Linking Macro and Micro Household Balance Sheet Data – time series estimation

Juha Honkkila
(European Central Bank)

Ilja Kristian Kavonius
(European Central Bank)

Lise Reynaert Lefebvre
(European Central Bank)

Paper prepared for the 35th IARIW General Conference

Copenhagen, Denmark, August 20-25, 2018

Session 7E-1: Financial Accounts

Time: Friday, August 24, 2018 [14:00-17:30]

Juha Honkkila

European Central Bank

E-mail: juha.honkkila@ecb.europa.eu

Ilja Kristian Kavonius

European Central Bank

E-mail: ilja_kristian.kavonius@ecb.europa.eu

Lise Reynaert Lefebvre

European Central Bank

E-mail: lise.reynaert_lefebvre@ecb.europa.eu

Linking macro and micro household balance sheet data – time series estimation[1]

Currently, there are several international initiatives in linking micro and macro household balance sheet, income and consumption data. Thus far, the focus has been on creating distributional accounts for a single point in time. However, the real value added of such accounts for the central bank analysts' toolkits would be either to provide more timely information than the surveys or to provide time series which are not already provided by the surveys. Previous attempts to estimate distributional time series show that simple extrapolation based on previous distributions is not enough to have reliable estimates on the changes in the balance sheets for various household groups.

The purpose of this paper is to develop more advanced tools combining micro and macro source for time series estimation. This paper tests and compares two methods for France, Germany, Italy and Spain on financial balance sheet items. The first method resorts on auxiliary data sources, i.e. the property income flows from the EU-SILC are used to estimate the development of their underlying assets/liabilities. The second one is a microsimulation method simulating the effect of recent macroeconomic changes on households at micro level. This paper concludes that neither of these methods is working for all the countries. The auxiliary data work relatively well for Italy and Spain, while the microsimulation gives relatively good results for Germany. The choice of method should this be thus country-specific.

[1] The views expressed in this paper are those of the authors and they do not necessarily reflect the views or policies of the European Central Bank or the European System of Central Banks. The paper benefited from useful comments by Henning Ahnert, Ioannis Ganoulis and Pierre Sola.

1. Introduction

Several international initiatives have emphasised the importance of having timely distributional measures for household income, saving and balance sheets. In the discussion related to the social developments, this was predominantly raised by the Stiglitz, Sen and Fitoussi Commission report (2009). These needs for distributional measures were later confirmed, in particular by the Vienna Memorandum, adopted by the European Statistical System Committee (ESSC) in September 2016. Central bankers have also recognised the importance of distributional issues to the financial stability. Thus, in 2009, the IMF and FSB recommended the assessment of distributional measures for financial and non-financial accounts to the G-20 Finance Ministers and Central Bank Governors.

Different expert groups have been set up to implement this work. At the European level this work has been divided into two: first, the OECD and European Commission have set up the Expert Group on Disparities in National Accounts (EG-DNA) which is focusing on developing distributional accounts for income, consumption and savings. Second, the household distributional balance sheets are tackled by the European System of Central Banks (ESCB) Expert Group on Linking Macro and Micro Data for the Household Sector (EG-LMM). This labour distribution is due to the fact that the European Commission (Eurostat) is typically responsible for the non-financial statistics, while the European Central Bank (ECB) is typically responsible for financial statistics and balance sheets. In addition, the ECB is responsible for the quarterly Financial Accounts (FA), as well as for coordinating the only European wide household wealth survey: the triannual Household Consumption and Finance Survey (HFCS).

The EG-DNA has worked already since 2011 with the distributional accounts.[2] The benefit of working in the field of income and consumption is that there are more potential data sources than in the area of household balance sheets. In estimating time series, the expert group has identified three ways of calculating those: (1.) to use other micro sources to estimate the missing years; (2.) to use auxiliary data, i.e. for instance indirect data to extrapolate the time series; and (3.) to apply the distribution of the previous years. Depending on the available data sources, the estimation can be done by: (1.) using top-down approach, i.e. to start from macro data and implement it to micro level; (2.) using a bottom-up approach, i.e. to estimate the development already at the micro level; or (3.) estimating the breakdowns at the meso-level, i.e. to estimate the missing years at the level of household groups (e.g. by income quintile).

As for the EG-LMM, it started in 2016 and focuses on understanding, quantifying and explaining the differences between the HFCS and FA. Compared to the work of the EG-DNA, the EG-LMM has a challenge that there are considerably less data sources related to balance sheet than income and consumption. This also excludes the possibility to use other micro data on balance sheets to estimate these time series for a large set of countries. The expert group work is based mostly on the link which was established by Kavonius and Törmälehto (2010), and later completed by Kavonius and Honkkila (2013). These studies created the first link between financial accounts and HFCS and also made the first comparisons for three countries. In some individual countries these comparisons were also carried out[3]. The first mandate was completed in 2017, and it was agreed that the group will continue closing the gaps between the two statistics. The idea would be to further develop FA breakdowns by using this link and

[2] See: Zwijnenburg et al. 2017.

[3] See: Andreasch et. al. 2013. Dettling et. al. 2015. Durier et. al. 2012.

consider methods to estimate time series for these breakdowns. This group should deliver its final report by summer 2019.[4]

The present paper complements the work of the EG-LMM as it aims at creating a framework which allows estimating more timely distributional data, rather than implementing breakdowns from the survey to the financial accounts' aggregates. There are only few previous attempts to estimate distributional time series which are using the approach of applying the distribution of an earlier year. The results of applying this methodology are not satisfactory.[5] Therefore, this paper focuses on other estimation methods investigating the possibility of using indirect auxiliary sources as well as microsimulation for estimating time series for the distributional financial accounts. For the simplicity, this paper focuses only on financial balance sheet items even though the EG-LMM covers the balance sheet.

2. Distributional national accounts indicators

The objective of this section is to combine macro and micro data to get more timely information on the distribution of household wealth, consistent with the macro level developments, i.e. produce Distributional National Accounts (DNA) indicators. More particularly, the aggregate level and portfolio structure of household wealth are taken from financial accounts or other macro data and distributional information by household groups is obtained or estimated from surveys or other micro data. This approach makes use of the benefits of both sources: macro data are timely and produced with low frequency compared to survey data, while distributional information by household groups is available only from surveys or other micro sources.

At any time *t*, when which both micro and macro data are available, the estimation of DNA indicators is pretty straight forward. However, there are several issues related to the comparability and coverage of these two statistics which should be in long run improved in order to have good quality indicators but this is not the topic of this paper. After adjusting for conceptual differences between the two data sources, the aggregate of each instrument from macro data is taken as the starting point. The distributions of each wealth component by household groups are calculated from the micro data. Within this step adjustments to the computed distributions to correct for the shortcomings in the micro data source (e.g. very rich households missing in the data) can be made. Subsequently, the (macro) assets/liabilities at asset type level are multiplied by the corresponding (micro) shares of household groups for each individual asset/liability type. This is analogous to the methodology of scaling up the micro data to the adjusted macro totals applied by the OECD Expert group on Disparities in the National Accounts framework (see Zwijnenburg et al. 2017).

