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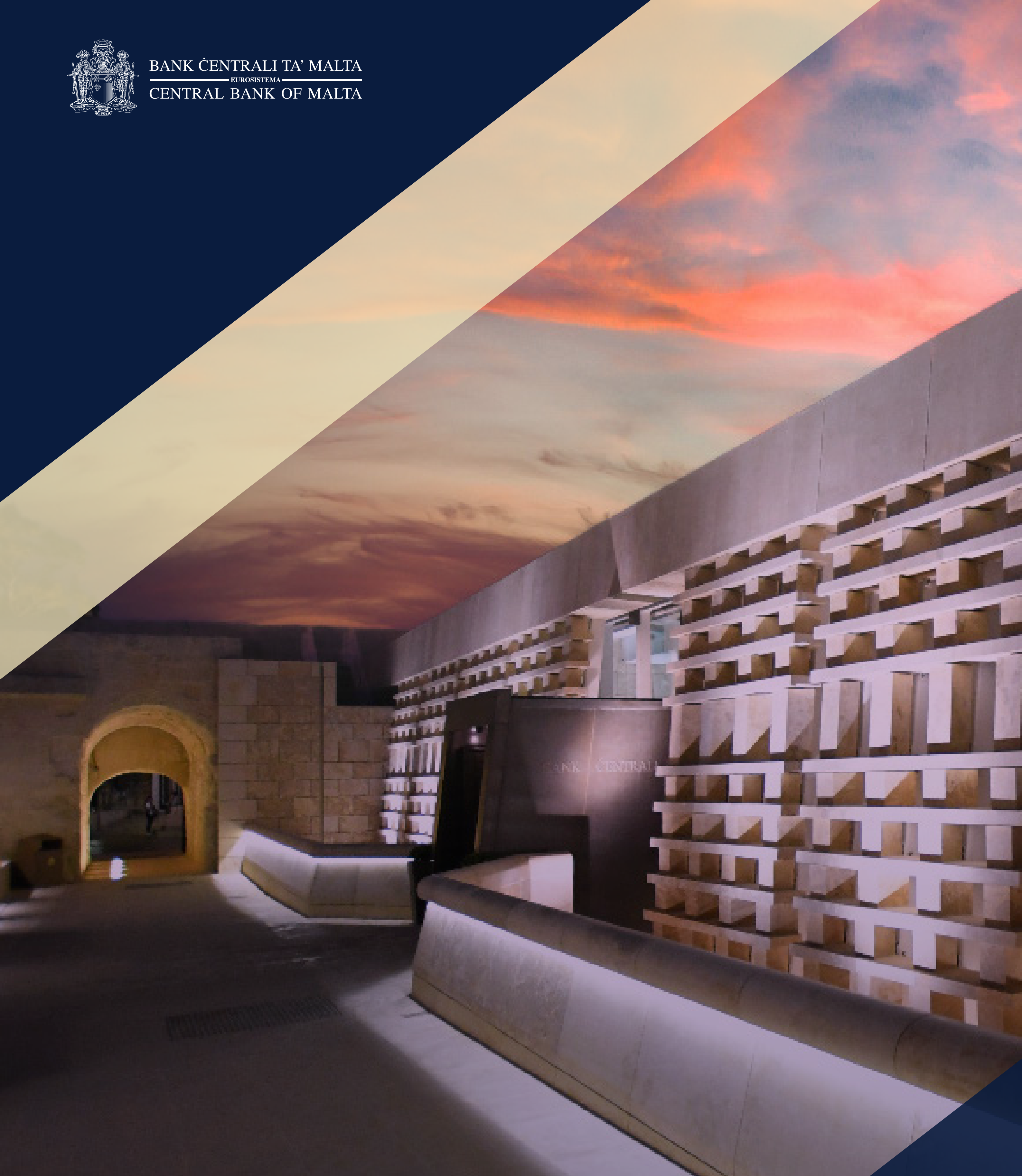

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WORKING PAPER

A STRESS TESTING FRAMEWORK FOR THE MALTESE HOUSEHOLD SECTOR

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Abstract

This paper outlines a stress testing framework for the household sector in Malta based on micro data. The analysis depends on granular data relating to income, expenses, and the value of liquid assets from the third wave of the Household Finance and Consumption Survey and assesses the financial resilience of households to macro-financial shocks. Households' vulnerability is evaluated based on probabilities of default, while loan losses to banks are quantified by means of the exposure at default and loss given default. The analysis examines the impact of four adverse shocks separately: a rise in interest rates, an increase in the unemployment rate, a fall in real estate prices, and a fall in the value of liquid assets. The results indicate that: (i) households are most vulnerable to potential interest rate shocks, (ii) Maltese households have an ample amount of liquid assets that can cover their losses, and (iii) potential loans losses to banks stemming from the household sector are limited. Lastly, to simulate unfavourable economic conditions, the individual shocks are assessed simultaneously by producing two combined stress test scenarios. It is found that the combined *high-scale* scenario results in a higher impact on the financial vulnerability metrics, but the effects are contained.

JEL classification: D14, E44, G01, G21

Keywords: Stress testing, financial stability, HFCS, household finance, household surveys, Malta

Abbreviations

BLC	basic living cost
bps	basis points
CBM	Central Bank of Malta
CCR	Central Credit Register
DI	disposable income
DS	debt service
DSTI	debt-service-to-income (ratio)
DTA	debt-to-asset (ratio)
EAD	exposure at default
EU-SILC	European Union Statistics on Income and Living Conditions
FM	financial margin
HFCS	Household Finance and Consumption Survey
LGD	loss given default
LTV	loan-to-value (ratio)
PD	probability of default
pps	percentage points

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Non-Technical Summary

This paper presents a stress testing framework to assess household vulnerability under different hypothetical adverse scenarios. It builds on data sourced from the third wave of the Household Finance and Consumption Survey which was carried out in 2017 among a sample of households who were interviewed on their asset holdings, consumption, and credit constraints over the previous year. The stress testing framework considers only households who hold any form of mortgage or other debt. These households are deemed to be vulnerable under the financial margin approach if their expenditure (including debt service, rental income, private transfers, and basic living costs) exceeds their income. However, households have a financial buffer in the form of liquid assets which could be used for a number of months and thus do not automatically default on their obligations. Indeed, Maltese households tend to hold a large amount of liquid assets and thus would be able to withstand adverse macro-economic conditions for a significant number of months. Households are subject to four separate macro-financial shocks, namely: an increase in interest rates, an increase in the unemployment rate, a decline in real estate prices, and a fall in the value of liquid assets. Shocks to interest rates have the strongest impact on households' probability of default and consequently the banks' exposure at default and loss given default, followed by a fall in real estate prices which only impacts the loss given default of banks. Moreover, a decline in the value of liquid assets does not have any visible effect on banks' losses given that the greater number of households' liquid assets is in the form of deposits which are not impacted by the shock. To further assess the impact of more severe economic conditions, these shocks are then repeated simultaneously under a *medium-* and *high-scale* scenario. These combined scenarios have a higher impact on households' vulnerability, and consequently on banks, but the impact is still deemed to be rather contained.

