HOUSEHOLDS' DEFAULT PROBABILITY: AN ANALYSIS BASED ON THE RESULTS OF THE HFCS*

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ABSTRACT

In an environment where the Portuguese banking system has a high exposure to the household sector, identifying the households' characteristics associated with a higher probability of default on loans is of great importance to monitor the outlook for credit risk and its consequences for the stability of the financial system. This article estimates a probability of default for households which depends on their economic and socio-demographic characteristics and takes into account the existence of shocks that adversely affected their financial situation. The estimated probability is used to characterize the distribution of credit risk for some household's groups, which differ on their situation in the debt market, and for different types of loans. The analysis uses data from the Household Finance and Consumption Survey which took place during the second quarter of 2010.

1. Introduction

Households default ratios remain at relatively contained levels compared to non-financial corporations but have been increasing gradually in recent years. In an environment where the Portuguese banking system has a high exposure to the household sector, the identification of the households' characteristics associated with a higher probability of default is of great importance to monitor the outlook for credit risk and its consequences for the stability of the financial system.

In this paper it is estimated a probability of default on loans for households which depends of their economic and socio-demographic characteristics and takes into account the existence of shocks that adversely affected their financial situation. The estimated probability is used to characterize the distribution of credit risk for some household's groups, which differ on their situation in the debt market, and for different types of loans. The analysis uses data from the Household Finance and Consumption Survey (HFCS) which took place during the second quarter of 2010.[1] This database allows the identification of households that had late or missed payments on loans in the twelve months prior to the survey and to combine this information with detailed data on the socio-demographic characteristics of households, their financial situation and on the characteristics of the loans they hold.

The literature on the determinants of households' default emphasizes households'characteristics that affect the ability to fulfil credit responsibilities as well as macroeconomic factors that determine changes in their financial situation. Since the HFCS database refers to a single point in time, this paper will focus mainly on the first group of factors. The HFCS has some questions that allow identifying households

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1 For a detailed presentation of the HFCS see Costa and Farinha (2012a).

who had adverse changes in their financial situation in the period preceding the survey, thus making it possible to evaluate the impact of these events on the probability of default. In the context of a proper risk assessment on the part of lenders and borrowers it is expected that the default events are largely determined by unanticipated negative shocks on the solvency of the debtors.

There are several articles in the literature using survey data to estimate default probabilities based on the characteristics of the households.[2] In Portugal, the estimation of default probabilities with micro-economic data has focused mainly in the sector of non-financial corporations (Antunes and Martinho (2012), Bonfim (2009) and Soares (2006)). In the case of households, Alves and Ribeiro (2011) study the relationship between risk measures of aggregate bank credit to the households sector in Portugal and macro-economic variables. They conclude that the annual flow of overdue credit and other doubtful loans, both for house purchase and for consumption and other purposes, increases with the level of interest rates and is broadly countercyclical. In turn, Farinha and Lacerda (2010) use micro data from the Central Credit Register managed by Banco de Portugal to examine the role of households' responsibilities vis-à-vis the banking system as determinants of entry into default. Duygan and Grant (2009) and Geargarakos *et al.* (2010) use the data from European Community Household Panel, a household survey conducted annually between 1994 and 2001 in several euro area countries (including Portugal), to analyze the determinants of default with a special focus on factors that explain cross-country differences. According to the findings of Duygan and Grant (2009) arrears are often precipitated by adverse shocks to household's income and health. The large differences found between countries in the households' reactions to these shocks are partially explained by the extent to which local financial and judicial institutions are effective in punishing default. In turn, Geargarakos *et al.* (2010) emphasize the role of social stigma in determining financial distress, concluding that this factor is more important in countries such as Portugal, where the proportion of households with mortgages is relatively low. As compared to the data used in the previous studies, the HFCS database have the advantage of including more comprehensive and updated information about the financial situation of households and in particular about their assets and liabilities.

This paper is organized as follows: section 2 includes a brief description of the methodology and data used; section 3 analyzes the incidence of default for different households types; section 4 presents the estimation results for the probability of default; section 5 analyzes the estimated probability according to the characteristics of households and of the loans they hold; and section 6 presents the main conclusions.

2. Methodology and data description

In the estimation of the probability of default on section 4 it is used a Logit model in which the dependent variable takes value 1 for households that had late or missed payments on loans in the twelve months prior to the survey and the value 0 for households that were indebted during this period but did not have any failures or delays in the payment on loans.[3]

The explanatory variables include the main economic and socio-demographic characteristics of the household, a dummy variable identifying whether there were adverse changes in the household financial situation in periods close to the interview and a variable that controls the type of loans that the household has.

