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Estimating the Mortgage Default Probability in Cyprus: Evidence using micro data

Savvas Antoniou [a,b], Ioanna Evangelou[a], Theodosis Kallenos [a, c]

and Nektarios A. Michail[a, d*]

[a] *Economic Analysis and Research Department, Central Bank of Cyprus*

[b] *Department of Economics, University of Cyprus*

[c] *Department of Accounting and Finance, University of Cyprus*

[d] *School of Economics and Management, Cyprus University of Technology*

Abstract

As financial institutions are exposed to the mortgage market, the identification of the characteristics associated with high default risk is crucial for the economy's financial stability and growth. In this paper, we examine for the determinants of mortgage default for households, using both their economic and socio-demographic characteristics. Using panel data from the Eurosystem Household Finance and Consumption Survey from 2009 to 2017, we find that the mortgage debt service to income ratio, as well as the debt to total household wealth ratio, are positively related with a higher mortgage default probability. In addition, salaried employment reduces such probability and households with more than four members are more prone to mortgage arrears.

Keywords: Eurosystem HFCS, survey, defaults, probability, households

1. Estimating the Mortgage Default Probability in Cyprus: Evidence using micro data

Over the last ten years, mortgage delinquency and arrears grew exponentially in Cyprus, especially at the household level, compromising financial institutions and their stability. As home ownership is usually the largest component in households' asset portfolio (Haliassos and Bertaut, 1995), mortgage default could potentially mean that individuals stand to lose the majority of their real assets, an event with broad macroeconomic and social repercussions. Consequences for mortgage delinquency range from late fees to credit impacts and possibly foreclosure on a home.

* Corresponding author: Nektarios A. Michail, Economic Analysis and Research Department, Central Bank of Cyprus, 80 Kennedy Avenue, 1076, Nicosia, Cyprus. Email: nektariosmichail@centralbank.cy Tel: +35722714414, Fax: +35722714984

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In the aftermath of the financial crisis, with the elevated levels of non-performing loans, which aggravated financial stability risks, it is now more than ever of paramount importance the in-depth surveillance and prudent assessment of risks faced by financial institutions. As such, adequate management of bad loans involves banks identifying the potential "high risk" borrowers at an early stage and thus taking the appropriate actions to protect their profitability and viability and, thus, safeguard their function in the financial system. Moreover, the significantly smaller amount of bad loans in the economy will increase banks' profitability and limit their exposure to excessive credit risk, having a positive effect on the overall system's financial stability, as well as long-term economic growth. Nonetheless, the identification of the household characteristics associated with higher default risk is a difficult task for financial institutions.

In this paper, we examine for the determinants of mortgage default for households, taking into account the household economic and socio-demographic characteristics. To conduct our analysis, we use data from all three waves of the Household Finance and Consumption Survey (HFCS) for Cyprus. The database allows identification of households that had late or missed mortgage payments by more than 90 days, in the 12 months prior to the survey and provides extended information regarding the households' financial status, its liabilities and its assets. The relatively large panel component of 721 households allows us to observe the behaviour of the households regarding their mortgage payments, during a period where unique financial events took place. These include the unsecured depositors bail in of 2013 and the subsequent economic recovery.

Our analysis mainly focuses on the effects that debt service to income and the debt to wealth ratios have on the probability of a household's default. We find that there is a significantly positive relationship between the debt service to income ratio and the household's probability of default. Households with a debt service to income ratio above 37% have a higher probability of default when compared to households in the lowest debt service to income ratio decile, with the probability in some cases rising up to 44%. Furthermore, our results also suggest a positive relationship between debt to wealth ratio and mortgage arrears.

Our findings also suggest that the employment status of the head of the household (the Reference Person[1]) affects the household's probability of default. Households with a head of household outside the labour force have a higher probability of mortgage default when compared to the households in which the head is either in paid employment or self-employed. Furthermore, households with a self-employed head of household have a higher probability of default relative to households in which the head is a salaried employee. This finding could be related with potential income fluctuations and increased risk associated with small business ownership. Finally, households with more than four people have a higher mortgage default probability.

