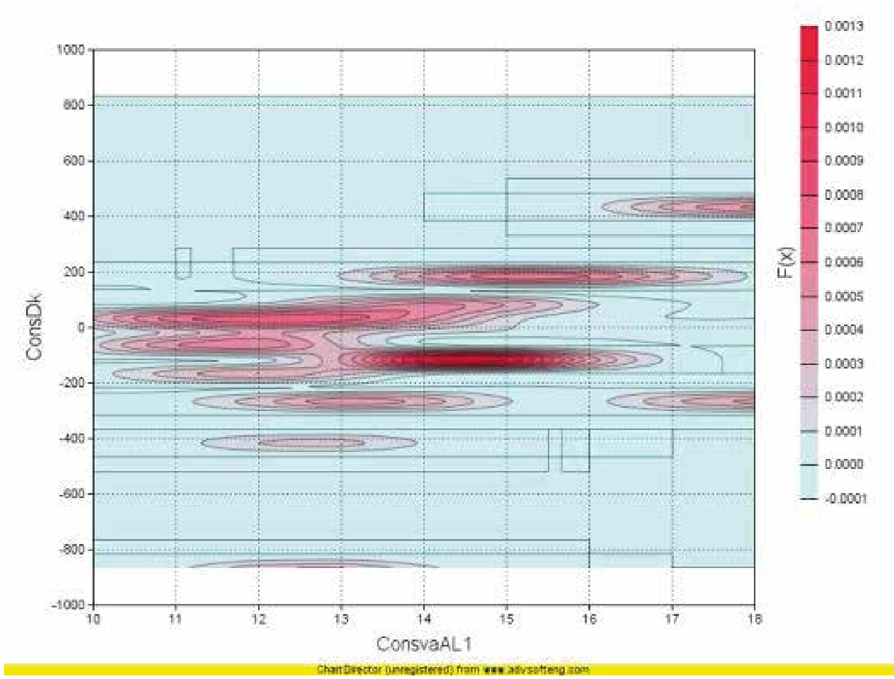


Figure 5.1b

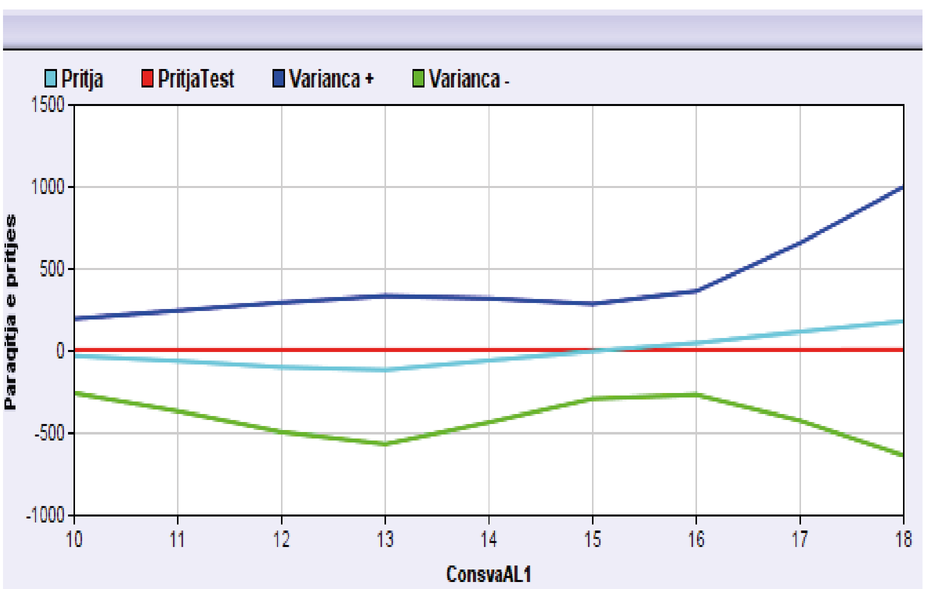


Figure 5.2a

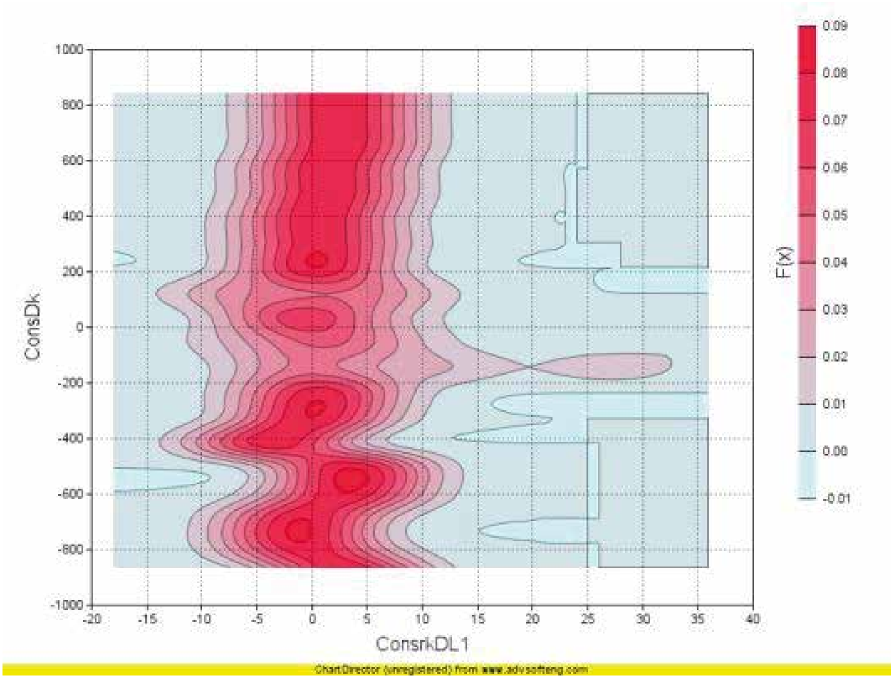


Figure 5.2b

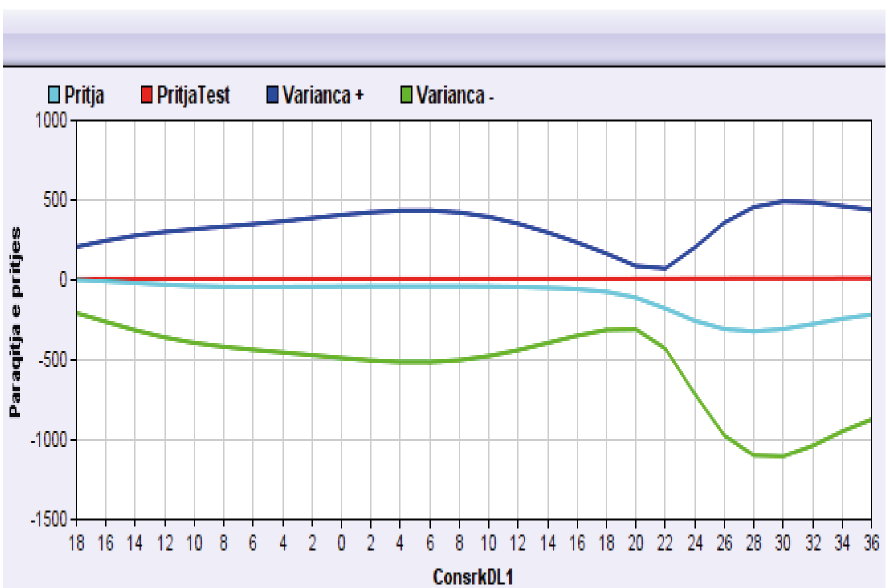


Figure 5.3a

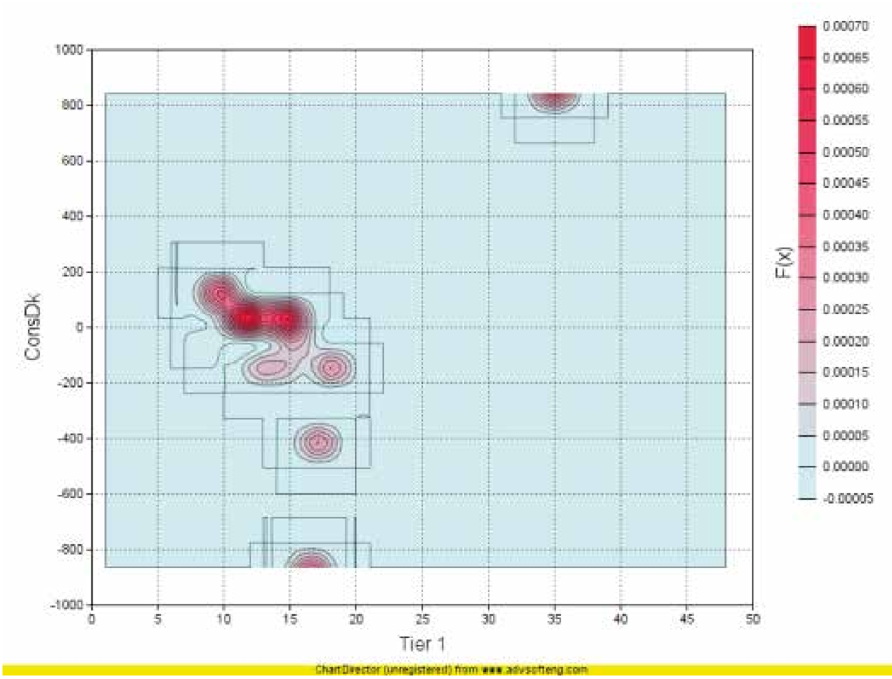


Figure 5.3b

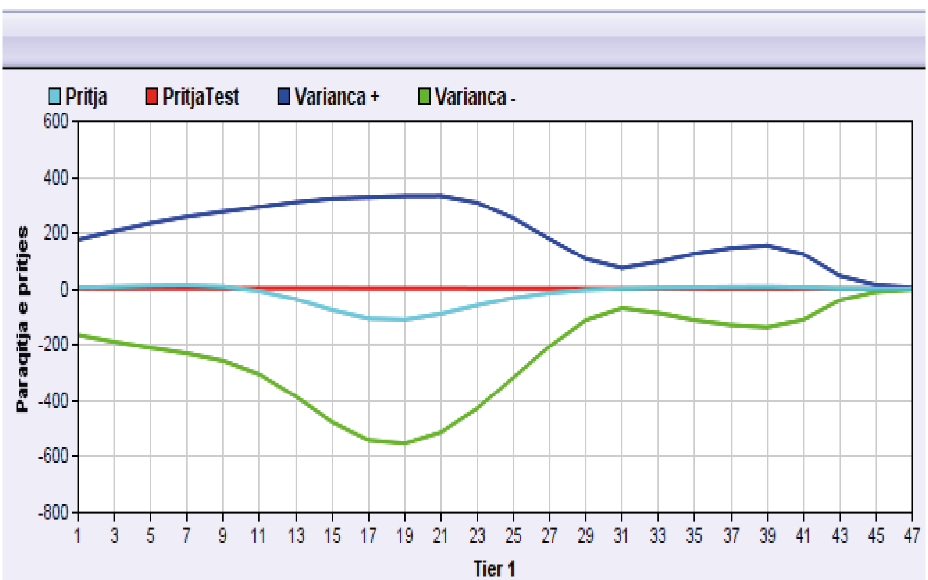


Figure 6.1a

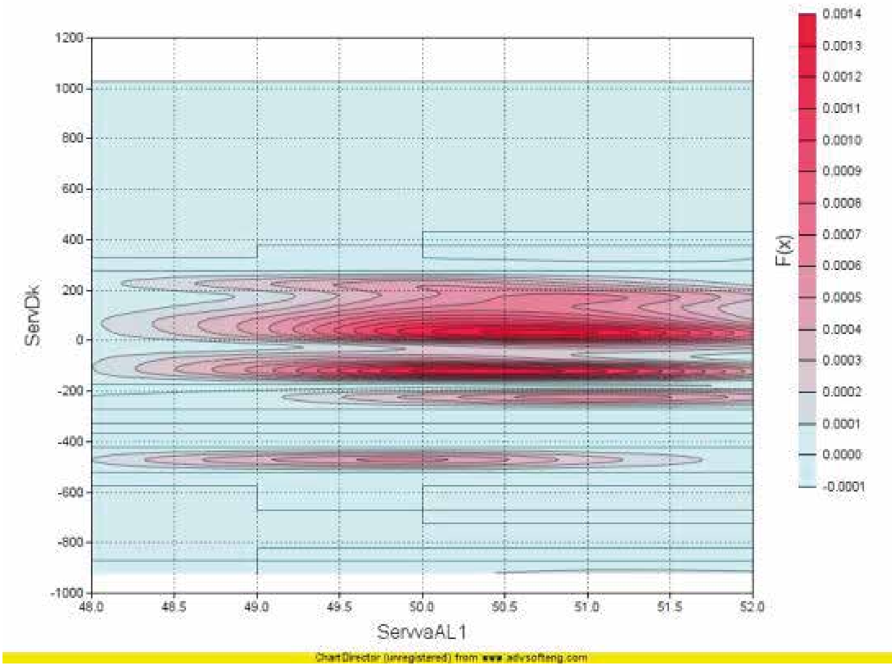


Figure 6.1b

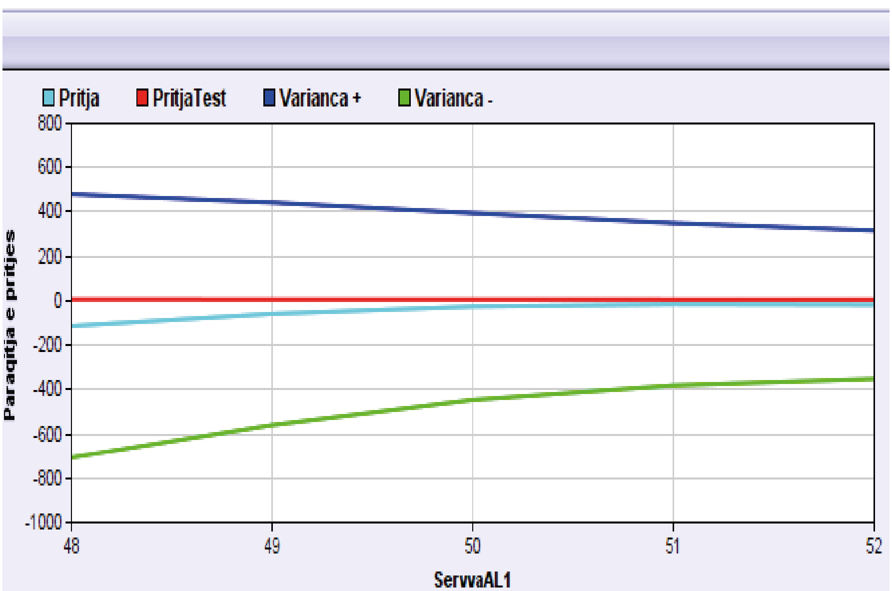


Figure 6.2a

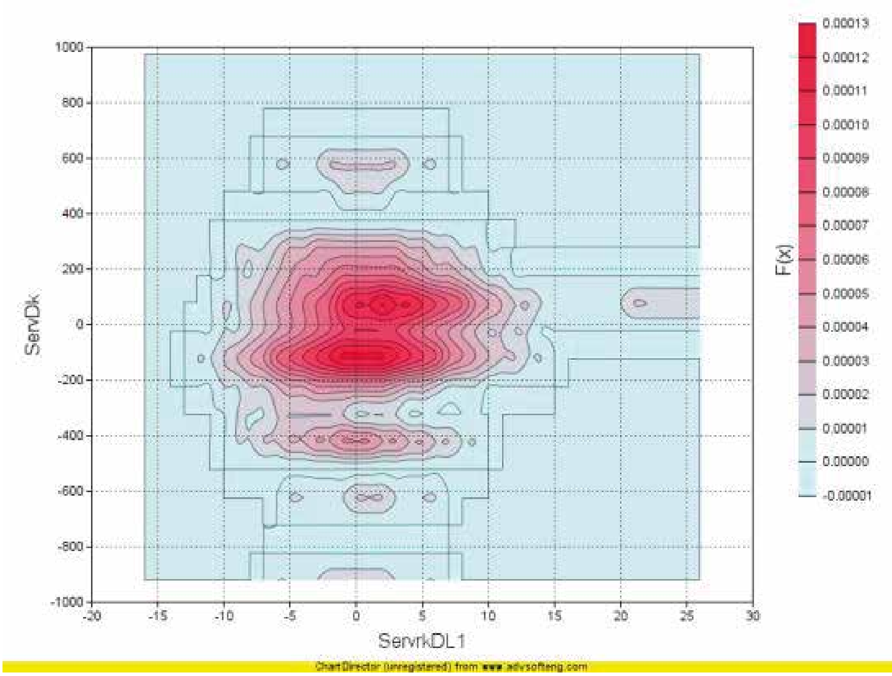


Figure 6.2b

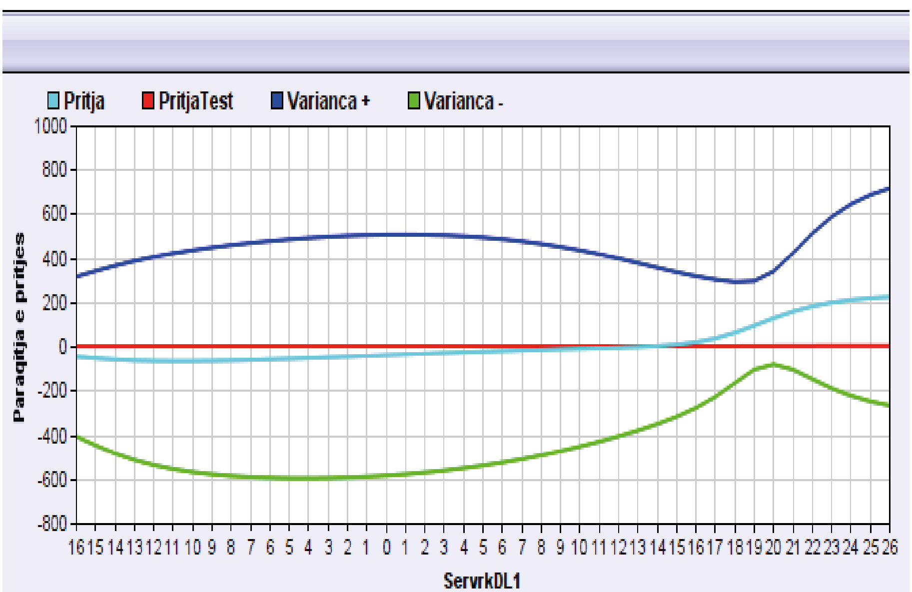


Figure 6.3a

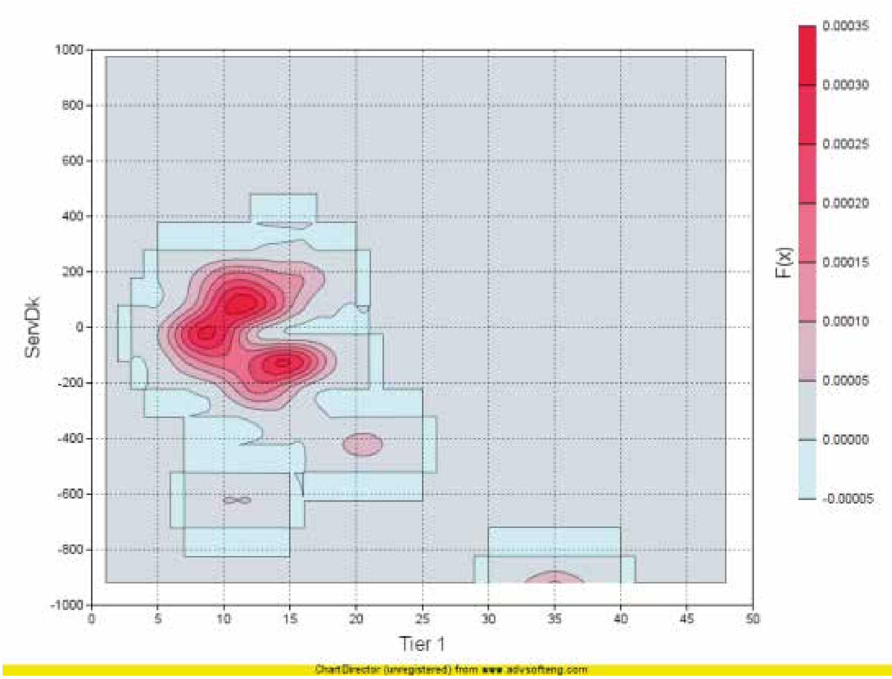
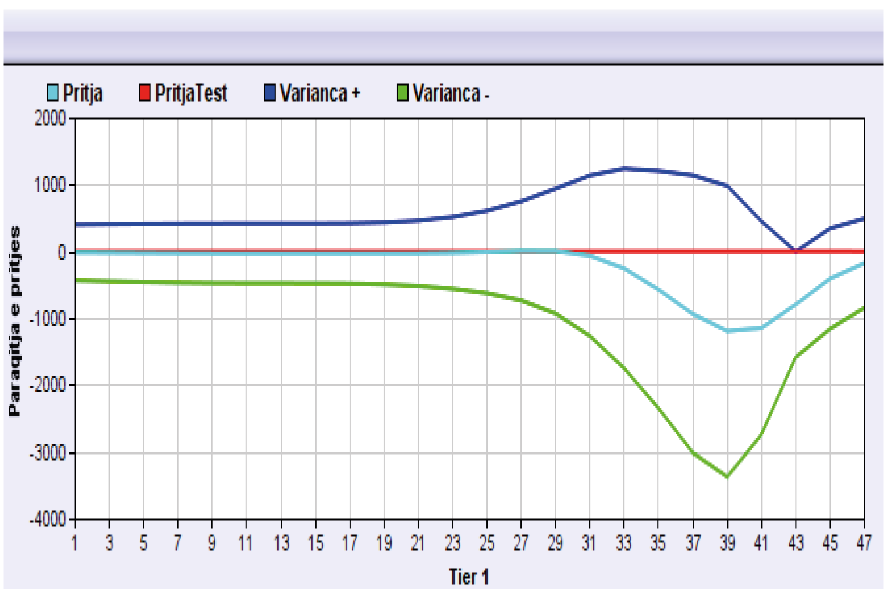


Figure 6.3b



Densities estimated for the **service** sector, depicted in panel a of Figures 6.1 to 6.3, are dominated by parallel multimodal nodes, which yield almost horizontal expected values for conditional densities (panel b, Figures 6.1 to 6.3). Credit to the services sector seems to respond relatively well only when the share of services to value added drops below 50%, and remains unchanged above this point. The other graphs indicate little or no response to changes in explanatory variables. AS in the case of the construction sector, the response is stronger in the tails of distributions. In particular, we observe a relatively strong increase in credit to this sector as the credit risk increases beyond 17%, and a strong decrease in credit only as the capital adequacy ratio increases beyond 39%. Our interpretation is that credit to the services sector adjusts to reflect the relative slowdown of the sector, during which the demand for funds probably falls. However, banks try to keep the flow of credit to this particular sector constant, despite developments in the sector's NPLs, and might even increase credit when the NPL situation aggravates in order to keep underperforming firms of the sector floating. This evidence of inefficiency of allocation is to be expected – the services sector is very important for banks, representing more than 50% of total credit to business, and the legacy costs are very high.

It is difficult to put these results in perspective due to the absence of previous studies on this important topic for the Albanian economy. Comparison of our results with the existing literature indicates that range of the credit response to changes in economic activity for the construction and services sectors is comparable to estimated elasticities for Germany, Korea and Japan. Whether this is reasonable cannot be stated with credible accuracy, since the credit response depends on the characteristics of each economy and on the choice of variables. In addition, our results indicate that the response is non-linear and that banks' reactions might differ depending on the particular value of the relative value added, credit risk and capital adequacy ratio.

7 Conclusions

This study investigates the efficiency of banks' credit portfolio allocations in response to changes in the composition of economic activity, credit risk and banking system indicators in the Albanian economy. The study introduces the application kernel density estimation and the cross-section method of Tanku and Ceca (2013, 2014) as a tool for empirical analysis on panel data. Our results show, for the first time, density estimates for credit broken down by its sectorial allocation and its behaviour in response to changes in the above explanatory variables.

We find that the response of credit activity – i.e. the incidence of reaction, its direction and magnitude – differs across sectors and across explanatory variables. Moreover, this response is not linear. On some occasions, credit behaviour reverses direction in response to 'extreme negative' developments (tail developments) in the explanatory variables, in particular in response to an increase in the credit risk indicator. On other occasions, the credit behaviour response is trivial, having no real impact on convergence of credit to the size of the sectors' contributions to economic activity. Banks seem to shield preferred and/or suffering sectors from really bad economic performance and credit risk. A stronger protection against credit risk is reserved for the services sector (which owns the largest share of total outstanding debt), and weaker protection for agriculture (owning the smallest share of debt), indicating that banks' exposure to the sector might play a role in the persistence and extent of such protection.

Banks' behaviour seems to provide protection for troubled sectors against market forces that could lead a better distribution of resources and economic restructuring. The misallocation of credit thus inhibits the efficiency of the central bank's monetary and financial policies and imposes a burden on economic recovery.

The response of credit to the capital adequacy ratio is more or less similar across sectors, but is puzzling. It could reflect the structure of the financial market (which is dominated by large banks), with the observed tail events dominated by small, less active banks. This requires further investigation and research in the future.

The presence of multimodal densities in our results could indicate the presence of bank-specific factors. Therefore, future research could focus on sub-samples of the dataset (i.e. groups of banks with similar characteristics).

Our interpretation of the results leads to two important conclusions. First, we find evidence of inefficiency in credit allocation, reflecting a general problem with banks' incentives. Second, we find that the kernel density estimation and cross-section method are useful tools for the empirical investigation and visualisation of panel data sets. Density estimation proves a useful alternative method to traditional panel data analysis. This kind of empirical analysis represents an alternative to traditional linear regression methods. Most importantly, its application and results are not constrained by the knowledge of the data-generating process, its functional form, the stochastic behaviour of the error term and endogeneity and autocorrelation status among variables, cross-section specific random effects and residuals.

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Credit allocation and the financial crisis in Bosnia and Herzegovina

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Central Bank of Bosnia and Herzegovina

1 Introduction

The subject of this analysis is the efficiency of credit allocation in Bosnia and Herzegovina (henceforth, "BH"). The goal is to answer the question of whether credit allocation in BH over the period 2009 to 2014 was efficient. The decision on the time horizon for the appraisal of credit allocation efficiency was influenced by objective circumstances: unavailability and/or inexistence of data for this kind of analysis.

This paper is structured in five section. In the first section, there is a survey of BH's banking sector development before and after 2008. A survey of the literature and the methodology for the appraisal of credit allocation efficiency is provided in the second section. This is followed by a section addressing the data and applied methodologies in our research. The results of the research and a discussion follows, and the final section contains conclusions and a survey of the literature.

2 The financial and banking system in BH before and after the financial crisis

The period 2003 to 2008 was marked by an extraordinary credit expansion, a deepening of financial intermediation, a decrease in non-performing loans (NPLs) and by bank profitability. In the period from 2008 to 2012 (Table 1), BH's banking sector performances changed dramatically: the rate of credit growth decreased and/or became negative (2008), NPLs increased quickly, and the profitability of banking sector decreased. Since 2013, the banking system has been consolidated and its performance has improved. Even before and during the crisis period, capital adequacy was, by EU bank standards, very high.

Table 1 The banking sector in Bosnia and Herzegovina

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Deposit growth	23.3	27.4	37.9	-1.8	1.8	3.6	3.7	2.6	6.9	7.9
Credit growth	27.3	21.9	28.8	22.4	-3.2	3.5	5.3	4.1	2.9	2.9
NPL	5.3	4.0	3.0	3.1	5.9	11.4	11.8	13.5	15.1	14.0
ROA	0.7	0.9	0.8	0.4	0.1	-0.6	0.7	0.6	-0.2	0.7
ROE	6.2	8.4	8.6	4.2	0.8	-5.5	5.8	4.9	-1.4	5.7
Capital adequacy	17.8	17.7	17.1	16.2	16.1	16.2	17.1	17.0	17.8	16.3
Growth rate of real GDP	3.9	5.7	6.0	5.6	-2.7	0.8	1.0	-1.2	1.6	0.7

Note: Data are in percentages.
Source: Central Bank of Bosnia and Herzegovina.

3 Review of the literature and methodology for the appraisal of credit allocation efficiency

According to some authors (e.g. Uesugi, 2008), the direct consequence of inefficient allocation of credit in the banking sector of Japan during the 1990s was NPL growth. To measure credit allocation efficiency, Uesugi uses capital ratio (total capital/total assets, as a percentage) and long-term borrowing ratio (long-term loans/total assets, as a percentage).