Total wealth, consisting of *n* wealth components (asset types), for household group *h* (out of *m* groups) at time *t* is:

(1) $$W_{h,t} = \sum_{i=1}^{n}\left(WF_{i,t} * \frac{WS_{i,h,t}}{\sum_{h=1}^{m} WS_{i,h,t}}\right)$$

where *WF* refers to wealth from macro data and *WS* to wealth from micro data. The same model should be applied in the calculation of total liabilities, consisting of *n* liability components.

---

[4] Additionally, the following papers have lately integrated micro and macro balance sheet data: Albacete and Fessler 2010. Bettocchi et al. 2016. Krimmel et al. 2013.

[5] Kavonius and Honkkila 2016. Bankowska et al. 2017.

Production of DNA indicators at a time *t+1*, when macro data are available, but micro data with a comparable wealth concept are not, requires estimations on the changes in the distribution between *t* and *t*+1 to be adapted to the calculations. Estimating household behaviour between the two periods is the key to deriving DNA indicators for *t+1*. Changes in financial wealth or debt of a household group can change for various reasons: 1) change in the value of the existing stock of assets changes even if no transactions occur; 2) change in the portfolios of households due to a) households using saving to acquire more assets; b) households using existing financial wealth for consumption or paying off debt or c) households taking new mortgages or other debt to buy real assets or selling real assets and paying off their existing mortgages or other debt; and finally 3) changes in the composition of the household groups due to changes in the household structure, or in the case of income quintiles, by positive or negative income shocks that occur between *t* and *t+1*. Additionally, there are three levels on which estimations for the changes of wealth distribution can be made: macro, meso and micro.

Ideally, DNA indicators could be produced for the wealth concept used in the financial accounts (FA). However, previous work on the comparisons between micro and macro data indicates that for some FA instruments, either micro data are not collected or the micro concept is not comparable with the macro concept.[6] Consequently, in this paper we use a concept of adjusted financial wealth (AFW) that includes only assets that are considered comparable between macro and micro sources: deposits, mutual fund shares, listed shares and bonds. This wealth concept can be interpreted as liquid financial wealth, almost identical to the corresponding FA definition. The only items of liquid financial wealth that is missing are cash, the collection of which has been proved difficult in household surveys due to sensitivity issues, and unlisted shares that are collected with different delineation criteria in financial accounts and in the HFCS. Households' liabilities collected in micro data are consistent with the FA concept (loans).

The main indicator of interest is debt-to-liquid financial wealth –ratio by household groups. To assess the performance of the estimations, results are also shown separately for both debt and liquid financial wealth. In this paper gross income quintiles are used as a classification variable. The models are applied to the data of the four biggest euro area countries, Germany, Spain, France and Italy.

2.1 Estimating at the macro and meso level

2.1.1 Macro level

For the macro level estimation there is practically one feasible option: the 't-1 approach', i.e. taking changes in the values of assets and portfolio structure from macro data, and adapting the distributional information from the latest available survey year. This is a rather naïve option and assumes the same behaviour for all household groups between *t* and *t+1*. With this methodology, any changes in the distribution of wealth are only a consequence of the portfolio structures across household groups, reflecting the changes in the portfolio structure of households in the macro data. In practice, this methodology is a slight modification of equation (1). The only difference is that the macro information on household wealth at asset/liability type level from the macro source is taken from point *t+1* instead of *t*.

(2) $W_{h,t+1} = \sum_{i=1}^{n} \left(WF_{i,t+1} * \frac{WS_{i,h,t}}{\sum_{h=1}^{m} WS_{i,h,t}} \right)$

[6] Honkkila and Kavonius 2013.

Bánkowska et al (2017) showed that at least in the crisis situation this assumption does not produce reliable results, since it does not capture different behaviour patterns between various household groups. This approach is, however, used as a benchmark in this document.

2.1.2 Meso level

At the meso level the changes in the distribution of wealth are estimated for different household groups. As the most straightforward option, one can adapt the average of the surrounding years as the share of wealth for a given household group. This is only feasible, if the aim is to estimate the information for missing years in the middle of existing survey time series (interpolation). However, this paper analyses methodologies that are feasible for extrapolation, i.e. estimating changes in distribution for a time *t+1* with no survey data available, in order to obtain more timely distributional data.

To estimate DNA indicators for periods after the latest available micro data on household wealth, auxiliary data are required to estimate the distributional component applied to observed macro totals. In the equation on total wealth, the estimate of this component *WS* is marked as $\acute{WS}$ (see equation 3). Ideally, variables used in the modelling of distributional changes should be ones that provide a good proxy of the stock of individual financial wealth and debt instruments. In case there is data available that can be used as a proxy for the stock variables (assets/liabilities), this variable can be used as such and total wealth/debt at time *t+1* is calculated as:

$$(3)\ W_{h,t+1} = \sum_{i=1}^{n} \left(WF_{i,t+1} * \frac{\acute{W}S_{i,h,t+1}}{\sum_{h=1}^{m} \acute{W}S_{i,h,t+1}} \right)$$

The problem is that data sources on stock variables are rarely available, at least for a large number of countries. Relevant administrative data sources are typically accessible only at national level, if at all. A second best approach is to estimate the changes in wealth and debt stock of various household groups with related flow variables, denoted as *IS* in equation 4. While such an approach may not produce accurate levels of individual variables at the macro level, they can be considered feasible proxies for distributional changes.

$$(4)\ \frac{\acute{W}S_{i,h,t+1}}{\sum_{h=1}^{m} \acute{W}S_{i,h,t+1}} = \frac{W_{h,t} * \left(1 + \frac{IS_{t+1}}{IS_{t}}\right)}{\sum_{h=1}^{m} \left(W_{h,t} * \left(1 + \frac{IS_{h,t+1}}{IS_{h,t}}\right)\right)}.$$

In the meso level estimation, changes in the values of auxiliary variables ideally reflect the changes in both the values of assets and changes in the portfolio of a household group. However, this method adjusts for changes in the values of assets and liabilities between two cross-sections. Consequently, it does not capture changes in the composition of the household groups. In the particular case of income quintiles, it fails to take into account that a relatively wealthy or indebted household may move to a lower income quintile and increase the average level of wealth or debt in that group, even if the wealth or debt of this individual household decreases.