Our study is the first to examine the effects of debt service to income and debt to wealth ratios on the probability of default of households in Cyprus, a country with a very high proportion non-performing loans relative to the magnitude of its population (Michail and Savva, 2018). Our findings contribute to the existing literature that studies the positive effect of the mortgage debt service to income ratio (see Campbell and Dietrich, 1983; Connor and Flavin, 2015; Aron and Muellbauer, 2016; O'Toole and Slaymaker, 2021), as well as by also including the debt to wealth ratio. In addition, we also account for the impact of household size on the probability of default

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[1] The Financially knowledgeable person (FKP)/Reference Person, according to the HFCS is defined as the person who is most knowledgeable on financial matters regarding both the household as a whole and its individual members. He/she provides all the information requested during the personal interview.

(for example Alfaro and Gallardo. 2012; Costa, 2012; Gerlach-Kristen and Lyons, 2018), while our study confirms the evidence found by previous studies that examine the effect of employment status on mortgage delinquency (e.g Elul et al., 2010; Wong et al., 2004; Costa (2012)). At the same time, we do not find evidence of strategic defaulting on the basis of home equity, implying that, in contrast with other countries/studies, perhaps cultural and other factors can potentially explain their existence.

2. Literature review

Estimating the mortgage default probability of households has been widely studied over the years due to its great importance and numerous applications. The risk of borrower default is an issue of primary importance to mortgage lenders. Being able to assess such a risk increases the efficiency of the mortgage market through improved pricing, term setting, and other credit allocation techniques. Conversely, inability to diagnose such risk can result in missed profit opportunities, loan losses, and risk-minimizing practices such as "red lining" (Vandell, 1978).

One of the first studies to provide an empirical assessment of the determinants of mortgage default is Jackson and Kaserman (1980), however, mainly focusing on intentional (strategic) default. The study makes a distinction between the two main competing theories of mortgage strategic default, i.e. a borrower's decision not to repay their loans even though they could potentially have the financial ability to do so. The first is the "negative equity" theory of default, and postulates that borrowers base their decisions on a rational comparison of the financial costs and financial returns, involved in continuing or discontinuing the periodic payments on their mortgage, maximizing the financial gain or minimizing the loss that occurs from their decision. The second, "ability-to-pay" theory, states that borrowers will not default as long as their income flow remains adequate to meet the periodic mortgage payments. The results report that households behave in a way that maximizes their financial gain or minimize the financial loss suggesting the equity theory of borrower default provides a more suitable description of household behaviour.

Numerous studies have since attempted to quantify the effects of negative amortization and negative equity on mortgage default. For instance, Bhutta et al., (2010), use data on non-prime mortgages for the year of 2006 from several states in the U.S, in order to identify the point where "under-water" homeowners strategically default on their mortgage debt. Their results provide support to the view that households exercise their option of strategic default when it is in their interest, i.e. when equity falls substantially relative to the residence's value.

The literature has evolved since then, and a number of studies have since identified various characteristics that have an effect on mortgage arrears as well as mortgage default. For example, current loan-to-value and original loan-to-value ratio, as well as the contemporaneous payment/income and mortgage debt to income ratio were found to be important determinants (see Campbell and Dietrich, 1983; Ciochetti et al., 2003; Wong et al., 2003).

Campbell and Cocco (2015), use US household data and a dynamic model of households' mortgage decisions incorporating labour income, house price, inflation, and interest rate risk. They find that the level of negative home equity that triggers default depends on household loan characteristics, such as high original mortgage loan to value, high loan to income ratios as well as the existence of borrowing constraints. They find that these characteristics are associated with an increased probability of negative equity and consequentially a higher probability of mortgage default.

In Europe, Holló et al (2008) employing household level micro data investigate the main individual driving forces of Hungarian household credit risk and measure the shock-absorbing capacity of the banking system in relation to adverse macroeconomic events. The study suggests that the main individual factors affecting household credit risk are disposable income, the income share of monthly debt servicing costs, the number of dependants and the employment status of the head of the household. Their findings also indicate that a relatively high proportion of debt is concentrated in the group of risky households, an unfavourable fact from a financial stability point of view.

