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Household vulnerability in the euro area[1]

Katarzyna Bańkowska, Juha Honkkila, Sébastien Pérez-Duarte
and Lise Reynaert Lefebvre,
European Central Bank

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Household vulnerability in the euro area

Katarzyna Bańkowska, Juha Honkkila[1], Sébastien Pérez-Duarte and Lise Reynaert

Abstract

The distribution of income and wealth and the vulnerability of households have become important elements in the analysis of financial stability and the transmission of monetary policy. The economic and financial crisis has highlighted the significance of monitoring indebtedness and risk of debt default of households, not only at the macroeconomic level, but also at the individual level. However, while micro data are the key to understanding developments at the household level, there is a significant lag between data collection and data release. Particularly during times of rapid changes in the economy the timeliness of micro data is not sufficient for making relevant policy conclusions.

This paper addresses these issues in two steps. In the first one, it uses data from the European Household Finance and Consumption Survey (HFCS) to measure the vulnerability of households on various dimensions. These measures include information on household income, wealth and indebtedness, as well as debt burden indicators constructed from the monetary variables, such as debt-to-asset ratio and debt-service-to-income ratio, and combined measures. The vulnerability analysis is complemented with various subjective indicators collected in the HFCS. The impact of the recent economic crisis on household vulnerability is assessed by comparing the results of the two survey waves.

The second part of this paper evaluates different methodologies to combine information from timelier macro level sources with survey data to nowcast indicators on vulnerability. In a first approach we use observed distributions from survey data to break down macro level indicators. In a second approach we present the possible use of microsimulation techniques to estimate the impact of macro developments on individual households.

Keywords: household indebtedness, debt burden, vulnerability, survey, balance sheets

JEL classification: D140, D310

[1] Contact person: juha.honkkila@ecb.europa.eu, tel. +49 69 1344 3929. All authors are from the European Central Bank.

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Introduction

The economic and financial crisis has highlighted the significance of monitoring indebtedness and risk of debt default of households, not only at the macroeconomic level, but also at the individual level. With the use of the Household Finance and Consumption Survey (HFCS) microdata, we analyse whether the euro area households became more vulnerable during the financial crisis and present the main features of the potentially vulnerable households. In the first chapter, we analyse a set of measures used to assess the vulnerability of households. We find that in the euro area as a whole there was only a limited increase, from 11% in wave 1 to 13% in wave 2 in the share of potentially vulnerable households, while the heterogeneity across countries remains strong.

To address the issue of timeliness of the results available from HFCS, we present methodologies to draw distributional information from national accounts totals to get more up-to-date information from the developments of various types of households. In the second chapter, we analyse the ratio between debt and (adjusted) financial wealth. This indicator signals how well households can react to an income shock by amortising debt with liquid assets. The aim is to assess the impact of indebtedness on household vulnerability by combining national accounts data with HFCS data, making use of the strengths of both data sets. In the nowcasting exercise, we show how distributional national accounts data could be produced when new national accounts data are available, but distributional information is derived from the data from the previous survey wave. The main findings are that the exercise fails to capture important developments in the distribution of wealth and debt for some groups of households.

Another promising nowcasting technique is microsimulation. In chapter three, we review and analyse the empirical literature on the use of microdata to model the link between macroeconomic development and household distress. We also identify sources of up-to-date macro-level information that could be used at a European level and comment on the necessary adjustments to project HFCS micro-data to the latest period. Finally, in the last chapter, we conclude and present potential ways of improvement for future implementations.

1. Households vulnerability in the euro area

Despite the decreased share of indebted household in the euro area, the median debt burden (conditional on holding debt) has increased between the two waves of Household Finance and Consumption Survey (HFCS). With the use of the HFCS microdata we analyse whether the euro area households became more vulnerable during the financial crisis and what kind of households may be classified as potentially vulnerable. For that purpose in the first part of the paper we present the commonly used indebtedness indicators as a well as subjective indicators collected about income.

1.1 Data and overview of indicators

To investigate whether during the financial crisis the economic situation of households has changed and whether they have become more vulnerable this paper uses the microdata from both waves of the Household Finance and Consumption Survey (HFCS). The survey provides individual household data collected in a harmonised way. For the first wave the most common reference period was 2010 and for the second wave 2014, for more details sees HFCS (2016b). The data, with its rich information about the assets and liabilities of households, allows for the calculation of debt burden indicators and the analysis of the distribution of selected measures. Table 1.1 presents the definition of the selected measures of indebtedness and subjective measures of the overall income situation.

Definition of indicators on household debt burden and income situation

Table 1.1

Name of the indicators	Definition	Threshold
Debt service to income ratio (DSI)	The level of total monthly debt payments divided by gross monthly income, calculated for indebted households with debt payments	30%
Debt to income ratio (DI)	The level of outstanding total debt divided by the value of annual gross income	300%
Debt to asset ratio (DA)	The level of outstanding total debt divided by the value of household's total gross assets	90%
Low income	Income over the last 12 months was unusually low compared to an expected "normal" year income	NA
High expenses	Regular expenses over the last 12 months were higher than the income	NA

Notes: NA – not applicable

The burden of holding debt is analysed with the use of three commonly used indicators that focus on i) the financial burden of interest and loan repayments – debt service to income ratio (DSI) that reflects the burden of short-term commitments, ii) the level of outstanding debt compared to household income – debt to income ratio (DI) that informs about the debt sustainability in the medium to long term and iii) the level of outstanding debt compared to the value of household's assets – debt to asset ratio (DA) used to assess the ultimate capacity to pay back the debt. These indicators can be calculated for the indebted households, defined as those holding any type of mortgage or non-mortgage debt. While analysing the results the focus is given to the households that exceed a pre-defined threshold that in principle can point at possible difficulties to repay debt.

Another set of measures used to assess the vulnerability of households are the qualitative subjective indicators reported about their overall income situation. While (i) the first one identifies households whose income is defined as unusually low in the last 12 months compared to a "normal" year, ii) the second one reports on households whose expenses exceeded income over the last 12 months. In general, these indicators are reported for all the households, independently from the level of debt.

There are various combinations of measures that can reflect on the financial soundness of households or their economic situation, see for example D'Alessio and Iezzi (2015). Some of them may focus on the indebted households and their ability to pay back debt, while the others reflect more the availability of liquid assets, stability of income or households' ability to react to unpredictable negative shocks. In this paper we define the composite measure of vulnerability using the five indicators on debt burden and self-assessed income situation presented earlier. While the thresholds applied to the indicators for the indebted households are arbitrarily chosen, they are commonly used in the literature on households' indebtedness. The composite vulnerability measure proposed in this paper identifies a household as potentially vulnerable if the conditions for two or more of the indicators, as presented in Table 1.1, are met. These multiple indicators approach is sensitive to the shocks related to i) the interest rates ii) income and iii) accumulated assets thus not exclusively focusing on the ability to repay debt but also on the expenditure side of the low income households. Please see chapter 3 on how the impact of these shocks on financial vulnerability indicators can be modelled at household level.

1.2 Results

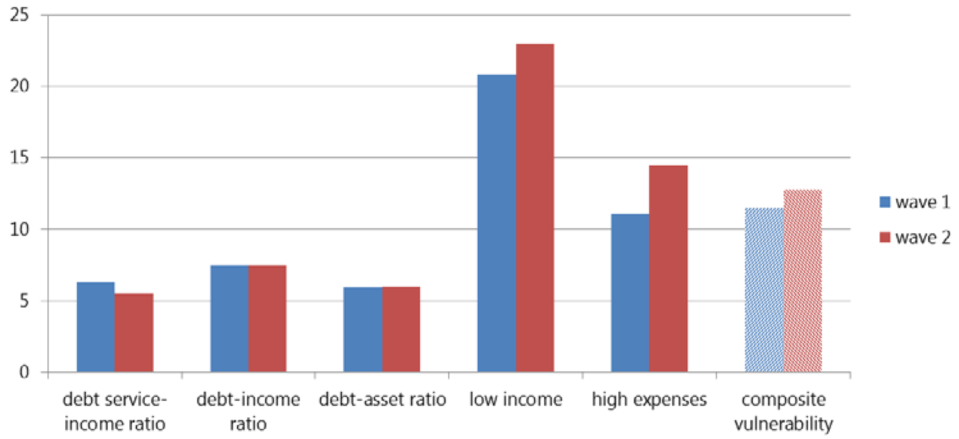
In this subsection we first present the results for each indicator of debt burden, self-assessed income situation and finally the composite vulnerability measure. We start with the share of households that fall into the predefined groups and comment on the overlaps of these indicators. In the next step we more closely look at households defined as potentially vulnerable to compare the cross country differences and changes over time. Finally, we present the main characteristics of the vulnerable groups and conclude.

When compared to wave 1, the share of indebted households in the euro area slightly declined in wave 2 (from 44.0% to 42.4%). The decrease was mainly driven by the lower debt participation rates of the upper part of the net wealth distribution, see HFCS (2016b). When looking however at the median outstanding amount of debt for the indebted households, it increased from EUR 24,000 to EUR 28,200 between the two waves. With the use of different measures we address the question of potential risk of households' unstable financial situation.

Figure 1.1 presents the shares of households that meet the criteria for a given indicator. The shares of the debt burden indicators above a certain threshold are in the range of 5% to 7% and stable across the two waves. These percentages are calculated out of all households not out of the indebted ones for the sake of calculating the composite vulnerability indicator that will apply also to all the households. When calculating the measures for households holding debt, the shares are between 13% and 18%. When looking at the subjective indicators reported about the overall income situation, 21% of households in wave 1 and 23% in wave 2 considered their income in the last 12 months as lower than average. At the same time 11% and 14% respectively reported that their regular expenses exceeded income.

Share of households in the euro area characterised by different measures, in %

Figure 1.1



Source: own calculations based on HFCS.

Note: euro area figures in wave 1 exclude FI, FR, IE, EE, LT, LV and in wave 2 exclude FI and LT. Thresholds for debt burden indicators as defined in Table 1.1.

Given various indicators of over-indebtedness and income situation, it is important to assess to what extent they overlap. The percentages presented in Table 1.2 show for each pair of indicators what the percentage of households is that meets both criteria (as defined by the column and the row of the table). Households who are identified as having large burden due to servicing debt (DSI) are in most of the cases also distinguished by high debt to income ratio (DI), which is not surprising. At the same time, only limited percentage of the households who assessed their income as low has been identified with a high debt burden indicator.