The economic and socio-demographic characteristics considered were in line with those commonly used in the literature. Specifically, it consisted on the value of income, the value of regular expenditure, the

2 See, for example, Alfaro and Gallardo (2012), Del Rio and Young (2005), Duygan and Grant (2009), Edelberg (2006), Geargarakos *et al.* (2010), Getter (2003), Magri and Pico (2011) and May and Tudela (2005).

3 Strictly speaking, the endogenous variable might reflect in some cases situations of delinquencies which will not be translated into default. However, since the two kinds of situations are strongly correlated, the estimated probability will be referred throughout the paper as a default probability, but should be interpreted as an upper limit to this probability.

value of assets, the value of debt, the type of household as well as variables at the individual level such as the age, education level and work status of the reference person.[4]

Household's income is given by the sum of regular income received individually by its members (employee income, income from self-employment, income from pensions and other social benefits) and household income (income from businesses and financial assets, rents on real estate and regular social and private transfers). The expenditure includes regular expenses with consumer goods and services, private transfers to other households, rents on the main residence, interest and repayments of loans and payments of leasing contracts. The value of assets is given by the sum of the value of real and financial assets, covering real estate, motor vehicles, businesses, other valuables goods, deposits, mutual funds, debt securities, shares, voluntary pension plans and other financial assets.[5] The debt amount includes the outstanding balances on mortgages, on other loans, credit cards, credit lines and bank overdrafts. The household type distinguishes households with only one member and households with several members and controls for the presence of dependents (individuals younger than 25 years that do not to work and are not the household reference person or his spouse/partner, or his parent/grandparent). The income reference period is 2009, while for the remaining variables it is the time of the interview (2nd quarter of 2010).

Different classes of income, expenditure, assets and debt are identified by dummy variables that were defined according to various percentiles.[6] Dummy variables were also created for the household type as well as for the age class, the work status and the education level of the reference person. [7]

The dummy variables for the adverse changes in the financial situation of the households were obtained with the information of some qualitative questions, which cover changes in the labor market situation, in the net worth, in income and in expenditure. The first variable identifies households in which any member has stated that, in the period of three years prior to the survey, lost his job, had to work shorter hours or had to accept other undesired changes on job. The second variable identifies households that in the three years prior to the interview had a substantial reduction in their net worth. The third variable identifies households who claimed that the income reported in the interview (which refers to 2009) was unusually low compared to the household income in a normal year. The fourth variable identifies households for whom regular expenses, during the twelve months preceding the interview, were higher than in a normal year. Finally, an aggregate variable, taking the value 1 for households which were affected by any of the previous negative shocks and value 0 for the remaining households, was constructed.

The use of this kind of variables to explain the probability of default is in line with the approaches followed in Duygan and Grant (2009) and Getter (2003). The purpose is to evaluate the effect on households' financial distress of unanticipated adverse events. The conclusion of Alves and Ribeiro (2011), that

4 The reference person corresponds to the person appointed by the household as such, if this person is male, or the partner/husband of this person, if this person is female and has a partner/husband in the household.

5 This definition of assets differs from the concept of the European System of National Accounts because it includes vehicles.

6 Six classes were defined both for income and expenditure corresponding to the households for whom these variables are below the 20th percentile, are between percentiles 20 and 40, 40 and 60, 60 and 80, 80 and 90 and for those that are above the 90th percentile. In the case of wealth and debt, the classes correspond to the households for whom this variables are below the 25th percentile, are between percentiles 25 and 50, 50 and 75, 75 and 90 and for those that are above the 90th percentile.

7 The dummies for the household type take the value 1, respectively, if the household comprises only one adult, if it comprises several members, all being adults, if it comprises only one adult and one or several dependents and if it comprises various adults and one or several dependents. For the sake of simplicity, in the remaining of the paper dependents are labelled as children. The age classes correspond, respectively, to the individuals with less than 35 years old, between 35 and 44, between 45 and 54, 55 and 64, 65 and 74 years and 75 years or more. The work status distinguishes employees with a permanent position, employees with temporary contracts, self-employed workers, unemployed, retirees and other situations of inactivity (such as the students and the persons dedicated to unpaid home tasks). The education levels considered are the first stage of the basic education, the second stage of the basic education, the secondary education and the tertiary education. These levels correspond to the levels effectively completed.

unemployment is an important determinant of the Portuguese households' default probability, seems to support the relevance of this kind of negative shocks. It is important to take into account that the variables constructed to measure the adverse changes in the financial situation of the households are only proxies for the unanticipated shocks. In fact, in some cases these variables might be capturing situations already taken into account in the loan decision. In any case, this is the only way to measure the effect of changes in time with the HFCS database.