Similarly, Costa (2012) also uses data from the Eurosystem HFCS, to examine the determinants of Portuguese households' probability of default. The study finds that income, wealth, employment status, high debt and expenditure levels are associated with a higher default probability. A higher probability of default is also observed in the case of households with children relative to households without children.
O'Toole and Slaymaker (2021) using household-level panel data on Irish households from the EU Survey of Income and Living Conditions (SILC), explore the impact of current household repayment capacity on the probability of mortgage default. Their findings suggest that a deterioration in the debt service ratio increases the likelihood of delinquencies and the effect is the effect is twice as large for those with a higher initial debt burden. The authors also show that the sensitivity of mortgage delinquencies to changes in the debt service ratio is higher during crises. However, the impact of the current loan to value ratio on mortgage delinquencies is found to be statistically insignificant.

Our study focuses on Cyprus, a country with a very high percentage of non-performing loans relative to the magnitude of its population (Michail and Savva, 2018). As mortgages represent the main loan category of Cypriot households, mortgage arrears pose a significant financial stability risk, impair the long-term economic growth, and reduce the banks' profitability and limit their ability to issue new credit to the real economy to the stability of Cypriot banks and limit Cypriot households' access to credit. However, the drivers of mortgage arrears in Cyprus are under-studied by the existing literature. To our knowledge, our study is the first to perform a country specific analysis for the probability of mortgage default in Cyprus.[2] Moreover, our study contributes to the aforementioned literature that examines the determinants of the household mortgage probability of default, using debt burden indicators, such as measures of mortgage, short-term and long-term repayment ability.

3. Methodology and data description

In order to estimate the determinants of the probability of mortgage default we employ a panel logit regression analysis. Our analysis focuses on households with an outstanding mortgage loan. The dependent variable takes the value of 1 for households that had late or missed payments on their mortgage in the 12 months prior to the survey and 0 if a household with a mortgage loan

[2] Gerlach-Kristen and Lyons (2018) perform a cross-country analysis using data from 15 European countries including Cyprus using country fixed effects to evaluate the country specific effects on mortgage arrears. In terms of Cyprus, they find that Cypriot households are particularly prone to miss mortgage payments.

did not have any missed or delayed payments during the same period. Late payments are defined as payments that were delayed by more than ninety days.

We use various explanatory variables including proxies of long-term and short-term repayment ability, as well as household characteristics. We use deciles of mortgage debt service to income ratio (DSTI) and mortgage debt to wealth ratio (DWT) to determine the short term and long-term household's ability to service its debt, respectively. The household demographics include a categorical variable regarding the employment status of the household's reference person and a dummy variable controlling for household size. The equation aiming to explain the determinants of mortgage default is specified as follows:

$$m90dpd_{i,t} = a + \sum_{j=2}^{10} b_{1,j} * dsti_{i,t,j} + \sum_{j=2}^{10} b_{2,j} * dwt_{i,t,j} + b_3 * emplstatus_{i,t} + b_4 * above4_{i,t} + b_5 * year + b_6 * LTVp90 + U_i + e_{i,t}$$

where $dsti_{i,t,j}$ represents the mortgage debt service to income, as measured by the ratio of monthly mortgage instalments to the household's monthly income while $dwt_{i,t,j}$ accounts for the mortgage debt to wealth calculated using the household's outstanding mortgage amount used as collateral over the total wealth. In both cases, we split the variables into *j* deciles (*j=9*), in order to capture potential non-linearities in the relationships with the probability of mortgage default. To gauge the households' long-term serviceability of their mortgage, we opt to include the mortgage debt to wealth ratio, instead of other commonly used indicators, such as the loan to value ratio (LTV).[3] We do so as this is a more suitable representation of a dwelling's long-term debt repayment capacity, since it accounts for the total wealth held by a household, and not just for the value of its main residence. The use of both $dsti_{i,t,j}$ and the loan-to-value allows us to test for both the "ability-to-pay" theory, as well as the "negative equity" theory of default.

Additional regressors were also included in the analysis and specifically, $emplstatus_{i,t}$ is a categorical variable that takes the value of 1 if the reference person is an employee, 2 if they are self-employed and 0 otherwise (i.e. unemployed or other not-working). $above4_{it}$ is a dummy variable identifying entities with household size of 4 or more members. Finally, $LTVp90$ captures the top decile of the loan-to-value ratio in order to examine whether strategic default exists if home equity turns negative. To capture any unexpected shocks, as well as the overall changes in the economic environment affecting households and their mortgage repayment ability, we include year dummies in our model. The term U_i is a vector containing the random effects of our explanatory categorical variables, as a mixed effects logistic regression is used for estimation.