If we consider in general any combination of at least two indicators meeting the specific criteria, referred here as a composite vulnerability measure, we identify 11% and 13% of households in waves 1 and 2 respectively as potentially vulnerable, see Figure 1.1. Substantial differences across countries and time are presented in Figure 1.2. While the percentage of households defined as potentially vulnerable is below 10% in wave 2 in Italy, Austria, Malta, Germany and Belgium in strong contrast are countries affected mostly in the recent economic crisis. This measure increased substantially for Cyprus (from 28% to 40%) and Greece (from 13% to 25%) mainly due to high surge of the households with high debt to asset ratio and income identified as low in Cyprus. At the same time in Greece both low income and high expenses were reported by significantly higher share of households in wave 2. For Malta a severe drop was recorded (from 18% to 7%) because of the limited improvement in income in wave 2 compared to wave 1 that was however reflected well as a decrease of low income and high expenses measures.

Percentage of households in the euro area as defined by two indicators according to both the row and column criteria across waves

Table 1.2

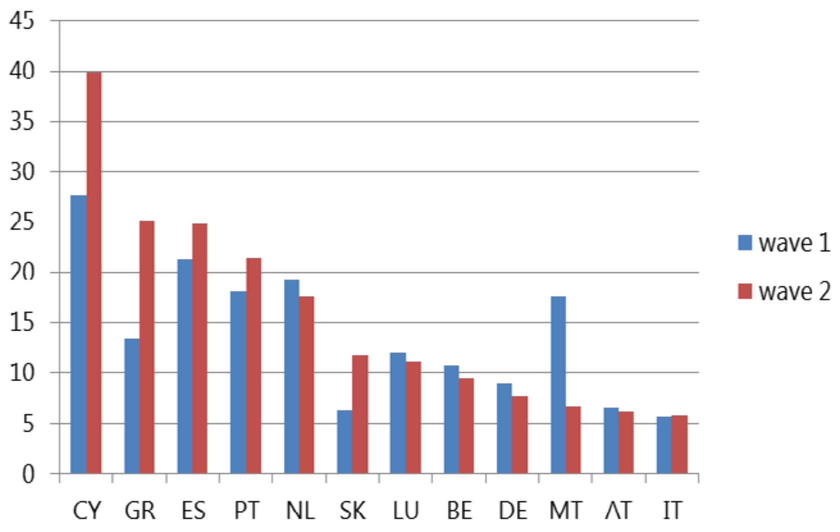
Wave 1	DSI	DI	DA	Low income	High expenses
DSI	6.3	4.2	1.2	2.4	1.5
DI	4.2	7.5	1.5	2.2	1.5
DA	1.2	1.5	5.9	1.6	1.6
Low income	2.4	2.2	1.6	20.8	4.6
High expenses	1.5	1.5	1.6	4.6	11.1
Wave 2					
DSI	5.5	3.6	1.0	2.2	1.5
DI	3.6	7.5	1.7	2.6	1.7
DA	1.0	1.7	6.0	1.5	1.7
Low income	2.2	2.6	1.5	23.0	6.1
High expenses	1.5	1.7	1.7	6.1	14.5

Source: own calculations based on HFCS.

Note: euro area figures in wave 1 exclude FI, FR, IE, EE, LT, LV and in wave 2 exclude FI and LT.

Share of vulnerable households by country and wave, in %

Figure 1.2



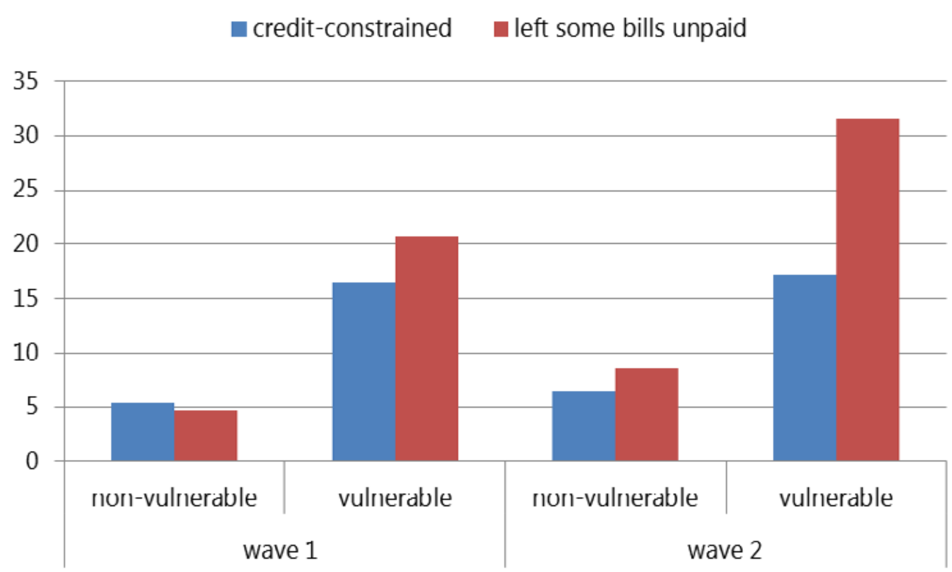
Source: own calculations based on HFCS.

Note: euro area figures in wave 1 exclude FI, FR, IE, EE, LT, LV and in wave 2 exclude FI and LT. Thresholds for debt burden indicators as defined in Table 1.1.

Focusing on the group of households classified as potentially vulnerable we identify some of their main features when compared to the other households. This group includes predominantly medium size households with 3-4 members with the mortgage on the household main residence (43% have the mortgage in the potentially vulnerable group compared to 16% in non-vulnerable one in wave 2). It also has substantially more households, as a proportion of the group that belong to the lowest income quintile and much less to the upper one. Taking the employment status of the reference person into consideration, there are more households for which that person is either self-employed or not working, but not retired. Other selected measures – the percentage of credit constrained households or those who left some bills unpaid point also at more financial difficulties for the potentially vulnerable households. As presented in Figure 1.3, these households are much more prone to be credit-constrained or not be able to pay all the bills. There were around 17% of households classified as credit-constrained in the vulnerable group while among the others there are only about 6%. These figures remained stable over the two waves considered. Substantial increase was reported however for the percentage of vulnerable households who left some bills unpaid. The indicator moved from 21% in wave 1 to 32% in wave 2 while the change for the non-vulnerable ones was much smaller (from 5% to 9% over the two waves).

Selected features by vulnerability groups in the euro area, in %

Figure 1.3



Source: own calculations based on HFCS.

Note: euro area figures in wave 1 exclude FI, FR, IE, EE, LT, LV and in wave 2 exclude FI and LT. Households are identified as potentially vulnerable if the conditions for two or more of the indicators, as presented in Table 1.1, are met.

While analysing different indicators reflecting the financial situation of households we conclude that there is a non-negligible share of households who can be classified as potentially vulnerable. Even if for the euro area as a whole there was only limited increase, from 11% in wave 1 to 13% in wave 2, the heterogeneity across countries remains strong. Furthermore, in case of the countries affected by the last economic crisis we also observe a substantial surge in the share of households defined as potentially vulnerable. With the HFCS data alone we are however not able to comment on any developments in the households financial situation in the most recent period, after 2014. For that reason in the next chapter of this paper we present a methodology to combine the information from the HFCS micro data with timelier macro aggregates from national accounts to address the issue of timeliness. Finally, in the third chapter we give an overview of microsimulation models used for nowcasting that are another way of computing the effect of recent macroeconomic changes on households.

2. Distributional information from National accounts

2.1 Motivation and literature

During the past decade, following the report by Stiglitz, Sen and Fitoussi (2009), substantial focus has been set on developing methodologies to derive distributional information from national accounts data on household sector income, consumption and wealth. The main motivation to produce distributional information from national accounts (NA) is timeliness. Usually there is a relatively large lag between the collection and release of survey data. Using methodologies to draw distributional information from NA totals could be used to get more up-to-date information from the developments of various types of households.

Most of the initiatives aiming to combine micro and macro data, such as the OECD Expert Group on disparities in a national accounts framework (see Zwijnenburg et al. 2016), have so far concentrated on income and consumption, since harmonised survey data on household wealth have not existed, unlike corresponding surveys on income and consumption. However, the Household Finance and Consumption Survey (HFCS), of which two waves have been conducted recently (HFCS 2016a), provide harmonised distributional information on household wealth for the euro area, Hungary and Poland. Outside Europe, household distribution tables combining micro and macro data have already been published by national statistical institutes of Canada and Australia (see van Rompaey, 2016 and Australian Bureau of Statistics, 2015).

This paper analyses the ratio between debt and (adjusted) financial wealth. This indicator signals, how well households can react to an income shock by amortising debt with liquid assets. The aim is to assess the impact of indebtedness on household vulnerability by combining NA data with HFCS data, making use of the strengths of both data sets. Empirical results are shown for the four biggest euro area countries, namely Germany, Spain, France and Italy. Although a limited set of countries and household breakdowns is shown, the methodology applied would allow calculating distributional indicators for any groups of households in any country conducting the HFCS or a corresponding wealth survey.

2.2 Methodology

The methodology applied in this paper to calculate distributional NA indicators follows broadly the one applied in the OECD Expert Group on disparities in a national accounts framework, where the estimation is done in five steps. In the first step, population adjustment is applied to national accounts figures. In the second step, relevant variables from both macro and micro sources are selected. In the third step, micro data are scaled to NA levels at the most detailed level possible. In the final steps households are clustered and relevant indicators are calculated.

The main difference to the OECD methodology is the procedure applied is in the second step. While the OECD expert group has decided to use the national accounts framework as the basis of estimation, this paper disregards wealth components that are not considered comparable across the two sources. A correspondence table presenting the comparability between various assets in HFCS and financial accounts is presented by Honkkila and Kavonius (2013), which indicates that some assets are available only in one of the two sources and for several types of financial wealth the comparability between the two sources is limited. Consequently, an adjusted concept of financial wealth is used in this paper, following the methodology of Kavonius and Honkkila (2016). This concept of adjusted financial wealth includes deposits, bonds, quoted shares, mutual funds and voluntary pension wealth.