2.2 Auxiliary data for the balance sheet

Since the HFCS is the only source on wealth distribution, the only possibility is to use indirect indicative data sources on its development. Practically, this refers to micro level data on income from surveys or administrative sources, i.e. in this case paid and received interest flows. As these flows are related to their underlying assets, the interest flows should reflect the development of asset/liability stock as well as changes in the interest rates. According to ESA2010, interest (D.41) is property income receivable by the owners of a financial asset for putting it at the disposal of another institutional unit. It applies to the following financial assets: (a) deposits (AF.2); (b) debt securities (AF.3); loans (AF.4) and other accounts receivable (AF.8).[7] For the other property income flows there is not such a direct relation between the income flow and underlying assets as in the case of interests, i.e. there is no a reference rate for instance for paid dividends.

This means that paid and received gross[8] interest should be consistent with these stocks, i.e. if these interest flows are divided by these stocks, the result should be either actually paid or received interest rate. It is important to notice that consistency does not mean one to one consistency with some reported market interest rate. The reason is that these "implicit paid/received interest rates" are based on interests that are paid/received on stocks which follow different interest contracts and therefore, the levels of these implicit rates cannot even correspond with the market interest rates. The correspondence and consistency should therefore appear in the development of the actual time series. The level of actual market interest rate and the implicit interest rate should even be different but the development/trend of these series should follow each other.

We will first analyse this consistency at macro level, i.e. we check whether this relation holds for the financial and non-financial accounts of Germany, France, Italy and Spain. This – in the national accounts' jargon – vertical consistency is in theory there but it is known that it is not always reached. In this part we analyse the consistency at macro level in order to assess the plausibility of these estimations. If at least a rough consistency was not reached at macro level, it would be unlikely to achieve it at the micro level. Additionally, the consistency has to be checked in time series. As the HFCS has been conducted only twice, there is not even theoretical possibility of checking the time series consistency. However, for these two points of time the implicit interest rates calculated from the interest flows of the EU-SILC and HFCS should be pretty consistent with the implicit interest rates that are based on the financial and non-financial accounts. This consistency will also be checked in this section. This is practically *the only way of validating the plausibility of this estimation method*. If the implicit interest rates based on the EU-SILC and HFCS were consistent with the reported and national accounts implicit interest rates and the national accounts interest rates time series were consistent with the reported interest rates, it would indicate that the data would be of sufficient quality to be used for this type of estimation.

Table 2.1 shows the summary statistics of these implicit interests calculated from financial and non-financial accounts for assets (in the table: implicit interest rate of invested portfolio) and liabilities (in the table: implicit interest rate of debt). The benchmark interest rate for the assets (in the table: deposit interest) is "cost of borrowing for house purchase" from the Monetary financial institutions (MFI) interest rate statistics and the benchmark rate for the liabilities (in the table: borrowing interest) is "bank interest rates - deposits from households with an agreed maturity of up to two years (on outstanding amounts)" from the MFI statistics. The lines "portfolio difference" and "debt difference" (**bold** and *italic*) show the differences between the implicit interest rate and the corresponding benchmark rate. It is important to notice that the quarterly figures are annualised by multiplying the numerator (flow) by four. This leads to the situation that annual and annualised estimates can in particular in turbulent

[7] ESA2010, 4.42.

[8] i.e. without FISIM adjustment. FISIM stands for Financial Intermediation Services Indirectly Measured. It is an estimate of the value of the services provided by financial intermediaries, such as banks, for which no explicit charges are made

times differ from the annual figures. The analysis is done for time series from 2008q1 to 2017q4. This time spam covers the both survey years as well as these data are most likely based on actual compilation methods rather than back data estimations.

Summary statistics show the minimum, the first quartile, the median (second quartile), the third quartile, and the maximum. From the analysis point of view, it is essential to focus on the portfolio and debt differences. As mentioned earlier, there can and also should be differences vis-à-vis to the market interest rates but it is essential that differences are pretty constant. If the all these statistical indicators are constant or roughly similar, it indicates that in the whole time series the differences are stable. However, it is possible that there are for instance large differences in the last observations or alternatively, some individual outliers. From that point of view, it is not so worrying if the minimum and/or maximum values are differing somewhat more as long as the first quartile, median and third quartile values are roughly similar.

Table 2.1: Summary statistics for the comparison of the implicit interest rates calculated from financial and non-financial accounts to the MFI interest rates.

		quarterly (annualised)					annual				
		min	1. quart.	median	3. quart.	max	min	1. quart.	median	3. quart.	max
DE	Implicit interest rate of invested portfolio	0.52	0.84	1.55	1.89	3.01	1.33	1.84	2.58	2.93	3.87
DE	Deposit interest	1.34	1.75	2.25	2.45	2.58	1.39	1.79	2.26	2.46	2.49
DE	***Portfolio difference***	***-0.91***	***-0.88***	***-0.83***	***-0.49***	***0.53***	***-0.06***	***0.05***	***0.26***	***0.54***	***1.39***
DE	implicit intrest rate of debt	3.13	3.85	4.56	5.05	5.49	3.18	3.88	4.55	5.00	5.49
DE	Borrowing interest	1.63	1.99	2.83	3.92	5.43	1.76	2.09	2.92	3.82	5.21
DE	***Debt difference***	***0.05***	***1.10***	***1.48***	***1.74***	***2.03***	***0.28***	***1.10***	***1.49***	***1.64***	***1.85***
FR	Implicit interest rate of invested portfolio	0.83	1.04	1.23	1.49	2.09	1.04	1.18	1.54	1.84	3.51
FR	Deposit interest	2.51	2.81	3.09	3.24	3.57	2.54	2.83	3.08	3.23	3.54
FR	***Portfolio difference***	***-2.26***	***-1.78***	***-1.77***	***-1.69***	***-1.42***	***-1.73***	***-1.62***	***-1.53***	***-1.31***	***-0.01***
FR	implicit intrest rate of debt	1.80	2.69	2.98	3.15	3.82	1.88	2.64	3.00	3.17	3.70
FR	Borrowing interest	1.52	2.29	3.37	3.93	5.27	1.60	2.47	3.41	3.79	5.02
FR	***Debt difference***	***-1.53***	***-0.86***	***-0.30***	***0.16***	***0.57***	***-1.32***	***-0.75***	***-0.35***	***0.17***	***0.35***
IT	Implicit interest rate of invested portfolio	1.34	1.77	2.38	2.74	4.12	1.47	1.97	2.45	2.89	4.74
IT	Deposit interest	1.78	2.58	2.82	2.93	3.68	1.89	2.61	2.83	2.89	3.47
IT	***Portfolio difference***	***-1.21***	***-0.67***	***-0.55***	***-0.34***	***1.30***	***-0.90***	***-0.70***	***-0.40***	***-0.04***	***1.86***
IT	implicit intrest rate of debt	2.22	2.60	3.35	3.86	5.23	2.35	2.61	3.27	3.85	4.93
IT	Borrowing interest	1.97	2.49	3.36	3.81	5.83	2.05	2.66	3.25	3.89	5.63
IT	***Debt difference***	***-0.81***	***-0.32***	***-0.04***	***0.38***	***0.72***	***-0.71***	***-0.25***	***-0.10***	***0.35***	***0.59***
ES	Implicit interest rate of invested portfolio	0.21	1.18	1.95	2.59	3.55	0.79	1.43	2.04	2.26	3.93
ES	Deposit interest	0.58	1.90	2.32	2.67	2.91	0.62	1.90	2.37	2.64	2.78
ES	***Portfolio difference***	***-1.21***	***-0.55***	***-0.17***	***0.09***	***0.92***	***-0.57***	***-0.33***	***-0.28***	***-0.13***	***1.16***
ES	implicit intrest rate of debt	1.81	2.45	3.06	3.54	6.08	1.99	2.49	3.13	3.44	5.67
ES	Borrowing interest	1.87	2.22	2.90	3.25	5.96	1.90	2.30	2.96	3.27	5.67
ES	***Debt difference***	***-0.44***	***-0.09***	***0.12***	***0.36***	***1.75***	***-0.23***	***0.01***	***0.13***	***0.25***	***1.45***