We use data from the three waves of the Eurosystem Household Finance and Consumption Survey (HFCS)[4]. The Household Finance and Consumption Network (HFCN) conducts the Eurosystem's HFCS, which collects household-level data on households' finances and consumption. The survey in Cyprus is conducted by the Central Bank of Cyprus[5] and the first wave of the survey was completed in 2010.

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[3] Even though not reported here, in addition to debt-to-wealth, we have also estimated the Loan-to-Value (LTV) ratio, both as a continuous variable and a categorical one. The results were non-significant and therefore not included, however, they are available upon request.
[4] Household Finance and Consumption Network (HFCN) (europa.eu)
[5] Cyprus is participating from the first wave of the survey (2009).

We construct the aggregate variables used in our analysis using individual HFCS questions, as per previous studies using the same dataset (Michail et al., 2020; 2021). For example, monthly income is calculated by the total annual household income, which consists of household employee income, self-employment income, rental income from real estate properties, income from financial assets and financial investments, as well as income from interest payments, pension programs, unemployment benefits etc. Total income is then divided by 12 to obtain the monthly amount. More details on the construction of the variables can be found in Appendix I.

Since the HFCS refers to a single point in time, for the purpose of our analysis, we exploit the panel component, i.e. we include Cypriot households who participated in all three waves (2009, 2014, and 2017) of the HFCS. Furthermore, observing the same households using all three waves, allows us to control for unobserved household heterogeneity, while it also allows us to control for any changes to a household's ability to service its mortgage. Our panel sample consists of 721 households.[6] This paper concentrates on mortgage indebted dwellings and out of those 721, 346 had mortgages of the household's main residence in the first wave, 316 in the second and 292 in the third. The sample is weighted using the formal population weights, while unit non-response, as well as oversampling of the wealthy is taken into consideration, following the HFCN and ECB guidelines. More information on household weights and imputation process for tacking item-non response can be found in Appendix II.

4. Estimation results

Table 1 presents the estimation results of logit regressions for the probability of mortgage default, as well as marginal effects for each regression.[7]As already discussed, we use decile categories for mortgage debt service to income ratio and the mortgage debt to wealth ratio employed for the analysis. To provide more insights with regards to the economic interpretation of the deciles, Table 2 exhibits the decile values of the ratios for each of the three HFCS waves, as well as the average value of each decile, across the three waves.

The results of our analysis display a significant positive relationship between mortgage default risk and the higher debt service to income deciles, (seventh to tenth decile across all four panels of Table 1). Specifically, a debt service to income ratio larger than 37.4% (Table 2) on average, is associated with an increase in default risk probability, ranging from 14.6% to 17.3%, depending on the specification relative to the lowest decile. The impact relative to the lowest decile is at its highest for entities in the top decile,[8] where the probability is between 32% and 44% higher.

Furthermore, when looking at mortgage debt to wealth ratio deciles, a general positive relationship is observed, however the relationship is weaker than the one in the case of debt service to income deciles. The results suggest that having a larger debt to wealth ratio increases the probability of having difficulties in mortgage repayment, even though this holds mostly at the top deciles. The effect is higher when the debt to wealth ratio, surpasses 73.3% (see Table 2)

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[6] In some of the households, members left and formed new dwellings. In our sample we kept only the pre-existing household. This change in household members may lead to a change in the household's financial situation, not caused by any adverse changes but rather from the departure of household members.
[7] As discussed earlier the use of year dummies implies that the relationships observed in Table 1 are free of any macroeconomic influences during the period examined.
[8] The top decile refers to values very close to 100% (see Table 2).

on average. Compared to households at the lowest decile of 5%, households in the top decile have a 14.3% higher probability of default.

The analysis also indicates that the employment status of the head of the household plays an important role in identifying dwellings with possible credit risk, as anticipated. Being a salaried employee reduces the probability of such risk by as much as 23%, when compared to the unemployed or other individuals not in the labour force. Being self-employed also has a negative impact; however smaller than the individuals in paid employment. A possible explanation for this weaker effect could be the risks and income volatility and uncertainty associated with the ownership of a self-employed/sole proprietorship business, especially if the business owned is comparably small.

