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Credit Rationing in Greece During and After the Financial Crisis*

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Abstract
The financial crisis has revealed the vulnerability of the Eurozone's banking sector to adverse macroeconomic shocks. In this paper we investigate corporate access to bank credit in Greece, combining microeconometric and macroeconometric empirical methods. We employ the Non-parametric Kernel estimate to identify credit rationing at the firm-level and a disequilibrium maximum likelihood approach to identify periods of credit market disequilibrium in Greece between 2003 Q1 and 2015 Q4. The empirical analysis reveals a credit crunch in Greece between 2008 Q4 and 2012 Q4 and provides evidence that credit rationing during this period was not only caused by banking sector factors but also by increasing firm-specific credit risk and by deterioration of the financial health indicators of companies.

1. Introduction

The recent financial crisis has dramatically impacted economic activity in the Eurozone economies. The closing of the interbank market, increasing risk and shortage of liquidity in the interbank market increased reliance on the European Central bank providing sufficient liquidity to the banking system (Ivashina, Scharfstein, 2010; Iyer et al., 2014). Despite massive monetary expansion, banks reduced lending and enterprises faced increased obstacles to access to bank credit (Artola, Genre, 2011; Wehinger, 2014). The credit crunch, i.e. reduction in the general availability of loans, or a sudden tightening of the conditions required to obtain them (Nguyen, Qian, 2014), was an alarming problem in Portugal and several other Eurozone countries (Iyer, 2014; Ferrando, Griesshaber, 2011). This situation creates a disequilibrium in the credit market in the form of an excess of credit demand (Ghosh and Ghosh, 1999). Despite the standard credit crunch definition in the literature being "a significant leftward shift in the supply curve for bank loans, holding constant both the safe real interest rate and the quality of potential borrower" (Bernanke and Lown, 1991), the performance of firms also determines the access of firms to bank credit. Financial health indicators play a key role in the success of credit applications (Lamont et al. 2001), and given the fact that the performance of firms, mainly small and medium-sized enterprises (SMEs), is strongly correlated

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with the business cycle (Fraser, 2012; Wehinger, 2014), a negative macroeconomic shock is supposed to lead to credit rationing.

In this paper, we investigate credit rationing in Greece, the most damaged economy in the Eurozone, using a combination of microeconometric and macroeconometric methods. This approach enables us to analyse microeconomic performance-related reasons for credit rationing and combine it with the analysis of factors at the aggregate level. Our microeconometric analysis focuses on credit rationing related to the performance of enterprises. We employ the Non-parametric Kernel estimate to analyse the distribution of the Kaplan-Zingales index proposed by Lamont et al (2001) of the sample of small and medium-sized enterprises (SMEs) during the period 2005-2011. The macroeconometric analysis employs the maximum likelihood method developed by Maddala and Nelson (1974) and applied by Herrera, Hurlin and Zaki (2013), Hurlin and Kierzenkowski, (2007), and Čeh, Durničič and Krznar (2011) to investigate credit market disequilibrium in Greece between 2003 Q1 and 2015 Q4.

In the literature, credit rationing is related to banking as well as corporate sector factors. Within the banking sector, access to interbank financing is a key factor affecting credit supply. In general, banks that rely more on interbank financing tend to reduce credit supply more intensely when the interbank market freezes (e.g. Iyer et al, 2014). Lending capacity determines the banks' ability to supply loanable funds. Commercial banks use bank deposits as a source of capital to finance bank credit (Herrera, Hurlin, Zaki, 2013). Excessive regulation of the banking sector forces banks to hold a high share of their capital as reserves. With the high amount of capital on their balance sheets, commercial banks tend to reduce the availability of credit to the private sector (Herrera, Hurlin, Zaki, 2013; Bernanke and Lown, 1991). The performance of companies determines the individual firm-specific credit risk. The balance sheet indicators of credit applicants influence the credit risk and have an effect on the decision on financing of the loan application and on the lending interest rate (Kaplan, Zingales, 1997; Lamont, Polk, Saá-Requejo, 2001).

The findings of our empirical analyses show a credit crunch in Greece between 2008 Q4 and 2012 Q4. Our estimates provide evidence that credit rationing in Greece during this period was not only caused by banking sector factors, but the excess of credit demand during this period was also caused by the poor financial performance of enterprises and by increasing firm-specific credit risk. Further exploration shows that this effect was more pronounced for firms which rely primarily on bank credit as the main source of external finance, than for firms which can also raise finance on the equity market.

The paper is structured as follows: after the introduction, the first part presents our data and descriptive statistics, the second part part introduces the empirical methods, the third part provides the results and checks on their robustness, and in the last part we provide the conclusions of the paper.

2. Data and Descriptive Statistics

We employ data from several sources to construct a dataset for our estimates. Our macroeconomic quarterly data on Greece are from Eurostat, ECB Statistical

Data Warehouse and Bank for International Settlements public database for the period 2003 Q1 to 2015 Q4.

Following Vouldis (2015), we choose to work with nominal variables reflecting the specifics of Greece for three reasons. Firstly banks and borrowers may perceive different rates of inflation. Therefore the real volume of credit may differ among the two types of agent and using the real credit as the dependent variable could lead to bias in the results (Vouldis, 2015; Kapounek, Lacina, 2011). Secondly the unstable tax environment prevailing in Greece hinders the construction of reliable corresponding real variables. For example the fiscal measures taken in 2010 and 2011 involved significant tax increases, intended to be temporary but remaining largely in place, therefore altering the expectations and the perception of real values of economic agents (Provopoulos 2014). Finally, using the real value of outstanding loans can be misleading due to the long duration of the loan contracts (Bernanke and Lown, 1991; Vouldis, 2015).

All variables are expressed as logarithms with the exception of interest rates. GDP is seasonally-adjusted for the purpose of the analysis. Following Poghosyan (2010), Vouldis (2015) and Herrera, Hurlin and Zaki (2013) we are working with data in levels, because we aim to identify possible credit demand (credit supply) gaps in absolute terms. This type of analysis only makes sense if the times series in both functions are cointegrated (see e.g. Čeh, Durničič and Krznar, 2011). This approach is also suggested by Granger (1986), arguing that to avoid spurious regression we should test before any regression whether the variables involved are cointegrated. For that reason we test the unit root hypothesis by the Augmented Dickey–Fuller (*ADF*) unit-root test and consequently determine the number of cointegrating vectors in a vector error-correction model (*VECM*) as proposed by Johansen (1995).