Source: ECB calculations. The implicit interest rates are calculated on the basis of financial and non-financial accounts; the deposit and borrowing interest are based on the MFI statistics

As can be seen in the table the German and French portfolio differences and the German debt differences across quartiles/time series are pretty stable. There are only some large differences in the minimum and maximum values which indicate that the differences are rather outliers than a structural feature. This is also confirmed in Figure 2.1 which shows the time series for these interest differences for 2008q1-2017q4. The few observed large differences are in the beginning of the time series. The French debt differences are relatively large and also these vary from negative to positive. The consistency for this can overall be concluded to be bad.

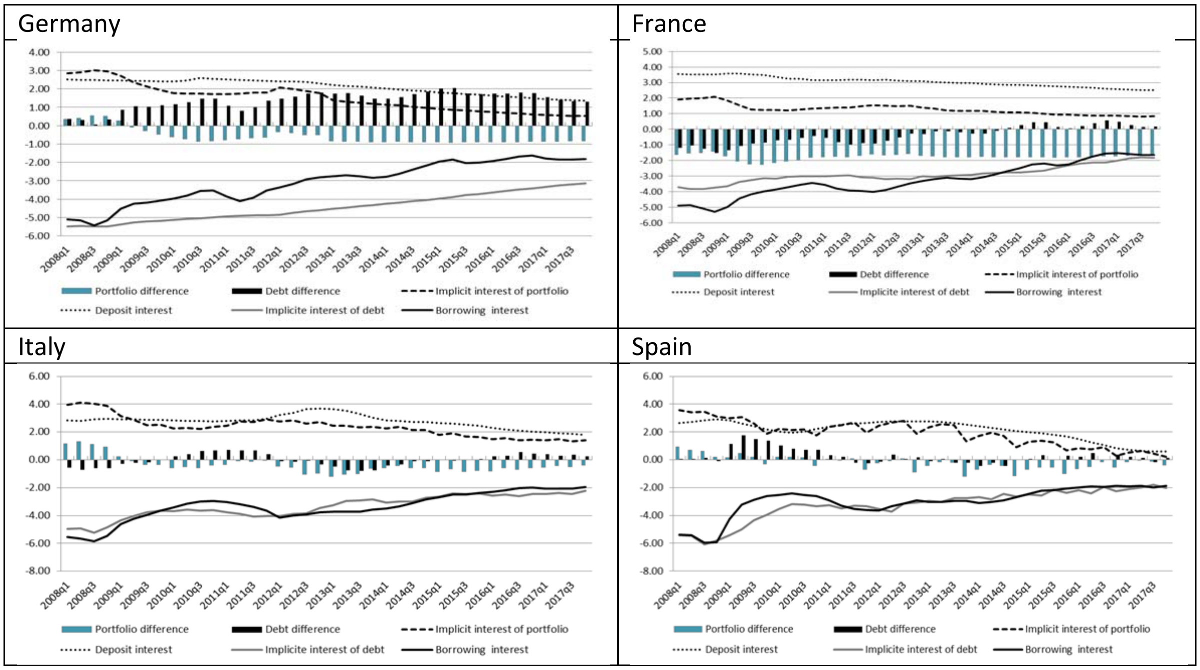
The Italian and Spanish differences for portfolio and debt can be concluded to be relatively small. This particularly well illustrated in Figure 2.1 where can be seen how the differences vary between negative and positive. This variation is inherited from the interest income rather than from the stocks. If this variation were evident also micro interest flows, it is clear that the distributional stocks would inherit development, i.e. the time series profile of the EU-SILC data is reflected in the stocks. However, it should be noticed that this development is more quarterly variation than annual development (see: table 2.1) and if the estimation is done at annual frequency the results should be relatively good.

This paragraph then discusses the consistency between EU-SILC/HFCS implicit rates and MFI/ financial accounts implicit rates. It is only checked at macro level as the consistency is far more difficult to verify at micro level. The macro level estimation would indicate that these types of indirect methods could be applied in the most of cases. Therefore, the only way is to analyse whether the micro level implicit interest rates roughly correspond with the ones calculated from the macro statistics. In the case of Germany the correspondence between implicit micro interest rate[9] and implicit macro interest rate[10] is good: the implicit interest rate in Germany for EU-SILC/the first wave HFCS was 5.2% as the corresponding macro interest rate is 5.1% and for the second wave the micro interest rate is 4.4% as the macro one is 4.1%. The Spanish first wave implicit interest is 5.9% as for the national accounts it is 5.7%. The corresponding implicit interests are for the second wave 3.1% and 3.4%. The French first wave EU-SILC/HFCS implicit interest is 4.8% and the corresponding financial accounts implicit interest is 3.0%. For the second wave the corresponding implicit interest rates are 3.5% and 2.8%. Finally, the Italian first wave EU-SILC/HFCS interest rate is 5.3% as the corresponding financial accounts implicit interest rate is 5.7 and for the second wave the corresponding implicit interest rates are 4.6% and 3.0%.

This analysis indicates that particularly the German and Spanish the implicit interest rates are relatively consistent and plausible. This give some reassurance to use these data in the estimation of stocks by using changes in the interest flows' distributions.[11] However, it should be remembered that the data consistency does not guarantee a good results either. The French and Italian the differences between the micro and macro estimates are larger than in the cases of Germany and Spain although the Italian first wave implicit interest rate is quite comparable with the macro implicit interest rate. Additionally, at the macro level the sign of differences are varying. This indicates that this method provides worse results for these countries than for Germany and Spain.

[9] Implicit interest rate of debt: EU-SILC mortgage interest payments / HFCS mortgage debt.
[10] Implicit interest rate of debt: Paid total gross interest / (deposits (AF.2) + debt securities (AF.3) + loans (AF.4) + other accounts receivable (AF.8)).
[11] The estimation method is presented in formula (4) of this paper.