The current mortgage loan to value ratio at the 90th percentile (Ltv.p90) examines whether households could potentially strategically default if their home equity declines. Unlike previous studies (e.g. Bhutta et al., 2010), we find no evidence of strategic defaulting due to a reduction in home equity values.[9] The insignificance of the current mortgage loan to value ratio could be interpreted as an indication that the behaviour of Cypriot households on mortgage default follows the "ability-to-pay" theory and not the "negative equity" theory of default.

The results also suggest a positive and significant effect of household size on the serviceability of a mortgage. Specifically, households with four or more members are 18.1% more likely to default on their mortgage, in comparison to households with less than four members. This result is consistent with our expectations, as bigger households are more likely to incur more debt than households with less members, because of their need of a bigger house to live in and greater needs as regards day-to-day living expenses.

Overall, our findings suggest that a higher debt service to income is linked with higher probability of mortgage default, a result consistent to the findings of previous studies, such as Ciochetti et al. (2003), Madeira et al., (2013), and O'Toole and Slaymaker (2021). In addition, in terms of the relationship between the debt to wealth ratio and the probability of default, a link not thoroughly examined in previous studies, our findings suggest that the higher the debt to wealth decile, the more likely it is that households will default on their mortgage. Furthermore, as anticipated, in paid employment significantly reduces the risk of mortgage arrears. In addition, households with more than four members are associated with a higher mortgage default risk. Consistent with O'Toole and Slaymaker (2021), but in contrast with Wong et al. (2004), and Campbell and Dietrich (1983), no statistically significant relationship between the top decile of the current loan to value ratio and the default probability is observed.

[9] As mentioned before (see footnote 3) the current mortgage loan to value ratio was included, but the results were insignificant.

Table 1
Logistic regression estimations

	(1)	Marginal Effects	(2)	Marginal Effects	(3)	Marginal Effects	(4)	Marginal Effects
2.m_dsti	.097		.132		.090		.171	
	(.693)		(.670)		(.684)		(.662)	
3.m_dsti	-.437		-.238		-.341		-.373	
	(.663)		(.681)		(.723)		(.748)	
4.m_dsti	-1.06		-1.15		-1.44*	-.086	-1.29*	-.072
	(.754)		(.768)		(.804)	(.053)	(.782)	(.053)
5.m_dsti	.104		.033		-.224		-.168	
	(.634)		(.669)		(.729)		(.662)	
6.m_dsti	-.289		-.302		-.387		-.209	
	(.593)		(.623)		(.657)		(.681)	
7.m_dsti	1.09*	.146	1.19**	.158	1.24**	.167	1.41**	.171
	(.608)	(.083)	(.593)	(.075)	(.609)	(.078)	(.662)	(.077)
8.m_dsti	1.38**	.202	1.51***	.217	1.34**	.188	1.64**	.208
	(.549)	(.075)	(.565)	(.074)	(.621)	(.080)	(.669)	(.075)
9.m_dsti	1.41**	.208	1.39**	.194	1.24*	.180	1.72**	.222
	(.587)	(.086)	(.624)	(.088)	(.676)	(.092)	(.700)	(.083)
10.m_dsti	2.41***	.437	2.18***	.358	1.98***	.322	2.29***	.324
	(.563)	(.086)	(.612)	(.095)	(.659)	(.098)	(.685)	(.085)
1.empl_status			-1.34***	-.194	-1.46***	-.205	-1.80***	-.232
			(.345)	(.057)	(.352)	(.058)	(.336)	(.048)
2.empl_status			-.932**	-.145	-1.04**	-.159	-1.02**	-.148
			(.469)	(.069)	(.483)	(.070)	(.439)	(.061)
2.m_dtw					.558		1.00*	.093
					(.566)		(.560)	(.053)
3.m_dtw					.012		.315	
					(.618)		(.573)	
4.m_dtw					.813		1.38**	.137
					(.657)		(.611)	(.065)
5.m_dtw					.949*	.111	1.27**	.124
					(.567)	(.065)	(.509)	(.049)
6.m_dtw					.744		1.09*	.103
					(.580)		(.593)	(.058)
7.m_dtw					.288		.842	
					(.753)		(.703)	
8.m_dtw					.390		.760	
					(.620)		(.569)	
9.m_dtw					.142		.498	
					(.668)		(.733)	
10.m_dtw					.942		1.57***	.163
					(.586)		(.598)	(.064)
above_4							1.68***	.181
							(.321)	(.030)
Ltv.p90							-.344	
							(0.525)	
Constant	-2.90***		-1.91***		-2.25***		-3.51***	
	(.517)		(.556)		(.634)		(.722)	
Observations	944		944		943		943	
Log- Likelihood	-76389.96		-72825.295		-71459.718		-64827.896	