The conclusion of some studies (Sekine et al., 2003; Peek and Rosengren, 2005) is that the allocation process is quite inefficient as, in order to avoid losses, banks increase their exposure to bad firms. The same conclusion was also reached for Japanese economy by others (Ahearne and Shinada, 2004; Caballero et al., 2006).

The IMF's methodology for the appraisal of credit allocation at the company level is defined in three ways (Borensztein and Jong-Wha, 1999).

- In the first interpretation of efficient allocation of credit, the dependent variable (i.e. the variable with which efficiency is measured) is the ratio of credit to capital, and the independent variables are: the ratio of credit to capital(-1), fixed assets (logarithm)(-1), the ratio of debt to capital (-1), and the profit rate (-1). The majority of this research is based on this methodology.
- In the second interpretation of credit allocation efficiency, the dependent variable is the profit rate, or capital productivity, and the previously stated variables are independent variables.
- In the third interpretation, the growth rate of real value added per worked hour is the dependent variable, while the independent variables are specific variables at the company level.

4 Data and methodology

In the first group of models, growth of credit (as a percentage) is presented as a function of structural business indicators (Equation 1). We start with the assumption that between structural business indicators and an increase in credit by business activities (14 business activities), there needs to exist a stable linear relation, i.e. $CREDIT_{growth} = f(business\ indicators)$. Official BH statistics publish five business indicators by activity (Table 2), which is sufficient for a credit allocation efficiency estimation by business activity using this method. However, its limitation is that no business indicators time series are sufficiently long – they exist only for two years (2012 and 2013). At the time of preparing this research, credit statistics by business activity were not available for 2014. This limitation had an impact on the multiple linear regression model specification, which we give in the form:

$$CREDIT_{growth\ 2013/2012} = f(TE_{13/12}, VA_{13/12}, PV_{13-12}, AC_{13/12}, GR_{13-12}) \quad (1)$$

Table 2 Structural business indicators

Structural business indicators	Calculation	Abbreviations
Turnover per person employed (2013/2012, %)	Obtained by dividing the total turnover by the total number of persons employed	TE
Value added per person employed (2013/2012, %)	Obtained by dividing the total value added by the total number of person employed	VA
Percentage of value added on production value (2013-2012, percentage points)	Obtained by dividing the total value added by the total production value	PV
Average personnel cost per employee (2013/2012, %)	Obtained by dividing the total personnel costs by the number of employees	AC
Gross operating rate (2013-2012, percentage points)	Represents the percentage of gross operating surplus in turnover	GR

In the second group of models, we test the relationship between credit growth/ return on asset and business indicator for firms included in the Stock Exchange Index of the Republika Srpska (BIRS). The (pooled least squares) models have the following specifications:

a) $dLC = f(FIX, CAR, dLC, ROA)$, where FIX is fixed asset (logarithm), CAR is the capital-to-asset ratio, dLC is the first difference of loan-to-capital ratio and ROA is return on asset.
b) $ROA = f(C, CAR, ROA, dLC, LtC, DtC)$, where ROA is return on asset, C is constant, LtC is the loan-to-capital ratio, dLC is the first difference of loan-to-capital ratio, and DtC is the debt-to-capital ratio.

5 Results and discussion

5.1 Models based on structural business indicators

Models developed on the basis of business indicators, which are diversified by activity, show that that credit allocation was partly efficient. The main criteria for awarding credit (**Model 1**) were turnover per employee (TE), percentage of value added on production value (PV), and average personnel cost per employee (AC). The coefficients for these regressors are highly statistically significant and have the expected sign. TE growth of one percentage point increases the credit growth rate by 2.36 percentage points, while PV growth of one percentage point increases credit growth by 4.6 percentage points. On the other hand, growth of AC of one percentage point decreases the credit growth by 3.84 percentage points (Table 3). However, the coefficient values for the other regressors – value added per person employed (VA) and gross operating result (GR) – are not statistically significant. It is not consistent with credit allocation efficiency that absolute or relative growth of value added does not lead to increased exposure of banks to those sectors. This economically unexpected relationship between value added and the increase in credit is probably caused by the partial absence of the value added concept in companies' credit rating assessment. We do not have an explanation for the negative relationship between the growth in the average gross operating result (GR) and credit growth.

Table 3 Models with structural business indicators

	Model 1	Model2
Dependent variable	Credit growth	Credit growth
Constant	14.31 (4.54)***	15.48 (5.30)***
Turnover per person employed (2013/2012, %)	2.36 (3.85)***	1.68 (4.67)***
Value added per person employed (2013/2012, %)	-0.39 (-0.48)	
Percent of value added on production value (2013-2012, percentage points)	4.60 (3.71)***	3.40 (3.70)***
Average personnel cost per employee (2013/2012, %)	-3.85 (-3.47)***	-4.51 (-4.71)***
Gross operating rate (2013-2012, percentage points)	-0.97 (-0.44)	
R^2	0.839	0.797
Method	Least squares	Least squares
Is credit allocation efficient?	Partly	Yes

Notes: t statistics in parenthesis; ***significant at the level of 1%, ** significant at the level of 5%, * significant at the level of 10%.

In the next model of this kind, we omit non-significant variables (**Model 2**) and obtain a model in which all variables/coefficients are significant and have the expected sign. In addition, the impact of changes in TE and PV on the dependent variable decreases, and the impact of changes in AC on dependent variable increases. A one percentage point increase in TE increases the rate of credit growth by 1.68 percentage points, while an increase in PV and AC by one percentage point increases the dependent variable by 3.4 percentage points and decreases it by 4.51 percentage points, respectively.

The impact of two of the five variables on credit growth is not consistent with credit allocation efficiency, so we conclude that credit allocation was partly efficient, i.e. it was more efficient than inefficient.

5.2 Models based on firms in the Stock Exchange Index of the Republika Srpska

Regression Model (**Model 3**), developed for firms from Stock Exchange Index of Republika Srpska (BIRS), did not identify the existence of credit allocation efficiency (Table 4). Despite the fact that all the coefficients are statistically significant, with a rather high coefficient of determination, the most important regressor (ROA) has, from an economic point of view, an unexpected sign. With the increase in profit rate (ROA), banks decrease instead of increasing their credit exposure. The growth in exposure to loss-making firms is not connected to efficiency. The connection between fixed assets and loans has economic logic but does not represent credit allocation efficiency – it is only an indicator of restrictive credit policy, which mostly relates to collateral in extending loans.

In the next group of models (**Models 4-7**), the dependent variable is return on assets (ROA), following the logic that more banking loans should be provided to the more profitable firms (Table 4). Growth in banking credit does not lead to growth in profitability (**Model 4**), which is an indicator of credit allocation inefficiency. The variables ROA(-1) and CAR(-1) have the expected negative sign. However, we cannot interpret the relationship between CAR (the inverse of asset/capital) and ROA as proof of credit allocation efficiency, because a firm's debt is composed not only of loans but also of other obligations (taxes, duties, wages, accounts payable, etc.).

In **Model 5**, in which one new variable is entered, the relationship between credit growth (ratio loans to capital/LtC) and ROA is such that we can talk about partial credit allocation efficiency. Growth in LtC by one percentage point increases ROA by 0.198 percentage points, and the sign of dLtC (the first difference of the loan-to-capital ratio) is still opposite to the expected one. All coefficients are significant at between the 1% and 6% levels. The degree of credit allocation efficiency in this case is much higher, and the chosen variables explain 78% of the variability in firms' profitability. It can therefore be said that, according to **Model 5**, partial credit allocation efficiency is demonstrated.