Our empirical analysis of microeconomic data is based on firm-level observations for small and medium-sized enterprises[1] from the Amadeus Bureau van Dijk database. The main sample consists of yearly observations of 8490 SMEs from Greece in the period 2006–2011. As the robustness check we use a subsample of 626 Limited Liability Companies (*LLC*). We expect that stressed credit conditions will affect the *LLCs* more intensely since these enterprises rely heavily on credit financing. According to legislation they cannot issue stocks and bond financing does not play a major role in their securing of external finance (European Commission, 2012).

The sample size is reduced because we worked with a balanced sample of enterprises throughout the whole period. The reason for the analysis of the balanced sample is that the kernel density estimates taking into account unbalanced datasets were uninterpretable. The exit and entry of firms represented outliers in our dataset and biased our estimates.

Summary statistics of firm-level and time series datasets are presented in Table A1 and Table A3 (in the Appendix). Table A2 reports pairwise correlations of *KZ* indices (Appendix).

[1] We use the definition of Small and Medium-Sized enterprise according to the Small Business Act for Europe (EC, 2008) which applies to all independent European Union companies which have fewer than 250 employees and a turnover of less than 50 million Euro.

3. Empirical Methodology

3.1. Microeconometric methods

To estimate obstacles to access to credit on the firm-level, we use the Kaplan-Zingales index (*KZ* index) introduced by Lamont, Polk and Saá-Requejo (2011).

The *KZ* index takes the firm performance indicators and with coefficients constructed from an ordered logit model in Kaplan and Zingales (1997) represents a measure for financing constraints. Although using these coefficients is an obvious disadvantage of the methodology, when no other options are available, this is the standard approach in the empirical literature on credit rationing (see Li 2011; Almeida, Campello and Weisbach, 2002; and Yena et al., 2014).

Companies with a higher *KZ* index are more likely to experience difficulties in securing external financing when financial conditions tighten. It is important to bear in mind that the increase of the *KZ* index indicates rising financing constraints. For each enterprise in the sample, the *KZ* index is calculated as follows:

$$KZ_{it} = -1.001909\frac{CF_{it}}{K_{it-1}} + 3.139193\frac{B_{it}}{TK_{it}} - 39.3678\frac{D_{it}}{K_{it-1}} - 1.314759\frac{C_{it}}{K_{it-1}} + 0.2826389Q_{it}, \quad (1)$$

where *CF* stands for cash-flow, *K* for property, plant and equipment, *B* for long-term debt plus short-term loans, *TK* for the total capital which comprises of long-term debt, short-term loans and the total shareholder's funds, *D* for the total dividends, *C* for cash holdings, *Q* for the Tobin Q and *t* refers to the time dimension of a firm *i*.

We use the exact specification of the *KZ* index, but within the Amadeus database we measure property, plant and equipment with tangible fixed assets. The ratio *D* was dropped from the calculation of the *KZ* index because we work with unlisted firms which do not pay dividends. Based on economic theory we excluded observations where sales, tangible fixed assets, long-term debt or loans had negative values, to prevent coding errors within the Amadeus database.

As the firms in our sample are unlisted, we are unable to assess their market value for the calculation of Tobin Q. We therefore follow Konings, Rizov and Vandenbusschedet (2003), Bakucs, Ferto and Fogarasi (2009), Guariglia, Tsoukalas and Tsoukalas (2010) and Behr, Norden and Noth (2013) who use the firm's sales growth as a proxy for Tobin Q. The proxy for Tobin Q is then calculated as:

$$Q_{it} = -(S_{it} / S_{it-1}), \quad (2)$$

where *S* stands for the sales of a firm *i* in time *t* .

The negative coefficient of Tobin Q proxy reflects the fact that a financially constrained firm probably faces a decline in sales. This consequently signals an increase in credit risk.

In our microeconometric analysis, we study the firm-level distribution of the *KZ* index on the sample of SMEs. More specifically, we estimate the density functions of the *KZ* index at the firm-level, and compare their development over the time period. Given the fact that the *KZ* index is constructed on the logic that companies with high values face high obstacles in accessing bank credit, and shifts in the estimated density functions signal changes in the ability of enterprises to secure bank credit.

Analytically, we follow the approach suggested by Botazzi et al (2012) who employ kernel densities to study corporate growth dynamics, and Juessen (2009) studying distribution dynamics of regional convergence using the same approach. Following Koráb and Poměnková (2014), we apply the Non-parametric Kernel density estimator to identify the dynamics of credit rationing at the firm-level.

The kernel density estimator generalizes a histogram using a weighting function in the form:

$$\hat{f}(x_0) = \frac{1}{N \cdot h} \sum_{i=1}^{N} K\left(\frac{x_i - x_0}{h}\right), \tag{3}$$

where $x_i, i = 1,..,N$ are the measured *KZ* index values, *h is* the bandwidth and x_0 is the design point for which the value of density is estimated. x_0 is any value of x and it is not necessarily equal to any of the x_i in the sample (Cameron and Trivedi, 2005).

The weighting function $K(\cdot)$ is called a kernel function (see Wand and Jones, 1995), and we assume that it satisfies the following conditions (Lee, 1996):

i) K(z) is symetric arround zero and is continuous.

ii) $\int K(z)dz = 1, \int zK(z)dz = 0$ and $\int |K(z)|dz < \infty$

iii) Either (a) K(z) = 0 if $|z| \geq z_0$ for some z_0 or (b) $|z|K(z) \to 0$ as $|z| \to \infty$

iv) $\int z^2\, K(z)dz = \kappa,$ where κ is a constant.

The density $\hat{f}(x_0)$ is calculated for a wide range of x_0 values. For theforming of the histogram, evaluation at sample values $x_1,\ldots, x_N.$ is used as the density estimator. From the group of kernels we use the Epanechnikov kernel (Poměnková, 2008).

