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LIQUIDITY-POOR HOUSEHOLDS IN THE MIDST OF THE COVID-19 PANDEMIC

by Mariano Graziano[*] and David Loschiavo[§]

Abstract

The Covid-19 pandemic led to a large and immediate decline in households' aggregate spending and a surge in bank and postal deposits; although little is known about how this was distributed. This paper overcomes the lack of timely micro-data on households' liquidity by looking at supervisory data on deposits, introducing a new method to estimate the trend in liquidity distribution and the percentage of liquidity-poor households. We find that in 2020 there was a decrease both in the degree of deposit inequality among Italian households and in the share of liquidity-poor households, alongside government support measures that allowed some households at the bottom of the liquidity ladder to save out of their declining income. The increase in households' liquidity improved their ability to repay debts and this could help spending patterns to rebound once confidence about the economic outlook is restored. Despite this, households with insufficient liquidity buffers still constitute a large share of population, making their debt repayment capacity dependent on the strength of the economic recovery.

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1. Introduction[1]

The outbreak of the Covid-19 pandemic led to an immediate and large decline in consumer spending and an increase in households' aggregate saving rates in many countries.[2] In Italy, in 2020 the propensity to save increased by 7.6 percentage points (peaking at 15.8 per cent) compared with the previous year, while income dropped 2.8 per cent over the same period. On average, households have therefore compressed their consumption proportionally more than the reduction in disposable income.[3] During the phase in which the contagion containment measures were more severe, consumption dropped more than income reflecting the impossibility of purchasing several goods and services due to the shutdown of non-essential activities (referred to as "forced" or "involuntary" savings). After the gradual lifting of social distancing regulations (since the middle of May 2020), the propensity to save has been boosted by the willingness of households to build up a buffer against unforeseen contingencies (known as "precautionary" savings) amidst growing concerns about the evolution of the pandemic and the timing of economic recovery (see Bank of Italy, Economic Bulletin, 2021, 1, pp. 26-9). In a context of increased risk aversion, the growth in the propensity to save resulted in soaring household liquidity; in December 2020 bank and postal deposits were up by 7 per cent on an annual basis, the highest growth rate since the end of the sovereign debt crisis.

Liquid assets allow households to deal promptly with adverse events such as sharp reductions in income, while maintaining reasonable levels of consumption and, for those who are indebted, continuing to service their financial commitments. Italian households' net financial wealth is structurally high by international standards and a significant part of it is invested in liquid instruments.[4] On average, the bank and postal deposits of an Italian household amounted to approximately 40,600 euros in December 2019. The increase in liquid resources in 2020 has further increased the average holdings of liquid assets.

However, aggregate liquidity data do not provide an accurate picture of households' resilience to income shocks as liquidity is not evenly distributed across them. In fact, household surveys suggest that a large share of the population does not have enough financial resources to meet their needs in the event of short periods of unemployment or loss of income. The latest available data from the Bank of Italy's "Survey on Household Income and Wealth" (SHIW), in reference to 2016, show that 45 per cent of the population did not have enough liquidity (bank and postal deposits) to avoid the risk of

[2] Cf. Dossche, M. and Zlatanos, S. (2020) for European countries and Bachas et al. (2020) for the US.
[3] According to John Maynard Keynes, households' propensity to save is determined by a set of objective and subjective factors, which vary greatly among individuals with different socioeconomic characteristics. The set of subjective motives identified by Keynes includes: precaution, foresight, calculation, improvement, independence, enterprise, pride, and avarice, Keynes (1936, p. 108). To these, Browning and Lusardi (1996, p. 1798) add the downpayment motive "to accumulate deposits to buy houses, cars, and other durable goods". By tracing the variation in the propensity to save to precautionary reasons, we are implicitly assuming that this was the prevailing motivation given the contingent circumstances, without however excluding the possible coexistence of another one of the multiple personal motivations capable of justifying a single act of saving. A coherent analysis of households' saving behaviour taking Italy as the field of research and emphasizing the roles of capital markets, private and government transfers and their interactions, as well as shifting demographic patterns, can be found in Ando, Guiso, and Visco, I. (1994).
[4] At the end of June 2020, Italian households' net financial wealth was equal to 2.9 times disposable income (2.5 times was the euro-area average) and around 35 per cent of it was held in cash, bank and postal deposits (Bank of Italy, 2020c).

falling into poverty,[5] in the absence of income for at least three months.[6] This condition of vulnerability was also widespread among indebted households, confirming how the risk of illiquidity can easily translate into difficulty in repaying debts. Indeed, 47 per cent of indebted households were in conditions of liquidity poverty and about 44 per cent of overall household debt was attributable to them.[7]

Given the lack of more recent data on the distribution of the financial liquidity of Italian households, we use supervisory reports on bank and postal deposits to infer the liquidity situation at the onset of the Covid-19 crisis and on its evolution during the subsequent months. Thanks to the availability of data on deposits divided into size buckets, we propose an approach to draw information not only on the change in aggregate household liquidity but also on its distribution among households in different wealth categories, shedding some light on the distributional effects of soaring savings.