Finally, the regressions for the probability of default include a variable that takes the value 1 for households that have mortgages and the value 0 for households that only have another type of loans. This variable allows evaluating if households with mortgages present a lower default probability, when their economic and socio-demographic characteristics are taken into account. In fact, the number of households in default on housing loans is generally smaller than the number of households in default on consumer credit. Additionally, according to the results of Farinha and Lacerda (2010) borrowers that have housing credit tend to have a lower probability of defaulting on other credit segments. These results do not control, however, for the socio-economic and demographic characteristics of debtors, since they are obtained with data from the Central Credit Register of Bank of Portugal, where these characteristics are not available.

In section 5 the estimated probability of default is used to characterize the distribution of credit risk for different household groups, which differ on their situation on the debt market, particularly by the existence of liquidity constraints and by the degree of indebtness. The combination of HFCS data for the households' debt with the estimated probability of default also enables to characterize the distribution of the credit risk for the outstanding amount of loans that existed on the second quarter of 2010. This analysis is made for all households' loans and by type of credit (mortgages and other loans). In the case of mortgages, the HFCS includes information about the year they were granted, which is not available for non-mortgage loans.[8] The distribution of credit risk by the mortgage lending period will be analyzed using these data.

3. Incidence of default on the HFCS data

Table 1 shows the percentage of households in default according to their socio-economic and demographic characteristics. Among the indebted households, about 12 percent had late or missed payments on loans in the twelve months prior to the survey (*i.e.* approximately between the second quarter of 2009 and the second quarter of 2010). The corresponding figure for households with mortgages is 9.7 percent, meaning that about 10 percent of these households had any failure or delay in payment of the mortgage loans or other loans. The percentage of households with some arrear is more than the double in the case of households with other loans.[9] These data are consistent with the empirical evidence that households with mortgages have on average a lower credit risk than households with other types of loans.

The proportion of households in default shows a sharp downward trend with the wealth and income. By contrast, expenditure does not present a clear link with the incidence of default. This reflects the need to analyse this variable together with income. Indeed, the proportion of households in default increases, as expected, with the percentiles of the expenditure to income ratio. A similar situation occurs in the case of debt, whose results are easier to interpret when controlling for the other characteristics of households, as will be done in the next section. The lowest percentage of households in default occurs

8 The HFCS includes detailed information for each household about each of the three major mortgages on the main residence and each of the three major mortgages on other properties that the household might have.

9 As expected these values are significantly higher than numbers calculated with the data from the Central Credit Register (CRC) for the percentage of households in default on housing loans and on consumer credit (respectively, about 5 and 13 percent, in mid-2010). For this situation contributes the fact that in the indicators calculated with the CRC data, only are considered households with delinquencies in a specific type of credit, in a specific month and with arrears that lasted at least 30 days.

Table 1 (continue)

PERCENTAGE OF INDEBTED HOUSEHOLDS WITH LATE OR MISSED PAYMENTS ON LOANS	
Total	**11.7**
Have mortgages	
Yes	9.7
No	14.2
Have non-mortgage loans	
Yes	21.5
No	7.9
Wealth percentile	
Less than 25	25.7
Between 25 and 50	11.9
Between 50 and 75	9.6
Between 75 and 90	6.7
More than 90	4.0
Income percentile	
Less than 20	22.9
Between 20 and 40	19.0
Between 40 and 60	11.2
Between 60 and 80	9.8
Between 80 and 90	7.1
More than 90	5.9
Expenditure percentile	
Less than 20	14.8
Between 20 and 40	11.5
Between 40 and 60	12.3
Between 60 and 80	10.2
Between 80 and 90	11.4
More than 90	13.2
Expenditure/Income percentile	
Less than 20	7.0
Between 20 and 40	7.2
Between 40 and 60	8.1
Between 60 and 80	12.6
Between 80 and 90	17.7
More than 90	26.1
Debt percentile	
Less than 25	15.5
Between 25 and 50	11.4
Between 50 and 75	10.8
Between 75 and 90	14.5
More than 90	8.8
Debt/Income percentile	
Less than 25	14.6
Between 25 and 50	9.4
Between 50 and 75	7.2
Between 75 and 90	15.9
More than 90	21.9
Household type	
One adult	7.8
Several adults	6.7
One adult and children(s)	27.7
Several adults and children(s)	14.5

Table 1 (continuation)