Results are presented in terms of the probability of default, the exposure at default and the loss given default. Despite the severity of the shocks, potential losses from the household sector are rather contained as they have an ample amount of liquid assets that they can use to cover losses arising from macro-financial shocks that they might encounter. The paper also finds that spill-overs to banks from the household sector would also be limited.

1. Introduction

The global financial crisis of 2007-09 highlighted the need, *inter alia,* for assessing household vulnerabilities and its potential impact on the financial system, both systemic as well as idiosyncratic for individual banks. Excessive accumulation of debt even in a small number of indebted households can lead to financial instability as credit institutions could incur substantial loan losses. Moreover, a vulnerable household sector can amplify the transmission of adverse macroeconomic and financial shocks given its relatively high representation in the economy. As highlighted in a series of recent studies, an increase in household debt can boost growth in the short term but increases macroeconomic and financial stability risks in the medium term (IMF, 2017).

Before the crisis, the assessment of household debt servicing capacity was largely based on aggregate macro indicators; however, this poses several limitations. As an example, aggregate disposable income can only partly reflect indebted households' ability to pay as both indebted and debt-free households are considered collectively, without a distinction between the two. In addition, the availability of financial buffers of indebted households in isolation cannot be determined from such indicators, thereby ignoring the ability of households to liquidate assets that could act as fall-back mechanisms against increased financial burden. Furthermore, vulnerable households with lower income are masked by those who are financially sound and are in a better position to service their debts. Hence, macro indicators partly address the build-up of vulnerabilities in the household sector. Given the limitations of aggregate data and the increasing availability of micro data, which is essential for stronger in-depth surveillance, many central banks started to employ micro-simulation models to analyse households' ability to repay debt. Such analyses can meaningfully supplement assessment of risk for credit institutions by providing micro-based elasticities of the household sector to macro-shocks.

In this regard, this paper uses micro data from the third wave of the Maltese Household Finance and Consumption Survey (HFCS) to stress test household balance sheets. The third wave of the HFCS was carried out during 2017 and based on 2016 data. Thereby, the paper assesses the debt-servicing capacity of households and the credit risk exposure of domestic banks. Survey-based information on the distribution of wealth and income allows one to identify those households that are particularly prone to adverse shocks. From the Central Bank of Malta's (CBM) perspective, the impact of monetary policy decisions on household creditworthiness can be assessed and used as an input to devise macro-prudential policies. The latter will help curb the potential build-up of risks to the financial system arising from the household sector, in the context of a fast-growing mortgage segment. Given the relatively high home ownership, Maltese households would appear to be sensitive to real estate market developments.

The model employed in this paper is based on the financial margin (FM) approach, where each indebted household is assigned a FM that is defined as the difference between each household's income and expenditure. Based on relevant literature, the probability of default (PD) is estimated for each household according to their respective FM and available liquid assets. The PDs allow for the estimation of an aggregate figure of the banks' exposure at default (EAD) and loss given default (LGD). The EAD calculates the share of defaulting loans held by vulnerable households to total debt, while the LGD measures the banks' loan losses to total debt.[2,3] In this framework, at a first stage, households are subjected to four separate economic shocks, namely: a rise in interest rates, an increase in the unemployment rate, a decline in real estate prices, and a fall in the value of liquid assets. At a second stage, two stress scenarios combine all the shocks in a simultaneous fashion to test the impact of *medium-* and *high-scale* stressed events.

This is the first documented exercise assessing the ability of the Maltese household sector to repay its debt and study their financial vulnerabilities using household-level data in a micro-simulation framework. Such a household stress test based on micro data and household characteristics can provide a useful assessment of households' insolvency risks. Thus, this paper contributes to the development of a comprehensive stress-testing framework for domestic households and the financial system.

The remainder of this paper is structured as follows. Section 2 provides an overview of the related literature. Section 3 describes the data used in this study and lays out the features of the stress testing model. Section 4 presents preliminary data analysis from the HFCS. Section 5 provides the methodology of the individual sensitivity tests, while Section 6 presents the results following the impact of these economic shocks as well as the combined *medium-* and *high-scale* shocks. Finally, Section 7 outlines the main conclusions and avenues for further research.

2. Literature Review

There is a relatively new and growing literature on micro-simulation models as a tool to assess household credit risk and the exposure of the financial system to this sector. Depending on the scope of the analysis, some papers aim at evaluating how different macroeconomic shocks (for example, income or employment shocks) affect the financial conditions of households (Djoudad, 2012), while other studies extend this framework to evaluate the exposure of the banking sector to households that are more likely to default (Albacete and Fessler, 2010). In general, there are two commonly used methods to assess the repayment capabilities of households: (i) the threshold approach and (ii) the FM approach.

The first approach assumes that households become financially vulnerable when at least one vulnerability indicator exceeds a certain threshold. Djoudad (2012) considers the debt-service-to-income (DSTI) ratio for Canada, Albacete and Lindner (2013) consider the debt-to-asset (DTA) ratio and the DSTI ratio for Austria, and Michelangeli and Pietrunti (2014) consider the DSTI ratio for Italy.[4] Threshold-based methods require fewer assumptions and variables compared to the FM approach. One issue with this approach is that the thresholds for vulnerability indicators are set rather arbitrarily and can be deemed as being too simplistic. For example, it may be too general to classify all households as vulnerable when total debt-servicing costs exceed a fixed percentage of income *ceteris*

[2] Banks can mitigate losses incurred following the recognition of new non-performing loans by liquidating the associated collateral.

[3] Maltese banks are not obliged to report PDs and LGDs given that they follow the standardised approach for quantification of capital requirements.

[4] For example, Djoudad (2012) and Albacete and Linder (2013) both consider households with debt-servicing costs above 40% of income are deemed to be vulnerable. Michelangeli and Pietrunti (2014) consider a threshold of 30%. For the DTA ratio, Albacete and Linder (2013) take a threshold of 75%.

paribus. Few recent studies propose more objective criteria (Bańbuła *et al.*, 2016), calibrating the DSTI/DTI limits to cater for policy makers' preference regarding type I and type II errors. Furthermore, the impact of different macroeconomic shocks on household vulnerability can be deemed as being crude and often depends on the indicator being analysed. For example, household vulnerability is unaffected by shocks to interest rate if the loan to value (LTV) ratio is considered as the main vulnerability indicator.

In the second approach, each household is assigned a FM, which is generally defined as the difference between a household's income and the sum of regular debt repayments and basic living costs (BLC). Studies applying this method include Johansson and Persson (2006) for Sweden, Holló and Papp (2007) for Hungary, Albacete *et al.* (2014) for Austria, and Bilston *et al.* (2015) for Australia. One common methodological approach of the above studies relates to the link between the FM and the PD. In the "binary default" interpretation, a household's PD is one (or zero) if the FM is below (or above) a specified threshold (normally zero).[5] However, in reality, not all households with a negative FM default on their obligation, as households may have a sufficient level of liquid assets that could cover their negative FM for some time, thus allowing them to maintain their expenses and avoid default. More recent studies account for the role of liquid asset holdings as a financial buffer against attenuating FMs. Technically, this translates into a PD that is also dependent on the level of households' liquid assets and can therefore take any value between zero and one. This approach is applied by Ampudia *et al.* (2016) for some euro area countries, Meriküll and Rõõm (2017) for Estonia, and Giordana and Ziegelmeyer (2018) for Luxembourg, and may be referred to as the "continuous default" approach.