The quality of the estimate is influenced by the value of the bandwidth. The optimum bandwidth value is identified by minimisation of the mean square error which is the sum of the variance and the square of the bias:

$$MSE\left(\hat{f}(x_0)\right) = E\left[\left(\hat{f}(x_0) - f(x_0)\right)^2\right] \tag{4}$$

Details about derivation are provided by Cameron and Trivedi (2005). To obtain a global measure of performance at all values of x_0 we follow integrated mean squared error (ISE):

$$ISE(h) = \int \left(\hat{f}(x_0) - f(x_0)\right)^2 dx_0. \tag{5}$$

The continuous analogue of summing squared error over all x_0 is in the discrete case.

As the last step in the microeconometric analysis we test the statistical significance of differences in median values of the *KZ* index between the years 2005

(2006) and 2011. We investigate possible differences between the years preceding the financial crisis and the years after the financial crisis erupted in the Eurozone. We apply a sign test which can be used as non-parametric analogy to the parametric t-test.

Let $x_1, x_2, \ldots, x_n$ be the sample from continuous distribution, m_0 the constant and *M* the median of the sample. We test the following hypotheses on the quality of medians:

$$H_0 : M = m_0, \text{ if } \left| \left(2n^+ - n\right) / \sqrt{n} \right| \le u_{1-\alpha/2}, \tag{6}$$

$$H_1 : M \ne m_0, \text{ if} \left| \left(2n^+ - n\right) / \sqrt{n} \right| > u_{1-\alpha/2}, \tag{7}$$

where *n* is the sample size, n^+ denotes number of cases when realisation is less then m_0 and $u_{1-\alpha/2}$ is the quantile of the standard normal distribution.

3.2 Macroeconometric methods

The objective of the macroeconometric analysis is to estimate credit supply and demand equations in line with the empirical literature on the topic, and identify periods of credit market disequilibrium.

Following Barajas and Steiner (2002), our identification variables in the credit demand equation include GDP which captures the macroeconomic environment that affects credit demand and the lending rate to non-financial corporations *(IR).* With regard to *GDP*, the theoretical sign of its parameter is indeterminate (Hurlin, Kierzenkowski, 2007). It is often used to approximate the expectations of firms and banks about future economic activity and is expected to have a positive coefficient (see Bernanke and Blinder, 1988). However this assumption is rather ambiguous if corporate loan demand is considered, since a drop in economic activity may strengthen the liquidity constraint of firms, thus increasing their short-term credit demand (Hurlin, Kierzenkowski, 2007). The lending interest rate (*IL*) determines the impact of credit prices on credit and is expected to have a negative sign in the credit demand function (Hurlin, Kierzenkowski, 2007; Herrera, Hurlin, Zaki, 2013).

Following theoretical expectations the credit demand function is specified as:

$$\ln(q)_t = \beta_0 + \beta_1 \ln(GDP)_t + \beta_2 IL_t + \varepsilon_t, \quad t = 1, \ldots, n \tag{8}$$

where *q* denotes the credit provided to non-financial corporations, *GDP* refers to nominal GDP, *IL* denotes the lending rate to non-financial corporations, and ε is an error term in time *t.*

Commercial banks should take into account the amount of available resources in deciding the amount of their credit portfolio (Čeh, Durničič and Krznar, 2011, Hurlin and Kierzenkowski, 2007; Poghosyan, 2010). The volume of deposits (*DEP*) is therefore expected to have a positive coefficient in the loan supply equation. Similarly the interbank interest rate *(INT)* reflects the cost of borrowing capital on the interbank market and is expected to have a negative effect on credit supply. The interest margin of lending and savings interest rates (*IRd*) is assumed to positively affect credit supply as this variable refers to the profitability of commercial banks.

The credit supply function is thus specified as:

$$\ln(q)_t = \beta_0 + \beta_1 INT_t + \beta_2 IRd_t + \beta_3 \ln(DEP)_t + \beta_4 \ln(GDP)_t + \varepsilon_t \quad t = 1,\ldots,n \qquad (9)$$

where q denotes the credit provided to non-financial corporations, *INT* is the interbank interest rate EURIBOR, *IRd* denotes the interest rate margin measured as the differential of the interest rates on deposits and the interest rate on credit provided to non-financial corporations, *DEP* is the volume of deposits held by commercial banks, *GDP* refers to nominal GDP and ε is an error term in the time t.

To estimate the credit demand and credit supply equations, we use the full-information maximum likelihood method (*MLL*) with the numerical maximization of the likelihood function, first introduced by Maddala and Nelson (1974). Following Laffont and Garcia (1977), our approach relaxes the market clearing assumption, allowing transitory excess supply or demand situations. The simplest model considered by the authors is as follows:

$$CD_t = x_{1,t}\beta_1 + \varepsilon_{1,t} \qquad (10)$$

$$CS_t = x_{2,t}\beta_2 + \varepsilon_{2,t} \qquad (11)$$

where CD_t denotes the unobservable credit demand, CS_t the unobservable credit supply, $x_{1,t}$ is a vector of explanatory variables that influence CD_t, and $x_{2,t}$ is a vector of explanatory variables which influence CS_t during time *t*, and β_1 and β_2 are vectors of parameters.

The equation (12) is the crucial disequilibrium hypothesis which allows for the possibility that the price of the exchanged goods is not perfectly flexible and credit rationing occurs. More generally the equation (12) indicates that any disequilibrium which takes place, i.e. any divergence between the credit supplied and credit demanded, results from the lack of complete price adjustment (Herrera, Hurlin and Zaki, 2013):

$$q_t = \min(CD_t, CS_t) \qquad (12)$$

each observation belongs to either supplied or demanded quantities. This condition helps to avoid the usual identification problems in credit market equilibrium models, given that, in each period, the volume of credit is determined by either supply or demand. The probability that observation q_t belongs to the demand regime is computed as suggested by Herrera, Hurlin and Zaki (2013):

$$\pi_t^{(d)} = P(CD_t < CS_t) = \Phi(h_t) = \frac{1}{\sqrt{2\pi}}\int_{-\infty}^{h_t} e^{-\frac{x^2}{2}}dx \tag{13}$$