In the measurement of distributional NA data, the level and structure of financial wealth is taken from NA and the distribution of each wealth component by household clusters (such as income quintile) is taken from the HFCS. Consequently, the sum of adjusted financial wealth (AFW), including *j=1 to y* wealth components, for household cluster *i*, where the household sector consists of *i=1 to x* clusters, is calculated as:

$$(1)\ AFW_i = \sum_{j=1}^{y}\left[\left(\frac{WH_{ij}}{\sum_{i=1}^{x} WH_{ij}}\right) * WN_j\right]$$

In equation (1), *WH* indicates wealth in the HFCS data and *WN* wealth in NA data.

Distributional NA data will be constructed in two different ways. First, data for the same period will be combined and the new indicators will reflect both the HFCS distribution and the NA structure of AFW at the same time *t* (first and second HFCS wave). Second, aiming to produce more timely indicators, the NA structure of wealth at time *t* (second HFCS wave) is broken down for household groups with HFCS distribution for time *t-1*, simulating a period where more recent distributional information is not available.

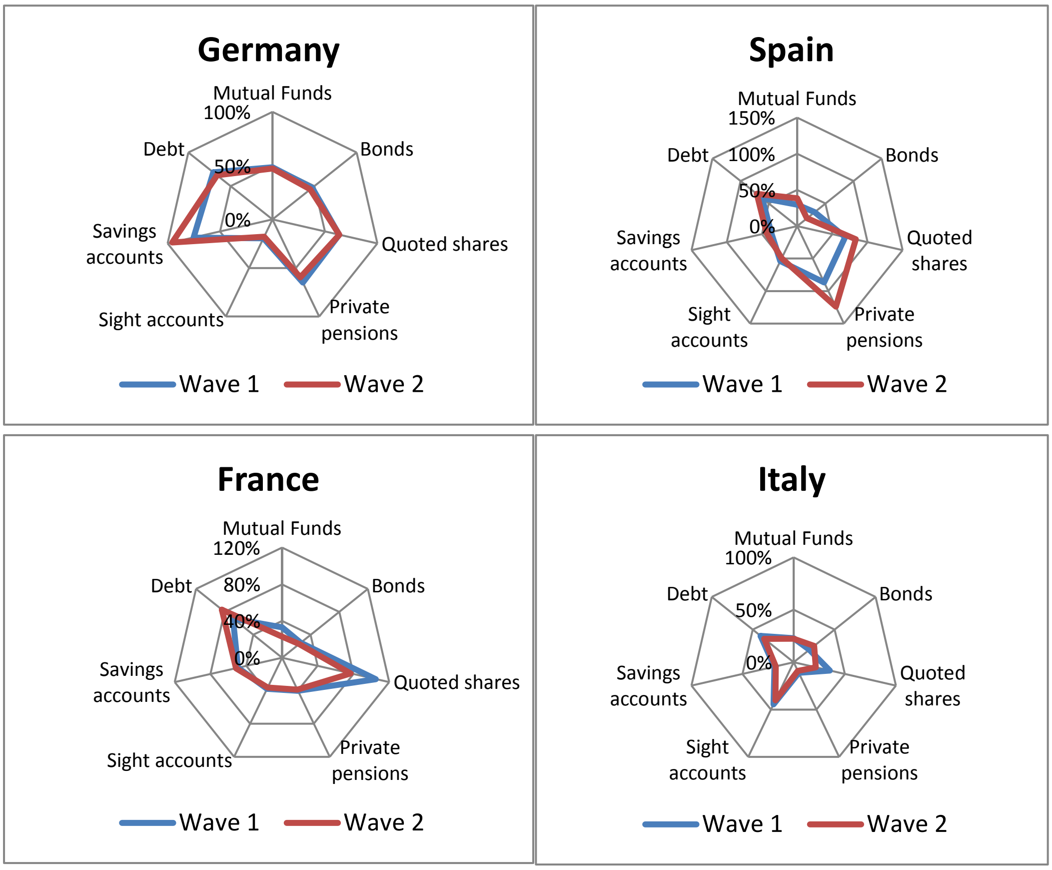
This methodology relies on two assumptions: i) reporting bias is not correlated with the indicator used to cluster the households (e.g. income) and ii) there is no sampling bias in the survey data, i.e. the distribution of the survey data reflects the true distribution. There are limited data available to assess the validity of the first assumption. Recent literature has tried to address the significance of the missing information from the upper tail of the wealth distribution (Vermeulen 2014). This paper does not intend to repeat these estimations, but recognises the need for further analysis on this topic.

2.3 Adjusting HFCS data on financial wealth to NA levels and structure

The first step in the calculation of distributional NA figures for adjusted financial wealth (AFW) is to multiply total sums of each individual wealth component with the inverse of the HFCS/NA coverage ratio. There are substantial differences between countries and between assets in the HFCS/NA coverage ratios (see Figure 2.1). The coverage ratios of adjusted financial wealth for the first / second HFCS wave are 55% (both waves) in Germany, 47% / 54% in Spain, 45% / 42% in France and 24% / 23% in Italy. For household debt, coverage ratios are higher in all countries, around 40% in Italy and between 62% and 84% in the three other countries. Except for a few individual cases the coverage ratios of individual assets in individual countries are relatively stable across the two survey waves. This indicates that the uncertainties in measurement are to a large extent systematic in individual countries and for individual wealth items. This observation is also a positive signal for the comparability between survey data across time in various countries.

HFCS/NA coverage ratio for selected assets and debt in Germany, Spain, France and Italy

Figure 2.1



Source: own calculations based on HFCS.

Note: Wave 1 refers to the year 2008 in Spain and the year 2010 in the other countries. Wave 2 refers to 2011 in Spain and 2014 in the other countries.

In the scaling up of HFCS data to NA totals, not only levels, but also distributions by different household clusters change. Because the adjusted financial wealth indicator is constructed from several components, the recalculated figures reflect the wealth structure of NA rather than the one of the HFCS. Reorganising equation (1), each wealth component will be multiplied by *WNj/WHj*. Consequently, if components that are more significant for wealthier household groups have lower coverage in the HFCS data, the distribution will become more unequal. For households' liabilities, the scaling of HFCS data up to NA levels has no impact on the distribution, since the concept of liabilities is consistent only at the aggregate level.

2.4 Empirical results

Figure 2.2 shows the differences of debt-to-adjusted financial wealth (DTAFW) ratios, i.e. sum of debt divided by sum of adjusted financial wealth for each gross income quintile, produced from HFCS and distributional NA data. There is a clear difference between the levels; the HFCS data provide higher levels of this indicator compared to NA. However, the differences between income quintiles are in most cases relatively small. There are several reasons for the difference between levels:

i) Underreporting of wealth by households

In a survey, wealth data are based on self-assessment of households. It is probable that households are not always able to provide accurate estimates of their financial wealth holdings. Underreporting has been observed to be more pronounced in the case of financial wealth than for liabilities. If we assume that underreporting is not correlated to the attributes used to group households, NA adjustment improves the measurements of DTAFW ratios by household groups.

ii) Sampling bias

Survey data are usually unable to capture information from the wealthiest households, who possess a significant share of total wealth, but probably a much smaller share of household debt. Adjusting wealth data to NA levels without capturing the missing tail of the wealth distribution will lead to an overestimation of financial wealth and underestimation of DTAFW ratios for the poorer household groups. In that sense the distributional NA data may provide biased results.

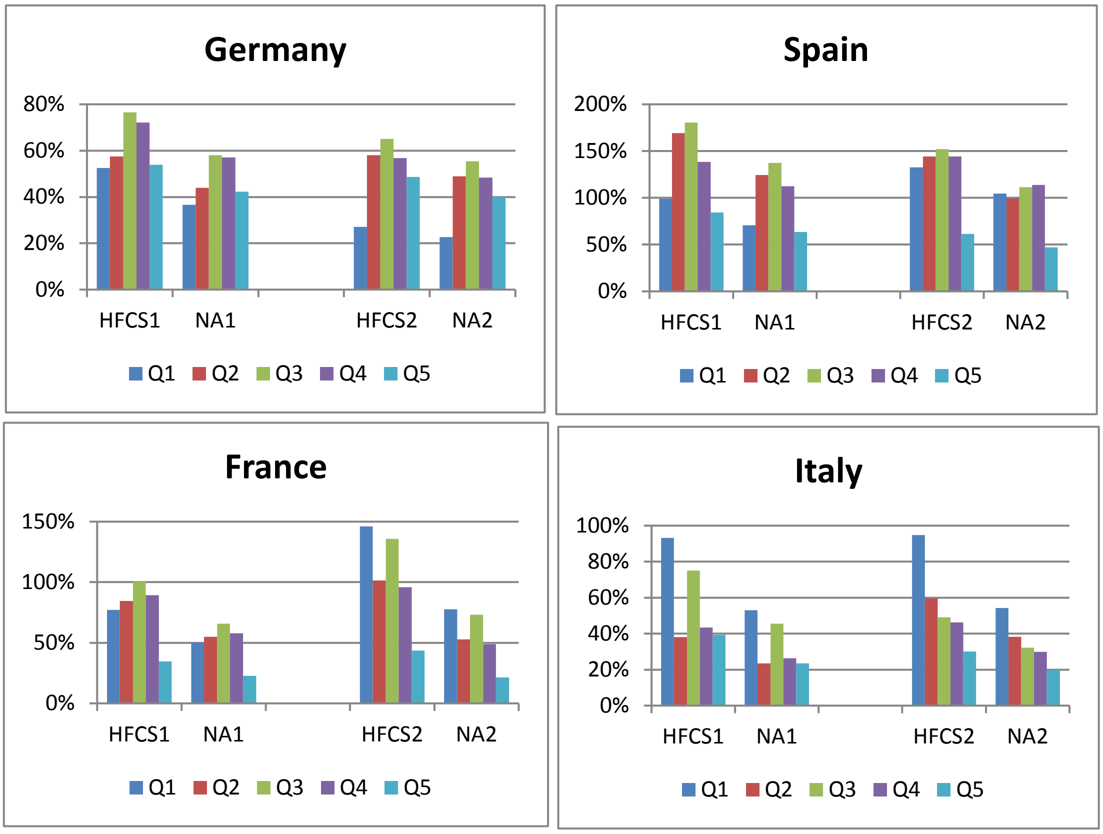
iii) Delineation between private and business wealth

Part of the missing wealth in the AFW concept can be included in the survey data under the variable "self-employment business wealth". This item is classified as real wealth in the HFCS. Small entrepreneurs who are not able to make a distinction between private and business wealth may report financial assets that NA classifies under the household sector, as business wealth. Similarly, NA data on household wealth are based on counterpart information. The delineation between households and small private businesses is not straight forward, and households' financial wealth in NA may include assets that are not classified as financial wealth of the household sector in the HFCS.