Table 4 Models based on firms in the Stock Exchange Index of the Republika Srpska

	Model 3	Model 4	Model 5	Model 6	Model 7
Dependent variable	dLC	ROA	ROA	ROA	ROA
Constant		4.027 (2.51)**	-2.694 (-1.96)**	-5.34 (-2.93)***	
Log (Fixed Asset) (-1)	1.338 (2.409)**				
Capital/asset (-1)	-0.123 (-2.156)**	-0.047 (-2.38)**	0.032 (1.909)*	0.059 (2.73)***	
Debt/Capital (-3)				0.54 (10.00)***	
Difference in Loans/Capital (-1)	-1.178 (-7.45)***	-0.1906 (-5.98)***	-0.402 (-12.20)***		
Loans/Capital (-1)			0.198 (3.114)***	0.161 (2.11)**	
Loans/Capital (-3)					0.70 (10.98)***
ROA (-1)		0.839 (6.73)***	0.649 (7.00)***	0.676 (5.25)***	0.75 (7.49)***
ROA (-3)	-0.283 (-1.983)**				
R^2	0.543	0.545	0.78	0.727	0.73
Sample (adjusted)	2011-2013	2010-2014	2010-2014	2011-2014	2011-2014
Method	Pooled Least Squares	Pooled Least Squares	Pooled Least Squares	Pooled Least Squares	Pooled Least Squares
Cross-sections included	17	16	16	16	16
Total pool ((balanced) observations	51	80	79	63	64
Is credit allocation efficient?	No	No	Partly	Yes	Yes

In the last two models, all coefficients have the expected sign, and almost all are significant at the 1% level. In **Model 6** we introduce the variable debt-to-capital ratio (DtC), and the variable difference in the ratio of loans to capital (dLtC) has been omitted. The coefficient of determination remained very high at 0.727, and between the key variables of the model (LtC and DtC) on one side, and ROA on the other side, a positive relationship is formed. Credit growth contributes to the increase in profitability, and this is proof of credit allocation efficiency; in other words, loans are directed to those firms whose profitability is increasing.

In the last model (**Model 7**) only two variables explain 73% of the variability in ROA. Growth in the loan-to-deposit ratio of one percentage point, with a time lag, leads to the growth in ROA by 0.70 percentage point.

6 Conclusion

The model which treats the credit increase as a function of the value of business statistics indicators demonstrates a certain, or full, degree of agreement with the principle of credit allocation efficiency. We also tested the credit allocation efficiency of a representative sample of joint stock companies. Our final conclusion is that with these models, we have succeeded in proving that credit allocation in Bosnia and Herzegovina over the period analysed was efficient.

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Dragan Jovic graduated from the Faculty of Economics of the University of Banjaluka in Bosnia and Herzegovina. After that, he worked in the Institute of Urbanism of the Republic of Srpska on economics research, and during his work in the commercial banking sector he was a Credit Officer and Head of Corporate Sector. Since 2002, he has been working in the Central Bank of Bosnia and Herzegovina in the banking department, and from 2013, in the Office of Chief Economist. He finished the postgraduate studies in Belgrade (Serbia), and he defended his doctoral thesis ("Stocks and Market Risk in Banking") in Niš (Serbia). He has published three books on banking in Bosnia and Herzegovina.

Misallocation of resources in Latvia

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Introduction

Latvia's productivity growth was outstanding between 1995 and 2007, when average annual total factor productivity (TFP) growth amounted to 6.8%. The financial crisis led to a temporary drop in productivity in 2008–2009. However, since 2010, TFP growth has been back on a positive track (close to 2–3%), albeit far behind the pre-crisis numbers. The rapid growth of productivity in the 1990s and early 2000s was, to a large extent, driven by initial convergence and an inflow of cheap credit from foreign-owned banks. These factors will not be repeated in the near future, so one should search for other ways to stimulate TFP growth in Latvia.

This paper investigates the allocation of resources in Latvia. I study how changes in the within-sector allocation of resources affected Latvia's TFP growth before and after the crisis. Moreover, I make an attempt to explain the driving forces behind the misallocation. To achieve that, I use the Hsieh and Klenow (2009) framework, specifically, its modified version with intermediate inputs introduced by Dias et al. (2014). This model is applied to Latvia's firm-level data between 2007 and 2013.

While interpreting the obtained results, I highlight two important issues that may affect the perception of misallocation, but are not captured by the original Hsieh and Klenow (2009) framework. The first issue is fragmentation of production. Outsourcing increases the role of intermediate inputs with respect to capital and labour, thus producing a systematic bias in the estimates of misallocation. Although I am not able to quantify this bias due to the lack of data on inter-firm trade, I stress the presence of outsourcing phenomenon in the obtained results. The second issue is related to export activities and different levels of competition in domestic and external markets.

1 This research was performed within the ESCB Competitiveness Research Network (CompNet). I am grateful to Richard Baldwin, Fabrizio Coricelli, Mārtiņš Kazāks, Carlos Robalo Marques, Sašo Polanec and participants at the first Policy Research Conference of the European Central Banking Network (CEPR and Banka Slovenije) for helpful comments. The views expressed in this paper are those of the author and do not necessarily reflect the stance of Latvijas Banka. The author assumes sole responsibility for any errors and omissions.

Description of the theoretical model

Firm-specific distortions and allocation of resources

This section briefly describes the framework of Hsieh and Klenow (2009) modified in the style of Dias et al. (2014). Hsieh and Klenow assume that a representative assembly firm combines the output of different industries into a homogenous final good using a Cobb-Douglas production function. There are S industries in the economy, while the output of each industry is a constant elasticity of substitution (CES) aggregate of N_s differentiated products Y_{si}. Unlike Hsieh and Klenow, I allow for industry-specific elasticity of substitution between products (σ_s), thus accounting for heterogeneous level of competition:

$$Y_s = \left(\sum_{i=1}^{N_s} Y_{si}^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\sigma_s}{\sigma_s - 1}} \tag{1}$$

Moreover, I follow Dias et al. (2014) and introduce intermediate inputs into the production function for a differentiated product:

$$Y_{si} = A_{si} K_{si}^{\alpha_s} L_{si}^{\beta_s} M_{si}^{1-\alpha_s-\beta_s}, \tag{2}$$

where A_{si} denotes firm-specific TFP, K_{si} is the firm's capital, L_{si} shows the number of employees, and M_{si} is intermediate inputs. The parameters of Cobb-Douglas production function can vary across industries, but not across firms within the same industry.

A firms' profit equation is perhaps the most important in Hsieh and Klenow (2009) framework, since it introduces 'distortions':

$$\pi_{si} = (1 - \tau_{Ysi}) P_{si} Y_{si} - (1 + \tau_{Ksi}) R_s K_{si} - (1 + \tau_{Lsi}) w_s L_{si} - P_s^M M_{si} \xrightarrow{L_{sj}, K_{si}, M_{si}} \max, \tag{3}$$

where π_{si} represents the firm's profits, P_{si} denotes the price of firm-specific output, R_s, and w_s and P_s^M are industry-specific capital costs, wage and price of intermediate inputs, respectively. As in the benchmark model, τ_{Ksi} refers to firm-specific capital distortion and τ_{Ysi} to size distortion. The third distortion is τ_{Lsi}, which relates to labour.

According to equations (4) to (6), which are the outcome of the profit maximisation problem, the allocation of resources is driven by firm-specific TFP levels and distortions. In the absence of distortions – when all firms are treated equally in terms of access to production factors – firms with higher TFP attract more labour and capital, and produce more output. However, when a firm faces a distortion, it creates a lower-than-normal allocation of the respective resource. For example, if a firm faces positive capital distortion ($\tau_{Ksi} > 0$) by paying a higher price for capital compared with the industry average (due, for example, to worsened access to bank lending), the firm uses less capital and produces less output. A positive labour distortion (e.g. the firm faces higher wage in comparison with industry average) or a positive size distortion (e.g. higher taxes or transportation costs) produce a similar effect.

$$Y_{si} \propto \frac{A_{si}^{\sigma_s}\left(1-\tau_{Ysi}\right)^{\sigma_s}}{\left(1+\tau_{Ksi}\right)^{\alpha_s\sigma_s}\left(1+\tau_{Lsi}\right)^{\beta_s\sigma_s}}; \tag{4}$$

$$L_{si} \propto \frac{A_{si}^{\sigma_s}\left(1-\tau_{Ysi}\right)^{\sigma_s}}{\left(1+\tau_{Ksi}\right)^{\alpha_s(\sigma_s-1)}\left(1+\tau_{Lsi}\right)^{\beta_s(\sigma_s-1)+1}}; \tag{5}$$

$$K_{si} \propto \frac{A_{si}^{\sigma_s}\left(1-\tau_{Ysi}\right)^{\sigma_s}}{\left(1+\tau_{Ksi}\right)^{\alpha_s(\sigma_s-1)+1}\left(1+\tau_{Lsi}\right)^{\beta_s(\sigma_s-1)}}. \tag{6}$$

If all firms were equally treated in terms of the access to production factors (i.e. all firms were facing the same capital, labour and size distortions), all marginal revenue products would be equal across enterprises in a given industry. In this 'efficient' case, industry TFP would equal:

$$\overline{A_s} = \left(\sum_{i=1}^{Ns} A_{si}^{\sigma_s-1}\right)^{\frac{1}{\sigma_s-1}}. \tag{7}$$

In reality, distortions differ across firms. This heterogeneity leads to the reallocation of resources from more distorted to less distorted firms, thus affecting the aggregate TFP of the industry. Following Hsieh and Klenow (2009), I calculate the ratio of actual aggregate TFP to hypothetical aggregate TFP under efficient allocation of resources (no discrimination of firms):

$$\frac{TFP}{TFP_{efficient}} = \prod_{s=1}^{S}\left[\sum_{i=1}^{N_s}\left(\frac{A_{si}}{\overline{A_s}}\left(\frac{\overline{MRPK_s}}{MRPK_{si}}\right)^{\alpha_s}\left(\frac{\overline{MRPL_s}}{MRPL_{si}}\right)^{\beta_s}\left(\frac{\overline{MRPM_s}}{MRPM_{si}}\right)^{1-\alpha_s-\beta_s}\right)^{\sigma_s-1}\right]^{\frac{\theta_s}{\sigma_s-1}}, \tag{8}$$

where $MRPK_{si}$, $MRPL_{si}$ and $MRPM_{si}$ represent firm-specific marginal revenue products of capital, labour and intermediate inputs, respectively, while $\overline{MRPK_s}$, $\overline{MRPL_s}$ and $\overline{MRPM_s}$ are industry marginal revenue products. Equation (8) compares the actual TFP level of the country with the 'efficient' TFP level ($TFP_{efficient}$) that would prevail if all firms were to be treated equally and the allocation of resources were to be determined by firm-level TFP only. Thus, I will use the ratio in equation (8) as the measure of potential gains from reallocation of resources in Latvia.

Identification of firm-specific TFP and distortions

Following the profit maximisation problem, the unobservable firm-specific TFP and distortions are expressed as a function of the observable data on a firm's output, capital, labour and intermediate inputs. Equations allowing for the quantification of the firm-level distortions are of the most interest for us. The capital distortion faced by individual firm is derived as:

$$1+\tau_{Ksi} = \frac{\alpha_s}{1-\alpha_s-\beta_s}\frac{P_s^M M_{si}}{R_s K_{si}}. \tag{9}$$

Specifically, lower-than-usual use of capital is a sign of capital restrictions. Similar logic is applied to equation (10), where the high ratio of intermediate inputs to labour costs implies high labour distortions:

$$1+\tau_{Lsi} = \frac{\beta_s}{1-\alpha_s-\beta_s}\frac{P_s^M M_{si}}{w_s L_{si}}. \tag{10}$$

Finally, the size (output) distortion is detected as a case of an abnormally low share of intermediate inputs in total output:

$$1-\tau_{Ysi} = \frac{\sigma_s}{\sigma_s-1}\frac{P_s^M M_{si}}{(1-\alpha_s-\beta_s)P_{si}Y_{si}}. \tag{11}$$

The interpretation of τ_{Ysi} is more complex in comparison to capital and labour distortions, since a large size distortion could be a sign of restrictions to total output (e.g. higher taxes after passing some threshold) or the consequence of restrictions to intermediate inputs (e.g. due to limited access to short-term loans).

Data description

I use a firm-level database that contains information on a representative sample of Latvian enterprises from 2006 to 2013, with the number of firms in the dataset varying between 61,159 in 2006 and 93,895 in 2013. The dataset includes commercial enterprises in all areas of activity, excluding credit institutions and insurance companies.

The data are provided by the Central Statistical Bureau of Latvia (CSB) and Latvijas Banka, and come from various sources. First, the dataset contains detailed information on firm balance sheets, profit/loss statements, value added, number of employees, personnel costs, production value and intermediate inputs. Second, the dataset includes information on firm-level external trade in goods. Third, data on external trade in goods are supplemented with the dataset on external trade in services. Finally, I also have information on external assets and liabilities of firms.

In this paper, I have excluded several sectors from the empirical analysis due to lack of data or the specific nature of the sector, namely: agriculture, forestry and fishing, financial and insurance activities, public administration and defence, education, health, arts, entertainment and recreation, and other services activities.

The dataset contains all the necessary information for an empirical evaluation of the theoretical model described above. However, some important variables are missing (due to non-reports) for many firms. All firms with missing/zero values for output, fixed capital (at the end of current and previous year), employment, intermediate inputs, wage bill and assets were excluded from the dataset for that particular year. Also, following the usual approach of resource allocation papers, I excluded outlying firms with TFP and distortions of capital, labour or size that are either too high or too low. Finally, I excluded several 4-digit sectors of activities due to the small number of observations (the threshold was set to 100 observations during 2007–2013, after the exclusion of outliers).

Major variables used in the empirical analysis are the firm's industry, output, capital (average of the stock at the beginning and end of the year), number of employees, wage bill, and intermediate inputs. I deflate intermediate inputs by an industry-specific deflator for intermediate inputs reported by the CSB. Capital is deflated by an industry-specific investment deflator, which is constructed taking into account the composition of capital in each corresponding industry. Finally, nominal capital costs are derived as the real interest rate plus depreciation rate, multiplied by the price of capital.

Evaluation of industry-specific parameters

I define an industry as a 4-digit NACE sector. Unlike Hsieh and Klenow (2009) or Dias et al. (2014), who assume σ=3 for all industries, I evaluate the elasticity from the actual firm-level data. Elasticity of substitution between products is related to the mark-up (μ_s) level, which could be derived by comparing nominal output to nominal costs at the industry level. The elasticity of substitution for a typical Latvian industry is close to 6.5, which roughly corresponds to a mark-up of 18%. However, the values of elasticity vary significantly across industries, pointing to different market structures.

I evaluate industry-specific production function parameters α_S and β_S using the data on cost structure. The coefficient of labour input (β_S) depends on industry-specific mark-up and the ratio of the industry's wage bill to its output, while the coefficient of capital input (α_S) is obtained as a remaining share from labour and intermediate inputs.[2]

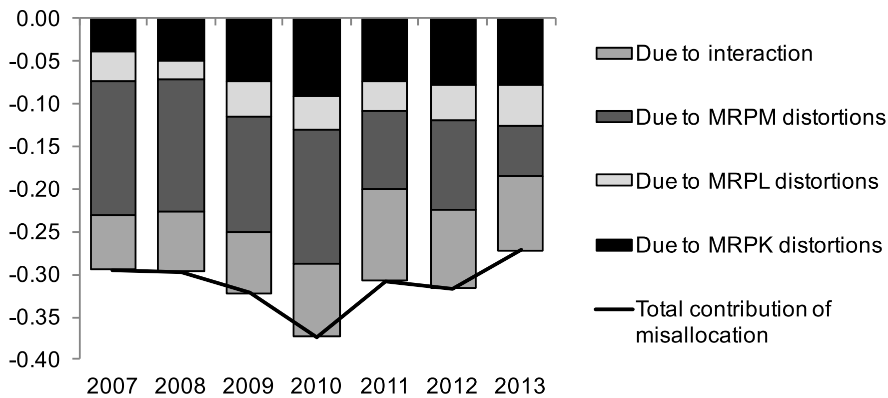
Misallocation of resources in Latvia

The application of the Dias et al. (2014) modification of the Hsieh and Klenow (2009) methodology to Latvia's firm-level data leads to the conclusion that potential TFP (and output) gains from the reallocation of resources were around 27% in 2013 (see Figure 1). This high indicator is in line with other empirical findings. Hsieh and Klenow (2009) argued that full liberalisation would boost aggregate manufacturing TFP by between 86% and 115% in China, between 100% and 128% in India, and between 30% and 43% in the US. Dias et

2 See Benkovskis (2015) for more details on the evaluation of industry-specific coefficients and discussion of the results.

al. (2014) showed that equalising TFPR within industries in Portugal would lead to a 30% gain in output in 2011.

Figure 1 Contribution from misallocation of resources to total TFP



We can observe two different tendencies during 2007–2013: growing misallocation of resources prior to and during the crisis, and improved allocation of resources after 2010. It is interesting that despite huge external and internal shocks during the financial crisis in Latvia, there were no major shifts in allocation efficiency in that period. I conclude that misallocation of resources was not the major driver of economic dynamics during the crisis; however, the contribution from declining misallocation to economic growth in 2011–2013 was positive.

For further analysis, I decompose the overall contribution from misallocation of resources into four parts: contributions to aggregate TFP due to misallocation of capital (MRPK), labour (MRPL), intermediate inputs (MRPM) and the interaction of the three above-mentioned factors. The largest contribution to potential TFP gains comes from the misallocation of intermediate inputs (here I deliberately ignore the interaction term, which is hard to interpret). Since MRPM is associated solely with τ_{Ysi}, one can conclude that size distortion contributes most to the misallocation of resources in Latvia.

Although the within-industry difference in MRPK was not amongst the most important drivers of misallocation in Latvia at the beginning of the sample period, its contribution increased over time and was similar in size to the contribution due to MRPM in 2013. Finally, the contribution of misallocation due to different MRPL is small and does not exhibit a clear trend, in line with the conclusion on high flexibility of the labour market in Braukša and Fadejeva (2016).