PERCENTAGE OF INDEBTED HOUSEHOLDS WITH LATE OR MISSED PAYMENTS ON LOANS	
Age	
Under 35	19.1
35-44	11.8
45-54	12.7
55-64	8.5
65-74	5.9
75 and over	7.4
Education	
First stage of basic	13.5
Second stage of basic	12.1
Secondary	9.3
Tertiary	6.7
Work status	
Employee	10.8
Permanent position	9.0
Temporary contract	24.7
Self-employed	11.8
Unemployed	28.8
Retired	7.5
Other not working	9.5
Undesired changes in job conditions	
Yes	18.8
No	7.9
Substancial decline in net worth	
Yes	21.1
No	7.5
Lower income than in a "normal" year	
Yes	19.1
No	8.9
Higher expenses than in a "normal" year	
Yes	15.4
No	9.9
Any adverse change in the financial situation	
Yes	15.6
No	3.3

Source: Household Finance and Consumption Survey.

for households with the highest debt levels. However, when the debt to income ratio is considered, the highest incidence of default is recorded in the highest percentile of the ratio.

By household type, the proportion of households in default is higher in households with children and in particular when there is only one adult. By age, the highest incidence of default occurs when the reference person is under 35 years and the lowest incidence in households whose reference person is in the oldest age classes. Regarding the work status, there is a significantly higher proportion of households in default when the reference person is unemployed or is an employee with a temporary contract than in remaining households. The percentage of households in default has a tendency to decrease with the level of education of the reference person.

Finally, households that suffered unfavorable changes in their financial situation in the years preceding the survey show significantly higher incidences of default than the remaining households. These results are common to any of the situations identified, *i.e.*, changes in the labor market situation, in net worth, in income or in expenditure. The incidence of default in households that have not undergone any of these unfavorable changes in their financial situation is rather low, which seems to support the relevance of these factors in determining the capacity of households to meet their credit responsibilities.

4. The estimation of the probability of default

Table 2 presents the estimation results of Logit regressions for the probability of default. The first column of the table includes the results when the dummy on the existence of adverse changes in the financial situation of households is not included in the regression, in the second column this variable is included and in the third column the sample is restricted to households where this variable takes value 1, *i.e.*, to those households who had adverse changes in their financial situation in the years preceding the interview.

Overall this multivariate analysis confirms the descriptive analysis performed in the previous section, pointing to a higher probability of default for households with the lowest wealth and income levels, for households with debt levels in the three highest classes, with a level of expenditure on highest percentile and for households with children.

Households where the reference person is unemployed have a higher probability of default than households where the reference person is an employee with a permanent position. Unlike the descriptive analysis seemed to suggest, there is no clear evidence that the probability of default for employees with a temporary contract is higher than for those with permanent contracts. With regard to education the fact that the reference person has completed the tertiary education seems to contribute to a decline in the default probability. This may reflect the greater ability of these households to take debt decisions appropriate to their financial situation. In the case of age, the results indicate that households where the reference person is in class 35-44 years old have a lower probability of default than households with younger reference persons. For the remaining age classes the coefficients are not significant. This contrasts with the descriptive analysis, which pointed to lower incidences of default in the older age classes. One explanation for this divergence of results might be the fact that the lowest default incidences in the highest age classes are determined by other characteristics of these households, such as their higher levels of wealth and income and their lower debt levels.

The coefficient associated with the dummy for the existence of mortgages has a negative sign but it is not statistically significant. So when controlling the economic and socio-demographic characteristics, the fact that a household has a mortgage does not seem in itself to contribute to a lower probability of default.

Finally, the results confirm that adverse changes in the financial situation of households contribute to a significant increase in the probability of default. When this variable is included in the regression, the results for the other explanatory variables remain broadly unchanged suggesting that the existence of negative shocks on the financial situation of households is, however, not the only factor determining the probability of default. The same conclusion is obtained when estimating the regression only for households who had adverse changes in their financial situation. As mentioned in the previous section the incidence of default for households that did not have negative shocks is very low. This prevents the estimation of a regression including only those cases. Nevertheless, these data suggest that in this period the existence of unfavorable shocks were largely a necessary, though not sufficient, condition for the occurrence of default. This conclusion is consistent with what one would expect in a context where credit decisions have been rational and these shocks were largely unanticipated. The assumption that the shocks were unanticipated seems reasonable given that the years leading up to the HFCS coincided with the onset of the financial and economic crisis, and later with the onset of the sovereign debt crisis in the euro area.