$h_t = (x_{2,t}\beta_2 - x_{1,t}\beta_1)/\sigma$ and $\Phi(x)$ denotes the cumulative distribution function. Similarly the probability of obtaining the supply regime is calculated as:

$$\pi_t^{(s)} = P(CS_t < CD_t) = 1 - \Phi(h_t) \tag{14}$$

In order to compute the marginal density $f_{Q_t}(q_t)$ [2] of the observable variable q_t we consider the joint density of demand and supply functions. Given the definition of the disequilibrium, we state that:

$$f_{Q_t}(q_t) = f_{Q_t|CD_t<CS_t}(q_t) + f_{Q_t|CS_t<CD_t}(q_t) \tag{15}$$

Consequently we obtain the corresponding marginal density of quantity on the two subsets:

$$f_{Q_t|CD_t<CS_t}(q_t) = \int_{q_t=CD_t}^{\infty} q_{CD_t,CS_t}(CD_t, z)dz \tag{16}$$

$$f_{Q_t|CS_t<CD_t}(q_t) = \int_{q_t=CS_t}^{\infty} q_{CD_t,CS_t}(z, CS_t)dz \tag{17}$$

Finally the unconditional density function of the quantity is defined as:

$$f_{Q_t}(q_t) = f_{Q_t}(q_t, \theta) = \int_{q_t}^{\infty} q_{CD_t,CS_t}(q_t, z)dz + \int_{q_t}^{\infty} q_{CD_t,CS_t}(z, q_t)dz \tag{18}$$

The log-likelihood function of the model is then defined to estimate the vector of structural parameters as follows:

$$L(\theta) = \sum_{t=1}^{T} \log[f_{Q_t}(q_t, \theta)] \tag{19}$$

Following Herrera, Hurlin and Zaki (2013), we use the Newton-Raphson iterative procedure to obtain the maximum likelihood estimates of the structural parameters. Given the estimated values of the parameters we compute the probability that the observation q_t belongs either to the demand $\pi_t^{(d)}$ or the supply $\pi_t^{(s)}$ regime.

[2] Computation of marginal density of the observable quantity of credit does not relate to the calculation of Tobin Q that was specified in the section 3.1.

4. Results

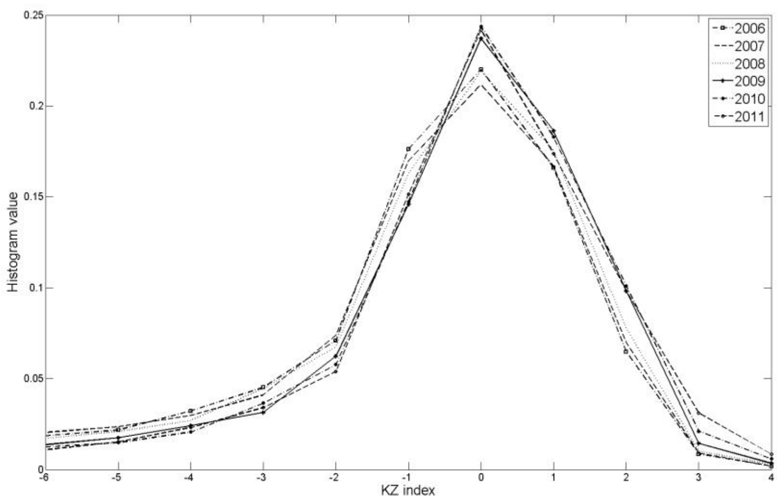
4.1 Results of microeconometric analysis

In this part we focus on the Kaplan-Zingales indices of the main sample of SMEs. Later in the Robustness section we compare the results with the subsample of Limited Liability Companies.

Descriptive statistics in Table A1 present mean and median values of *KZ* indices for the main sample of enterprises. Mean and median values greatly differ due to the outliers in the sample. The interpretation of results therefore focuses on median values rather than mean scores, since we expect a bias using mean scores in the empirical analysis.

Estimated kernel densities do not surprisingly show large shifts in the density functions on the horizontal axis. We nevertheless may observe differences in the position of density function between the pre-crisis (2006-2008) and crisis (2009-2011) years. Descriptive statistics also show an increase of *KZ* index medians from - 0.6249 and - 0.4962 in 2007 and 2008, resp., to - 0.2959 in 2009 and - 0.2291 in 2010.

Figure 1 Non-parametric kernel density estimates of the KZ index



Notes: The figure shows estimation of a histogram via a non-parametric kernel estimate for the Kaplan-Zingales index in a two-dimensional presentation.

The question of whether the medians of *KZ* indices are significantly different between the pre-crisis and crisis years is the core of our attention in the next step. Table 1 presents the non-parametric sign tests of median equality of *KZ* indices in different years. The results show that the *KZ* index medians are statistically different between the two sub-periods (2006 and 2007, and 2008-2011). The analysis showed that the year 2008 can be taken as the breaking period.

Table 1 Non-parametric test of median equality

Year		*2006*	*2007*	*2008*	*2009*	*2010*	*2011*
	Median	*-0.5905*	*-0.62486*	*-0.49622*	*-0.29589*	*-0.22907*	*-0.20794*
2006	-0.5905	0	0	1	1	1	1
2007	-0.6249	0	0	1	1	1	1
2008	-0.4962	1	1	0	1	1	1
2009	-0.2959	1	1	1	0	1	1
2010	-0.2291	1	1	1	1	0	0
2011	-0.2079	1	1	1	1	0	0

Notes: 0 refers to "acceptance" of H0: data have such median, 1 denotes rejection of H0: data have such median, referred to the 5% significance level. Testing is performed for each median with respect to each year.

Based on the previous findings, the microeconometric estimates imply that the access to bank credit of SMEs in Greece worsened in 2009 due to balance-sheet performance indicators. The poor financial health of enterprises raised firm-specific credit risk and SMEs faced significantly worse conditions for accessing bank credit.

4.2 Results of macroeconometric estimates

Given the fact that the macroeconometric estimation strategy uses data in levels (see part 2 Data and Descriptive Statistics for explanation), the estimated results are reasonable only if there is a cointegration link between observed credit and the variables in credit supply and credit demand equations. To test cointegration of the time series in models (8) and (9) we perform the Johansen test, the unit root hypothesis is tested by the *ADF* test (Table 2). The optimal lag length of the AR-model for the *ADF* test is obtained on the basis of Akaike's information criterion. The unit root test without the deterministic trend shows that all time series in our models are *I(1)* (Table 2).

We find cointegrating vectors both in the credit demand and credit supply equations at a 1% significance level (Table 3). The time series are cointegrated in both functions, i.e. there is a long-term relationship, and therefore the maximum likelihood estimation of both equations may be performed.