Nonetheless, both approaches of data collection serve very well the purposes of the corresponding statistics. The HFCS aims at providing distributional information of household wealth and indebtedness, and most valuable indicators are ones that describe events at certain points of distribution or ones that indicate the share of households owning certain assets or holding certain types of debt. Financial accounts aim at providing a comprehensive picture of wealth and indebtedness at the whole economy level. Due to the balancing adjustments some inaccuracy may need to be allowed for the household sector, and naturally NA data lacks any distributional information.

Debt-to-adjusted financial wealth ratios by income quintile in HFCS and distributional national accounts

Figure 2.2



Source: own calculations based on HFCS.

Note: Wave 1 refers to the year 2008 in Spain and the year 2010 in the other countries. Wave 2 refers to 2011 in Spain and 2014 in the other countries.

As a last step, we look at how changes in DTAFW and its components could be estimated for household groups in a timely manner, using distributional information from past surveys. The methodology used here is a simple one, combining two sets of indicators from publicly available statistical sources, with no intention to estimate the impact of the macro level changes on the distributions.

Figures 2.3 show the changes in AFW, debt and DTAFW for gross income quintiles in Germany, Spain, France and Italy. The first bars – called 'N' for nowcasting and marked with a pattern fill – show a simulation of how distributional NA data could be produced when new NA data are available, but distributional information is derived from the data from the previous survey wave. This approach takes into account the changes in the levels as well as in the structure of financial wealth by wealth components, but is unable to capture the changes in the distribution of wealth and indebtedness. Any changes in the distribution of wealth are caused by the change in the share of individual wealth components in the households' portfolios.

The second bars – called 'A' for actual – compare NA adjusted data from both waves, showing the results that can be acquired when the new survey data become available. This approach takes into account the changes in the levels and the structure of financial wealth by wealth components, as well as the differences in the distribution of individual wealth components and debt between different household groups.

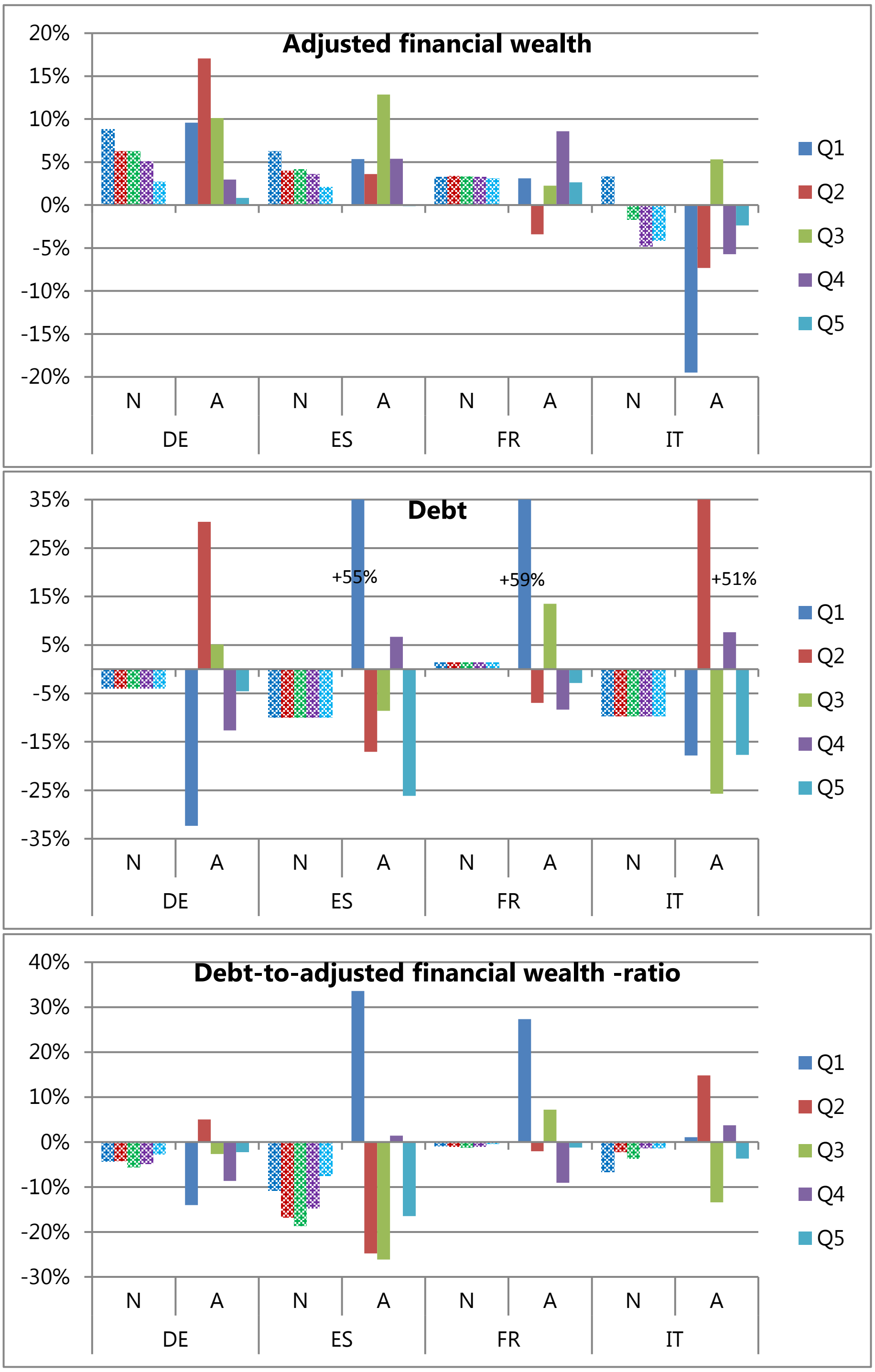
Both sets of calculations have the same denominator, and the difference between the changes show how much bias will be caused by assuming a stable distribution of financial wealth components and debt. Changes in adjusted financial wealth and debt are shown in percentages, changes in the debt to adjusted financial wealth ratio in percentage points.

For all indicators, this nowcasting exercise fails to capture important developments in the distribution of wealth and debt for some groups of households, particularly in the bottom part of the income distribution. In the case of adjusted financial wealth, the differences between nowcasting and actual data are still mostly within a manageable degree. More biased results are observed for changes in debt by income quintile at the bottom of the distribution. The bias in the estimation of debt is caused by two reasons: first of all, household indebtedness has declined during the crisis, and low income households are more frequently credit constrained (HFCS 2016b). On the other hand, many households who incurred debt before the crisis have experienced an income shock and fallen to the bottom of the income distribution, increasing the average debt in the bottom part of the distribution.

As a consequence of rapidly changing distributions of both financial wealth and debt, this nowcasting exercise fails also in providing reliable estimates of the debt-to-adjusted financial wealth –ratios for several parts of the distribution. While some changes more or less cancel each other out (increase in both wealth and debt for Q2 in Germany, decrease in both wealth and debt for Q1 in Italy), simply applying past distributions for relatively large clusters of households is not sufficient to get good estimates of household indebtedness and vulnerability, at least during times of financial crisis. A more promising solution would be to apply some types of microsimulation models to estimate the macro developments at the micro level.

Comparison of changes in AFW, debt and DTAFW ratio: nowcasting and actual distributional NA data

Figure 2.3



Source: own calculations based on HFCS.

3. The way forward: nowcasting with microsimulation models

Microsimulation constitutes another promising nowcasting technique. Instead of calibrating microdata to National Accounts, this technique consists in simulating the effect of recent macroeconomic changes on households, at a micro level, in order to draw conclusions that apply to higher levels of aggregation. These models are based on an analytical representation of specific financial, economic and institutional constraints faced by households (static or cross-sectional component), their behavioural response to the modification of these constraints (behavioural component) and - if possible - the way of adapting their behaviour overtime (dynamic or longitudinal component). Nowcasting microsimulation models depend on the availability and quality of microdata[2] and timely macro information, as well as micro-economic understanding of household behaviour. Although no microsimulation model - as fine-tuned as it could be - is an adequate substitute for a new collection of microdata, the method can preserve important layers of idiosyncrasy and provide reliable answer to questions where timeliness is important[3]. In addition, microsimulations are also widely used to stress test households under various hypothetical shock scenarios, even if no single model can provide a comprehensive account of all possible risk factors.

Several microsimulation studies originating mostly from NCBs already focused on household financial distress, with a view to better assess the risks to financial stability by looking into the accumulation of imbalances in the household sector. These studies quantify the impact on financial stability by simulating changes or shocks in household income, employment and balance sheet thanks to static microsimulation models. Overall, the impact of these changes depends on household heterogeneity, as holdings of different types of assets and liabilities differ according to economic and socio-demographic characteristics, as well as country specific institutional factor. For example, countries where mortgages have more adjustable-rate are more affected by an interest rate shock.

In this section, we aim at reviewing and analysing the empirical literature on the use of microdata to model the link between macroeconomic development and household distress. We first present an overview of the existing literature and identify sources of up-to-date macro-level information that could be used at a European level. We then describe in more detail the necessary adjustments to project HFCS micro-data forward to "now". Finally, we mention potential ways of improvement for future implementations.

3.1 An overview of empirical literature

So far, to our knowledge, only Ampudia et al. (2014a and 2014b) implemented a microsimulation framework using the HFCS at the euro area level, both to nowcast

[2] Administrative data, census data, household survey data, synthetic dataset, etc.

[3] This is worth noticing that some of the empirical literature (Sutherland, 2013), have concentrated on nowcasting income, poverty risk and inequality in a 2-3 years horizon using EU-SILC together with the European Union tax-benefit microsimulation model EUROMOD.

and stress test households' financial vulnerability. The six country specific studies that used the HFCS are Albacete and Fessler (2010) for Austria[4], IMF (2012) for Spain, IMF (2013), Michelangeli and Pietrunti (2014) and Bettocchi et al. (2016) for Italy, and Meriküll and Rõõm (2017) for Estonia.