Table 2 (continue)

REGRESSION RESULTS FOR THE PROBABILITY OF DEFAULT

	Indebted households		Indebted households with unfavorable changes of their financial situation
	(1)	(2)	(3)
Wealth percentile			
Between 25 and 50	-1.185***	-1.123***	-1.511***
	(-3.38)	(-3.25)	(-3.8)
Between 50 and 75	-1.494***	-1.422***	-1.926***
	(-3.69)	(-3.54)	(-4.17)
Between 75 and 90	-1.901***	-1.785***	-2.264***
	(-4.19)	(-4.04)	(-4.57)
More than 90	-2.466***	-2.355***	-2.822***
	(-3.96)	(-3.94)	(-4.14)
Debt percentile			
Between 25 and 50	0.523	0.494	0.583
	(1.59)	(1.53)	(1.63)
Between 50 and 75	1.029**	0.962**	1.11**
	(2.57)	(2.42)	(2.49)
Between 75 and 90	1.516***	1.449***	1.563***
	(3.28)	(3.12)	(3.11)
More than 90	1.346***	1.287**	1.456***
	(2.62)	(2.53)	(2.69)
Income percentile			
Between 20 and 40	-0.575	-0.633	-0.877*
	(-1.25)	(-1.38)	(-1.76)
Between 40 and 60	-1.13**	-1.128**	-1.249**
	(-2.4)	(-2.46)	(-2.53)
Between 60 and 80	-1.154**	-1.083**	-1.206**
	(-2.47)	(-2.38)	(-2.46)
Between 80 and 90	-1.438**	-1.397**	-1.765***
	(-2.44)	(-2.37)	(-2.64)
More than 90	-1.119**	-1.076*	-1.126*
	(-1.97)	(-1.95)	(-1.89)
Expenditure percentile			
Between 20 and 40	-0.068	0.086	0.086
	(-0.1)	(0.13)	(0.12)
Between 40 and 60	0.632	0.754	0.838
	(1.09)	(1.29)	(1.41)
Between 60 and 80	0.399	0.489	0.566
	(0.7)	(0.87)	(0.96)
Between 80 and 90	0.888	0.943	1.088*
	(1.51)	(1.61)	(1.76)
More than 90	1.167**	1.211**	1.204**
	(2)	(2.11)	(1.97)
Household type			
Several adults	-0.186	-0.299	-0.258
	(-0.47)	(-0.75)	(-0.58)
One adult and children(s)	1.545***	1.386***	1.8***
	(3.54)	(3.18)	(3.68)
Several adults and children(s)	0.788**	0.603	0.87**
	(2.05)	(1.6)	(2.1)

Table 2 (continuation)

REGRESSION RESULTS FOR THE PROBABILITY OF DEFAULT	Indebted households		Indebted households with unfavorable changes of their financial situation
	(1)	(2)	(3)
Age			
35-44	-0.872**	-0.825**	-0.782**
	(-2.51)	(-2.37)	(-2.04)
45-54	-0.461	-0.406	-0.242
	(-1.3)	(-1.15)	(-0.63)
55-64	-0.65	-0.619	-0.405
	(-1.57)	(-1.48)	(-0.87)
65-74	-0.685	-0.738	-0.888
	(-1.17)	(-1.25)	(-1.29)
75 and over	-0.523	-0.466	-0.638
	(-0.68)	(-0.57)	(-0.73)
Education			
Second stage of basic	-0.244	-0.189	-0.145
	(-0.93)	(-0.74)	(-0.53)
Secondary	-0.38	-0.281	-0.287
	(-1.09)	(-0.81)	(-0.75)
Tertiary	-0.764*	-0.684*	-0.971**
	(-1.92)	(-1.74)	(-2.12)
Work status			
Employee with temporary contract	0.708*	0.558	0.585
	(1.89)	(1.47)	(1.43)
Self-employed	0.484	0.486	0.649*
	(1.45)	(1.49)	(1.82)
Unemployed	1.016***	0.797***	0.761**
	(3.46)	(2.69)	(2.45)
Retired	0.559	0.659	0.654
	(1.39)	(1.64)	(1.37)
Other not working	-0.276	-0.437	-0.739
	(-0.41)	(-0.66)	(-0.94)
Have mortgages	-0.499	-0.467	-0.197
	(-1.52)	(-1.38)	(-0.5)
Any adverse change in the financial situation	-	1.225***	-
	-	(4.41)	-
Constant	-0.902	-1.931***	-0.856
	(-1.37)	(-2.69)	(-1.2)
Number of observations	1619	1619	1106

Source: Household Finance and Consumption Survey.