Deposits are the most liquid form of savings as they can be readily used in case of need without incurring any potential losses by liquidating other financial assets. This holds especially true in a period of crisis, in which sharp fluctuations in share prices and bond yields are recorded. Indeed, short-term Treasury bonds and money market fund shares are also forms of wealth that could easily be liquidated with very limited losses. Given the absence of the necessary information, we exclude Treasury short-term bills and money market funds from the analysis. Nevertheless, the conclusions of our analysis are not significantly affected since these assets represent only a negligible fraction of the financial wealth of Italian households (well below 1 per cent at the end of 2019).[8]

To measure the degree of deposit concentration and its evolution over time, we construct a Gini inequality index taking into account that the available data allow us to know only the values at certain intervals of the Lorenz curve. To make the concept of financial resilience operational, we introduce the notion of "liquidity-poor" households, which are defined as those households without sufficient bank and postal deposit holdings to avoid, in the absence of income, falling below the risk-of-poverty threshold. We provide an estimated range of liquidity-poor households under various assumptions, building on the recently released Federal Reserve's Distributional Financial Accounts methodology. Using data from a recent survey on Italian households, we also extend the analysis to differences in liquidity conditions across demographic and economic groups that could be differently affected by the crisis. There are at least two reasons why it is important to have timely information on the distribution of liquidity among households. First, such information is useful to assess the financial resilience of households, that is, their capacity to continue servicing their financial commitments while maintaining reasonable levels of consumption. Second, it provides insights on households' spending capacity and, in turn, on the timing of the economic recovery. From the point of view of financial resilience, the risk is that if the surge in average liquidity had been driven exclusively by affluent

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[5] The European Commission sets the at-risk-of-poverty threshold at 60 per cent of national median equivalent disposable income. For a comprehensive discussion on the asset-based measures of poverty, see Brandolini et al., 2010.

[6] See also Bank of Italy (2018), p. 12. According to the Bank of Italy (2020a), this percentage drops to 40 per cent when other financial assets (such as long-term Treasury bonds and shares) are included in the estimation. In comparison with the main economies of the euro area, the share of financially poor households was in line with that of France and Spain, but about 7 percentage points higher than that recorded in Germany.

[7] These shares remain large (42 and 37 per cent, respectively), even when considering all financial assets and not only the most liquid ones.

[8] Indeed, according to Bank of Italy (2018), p. 12, by including a wider set of liquid financial assets, the share of liquidity-poor households remains almost unchanged (from 45 to 44 per cent of total households). This result confirms that the forms of financial wealth different from deposits are concentrated in the top part of the wealth distribution and excluding them from the analysis should not substantially affect our estimates, which are focused on the lower end of the wealth ladder.

households, it could have resulted in an increase in the share of households who would not be able to meet their financial commitments in the following months due to the absence of adequate buffers.[9] From the point of view of spending capacity and the timing of the economic recovery, the risk is that soaring deposits may reflect a generalized propensity to save for precautionary reasons whether or not a household incurred significant income losses. If continued over time, this would risk slowing down the timing of the economic recovery, exacerbating adverse underlying trends already in place before the crisis (see Blanchard, 2020; Goy and End, 2020).

Our analysis shows that the existing trend towards an increase in the degree of concentration of deposits has reversed in the aftermath of the Covid-19 outbreak. Furthermore we find that, between December 2019 and December 2020, the share of liquidity-poor households decreased, albeit remaining large (between 33.5 and 43.6 per cent of households). Data indicate that both the decrease in the degree of deposit concentration and liquidity-poor households began in the first half of 2020.

Overall, the analysis suggests that during the crisis a part of the less wealthy households was also able to build up liquidity buffers to support their financial conditions in the coming months, arguably due in part to government action to protect workforce income from the sharp downturn. Policy interventions - such as short-time working allowances, temporary income-support schemes for self-employed workers, and debt moratoriums - may have also allowed households at the bottom end of liquidity ladder to save out of their declining income. This result is in line with Bachas et al. (2020), who find that the initial impact of the pandemic on household wealth was a shift in US households' liquid-balances distribution towards low-income households.[10]

The results of the analysis on the differences in liquidity conditions across demographic and economic groups indicate that being indebted increases significantly the chance of being liquidity-poor. Given the large share of liquidity-poor households, this implies that many households might not weather a protracted spell of unemployment without falling behind on debt repayments, if the recovery were slow and government support significantly scaled down.

The remainder of the paper is structured as follows. Section 2 describes the data and provides the first descriptive evidence on liquidity growth in 2020. Section 3 presents the trends in liquidity distribution during the Covid-19 crisis. Section 4 provides estimates of the share of liquidity-poor households, while Section 5 presents evidence on heterogeneity in liquidity conditions across demographic and economic groups with a focus on indebted households. Section 6 shows that the results on the share of liquidity-poor households are robust to alternative estimates using the Distributional Financial Accounts/Chow-Lin approach to interpolation and forecasting. Section 7 concludes. Appendix A examines the contributions of changes in the number of deposits and the average amount deposited to the size buckets' growth. Appendix B describes the methodology used to construct the Gini inequality index. Appendix C illustrates the reconciliation exercise, which is a prerequisite to the Distributional Financial Accounts/Chow-Lin approach.

2. Data and descriptive evidence

To overcome the lack of high-frequency information on the distribution of households' liquidity, this work uses the Bank of Italy's Supervisory Reports (SR) on bank and postal

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[9] The underlying assumption is that households will respond to an adverse income shock by reducing consumption to some minimum level (by cutting expenditure on non-essentials and durables), before eventually starting to fall behind on debt repayments; see, for instance, Zabai (2020).

[10] Bachas et al. (2020) show that such a shift reflects the fact that stimulus checks and expanded unemployment insurance benefits provided a disproportionate increase in income for low-income households.

deposits by size buckets. Data are provided every six months and report households' outstanding amounts and number of deposits at 30 June and 31 December of each year for each of the five size buckets (see table 1 for the amounts defining the buckets). [11]

At the end of 2020, bank and postal deposits of Italian households amounted to 1,138 billion euros, up by about 74 billion euros from a year earlier (see table 1). Comparing the stock of deposits to the number of households resident in Italy, the average balance per household was approximately € 43,500 in 2020 from € 40,600 at the end of 2019.