Possible drivers of observed misallocation

The previous section evaluated the level of misallocation, but did not reveal its driving forces. The current section contains several potential explanations focusing on different aspects. The aspects in the first two stories about fragmentation of production and differences in competition levels are, to some extent, overlooked in the resource allocation literature. The third story is inspired by the credit-less recovery after the financial crisis.

Fragmentation of production

The original methodology by Hsieh and Klenow (2009) does not account for the fact that production process can be fragmented, i.e. split across different firms. In general, this is the weak point – obviously driven by the lack of necessary data – in most firm-level empirical studies. Although there are unique datasets containing some information on linkages between firms (e.g. the Norwegian transaction-level custom data, which also identify buyers, used by Bernard et al., 2014), these are exceptions. However, the fragmentation of production may seriously bias estimations of misallocation. Assume that a firm outsources its book-keeping services – this will lower the share of labour, while raising the share of intermediate inputs in total production costs. If there is no information about the outsourcing, the Hsieh and Klenow (2009) methodology would misinterpret this as a positive labour distortion. Another example: if a firm rents machinery and equipment rather than uses its own capital, one would observe lower capital costs and higher intermediate inputs costs – the sign of a positive capital distortion. Thus, the fragmentation of production leads to the overestimation of capital and labour distortions, while size distortions are underestimated.

Ideally, one would need the data on transactions between individual firms (or at least one may use very detailed input-output data, as in Acemoglu et al., 2013). This would allow the whole production chain to be restored, capital and labour costs of production at all stages to be estimated, and the original Hsieh and Klenow (2009) methodology to be used with two factors of production. Such data are unavailable for Latvia, however.

Ignoring the production fragmentation phenomenon may bias overall conclusions, especially taking into account the growing role of outsourcing (Los et al., 2015, for example, stress the increasing international fragmentation of production). However, it is not easy to predict how the aggregated measure of misallocation would be affected. On the one hand, overvaluation of firm-specific TFP as well as capital and labour distortions should boost the perception of misallocation (more productive firms are seemingly more distorted). On the other hand, growing fragmentation leads to an underestimation of the size distortion and a better perception of the allocation efficiency. In any case, this drawback of the methodology should be kept in mind while interpreting the results.

Level of competition

The importance of the size distortion in explaining misallocations may depend on different levels of competition in domestic and external markets. The Hsieh and Klenow (2009) framework assumes a closed economy. In an open economy, local producers can supply products to domestic and foreign consumers. If elasticities of substitution in domestic and foreign markets differ, exporters face higher size distortions than local customer-oriented companies. Equation (11) shows that a higher elasticity of substitution (and greater competition) means a higher size distortion, since a company faces more hurdles while expanding in a competitive environment. Assuming that Latvia's exporters are more productive than non-exporters, and the level of competition in international markets exceeds that in Latvia's domestic market, the importance of size distortions for misallocation could be partly explained.

Table 1 Degree of competition in domestic and foreign market for firms' main product in 2013 (%)

	Weak	Moderate	Severe	Very severe	Non applicable
			Domestic market		
Manufacturing	2.2	40.1	34.0	18.1	5.5
Construction	7.1	22.4	33.5	35.5	1.5
Trade	3.7	22.8	30.0	43.5	0.0
Business services	0.0	18.2	22.0	59.8	0.0
			Foreign market		
Manufacturing	0.9	29.6	47.5	21.2	0.8
Construction	0.0	27.0	45.6	27.4	0.0
Trade	5.2	26.1	27.9	35.8	5.0
Business services	1.3	24.0	35.9	38.5	0.2

Source: Fadejeva and Krasnopjorovs (2015), Tables A.100 and A.101.

Regarding the first part of the above assumption, it is in line with international empirical evidence about productivity premia for exporting enterprises (e.g. Berthou et al., 2015). As to the comparative level of competition, I refer to the most recent evidence obtained by Fadejeva and Krasnopjorovs (2015) from the Eurosystem's Wage Dynamics Network (WDN) survey in Latvia.

Table 1 reproduces the survey results with respect to firms' perception of the level of competition in Latvia and abroad. Answering the question about the degree of competition in domestic and foreign markets in 2013, the mode answer from manufacturing firms regarding the domestic market was "moderate", while for the foreign market it was "severe".

Table 2 Change in the competitive pressure on main product in domestic and foreign markets compared to the situation before 2008 (%)

	Domestic market		Foreign market	
	2008–2009	2010–2013	2008–2009	2010–2013
Strong decrease	2.9	2.2	0.9	1.0
Moderate decrease	11.8	3.8	7.6	5.9
Unchanged	33.8	24.7	45.7	51.5
Moderate increase	30.0	28.1	25.2	19.7
Strong increase	18.7	38.5	11.2	8.8
Does not apply	2.8	2.8	9.4	13.1

Source: Fadejeva and Krasnopjorovs (2015), Table A.102.

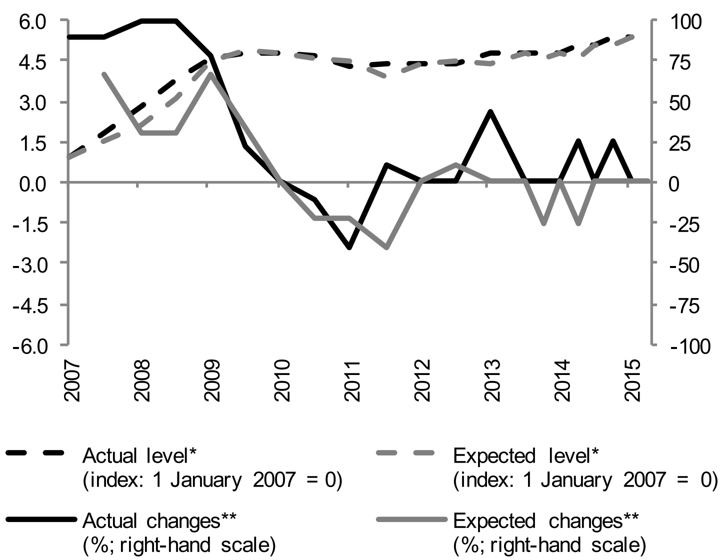
Table 2 contains another result from the WDN survey reported by Fadejeva and Krasnopjorovs (2015). It compares the perception of firms regarding variation in the level of competition in Latvia and abroad. While the relative level of competition did not change much during 2008–2009 (the mode answer in both cases is "unchanged"), the responses indicate a substantial tightening of competition in the domestic market (38.5% of respondents answered "strong increase") but no changes in the foreign market (51.5% of respondents answered "unchanged") in 2010–2013. One can conclude that the level of competition in the domestic market was much lower than in the foreign market before 2010, but that the gap narrowed in 2011–2013. Changes in the economic situation induced growing severity of domestic competition. During the boom period before 2008, the domestic market grew rapidly and the behaviour of competitors was not binding. This reduced the size distortion for domestically oriented (and less productive) firms. Lower growth rates after the crisis tightened competition in the domestic market, generating similar (or not much lower) size distortions for domestically oriented enterprises.

Supply of credit

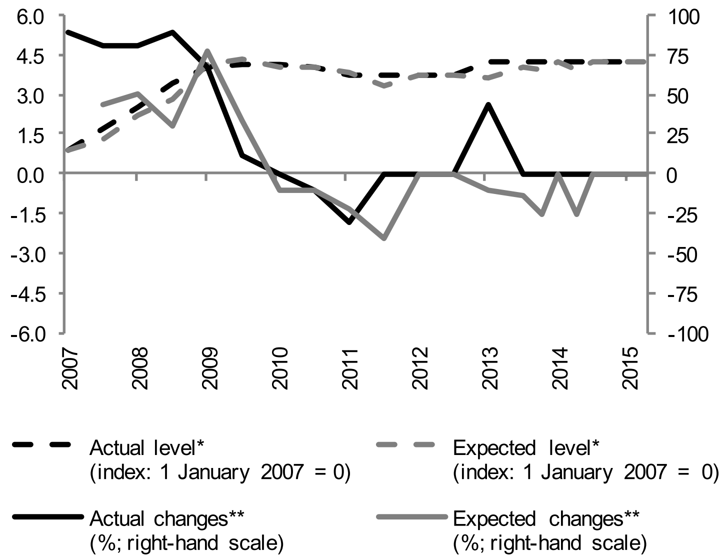
The growing role of capital misallocation after the financial crisis calls for a closer look at credit availability. The tightening of credit standards in Latvia started in 2008 as shown in Figure 2, which reports the results of the Eurozone bank lending survey for Latvia.

Figure 2 Credit standards in Latvia

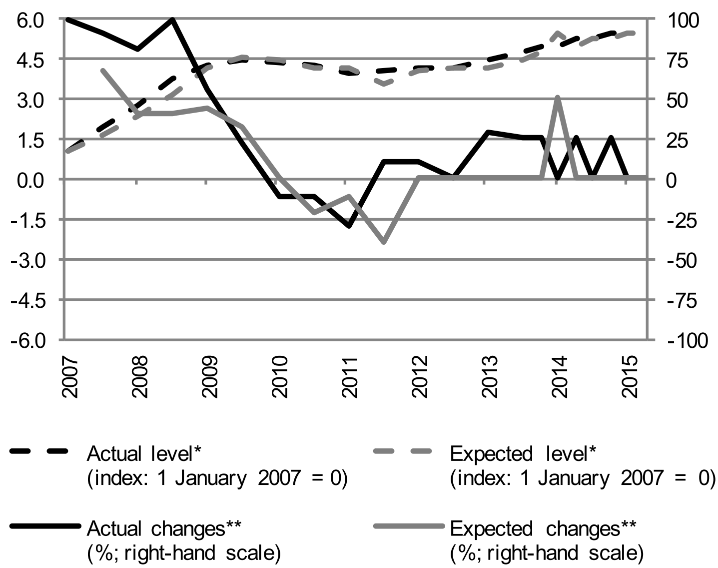
a) Total loans to non-financial corporations



b) Short-term loans to non-financial corporations



c) Long-term loans to non-financial corporations



Notes: * Net cumulative changes of credit institutions reporting tightening credit standards. ** Net percentage of credit institutions reporting tightening credit standards. Higher value refers to the tighter credit standard.

Source: "Euro area bank lending survey of June 2015: main results for Latvia", Latvijas Banka (2015), Riga. Available at https://www.bank.lv/images/stories/pielikumi/publikacijas/BLS_6_2015_en.pdf

Tightening of the supply side per se does not lead to the misallocation of capital, however. The results in Figure 1 suggest that highly productive firms are more constrained in capital than other enterprises. It could be a combination of both supply and demand factors. Perhaps more productive firms have a higher demand for loans, which cannot be fully satisfied due to reduced loan supply, thus leading to positive capital distortions. As to low productive firms, the lack of supply may coincide with the lack of demand, thus, compared with highly productive enterprises, capital distortions are lower. While credit demand and credit supply cannot be directly observed from the data, I attempt to assess them using an econometric model in the next section.

Econometric analysis of misallocation

In this section, I conduct an econometric analysis to uncover firm-specific characteristics that affect TFP and capital, labour and size distortions. I test the effect of 13 different variables available from Latvia's firm-level database. The first two variables are firm age and total assets. A block of five variables is related to financing conditions: ratios of short-term and long-term debt to assets, the ratio of profits to turnover, and the presence of a foreign owner (from OECD or non-OECD countries). The next three variables describe firm export activities: the share of domestically produced goods exports (exports of goods net of re-exports)[3] and the share of service exports in turnover. While the lack of data on inter-firm trade does not allow the degree of production fragmentation to be evaluated directly, I introduce two indicators that are associated with the outsourcing process: the share of services in intermediate inputs and the share of imports in intermediate inputs. The last variable is a micro-enterprise tax dummy, which equals one if a firm satisfies the requirements that are necessary to apply for the micro-enterprise tax after 2011.

The model explaining firm-specific TFP and distortions is as follows:

$$y_{i,t} = \beta \cdot x_{i,t} + \gamma_t + \eta_i + v_{i,t}, \tag{12}$$

where $y_{i,t}$ denotes dependent variable, $x_{i,t}$ is the vector of explanatory variables, γ_t refers to time-fixed effects, η_i denotes entity-fixed effects, and $v_{i,t} = \rho v_{i,t-1} + e_{i,t}$. Therefore,

$$y_{i,t} = \rho y_{i,t-1} + \left(\beta \cdot x_{i,t} - \rho\beta \cdot x_{i,t-1}\right) + \left(\gamma_t - \rho\gamma_{t-1}\right) + \eta_i\left(1-\rho\right) + e_{i,t}. \tag{13}$$

I estimate equation (13) by system GMM (see Blundell and Bond 2000). All variables (except firm age) are treated as endogenous variables.

3 Although hard data on re-export activities are not available, re-exports were evaluated using firm-level data in Benkovskis et al. (2015).

Table 3 Determinants of firm-level TFP and distortions

Dependent variable	Relative TFP, $\ln(A_{is}N_s^{1/(\sigma s-1)}/\overline{A}_s)$	Capital distortion, $\ln(1+\tau_{Ksi})$	Labour distortion, $\ln(1+\tau_{Ksi})$	Size distortion, $\ln(1+\tau_{Ksi})$
Lagged dependent variable	0.209***	0.811***	0.539***	0.162***
Log of firm's age	-0.581***	-0.304	-0.218	-0.408**
its first lag	0.492***	0.268	-0.0852	0.454***
Log of assets (size)	0.471***	-0.918***	-1.074***	0.804***
its first lag	-0.354***	0.737***	0.974***	-0.749***
Short term debt to assets ratio	0.0178**	-0.0363**	-0.0392***	0.0290***
its first lag	0.00631	0.0339*	0.0215*	-0.0229**
Long term debt to assets ratio	0.0098	0.0208	-0.018	-0.0136
its first lag	0.00658	-0.0284	0.00745	0.0234*
Profits to turnover ratio	0.0118***	-0.0125***	-0.00822**	0.0138***
its first lag	0.0581***	0.0238*	-0.0216**	0.0485***
Share of foreign capital (OECD countries)	0.372**	0.945***	0.405*	-0.0807
its first lag	-0.186	-0.514***	-0.357*	0.0509
Share of foreign capital (non-OECD countries)	-0.326*	-0.917***	-0.486*	0.0791
its first lag	0.241*	0.0696***	0.0446**	-0.0399
Share of goods exports in turnover	1.131***	1.942***	0.0698	0.0168
its first lag	-1.015***	-1.284**	-0.226	-0.169
Share of re-exports in turnover	0.687	4.966***	5.498***	-1.280**
its first lag	0.0464	-3.928***	-4.264***	1.312***
Share of service exports in turnover	0.43	0.954	-1.733*	-0.0461
its first lag	0.0691	-0.442	1.814**	0.181

Dependent variable	Relative TFP, $\ln(A_{is}N_s^{1/(\sigma s-1)}/\overline{A}_s)$	Capital distortion, $\ln(1+\tau_{Ksi})$	Labour distortion, $\ln(1+\tau_{Ksi})$	Size distortion, $\ln(1+\tau_{Ksi})$
Share of services in intermediate inputs	0.727***	-0.632*	-0.0108	0.199
its first lag	-0.320*	0.434	-0.131	-0.027
Share of imports in intermediate inputs	0.249*	0.803***	0.272	0.0799
its first lag	-0.268**	-0.397**	-0.256	-0.186*
Micro-enterprise tax dummy	-0.0677***	0.124***	-0.0507*	-0.0784***
its first lag	0.0117	-0.271***	-0.133***	0.0896***
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
m1	-30.70***	-33.62***	-32.35***	-40.09***
m2	1.692*	-3.573***	-3.902***	-6.122***
Sargan	65.7	279.6	68.7	151.7
Number of observations	103,848	103,848	104,244	104,244
Number of firms	35'962	35'962	36'091	36'091

Notes: *** p-value<0.01, ** p-value <0.05, * p-value <0.1

The results reported in Table 3 support possible biases due to the fragmentation of production and outsourcing – this is clearly signalled by the coefficients before the re-exports variable. As expected, the fragmentation of production process (which is definitely present for re-exporting firms) leads to overestimation of capital and labour distortions, while the size distortion is underestimated. The presence of bias is also confirmed by the positive coefficient before the share of imports in intermediate inputs in the equation for capital distortions.

Unfortunately, the lack of information on trade between firms complicates the economic interpretation of Table 3 in many cases. In particular, it is unclear whether I can interpret the positive impact of foreign capital from OECD countries on a firms' TFP as the effect of technology transfers and knowledge spillovers. Higher TFP for exporters of goods raises similar doubts: is it related with better productivity, or is it simply a misperception because of the fragmentation of production? Let me list several conclusions that still can be obtained from Table 3.

It appears that large firms tend to have higher TFP. I also find that new enterprises are expected to be more productive than old ones. Firms with foreign capital from non-OECD countries are found to be less productive and less capital-constrained (I have no reason to expect that these effects are due to smaller involvement of such firms in vertical integration). Therefore, investment from non-OECD countries does not increase productivity, but provides an alternative way of enterprise financing.

The hypothesis that exporters face higher competition, leading to positive size distortions in external markets, is neither rejected nor confirmed by Table 3. On the one hand, size distortions for exporters of goods and services do not differ significantly from those for non-exporters. On the other hand, fragmentation of production (which is arguably more pronounced for exporters) may conceal this effect.

Finally, the results in Table 3 suggest that costs of capital are lower for large non-exporting firms with high profits and high short-term debt. This reflects the importance of profits as a source of financing capital for Latvian enterprises. Higher costs for exporters could be due to higher demand for capital (which banks do not fully satisfy), while larger firms face higher supply of loans. However, the two latter effects may be subject to the fragmentation bias mentioned above. The negative coefficient before short-term debt is puzzling and contradicts the findings of Lopez-Garcia et al. (2015).

Conclusions

In this paper, I analyse the misallocation of resources in Latvia using a modified Hsieh and Klenow (2009) framework with three production factors: capital, labour and intermediate inputs. My empirical analysis is based on Latvia's firm-level data for 2007–2013, a representative dataset provided by the CSB and Latvijas Banka. The dataset covers the period including the financial crisis, and thus gives an opportunity to uncover changes in resource allocation in a period of large shocks.