Notes: The results must be interpreted against the omitted categories in the regression which correspond to households with wealth below the 25th percentile, with debt below the 25th percentile, with income below the 20th percentile, with expenses below the 20th percentile, with only one adult, whose reference person has less than 35 years, has an educational level corresponding to the first stage of basic education, is an employee with a permanent position, to households without mortgages and to households that did not have any adverse change in their financial situation. The coefficients presented correspond to the regression coefficients whose magnitude cannot be interpreted as the marginal effect of explanatory variable on the variable to be explained. In the Logit models marginal effects have the same sign and significance of the estimated coefficients, but vary with the value of the regressors. The symbols *, ** and *** indicate that the coefficients are statistically significant at 10, 5 and 1 per cent confidence level, respectively.

5. Analysis of the probability of default for different types of households and loans

The model estimated in the previous section was used to calculate the probability of default of each indebted household.[10] This section analyzes the distribution of the probability of default for some household's groups, which differ on their situation in the debt market, and for different types of loans. These distributions were obtained taking into account the sample weights so as to be representative of the population.

The average default probability of the indebted households stands at about 13 percent, the median probability at about 9 percent and the 25 and 75 percentiles at about 5 and 16 percent, respectively. It is expected that households with higher indebtedness levels have greater difficulties in fulfilling the responsibilities associated with debt. Chart 1 shows the distribution of the probability of default for all indebted households, together with the distributions for households in which the debt to income ratio, the debt to wealth ratio and the ratio of debt service to income exceed certain threshold levels.[11] These distributions confirm that very high levels of indebtedness are usually associated with high default probabilities.

Chart 2 compares the distribution of the probability of default for households with and without liquidity constraints in the three years leading up to the HFCS.[12] Households with liquidity constraints correspond to households whose applications for loans were turned down or only partially satisfied or to households that did not apply for credit because they thought their application would be rejected. Households without liquidity constraints correspond to households who did not have loan applications rejected or only partially satisfied and that did not give up making loan requests due to perceived credit constraints. The average probability of default for liquidity constrained households is significantly higher than for unconstrained households (about 20 and 10 percent, respectively) and there are a substantial proportion of households with liquidity constraints with high levels of probability of default. This suggests that, in the three years leading up to HFCS, the credit risk was an important determinant of decisions of financial institutions to grant loans.

The estimated probability of default can be used to measure the credit risk of the outstanding household loans in the second quarter of 2010. In this period the concentration of household loans declines slightly in the highest levels of credit risk (Chart 3). Indeed, 53 percent of the household loans were granted to households with probability of default lower than the median value and 7 percent of the loans were granted to households in the highest decile of default probability. This distribution reflects the credit risk of mortgage loans, which have a dominant weight in the total loans granted to households. The data show that non-mortgage loans were more concentrated in households with higher probability of default than in households with low credit risk. In the second quarter of 2010 about 18 percent of the outstanding amounts of these loans correspond to households with probability of default in the highest decile of credit risk.

As expected, the proportion of high credit risk households is bigger in the case of non collaterised loans than in the case of mortgages (Chart 4). However, in the second quarter of 2010, the mean and median of the outstanding amounts of loans per household declines slightly for higher levels of credit risk, in

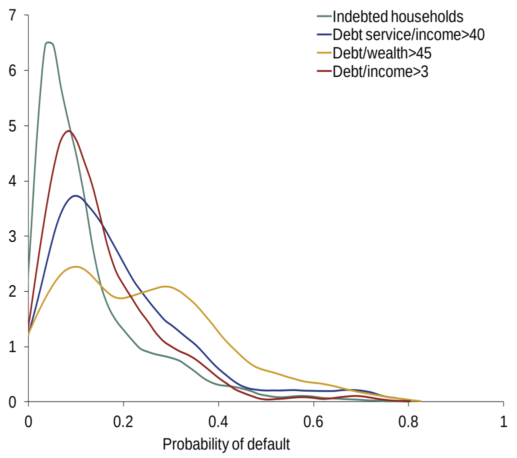
10 The results were obtained with the regression of the second column of Table 2.

11 For a description and interpretation of these ratios and an analysis of the characteristics of the households with high levels of debt see Costa and Farinha (2012b).

12 The households with liquidity constraints included in the chart do have some debt. This is due to the fact that the model used to estimate the probability of default includes the debt's percentiles as explanatory variables, which are not defined for households without debt. Nevertheless, the results obtained using a probability of default calculated for all households in the sample (based on a regression that does not consider the debt level) also points to a credit risk much higher for households with liquidity constraints than for the remaining households.