A common issue often associated with the FM approach is its sensitivity to the estimation of the BLC. There are many approaches to defining and estimating basic consumption. Meriküll and Rõõm (2017) obtain an official estimate of the subsistence minimum consumption from Statistics Estonia. Other studies define basic consumption as the subsistence minimum or poverty line (Bilston *et al.*, 2015; Ampudia *et al.*, 2016). Albacete and Fessler (2010) estimate the BLC using data from the European Union Statistics on Income and Living Conditions (EU-SILC) survey.

3. Data and Methodology

This paper employs data from the third wave of the HFCS as the most recent micro dataset available which was conducted in 2017 and based on 2016 data.[6] The survey is conducted in three-year intervals and includes detailed questions about households' balance sheet, consumption and specific forms of credit constraints which are preferably answered by the most financially knowledgeable household member. Weights are assigned to each individual household to ensure the representativeness of the survey.[7] To address the issue of missing values, the dataset is multiply-imputed (five times) using multivariate imputation by chained equations following the methodology presented in Rubin (1987).

[5] In the "binary default" approach, households with negative financial margins are assumed to automatically default on their obligations since no liquid assets are considered as a financial buffer.
[6] The results are available from https://www.centralbankmalta.org/file.aspx?f=82580. It is worth emphasizing that the results take into consideration the full population, whilst in this study only those households who are indebted are considered, hence some results may vary.
[7] The household weight is obtained from the design weight, which is the inverse of the probability of selecting a household, adjusted for non-response.

In addition to the multiple-imputation procedure, the information is upscaled to become representative of the population. Weights are assigned to individual households depending on their degree of representativeness of the population. Whilst the HFCS considers all types of households, this study eliminates those households that do not hold any debt from the sample. From the (weighted) total of 168,467 households in the HFCS survey, this leaves a (weighted) total of 57,206 households, which means that around one third of Maltese households hold some form of debt.[8] Thus, the reference population for this study consists of households who hold any form of mortgage debt (on the household main residence or on other real estate property) or non-mortgage debt (including outstanding balances on overdrafts and credit card debt, as well as consumer and private loans), or both.

The survey data is used to calculate the FM for each household (FM_i), as follows:

$$FM_i = DI_i - DS_i - R_i - PT_i - BLC_i \tag{1}$$

where DI_i is the disposable income for household i, obtained after adjusting gross household income for taxes and social security contributions. DS_i is the current debt service, defined as the monthly payments for mortgage and non-mortgage debt. R_i is rental payments (if any), and PT_i is the amount related to private transfers per month (if any), such as maintenance and child support, regular cash support to persons other than household members, or regular donations given to charities or institutions. BLC_i is a measure of the BLC that is quantified using alternative definitions. All measures are expressed in monthly figures.

It is important to note that the income variables in the HFCS survey are all reported at gross level. The survey collects income data both at an individual level, such as employment-related income and pension income, as well as at the household level, such as income from financial investments. For data collected at the individual level, this is multiply imputed to obtain a total value attributable to all household members. Several assumptions are required to obtain an estimate for disposable income. To calculate tax, the aggregate gross income is considered for the whole household and tax rates as of 2016 are applied to total gross income since tax is assumed to be paid on all sources of income. For the social security contribution, a proxy is first obtained for the number of working adults in the household; and, using this proxy, an estimate of the employment income for each household member is obtained. Finally, using the social security contribution rates as of 2016, the social security contribution for each working adult is deducted from their gross employment income.[9]

To assess the robustness of the results, four measures of the BLC are considered and are reflected in four different measures of FMs. Each measure exploits different information from relevant HFCS questions. The first measure, abbreviated as FM1, is based on the monthly consumption of goods and services.[10] The second measure (FM2) considers the median value of the BLC in FM1 for the

[8] In the survey itself, this amount corresponds to 281 households being considered in this study, out of the 1004 households interviewed.

[9] In 2016, based on EU-SILC data, the average disposable household income stood at €27,722, whilst in this paper (after accounting for income tax and social security contributions) a value of €23,487 is obtained.

[10] The question in the survey is formulated as follows: "*So overall, about how much does your household spend on average by month on all consumer goods and services? Consider all household expenses including food, utilities, etc. but excluding consumer durables (e.g. cars, household appliances, etc.), rent, loan repayments, insurance policies, renovation, etc.*"

households in the sample; thus, the BLC is common for all households. The third measure (FM3) is based on three separate questions from the HFCS and includes the amount spent on utilities (heating, electricity, and water) and food consumed at home plus 50% of the amount spent on food outside of home.[11] The fourth measure (FM4) takes the median of the BLC in FM3 for the households in the sample and thus the BLC is also common for all households. The main analyses presented in this paper are based on the definition of BLC as per FM1 while the remaining FMs are presented in the appendix as robustness checks.

FM1 is preferable over FM3 since it includes all consumption and is not limited to only food and utilities. On the other hand, FM2 and FM4, which give a common level of BLC for all households based on the median of the BLC in FM1 and FM3, respectively, are not preferable given that these are non-granular but rather based on a common BLC for all households; however, they can still serve as a robustness check of the results based on the sample chosen. In this regard, the results for FM2 to FM4 are in the appendix to test the robustness of the results, similar to the approach by Giordana and Ziegelmeyer (2018).

The PD of a household is calculated based on the respective FM and the value of liquid assets available at their disposal. It is assumed that households do not automatically default as soon as their FM becomes negative as a sufficient level of liquid assets can act as a financial buffer. These households would be able to persevere for a number of months with a negative FM and yet continue to cover their BLC as well as servicing their debt. Consequently, households are considered as vulnerable only if they have insufficient liquid assets to make up for negative margins for a fixed minimum number of months M. Thus, the PD is considered to be a decreasing function of liquid asset holdings for households with a negative FM.

Following Ampudia *et al.* (2016), the PD for each household i is defined as follows:

$$PD_i = \begin{cases} 0 & , if\ FM_i \geq 0\ or\ \ |FM_i| * M \leq LIQ_i \\ 1 - \frac{LIQ_i}{|FM_i| * M} & , if\ FM_i < 0\ and\ |FM_i| * M > LIQ_i \end{cases} \qquad (2)$$

where LIQ_i is the amount of liquid assets held by household i and M is the number of months during which a negative FM_i can be covered by the level of liquid assets. Liquid assets in this case are defined as the sum of deposits, bonds, stocks, managed accounts, and less liquid financial assets (which represent the value of non-self-employment not publicly traded businesses). The PD_i is zero if FM_i is positive or if a household's liquid assets suffice to cover a negative FM for more than M months. For households with a negative FM_i, the PD_i is equal to one if LIQ_i is zero (meaning that the household reported that they do not have any liquid assets). If the level of liquid assets cannot cover the negative FM for more than M months, then the PD is greater than zero and less than one. Therefore, vulnerable households have a PD_i greater than zero. A corollary to the above is that PDs decrease when liquid assets holdings increase; given that households have more liquid assets to cover their debt. Alternatively, PDs decrease if the threshold M is shortened, hence households would be required to withstand a negative FM for less months, leading to a decrease in the proportion of households that would be unable to finance their debt.