The table presents the results of a logistic regression using npl_90d as the dependent variable. npl_90dpd takes the value of 1 if the household had a delayed mortgage loan payment that was overdue by more than 90 days and 0 otherwise. The dependent variables include m_dsticat, m_dtwcat, empl_status above_4, cltv>p90. m_dsticat is a categorical variable, which takes value i if the household's mortgage debt service to income ratio (monthly mortgage instalments/monthly income) belongs in the i-th decile. Similarly, the variable m_dtwcat is calculated based on the mortgage debt to wealth (total outstanding mortgage amount/total household wealth) deciles. empl_status signifies whether the person is an employee (=1), self-employed (=2) or unemployed or other not working (=0), while above_4 is a dummy variable regarding household size, taking the value of 1 if the household has 4 or more members, and 0 otherwise. "cltv>p90" is a dummy variable, taking the value of 1 when the current loan to value ratio is larger than the 90th decile, and 0 otherwise. All models include time fixed effects. ***, **,* denote significance at the 1%, 5% and 10% respectively.

Table 2

Decile values of ratios per wave

	Deciles of mortgage debt service to income ratio per wave				Deciles of mortgage debt to wealth per wave			
	Wave 1	Wave 2	Wave 3	Average	Wave 1	Wave 2	Wave 3	Average
2nd	.118	.160	.126	.135	.035	.052	.047	.045
3rd	.167	.223	.170	.187	.066	.128	.088	.094
4th	.209	.263	.205	.226	.121	.179	.139	.146
5th	.250	.330	.252	.277	.166	.205	.187	.186
6th	.276	.371	.277	.308	.199	.291	.253	.248
7th	.344	.460	.317	.374	.260	.366	.330	.319
8th	.421	.531	.398	.450	.326	.474	.439	.413
9th	.553	.788	.586	.642	.415	.674	.529	.539
10th	.882	1.84	.944	1.22	.599	.850	.751	.733

Table 2 presents the decile values of the mortgage debt service to income and mortgage debt to wealth ratio, on which the categories of the ratios we included were based, for the three waves of the survey. For example, the DSTI in the 3rd decile for the first wave is 0.167. Given their variation over time, we employ the three-wave average in our interpretation of the results.

5. Conclusions

The main goal of this study is to identify the household characteristics that are associated with a higher household's mortgage default probability. The identification of these characteristics is of the utmost importance for loan granting policies and macro prudential reasons, both in Cyprus and in general, as financial institutions, are heavily exposed in the mortgage market. After the global financial crisis, many banks, particularly in Cyprus, have struggled with high levels of non-performing loans, an issue that has had an adverse impact on the functioning of the broader financial system, economic development and financial stability. We use panel data from the three waves of the Eurosystem Household Finance and Consumption Survey (HFCS) to estimate a probability of default on a mortgage for households, based on their economic and socio-demographic characteristics. In particular, we focus on the debt service to income and debt to wealth ratios, while also controlling for household size and employment status.

The results suggest that the probability of mortgage default is higher for households with high debt service to income (DSTI) ratio, high debt to wealth (DTW) ratio, as well as for larger households, constituting of more than four members. Households with a DSTI level of approximately 37.4% face a higher probability of default relative to low DSTI households, while the probability increases further once the ratio exceeds 46%. With regards to the DTW ratio, it appears that the higher the ratio, the larger the probability to default in general. This peaks at the highest DTW decile, where the probability to default is 14% higher than in the lowest decile. Furthermore, the probability of default declines for individuals in paid employment and the self-employed, albeit to a lower extent for the latter.