Other European national studies used Household Budget Surveys, like Galuščák et al. (2014) for Czech Republic or Zajączkowski and Żochowski (2007) for Poland, or income surveys like Herrala and Kauko (2007) for Finland, or Danmarks Nationalbank Financial Stability Report (2007).

Outside Europe, Bank of Canada notably implemented a dynamic and flexible microsimulation framework (Peterson and Roberts, 2016[5]), extending the analysis to a multi-year horizon by allowing risks to evolve overtime. The Federal Reserve Bank of St. Louis (Krimmel et al., 2013) updated mechanically the Survey of Consumer Finances microdata using financial accounts and other macro data sources. Finally, the Reserve Bank of Australia also carried out a stress-test (Bilston et al., 2015) that shares many features with Albacete and Fessler (2010).

Please see Table A in annex for a non-exhaustive overview of empirical literature linking household financial vulnerability and macroeconomic developments.

A common structure

All of these studies display a common structure. First, a measure of financial distress and the macroeconomic changes or shocks are defined, and then the impact on the households' distress measure of the macroeconomic changes is quantified. Finally, the impact on the banks is analysed thanks to measures like exposure at default and losses given default[6].

The first step consists in choosing a measure to classify a household as financially vulnerable. Most studies used indicators relating to households' monthly cash flow position, i.e. either the financial margin[7] like Johansson and Persson (2006), Herrala and Kauko (2007), Zajączkowski and Żochowski (2007), Danmarks Nationalbank Financial Stability report (2007), Sveriges Riksbank Financial Stability Report (2009), Albacete and Fessler (2010), Galuščák et al. (2014), Bettocchi et al. (2016) or the debt-service-to-income-ratio like Djoudad (2010), IMF (2012) for Spain, IMF (2013) for Italy, Michelangeli and Pietrunti (2014). Ampudia et al. (2014b) put forward a comprehensive measure of financial distress that takes into account liquidity and

4 Apart from HFCS, Albacete and Fessler (2010) also used EU-SILC, the Austrian Consumption Survey to determine the minimum expense, and a Survey on Financial Household Wealth.

5 This report combines, updates, and expands on content from reports and discussion papers that have previously been published on this topic (Faruqui et al. (2012) and Djoudad (2010, 2012)) by the Bank of Canada.

6 Exposure at default represents the debt held by vulnerable households as a percentage of total debt. Losses given default represents the potential losses faced by the banking sector as a percentage of total debt.

7 The financial margin is defined as income net of debt service costs and essential living costs. The current empirical literature have taken different approaches to defining essential living costs: Bilston et al, (2015), Ampudia et al (2014) and Meriküll and Rõõm (2017) defined it as the poverty line, Albacete and Fessler (2010) as the household self-reported minimum subsistence level, and Galuščák et al. (2016) as the consumption of food, energy, health and rent.

solvency, since only if those two conditions are met the household is forced to default. Bettocchi et al. (2016) used this alternative measure of financial distress.

The macroeconomic changes or shocks, and their modelling are then determined. Risk factors that are frequently analysed in the literature are interest rates, asset prices, unemployment and income, while changes in debt, expenditures, inflation and exchange rates have been less often implemented. A stochastic component is introduced to incorporate household heterogeneity in the modelling of macroeconomic developments, mostly for income growth (Ampudia et al., 2014; Michelangeli and Pietrunti; 2014), unemployment (Djoudad 2010; Ampudia et al., 2014; Zajączkowski and Żochowski, 2007; Albacete and Fessler, 2010; Peterson and Roberts, 2016) and debt growth (Peterson and Roberts, 2016);

Finally, the impact on the households' distress measure of the macroeconomic changes is quantified, and the impact on the banks analysed. When the modelling includes a stochastic component, these steps were usually repeated in a Monte Carlo simulation from 50 to 1,000 times and the vulnerability indicators are calculated in each step, and the means are then computed over all the simulated draws (Johansson and Persson, 2006; Zajączkowski and Żochowski, 2007; Danmarks Nationalbank Financial Stability report, 2007; Albacete and Fessler, 2010; Michelangeli and Pietrunti, 2014). Monte Carlo simulations can then be used to assess statistical significance. Confidence intervals are only provided in Michelangeli and Pietrunti, (2014).

3.2 Macrodata availability

One of the main challenges in nowcasting is to identify sources of timely, comparable across countries and consistent macro-level information on the important dimensions with a sufficient level of details. In addition, when integrating micro and macro data sources in such a simulation exercise, an important issue consists in reconciling the economic concepts and measurement used in the two data sources.

Euro Area Accounts (EAA) provide a consistent and comprehensive information on recent[8] macroeconomic developments by institutional sectors, and therefore for the households. It covers the three dimensions of interest for household financial vulnerability: consumption, income and wealth. However, not all variables are comparable between the EAA and the HFCS and therefore some adjustments must be made. See Honkkila and Kavonius (2013) for a bridging table comparing various assets, income and liability in both sources.

Regarding labour market changes, we can resort on information from the EU Labour Force Survey (LFS). However, we need to take into account that labour market concepts do not align perfectly between the HFCS and LFS. The most up-to-date source of LFS information is the quarterly aggregate statistics published by Eurostat, which are made available three to four months after the end of the reference quarter. These provide estimates by three sets of characteristics: age group, gender and education level (a total of 18 strata).

[8] The EAA are published about four months after the end of the reference quarter.

In addition to EAA and LFS information, Ampudia et al. (2014 a) also resorted to house price indexes, and indexes of quoted and unquoted stocks, and bonds.

3.3 Components of the nowcasting process

Most studies have used microsimulation models to stress test households, while rather few[9] introduced a nowcasting part in a short to medium time horizon – i.e. one to three years - (Johansson and Persson, 2006; Djoudad 2010; IMF, 2012; Michelangeli and Pietrunti, 2014; Ampudia et al. Aug. 2014a; Bettocchi et al., 2016). Peterson and Roberts (2016) focused on a longer time horizon of three to five years.

The traditional adjustments necessary to project HFCS micro-data forward to "now" consist of three components:

1) Updating mechanically income, asset prices, and debt service from the reference income year or balance sheet year to the point in time corresponding to the latest published indexes, and possibly to macro-level forecasts or assumptions.

2) Accounting for labour market change and debt growth rate between the reference year and the most recently available information. These adjustments can incorporate household heterogeneity by allowing the labour market status or debt growth of each household to depend on its specific socioeconomic characteristics and certain empirical relationships.

3) Accounting for demographic and compositional change. In case of no major demographic or compositional shift during the time lag, this step could be avoided. However, it is possible that in time of rapid economic change, the effects of economic migration for example could have an impact on the results.

Updating wealth, income and debt service

To approximate the evolution of the distribution of wealth, income and debt service, Ampudia et al. (2014a) and Krimmel et al. (2013) updated the valuation of the different asset types, income components and rate of debt service with country-level aggregate data. These adjustments to asset values and income are only estimates, as each household will experience its own specific change. However, these indexes capture the average movement of asset values and income since the last wave of the HFCS.

Put into practice, Ampudia et al. (2014a) used the following external information to estimate changes in asset valuation: house price indexes, Harmonised Indices of Consumer Prices (HICP), and indexes of quoted and unquoted shares, and bonds. As for changes in income, an extension was also performed using wages per employee, gross operating surplus and mixed income, interests and HICP. In addition, the debt service was adjusted for the adjustable-rate mortgages, assuming a complete pass-through[10].

Modelling labour market changes

9 Only one-third of the microsimulation papers introduced a nowcasting exercise.

10 Assessing the pass-through of interest rates to lending rates is quite challenging, considering that that the microsimulation is at a Euro Area level and that each country has different financial products and banking practices.

Estimating the impact of changes in work status on household income and therefore on their financial margin consists in two steps: first, the work status for each individual is simulated and then, for those whose work status changed, the income is appropriately adjusted.

In addition, Peterson and Roberts (2016) introduced the duration of unemployment as another source of uncertainty.

Changes in work status

Regarding the first step, the simplest approaches assume equal unemployment risk across individuals (Johansson and Persson, 2006; Herrala and Kaukko, 2007), while more advanced approaches take into account the fact that individuals with different personal characteristics such as age, gender and education have a different propensity for becoming unemployed (Albacete and Fessler, 2010; Bilston et al., 2015; Meriküll and Rõõm (2017), Galuščák et al., 2016; Ampudia et al., 2014b, and Bańbuła et al., 2015). The three last studies also modelled transitions from unemployment to employment, in addition to the probability of becoming unemployed.

Albacete and Fessler (2010), Ampudia et al. (2014), Meriküll and Rõõm (2017) used a quite similar approach to simulate the change in work status. For each individual (or employed head), the probability of becoming unemployed is determined in relation to demographic and socio-economic characteristics. A rise in the unemployment rate is simulated by increasing this estimated probability by a shock. Ampudia et al. (2014a) introduced a sector-specific shock and accounts for the fact that unemployment exhibits different dynamics across economic sectors. If the increased probability of being unemployed is greater than a random number drawn from a uniform distribution, the person is assumed to be unemployed and receiving unemployment benefit.

Income adjustment

For the newly employed workers, the employment benefits are replaced with predicted labor income (Ampudia et al., 2014), while the labor income of the newly unemployed individual are replaced with unemployment benefits. These unemployment benefits are often computed roughly using the long term net replacement rates (Albacete and Fessler, 2010; IMF, 2012; Ampudia et al, 2014, Meriküll and Rõõm, 2017). Some national studies tried to simulate their national unemployment benefit system (Herrala and Kauko, 2007; Danmarks National bank Financial Stability report, 2007; Galuščák et al., 2014).

Modelling debt growth rate

The simplest approaches simply update debt growth rate (Johansson and Persson, 2006; Herrala and Kauko, 2007). A slightly more complex method by Michelangeli and Pietrunti (2014) for the Italian HFCS, distinguishes between existing debt and new originations. For new mortgage originations[11], they used pseudo-panel groups based on the last three waves to compute the number of new originations. For each group, the number of new mortgages is kept constant. To

[11] A new mortgage origination occurs when a household has a mortgage debt equal to zero at time t-1 and a positive mortgage debt at time t.

each household with a new mortgage, a debt amount is assigned and it equals the mean debt at origination for households belonging to the same group who had an origination between the last two waves. The amount of debt associated with new originations is then adjusted to match the macro data.