[11] 50% is chosen so that the total amount spent on food is closer to a similar estimate (€517.56) found in the study 'A Minimum Essential Budget for a Decent Living-2016' conducted by Caritas.

Two measures are used to quantify how banks are affected by defaulting households: (i) EAD and (ii) LGD. By way of definition, the banks' EAD measures the share of defaulting loans to the total stock of outstanding loans, while LGD provides an estimate of the expected aggregate banks' loan losses caused by defaulting households after considering the liquidation of collateral particularly that which is real-estate related. Mathematically, the two measures are defined as:

$$EAD = \frac{\sum_i PD_i * D_i}{\sum_i D_i} \quad (3)$$

$$LGD = \frac{\sum_i PD_i * (D_i - A_i)}{\sum_i D_i} \quad (4)$$

where D_i is the total outstanding debt and A_i is the value of real estate assets that banks can recover in case of default on the respective debt for each household i. It is assumed that all non-mortgage debt is uncollateralised, meaning that banks cannot recover any of the debt in case of default. In such case, the A_i in the equation of the LGD is 0 and so the LGD would be equal to the EAD.

Following Ampudia *et al.* (2016), Meriküll and Rõõm (2017), and Ziegelmeyer and Giordana (2018), the number of months M is calibrated so that the estimated EAD ratio matches the ratio of household non-performing loans ratio. This is done through trial-and-error by substituting different values of the months M in equation (2) to obtain the desired target-level EAD ratio in equation (3). In the case of Malta, the value of M is set to 36 months in order to achieve an EAD of 2.6% corresponding to the resident mortgage NPL ratio stated in the *Financial Stability Report 2016* published by the CBM (refer to Table 4).[12] In other words, a household is considered to default if it does not have enough liquid assets to cover its debt for a period of 36 months (3 years). The resident mortgage NPL ratio was chosen for the calibration of the value of M as the majority of the debt held by households is in the form of mortgage debt. Indeed, around 88% of total debt is in the form of mortgage debt. This implies that calibration of M on the basis of the household NPL ratio yields more representative stress test results than calibrating M on the basis of the entire household sector. When comparing to the value of M obtained to that of the other studies, this value is quite large. According to Meriküll and Rõõm (2017), based on the second wave of the HFCS, Malta has by far the highest (median) liquid assets to gross income ratio for the whole sample of households (close to 80%) as well as for the subgroup of indebted households (almost 60%). Second in the ranking is Belgium with approximate ratios of 32% and 22%, respectively. The ratio would be higher if the denominator of the ratio is replaced by net disposable income. It appears therefore from this survey that Maltese households have a high amount of financial buffers that can be used in case of negative shocks.

4. Preliminary Data Analysis

In order to have a better understanding of the outcomes, a deep-dive analysis into the data is carried out to provide an indication of the financial resilience of both households as well as banks. Primarily, summary statistics for all the alternative definitions of the FM are provided. As can be seen in Table

[12] While M is calibrated on the basis of setting the EAD ratio to the observed NPL ratio of 2.6% for 2016, a sensitivity analysis was also carried out to assess the impact on household defaults. Indeed, by varying M by up to four months (i.e., between 32 and 40 months), the share of households with insufficient liquid assets to cover their negative FM does not change. Thus, while PDs and EADs would adjust accordingly to the chosen value of M, the impact on household defaults is not as sensitive to a change in the number of months chosen.

1, the mean monthly FM shows little variation ranging from €1,277 (FM1) to €1,626 (FM4). Alternatively, the median monthly FM ranges from €973 (FM1) to €1,278 (FM4). The number of households with a negative FM varies between 3,879 and 6,686. In other words, between 3,879 and 6,686 of the households in the sample have an expenditure exceeding their income. The mean FM for households with a negative FM varies between - €386 and - €614.

Table 1: Summary statistics on the FM variants for indebted households

FM	All indebted HHs (full sample of 57,206 households) (€)							Indebted HHs with FM<0 (€)		Number of HHs with FM<0
	Mean	25th pctl	Median	75th pctl	Min	Max	St. Dev.	Mean	Median	
FM1	1,277	385	973	1,643	-11,603	32,731	2,420	-614	-350	6,686
FM2	1,551	609	1,203	1,902	-3,404	33,731	2,478	-460	-367	4,895
FM3	1,516	593	1,114	1,788	-3,104	33,280	2,423	-386	-305	3,879
FM4	1,626	684	1,278	1,977	-3,329	33,805	2,478	-460	-292	4,166

Source: HFCS, Authors' calculations. Data are multiply imputed and weighted.

Table 2 is intended to provide more insight into the five components that make up the FM.[13] To note that not all households include all the components of the FM. For example, the summary statistics for the rental payments provided in Table 2 are for those 6.9% of the households which have some form of rental payment, as not all households will have this particular debt obligation. One caveat relates to the debt service, which shows that 81.3% of households have some form of regular debt servicing costs; implying that the remaining households have some form of debt but are not currently repaying their debt obligations. This can seem contradictory given that, as aforementioned, the framework only considers the indebted households in the sample. In addition, the summary statistics for the BLC of FM1 and FM3 are shown since the BLC for FM2 and FM4 is constant for all households.

Table 2: Summary statistics on components of the FM

FM Components	All indebted HHs (€)							% with value > 0
	Mean	25th pctl	Median	75th pctl	Min	Max	St. Dev.	
Disposable Income	2,789	1,738	2,363	3,197	267	34,481	2,529	99.1%
Debt Services	536	280	435	700	50	3,531	398	81.3%
Rental Payments	117	17	51	142	17	452	149	6.9%
Private Transfers	284	200	291	351	100	480	121	5.9%
BLC of FM1	1,025	700	870	1,150	51	14,544	868	100%
BLC of FM3	786	560	751	950	160	3,048	343	100%

Source: HFCS, Authors' calculations. Data are multiply imputed and weighted.

As mentioned earlier, households with a negative FM do not automatically default if they have sufficient liquid assets that they can resort to. To obtain an indication of the significance of liquid asset reserves, Table 3 provides a summary of the liquid assets held by indebted households. One can observe that the mean level of liquid assets for households with a negative margin is lower when compared to those with a non-negative margin. There is no significant change in the mean liquid assets holdings for households with a negative FM under FM1 and FM3. Contrary to the homogeneity shown in Tables 1 and 2, data for liquid assets seems to be more skewed, as can be observed by the difference between the mean and median. This can be attributed to the higher asymmetry and more outliers in

[13] Components with a value of 0 are not included in the table so as not to bias the results towards 0.

liquid asset holdings. From Table 3, among indebted households with a negative FM, 8.5% do not have any liquid assets under FM1. These households are automatically assigned a PD of 1.