Consequently, employing the maximum likelihood, we estimate coefficients of credit supply and credit demand equations (Table 4). We estimate (1) – (4) model specifications including lending interest rate into credit supply equation (model 4), and excluding insignificant variables (models 2 and 3).

Table 2 Results of ADF unit root test

	Test statistics	
Variable	*Levels*	*First differences*
Credit	0,0669	-1.763 **
GDP	-0,518	-2.003 **
IL	-0,297	-3.420 ***
INT	-1,393	-3.540 ***
IRdiff	-0,227	4.199 ***
DEP	0,627	-3.098 ***

Notes: **, *** denote a statistical significance of rejection of the null hypothesis on the existence of a unit root at 5%, and 1%, resp.

Table 3 Results of Johansen rank tests for cointegration

	Trace test				***Maximum eigenvalue test***			
	lag	***r = 0***	***r = 1***	***r = 2***	***lag***	***r = 0***	***r = 1***	***r = 2***
Credit demand	1	45.277 ***	11.105	2.093	1	34.172 ***	9.011	2.093
Credit supply	1	113.931 ***	58.338 **	34.477	1	55.593 ***	23.861	19.528

Notes: ** and *** denote significance at the 5, and 1% level, r refers to the cointegration rank.

In the credit demand equation in model (1) GDP has a significant positive effect on credit demand. On the contrary, the lending interest rate (*IL*) is insignificant within our estimates and does not affect corporate credit demand. In the credit supply function, deposits held at commercial banks (*DEP*) and GDP positively affect credit supply in Greece. The effect of interbank lending (*INT*) is negative, which is in accordance with economic theory expectations. The interest rate margin (*IRd*) is insignificant in our estimate, likely due to its very small size during the period after the financial crisis.

Excluding insignificant variables in the model (2), the estimates show similar results (Table 4). We consequently replace the interbank interest rate (*INT*) in the credit supply function with commercial banks' lending interest (*IL*) which may have a larger effect on credit supply (model 3). The estimations show a similar significant effect on credit supply in accordance with the theory.

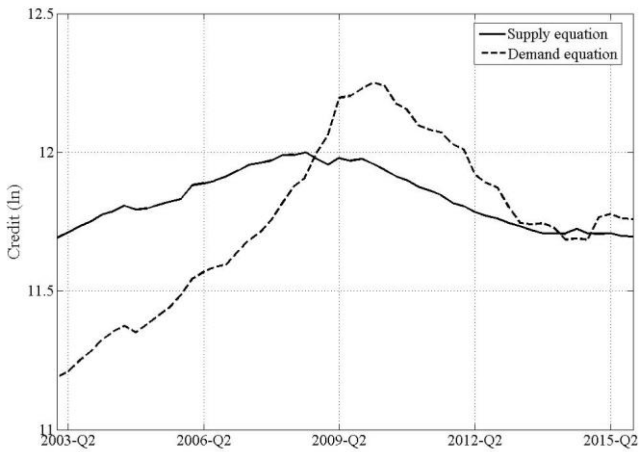
Figure 2 presents estimated quantities of credit supply and credit demand over the period 2003 Q1 and 2015 Q4. The estimates show a period of excess credit supply from 2003 Q1 to 2008 Q3. We find a credit crunch in Greece between 2008 Q4 and 2012 Q4. During the recovery from the financial crisis (2013 Q1 – 2015 Q4) the estimates do not reveal significant credit supply/credit demand gaps.

Table 4 Maximum likelihood estimates of credit supply and credit demand

Loans granted to non-financial corporations				
	(1)	*(2)*	*(3)*	*(4)*
Demand				
Constant	2.259 ***	4.988 ***	2.392 ***	5.246 ***
GDP	0.882 ***	0.633 ***	0.871 ***	0.610 ***
IL	0.0028		0.0007	
Supply				
Constant	-9.425 ***	-7.982 ***	-8.517 ***	-6.249 ***
IRd	0.067		0.063	
INT	-0.036 **	-0.035 ***		
DEP	0.915 ***	0.729 ***	1.041 ***	0.828 ***
GDP	0.893 ***	0.988 ***	0.694 ***	0.728 ***
IL			-0.061 **	-0.035 *
Log-Likelihood	-115.307	-115.315	-115.807	-112.114
R- sq	0.981	0.985	0.981	0.983
N	52	52	52	52

Notes: The table reports coefficients for a maximum likelihood estimate of credit supply and credit demand equations. ***, (**), (*) refer to significance at the 1% (5%) (10%) level, respectively. R-sq is the within R2 value, while N is the number of observations.

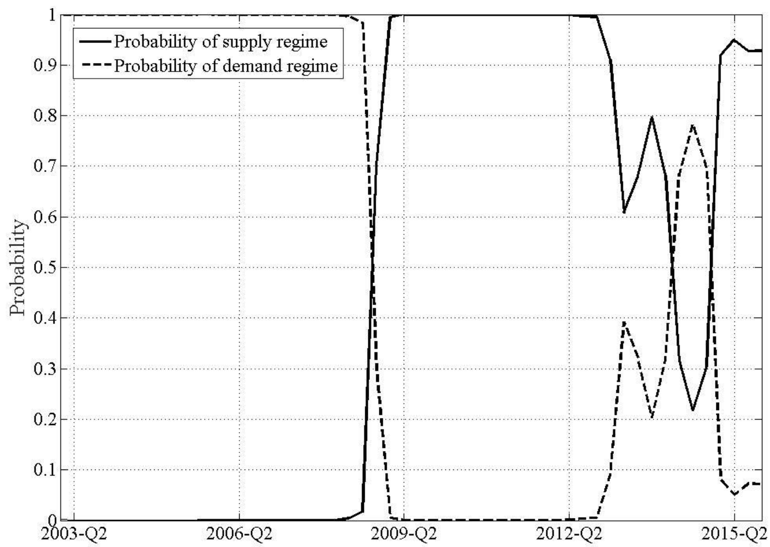
Figure 2 Estimated quantities of credit demand and credit supply



Notes: The figure presents estimated credit supply and credit demand in natural logarithms on the vertical axis over the time period on the horizontal axis. The full line shows the estimated credit supply, the dashed line is the estimated credit demand.