Table 1

Italian household deposits at the end of 2020

Liquidity bucket	Numbers (thousands)	Share on the total number	Outstanding amounts (millions of euros)	Share on the total outstanding amount	Average outstanding amounts (euros)
up to €12,500	58,482	77.1	129,875	11.4	2,221
€12,500-50,000	11,744	15.5	300,150	26.4	25,557
€50,000-250,000	5,227	6.9	494,774	43.5	94,660
€250-500,000	332	0.4	108,324	9.5	325,928
over €500,000	115	0.2	103,917	9.1	906,992
Total	**75,900**	**100**	**1,137,717**	**100**	**14,981**

Italian household deposits at the end of 2019

Liquidity bucket	Numbers (thousands)	Share on the total number	Outstanding amounts (millions of euros)	Share on the total outstanding amount	Average outstanding amounts (euros)
up to €12,500	59,862	78.8	124,141	11.7	2,074
€12,500-50,000	10,847	14.3	276,994	26.0	25,537
€50,000-250,000	4,827	6.4	457,753	43.0	94,841
€250-500,000	314	0.4	102,371	9.6	325,985
over €500,000	111	0.1	102,353	9.6	922,153
Total	**75,961**	**100**	**1,063,613**	**100**	**14,002**

Source: Bank of Italy Supervisory Reports.

Different factors contributed to the increase, including pent-up consumer demand and higher precautionary savings. A potential competitive explanation for the surge in deposits during the Covid-19 pandemic is people fleeing from risky assets into deposits due to the increased volatility and the poor performance of stock markets. If that were the prevailing case, the massive increase in deposits and the changes in their distribution might have more to do with investors' assets reallocation triggered by financial markets panic than with actions driven by a purely precautionary (and forced) savings motive. However, by analyzing the net flows reported in Financial Accounts we can rule out such a "flight-to-safety" view (see also Bank of Italy, 2021 section 1.2). In fact, during the first three quarters of 2020 negative flows in the rest of household net financial wealth assets explain only 1.5 per cent of the surge in deposits. This implies that the reallocation of risky investments was not the main source of the flow of funds into deposits.

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[11] They include overnight and demand deposits, checking accounts, time deposits (certificates of deposit, time checking accounts and time/savings deposits) and those redeemable at notice (free savings deposits and other deposits not usable for retail payments), postal savings bonds. The distinction in SR data between checking accounts and other (time and savings) deposits is available only for the number of deposits but not for the outstanding amounts.

Between 2019 and 2020, the increase in deposits had affected all size buckets. In absolute terms, the greater increase was recorded in the outstanding amounts of the second bucket (12, 500-50,000 euros; see table 1). Yet, the average amount deposited in each size bucket increased only for the lower size bucket (up to 12,500 euros), while it shrank for the upper three size buckets and remained stable for the second-last one.

The percentage change in the outstanding amount of deposits by size buckets can be broken down into percentage changes in the number of deposits and the average amount deposited. In Appendix A, we show that the analysis of contributions to deposit growth in each size bucket suggests that the surge in average stocks in the lower bucket did not stem from an outflow of deposits from the adjacent bucket.

At the end of 2020, 77 per cent of household deposit accounts did not exceed a balance of € 12,500. Such households held a large number of accounts (58 millions) but with a limited average balance (approximately € 2,200).

Indeed, the SR data statistical unit is the bank-province-size bucket cell which is built aggregating information on bank-customer relationships. Hence, an individual holding multiple deposits with different banks is counted several times in the aggregate data. In addition to this, joint accounts are not split between holders but considered as a different client. For instance, if two clients have one bank account each and one joint account, the bank registers three individual clients.

Unlike firms, most households usually have a limited number of banking relationships, mainly because most deposit contracts are costly. According to the SHIW, in 2016 about 65 per cent of households had deposits with a single intermediary at most. Furthermore, the share of households having multiple bank accounts decreased steeply as the number of accounts increased (see figure 1).

Figure 1 – Share of households by number of deposit accounts

(Cumulative frequencies)
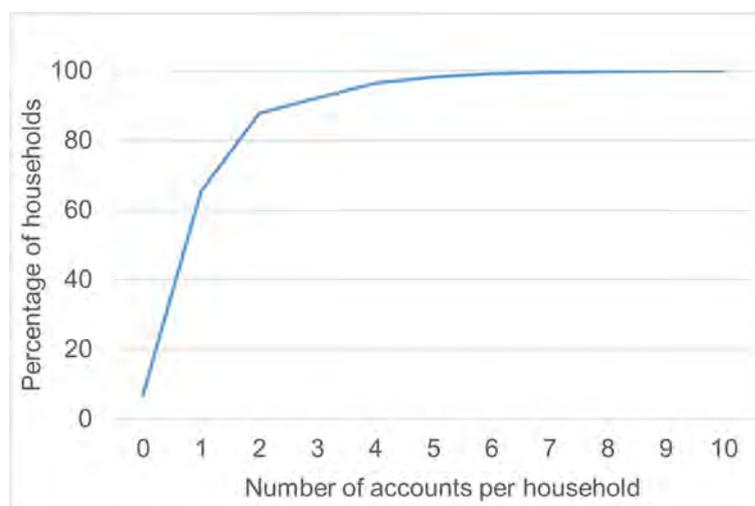
Source: SHIW 2016. The frequencies are weighted and refer to the whole sample of households.

The number of accounts held on average by a household grows rapidly as its liquidity increases but it hinges also on households' characteristics such as, for instance, the number of income earners, working status and education of the household members. Therefore sampling variability may affect the observed distribution of the average number of households' accounts across the liquidity ladder. To take this issue into account, in

column 1 of table 2 we show the distribution of the regression-adjusted[12] average number of deposits by size buckets in 2016.