I find that potential TFP gains from reallocation were close to 27% in 2013. The misallocation of resources increased prior and during the financial crisis, but declined afterwards. While changes in the allocation of resources were not the major driver of economic dynamics during the crisis, there was a positive contribution from declined misallocation to the economic growth in 2011–2013.

The major source of potential TFP gains is the size distortion that affects the allocation of all three production factors across firms. One of the possible explanations behind higher size distortions for more productive firms in Latvia is the different level of competition in domestic and foreign markets. According to a recent survey, exporting firms face a notably higher level of competition than domestically oriented enterprises, which results in a misallocation of resources since exporting firms tend to be more productive (as proved by econometric estimates). The gap between the level of competition in the domestic Latvian market and the foreign market narrowed after the crisis, which partially explains the improved allocation of resources after 2010.

Although misallocation of capital was small at the beginning of the sample, it increased over time and became an important source of TFP losses in 2013. This increased misallocation of capital could be related to tighter credit conditions of Latvia's banks. The econometric evidence is inconclusive due to fragmentation bias. However, there is some weak evidence that exporters of goods face higher capital costs due to restricted credit supply.

Unfortunately, the Hsieh and Klenow (2009) framework does not account for the fact that the production process can be fragmented, i.e. split across different firms. In the absence of network data on inter-firm trade, this leads to biased estimates – the methodology tends to overestimate TFP and capital and labour distortions, while simultaneously underestimating size distortions of firms involved into outsourcing process. Although available data on transactions between different firms are rare, this is the direction in which to proceed with the empirical analysis of misallocation.

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Discussion of papers from the session on " Credit allocation (or misallocation)"

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1 Evolving views on credit and economic performance

A common theme of the papers in the session "Credit allocation (or misallocation)" is the relationship between credit allocation and real sector performance. This topic is, of course, not new. A century ago, Schumpeter (1912) elaborated in his *Theory of Economic Development* how well-functioning banks spurred technological innovation by identifying and funding those entrepreneurs who had the best chances of successfully implementing innovative products and production processes. In the 1950s, development economists realised that "comparative financial morphology and dynamics [were] essential parts of any comparative study of economic growth and structure" (Goldsmith, 1959, p. 114). By the mid-1990s, a *Journal of Economic Literature* article surveying this burgeoning field established that "preponderance of theoretical reasoning and empirical evidence suggest[ed] a positive, first-order relationship between financial development and economic growth. … Moreover, cross country, case study, industry- and firm-level analyses document extensive periods when financial development – or the lack thereof – crucially affects the speed and pattern of economic development" (Levine, 1997, pp. 688–689).

The global financial crisis thoroughly shook our confidence in this vision. In contrast to the pre-crisis view, the literature now finds that the level of financial development is good only up to a point, after which it becomes a drag on growth. More specifically, when the share of credit in GDP is relatively low, or the financial sector's share of employment is modest, higher levels of debt add to growth. But when a country's government, corporate or household debt exceed 100% of GDP, total factor productivity (TFP) grows more slowly (Reinhart and Rogoff, 2010; Cecchetti et al., 2011; Cecchetti and Kharroubi, 2012). Moreover, unlike the level relationship – where finance is good for a while – the effect of *changes* in the size of the financial system on growth is unambiguously negative: the faster the financial sector grows, the worse it is for TFP growth (Cecchetti and Kharroubi, 2015).

In a parallel development, spawned by a series of technological shocks to our profession – the discovery of 'big data', the increase in computing power and the

1 The views expressed in this note are those of the author, not necessarily those of the BIS.

refinement of panel econometric techniques – economists have started combining bank- and firm-level data to gain new insights on the relationship between credit allocation and firm performance. The use of loan data and even loan-application data has allowed researchers to start disentangling various supply and demand factors, an issue that could never be fully resolved with aggregate or sectoral data.

What the new micro-data literature has established so far has generally reinforced the view of a rather discordant relationship between bank credit and real sector performance. Albertazzi and Marchetti (2010) found, for instance, that the contraction of credit supply in Italy during the recent crisis had little to do with firm characteristics; it was associated with low bank capitalisation and scarce liquidity. Larger, less capitalised banks contributed to credit procyclicality by reallocating loans to safer but less dynamic firms; smaller less-capitalised banks actively engaged in 'evergreening practices', delaying the recognition of losses on their credit portfolio by rolling over loans to high-risk borrowers in order not to further impair their reported capital and profitability. Jiménez et al. (2012) provided strong micro-based evidence of a credit crunch: under tighter monetary or economic conditions, Spanish banks with weaker balance sheets granted fewer loan applications; and firms rejected in their initial loan application could not get loans from other banks, regardless of their performance. Several papers presented at this conference are part of this rapidly growing literature.

Several other studies analysed the interplay between house prices and activity of firms. This issue is particularly important for small and medium-sized enterprises, which typically rely on the owner's housing as collateral for obtaining bank loans. Banerjee and Blickle (2016) thus estimated the impact of changes in regional residential house prices on extremely small firms versus slightly larger firms, and on young firms versus similarly sized older firms. They found that changes in local house prices had a larger impact on firms that were more likely to be financially constrained, and that these effects were stronger in countries where the use of housing collateral was more prevalent, such as Italy and Spain. In other words, what matters for allocation of bank credit to small firms in particular is often the state of the housing market rather than the state of firms' balance sheets and the quality of their business plans. At a macroeconomic level, such a pattern of lending is clearly inefficient – because young firms are typically more productive – and highly procyclical, as housing and credit booms and busts can reinforce each other over prolonged periods.

To be sure, some economists have never been convinced of the importance of finance in economic growth. Robinson (1952) held that economic development created demands for particular types of financial arrangements, and the financial system responded more or less automatically to these demands. Lucas (1988) argued that economists badly over-stressed the role of financial factors in economic growth. And development economists frequently expressed their scepticism by ignoring the role of the financial system altogether. Levine (1997, p. 688) noticed that Stern's (1989) review of development economics did not discuss the financial system at all – not even in the section that listed omitted topics!

Separately, economists have been puzzled by a 'financial paradox': periods of sustained economic growth in Western Europe, Japan and Korea, among other economies, took place in an environment of severe financial repression, characterised by heavy state intervention in credit allocation. During the 'golden age' of European growth from 1945 to 1973, for instance, authorities throughout

Western Europe created public and semi-public specialised credit institutions and conducted monetary and regulatory policies to ensure that priority sectors obtained adequate supply of medium- and long-term financing (Monnet, 2012). Wyplosz (1999, p. 31) observed that the correlation between high growth and financial restraints in post-war Europe was a “robust fact”, and concluded that this was “an indication that, for a host of reasons, the much trumpeted distortions of [financial restraints] were less serious than (simple) theory predicted. After all France and Italy were considered as stunning post-war successes, as were Korea and Japan, while they were actively stifling financial freewheeling.”

2 Evidence from Albania, Bosnia and Herzegovina, Latvia and Slovenia

How do the findings of the papers in this session fit into this broader picture?

The paper by Banerjee, Masten, Polanec and Volk is part of the latest empirical literature analysing credit allocation and firm performance with micro-level data. It uses very rich credit registry data (with up to three million observations) on bank loans to some 32,000 Slovenian firms. This dataset and state-of-the-art estimation techniques allow the authors to study three important issues: (i) the allocation of credit in relation to firms’ characteristics (e.g., size of assets and sales) and performance (e.g., return on assets); (ii) the probability that firm i has a bank loan in period t, and the expected value of the loan for those firms that have it; and (iii) the probability that bank b has loan exposure to firm i in period t, and the expected value of that loan.

The findings of this analysis are striking. Bank credit in Slovenia was already poorly allocated before the crisis: firm-level variables were not significant determinants of the probability of having a loan or amount of the loan. More worryingly, the relationship weakened after the crisis: Slovenian banks have been significantly less willing to lend even to better performing firms since 2009. The worst credit allocation outcomes have been associated with state-owned banks, which accumulated the largest proportion of non-performing loans and continued to grant loans during the crisis (though to a smaller extent) despite weaker capital positions.

Benkovskis also uses firm-level data, but studies a broader issue of how within-sector allocation of capital, labour and intermediate inputs affected Latvia’s growth rate from 2006 to 2013. He finds that the allocation of resources in Latvian firms generally improved after 2010, but the allocation of capital deteriorated. Although bank credit to firms is only one determinant of this deterioration, and one cannot neatly separate supply and demand factors in this setup, Benkovskis’ findings are quite suggestive of credit misallocation.

In particular, costs of borrowing for some 36,000 Latvian firms were found to be higher for exporting firms and lower for large non-exporting firms, including those with high short-term debt and high profits. In theory, higher borrowing costs for exporters could reflect the inability of domestic banks to fully satisfy the relatively high demand for capital of such firms. But Latvian banks at the same time seemed to have no supply constraints vis-à-vis large non-exporting firms, which often didn’t need bank loans in the first place due to high profits.

Dias, Robalo Marques and Richmond provide similar evidence for Portuguese firms in a paper presented in a parallel session. They found that within-industry misallocation in Portugal almost doubled between 1996 and 2011. Misallocation was concentrated in the micro and small firms, especially in the service sector. The main reason was labour and capital cost subsidies provided by the government, the latter in the form of special credit lines to small and medium-sized enterprises through the banking sector.

Tanku, Dushku and Ceca study the allocation of Albanian banks' credit portfolios at the sectoral level. They ask whether the distribution of credit to different sectors after 2008 reflected business performance of the sectors and banks' own performance characteristics. Using an innovative non-parametric technique, they find widespread evidence of credit misallocation.

More specifically, credit to agriculture responded to none of the performance characteristics of either firms or banks. In fact, the agricultural sector in Albania received hardly any bank loans at all, even though it accounted for nearly a quarter of total value added in the economy. Credit to industrial firms seemed to be better allocated: it responded positively to the value added created by the sector, and negatively to the size of industry's non-performing loans. But the relationship with banks' capital was mixed: some banks expanded their lending to industrial firms even at times when their capital ratios were declining.

Credit to the construction sector increased strongly when the value added of the sector was rising, but did not fall when the construction activity slowed – before cutting back the loans, banks simply stopped new lending and waited until non-performing loans of construction firms approached 30%. Another piece of evidence on misallocation was the absence of any relationship between credit to the construction sector and bank's capital adequacy ratios.

A similar pattern of misallocation was present in lending to the service sector, which accounts for more than half of Albanian banks' total credit. Banks continued to extend credit to service sector firms even when output in the sector as a whole declined, but reduced lending when the share of loans to the sector dropped below 50% of banks' loan portfolio. The relationship between bank lending and non-performing loans (NPLs) of the service sector was particularly perverse: as NPLs rose to around 15%, banks did not cut back on loans; as NPLs continued rising to close to 40%, banks actually *increased* their lending to the sector; and only when the NPLs exceeded 40% did they start cutting back the loans.

Finally, Jović studies credit allocation in Bosnia and Herzegovina by pooling sector-level data. Because of the short time series, he can use only a small number of observations relating credit growth to business performance indicators for agriculture, mining, industry and service sectors. In line with the traditional literature on finance and growth, Jovi finds a positive correlation between credit growth and turnover per person employed, as well as credit growth and sectoral share of value added. He also finds a negative correlation between credit growth and unit labour costs. However, the relationship between credit growth and two other key performance indicators – output per worker and profitability of the sector – is negative, though not statistically significant. Separately, Jovi finds that listed firms' profitability is positively correlated with the relative amount of bank loans they received.

3 Concluding remarks

What, then, are the main takeaways from the papers presented in this session of the ECBN conference and the recent literature? Is much of the bank credit really misallocated from the perspective of firms, banks and the economy?

Despite doubts about the finance-growth nexus expressed in recent studies, it seems fair to say that the mainstream view continues to favour a developed and well-functioning financial system as an essential condition for sustainable long-term growth. This is particularly the case for economies in Central, Eastern and Southeastern Europe, where market-based banking systems are still young and not fully formed. The real sector in these economies needs banks to help supply the working and investment capital necessary for normal business operation and growth. Alternative sources of financing are simply not available for most firms – or may not be worth the effort of developing from a social benefit-cost perspective. One reason is the small size of these economies; another is the fact that even in the much larger and financially much more developed Eurozone, the financial system will most likely remain predominantly bank based.

Moreover, the new literature, if anything, reinforces the message that banks need to be sound and function well in order to allocate credit properly. Most studies in this literature focus on the traumatic post-crisis experience in Europe, which is in several aspects unique: unprecedented housing booms, links between sovereign debt and banking fragility, limited ability of individual central banks in the Eurozone to take country-specific measures, and so on. These experiences cannot be transposed to other countries without qualifications. One should also take the results of these studies with more than the usual measure of caution: the empirical approaches that are being developed have not been fully tested, and one can have reasonable doubts about the quality of data and reliability of analysis in samples with millions of observations.

Finally, in interpreting the findings of the 'financial paradox' literature, one should not jump to the conclusion that countries with less developed financial systems might do better under arrangements with more directed credit and less market-based banking. Reviewing the French experience, Sicsic and Wyplosz (1996) suggested that the high growth rates of the 1960s and early 1970s might have even been higher absent widespread public intervention. Importantly, Monnet (2012) highlighted efficient public administration within well-developed legal and financial systems as key preconditions for the relative success of credit controls in Western Europe. These preconditions are evidently lacking in much of Southeastern Europe. The Slovenian experience, with state-owned banks allocating credit the least efficiently by far, provides further evidence against misguided suggestions to revert to directed credit allocation.

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Foreign currency household loans in Austria: A micro view on a macro issue

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1 Introduction

From the mid-1990s onwards, Austria experienced a surge in foreign currency (FX) loans to the private non-bank sectors – and in particular, to the household sector – that had been without parallel in the Eurozone. At one point in time, Austria accounted for 48% of all FX loans to households in the Eurozone, compared to a share in the total volume of household loans (including euro-denominated loans) of less than 3%.

This paper summarises the available evidence on FX loans to the household sector from both a macro and a micro perspective in order to get a broad picture of this type of debt. Although FX loans to the corporate sector also experienced a strong increase, they constituted less of a risk as the FX share never reached the values recorded for the household sector. [1] Moreover, the corporate sector had more ways to hedge against these risks. Thus, they are not addressed in this paper. Likewise, the risks arising from lending to households in foreign currency for the banking sector are outside the scope of this paper.

From a macro perspective, Section 2 of the paper analyses the factors behind the rise and eventual retreat of FX loans to households in Austria, and Section 3 discusses their main characteristics and the risks associated with this form of financing. To put their development into perspective, wherever appropriate, the features of FX loans are contrasted with euro loans to the extent possible.

The macro data on which Sections 2 and 3 are based are derived from the regular reports submitted by the Austrian banks to the Oesterreichische Nationalbank (OeNB). In a way, the increasing availability of data on FX loans over the past two decades reflects the developing interest of the authorities in this issue. Up to the mid-1990s, bank supervisory reporting requirements broke down loans to households (as well as other sectors) only into whether they were denominated

1 The FX share in bank loans to nonfinancial corporations in Austria peaked at 20% (in 2002) and began to decrease earlier than for the household sector. Lately, it has even fallen below the Eurozone average (OeNB, 2015).

in schilling or FX, but did not detail the latter by the denomination of the loans. In 1997, these supervisory statistics, which have been compiled nationally, were supplemented by the MFI Balance Sheet Items (BSI) statistics, which has since then been collected by all national central banks of the Eurosystem on a harmonised basis. It introduced a breakdown of loans granted by the banks by a number of currencies, but only for loans to non-banks overall, without providing a breakdown by borrowing sector. This feature had been incorporated into the BSI statistics in October 2002.[2] In 2007, as part of the transition to a new risk-oriented reporting system, the OeNB implemented new statistics specifically aimed at gauging the structure and the volume of FX loans in Austria in greater detail. The OeNB also addressed the issue in a number of ad hoc surveys with the major banks engaged in FX lending in Austria. Thus, the nearer we come to the present, the fuller the picture becomes, although many aspects remain still uncovered by the data.

From a micro perspective, Section 4 of the paper analyses the characteristics of Austrian households with FX loans. Additionally, a set of risk indicators is developed to evaluate the risk-bearing capacity of these households and to assess the aggregated risk to financial stability stemming from FX loans in the household sector.

The micro data on which Section 4 is based are taken from the first wave of the Household Finance and Consumption Survey (HFCS) in Austria, which was conducted in 2010 and 2011. The HFCS is a Eurozone-wide project coordinated by the European Central Bank;[3] the OeNB is responsible for conducting the survey in Austria. HFCS data provide detailed information on the whole balance sheet as well as several socioeconomic and socio-demographic characteristics of households in the Eurozone.[4] Additionally, we use some specific variables on FX loans which are not part of the core variables of the HFCS but have been additionally collected in Austria due to the high prevalence, and thus importance, of this type of credit.

Unless otherwise noted, all estimates are calculated using the final household weights and the survey's multiple imputations provided by the data producer (for a detailed description of the survey methodology in Austria, see Albacete et al., 2012b).[5]

We define a household's debt stock as the sum of the outstanding balance of mortgage debt and the outstanding balance of non-mortgage debt. Non-mortgage debt includes all liabilities that are not collateralised with real estate, i.e. consumer loans, credit lines/overdrafts, and credit card debt above the monthly repayment. We observe in the data the currency of mortgages and consumer loans, but not information about the denomination of other non-mortgage debt;

2 However, some breaks in the time series compromise the long-term comparability of the data. In June 2004, the professions had been shifted from the corporate to the household sector, and from June 2005 onwards, Austrian loan data had to be reported in gross terms (that is, including valuation adjustments), in line with the practice in other countries.

3 The HFCS is envisaged to be conducted about every three years. The HFCS in Austria has no panel component.

4 In the first wave of the HFCS, 15 out of the 17 Eurozone countries at the time of the field period collected the data; Estonia and Ireland will be included in the second wave.

5 An extensive methodological documentation of the Eurozone HFCS can be found in ECB (2013).

however, we find it reasonable to assume in the present analysis that this share of non-mortgage debt, which concerns only sight accounts and credit cards, is held in euro. Gross wealth is defined as the sum of total real assets (main residence, other real estate property, vehicles, valuables, and self-employment businesses) and total financial assets (deposits, mutual fund shares, bonds, non-self-employment private businesses, publicly traded shares, managed accounts, money owed to households, voluntary pension/whole life insurance contracts and other financial assets).