CHART 1

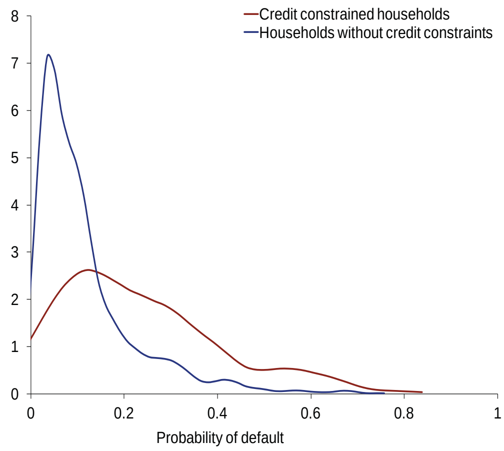
EMPIRICAL DISTRIBUTION OF THE PROBABILITY OF DEFAULT FOR THE HOUSEHOLDS WITH THE HIGHEST INDEBTEDNESS RATIOS



Source: Household Finance and Consumption Survey.

CHART 2

EMPIRICAL DISTRIBUTION OF THE PROBABILITY OF DEFAULT FOR HOUSEHOLDS WITH OR WITHOUT CREDIT CONSTRAINTS



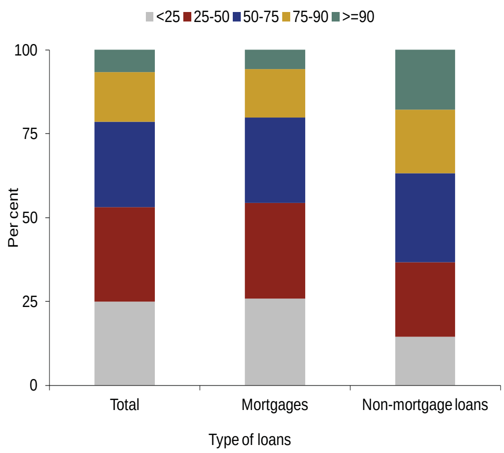
Source: Household Finance and Consumption Survey.

the case of non collaterised loans, which is not observed in the case of mortgages (Charts 5 and 6). Thus, although there were a significant proportion of non-mortgage loans assigned to high credit risk households, the typical outstanding amount of these loans was relatively low compared with the levels of the non-mortgage loans for households with low credit risk.

For existing mortgages in the second quarter of 2010 it is possible to analyze the distribution of credit risk per year of lending (Chart 7). In general, the weight of loans tends to increase with the years of lending, reflecting the fact that older loans have a higher probability of having already reached the maturity. The loans granted in the years 2005-2007 stand out, however, by having a high weight in the total outstanding amounts in the second quarter of 2010. This reflects the strong credit growth

CHART 3

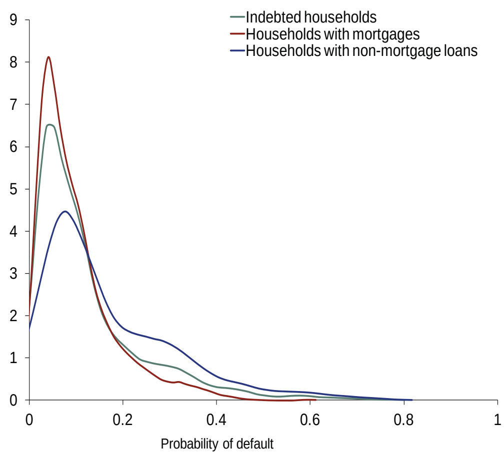
DISTRIBUTION OF THE OUTSTANDING AMOUNTS ON HOUSEHOLDS' LOANS BY PROBABILITY OF DEFAULT PERCENTILE | DATA FOR THE SECOND QUARTER OF 2010



Source: Household Finance and Consumption Survey.

CHART 4

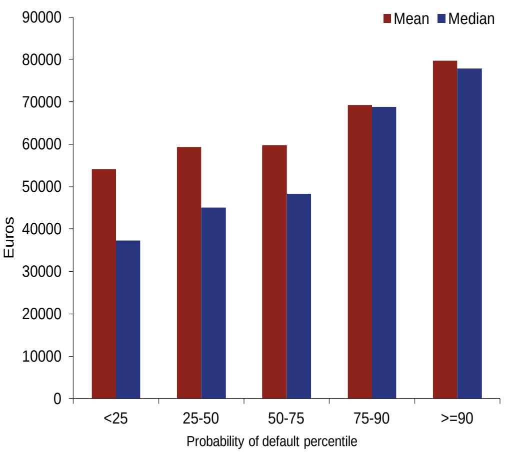
EMPIRICAL DISTRIBUTION OF THE HOUSEHOLDS' PROBABILITY OF DEFAULT ACCORDING TO THE TYPE OF LOANS



Source: Household Finance and Consumption Survey.