Table 2

Size bucket*	Average number of accounts per household in SHIW (1)	Share of households in SHIW (2)	Share of deposit accounts in SR (3)	Average deposit holdings in SHIW - euros (4)	Average deposit holdings in SR - euros (5)
up to €12,500	1.44	78.4	76.6	2,315	2,399
€12,500-50,000	2.16	17.3	16.1	26,597	25,238
€50,000-250,000	2.52	3.7	6.8	98,213	93,258
€250-500,000	1.93	0.4	0.4	360,975	326,084
over €500,000	3.21	0.2	0.1	891,533	994,389

Sources: Survey on Household Income and Wealth 2016 and Supervisory reports. * Due to the inconsistencies in the reports of postal saving deposits and bonds in 2016 (last SHIW wave available), such assets are excluded from the figures reported in the table in order to have a comparable distribution between SHIW and SR.

Obviously, the unit of observation in SR statistics (individual accounts) differs from the one in SHIW (households accounts), since in the former different components of the same household unit are treated as separate clients. According to SHIW, on average households hold 1.7 deposit accounts. The reconciliation problem between the number of accounts and the number of households in each liquidity class will be formally addressed in sections 4 and 6. More specifically, in section 4 we start from the SR data and apply the distribution of accounts observed in SHIW while in section 6, building on the Distributional Financial Accounts approach, we start from SHIW households' balance sheet and we interpolate and forecast them in semesters when only the SR and other macroeconomic data are available. At this stage, it is worth noting that the share of households falling within each bucket in 2016 (estimated using SHIW data, column 2) was very similar to that of the percentage of deposit accounts falling within the corresponding bucket in the same year (from SR, column 3). The similarity of the two distributions is also confirmed when, for each bucket, the average amount of deposits corrected by the regression-adjusted number of accounts per household (column 4, SHIW data) is compared with the average amount of the accounts (column 5, SR data).

3. Liquidity distribution inequality measures

One of the aims of this work is to study the trend in the distribution of liquid assets between households after the Covid-19 outbreak. For this, in addition to the evidence given above through the analysis of the relative trend of size buckets, we take a step further and provide a synthetic index that measures the concentration of deposits relying on the Gini coefficient.[13] It is worth noting that SR data are available since December 2012; however, due to inconsistencies in the reporting of time and saving postal deposits

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[12] In table 1, we report the predicted values for a linear regression where the dependent variable is the households' number of deposits and the independent variables are: the stock bracket (as a factor variable), the number of income earners, the equivalized disposable income (see footnote 17 for the definition), the working status and the education of the head of the household. The estimations are run on SHIW household-level data, are weighted using SHIW sampling weights, and standard errors are corrected for heteroscedasticity. In table A.1 we report the regression-adjusted number of accounts (and the corresponding underlying regressions) for each SHIW wave and, differently from column 1 of table 1, including the full set of deposits.

[13] Appendix B describes the procedure adopted to compute the Gini coefficient in case of grouped data.

between December 2014 and June 2017, only the data relating to bank (checking and saving) and postal (checking) deposits can be used in time series during that time span.

Figure 2 shows that, in the months following the Covid-19 emergency, the Gini coefficient for deposits by size buckets has decreased, lowering to 76.0. Despite being still a very high value,[14] the index reduction was marked since it returned to the values recorded at the end of 2014. The decreasing trend in 2020 is also confirmed for all bank and postal deposits observable since the end of 2017, the date from which information on the latter type of deposits is again available.

Figure 2 – Different measures of deposit concentration
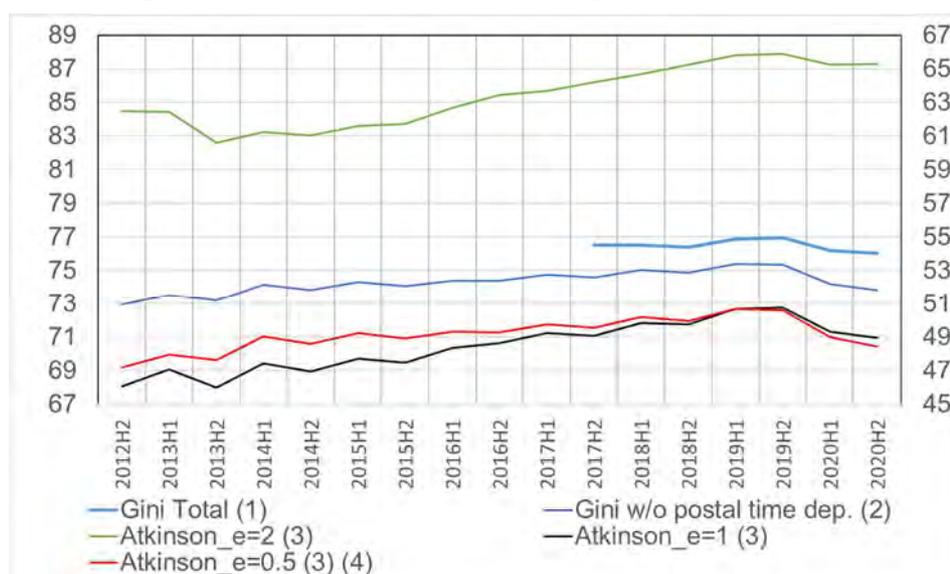
Sources: Bank of Italy Supervisory Reports (SR).
(1) The Gini coefficient refers to the total deposits. (2) Gini coefficient excluding postal time deposits. (3) Atkinson index with inequality-aversion parameter values of 0.5, 1, 2. (4) Right-hand scale.