Ampudia et al. (2014a) and Peterson and Roberts (2017) incorporated household heterogeneity in debt growth dynamics by allowing the growth of each household's debt to depend on its specific socioeconomic characteristics and certain empirical relationship. Ampudia et al. uses the logic of life-cycle behaviour by trying to approximate life-cycle profile of debt holding, while Peterson and Roberts makes a specific distinction between first-time homebuyers, who have yet to contract mortgage debt, and all others. To be eligible to be a first-time homebuyer, a household must first satisfy certain demographic conditions and then be able to afford to purchase a starter home in the region in which it lives.

Accounting for demographic changes

So far, to our knowledge, all nowcasting microsimulation exercises regarding household financial distress kept constant the information on demographic characteristics of individuals. Except in exceptional circumstances this should not pose a problem when simulating policy changes within a short-term time frame, as major demographic or compositional shifts are unlikely. However, it is worth noticing that a lag longer than three year may be vulnerable to shifts in household characteristics.

In such cases the appropriate methodology would be re-weighting, as an explicit simulation would require the full power of a dynamic microsimulation model.

Re-weighting for this kind of change requires up-to-date information on the dimensions to be changed. Further work is required to establish whether such information exists, how up-to-date and comparable across countries it is and whether it is available in a form that is consistent with corresponding variables in the HFCS.

Multi-country microsimulation

The main methodological choice when implementing a multi-country microsimulation is whether to assemble together models built for the purpose of national analysis, or to build a model that covers many countries in a consistent way (like Ampudia et al., 2014b). In principle, microsimulation analysis could be carried out using side by side a set of pre-existing national models. However, in our case, it is highly unlikely that national models would be made available at the Euro Area level.

Model validation

It is important to validate the model in order to assess its reliability and the validity of its main mechanisms. For the nowcasting part, an ex post analysis or a cross-check with alternative data could be implemented. The ex post analysis consists in running the model forward from one wave of the survey to the next published one (e.g. from 2010 to 2014), the "nowcasted" results could be compared to what has actually happened. The cross-check analysis consists in comparing the results with an alternative data source. Michelangeli and Pietrunti (2014), and Peterson and Roberts (2016) performed an ex post analysis, while Ampudia et al.

(2014a) cross-checked with the preview of results of the 2011 wave of the Spanish Survey of Household Finances (EFF).

All of these three validation checks had positive conclusions about the validity of the models mechanisms. Michelangeli and Pietrunti (2014) found that they are able to replicate quite well the percentage of vulnerable households in 2010 and 2012 starting from the 2008 and 2010 waves. Peterson and Roberts (2016) also found that overall the backtesting exercise provides evidence of the validity of the main mechanism of their model. However, while their model can produce an increase in financial distress of a similar magnitude, this increase is delayed by a couple of quarters. Peterson and Roberts explained this delay by the fact that their model does not account for forward-looking behaviour, which might otherwise contribute to a certain extent to strategic default. Ampudia et al. (2014a) found that their approximation matches quite closely the income and net wealth medians.

4. Conclusion

In this paper, we aim at assessing whether euro area households became more vulnerable in the context of the financial crisis using HFCS microdata. We defined a household as vulnerable if the conditions for two or more indicators on debt burden and self-assessed income situation are met. This definition has the advantage not only to focus on the ability to repay debt, but also on the expenditure side of the low income households.

The share of households defined as vulnerable is non-negligible and increased slightly in the euro area between 2010 and 2014. However, the heterogeneity across countries remains strong. In particular, among countries affected by the last economic crisis, the share of potentially vulnerable households surged.

To nowcast the vulnerability indicators after 2014, timelier macro level sources were combined with HFCS data. The method we implemented consists in drawing distributional information from national accounts totals. However, the *ex post* analysis had negative conclusions about the validity of this method, due to the rapidly changing distributions of both financial wealth and debt.

In a second approach we present the possible and promising use of microsimulation modelling to nowcast vulnerability indicators through a review of literature.

Possible future direction

The microsimulation models that have been implemented so far take into account as much as possible household heterogeneity in terms of income, portfolio structure and age, and include a high degree of micro detail. All of these models except Peterson and Roberts (2016) are static, as they evaluate immediate distributional impact upon household of macroeconomic developments without reference to the time dimension. Peterson and Roberts extended the static models by allowing individuals to change their characteristics due to endogenous factors within the model and let households evolve overtime, in a three to five years horizon. Compared with static models, this dynamic simulation model comes with a cost: it is more complex to develop, to comprehend and control, and has more methodological challenges.

It is essential to properly validate this kind of static model before increasing its complexity by adding dynamic and behavioural components. This validation would help determine the validity and reliability of its mechanism, and whether further complexity would be desirable. Unfortunately, so far, only limited validation has been performed due notably to the unavailability of two consecutive waves of the HFCS at the time of the nowcasting exercise.

For future directions, a realistic strategy would be to implement a very detailed static microsimulation model based on what was already implemented. In addition to what was already done, the demographic changes and other changes in the structure of the population or asset ownership could also be taken into account with a re-weighting method. The model reliability should then be fully evaluated using ex post analysis, and the results would help determine whether further refinements are necessary. The first static version of the model could then be expanded into a more complex one.

As a possible refinement, Ampudia et al. (2014a) proposed to further improve household behavioural responses: one could consider life-cycle models, such as "consumption-saving choices under uncertainty, portfolio choice, borrowing for housing and durable consumption goods, saving for retirement". Ampudia et al. also suggested to better model income and social benefits in case of unemployment (e.g. see Rehder Harris, 2005).

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Non exhaustive overview of current empirical literature linking household financial vulnerability and macroeconomic developments Table A

	Country	Microdata source	Measure of financial vulnerability	Nowcasting?	Stress-testing?	Static/ Dynamic	Monte-carlo simulations?	Model validation?
Johansson and Persson (2006)	Sweden	Wealth and income data (HEK)	Negative financial margin (FM)	Yes: from 2004 to 2005	Yes	Static	Yes: 1000 iterations	No
Herrala and Kauko (2007)	Finland	Income data	Negative (FM + pledgeable amount of wealth)	Yes: from 2004 to 2005	Yes	Static	No	No
Zajączkowski and Żochowski (2007)	Poland	Household Budget Survey	Negative FM	No	Yes	Static	Yes: 1000 iterations	No
Danmarks Nationalbank Financial Stability report (2007)	Danmarks	Income data	Negative FM	No	Yes	Static	Yes: 500 iterations	No
Sveriges Riksbank Financial Stability Report (2009)	Sweden	Wealth and income data (HEK)	Negative FM	No	Yes	Static	No	No
Albacete and Fessler (2010)	Austria	Household Finance and Consumption Survey (HFCS)	Negative FM	No	Yes	Static	Yes: 1000 iterations	No
Djoudad (2010)	Canada	Canadian Financial Monitor survey	DSTI > 30%	Yes	Yes	Static	No	No
Sugawara and Zalduendo (2011)	Croatia	Household Budget Survey	1) Negative FM 2) DSTI > 35%	No	Yes	Static	No	No
IMF (2011)	UK	NMG Consulting survey	DSTI > 40%	No	Yes	Static	No	No
Faruqui et al. (2012)	Canada	Canadian Financial Monitor survey	DSTI > 40%	No	Yes	Dynamic	No	No
IMF (2012)	Spain	HFCS	DSTI > 40%	Yes: from 2008 to 2011	Yes	Static	No	No
IMF (2013)	Italy	HFCS	DSTI > 30%	No	Yes	Static	No	No
Michelangeli and Pietrunti (2014)	Italy	HFCS	DSTI > 30% and income below the median in population	Yes	Yes	Static	Yes: 50 iterations	Yes: ex post analysis
Galuščák et al. (2014)	Czech Republic	Household Budget Survey	Negative FM	No	Yes	Static	No	No
Ampudia et al. (2014a)	Euro Area	HFCS	-	Yes: from 2010 to 2013	No	Static	No	Yes: cross-check with alternative data
Ampudia et al. (2014b)	Euro Area	HFCS	Negative FM and negative cash flow > liquid assets for a certain timescale	No	Yes	Static	No	No
Bilston et al. (2015)	Australia	Household, Income and Labour Dynamics (HILDA)	Negative financial margin (FM)	No	Yes	Static	Yes: 1000 iterations	No
Bettocchi et al. (2016)	Italy	HFCS	Negative FM and negative cash flow > liquid assets for a certain timescale	Yes: from 2014 to 2017	Yes	Static	No	No
Peterson and Roberts (2016)	Canada	Canadian Financial Monitor survey	DSTI > 40%	Yes: 3 to 5 years	Yes	Dynamic	No	Yes: ex post analysis
Meriküll and Rõõm (2017)	Estonia	HFCS	Negative FM and negative cash flow > liquid assets for a certain timescale	No	Yes	Static	Yes: 1000 iterations	No

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IFC-National Bank of Belgium Workshop on "*Data needs and Statistics compilation for macroprudential analysis*"

Brussels, Belgium, 18-19 May 2017

Household vulnerability in the euro area[1]

Katarzyna Bańkowska, Juha Honkkila, Sébastien Pérez-Duarte and Lise Reynaert Lefebvre,
European Central Bank

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

EUROPEAN CENTRAL BANK
EUROSYSTEM

Katarzyna Bańkowska
Juha Honkkila
Sébastien Pérez-Duarte
Lise Reynaert

DG-Statistics, European Central Bank

Household vulnerability in the euro area

IFC-NBB Workshop
Data needs and statistics compilation for macroprudential analysis
19 May 2017, Brussels

Overview

1 Introduction

2 Vulnerability of households

3 Nowcasting by adjusting HFCS data to NA levels and structure

4 Nowcasting with microsimulation modelling

5 Conclusion

Introduction

- **Motivation:**

Households asset-liability matching

Behaviour of sub-population

Financial stability analysis

- **Dataset:**

HFCS

Household Finance and Consumption Survey

- Data mostly for 2010 and 2014
- Available every 3 years
- Euro area countries (without LT), Hungary and Poland
- Cross-country comparable micro data on assets and liabilities, income, consumption and credit constraints

Measures of vulnerability

A. Focused on debt burden for indebted households (from the perspective of repaying debt):

- Debt service to income ratio (threshold: > 30%) – financial burden of interest and loan repayments;
- Debt to income ratio (threshold: > 300%) – level of outstanding debt compared to household income;
- Debt to asset ratio (threshold > 90%) – level of outstanding debt compared to the values of household's assets.