The estimates underline the need to conduct proper and prudent estimates of the probability of default by financial institutions, in order to ensure, at an early stage, that a loan can potentially be a conservative investment and not associated with a high risk of default. This would allow for an improved credit risk handing, potentially reducing losses and improving capital adequacy Therefore, the early identification of the household characteristics associated with a higher probability of default, is crucial for the well-being of such entities with further implications for the whole financial system and its long-term stability.

While we do not profess that these factors should be viewed in isolation, it would perhaps be useful to view a DSTI ratio larger than 0.374 as a warning sign. While some default risk is unavoidable when it comes to any investment, having some practical rules of thumb would be useful to support a decision to accept or reject a loan application. It is also important to acknowledge the impact of household wealth in possible mortgage insolvency issues, such as the ratio of debt to wealth, which expresses the long-term ability of the household to repay its debt.

Concluding, while the results can be useful as rules of thumb and potential indicators and trackers for repayment ability, they also suggest that none of the abovementioned ratios can identify by itself a household with possible high default risk in its entirety. As such, each case should be viewed with its own unique characteristics, while at the same time more detailed analysis (perhaps even at the loan level) could potentially be employed in the future to provide a clearer insight on the potential drivers of households' loan arrears.

Appendix I

HFCS Aggregate Variables

Total Household Income = gross labour income (PG0110) + gross income from self-employment (PG0210) + gross income from public pensions (PG0310) + gross income from occupational and private pension plans (PG0410) + gross income from unemployment benefits (PG0510) + income from public/regular social transfers (HG0110) + gross rental income from real estate property (HG0310) + gross income from financial investments (HG0410) + gross income from private businesses other than self-employment (HG0510) + income from regular private transfers (HG0210) + gross income from other sources (HG0610)

Total household monthly income = Total household income/12

Total household monthly mortgage payments = HB2001 + HB2002 + HB2003

Total Mortgage Liabilities = Total outstanding amount on collateralised debt (the sum of 3 main mortgages collateralised on the household's main residence) = HB1701 + HB1702 + HB1703

Total Real Assets = Current value of the main residence of the household (HB0900) + current value of other real estate owned by the household (HB2801 + HB2802 + HB2803 + HB2900) + value of any valuables owned by the household (HB4710) + Total value of cars (HB4400)

Total Financial Assets = value of sight accounts (HD1110) + value of saving accounts (HD1210) + market value of mutual funds (HD1330) + market value of bonds (HD1420) + value of publicly traded shares (HD1510) + value of additional assets in managed accounts (HD1620) + value of any other financial assets (options, futures, index certificates, etc.) HD1920

Total Household Wealth / Total assets = Total real assets + Total financial assets

Appendix II

Imputation and Weights

In the HFCS, observations for which no valid response was received from the households should be imputed. Item non-response (missing values in the variables) is tackled by imputing the missing non-reported figures using multiple stochastic imputation method. MI in the HCFS is based on the assumption of "missing at random", meaning that the distribution of the complete data only depends on the observed data, conditional on the determinants of item non-response and other covariates.

Consequently, this complete set of variables has to be incorporated to the imputation models (Barceló, 2006). HFCS datasets include five implicates (imputed sets of values) for each missing observation. In Cyprus and many other participating countries MeDaMi (Stata software package) was used to correct for item non-response software package called ICE (Royston, 2004) is based on the same multiple imputation algorithm and implementation of Gibbs sampling as €MIR, which developed for the purpose of multiply imputing HFCS data. The main part of the program, the imputation model itself, is based on the FRITZ program created for the imputation of the Survey on Consumer Finances at the Federal Reserve Board. The program is structured as an SAS macro embedded in a wider framework determined by the implementation of Gibbs sampling (Eurosystem HFCN, 2016a, b).

Regarding the weighting procedure, the standard HFCS proposed procedure for computing and adjusting survey weights takes into account: (i) the unit's probability of selection; (ii) coverage issues; (iii) unit non-response; and (iv) an adjustment of weights to external data (calibration). The methodology is coherent with existing international standards (Eurostat, 2011a and United Nations, 2005). Possible discrepancies between the presented figures in this paper and the respective ones calculated by the ECB in the HFCS Statistical Tables can be attributed to the different methodology in the use of weights. In this paper we weight the sample figures to the population using **only the household weights** (i.e. hw0010 for all waves = design weights adjusted for oversampling of the wealthy and unit non-response).

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