However, the Gini coefficient is sometimes criticized as being too sensitive to relative changes around the middle of the income distribution (more precisely, the mode). Adopting as a measure of inequality the Atkinson indices, which are more sensitive than Gini coefficient to differences in different parts of the distribution[15], the overall picture does not change: both the increasing trend in deposit concentration in 2012-2019 and the following decrease in inequality in 2020 are confirmed. More in detail we use the Atkinson class A(e) for e = 0.5, 1, 2, where e is the inequality-aversion parameter. The more positive e is, the more sensitive is the inequality index to differences at the bottom of the distribution. The pattern shown by the Atkinson indices for e = 0.5, 1 are very similar to those of Gini coefficients. According to the Atkinson index with inequality aversion parameter of 2, which is the most sensitive to changes affecting the lower tail of the distribution, there was a steep decline in liquidity concentration in the first half of 2020, supporting the robustness of the finding of a growth of deposits during the crisis mainly concentrated among households with less liquidity, under varying inequality measures.

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[14] Gini coefficient ranges between 0 in the case of equidistribution and 100 in the case of maximum concentration. As a term of comparison, when computed for the year 2016, the latest year with available microdata from the SHIW, the Gini coefficient of deposits was almost equal to the same index computed on SHIW data and higher than that of the total net wealth of Italian households but lower than that of total financial wealth, consistent with the evidence that forms of investment in financial assets with a higher return-risk combination are more widespread among the upper percentiles of wealth distribution.

[15] For the inequality indices differing in their sensitivities to income differences in different parts of the distribution see, for instance, Cowell and Jenkins (1995), Atkinson (1970), and Shorrocks (1984).

This result supports the hypothesis that the growth of household savings in the first months of the crisis has mostly affected those with less liquidity. The surge in deposits for the lower-end of the liquidity ladder is due in part to the combination of precautionary and forced savings by those households protected from the sharp downturn by government's actions. In fact, even though large numbers of households have suffered falls in earnings during the pandemic, their incomes have been partly protected, through both welfare systems and various support measures such as short-time working allowances, temporary income-support schemes for self-employed workers, debt moratoriums (Carta and De Philippis, 2021).

In line with this, results of the Special Survey of Italian Households conducted in March 2021 shows that almost one third of households who received at least one form of income support was also able to save out of their income in 2020 (32.5 per cent of them compared with 38.8 per cent of the whole sample; figure 3); over 8 percentage points more than households that reporting having a lower income than the one normally earned before the pandemic. According to this suggestive evidence, support measures allowed some households to save even in the face of declining incomes; a result in line with evidence from the US (see Bachas et al., 2020). Liquidity reserves accumulated during the crisis may help households either to weather a longer than expected unemployment spell or, should confidence on economic prospects be restored early, spending patterns to rebound.

Figure 3 – Share of households with positive savings in 2020

(per cent)
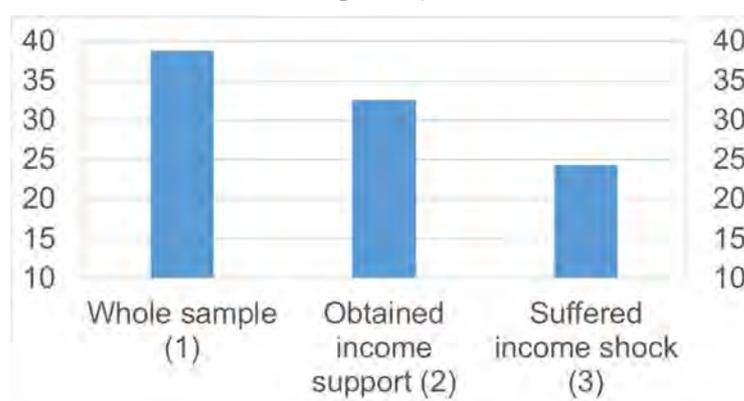
Sources: Bank of Italy *Special Survey of Italian Households* - March 2021. Data are weighted using survey weights. (1) Share of individuals reporting positive savings in 2021 on the total interviewed (2,806). (2) Share of individuals reporting positive savings in 2021 among those who received some form of income support in the 3 months preceding the interview. (3) Share of individuals reporting positive savings in 2021 among those who in the last month earned an income lower than one normal earned before the pandemic and that did not received some form of income support in the 3 months preceding the interview.

4. Liquidity-poor households

A lower concentration of liquidity does not necessarily imply a decrease in the share of households able to face short periods of economic difficulty with their liquid assets, which instead depends on the absolute amount of liquid resources available at the bottom of liquidity distribution. To this end, we define as liquidity poor those households having bank and postal deposits holdings lower than a quarter of the threshold that identifies the risk of poverty (60 per cent of the median equivalent income).[16] In other words, a household is liquidity poor if it would not have sufficient resources to sustain its essential

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[16] In line with the definition of poverty threshold adopted by the European Commission (see footnote 5).

consumption for at least three months even if it liquidated all its immediately available financial assets.

To make this definition operational, we need to determine the amount of resources needed to support essential consumption. To this end, we first calculate the median equivalent income[17] from the 2018 Eu Silc survey data. The income for the years 2018 and 2019[18] is obtained by applying to the Eu Silc median equivalent income the annual percentage changes in household disposable income between 2017 and 2019 from the Istat National Economic Accounts. The individual poverty threshold at three months is then the 15 per cent of such an income. Finally, to get the household-level poverty threshold we need multiplying it by the relative equivalence scale of a reference household.[19]

<div align="right">**Table 3**</div>

Poverty thresholds for different household compositions (1)

Type of household	Equivalent adults	Poverty line for 3 months	Poverty line for 1 year
Median (head's age <45) (2)	1.8	5,001	20,003
Median (whole sample)	2.0	5,557	22,227
Modal	2.0	5,557	22,228
3 adults and 2 minors (3)	2.6	7,225	28,901
1 adult and 1 minor (3)	1.3	3,612	14,450

Sources: Authors' elaborations on data from Eu-Silc and Istat - National Economic Accounts. (1) Poverty thresholds are referred to the 2019 median equivalent income of 18,525 euros. (2) Household made up of two adults and a minor (aged under 14) with its head aged 44 or under. (3) Minor aged 14 or less.