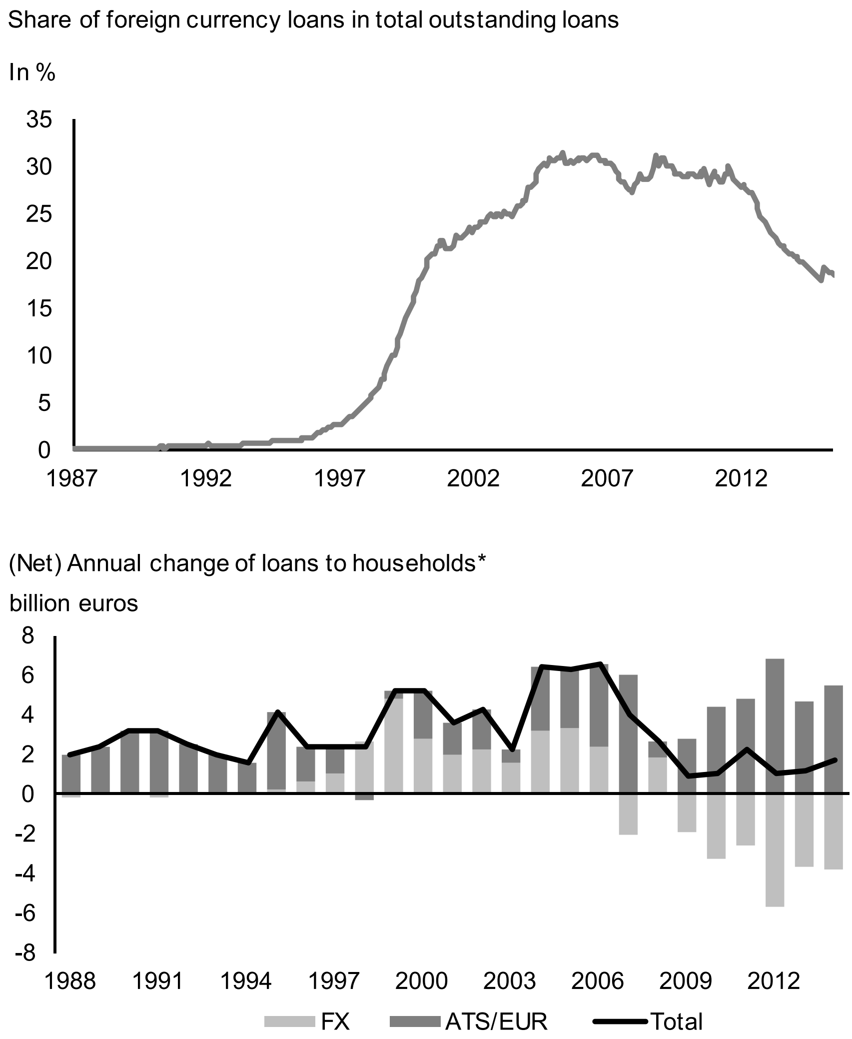
There are 2,380 households in the net sample of the HFCS in Austria. A total of 803 of these households hold debt – 77 households in FX, and 726 only in euros. The sample size of the first wave of the HFCS in Austria, and hence this relatively small number of observations, restricts the estimation of some subpopulations of FX loan holders.

2 The tide and ebb of FX loans

The boom in FX borrowing took off in Austria's westernmost province, Vorarlberg, where household borrowing in FX had been markedly higher than in the other Austrian provinces for some time. As early as by the end of the 1980s, the share of FX loans in the total amount of household loans came to 4% to 5% in Vorarlberg alone, but to a mere 0.2% in Austria. The popularity of borrowing in Swiss francs in Vorarlberg has to be seen against the backdrop of the region's close economic ties with Switzerland in general, and the relatively large number of persons working in Switzerland and Liechtenstein in particular. In the mid-1990s, FX borrowing started to spread to the other Austrian provinces. The share of FX loans in total outstanding bank lending to households rose from less than 1% in 1994 to a peak of more than 30% in 2006. For eight consecutive years from 1998 to 2005, FX loans accounted for at least 50% of new household borrowing at banks (see the right-hand panel of Figure 1).

Since then, and particularly since the autumn of 2008 when the Austrian authorities tightened their stance on lending in FX to households (see below), FX loans to households receded. Yet, the share of FX in total outstanding loans was not only impacted by the decisions of banks and customers, but also by the movements of the exchange rates in which these loans are denominated. Thus, although FX loans shrank on an FX-adjusted basis since late 2008, due to the appreciation of the Swiss franc (CHF), the major denomination of these loans, the FX share did not come down before 2011, when the Swiss National Bank (SNB) set a maximum exchange rate of CHF 1.20 to the euro. Until end-2014, the FX share in total household loans fell to 18%. However, following the decision of the Swiss National Bank to discontinue the minimum exchange rate of CHF 1.20 to the euro in January 2015, the FX share rose from 18.0% to 19.5% within one month, although in the following months it continued to edge down to stand at 18.5% in June 2015. At that date, the volume of households' FX loans outstanding amounted to €26.8 billion, implying a drop of 50%, or €21 billion, since October 2008 on an FX-adjusted basis (unadjusted, the volume decreased by just €14 billion, or 35%, due to the strong appreciation of the franc).

Figure 1 Foreign currency loans to households in Austria



Note: Breaks in time series in 12/1995 and 1/1999. * Until 1998, change in outstanding loans. Since 1999, net transactions (changes in outstanding volumes adjusted for reclassifications, valuation changes and exchange rate effects).

Source: OeNB.

To a large extent, the boom in FX loans appears to have reflected currency substitution. Indeed, in 1998, the contribution of FX loans to the annual growth of total loans to households exceeded 100%, implying that schilling or euro loans had been switched into FX loans. Since around 2009, the opposite development took place with FX loans being converted into euros. Nevertheless, it is striking that in the years of the strong recourse to FX loans, the expansion of loans to the household sector had been higher than in the years before and after. After averaging at €2.4 billion in 1988-94, the annual increase of monetary financial institution (MFI) loans to households rose to €4.3 billion in 1995-2006, and fell back to €1.8 billion in 2007-2014. But despite this growth spike, the expansion of loans to households remained relatively moderate in the years when the FX loan boom took off, and the indebtedness of Austrian households was low in international comparison throughout the whole period. [6]

That this boom in FX loans had happened in Austria puzzled many. On the one hand, some observers named supply-side factors as a relevant impact. For example, Tzanninis (2005) relates this development – among others factors – to structural changes in the Austrian banking system that had begun in the mid-1990s, such as the Bank Act in 1994, which removed the ability of banks to set common interest rates, and Austria's entry into the European Union in 1995, which removed the last remaining financial restrictions. Likewise, Braumann (2004) saw FX loans as an instrument of competition for market share among banks. On the other hand, banks claimed that the market for Swiss franc housing loans was mainly driven by demand and that the intensity of competition in the Austrian banking sector did not allow them not to offer Swiss franc housing loans (Jetzer, 2005); in a sense, this would vindicate Braumann's argument.

Another factor facilitating the spread of FX loans may been the belief in the stability of the exchange rate deriving from Austria's hard currency policy since 1980 (Tzanninis, 2005). The success of this policy may have created a psychology of an exchange rate immune from risks, notwithstanding the appreciation of the Swiss franc since the mid-1980s. But this still raises the question of why this development took place only in Austria and not in other countries such as Germany, to whose former currency — the Deutsche mark — Austria had pegged its schilling for many years, or the Netherlands, which had pursued a similar exchange rate policy. Hence it is fair to assume that specific Austrian factors played a key role. Some observers have stressed the role of independent financial advisors, whose aggressive promotion helped spread the popularity of FX loans to the rest of the country (e.g. Boss, 2003; and, in a more defensive way, Abele and Schäfer, 2003). Survey results corroborate this view. For example, data from the 2004 financial wealth survey of Austrian households suggest that independent financial advisers were an important source of information on financial matters for households that took out FX loans. In the survey, 27% of households with a

6 Moreover, there are no signs that the FX loan boom encouraged the emergence of an asset price bubble. Real estate prices stagnated or even declined in the years of the strong surge in FX lending from the mid-1990s until 2007, and started to increase only when FX loans did not grow any more. Likewise, price developments in the Austrian stock markets were extremely weak during most of the relevant time period.

FX loan mentioned independent financial advisers as one of their information sources, compared to only 13% of households with a loan in euros (Beer et al. 2010).

In this context, the formation of herd behaviour has been put forward as an explanation for the popularity of FX loans in Austria (Waschiczek, 2002; and in a more formal way, Tsanninis, 2005). Herding occurs when individuals disregard available (incomplete) relevant information when making decisions and imitate the decisions of other people instead (Banerjee, 1992). The suppression of private information in favour of publicly available information can lead to 'information cascades' when decisions are made sequentially and a large enough number of people choose identical actions. The prevalence of FX loans in Vorarlberg (which did not exist in other provinces) can be viewed as the initial condition for the emergence of an information cascade, and the increasing attention that the Austrian media have paid to the issue since the mid-1990s, just as with the role of loan brokers, as the public signal was constantly reinforced (obviously much more strongly than the private signal). Thus, the theory of rational herd behaviour might help explain why FX borrowers did not consider all the risks involved in their decisions.

Since the onset of the FX boom, the OeNB and the Financial Market Authority (FMA) had pursued a wide range of prudential measures and activities aimed at curbing FX loans and repayment vehicle-linked loans to households in Austria. The first measures were aimed at improving borrowers' and lenders' risk awareness.[7] In its first financial stability report, published in 2001, the OeNB had already underlined the risk of lending and borrowing in FX. It continued its warnings at subsequent press conferences and in various publications (which prompted the financial advisors to commission a study of their own; see Abele and Schäfer, 2003).

In 2003, the FMA issued Minimum Standards[8] for granting and managing FX loans and for loans with repayment vehicles. These Minimum Standards required banks to draw up written guidelines on the granting and managing of FX loans, to determine quantitative limits on the volumes of individual FX loans as well as the entire FX loan portfolio, to lay down requirements for the credit rating of the borrower and related risk markups, to ascertain whether the borrower has sufficient income and/or assets, and so on.

However, the effect of these measures turned out to be limited. It took the lessons learned from the financial crisis and a more stringent supervisory approach to achieve a sustained reduction in FX lending. Since the onset of the crisis in 2008, the Swiss franc experienced a strong appreciation, which reduced the appeal of FX loans considerably. In October 2008, the FMA issued an urgent recommendation calling on banks to stop granting FX loans to (unhedged)

7 In terms of the theory of rational herding, this can be seen as an attempt to tilt the public signal in the direction of a higher degree of prudence.

8 The FMA's Minimum Standards do not constitute a regulation in the legal sense. However, the FMA expects credit institutions to adhere to these standards when granting and managing FX loans.

households. This recommendation proved to be the turning point for FX lending in Austria. Since that date, FX loans to households have started to decline.

Following this recommendation, the OeNB and the FMA drew up supplementary provisions to the FMA's minimum standards mentioned above, which were published in March 2010, in order to achieve a lasting reduction in the risks arising from FX loans to households. These new provisions imposed strict criteria on the granting of new FX loans to private consumers and limited them to households with a natural hedge or with the highest creditworthiness. In addition, banks were requested to develop strategies for a sustained reduction in the volume of FX loans and repayment vehicle-linked loans and for mitigating the refinancing risk of FX loans. Finally, banks committed themselves to fulfilling the enhanced consumer information requirements set out in the new EU Directive on credit agreements for consumers. Consumers wishing to reduce their risk from (existing) FX and repayment vehicle-linked loans by converting these loans into euro-denominated loans had to receive active support from their bank. Moreover, Austria has implemented the set of seven recommendations published by the European Systemic Risk Board (ESRB) in the autumn of 2011 with a view to curbing lending in FX.

In the beginning of 2013, the FMA issued a new version of the "Minimum Standards for the Risk Management and Granting of FX Loans and Loans with Repayment Vehicles" (FMA, 2013). The new FMA Minimum Standards took account of the ESRB's recommendations and integrated the additional supervisory experiences made by Austrian authorities over the past years. They targeted both domestic and foreign exposures and introduced the principle of reciprocity, i.e. rules targeting FX loans in foreign countries must be adhered to not only by Austrian banks' subsidiaries, but also in cross-border activities.

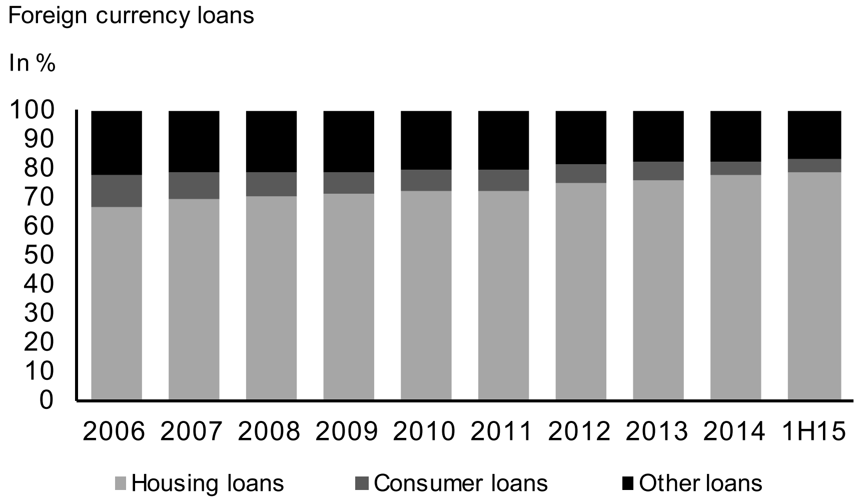
3 Main features and risks of FX loans

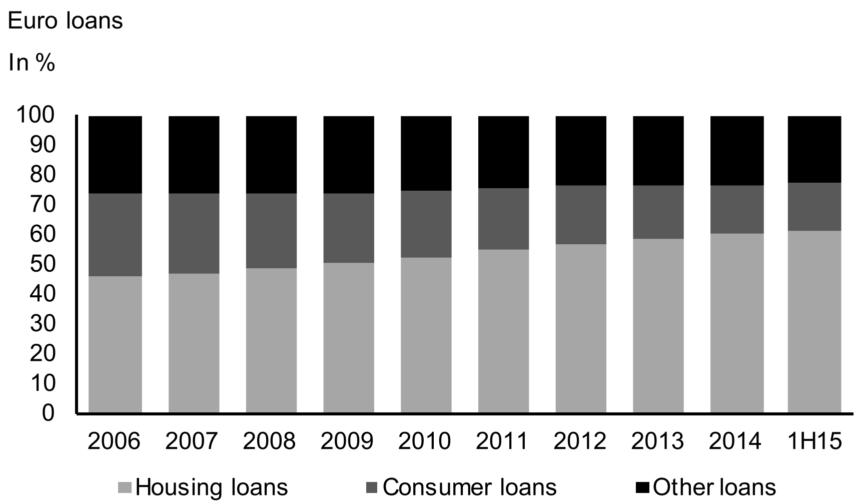
Households use FX loans predominantly for housing purposes (see Figure 2). By mid-2015, about 78% of all FX loans had been taken out for this purpose, compared to 61% for euro-denominated loans. Consumer loans accounted for 5% of the outstanding volume of FX loans (against 16% of euro loans) in June 2015, and 17% was attributable to other loans.[9]

The primary purpose of FX loans as housing loans is reflected in their long maturities. A (albeit coarse) breakdown by original maturities is provided by the BSI statistics since 2002. According to these data, almost 95% of all FX loans outstanding in June 2015 had an original maturity of more than five years, compared to around 80% for loans in euros. Since the beginning of this time series, the share of long-term FX loans has been above 90%.

9 Other loans comprise loans to the liberal professions and the self-employed, as well as loans for business purposes, debt consolidation, education and investments in pension provision models, and overdrafts of current accounts whose purpose is unknown.

Figure 2 Loans to households in Austria by purpose



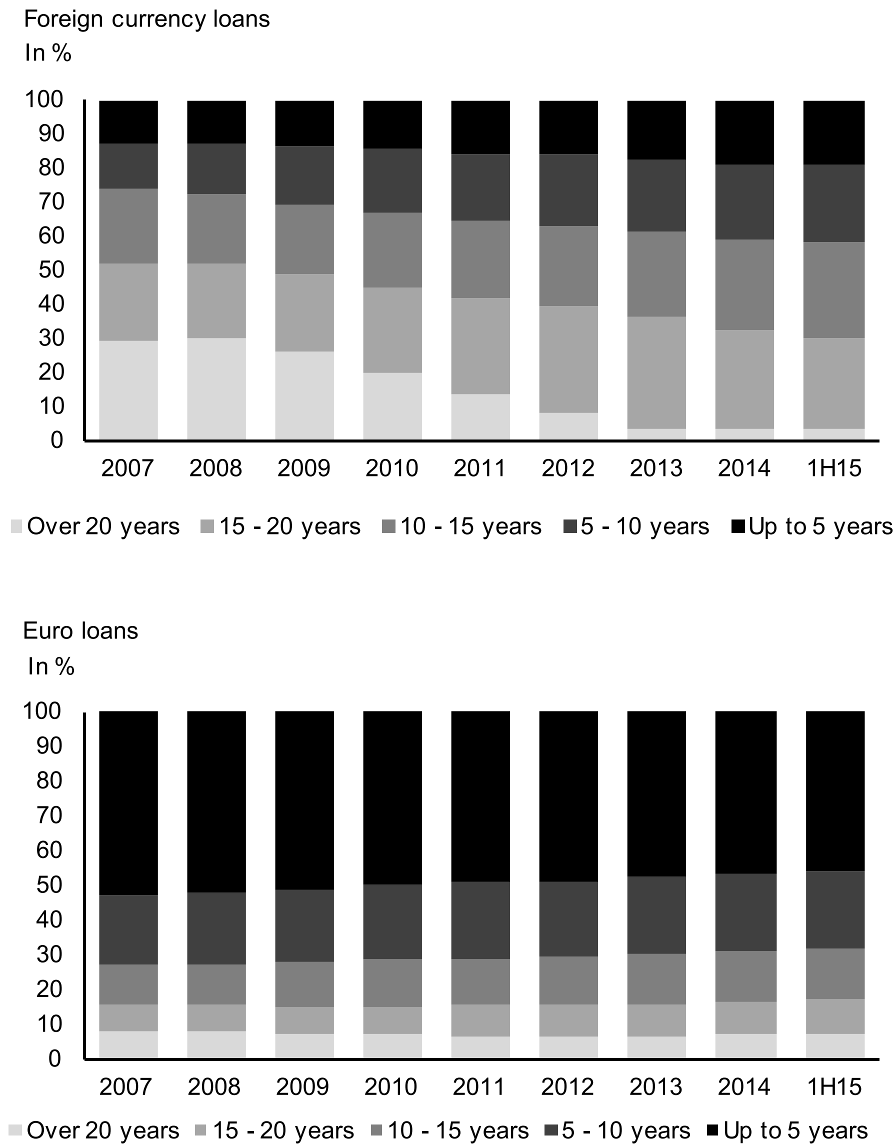


Source: OeNB.