Table 3: Summary statistics on liquid assets for indebted households

	Liquid Assets (€)							Number of HHs with no liquid assets
	Mean	25th pctl	Median	75th pctl	Min	Max	St. Dev.	
All indebted HHs	39,623	4,217	12,316	38,168	-	975,002	105,773	1,111
Indebted HHs with FM<0								
FM1	25,481	3,667	8,967	17,668	-	450,000	62,740	570
FM2	11,421	301	3,751	14,393	-	102,894	22,057	940
FM3	26,881	176	7,000	14,672	-	450,000	81,018	854
FM4	10,508	301	1,751	7,000	-	102,894	23,142	940

Source: HFCS, Authors' calculations. Data are multiply imputed and weighted.

Table 4 reports the liquid asset holdings across all indebted households and the share of households who cannot cover their negative FM by liquidating their assets for a given number of months M, representing the results for the average household. The fact that Maltese households have a large level of liquid assets leads to a higher M compared to other countries due to being able to resort to liquid assets for a higher number of months. Thus, a higher M is necessary for a more stringent survival criterion under the FM approach. In addition, the bottom rows of Table 4 displays the average PD and EAD across all indebted households as the required number of months is lengthened. The EAD ratio of 2.62%, obtained when $M = 36$, is the closest EAD ratio to the resident mortgage NPL ratio from the *Financial Stability Report 2016*.

Table 4: Summary statistics on liquid assets and share of households with insufficient liquid assets to cover their negative FM for the indicated number of months

	Liquid Assets (€)		Share of households with insufficient liquid assets to cover their negative FM for a given number of months *M*				
	Mean	Median	1	6	12	24	36
All indebted HHs	39,623	12,316	1.29%	2.68%	3.96%	5.04%	6.39%
All indebted HHs with FM < 0	25,481	8,967	11.01%	22.94%	33.86%	43.13%	54.71%
			Average PD				
			1	6	12	24	36
All indebted HHs	39,623	12,316	1.15%	1.64%	2.55%	3.59%	4.35%
			Average EAD				
			1	6	12	24	36
All indebted HHs	39,623	12,316	0.33%	0.66%	1.46%	2.01%	2.62%

Source: HFCS, Authors' calculations. Data are multiply imputed and weighted.

Alternatively, the case of the binary approach can be considered, meaning that the liquid assets of households are not taken into consideration for the calculation of the PD. This means that all households with a negative FM are automatically assigned a PD of 1. In this case, the average PD would be equal to 11.69%, while the average EAD would be 14.04%, which is quite high when compared to the values in Table 4. This is expected as, unlike in the continuous approach, all households with a negative FM are assigned a PD of 1, irrelevant of the extent that the FM is below zero or the level of liquid asset holdings that could be available to cover their losses.

5. Methodology of the Simulated Shocks

This section presents a methodological description of four different shocks, that is, a rise in interest rates, an increase in the unemployment rate, a decline in real estate prices, and a fall in the value of liquid assets. Such sensitivity tests can provide insights on the contribution of each shock to assess the financial resilience of households, as well as, to determine which shock has the most severe impact. To note that these scenarios are based on instantaneous shocks which take into consideration the survival period of 36 months obtained in Section 4. For a more holistic approach, these individual shocks can also be combined to assess the impact of the contemplated shocks occurring simultaneously via a *medium* and *high-scale* scenario. Table 5 describes the magnitude of these combined scenarios.

Table 5: Magnitudes of the shocks under each combined stress test scenario[14]

Stress test scenarios	Interest rate	Unemployment rate	Real estate prices	Liquid assets (stocks, bonds, and less liquid assets, respectively)
Medium-scale	+2 pps	+2 pps	-20%	-20%, -20%, -40%
High-scale	+3 pps	+3 pps	-30%	-30%, -30%, -60%

Source: Central Bank of Malta.

An important assumption of this framework is that, unless otherwise specified, income and expenditure are assumed to remain constant under any of the applied shocks. Furthermore, the BLC remains the same under all the sensitivity analyses. The framework is based on a partial equilibrium model, meaning that only one component is shocked *ceteris paribus*. This may not reflect reality where households, when faced with a significant adverse shock would alter their consumption patterns. Indeed, during a recessionary period, as the marginal propensity to save increases due to heightened uncertainty, a household is expected to reduce its consumption of goods and services to adapt to the new circumstances. In addition, if a household is in financial stress, it can decide to sell the underlying collateral and pay the loan. Nonetheless, a partial equilibrium framework would allow the assessment of the impact stemming from the individual shocks.

Before delving into the description of the sensitivity tests, one can note that the calculation of the LGD incorporates the assumption that in the case of a default, banks recover collateral which could be composed of the households' main residences and other real estate assets. More specifically, a 20% haircut is applied to the value of property related collateral, which acts as a buffer for the banks against potential losses, to account for any transaction and other costs incurred in the process of a forced sale.[15]

[14] The magnitudes of the shocks are informed from literature but also applicable in the local context. For example, in the case of the unemployment rate shock, a 1% increase is roughly equivalent to 1 historical standard deviation. For the shock to real estate prices, the most extreme shock of a 30% drop in house prices is equivalent to four historical standard deviations of the house price index.

[15] The collateral haircut of 20% is also used by Giordana and Ziegelmeyer (2018).

5.1. Simulating a Rise in Interest Rates

An increase in the interest rate leads to a higher debt service cost (DS_i) due to higher monthly interest payments, which results in a lower FM across all households impacted by such shock and consequently a higher PD for households with a negative FM. It is assumed that the loan and interest payments are adjusted to reflect the shock while not extending the maturity of the loan. In addition, interest rate increases are assumed to affect those mortgage loans having an adjustable interest rate and all non-mortgage loans. Given that, from a preliminary study using the CBM's Central Credit Register (CCR), the share of adjustable interest rate mortgages on homes for Maltese banks is over 93% of the total mortgage stock, the impact of this shock on the FM is anticipated to be large. The analysis considers the impact of an increase of up to 3 percentage points (pps) in the interest rate.

5.2. Simulating a Rise in the Unemployment Rate

For the purpose of implementing the unemployment shock, the focus is on absolute changes in the employment level of the reference person responding to the survey. People outside the labour market, such as students, women on maternity leave, and people with long-term sick leave are assumed to remain economically inactive. Hence, their share is unchanged by the shock and is not impacted in the estimates. Finally, people currently actively seeking employment are assumed to remain unemployed after the shock.