The calculated probability of the existence of credit supply and credit demand regimes in (10) supports previous findings. Figure 3 presents the probabilities of both regimes and shows that during the financial crisis and also during the recovery period there was a credit demand gap on the credit market in Greece.

Figure 3 Unconditional probabilities of credit demand and credit supply regimes



Notes: The figure shows the probability of existence of credit supply and credit demand regime in the sense of (10). A probability of existence of credit supply > 0.5 indicates that credit demand is equal or higher, and vice versa.

4.3 Robustness

We performed robustness checks on both microeconometric and macroeconometric estimates. To check the robustness of the micro-level analysis, we calculated *KZ* indices for the subsample of 626 Limited Liability Greek SMEs. The robustness check of maximum likelihood estimates is done by OLS.

Descriptive statistics of firm-level data in Table 5 show large differences between median and mean *KZ* indices during the period 2005 to 2011, which is explained by outliers in the sample. As in the main sample, the interpretation of the results therefore focuses on median rather than mean scores. Median *KZ* index values rose in 2009 (from - 2.415 in 2008 to - 1.451 in 2009) and remained at this level in 2010 (- 1.289) and in 2011 (- 1.310), (Table 5). The increase is larger than in the main sample of firms.

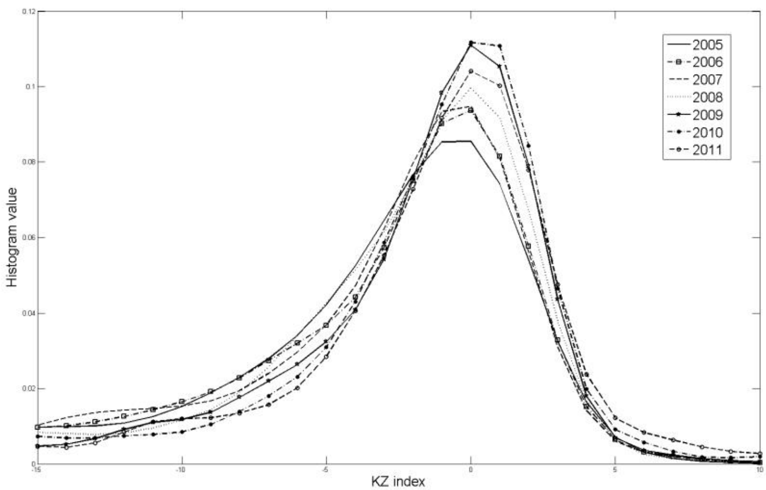
Table 5 Descriptive statistics – robustness check

Year	*Mean*	*St. Dev.*	*Min.*	*1. p.*	*Median*	*99 p.*	*Max.*
2005	-928,745	16256,190	-327525,875	-407,054	-3,186	3,048	7,361
2006	-333,133	7680,438	-192141,391	-437,568	-2,666	5,577	34,904
2007	-604,615	8385,768	-145998,141	-964,081	-2,664	5,119	26,828
2008	-505,038	10088,630	-250363,641	-889,079	-2,415	3,832	12,211
2009	-1686,036	22876,370	-460127,094	-1538,764	-1,451	7,591	48,870
2010	-1212,839	14606,040	-272051,781	-16330,103	-1,289	11,952	40,284
2011	-2055,528	21310,9	-387428,125	-47241,523	-1,310	16,466	815,144

Notes: The table reports summary statistics of KZ indices for the sample of enterprises. The number of observations is 626 for all years.

The density functions estimated by the Non-parametric Kernel approach shifted rightwards on the horizontal axis between 2005 and 2010 (Figure 4). The largest shift is visible between 2007 and 2008 and 2008 and 2009.

Figure 4 Non-parametric kernel density estimates of the KZ index – robustness check



Notes: The figure shows estimated kernel density functions with the Kaplan-Zingales index on the horizontal axis and the histogram values of the number of firms on the vertical axis in a two-dimensional presentation.

The differences presented in descriptive statistics and estimated Kernel densities show larger differences in pre-crisis (2005-2007) and crisis (2008-2009) years than the analysis of the main sample of enterprises presented in part 4.1. To test whether this effect is significant, Table 6 presents the results of the non-parametric sing test. Medians of *KZ* indices are significantly different between these two subperiods (2005-2007 and 2008-2011).

Table 6 Non-parametric test of median equality - robustness check

Year		*2005*	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*
	Median	*-3.1862*	*-2.6664*	*-2.6639*	*-2.4146*	*-1.4510*	*-1.2890*	*-1.3105*
2005	-3.1862	0	0	0	1	1	1	1
2006	-2.6664	0	0	0	0	1	1	1
2007	-2.6639	0	0	0	0	1	1	1
2008	-2.4146	1	0	0	0	1	1	1
2009	-1.4510	1	1	1	1	0	0	0
2010	-1.2890	1	1	1	1	0	0	0
2011	-1.3105	1	1	1	1	0	0	0

Notes: 0 refers to "acceptance" of H0: data have such median, 1 denotes rejection of H0: data have such median, referred to the 5% significance level. Testing is performed for each median with respect to each year.

The reason for larger differences compared to the main sample can probably be attributed to the fact that Limited Liability Companies in the subsample cannot raise finance, by law, at the equity market and do not use bond financing in large scale. Any negative macroeconomic shock therefore affects these firms more heavily (see e.g. Fraser, 2012; Wehinger, 2014)

A further robustness check of the macroeconometric estimates of credit demand and credit supply equations is done by estimating both equations separately by OLS (Table 7). Essentially, the OLS represents the Granger-Engle estimation approach of cointegration and is therefore a convenient robustness check method.

The coefficients in the credit demand function and their statistical significance are in accordance with the maximum likelihood estimate. GDP positively affects credit demand while the effect of the lending interest rate on the credit demand of firms is insignificant. In the credit supply equation (model 1), coefficients for deposit (*DEP*) and GDP are in line with MLE estimates. The coefficient of interest rate margin (*IRd*) is positive and insignificant (MLE) while OLS estimates show positive and significant results at a 10% significance level. The only statistically significant coefficient which has a different sign estimating OLS and MLE is the interbank interest rate (*INT*) which has a negative sign in MLE and a positive sign in OLS estimates. Similarly, lending interest rate (*IL*) has a positive coefficient in OLS but negative sign in MLE estimates in the credit supply equation (model 2).