Figure 2.1: The comparison of the implicit asset and liabilities interest rates and benchmark interest rates from the MFI interest rate statistics for Germany, France, Italy and Spain. The lines in the graphs are the interest rates and the bars show the difference between the implicit interest rate and corresponding benchmark interest rate.



Source: ECB calculations

2.3 Estimating change in liquid financial assets

Components of liquid financial wealth generate income. Unfortunately, the relationship between financial income and financial asset holdings is not straight forward and the method seen in section 2.2 cannot be applied. Various kinds of financial assets generate income in different ways and even at the macro level the ratio between financial income and financial wealth is not consistent over time. Estimating levels or even changes in levels of financial assets with financial income would probably lead to biased results. However, the aim of the distributional component in DNA indicators equations is only to estimate changes in the distributions. Consequently, financial income can be considered a best existing source for measuring changes in the distribution of financial wealth only under the assumption that the ratio between financial income and financial wealth changes in a similar way across different household groups. However, it should be borne in mind that while the relation between paid/received interests and liabilities is direct as there is a direct binding link between these two (interest rate), the link between financial income other than interest and financial asset is not so clear. In the case of dividends there is neither a stable ratio between the flow and underlying assets nor a rule when the dividends are paid.

Financial income is measured not only in wealth surveys, but also in income surveys, such as the EU Statistics on Income and Living Conditions (EU-SILC). The benefit of the EU-SILC are that it is annual survey (versus triennial for the HFCS) . The EU-SILC variable on financial income (“Income from interest, dividends, and profit from capital investments in unincorporated business[12]") is an aggregate of all income components of liquid financial wealth. This doesn't allow a distinction between different ways various wealth items generate income. Consequently, we need to assume that changes in this aggregate income variable reflect the distributional changes of wealth for each instrument individually. As referred above, the fact that received interests and other financial income cannot be separated weakens the assumption of this calculation.

Another limitation in survey data is that income from sight accounts is usually very limited at times of low interest rates and may be significantly underreported. This assumption is supported by comparing the shares of households receiving financial income to households owning various types of financial assets in the HFCS data. The former share is in all four countries lower than the share of households owning liquid financial assets (including sight accounts), but close to the share of households owning types of liquid financial assets other than sight accounts.

Given this observation, we apply a model where the changes in the distribution of financial income (*IS* in equation 4) are used to estimate changes in savings accounts, mutual funds, bonds and quoted shares. For the estimation of the distribution of sight accounts, we use the last known distribution, applying equation 2[13].

2.4 Estimating change in liabilities

As discussed in Chapter 2.2, interest payments on loans can be used to estimate the debt stock of the household. For this analysis a distinction between mortgage and non-mortgage debt would be useful due to differences in interest rates levels between these types of debt. At the macro level, financial accounts do not allow such a distinction, but statistics on balance sheet items of monetary and financial institutions (MFI BSI) enable a distinction between mortgages taken to purchase the household main residence (HMR) and other loans. To maintain the levels of debt consistent with the levels of assets, we take the value of total household debt from FA. In addition, we apply the portfolio structure of debt from MFI BSI statistics to the FA data to enable a distinction between mortgages and non-mortgage loans in our analysis.

Information on interest payments on the mortgage taken to purchase the HMR is collected in EU-SILC and can be used as a proxy for HMR mortgages. As indicated earlier, the relationship between interest payments on mortgages and the stock of mortgages is pretty stable at the macro level, and survey information on this relationship is consistent with the macro data. On the other hand, no feasible proxy can be found for non-mortgage loans. Since HMR mortgages account for 2/3 of households' liabilities in the euro area, we can expect to improve the estimation significantly by estimating the changes in the distribution of this component only. We apply the changes in interest payments on mortgage from EU-SILC (IS in equation 4) to estimate the change in the distribution of HMR mortgage debt by household groups. For other loans, we apply the past distribution, i.e. equation 2.

[12] Survey definition: "Interest (not included in the profit/loss of an unincorporated enterprise), dividends, profits from capital investment in an unincorporated business refer to the amount of interest from assets such as bank accounts, certificates of deposit, bonds, etc., dividends and profits from capital investment in an unincorporated business, in which the person does not work, received during the income reference period (less expenses incurred)."(European Commission 2017)

[13] Sight accounts could also be estimated reflecting changes in net income, but this approach did not improve the estimations.

3. Estimation at the micro level

Microsimulation constitutes another option: this technique consists of simulating the effect of recent macroeconomic changes on households at the micro level, in order to draw conclusions that apply to higher levels of aggregation. In this section, we replicate the model implemented by Ampudia et al. (2014) which has the advantage of being rather simple and transparent. The model is composed of a mechanical extension of assets, income and debt, as well as a modelling part accounting for changes in unemployment. This model will simulate both the changes in the value of assets and debt, as well changes in the composition of income quintiles. As a second step, we estimate the changes in the portfolio structure not captured in the first step.[14]

We will consider the variable of interest: debt-to-liquid financial wealth (DTLFW) –ratio by income quintile, as well as its components, as defined in the previous Chapter.

3.1 Updating HFCS using aggregate data

First, we mechanically update one by one the various assets, income components and rate of debt services with their country level aggregate, as described in table 3.1. In particular, house price indexes are used to update real estate value; for the other asset types, indexes of quoted and unquoted stocks and bonds are used. For the liabilities, we assume that debt is constant in real terms.

For debt services, we proceed as follows. No adjustment was made for fixed interest rate loan contracts; for adjustable-rate mortgages, a complete pass-through is assumed of the change in the interest rate to the individual loan rate.

Table 3.1: Aggregate series used to extrapolate the balance sheet

	HFCS variable	Aggregate Series Used to Extrapolate
Real assets	Value of household's main residence	House price index
	Value of other real estate property	House price index
	Value of household's vehicles	HICP
	Valuables	HICP
	Value of self-employment businesses	Unquoted shares and other equity[1]
Financial Assets	Deposits	Deposits
	Mutual funds	Stock price index
	Bonds	Zero-coupon-bond price index
	Value of non-self-employment private business	Unquoted shares and other equity [1]
	Shares, publicly traded	Stock price index
	Managed accounts	HICP
	Money owed to households	HICP
	Other assets	HICP
	Voluntary pension/whole life insurance	Insurance technical reserves
Income	Employee income	Wages per employee
	Self-employment income	Gross operating surplus and mixed income[2]
	Rental income from real estate property	Gross operating surplus and mixed income[2]
	Income from financial investments	Interests
	Income from pensions	HICP
	Regular social transfers (except pensions)	HICP
	Income from private transfers	Miscellaneous current transfers[2]
	Other income	HICP
Debt and Financial Pressure	Total liabilities	HICP
	Payments for mortgages[4]	House purchase interest rate
	Payments for non-collaterised debt[4]	Consumption interest rate

1 Stock price index used for Germany
2 HICP used for countries with missing values
4 The increase in interest payments is calculated for the outstanding amounts of debt using formula (1).