According to the latest available data from the Eu Silc (*Statistics on Income and Living Conditions*) survey, between 2015 and 2018 the median household in Italy was made up of two adults and a minor[20] with its head aged 44 or under. We will therefore adopt this composition as benchmark to define our reference household. As a result, in 2019 the median household had an annual income of just over 33,000 euros and the corresponding poverty threshold was 20,000 euros[21] (5,000 if calculated for 3 months, the reference period of this analysis; see table 3). It is worth noting that, even though adopting different criteria defining the composition of the reference household changes the corresponding

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[17] Median equivalent income is a good measure for approximating individual financial well-being taking account of household size and resulting economies of scale. More precisely, equivalent income is the income required by a member of the median household to attain the same level of well-being that she would have living alone. It is calculated by assigning to each member of the household a weight based on their age. The sum of these weights yields the number of equivalent adults in the household. Equivalent income is equal to the ratio of total household income to the number of equivalent adults. We adopt the OECD-modified equivalence scale, which assigns a value of 1 to the household head, a value of 0.5 to each member aged 14 or over, and a value of 0.3 to each member under age 14. In our analysis, we consider monetary disposable income, i.e. disposable household income net of imputed rents and gross of negative interests.

[18] In the Eu Silc survey, the income refers to the calendar year preceding interview. Since the latest survey available is that of 2018, the latest income data relates to 2017.

[19] The OECD-modified equivalence scale assigns a value of 1.8 to a household made up of two adults and a child under 14. Therefore, we obtain the income of the median household by multiplying the median equivalent income by such a factor.

[20] According to the most recent data on the resident population provided by the National Institute of Statistics (Istat), the average number of members per household in 2019 was 2.3.

[21] According to the latest SHIW data, in 2016 the individual poverty threshold was 830 euros per month (see Bank of Italy, 2018), or just under 1,500 euros per month for the median household which is substantially in line with the poverty line determined using Eu Silc data for the corresponding year (1,590 euros).

poverty threshold (see table 3), as we discuss below in footnote 22, this would substantially leave unaffected the estimates of the liquidity-poor households share. While we are aware that this do not completely address the ongoing debate about the arbitrariness of the choice of the thresholds and the insensitivity to the severity of poverty (see, for instance, Aaberge et al., 2021), we recognize that SR data, by being aggregated, are not suited for a multidimensional definition of financial poverty thresholds. Yet, in absence of timely alternative sources of information we deem SR data reliable enough to draw evidence on the change in the share of liquidity-poor households.

Indeed, according to SR data 77.1 per cent of the deposit accounts are concentrated in the lower size bucket. It follows that even if a household had two accounts with a balance equal to the average of that size bucket (about 2,200 euros; see table 1), it would not exceed the poverty threshold of 5,000 euros (table 3) for the median household of two adults and a minor.[22] On the other hand, the remaining 22.2 per cent of the accounts have deposit stocks above 12,500 euros, i.e. significantly above the poverty line.

In order to assess the change in adequacy of household liquidity stocks, we should therefore estimate the number of liquidity-poor households. Since the number of accounts (75.9 millions) is higher than that of households (26.2 millions), a method is needed to link the SR number of accounts to the number of deposit accounts actually owned by households belonging to different size buckets. To this end, we will make two alternative hypotheses that allow us to identify an upper bound and a lower bound for the number of liquidity-poor households, using the estimates of the distribution of accounts that households have on average for each size bucket (presented in table A.1 – see also table 2 for reference).

For the upper bound case, we assume that all households have at least one account in the lower size bucket.[23] To determine the number of households that have accounts in the upper size buckets, we then divide the number of accounts in each bucket by the corresponding regression-adjusted average number of accounts per household in that buckets (see table A.1) minus one (since by hypothesis all households have at least one account in the lower bucket). The sum of the number (thus determined) of households belonging to the upper size buckets (and therefore that certainly exceed the poverty threshold) in relation to the total number of households indicates the percentage of financially resilient households (i.e. with liquidity above the threshold of poverty). The complement to one of this percentage is the upper bound on the share of liquidity-poor households. Such algorithm can be represented as follows:

$$NLP_{min} = \sum_{i=2}^{5} \frac{N_i}{(n_i - 1)}$$

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[22] This holds true even for different compositions of the reference household such as the modal household, the median household regardless of the age of its head or any composition with a larger number of equivalent adults since, *a fortiori*, the poverty threshold is higher (see table 3). Differently, adopting as a reference household one made up of only one adult and a minor lowers the poverty threshold which nonetheless remain above the average balance of the lower size bucket since one can reasonably assume that this type of households, by being composed by just one adult, do not hold accounts with more than one bank (i.e. more than one account in SR data).

[23] The use of current accounts is widespread among Italian households for the management of current economic activities (salary transfers, utility payments, use of payment cards, etc.). As shown in figure 1, more than 90 per cent of the households interviewed in the 2016 SHIW held at least one current account or deposit.

$$LP_{max} = 1 - \frac{NLP_{min}}{NH_{tot}}$$

where N_i is the number of accounts in size bucket i (indexed in ascending order and where 1 is the bucket up to € 12,500, 2 that between € 12,500 and 50,000 and so on); n_i is the estimate of the average number of accounts per household in size bucket i (see table A.1), NLP_{min} is the estimate of the minimum number of households that are not in a condition of liquidity poverty (i.e. they are financially resilient), LP_{max} is the corresponding upper bound to the share of liquidity-poor households and NH_{tot} is the total number of households.