Table 7 OLS robustness check

Loans granted to non-financial corporations					
Demand			*Supply*		
	(1)	***(2)***		***(1)***	***(2)***
Constant	0.1383 (2.6276)	0.661 (0.728)	Constant	-1,1683 (0.8856)	-2.524 *** (0.7282)
GDP	1.0835 *** (0.2506)	1.016 ***(0.232)	IRd	0.0288 * (0.0170)	0.046 *** (0.011)
IL	-0.035 (0.4811)		INT	0.0252 ** (0.0097)	
			IL		0.041 *** (0.011) ~~(0.011)~~
			DEP	0.8069 *** (0.0567)	0.765 *** (0.042)
			GDP	0.2501 ** (0.1064)	0.401 *** (0.059)
F-stat.	9.77 ***	19.18 ***		317.92 ***	351.91 ***
R-sq	0,285	0.2773		0,9644	0.9677
N	52	52		52	52

Notes: The table reports coefficients for an OLS estimate of credit supply and credit demand equations. ***, (**), (*) refer to significance at the 1% (5%) (10%) level, respectively. F-stat is F-statistics, R-sq is the within R2 value, while N is the number of observations. Standard errors are in parentheses.

5. Conclusions

In this paper we investigate credit rationing in Greece before, during and after the recent financial crisis. The empirical analysis combines firm-level estimates of SMEs' access to bank credit with a country-level credit market disequilibrium model. The combination of both levels of the analysis provides a more precise picture of the reasons for credit rationing in Greece since it allows for the analysis of firms' performance-related as well as macreoeconomic factors.

The microeconometric approach explores the distribution of the Kaplan-Zingales index and analyses the non-parametric kernel density functions during the time horizon 2005–2011. The main sample is compared with the subsample of Greek Limited Liability Companies as a control of robustness. The macroeconometric approach uses the standard disequilibrium model of the credit developed by Maddala and Nelson (1974) and Laffont and Garcia (1977) using data from 2003 Q1 to 2015 Q4.

The macroeconometric estimates show an excess of credit supply before the financial crisis from 2003 Q1 to 2008 Q3. We find a credit crunch in Greece between 2008 Q4 and 2012 Q4. At the country-level, reduction of bank deposits and GDP growth are the most significant factors explaining the credit demand gap. We do not find a significant effect of lending interest rate on credit demand of enterprises.

Firm-level analysis has shown that SMEs faced significantly higher obstacles to accessing bank credit after 2008 due to worsening financial health indicators. Further research has shown that this effect was more pronounced for firms which rely primarily on bank credit as the main source of external finance, than for firms which can also raise finance at the equity market.

Our estimations contribute to the current debates about the credit crunch in the Eurozone countries, and provides evidence that credit rationing in Greece during the financial crisis and shortly afterwards was not only caused by banking sector factors, but that the denial of a vast number of credit applications during this period was also caused by the poor financial performance of enterprises and by increasing firm-specific credit risk.

APPENDIX

Table A1 Descriptive statistics: firm-level data

Year	*Mean*	*St. Dev.*	*Min.*	*1. p.*	*Median*	*99 p.*	*Max.*
KZ2006	-245,0484	12356,95	-1064735	-167,0414	-0,5904975	3,261808	302,0435
KZ2007	-357,5703	10939,97	-583926,6	-230,7738	-0,6248557	3,112766	532,1138
KZ2008	-313,6828	12400,63	-897345,5	-239,9543	-0,4962175	4,098321	130293,4
KZ2009	-289,4409	10396,46	-666288,8	-245,6146	-0,295885	7,560334	170250,8
KZ2010	-266,7365	8094,395	-359141,6	-270,1066	-0,2290699	9,966209	210150,7
KZ2011	-274,3482	7987,87	-387428,1	-316,9881	-0,2079389	18,77461	132142

Notes: The table reports summary statistics of KZ indices for the sample of 8490 enterprises. Number of observations is the same for all years.

Table A2 Pairwise correlations of KZ indices

	KZ2006	*KZ2007*	*KZ2008*	*KZ2009*	*KZ2010*	*KZ2011*
KZ2006	1					
KZ2007	0.5965 ***	1				
KZ2008	0.3261 ***	0.3833 ***	1			
KZ2009	0.0461 ***	0.3713 ***	0.2247 ***	1		
KZ2010	0.0613 ***	0.056 ***	0.0914 ***	0.3764 ***	1	
KZ2011	0.0506 ***	0.0373 ***	0.0693 ***	0.2405 ***	0.4904 ***	1

Notes: The table reports yearly pairwise correlations of Kaplan-Zingales indices between 2006 and 2011, *** denotes 1% significance level.

Table A3 Descriptive statistics: time series data

Variable	*Mean*	*St.Dev.*	*Min.*	*Median*	*Max.*
ln(q)	11,678	0,224	11,188	11,691	11,948
ln(GDP)	10,836	0,116	10,674	10,815	11,021
IL	5,757	0,603	4,760	5,688	7,123
IRd	2,660	0,690	1,380	2,840	3,630
INT	1,489	1,408	-0,160	1,010	4,250
ln(DEP)	12,418	0,295	11,931	12,467	12,836

Notes: The table reports descriptive statistics for time series used in the macroeconometric analysis. The variables refer to the models in (6) and (7). The number of observations is 52 for all variables

Table A4 Pairwise correlations - robustness check

	KZ2005	*KZ2006*	*KZ2007*	*KZ2008*	*KZ2009*	*KZ2010*	*KZ2011*
KZ2005	1						
KZ2006	0.592 ***	1					
KZ2007	0.340 ***	0.578 ***	1				
KZ2008	0.587 ***	0.992 ***	0.575 ***	1			
KZ2009	0.260 ***	0.443 ***	0.258 ***	0.456 ***	1		
KZ2010	0.438 ***	0.743 ***	0.431 ***	0.754 ***	0.673 ***	1	
KZ2011	0.243 ***	0.414 ***	0.238 ***	0.419 ***	0.521 ***	0.556 ***	1

Notes: The table reports yearly pairwise correlations of Kaplan-Zingales indices between 2005 and 2011, *** denotes 1% significance level.

REFERENCES

Almeida H, Campello M, Weisbach MS (2002): Corporate Demand for Liquidity. National Bureau for Economic Research Working Paper no. 9253.