Since 2007, information on remaining maturities has also been available. By mid-2015, more than 80% of FX loans to households had a remaining maturity of more than five years, down from 87% at the start of the time series in 2007 (see Figure 3). This reflects the very low volume of new FX loans, so that on average, remaining maturities have become increasingly shorter than original maturities. While the data show that there is still some time until the bulk of FX loans will mature, it also shows that this point of time is drawing nearer. While in 2007, more than half (52%) of FX loans had a remaining maturity of more than 15 years, this percentage had come down to less than one third (32%) by mid-2015.

However, this percentage was still almost twice the respective value for loans denominated in euros (17%). In any case, FX loans will be around for some time, as the last ones will not mature until after 2035.

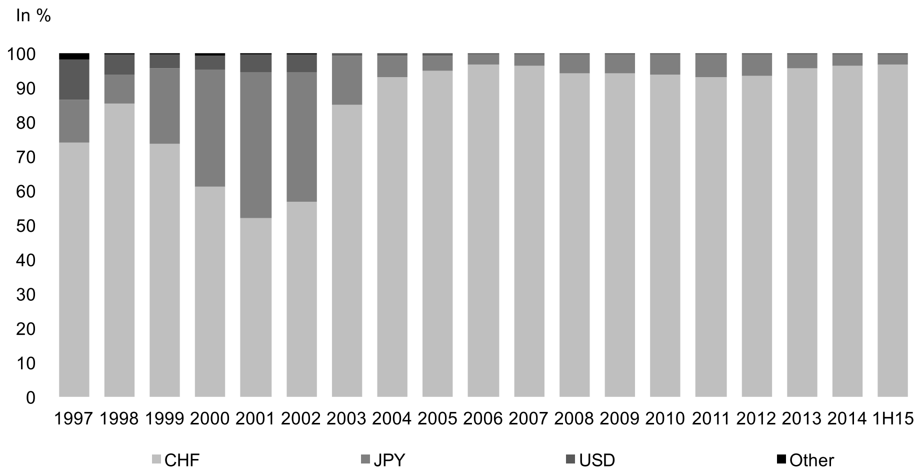
Figure 3 Loans to households in Austria by remaining maturity



Source: OeNB.

The primary currency employed in FX loans to households in Austria is the Swiss franc, the currency in which the bulk of FX loans had been taken out when the boom set in. However, for some time – especially from about 1999 to 2002 – the Japanese yen gained in popularity, reaching a share of more than 43% in late 2001, until borrowers apparently took advantage of the depreciating trend of the yen and converted their loans into euro-denominated or Swiss franc-denominated loans. Since then, the share of yen-denominated loans has fallen to 3% so that almost all outstanding FX loans are now denominated in Swiss francs (close to 97%). Other currencies played a minor role in FX loans to Austrian households. [10]

Figure 4 Foreign currency loans to households in Austria by currency



Note: Until 2002, loans to all domestic non-banks.
Source: OeNB.

In most cases, households with FX loans are directly exposed to foreign exchange risk. Available data on this issue are scarce, but it is likely that households usually do not hedge their FX exposure. Therefore, shifts in exchange rates affect both the euro-denominated value of the FX liabilities as well as the interest to be paid on the FX loans outstanding. As exchange rate movements not only feed through to interest expenses, but also affect the euro amount of the principal at maturity (even if they may be considered unrealised valuation changes in bullet loans), they may well impact current payments through the need for measures to cover this increase and to be able to repay the loan when the exchange rate risk eventually materialises at maturity date.

The main appeal of FX loans had been the lower interest rates of the borrowed currencies. FX loans typically carry a variable interest rate, with interest rates on these loans linked to the London interbank offer rate (LIBOR) of the relevant currency (Dlaska, 2002; Waschiczek, 2002; Boss, 2003). The bank charges

10 Data on the breakdown of loans to households by currency are available since 2003. For the time before, loans to all domestic non-banks are used instead. Over the period of time for which both time series are available, the difference between the two was not very substantial.

an additional 1.5% to 2%, depending on the size of the loan, the customer relations, the collateral provided, and so on. The loan is rolled over every three or six months, when it is repriced. In most cases, the loan contract offers the borrower a fee-paying option to switch to another currency (including the euro) at contractually specified rollover dates (usually the repricing/rollover dates), and it often also includes forced conversion clauses, allowing the bank to convert the loan into a euro loan at any time without the borrower's consent. In many cases, the borrower can repay the loan before it is due.[11]

At least in part, the lower interest rate was offset by higher fees. Regular bank fees do not seem higher on Swiss franc loans than on euro loans for comparable services. However, there are various fees and commissions on the FX components of the transaction (e.g. the currency conversion fee paid each time interest or amortisation payments are made, the fixed fee for maintaining a FX bank account in addition to the regular euro account, or the fee for switching currencies), and additional fees occur for the repayment vehicle (Dlaska, 2002; Boss, 2003; Prantner, 2005). Moreover, should the borrower wish to hedge against exchange rate or interest rate risk (through derivatives such as option or future contracts), additional costs would occur.

The repayment structure of loans in FX taken out by Austrian households is very different to typical borrowings in euros as the former have another distinctive feature: in most cases, FX loans are structured as bullet loans involving quarterly payments of interest only, with full principal to be repaid at maturity. While in euros, 88% of the loans are repaid continuously during the lifetime (either constant capital repayments or annuities), almost three quarters of all FX loans are bullet loans.[12] In order to accumulate the capital required to repay the principal at maturity, borrowers pay regular instalments for investment in separate repayment vehicles (predominantly capital market-orientated types of investment, such as life insurance contracts or, to a lesser extent, mutual funds), which are expected to cover the total outstanding loan at maturity. These repayment vehicles usually do not hedge against exchange rate or interest rate risk; rather, they add risk to the entire borrowing scheme. Depending on the chosen scheme, the repayment of the principal is exposed to additional exchange rate, interest rate and market risks.[13] Thus, in most cases FX loans are also exposed to the performance risk of the repayment vehicle. In this sense, private FX borrowers in Austria often act as carry traders, only without having at their disposal the methods and knowledge of professional carry traders (Beer et al., 2010).

In many cases, the performance of these repayment vehicles could not keep up with the assumptions used in the provider's model calculations. In order to get a read on the funding gaps of repayment vehicle loans, the FMA and OeNB

11 FX loans at fixed interest rates are granted very rarely. In this case, however, borrowers do not have the option to repay the FX loan before maturity.

12 The number of euro-denominated loans includes those loans that have been converted from foreign currencies.

13 These risks can only be averted at additional costs, if at all, for instance by switching from one investment vehicle to another. Cancelling a life insurance policy, for example, always involves considerable costs, which must be taken into account when the borrower wishes to change the entire arrangement.

conducted surveys with the major Austrian banks in 2009, 2011 and early 2015 (OeNB, 2015).[14] The finding was that the aggregate funding gap of repayment vehicle loans amounted to 14% of the outstanding amount, or €3.3 billion, as of end 2014. This would constitute a reduction from the June 2011 numbers both in relative terms (20% in 2011) and absolute terms (€5.8 billion in 2011). However, these numbers do not take into account that the outstanding volumes have declined over the last years. Moreover, the Swiss franc appreciated since mid-January 2015, when the Swiss National Bank discontinued the minimum exchange rate of CHF 1.20 to the euro. Factoring in the appreciation of the Swiss franc vis-à-vis the euro by 15% between end of 2014 and 30 April 2015, the funding gaps would have widened to an estimated 23%, or around €6 billion.

4 Characteristics of FX borrowers

Against this background, two questions arise at the micro-level: Who are the FX borrowers in Austria? And how large is their risk-bearing capacity? The answers to these questions are given in the following two sections.

Table 1 shows how the share of indebted households in general, and the share of FX borrowers in particular, vary across different household groups. Overall, about 36% of all households living in Austria hold some kind of debt, either mortgage or non-mortgage.[15] About 11% of these households (around 150,000 households) have FX loans. These numbers also imply that most households (64%) do not have debt.

Comparing different income groups, it can be seen that the by far highest concentration of FX borrowers is located in the highest gross income quintile. While 20% of indebted households in the highest income quintile have FX loans, this share falls to 1% in the lowest income quintile. We get a similar picture when looking at different wealth groups: while 20% of indebted households in the highest gross wealth quintile have FX loans, this share falls to less than 1% in the lowest wealth quintile. These numbers suggest that FX borrowers are households with above-average economic resources.

With regard to employment status, highest share of FX borrowers (17%) is among households with self-employed reference persons,[16] followed by households with employed reference persons (12%). The share of FX borrowers among non-employed households is far below average.

Finally, education also seems to play an important role in holding FX loans. While 16% of households with a reference person with a tertiary education have FX loans, among the low education group this share amounts to only 10%.

14 The 2015 survey comprised 35 Austrian banks which cover more than 85% of outstanding repayment vehicle loans.

15 See above for how we define household debt in the HFCS.

16 The reference person is defined as the household member with the highest income.

Table 1 Share of foreign currency borrowers by household characteristics

	Share of households with debt (%)	Share of households with FX debt conditional on having debt (%)
All households	**35.6**	**10.5**
Household gross income		
1-20 percentile	24.0	1.3
21-40 percentile	28.7	7.6
41-60 percentile	34.7	9.2
61-80 percentile	42.0	7.7
81-100 percentile	48.6	20.2
Household gross wealth		
1-20 percentile	32.8	0.3
21-40 percentile	24.1	1.6
41-60 percentile	32.0	6.7
61-80 percentile	43.1	15.7
81-100 percentile	45.9	20.2
Household reference person's employment status		
Employee	46.8	11.7
Self-employed	46.2	17.3
Unemployed	42.5	5.6
Retired	18.7	5.0
Other	32.9	7.2
Household reference person's education		
Primary or no education	74.6	10.2
Secondary	35.6	8.6
Tertiary	35.0	15.6

Note: The household's reference person is defined as the household member with the highest income.
Source: HFCS Austria 2010, OeNB.

The results obtained so far are based on a univariate analysis. Albacete and Lindner (2015) carried out a multivariate analysis to isolate the effect of one characteristic from another using the same data and definitions. They find that gross income has a positive significant effect on the probability of having FX debt. In contrast, the effect of gross wealth is not statistically significant. Furthermore, a conditional increase of one unit in the number of adults in the household decreases the probability of having FX debt by 8 percentage points. The authors do not find evidence of a statistically significant effect of the reference person having a tertiary degree or of being risk averse. However, they do find a statistically significant effect of the household's geographical distance to the Swiss border: the larger the distance, the lower the probability of having FX debt. As pointed out in Section 2, households living close to the border are more likely to have income in

Swiss francs (the dominant currency of FX loans in Austria), which makes a loan in Swiss francs a more natural decision. Finally, Albacete and Lindner find that one of the most important determinants of choosing FX loans over euro debt was the interest rate differential between Austria and Switzerland at the time the loan was taken out. An increase of 1 percentage point in this difference measured in terms of three-month interbank rates increased the probability of having FX debt by 16 percentage points. Surprisingly, exchange rate expectations were not found to play a statistically significant role in the loan currency decision.

5 Risk-bearing capacity of FX borrowers[17]

The following two subsections assess the risk-bearing capacity of FX borrowers by developing micro-based risk indicators and constructing an estimate for the aggregated risk stemming from the household sector to the banking sector.

5.1 Risk indicators

In order to assess the risk-bearing capacity[18] of FX borrowers, this section presents a large set of risk indicators obtained from the HFCS. The set can be divided into four groups: household characteristics, properties of a household's highest loan, subjective risk measures and debt ratios.

The first group includes variables describing general socioeconomic characteristics of households, such as income, wealth, negative net wealth, unemployed reference person or risk aversion.[19] The second group includes the properties of a household's highest loan that are relevant for a risk assessment of the household, such as the interest rate, adjustable or fixed interest rate, total maturity of the loan or its remaining maturity. The third group of risk indicators consists of the household's self-assessment, for example, whether expenses were above income in the last 12 months, whether expenses were higher than average in the last 12 months, or whether the household would be able to get €5,000 from friends. The last group includes objective risk measures, such as the initial LTV ratio at the time the mortgage was taken out, the current LTV ratio, the debt-to-assets ratio, the debt-to-gross income ratio, or the debt service[20]-to-gross income ratio.

Table 2 shows the means or medians of these indicators for households with debt in FX and compares them with those of households with exclusively euro-denominated debt. For convenience, column 3 shows the differences between the two subpopulations. FX borrowers have considerably higher median gross

17 Parts of this analysis can also be found in Albacete and Lindner (2015) and OeNB (2015).

18 General information on the risk-bearing capacity of households in Austria can also be found in Albacete and Linder (2013) and Albacete et al. (2014).

19 We measure risk aversion with the following question: "Which of the following statements comes closest to describing the amount of financial risk that you (and your husband/wife/partner) are willing to take when you save or make investments?" We classify a household as risk averse if its answer was "Not willing to take any financial risk", and we classify it as not risk averse in all other cases.

20 Payments into the repayment vehicle linked to a FX loan are not defined as part of the debt service of FX loans, since these loans are repaid at the end of maturity.

income and net wealth than non-FX borrowers. Also, the top 5% wealth class is more often represented among FX borrowers. Furthermore, there are substantially fewer households with negative net wealth among FX loan holders, fewer households whose expenses are above income or above average, more households that are able to get money from friends and fewer unemployed households, and mortgages in this group have a lower median interest rate and longer median maturities. All in all, these results point toward a relatively high risk-bearing capacity of FX borrowers compared to euro-only borrowers (see also Albacete et al., 2012a).

However, we also find that all debt ratio measures point toward a higher indebtedness of FX borrowers relative to their income or assets (see the bottom panel of Table 2). As a case in point, the debt-to-assets ratio is 24 percentage points higher for FX loan holders than for euro debt holders. This indicator clearly mirrors the relatively high share of mortgage loans in FX loans (see Table 1). Moreover, the proportion of households whose highest mortgage has an adjustable interest rate is also higher among FX borrowers than among non-FX borrowers. In general, FX loan holders are less risk averse than other indebted households.

As mentioned in Section 1, FX loans carry particular risks, such as exchange rate risk, the risk of the interest rate differential and the performance risk of the repayment vehicle. As FX loans in Austria are usually bullet loans (see Section 1), these risks can only materialise at the end of maturity. In order to assess how these risks have changed 'virtually' for each FX borrower since they took out their highest FX loan, it is necessary to perform a more dynamic analysis than the one carried out in Table 2. Table 3 shows the CHF/euro exchange rate as well as the interest rate differential between Austria and Switzerland, and three measures of capital market performance, both at the time when the highest FX loan was taken out and at the present time (18 June 2015).[21]

It can be seen that both the mean and the median level of all three types of risk have increased (except the ATX index and the Eurostoxx). In particular, the median exchange rate relevant for households with FX loans has virtually decreased by about 33% from CHF/euro 1.6 at the time the corresponding household took out its highest FX loan to CHF/euro 1.05 on 18 June 2015. Obviously, as long as this loan has a remaining maturity, these losses are unrealised losses that do not necessarily materialise;[22] in this case, households are only affected by higher interest payments. Indeed, in Table 2 we see that the median remaining maturity of FX loans is 16 years, compared to 12 years for non-FX loans. In other words, the risks to financial stability emanating from FX holders depend on the future development of the exchange rate of the loan currency as well as the performance of the repayment vehicle. Therefore, these risks are difficult to predict and will

21 For the sake of simplicity, the following analysis assumes that all FX loans are in Swiss francs and that all FX loans are bullet loans.

22 Some FX loan contracts in Austria include a so-called 'stop loss clause'; in this case, losses may indeed have materialised, especially since the Swiss central bank removed the exchange rate ceiling. However, in these cases the FMA recommends renegotiating the loan contract in order to find alternative solutions.

need to be monitored until (at least a substantial part of) the FX loans currently outstanding have been repaid.

Table 2 Risk indicators for households with FX debt and households with euro debt

	Households with debt in FX	Households with debt only in euro	Difference
Household characteristics			
Gross income (EUR, median)	63,102	38,633	24,469
Net wealth (EUR, median)	212,794	87,234	125,559
Part of top 5% wealth class	6.8	6.0	0.8
Has negative net wealth	7.8	15.7	-7.9
Unemployed household reference person*)	5.6	5.7	-0.1
Risk averse household	50.4	57.7	-7.3
Properties of highest loan			
Interest rate (median)	2.274	2.900	-0.626
Proportion with adjustable interest rate	76.2	66.4	9.8
Total maturity (median)	20	19	1
Remaining maturity (median)	16	12	4
Subjective risk measures			
Households whose expenses exceed income	11.7	18.8	-7.1
Households with above-average expenses	34.2	35.8	-1.6
Households able to get EUR 5,000 from friends	68.0	52.4	15.6
Debt ratios			
Initial LTV ratio for main residence (median)	0.776	0.517	0.259
LTV ratio for main residence (median)	0.379	0.138	0.240
Debt-to-assets ratio (median)	0.252	0.148	0.104
Debt-to-gross income ratio (median)	1.411	0.281	1.130
Debt service-to-gross income ratio (median)	0.113	0.090	0.023
Number of households	77	726	

Note: *Reference person is defined as the household member with the highest income. Households whose highest loan was not a mortgage are excluded from the computation of interest rate and maturation. Households without loans but other non-mortgage debt are excluded from the computation of the proportion with adjustable interest rates and total maturity.