CHART 5

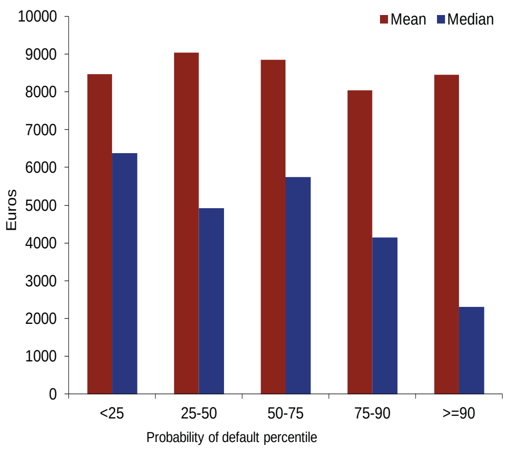
MEAN AND MEDIAN OF THE OUTSTANDING AMOUNTS ON MORTGAGES IN THE SECOND QUARTER OF 2010



Source: Household Finance and Consumption Survey.

CHART 6

MEAN AND MEDIAN OF THE OUTSTANDING AMOUNTS ON NON-MORTGAGE LOANS IN THE SECOND QUARTER OF 2010

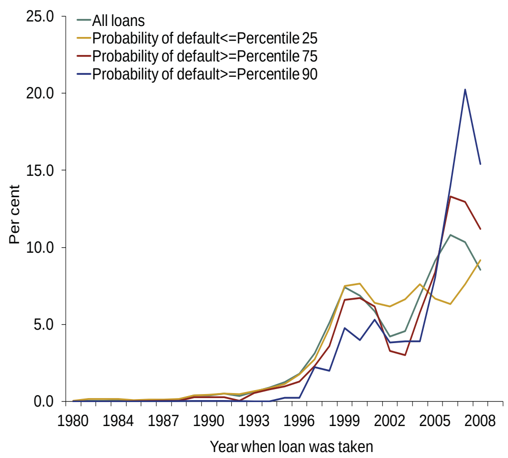


Source: Household Finance and Consumption Survey.

registered during this period. The largest share of loans granted in the period 2005-2007 is particularly marked when considering only loans with high credit risk. This is consistent with the data that point to a decline in the degree of tightening of the credit standards applied to the approval of loans by banks in this period and to its increase in the following years, in the context of economic and financial crisis and then of the euro area sovereign debt crisis.[13]

CHART 7

PERCENTAGE OF THE OUTSTANDING AMOUNT OF MORTGAGES IN SECOND QUARTER 2010 THAT WERE TAKEN EACH YEAR[(a)]



Source: Household Finance and Consumption Survey.

Note: (a) Three year centered mean of the percentages. The chart does not include values for 2010 because the HFCS database only includes loans taken until the second quarter of that year.

13 See, for example, the results of the Bank Lending Survey.

6. Conclusions

In this paper we use data from the HFCS 2010 to estimate a probability of default for Portuguese households according to their economic and socio-demographic characteristics. The results suggest that the probability of default is higher for households with lower levels of wealth and income, with high levels of expenditure and debt, for households with children, whose reference person is unemployed or for households whose reference person has a lower level of education than the tertiary. When controlling for these characteristics, the age of the reference person does not seem to have a significant effect on the probability of default. Additionally, no evidence was obtained for the fact that having a mortgage contributes to a lower probability of default. The results suggest that adverse changes in the financial situation of households contribute to a significant increase in the probability of default.

According to the HFCS data, a very high percentage of the households with late or missed payments on loans in the twelve months prior to the survey (second quarter 2010), claimed to have had an adverse change of their financial situation. Thus, the occurrence of these types of shocks seems to have been in this period a necessary, though not sufficient, condition for default events. This conclusion is consistent with what one would expect in a context where credit decisions have been taken in a rational way, and the shocks were largely unanticipated.

The estimated probability of default was used to perform a characterization of the distribution of credit risk for different household groups, which differ on their situation in the debt market, and for different types of loans. This analysis confirmed that the liquidity constrained households have an average level of credit risk higher than households who can get the credit they want. As expected, among indebted households, the average credit risk also appears to be greater when levels of indebtedness are very high. With respect to loans, the results indicate that in the second quarter of 2010 the concentration of mortgage loans was lower in the higher levels of credit risk than in the lower levels. By contrast, loans not collateralized by real estate were more concentrated in households with higher probability of default. In the case of mortgages, the existence of information about the year they were granted permits to conclude that a significant proportion of the mortgages with higher credit risk existing in the second quarter of 2010, had been granted in the years before the financial and economic crisis. This is consistent with the reduction in the tightening of the credit standards applied to the approval of loans by banks in this period in the context of the high liquidity that prevailed in international financial markets.

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