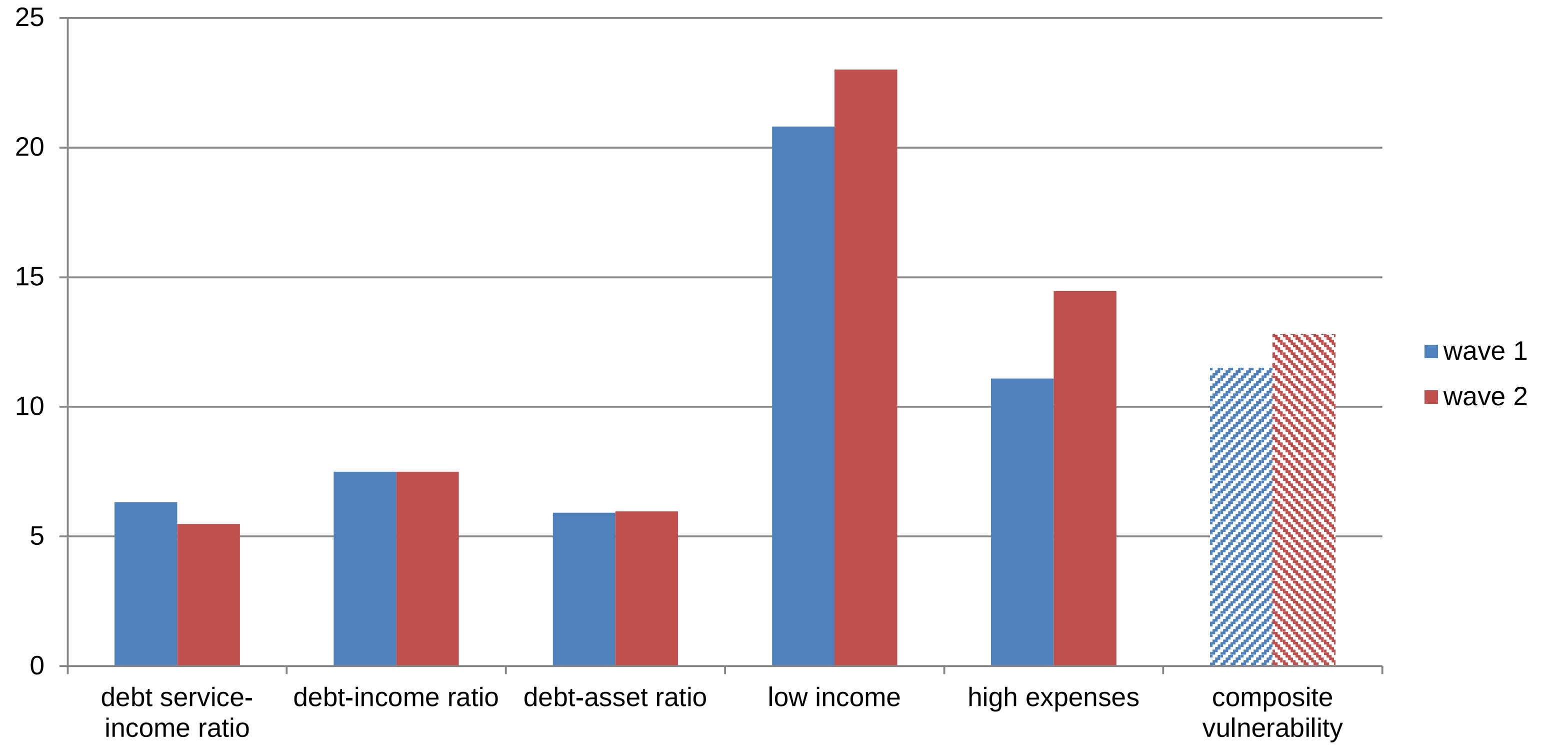
B. Focused on the overall income situation (from the perspective of affecting consumption), qualitative self-assessment:

- Income defined as "low" in the reference period of 12 months;
- Expenses exceed income in the last 12 month.

Composite measures of vulnerability

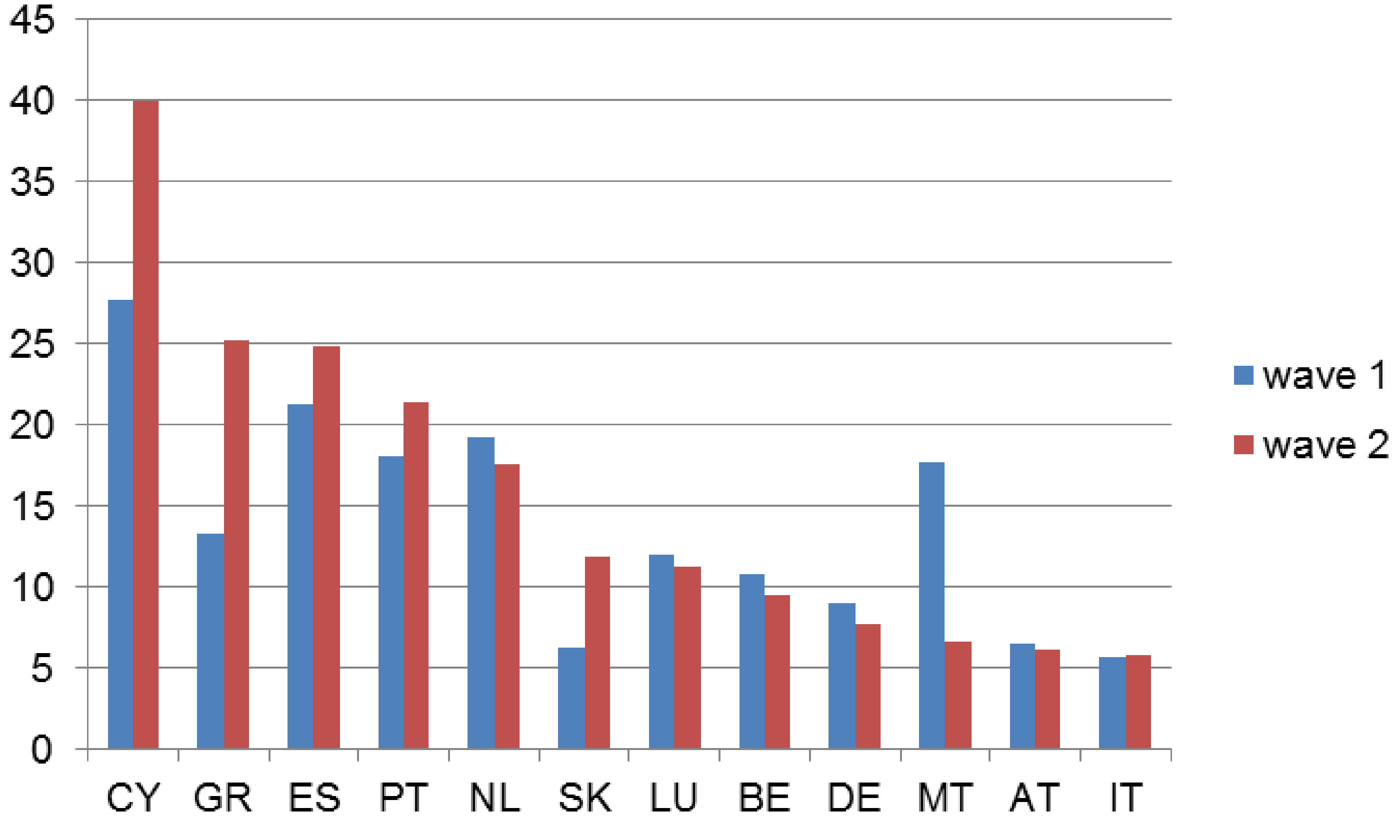
- It defines households as potentially vulnerable if the conditions for two or more of the debt burden or income indicators are met
- It is sensitive to the shocks related to i) the interest rates ii) income and iii) accumulated assets thus not exclusively focusing on the ability to repay debt but also on the expenditure site of the low income households

Share of households characterised by different measures, in %



Note: euro area figures in wave 1 exclude FI, FR, IE, EE, LT, LV and in wave 2 exclude FI and LT.
Source: HFCS and own calculations.

Share of vulnerable households by country and wave, in %



Note: data for IE, EE, LV are available only for wave 2. Data for FI and FR are excluded due to missing indicators for some of the measures.

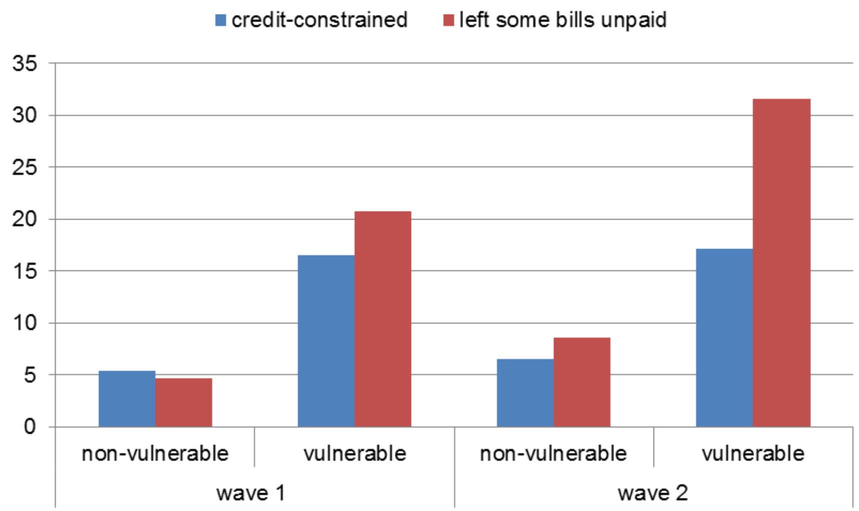
Source: HFCS and own calculations.

Main characteristics of vulnerable households

The group of households defined as vulnerable in wave 2 compared to non-vulnerable ones includes more:

- Middle size HHs of 3-4 members
- HHs with mortgage on the household main residence
- HHs from bottom income quintile
- self-employed and not working
- credit-constrained
- prone to have bills left unpaid

Selected features by vulnerability groups, in %



Note: euro area figures in wave 1 exclude FI, FR, IE, EE, LT, LV and in wave 2 exclude FI and LT.
Source: HFCS and own calculations.