There are two general approaches to modelling the impact of the unemployment shock on the FM. On the one hand, some studies assume an equal probability of becoming unemployed across individuals (Johansson and Persson, 2006; Herrala and Kaukko, 2007). On the other hand, more advanced methods model the probability of becoming unemployed for each person separately, on account of households having different personal attributes (such as education level) as well as different propensities for becoming unemployed (Albacete and Fessler, 2010; Ampudia *et al.*, 2016; Bańbuła *et al.* 2015). These studies suggest that, among other factors, the more skilled a person is, the less the propensity to become unemployed. To compute the probability of unemployment for individual households, the approach in Albacete and Fessler (2010) is adopted and the following logit model is estimated for the employment status of the reference person for each household aged between 20 and 64 years:

$$pu_j = \Pr(unemployed|X) = \Lambda(\beta' X) = \frac{1}{1+e^{-\beta' X}} \tag{5}$$

where pu_j is the probability of unemployment for each reference person j, $\Lambda(.)$ is the cumulative distribution function of the logistic distribution, and X is a vector of regressors, with β being the vector of coefficients. In this study, the probability of unemployment includes four key determinants: gender, age, highest educational attainment, and gross income, which are regressed against an indicator variable representing the probability of becoming unemployed for the reference person. Increases of 1, 2, and 3 pps in the overall unemployment rate are considered, on the basis of data extracted from the survey, and the shock is implemented as follows: first, the estimated coefficients of the model are used to compute the probability of becoming unemployed for each reference person; second, the constant term of the logistic regression is calibrated to meet the post-shock unemployment rate; and finally, to designate a reference person as unemployed, a real number (η) is drawn at random from a uniform distribution in the interval (0,1). If $pu_j \geqslant \eta_j$, the reference person is designated as unemployed. In this case, the income of one working adult, which was estimated from the proxy of number of working adults in a household, is deducted from the total disposable income and replaced with the unemployment benefit, computed as of 2016, which in Malta corresponded to the daily rate of €12.18.[16] The above procedure is repeated 1,000 times using Monte Carlo simulation and the reported results in the following paragraph represent the averages over all the simulations.

The daily rate of €12.18 for the unemployment benefit averages to around a monthly rate of €316.68 since the unemployment benefit is paid on a 6-day week basis and covers payments from Monday to Saturday. These payments are made from the first day of unemployment and continue for a period of 156 days, equivalent to around 6 months. The analysis assumes that once an individual becomes unemployed, the individual remains unemployed until the end of the reference period and still receives the unemployment benefit. This would be more conservative than the individual returning to work, given that the average monthly unemployment benefit of €316.68 is significantly less than the average minimum wage of €728.04 (sourced from Eurostat), meaning that the unemployment benefit is less than half of the minimum wage.

The unemployment rate benefit in Malta varies significantly from that of other countries. Albacate and Fessler (2010) assume for Austrian households that after becoming unemployed, the reference person still received 55% of the monthly salary in unemployment benefits and subtract only 45% of the person's wage from total household income. Meriküll and Rõõm (2017) assume that after becoming unemployed, individuals are assigned a new gross income to the previous gross wage income times the average replacement rate of 15%. Finally, Giordana and Ziegelmeyer (2018) assume unemployment benefits for Luxembourg equivalent to 80% of previous salary. However, the first six months cannot exceed 2.5 times the minimum wage, and the following six months cannot exceed 2.0 times the minimum wage. For Malta, the previous salary is not considered, and a fixed unemployment benefit rate is assumed for all individuals which is much smaller than the minimum wage.

5.3. Simulating a Decline in Real Estate Prices

This section presents the impact of a decline by 10%, 20%, and 30% in the market value of real estate assets, assuming that prices are identical across different types of real estate assets (houses, apartments, non-residential properties) and different regions. Real estate related collateral represents the highest share of collateral for the banks. The only metric that is affected by this type of shock directly is the LGD as it depletes the value of collateral that banks recover in forced sales. Conversely, the mean PD and the EAD ratio do not change as a result of the shock.

As a robustness check, the impact of declines in real estate prices for each household is modelled after accounting for heterogeneity in house prices (e.g. regional variation) in a fairly simplistic manner, which is modelled as a draw from a normal distribution:

$$hp_i \sim N(hp_t, \sigma^2)$$

where hp_i is a house price shock for household i, hp_t represents the mean shock to real estate prices ($hp_t = -10, -20$ and -30 for $t = 1, 2$ and 3, respectively), and σ^2 is the variance in the house price

[16] There are two main different unemployment benefit rates that an unemployed person can be entitled to: the unemployment benefit and the special unemployment benefit. The latter, which is higher, is given to those persons qualifying following the assessment of a means test. In the analysis the former benefit is used, for the sake of conservatism, since the means test cannot be replicated to determine whether a household qualifies the special unemployment benefit or otherwise.

series growth. The latter is based on historical data on the house price index from Eurostat for the period 2006Q1-2018Q2.

5.4. Simulating a Decline in the Value of Liquid Assets

The level of holdings of liquid assets influences the PD, which in turn impacts the EAD and LGD ratios. The value of stocks and bonds are assumed to decline by 10%, 20% and 30% and that "less liquid assets" lose 20%, 40% and 60% of their value in the three respective shocks. The case of bank failures is not considered in this paper and therefore deposits are unaffected.

6. Simulation Results

This section presents the results of the hypothetical sensitivity shocks applied and their impact in terms of PDs, EADs, and LGDs. The individual shocks are also applied simultaneously in two separate scenarios; a *medium-scale* and *high-scale* scenario, as described in Table 5.[17]

One must also note that the HFCS data used in the study relates to a period of unprecedented economic growth and wealth accumulation – meaning that the results may not be representative of the 'long run average' since the assessment is based on information available at a particular point in time.

Table 6 presents the number of households having a negative FM, under the baseline scenario as well as after applying shocks to interest rates and unemployment, and the combined scenarios. As an example, out of the 57,206 households in scope of this study, there are 6,686 households who have a negative FM (11.7% of total households in the sample, as shown in Table 1) under FM1. While the interest rate shock affects the households' debt service (DS_i) directly; the shock to unemployment rate affects the households' disposable income (DI_i). The remaining sensitivity shocks are not included in the Table as these do not have an impact on the FM of households. Specifically, the fall in real estate prices affects only the banks' LGD, whilst the fall in value of liquid assets has no impact on the FM itself, but it has an impact on households' availability of liquid assets to sustain the same negative FM.

Table 6: Number of households having a negative FM

		FM1	FM2	FM3	FM4
Baseline		6,686	4,895	3,879	4,166
Interest rate shock	+1 pp	7,227	5,374	4,028	4,333
	+2 pps	7,811	5,374	4,028	4,333
	+3 pps	8,316	5,872	4,318	4,812
Unemployment rate shock	+1 pp	7,216	5,154	4,185	4,461
	+2 pps	7,310	5,220	4,274	4,538
	+3 pps	7,424	5,296	4,381	4,626
Medium-scale scenario		8,929	6,177	4,028	4,814
High-scale scenario		9,434	6,675	4,573	5,548

Source: HFCS, Authors' calculations. Data are multiply imputed and weighted.

[17] The combined scenarios do not include the case where a real estate shock is implemented based on a normal distribution as it does not change the results qualitatively.

Table 7 displays the impact of the simulated shocks to the estimates of the mean PD, the EAD, and the LGD, the latter two expressed as a ratio of total debt. The first row gives the pre-shocked estimates, followed by the estimates obtained for each shock and the combined scenarios. The low LGD ratio indicates that housing loans are well-collateralised, particularly for mortgages on households' main residence.