To determine the lower bound for the share of liquidity-poor households, we assume that households have at most one account in size buckets above € 12,500 and, consequently, that the number of households with liquidity above the poverty line is equal to the number of accounts in those buckets. The complement to one of this number in relation to total households is the lower bound for the share of liquidity-poor households. In formulas:

$$NLP_{max} = \sum_{i=2}^{5} N_i$$

$$LP_{min} = 1 - \frac{NLP_{max}}{NH_{tot}}$$

where the meaning of the notation can be easily deduced from above.

It is worth nothing that the adopted algorithm implies one corollary and an unstated assumption. The former being that households with no deposits are always included among liquidity-poor households since by construction the latter are obtained as a difference from those who are certainly not. The unstated assumption is that financially resilient households hold at least one deposit account in the lower size bucket.[24] We deem reasonable such a hypothesis since highly liquid households tend to concentrate their liquidity in a small number of accounts from which they can obtain some remuneration but they also hold deposits with a limited amount of resources for other purposes (e.g., those of dependants or for payment of bills by direct debit).

According to these estimates, the percentage of liquidity-poor households in June 2020 was between 36.0 and 45.7 per cent: both values are lower from those at the end of 2019 (between 38.5 and 47.8; fig. 4).

In the second semester of 2020 households' deposits continued to rally, hovering near record highs of the last decade (in December 2020 up by 7.0 per cent on an annual basis). Like in the first half of 2020, the deposit growth had affected the lower size buckets (+2.1 per cent). The additional increase in the absolute amount of liquid resources available at the bottom of liquidity distribution translated in a further reduction of liquidity-poor households that, at the end of 2020, represented a share between 33.5 and 43.6 per cent of Italian households, down by about 2.5 (2.1) percentage points for the lower (upper) end of the estimate range in June 2020 and by about 5 (4.3) percentage points for the lower (upper) end of the estimate range in December 2019 (figure 4). Hence, together with the evidence of the lower concentration of deposits, the reduction in the share of households with insufficient liquidity buffers confirms that the increase in deposits in 2020 has improved the financial resilience of Italian households.

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[24] This assumption implies that the number of accounts held by financially resilient households in the lower size bucket is 14.8 (17.4) millions in the upper (lower) bound case, leaving 43.7 (41.1) of the overall 58.5 millions of deposit accounts in that bucket to the liquidity-poor households (and with an average of roughly 1.6 account per liquidity-poor household).

Figure 4 – Share of liquidity-poor households
(per cent)
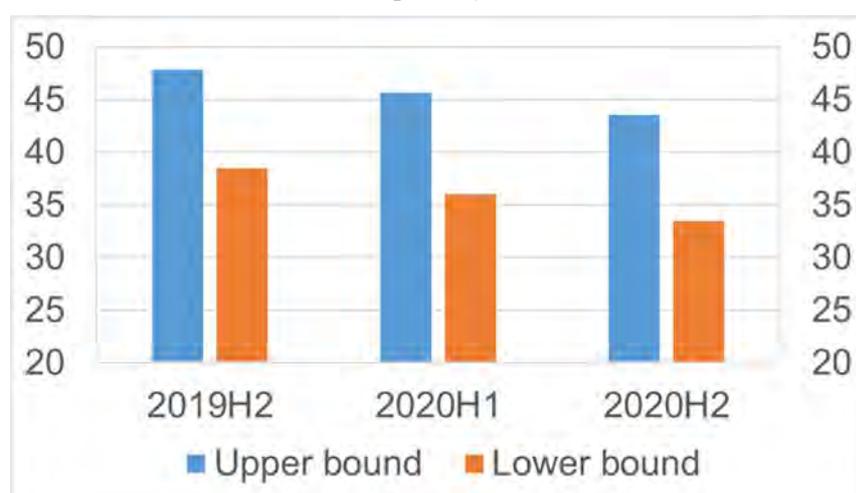
One may argue that we are overestimating the share of liquidity-poor households since some of them may have accounts with a balance above poverty threshold (between 5,000 and 12,500 euros) but still in the lower size bucket. This may be the case only if such a share is not offset by those accounts held by households who have at least one account in the lower size bucket and, at the same time, have other accounts in the upper size buckets (since, by construction, accounts held by the latter households in the lower size bucket are subtracted from the liquidity poor computation). However, to address this issue we exploit the variability in the average balance among bank-province cells of SR data to compare it with the distribution of deposits per account by percentile in SHIW. Table A2 shows that the average amounts of SR deposit holdings by percentiles approximate reasonably well the distribution of average deposit amounts by percentiles in SHIW data up to the poverty threshold of 5,000 euros, which is located around the 90th percentile.

In addition to this, figure 5 shows that both SHIW and SR empirical cumulative distribution functions (CDF) fit well Weibull CDF[25]. More in detail, the share of households with deposits in the lower size bucket and with an outstanding amount above the poverty line is 87 per cent in SHIW while the correspondent share of accounts in SR data is 91 per cent. We therefore exclude from the computation of liquidity poor share both the percentage of number of accounts that in SHIW exceeds the poverty threshold (13 per cent) and the number of accounts in size buckets above the lower (each one corrected by the relevant estimated average number of accounts per household). Applying such method, we obtain shares of liquidity-poor households equal to 41.7 per cent in 2020H2, 42.3 in 2019H2, both values in line with the corresponding estimated ranges of figure 4.