[14] See also:: Michelangeli and Pietrunti 2014. O'Donoghue and Loughrey 2014.

3.2 Modelling change in unemployment

Second, we account for the change in employment. Basically, work status of individuals is modified to reach the target unemployment rate, and then the labour income of the individuals for whom the work status changed is updated accordingly.

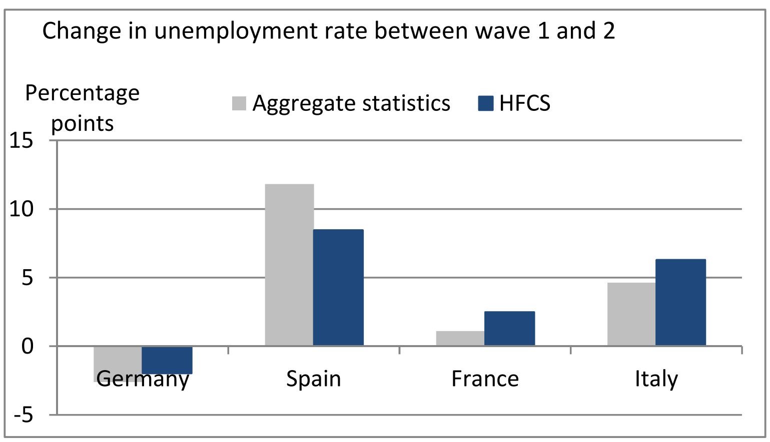
Each country target unemployment rate is defined as: $u^*_{c,t} = \frac{U_{c,t}}{U_{c,r}} \times u_{c,r}$

Where:

- $U_{c,t}$ is the unemployment rate from country's c aggregate statistics at time t ;
- $u_{c,r}$ the unemployment rate from the HFCS, r indicating the reference year of income from the survey.

Figure 3.1 displays the change in unemployment rate between wave 1 and wave 2 using national aggregate statistics.

Figure 3.1 change in unemployment rate between wave 1 and wave 2 for Germany, Spain, France and Italy, in percentage points



These four steps are then applied to account for changes in individuals work status:

1 – Using a country-specific probit, we estimate the parameter vector $\widehat{\beta_c}$:

$$Probability(Y = 1/X = x) = \varphi(x'_{c,i}\,\widehat{\beta_c})$$

Where Y is the work status, and $x_{c,i}$ are explanatory characteristics: gender, education, age in brackets, marital status, and the presence of dependent children in the household.

2 – We then compute for each individual the probability of having a job $\widehat{Y_{c,\iota}}$, given their characteristics.

3 - We calculate a measure of the probability of being unemployed:

$$\Delta_{c,i} = \epsilon_{c,i} + \mu_{c,i} - \widehat{Y_{c,\iota}}$$

Where:

- $\epsilon_{c,i}$ is a random number drawn from a uniform distribution;
- $\mu_{c,i}$ is a sector specific chock, which account for the fact that unemployment exhibits different dynamics across economic sectors.

4 – We use $\Delta_{c,i}$ to construct a ranking of the marginal probability of becoming unemployed. Using this ranking, we determine the marginal employees losing their job/finding a job, so that the increase in the simulated sample employment matches the change in the unemployment target.

Finally, for the individual for whom the work status changed, we update their income accordingly. For the newly employed worker, we replace their current unemployment benefits with the predicted labour income[15].When people become unemployed; we replace their current income with unemployment benefits, using long-term net replacement rates[16].

3.3 Modelling changes in the portfolio

The model above estimates changes in assets and liabilities by applying macro level external information at the household level. While this is a feasible approach to estimate changes in the value of the existing portfolios, it fails to capture any portfolio changes that probably occur particularly when households experience income shocks.

As a follow-up model, the simulated levels of financial assets are adjusted for changes in income between the first wave (observed) and the second wave (simulated). This is done for both positive and negative income shocks. First, we assume that household who experience a decrease in income compensate for this loss by selling liquid financial assets. The importance of the compensation is set as a random percentage between 0 and 100% of the decrease in income, and does not take into account the household saving rates[17]. Second, we assume that households who experience an increase in income will use part of this income (as above, a random percentage of the income increase) either to purchase liquid financial assets or to pay off debt. The allocation between buying assets and paying off debt is determined by the ratio between income and total debt. In both cases the increase/decrease in LFW and debt is estimated at the instrument level, assuming an unchanged portfolio structure of LFW and debt.

After the simulation has been conducted at the micro level, the distribution of LFW and debt is calculated from the simulated data. This distribution is applied at the instrument level to the macro totals, i.e. multiplying the macro aggregate with the wealth/debt share of each income quintile for each wealth and debt component. The principle is shown in equation 3.

Combining the two models, one should be able to estimate the distributional changes caused by changes in the value of assets, changes in the composition of income quintiles and changes in the portfolios of households' financial wealth and debt caused by income shocks. However, the model does not consider purchases and sales of real assets and consequently new or completely paid off mortgages.

[15] The labour income is estimated using a two-step Heckman selection model. The regressors are gender, education (dummies for having completed high school and having completed college) and age in brackets.
[16] The net replacement rates vary along three dimensions: income, marital status, and presence of dependent children.
[17] The use of random compensation percentages is applied for simplicity. Households with medium or high saving rates may adjust consumption and/or saving instead. In the future the model could be developed to take into account household-specific characteristics to determine the share of income loss compensated by selling financial wealth, by using e.g. regression models.

4. The results

Tables 4.1 to 4.4 compare the results of the estimations for liquid financial wealth. The first column shows the DNA indicator on per capita liquid financial wealth using the observed distributions from the HFCS first wave[18]. Other columns indicate the changes in per capita LFW compared to HFCS wave 1, in real terms. The second column uses the observed distributions from the HFCS second wave. This is the 'true' value used to assess the correctness of the estimations.

The third column ('fixed distribution') shows results from the macro estimation, applying wave 1 distributions at the instrument level to the financial accounts data of the wave 2 reference period. The fourth column ('estimated distribution') shows the results from the meso-level estimation, as described in Chapter 2.3 and the rightmost column ('Microsimulation') shows the results from the microsimulation, as described in Chapter 3.

In the German HFCS, a large increase in the LFW of the second income quintile was observed, while the LFW of the middle income classes declined. This is most probably due to the change in the composition of the quintiles, where a number of relatively wealthy households experienced a negative income shock. As expected, this was not captured by the macro or meso-models, but the microsimulation model produced very coherent results for the second quintile. On the other hand, the microsimulation model underestimated the increase in LFW of income wealthy households.