Table 7: Stress test results for all indebted households

	Type of shock	Size of shock	Mean PD	EAD in % of debt	LGD in % of debt	Growth of LGD relative to baseline
	No Shock Baseline		4.35	2.62	0.10	
Individual shocks	Interest Rate	+1 pp	4.62	3.12	0.18	1.74
		+2 pps	5.60	4.61	0.24	2.34
		+3 pps	6.66	6.36	0.28	2.70
	Unemployment	+1 pp	4.39	2.67	0.11	1.04
		+2 pps	4.41	2.69	0.11	1.06
		+3 pps	4.44	2.74	0.11	1.10
	Real Estate	-10%	4.35	2.62	0.12	1.14
		-20%	4.35	2.62	0.18	1.69
		-30%	4.35	2.62	0.25	2.39
	Liquid Assets (stocks, bonds; less liquid assets)	-10%; -20%	4.35	2.62	0.10	1.00
		-20%; -40%	4.35	2.62	0.10	1.00
		-30%; -60%	4.35	2.62	0.10	1.00
	Combined Shocks	Medium-Scale	6.62	4.56	0.38	3.63
		High-Scale	7.85	6.68	0.67	6.42

Source: HFCS, Authors' calculations. Data are multiply imputed and weighted.

Although a direct comparison of these results with those found in the relevant literature is not entirely straightforward due to differences in methodologies and data, the most relevant studies are briefly mentioned. For example, Ampudia *et al.* (2016) estimate EAD ratios for 10 different countries based on the first wave of the HFCS survey. The resulting estimates vary from 3.5% in France to 9.3% in Greece. Similarly, LGD ratios (no haircut is applied) range from 0.36% for Belgium to 2.46% for Greece. For the case of Estonia, Meriküll and Rõõm (2017) estimate an EAD ratio of 3.4% and a LGD ratio of 0.4%, but the calibrated number of months is set to one. In a closely related study, Giordana and Ziegelmeyer (2018), based on a similar definition for one of the FMs in the appendix (FM3), estimate an EAD ratio of 3.1% and LGD ratio of 0.51% for Luxembourg.

The effects of the simulated increases in interest rates cause upswings in all three risk metrics (the PD, LGD, and EAD). The impact on the LGD ratios is not too severe, suggesting that households' real estate wealth can cover most of their debt.

The outcome of the simulation of the unemployment shock shows that households are rather resilient to increases in the unemployment rate and the consequent change in income. The outcome from this shock is rather in line other studies. For example, Johansson and Persson (2006) find that an increase in the unemployment rate by 3 pps increases the EAD ratio by 0.7 pp, while bank loan losses are unaffected. Giordana and Ziegelmeyer (2018) estimate that an unemployment shock of 3 pps lead to a rise in EAD by 0.4 pp, while LGD goes up by 0.04 pp.

For the real estate shock, the impact is only visible on the LGD, but it is also not too severe. Under the alternative approach of accounting for the heterogeneity in house prices based on the normal distribution, the effects of such a shock are found to be slightly more pronounced compared to the case of a uniform reduction in prices across properties. Under the three severity metrics for the alternative approach (10%, 20% and 30% drop in property prices based on the normal distribution), the LGD ratio rises to 0.14%, 0.20% and 0.28%, respectively.

The results of the declines in the value of liquid assets do not show any visible impact on neither the household PDs nor the bank EAD and LGD ratio. This is explained by examining the composition of liquid assets. Among indebted households, deposits account for 69% of their liquid assets, stocks comprise 28% whilst bonds represent 3% of their portfolio. Therefore, the volume of deposits held by those households comfortably exceeds their expenditure. Furthermore, deposits are assumed to remain unaffected by the liquid assets shock and consequently, the average PD and the EAD and LGD ratios are expected to be affected marginally by the impact on other liquid assets, if at all, since none of the indebted households have "less liquid assets" in their portfolio.

As expected, the two scenarios produce more pronounced impacts than the individual sensitivity shocks. Compared to the baseline scenario, the results of these two combined scenarios suggest more visible increases in the mean PD and in the EAD ratio. With respect to the LGD ratio, the impact is also more visible due to the combination of the interest rate shock and real estate shock, although they are still not so large. This indicates that banks are not very sensitive to strong negative economic shocks in the household sector, while bank loan losses appear to be contained.

The low estimates of the LGD ratio can mainly be attributed to two reasons. First, liquid assets can act as a mitigating factor against financial troubles, and Malta has by far the highest (median) liquid assets to gross income ratio for all households (including indebted households) in the EU. This suggests that the Maltese households could comfortably pay off current debt obligations without needing to liquidate assets. Second, the DSTI, which reflects the capacity of the household to repay its debt without resorting to selling assets, was in 2013 one of the lowest among the participant countries in the HFCS survey, sourced from Ampudia *et al.* (2016). In this study, Ampudia *et al.* calculate the percentage of Maltese households with a DSTI exceeding the benchmark value of 40% and finds that only 4.2% of all indebted households are above this threshold.[18]

7. Conclusions

The aim of this paper is to assess the financial strength of the Maltese household sector as well as to evaluate the potential banking sector loan losses from household defaults under unfavourable macro financial conditions. A stress testing model has been developed based on household-level data sourced from the Maltese HFCS, a representative survey which was last conducted in 2017 based on 2016 data. Primarily, the FM of each household is calculated, which depends on household income, expenses, and the level of liquid assets. The PDs are then calculated, together with the aggregate bank

[18] The CBM's Directive No. 16 relates to the regulation on borrower-based measures, where banks, amongst other policy limits, cannot extend loans with a stressed DSTI ratio that is higher than 40%.

EAD and aggregate bank LGD by assuming that banks can liquidate collateral in the form of real estate assets from defaulting households following the application of a haircut to the real estate value. Next, the stress-test elasticities of household default rates and bank losses are estimated separately under four adverse sensitivity shocks: an increase in interest rates, higher unemployment rate, a fall in real estate prices, and lower value of liquid assets. In addition, to assess the impact of severe economic conditions, the same analyses are repeated simultaneously by introducing shocks under a *medium*- and *high-scale* scenario.

Shocks to interest and, to a lesser extent, unemployment rates have the most visible impact on households' PD, and consequently, on the EAD and LGD of the banks. Increases in the PD are stronger in response to the interest rate shock. The real estate price shock also has a visible impact on the LGD, but to a marginally smaller extent than the interest rate shock. Moreover, a fall in the value of liquid assets does not have a significant effect on the banks' losses as deposits constitute by far the largest item held in the portfolio of indebted households, and these are unaffected by the shock to liquid assets since bank defaults are not considered. Finally, although the *medium*- and *high-scale* scenarios cause stronger changes on defaults and bank losses vis-à-vis baseline scenario, their impact is modest.

This paper is the first attempt to develop a stress test model using granular household data for Malta. Accordingly, it contributes to the development of a more comprehensive stress-testing framework for the Maltese financial system. Despite some technical differences which also prevailed in similar studies, the results presented are mostly similar to those for other euro area countries (Ampudia *et al.*, 2016; Meriküll and Rõõm, 2017; Giordana and Ziegelmeyer, 2018).

This paper draws two main conclusions. First, the household sector is rather resilient to the adverse economic shocks considered. Second, potential bank losses from exposures to households' debt appear to be rather limited. There are two supporting arguments to these findings: the Maltese households hold substantial level of liquid assets that they can withdraw to cover expenses for several months under financial stress and secondly; many households have repaid a relatively big part of their mortgages, which along with sustained increases in house prices has led to reduced leverage levels among indebted households and strong collateral values. Moreover, banks extend relatively low LTVs and ensure low DSTIs thereby ensuring that households are more resilient.