Source: HFCS Austria 2010, OeNB.

Table 3 Market price developments for households with FX debt

	At the time the highest FX loan was taken out (household level)		June 18, 2015 (macro level)	Difference	
	Median	Mean		Median	Mean
CHF/EUR*) exchange rate	1.550	1.583	1.046	-0.504	-0.537
3m EURIBOR**) – 3m LIBOR CHF	1.569	1.595	0.775	-0.794	-0.820
Austrian 10Y bonds	4.267	4.454	1.027	-3.241	-3.427
ATX index	1,977	2,293	2,443	466	151
Eurostoxx	3,252	3,308	3,450	198	143

Notes: * Up to end-1998: ATS; ** UP to end-1998: VIBOR. Households whose highest loan was not a mortgage are excluded from the computation.

Source: HFCS Austria 2010; OeNB; Thomson Reuters.

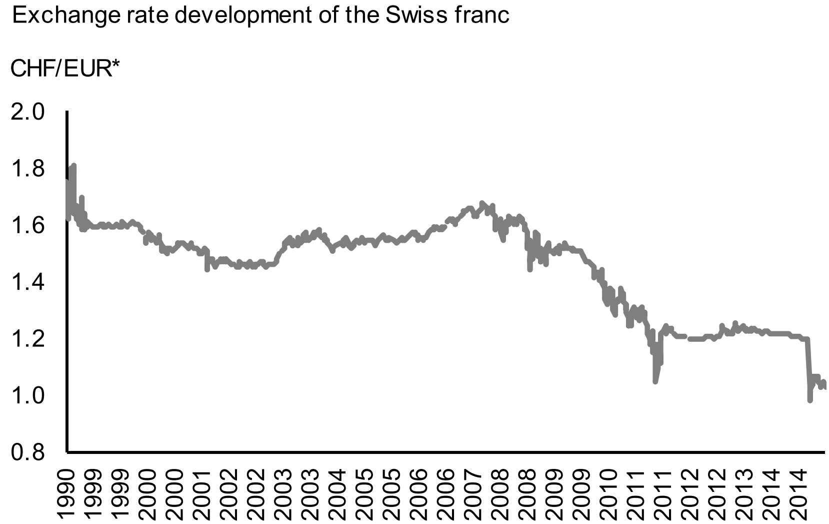
5.2 Microsimulation of exchange rate shocks

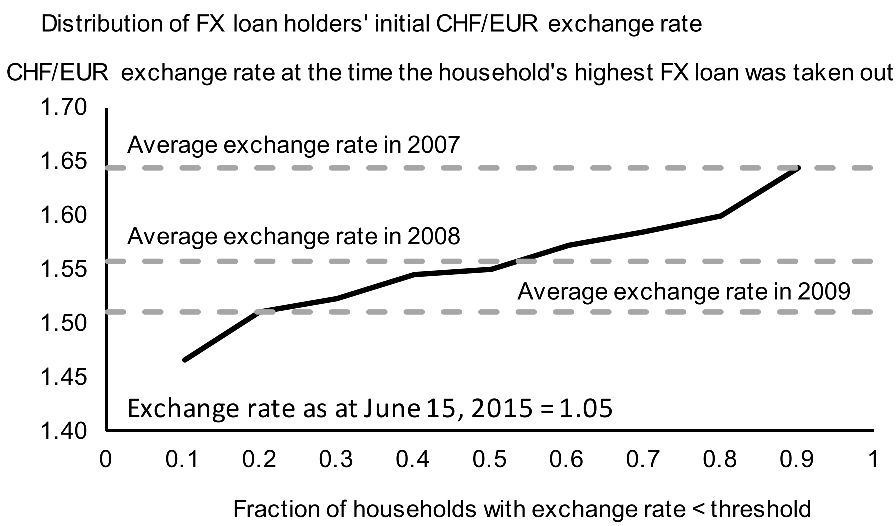
We can get a closer look at how these exchange rate developments could affect FX borrowers by combining exchange rate time series macrodata with the household-level microdata from the HFCS. By matching the average exchange rate in each year with the year in which a household's highest FX loan was taken out, we obtain the initial exchange rate for each household's FX loan[23] in the HFCS. This makes it possible to look at the distribution of initial exchange rates across FX borrowers and to simulate the effect of different exchange rate shocks on FX borrowers.

The right-hand panel in Figure 5 shows how the initial CHF/euro exchange rate at the time a household's FX loan was taken out is distributed across all Austrian households with FX loans. Ninety per cent of FX borrowers took out their FX loans at an exchange rate of 1.47 or higher, 50% at an exchange rate of 1.55 or higher, and 10% at an initial exchange rate of 1.64 or higher. If these exchange rates are compared with the current exchange rate, it is obvious that households are currently experiencing large (unrealised) losses due to the appreciation of the Swiss franc. At the current CHF/euro exchange rate of 1.05 (as at 5 June 2015), the median FX borrower is suffering (unrealised) losses of 47% of the initial outstanding amount of his or her FX loan. This comparison also suggests that currently no FX borrower is enjoying (unrealised) profits from a favourable exchange rate development.

23 In the following, any references to a household's FX loan should be understood as the household's highest FX loan if a household has several FX loans.

Figure 5 Development and distribution of the initial CHF/euro exchange rate among FX borrowers





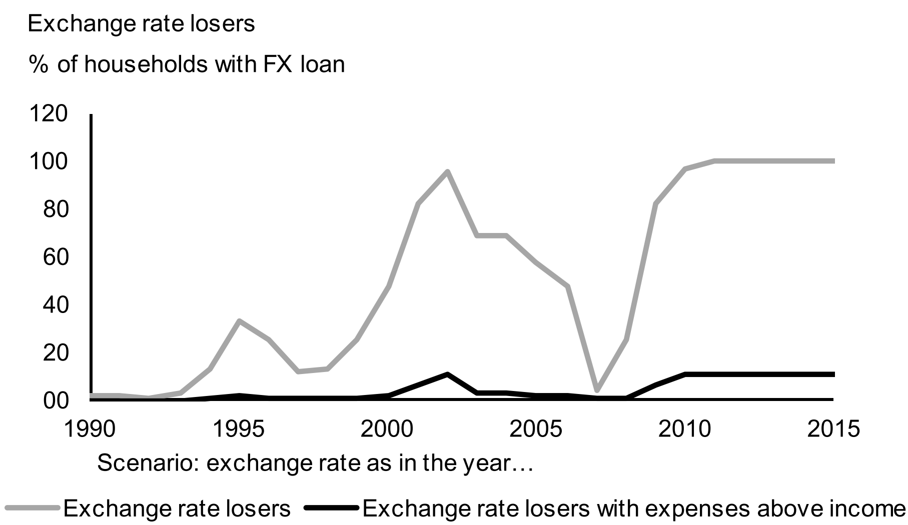
Note: * Up to end-1998: ATS.

Source: OeNB; HFCS 2010.

Figure 6 shows the results of simulating the effects of a return to exchange rate levels as those experienced between 1990 and 2015 (shown in the left-hand panel of Figure 5) on each FX borrower in the HFCS. Households which took out their FX loans at a time when the exchange rate was lower than the simulated one are defined as 'exchange rate losers' because they would be experiencing (unrealised) losses. The left-hand panel in Figure 6 shows that if the Swiss franc had become as weak as it was during the early 1990s or in 2007, the share of exchange rate losers would be very low, at below 5% of FX borrowers. However, simulating exchange rates similar to those observed in 2002 or since 2010 produces shares of exchange rate losers of more than 95%. In any case, most exchange rate losers indicate having enough income to cover their expenses. The share of exchange rate losers with expenses above income ranges between 0% and 12% in all simulations.

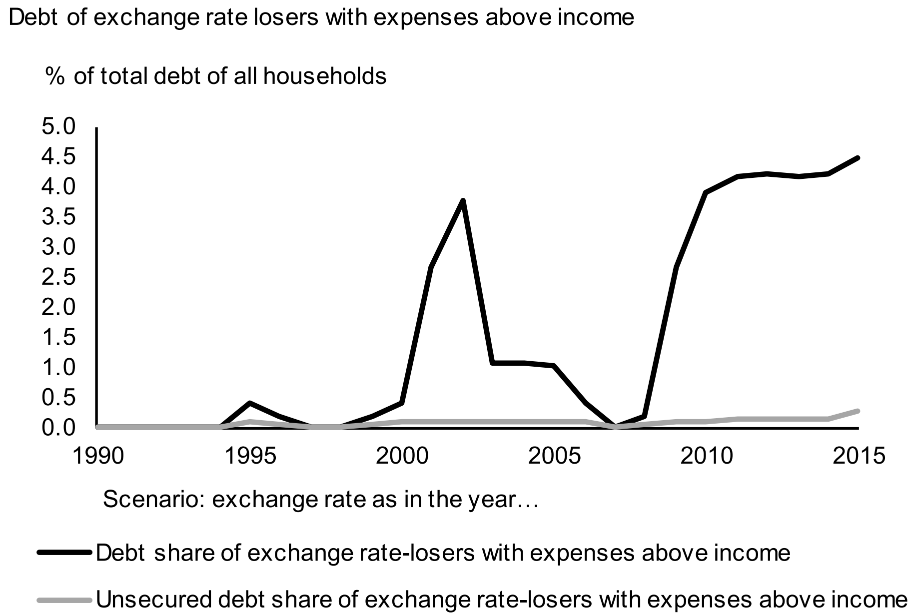
The right-hand panel in Figure 6 shows the debt share held by the exchange rate losers with expenses above the income derived from the above simulation. It ranges from less than 1% of aggregated household debt if exchange rates were as in the early 1990s or in 2007, to around 4% if exchange rates were as in 2002 or since 2010. Still, the risks to financial stability stemming from such scenarios seem to be rather low, as the unsecured[24] debt share held by the exchange rate losers in the simulation is below 0.3% in all scenarios.[25] This suggests that most Austrian FX borrowers should have enough resources to repay their FX debt.

Figure 6 Microsimulation of exchange rate scenarios



24 A household's unsecured debt is defined as the household's debt that remains after deducing the household's total financial and real assets.

25 Especially, since experiencing (unrealised) exchange rate losses is in most cases far away from experiencing a default (households usually have alternative sources to finance their income).



Source: HCFS 2010; OeNB.

6 Summary

For more than a decade, Austria experienced a wave of FX loans to households, predominantly granted to finance the purchase of a home. While borrowing in foreign currency may have offered households some immediate benefits in the short term, such as lower interest rates, in the long term the risks involved have been substantial. FX borrowers are not only exposed to significant exchange rate and interest rate risks, but also to the risks arising from the repayment vehicle, as these usually do not hedge against exchange rate or interest rate risk but add further substantial risks to the entire borrowing scheme.

These risks were addressed by the authorities early on, from warnings aimed at improving borrowers' and lenders' risk awareness, to guidelines on the granting and managing of FX loans, to an outright recommendation to banks to stop granting FX loans to households. Although these measures eventually succeeded in reducing FX loans, the still very high share of FX loans in total borrowing remains a major risk factor for the financial position of Austrian households. This risk was highlighted in January 2015 when, as a result of the strong appreciation of the Swiss franc following the decision by the SNB to discontinue the minimum exchange rate of CHF 1.20 to the euro, the foreign currency share rose sharply within one month. Likewise, in many cases, the performance of the repayment vehicles could not keep up with the assumptions used in the provider's model calculations, resulting in substantial funding gaps. Although the asset valuation of many repayment vehicles may have benefitted from the asset price surges in financial markets spurred by low interest rates in the major world economies over the last years, these asset valuations might erode when financial markets turn, which would widen funding gaps even further. And although it may be some years before the majority of FX bullet loans eventually mature, hoping for FX markets to turn for the better is a risky strategy.

However, although the risks related to FX loans are generally increasing, the risk-bearing capacity of FX borrowers is also relatively high. Compared to euro-only borrowers, FX borrowers have considerably higher median gross income and net wealth , and the top 5% wealth class is more often represented among FX borrowers. Furthermore, there are substantially fewer households with negative net wealth among FX loan holders, fewer households whose expenses are above income or above average, more households that are able to get money from friends and fewer unemployed households, and mortgages in this group have a lower median interest rate and longer median maturities.

Furthermore, microsimulations of the effects of strong appreciations of the Swiss franc such as those observed in 2002 or since 2010 show that although they result in shares of exchange rate losers of more than 95% of all FX borrowers, most of these losers seem to have enough income and wealth to cover their expenses. In these simulated scenarios, only 0.3% of total household debt in Austria is held by FX borrowers who have expenses above their income and who cannot cover their debt by their total wealth. This suggests that the risks to financial stability stemming from such scenarios seem to be rather low.

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Discussion of "Foreign currency household loans in Austria: A micro view on a macro issue"

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Housing loans denominated in domestic currency typically carry two main sources of risk: declining prices of houses used as collateral, and increasing interest rates linked to interbank money markets. The loans denominated in foreign currency, however, feature an additional source of risk: appreciation of the value of currency in which loan is denominated. While during the subprime mortgage crisis of 2007-09, the main culprit for the rather high default rates and consequent bank run on the shadow banking system were falling prices of housing after 2005 (Mishkin, 2011, p. 50), several Eastern European countries recently faced high default rates on household mortgage loans triggered a 50% increase of the exchange rate of the Swiss franc to the euro that started after the beginning of the global financial crisis in 2008.[1] In order to prevent large number of defaults, Croatia passed a legislation that allowed its citizens to freely convert loans denominated in Swiss francs to euros.[2]

In their paper, Albacete, Ritzberger-Grünwald and Waschiczek analyse foreign exchange (FX) household loans granted by Austrian banks. Austria is a particularly interesting case as these FX loans, mainly given in Swiss francs, represented more than 30% of total outstanding loans in the country at the peak (in 2005).[3] The majority of the loans were long-term loans for the purchase of housing. These were typically bullet loans, expected to be repaid in full at maturity, and were used with repayment vehicles in the form of bonds or stocks. The loans were therefore highly risky and could have large welfare consequences for the households and pose a serious threat to the stability of the national banking system. Moreover, in spite of several actions by the regulator of the banking sector in the form of minimum standards passed in 2003 and revised in 2008 and 2011, Austria continues to face a serious threat from these exchange rate shocks, with the share of such loans lingering at around 20% even in 2015.

As aggregate shares of FX loans do not simply translate into aggregate risk, Albacete et al. address two empirical questions in their paper using data from the Oesterreichische Nationalbank surveys of household borrowers. First, they

1 Croatia, Bosnia, Bulgaria, Hungary, Montenegro, Poland and Ukraine are some of the most affected countries (see www.fxloans.org for more information).

2 The free conversion imposes large costs on the mainly foreign (Austrian and German) banks, which is estimated at around 30% of the outstanding value of loans. The banks announced they will dispute this conversion in the courts.

3 In fact, Austrian transnational banks were frequent promoters of FX loans in Eastern European countries.

characterise the FX borrowers by comparing them to borrowers in domestic currency; and second, they attempt to evaluate their risk-bearing capacity. In order to address the first question, the authors compare the characteristics of euro and FX borrowers. Their main finding from the 2010 survey is that FX debt is concentrated among those with higher incomes and wealth, and it is more frequent among employed and self-employed, and more educated persons. This result suggests that, at least in part, the FX borrowers were aware of the trade-off between lower interest rates for loans denominated in foreign currency and higher risk. Moreover, their result suggests that preferences regarding risk could be described by decreasing absolute risk aversion, which is also empirically confirmed in other contexts. Nevertheless, an important fraction of households with rather low income and wealth, and even the unemployed, had FX loans, which suggests that at least part of these loans were not allocated efficiently.

The second question the authors address is related to the ability of individuals to bear the foreign exchange risk. This is the key question from the viewpoint of banking sector stability. The authors show that during the period of analysis, FX borrowers faced an appreciating Swiss franc, a lower decline in interest rates than those borrowing in euros, and lower returns of underlying repayment vehicles. The only positive evolution was increases in the prices of stocks. The authors use the survey data and simulate the effects of exchange rates to show that the exchange rates observed during 2002-2010 negatively affected 95% of all borrowers, whereas only 5% of these would have been affected if the Swiss franc had not appreciated. This result suggests that adaptive expectations regarding the volatility of exchange rates during the period prior to 2007 could mislead the FX borrowers that lower interest rates on the Swiss franc was a 'free lunch'. In other words, their result hints that better understanding of dynamics of exchange rates could result in better choices of individuals, especially in the light of evidence that after exchange rate appreciation such loans were largely refinanced.

The paper by Albacete et al. leaves open many important questions. Ideally, with accessible data at the level of bank-borrower, one would like to understand the determinants of both demand and supply in a multivariate context. Taking out and granting FX loans allows for several theoretical explanations for such risk-taking behaviour by lenders and borrowers. Regarding the supply side, one could exploit information on differences of granted FX loans across banks and link them to their fields of specialisation, selling strategies, motivation schemes for employees and managers, and methodologies used by risk departments in forecasting expected losses. Regarding the demand side for FX loans, it would be interesting to understand the effects of interest rates (FX versus domestic), the importance of the share of earnings in foreign currency, household incomes, heterogeneity of preferences proxied with household characteristics, or differences in information acquired and capacity for rational choice under uncertainty. In fact, although we learn from the simulation exercise that the observed exchange rate of the Swiss franc could affect borrowers, we do not know whether the probabilities of default and the losses given default for FX loans were any different than for loans denominated in domestic currency. Without this information, it is hard to pass judgement regarding the needed intervention by authorities. Furthermore, one may be interested in the extent to which the negative implications of exchange rate shocks were avoided due to refinancing of loans in Swiss francs with loans in euros. It is also unclear to what extent the prudential measures, in the form of minimum standards, were important for the changes in behaviour of banks and households as opposed to, for example, observed dynamics of exchange rates. Answering these questions might help households and banks to make better choices, and would be instructive for the central banks in devising their macroprudential policies for FX loans. As shown by Korinek and Simsek (2016), the benefit of macroprudential policies is far greater in dealing with excessive leverage than the interest rate policy of central banks due to the zero lower bound.

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