On the other hand, the microsimulation model performed poorly in both France and Italy. In Italy the meso-level approach worked very well and produced a distribution very close to the observed one. In France, the HFCS data showed limited changes in the distribution of LFW across income quintiles. Consequently, any attempts to estimate changes in the distribution, failed.

Table 4.1 Distributional National Accounts estimations for liquid financial wealth – Germany

	Per capita	**Change in per capita from HFCS wave 1**			
Income quintile	**HFCS wave 1**	**HFCS wave 2**	**Fixed Distribution**	**Estimated distribution**	**Micro-simulation**
I	2,230	192	143	61	63
II	3,006	911	242	162	851
III	4,992	- 326	278	21	- 69
IV	6,450	- 168	83	182	173
V	15,542	620	482	802	211

Table 4.2 Distributional National Accounts estimations for liquid financial wealth – Spain

	Per capita	**Change in per capita from HFCS wave 1**			
Income quintile	**HFCS wave 1**	**HFCS wave 2**	**Fixed Distribution**	**Estimated distribution**	**Micro-simulation**
I	1,846	- 216	8	- 79	38
II	2,004	260	160	- 18	194
III	2,563	337	106	85	173
IV	4,016	514	123	358	202
V	11,107	- 125	372	424	164

[18] Reference years for the first wave are 2010 for DE, FR and IT and 2008 For ES; and for the second wave 2014 for DE, FR and IT and 2012 for ES.

Table 4.3 Distributional National Accounts estimations for liquid financial wealth – France

Income quintile	Per capita	Change in per capita from HFCS wave 1			
	HFCS wave 1	HFCS wave 2	Fixed Distribution	Estimated distribution	Micro-simulation
I	1,541	- 67	51	206	816
II	2,292	- 52	71	- 170	519
III	3,182	67	102	- 136	643
IV	4,886	427	151	- 322	539
V	13,970	432	431	1,228	- 1,712

Table 4.4 Distributional National Accounts estimations for liquid financial wealth – Italy

Income quintile	Per capita	Change in per capita from HFCS wave 1			
	HFCS wave 1	HFCS wave 2	Fixed Distribution	Estimated distribution	Micro-simulation
I	1,753	- 355	- 31	- 251	1,383
II	2,993	- 71	- 177	- 29	267
III	4,930	- 565	- 347	- 387	- 189
IV	7,344	- 424	- 672	- 632	- 558
V	19,981	- 1,378	- 1,566	- 1,494	- 3,696

Tables 4.5 to 4.8 compare the results of the estimations for households' liabilities, with similar contents than in tables 4.1 to 4.4. In the case of liabilities, the performance of the estimation methods is rather disappointing. The only exception is the meso-level approach that produces a relatively close fit to the observed distribution in Italy. Microsimulation does not produce accurate results in any country. In Germany, where the developments of LFW in the low income groups were well estimated by microsimulation, the increase in liabilities in the second income quintile is not captured. In Italy, microsimulation overestimates the debt levels of income poor households significantly.

Table 4.5 Distributional National Accounts estimations for liabilities – Germany

Income quintile	Per capita	Change in per capita from HFCS wave 1			
	HFCS wave 1	HFCS wave 2	Fixed Distribution	Estimated distribution	Micro-simulation
I	676	- 189	- 43	25	- 68
II	699	761	- 37	- 18	- 15
III	2,908	- 416	- 97	- 422	- 14
IV	5,235	- 191	- 167	- 124	- 124
V	10,771	- 658	- 350	- 153	- 472

Table 4.6 Distributional National Accounts estimations for liabilities – Spain

Income quintile	Per capita HFCS wave 1	Change in per capita from HFCS wave 1 HFCS wave 2	Fixed Distribution	Estimated distribution	Micro-simulation
I	628	217	- 79	5	17
II	2,423	- 167	- 300	- 482	- 168
III	5,157	- 1,264	- 636	- 837	- 675
IV	5,586	- 313	- 732	- 1,023	- 1,061
V	8,036	- 1,437	- 1,218	- 628	- 1,078

Table 4.7 Distributional National Accounts estimations for liabilities – France

Income quintile	Per capita HFCS wave 1	Change in per capita from HFCS wave 1 HFCS wave 2	Fixed Distribution	Estimated distribution	Micro-simulation
I	666	165	- 52	12	- 53
II	1,346	56	- 94	- 213	- 132
III	3,110	- 326	- 208	- 386	- 548
IV	6,633	- 818	- 425	- 937	- 813
V	10,366	609	- 753	- 8	13

Table 4.8 Distributional National Accounts estimations for liabilities – Italy

Income quintile	Per capita HFCS wave 1	Change in per capita from HFCS wave 1 HFCS wave 2	Fixed Distribution	Estimated distribution	Micro-simulation
I	694	- 38	- 67	- 23	2,791
II	1,421	- 201	- 128	- 233	- 197
III	2,328	67	- 218	- 307	- 438
IV	4,238	- 445	- 379	- 642	- 1,342
V	7,748	- 891	- 716	- 302	- 2,322

Figures 4.1 to 4.4 show the estimation results for the debt-to-liquid financial wealth (DTLFW) –ratio, by income quintile, using the methodologies presented in Chapters 2 and 3. The first two columns with no patterns represent the DNA-indicators calculated from the two cross-sections with equation 1. The third, dotted column represents the results calculated by assuming stable distributions for both assets and liabilities derived with equation 2. The fourth striped columns show the results of the meso-level estimation using more up-to-date data on income and debt repayments. The last columns show the results from microsimulation.

Figures 4.1 – 4.4 Distributional National Accounts estimations for debt-to-LFW ratio

Since our main interest is to estimate a variable that measures financial vulnerability, it is worth looking more closely to what happens in the estimation of the bottom income quintiles. A combination of high indebtedness relative to financial wealth for low income households is of particular interest for financial stability.

In the combined analysis of HFCS and FA cross-sections significant changes in the DTLFW-ratio are observed for the bottom two income quintiles in Germany, and to a lesser extent in Spain. In Germany, the bottom income quintile becomes less vulnerable between the two HFCS waves, while the second lowest income quintile becomes more vulnerable. In the bottom income quintile liquid financial wealth increases, which is pretty well captured by the estimated distribution -model. However, the simultaneous decrease in indebtedness is not captured by this estimation model. For the second income quintile in Germany, both liquid financial wealth and indebtedness increase substantially, but only the microsimulation model succeeds in approximating the increase in wealth, and none of the models captures the increase in indebtedness. Changes in the DTLFW-ratio of the three highest income quintiles are smaller in relative terms, and the estimation model succeeds well in simulating these changes.