The framework of this paper can be extended to assess the impact of changes in other variables, such as changes in household income or basic consumer goods. Similar stress testing exercises can be repeated once new HFCS data become available. The model can also be applied to years in which the HFCS is not conducted by projecting the financial situation of the Maltese households into the future through the application of the respective growth rates relevant for the components of the household FM. Lastly, the scenarios can also be studied within the context of a model that can reasonably capture general equilibrium effects to get an aggregate analysis of the impact of the shocks on household finance and credit institutions.

As a way forward, this exercise can be complemented by a new framework which may run in parallel to this framework but using a new granular dataset of attributes that is based on all new loans granted by domestic banks within each quarter. While the HFCS is a more comprehensive exercise which includes a wealth of information, it is conducted every three years. The new survey will be collected at a higher frequency but contains less information. Thus, this reduced scope dataset can address the main limitation of the HFCS in terms of timing. The parallel study would focus more on lending practices based on vulnerability indicators such as the LTV ratio, loan-to-income ratio and DSTI ratio as well as the maturities of the lending practices. Additionally, further work in this area can be carried out to calibrate vulnerability thresholds of these parameters specifically for the domestic context.

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Appendix

Table 8: Summary statistics on liquid assets and share of households with insufficient liquid assets to cover their negative FM for the indicated number of months

	Liquid Assets (€)		Share of households with insufficient liquid assets to cover their negative FM for a given number of months *M*				
	Mean	**Median**	**1**	**6**	**12**	**24**	**36**
All indebted HHs							
FM2: Goods & services (median)	39,623	12,316	1.74%	3.64%	4.92%	6.59%	6.84%
FM3: Foods & utilities (individual)	39,623	12,316	1.59%	1.75%	2.55%	3.86%	5.04%
FM4: Foods & utilities (median)	39,623	12,316	1.74%	3.39%	4.58%	5.75%	6.59%
All indebted HHs with FM < 0							
FM2: Goods & services (median)	11,421	3,751	20.36%	42.55%	57.47%	77.04%	79.92%
FM3: Foods & utilities (individual)	26,881	7,000	23.47%	25.82%	37.57%	56.87%	74.36%
FM4: Foods & utilities (median)	10,508	3,667	23.92%	46.51%	62.88%	79.01%	90.51%
			Average PD				
			1	**6**	**12**	**24**	**36**
All indebted HHs							
FM2: Goods & services (median)	39,623	12,316	1.69%	2.69%	3.51%	4.77%	5.44%
FM3: Foods & utilities (individual)	39,623	12,316	1.54%	1.66%	1.97%	2.78%	3.35%
FM4: Foods & utilities (median)	39,623	12,316	1.69%	2.14%	3.05%	4.25%	4.99%
			Average EAD				
			1	**6**	**12**	**24**	**36**
All indebted HHs							
FM2: Goods & services (median)	39,623	12,316	0.29%	1.12%	1.55%	2.36%	2.70%
FM3: Foods & utilities (individual)	39,623	12,316	0.28%	0.30%	0.53%	1.07%	1.63%
FM4: Foods & utilities (median)	39,623	12,316	0.29%	0.68%	1.19%	2.12%	2.54%

Source: HFCS, Authors' calculations. Data are multiply imputed and weighted.

Table 9: PD, EAD and LGD for all indebted households (Based on FM2: Goods and services (median))

	Type of shock	Size of shock	Mean PD	EAD in % of debt	LGD in % of debt	Growth of LGD relative to baseline
	No Shock Baseline		5.44	2.70	0.26	
Individual shocks	Interest Rate	+1 pp	5.47	2.77	0.26	1.00
		+2 pps	5.50	2.81	0.26	1.00
		+3 pps	5.73	3.41	0.26	1.00
	Unemployment	+1 pp	5.72	2.74	0.28	1.08
		+2 pps	5.78	2.76	0.29	1.10
		+3 pps	5.85	2.79	0.29	1.12
	Real Estate	-10%	5.44	2.70	0.35	1.36
		-20%	5.44	2.70	0.49	1.86
		-30%	5.44	2.70	0.62	2.39
	Liquid Assets (stocks, bonds; less liquid assets)	-10%; -20%	5.44	2.70	0.26	1.00
		-20%; -40%	5.44	2.70	0.26	1.00
		-30%; -60%	5.44	2.70	0.26	1.00
	Combined Shocks	Medium-Scale	6.18	2.93	0.54	2.09
		High-Scale	6.41	3.54	0.69	2.66

Source: HFCS, Authors' calculations. Data are multiply imputed and weighted.

Table 10: PD, EAD and LGD for all indebted households (Based on FM3: Food at home, utilities and 50% of food outside at home)

	Type of shock	Size of shock	Mean PD	EAD in % of debt	LGD in % of debt	Growth of LGD relative to baseline
	No Shock Baseline		3.35	1.63	0.04	
Individual shocks	Interest Rate	+1 pp	3.42	1.73	0.04	1.00
		+2 pps	3.47	1.80	0.04	1.00
		+3 pps	3.74	2.44	0.04	1.00
	Unemployment	+1 pp	3.71	1.70	0.08	1.73
		+2 pps	3.80	1.73	0.08	1.92
		+3 pps	3.91	1.79	0.09	2.14
	Real Estate	-10%	3.35	1.63	0.05	1.24
		-20%	3.35	1.63	0.10	2.41
		-30%	3.35	1.63	0.16	3.69
	Liquid Assets (stocks, bonds; less liquid assets)	-10%; -20%	3.35	1.63	0.04	1.00
		-20%; -40%	3.35	1.63	0.04	1.00
		-30%; -60%	3.35	1.63	0.04	1.00
	Combined Shocks	Medium-Scale	3.47	1.80	0.11	2.61
		High-Scale	3.74	2.44	0.18	4.13

Source: HFCS, Authors' calculations. Data are multiply imputed and weighted.

Table 11: PD, EAD and LGD for all indebted households (Based on FM4: Food at home, utilities and 50% of food outside at home (median))

	Type of shock	Size of shock	Mean PD	EAD in % of debt	LGD in % of debt	Growth of LGD relative to baseline
	No Shock Baseline		4.99	2.54	0.24	
Individual shocks	Interest Rate	+1 pp	5.03	2.63	0.24	1.00
		+2 pps	5.06	2.68	0.24	1.00
		+3 pps	5.08	2.72	0.24	1.00
	Unemployment	+1 pp	5.14	2.57	0.26	1.05
		+2 pps	5.17	2.58	0.26	1.06
		+3 pps	5.22	2.60	0.26	1.07
	Real Estate	-10%	4.99	2.54	0.33	1.35
		-20%	4.99	2.54	0.45	1.85
		-30%	6.24	2.58	0.58	2.37
	Liquid Assets (stocks, bonds; less liquid assets)	-10%; -20%	4.99	2.54	0.24	1.00
		-20%; -40%	4.99	2.54	0.24	1.00
		-30%; -60%	4.99	2.54	0.24	1.00
	Combined Shocks	Medium-Scale	5.37	2.71	0.49	2.02
		High-Scale	5.39	2.75	0.64	2.60

Source: HFCS, Authors' calculations. Data are multiply imputed and weighted.