Distributional information from National accounts

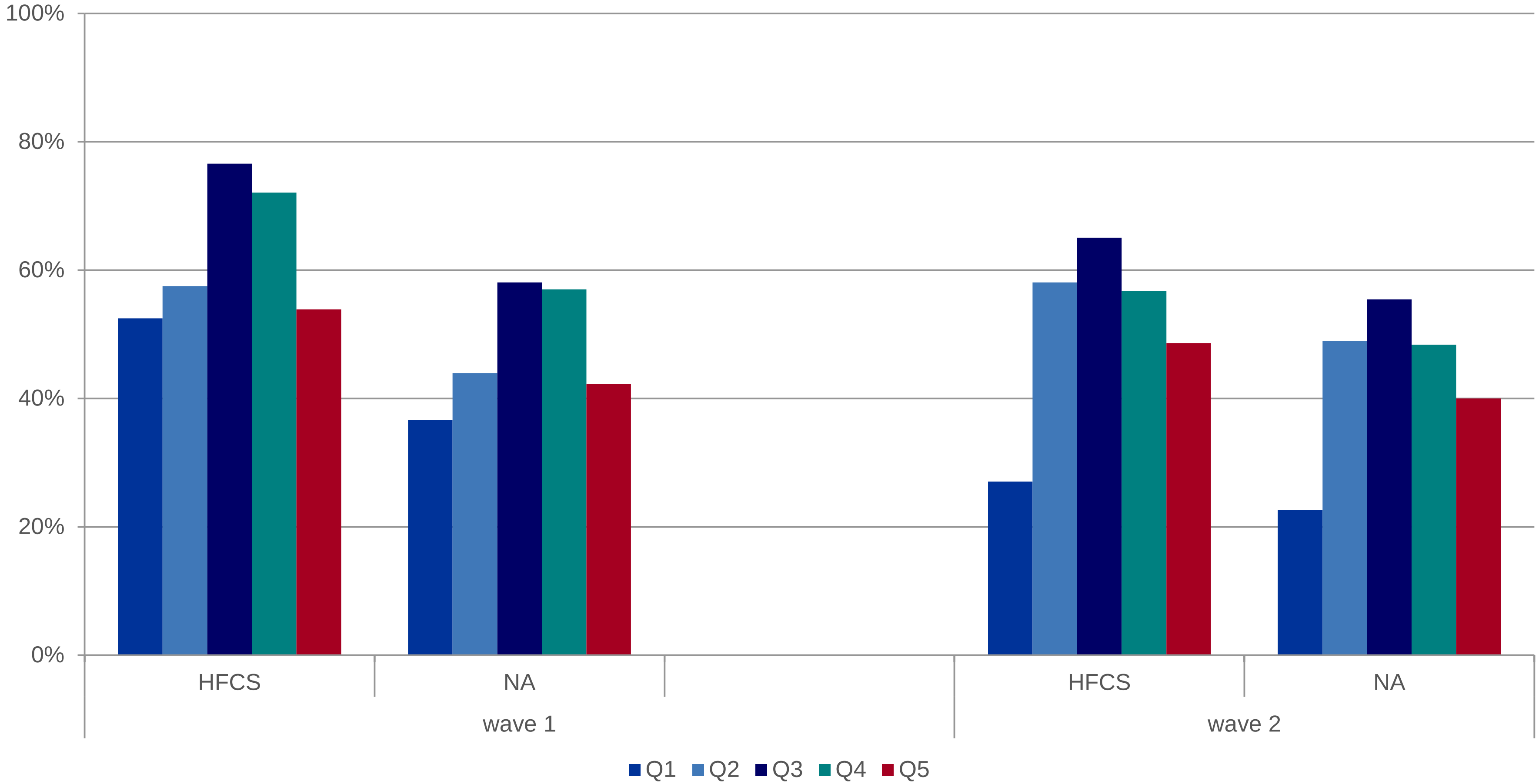
- Combining macro aggregates and household surveys to get **timely indicators** on the distribution of income, wealth and indebtedness consistent with **NA levels**

  - Population adjustments
  - Select comparable variables
  - Scale micro data to NA levels at the most detailed level possible
  - Cluster households
  - Calculate indicators

Debt-to-(adjusted)-financial wealth ratio (DTAFW)

T of macro with T of micro

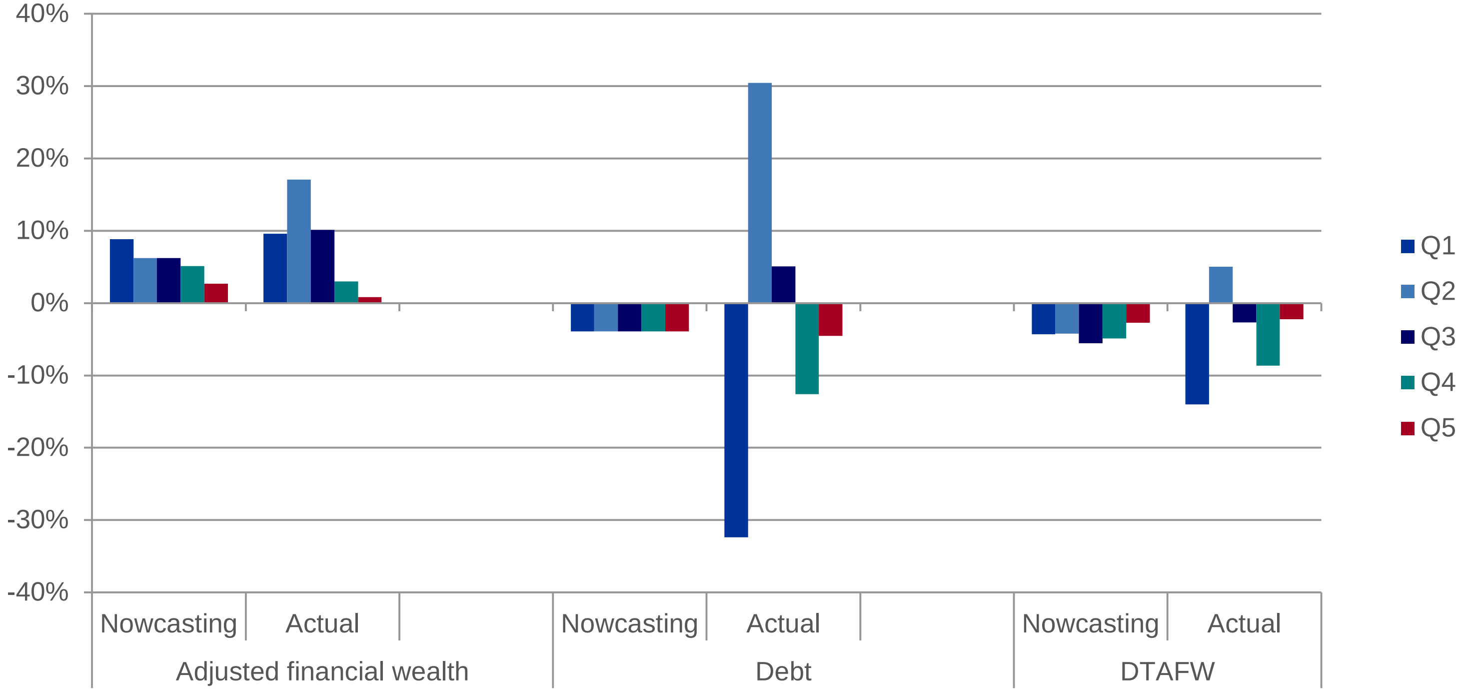
DTAFW ratio by income quintile - Germany, in %



Source: HFCS, ESA2010 and own calculations.

Nowcasting exercise: T-1 of micro with T of macro

Change in AFW, debt and DTAFW by income quintile in Germany, in % and pp



Source: HFCS, ESA2010 and own calculations.

Overview of microsimulation modelling

- Simulating the effects of macro changes on households, at a micro level
- Based on an analytical representation of:
  - the constraints faced by households (static component);
  - their behavioural response to the modification of these constraints (behavioural component);
  - the way of adapting their behaviour overtime (dynamic component).
- Microsimulation can be used for nowcasting and stress-testing under various hypothetical scenarios
- The quality of the nowcasted results will eventually depend on:
  - The quality of the microdata source;
  - The availability of timely, comparable and consistent macro-level information;
  - Micro-economic understandings and modelling of household behaviours.

Review of literature

- Several studies quantified the impact of household vulnerability on financial stability, by simulating changes in income, employment, interest rates and balance sheet at a micro level

- Microsimulation studies with the HFCS:

	Albacete & Fessler (2010)	**IMF (2012)**	**IMF (2013)**	**Michelangeli & Pietrunti (2014)**	**Ampudia *et al.* (2014a)**	**Ampudia *et al.* (2014b)**	**Bettocchi *et al.* (2016)**	**Meriküll & Rõõm (2017)**
Countries covered	Austria	Spain	Italy	Italy	Euro area	Euro area	Italy	Estonia
Static or dynamic	Static	Static	Static	Static	Static	Static	Static	Static
Nowcasting	✗	✓	✗	✓	✓	✗	✓	✗
Time horizon		3 years		3 years	3 years		3 years	
Stress-testing	✓	✓	✓	✓	✗	✓	✓	✓

Review of literature: features of the modelling

- Macro-level information at the EA-level: EAA, LFS, House Price Index, HICP and other indices (Ampudia *et. al*, 2014)

- Possible components of the nowcasting process:
  - Update income, asset prices and debt service
  - Accounting for labour market change and debt growth rate
  - Accounting for demographic and compositional change

- E*x post* analysis or cross-check are limited: only Michelangeli and Pietrunti (2014) for Italy, and Ampudia *et al.* (2014) for Spain
  - Overall positive conclusions about model reliability
  - Further validation should be performed to determine if further refinements are desirable

Conclusion

- The HFCS captures the heterogeneity in household finances
- It is useful to detect group of households that displays various form of financial vulnerability
- However the data is available with a long time lag
- Timelier macro information can be used to nowcast vulnerability

Two nowcasting techniques:

- Adjusting HFCS data to NA levels and structure
    - *It fails to capture important developments in the distribution of households' balance sheet*
- Microsimulation modelling
    - *Several static models have already been implemented to nowcast using HFCS (only one at the EA-level)*
    - *Validation procedures are limited and should be further developed to determine the need for complex and costly refinements (Peterson and Roberts, 2016)*

Thank you for your attention