Artola C, Genre, V (2011): Euro Area SMEs Under Financial Constraints: Belief or Reality? CESifo Working Paper no. 3650.

Bakucs L, Ferto I, Fogarasi J (2009): Investment and Financial Constraints in Hungarian Agriculture. *Economics Letters*, 104(3): 122 – 124.

Barajas A, Steiner R (2002): Why Don't They Lend? Credit Stagnation in Latin America. IMF Staff Papers no. 2002/49.

Behr P, Norden L, Noth F, (2013): Financial Constraints of Private Firms and Bank Lending Behavior. *Journal of Banking and Finance*, 37(9): 3472 – 3485.

Bernanke BS, Blinder AS (1988): Credit, Money, and Aggregate Demand. *The American Economic Review*, 78 (2): 435 – 439.

Bernanke BS , Lown CS (1991): The Credit Crunch. *Brookings Papers on Economic Activity*, 1991(2): 205 – 239.

Bozatti G, Secchi, A, Tamagni F (2012): Financial Constraints and firm dynamics. In: DIME Final conference, 6-8. 4. 2011. Maastricht.

Cameron AC, Trivedi, PK (2005): *Microeconometrics: Methods and Applications*. Cambridge University Press, Cambridge.

Čeh AM, Durničič M, Krznar I (2011): Credit Market Disequilibrium Model And Periods of Credit Crunch. Croatian National Bank Working Paper no. 28.

European Commission (2008). The Small Business Act for Europe.

European Commission (2012). Enterprise and Industry – Greece BA Fact Sheet 2012.

Ferrando A, Griesshaber N (2011): Financing Obstacles Among Euro Area Firms. Who Suffers the Most? ECB working Paper no. 1293.

Fraser S (2012): The Impact of the Financial Crisis on Bank Lending to SMEs. Warwick Business School Report Prepared for BIS/ Breedon Review, July 2012.

Ghosh SR, Ghosh, AR (1999): East Asia in the Aftermath: Was There a Crunch? IMF Working Paper no. 99/38.

Granger CW (1986): Developments in the study of cointegrated economic variables. *Oxford Bulletin of economics and statistics*, 48(3): 213-228.

Guariglia A, Tsoukalas J, Tsoukalas S (2010): Investment, Irreversibility, and Financing Constraints in Transition Economies. University of Nottingham Discussion Paper no. 10/03.

Herrera S, Hurlin C, Zaki C (2013): Why don't banks lend to Egypt's private sector? *Economic Modelling*, 33(1): 347-356.

Hurlin C, Kierzenkowski R (2007): Credit market disequilibrium in Poland: Can we find what we expect? Non-stationarity and the short-side rule. *Economic Systems*, 31(2): 157-183.

Ivashina V, Scharfstein D (2010): Bank lending during the financial crisis of 2008. *Journal of Financial Economics*, 97: 319 – 338.

Iyer R, Peydro JL, Da-Rocha-Lopes S, Schoar A (2014): Interbank Liquidity Crunch and the Firm Credit Crunch: Evidence from the 2007–2009 Crisis. *The Review of Financial Studies*, 27(1): 125-141.

Johansen S (1995): Likelihood-Based Inference in Cointegrated Vector Autoregressive Models. Oxford University Press, Oxford.

Juessen F (2009): A Distribution Dynamics Approach to Regional GDP Convergence in Unified Germany. IZA Discussion Paper no. 4177.

Kaplan SN, Zingales L (1997): Do Investment-Cash Flow Sensitivities Provide Useful Measures of Financing Constraints? *Quarterly Journal of Economics*, 112(1): 168 – 216.

Kapounek S, Lacina L (2011): Inflation Perceptions and Anticipations in the Old Eurozone Member States. *Prague Economic Papers*, 20(2): 120-139.

Konings J, Rizov M, Vandebusschedet H (2003): Investment and Financial Constraints in Transition Economies: Micro Evidence from Poland, the Czech Republic, Bulgaria and Romania. *Economics Letters*, 78(2): 253 – 258.

Koráb P, Poměnková J (2014): Financial crisis and financing constraints of SMEs in Visegrad countries. *Ekonomický Časopis*, 62(9): 887-902.

Laffont J-J, Garcia R (1977): Disequilibrium Econometrics for Business Loans. *Econometrica*, 45(5): 1187-1204.

Lamont O, Polk C, Saá-Requejo J (2001): Financial Constraints and Stock Returns. *The Review of Financial Studies*, 14(2): 529 – 554.

Lee MJ (1996): *Methods of Moments and Semiparametric Econometrics for Limited Dependent Variable Models.* Springer-Verlag, Berlin/New York.

Li D (2011): Financial Constraints, R&D Investment, and Stock Returns. *The Review of Financial Studies*, 24(9): 2974 – 3007.

Maddala G S, Nelson F D (1974): Maximum Likelihood Methods for Models of Markets in Disequilibrium. *Econometrica*, 42(6): 1013-1030.

Nguyen H, Qian R (2014): Demand collapse or credit crunch to firms? Evidence from the World Bank's financial crisis survey in Eastern Europe. *Journal of International Money and Finance*, 47(7): 125-144.

Poghosyan T (2010): Slowdown of credit flows in Jordan in the wake of the global financial crisis: supply or demand driven? IMF Working paper no. 10/256.

Poměnková J (2008): Remarks to Optimum Kernels and Boundary Optimum Kernels. *Applications of Mathematics*, 53(4): 305 – 317.

Provopoulos G (2014): The Greek Economy and Banking System: Recent Developments and the Way Forward. *Journal of Macroeconomics,* 39: 240-249.

Rice J (1984): Bandwidth Choice for Nonparametric Regression. *The Annals of Statistics,* 12(4): 1215 – 1230.

Vouldis A (2015): Credit market disequilibrium in Greece (2003-2011) - a Bayesian approach. European Central Bank Working Paper no. 1805.

Wand MP, Jones MS (1995): *Kernel Smoothing*. Chapman and Hall, London.

Wehinger G (2014): SMEs and the credit crunch: Current financing difficulties, policy measures and a review of literature. *OECD Journal: Financial Market Trends*, 2013(2).

Yena JF, Chenb YS, Linc CY, Tsaib CH (2014): Can Political and Business Connections Alleviate Financial Constraints? *Applied Economics Letters*, 21(8): 550 – 555.