In Spain, opposite developments occur in the bottom two quintiles. The lowest quintile becomes more vulnerable, while the DTLFW-ratio of the second quintile decreases from 121% to 100%. The decrease in financial wealth of the bottom quintile is to some extent estimated with the meso-level model, but the increase in indebtedness is not. In France, the estimation models work relatively well for the highest three income quintiles. In Italy the estimated distribution –model performs well for all other income groups except for the middle quintile.

5. Conclusions and the way forward

The first conclusion is that no model produces ‘perfect results’, but some of the models work for individual analyses in individual countries. Same models may not be applicable in all countries. This has been the approach by the OECD EG-DNA, where each country should select a suitable model to assess distributional developments, based on data availability and applicability at the national level.

The meso-level approach applying estimated distributions at a household group level uses a very broad measure of financial income that is applied at the instrument level. Furthermore, the relationship between financial income and financial wealth is not very stable at the macro level. In spite of these limitations, the meso-level approach works well in Italy and relatively well in Spain for the estimation of the change in the distribution of liquid financial wealth. In Italy, the portfolio share of bonds and mutual funds in LFW is clearly higher than in the other three countries. One may assume that income generated by these assets is better covered by households surveys (vis-à-vis deposits), and thus changes in the distribution of financial income provide a feasible proxy for changes in financial wealth.

In Germany, microsimulation provides very promising results that capture an unusually high increase in liquid financial wealth of the second income quintile. This proves that accounting for income mobility can be important. It is worth noticing that the microsimulation model produces relatively limited income mobility for Germany, only 5% of households in the second simulated income quintile were in higher income groups in the first wave. But nevertheless, the model was able to estimate satisfactorily the impact of income mobility on LFW distribution. In Italy, microsimulation overestimates income mobility. For example, more than 35% of households are estimated to move from upper income quintiles to the bottom quintile. This explains the vast overestimation of both wealth and liabilities in QI.

In spite of good macro level coherence between interest paid and liabilities, neither the meso-level estimation nor microsimulation produce results that are very reliable. The key to improving the estimation of the distribution of liabilities is to find methods that take into account the sale or purchase of real assets. Portfolio changes related to financial assets are assumedly limited. Households are rarely able to increase their savings by a large margin even in the medium term, neither are they usually forced to sell large amounts of assets to compensate for a sudden income loss. For liabilities, the story is different. Because liabilities are frequently collateralised by real estate assets, a household may take significant amounts of debt from one day to another, if it purchases e.g. its main residence. Similarly, if a household changes its tenure status from owner to renter for any reason, its debt stock decreases from up to several hundred thousand euros to zero overnight.

References

Albacete, N. and P. Fessler (2010):” Stress testing Austrian households”, Financial Stability report 19, June, European Central Bank.

Ampudia, M., A. Pavlickova, J. Slacalek and E. Vogel (2014): ”Household heterogeneity in the Euro Area since the onset of the great recession”, ECB Working Paper Series No 1705.

Andreasch, M., P. Fessler and P. Lindner (2013): “Linking Microdata and Macrodata on Austrian Household Financial Wealth Using HFCS and Financial Accounts Data”. Statistiken, Special Issue, pp. 14-23, Oesterreichische Nationalbank.

Bankowska, K., J. Honkkila, S. Pérez-Duarte and L. Reynaert Lefebvre (2017): "Household vulnerability in the euro area," IFC Bulletins chapters, in: Bank for International Settlements (ed.), Data needs and Statistics compilation for macroprudential analysis, volume 46 Bank for International Settlements.

Bettocchi, A., C. Moriconi, E. Giarda, F. Orsini, R. Romeo (2016): “Assessing and Predicting Financial Vulnerability of Italian Households: A Micro-Macro Approach”, Prometeia.

Dettling, L. J.; S. Devlin-Foltz; J. Krimmel; S. Pack and J.P. Thompson (2015): “Comparing Micro and Macro Sources for Household Accounts in the United States: Evidence from the Survey of Consumer Finances”, FEDS Working Paper No. 2015-086, http://dx.doi.org/10.17016/FEDS.2015.086

Durier, S.; L. Richet-Mastain and M. Vanderschelden (2012): “Une décomposition du compte de patrimoine des ménages de la comptabilité nationale per categories de ménages en 2003”, Direction des Statistiques Démographiques et Sociales N° F1204.

European Commission (2017): Methodological Guidelines and Description of EU-SILC Target Variables. Eurostat, Directorate F Social Statistics.

European System of Accounts 2010 (ESA2010), Publications Office of European Union, Luxembourg 2013.

Honkkila, J. and Kavonius, I. K. (2013): “Micro and Macro Analysis on Household Income, Wealth and Saving in the Euro Area”, ECB Working Paper Series No 1619.

Household Finance and Consumption Network (HFCN 2016): The Household Finance and Consumption Survey: methodological report of the second wave. ECB Statistics Paper No 17, December 2016.

IMF/FSB report to the G-20 Finance Ministers and Central Bank Governors, http://www.financialstabilityboard.org/publications/r_091107e.pdf

Kavonius, I. K. and J. Honkkila (2016): ”Deriving Household Indebtedness Indicators by Linking Micro and Macro Balance Sheet Data”, Statistical Journal of the IAOS (International Association for Official Statistics), Issue 2016/32, pp 693-708, IOS Press.

Kavonius, I.K. and V.-M. Törmälehto (2010): “Integrating Micro and Macro Accounts – The Linkages between Euro Area Household Wealth Survey and Aggregate Balance Sheets for Households”, the 31st General Conference of the International Association for Research in Income and Wealth (IARIW) in St. Gallen, Switzerland, August 2010.

Krimmel, J., K. B. Moore, J. Sabelhaus, and P. Smith (2013): “The Current State of U.S. Household balance sheets”, Federal Reserve of Bank of Saint Louis Review, 95(5), 337-359.

Michelangeli, V. and M. Pietrunti (2014): ”A microsimulation model to evaluate Italian households’ financial vulnerability”, International Journal of microsimulation (2014) 7(3) 53-79.

O’Donoghue, C., J. Loughrey (2014): ”Nowcasting in microsimulation models: a methodological survey”, Journal of Artificial Societies and Social Simulation 17 (4) 12.

Stiglitz, J.E.; A. Sen & J-P Fitoussi (2009): “Report by the Commission on the Measurement of Economic Performance and Social Progress”, www.stiglitz-sen-fitoussi.fr.

Vienna Memorandum, European Statistical System Committee, 26-27 September 2016, http://ec.europa.eu/eurostat/documents/7330775/7339365/DGINS+Memorandum+2016/4ebdf162-1b20-4d9e-a8c7-ae880eca9afd

Zwijnenburg, J., S. Bournot and F. Giovannelli (2017), "Expert Group on Disparities in a National Accounts Framework: Results from the 2015 Exercise", OECD Statistics Working Papers, No. 2016/10, OECD Publishing, Paris, https://doi.org/10.1787/2daa921e-en.