Furthermore, in section 6 we present a sensitive analysis of our results where, building on the Distributional Financial Accounts approach, the share of liquidity-poor households is obtained starting from SHIW households' balance sheet that are then interpolated and forecasted in semesters when only the SR data are available.

In addition to this, an important external validation of these estimates comes from Special Surveys of Italian Households conducted in 2020,[26] according to which 42.2 per cent of

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[25] We have compared the fit of other distributions (such as Gamma and Lognormal) on the SHIW and SR data sets and we have found that goodness-of-fit statistics based both on the empirical distribution function (Kolmogorov-Smirnov, Anderson-Darling and Cramer von Mises) and on information criteria (AIC, BIC) indicate that Weibull distribution fits the SHIW and SR data best.

[26] See section 5 and Bank of Italy, 2020b for further details on the surveys.

individuals declared that they had sufficient liquid financial resources for less than 3 months to cover expenses for essential household consumption in the absence of income; a percentage that is still falling within our estimate range.[27]

Figure 5 – Comparison between empirical and fitted distributions
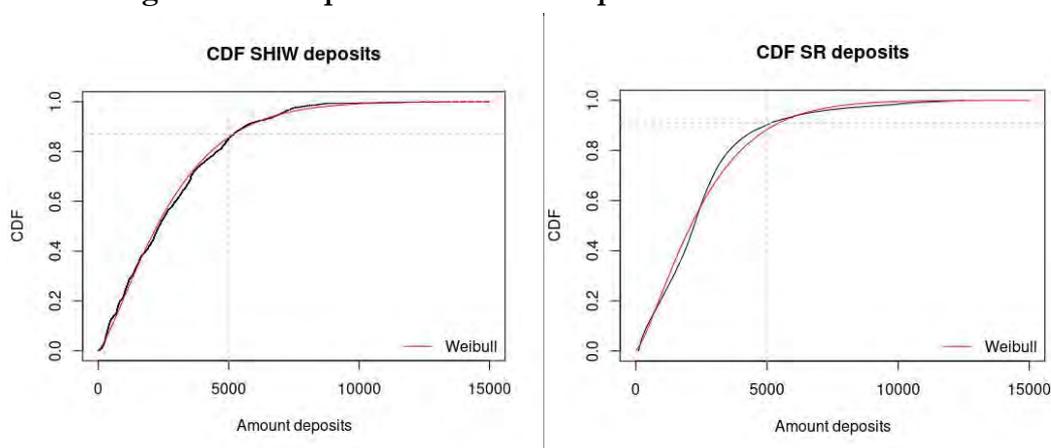
5. Which households are liquidity poor?

In this section, we extend the analysis to differences in liquidity conditions across demographic and economic groups that could be differently hit by the crisis. We are particularly interested in exploring how much the liquidity poverty condition is spread among indebted households. To do so, we use data taken from the *Special Surveys of Italian households in 2020* that the Bank of Italy with the purpose of collecting information on the financial situation and expectations of households during the crisis linked to the Covid-19 pandemic.

The survey was administered to 5,156 individuals aged over 18 (3,079 in the wave conducted between April and May 2020 and 2,077 in the wave of December 2020) and was carried out using three different survey techniques[28].

We measure liquidity poverty using the question: *How long your household can cover the expenses for essential consumption (e.g. food, heating, hygiene, etc.) and, if it is indebted, to service debts using its financial assets (include cash, current accounts, savings deposits, stocks and bonds)?* Possible answers to this question were: *Not even for a month; At least for a month; At least for 3 months; At least till the end of the year.*

We classify as liquidity poor, respondents who stated that they could not cover 3 months expenses or less. This question has proven to be a very good indicator of respondents' financial resilience (see Clark et al. 2020). It is worth noting that in the survey question are included not only the most liquid financial assets (such as deposits) but also stocks and (both private and government) bonds. Therefore, the following analysis is also important to assess how sensitive our previous results are to the inclusion of other financial resources.

Univariate Analysis

In the survey, 42.2 per cent of respondents reported themselves to be liquidity poor.[29] As already pointed out in section 4, this figure is well within our liquidity poor share estimate

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[27] Respondents of the survey were asked to include among their liquid resources not only deposits but also shares, bonds and Treasury bills.

[28] Namely, CATI (Computer-Assisted Telephone Interviewing), CAWI (Computer-Assisted Web Interviewing) and through a remote connection device.

[29] For reference, in a similar survey-based study on US households, Clark et al. (2020) find that 18.9 per cent of respondents interviewed in April and May 2020 reported themselves to be financially fragile since

range and closer to its upper bound, most likely because of the inclusion of service of debt among expenses.

Table A4 shows that indebted households were more likely to be liquidity poor (46.4 per cent compared with 39 per cent of households with no debt). Among indebted households, we find that 46.1 per cent of those with a mortgage for home purchase and 48.6 per cent of those with consumer credit reported themselves as liquidity poor. Furthermore, almost 60 per cent of indebted households with problems supporting consumption for a quarter with their financial assets, including less liquid ones, also highlighted difficulties in meeting their financial obligations. This confirms how being short in liquid assets can easily translate into difficulties in repaying debts in a period during which many households are experiencing declining incomes.

As for the other demographic and economic characteristics, table A4 shows that the liquidity poverty condition is more spread in the middle age (between 40 and 59), among the less educated, workers with part-time or temporary jobs, residents of the Islands and of smaller cities (less than 10,000 inhabitants). Interestingly, nearly a third of the liquidity-poor households declared to expect to accumulate savings in the next 12 months, confirming that even in the face of the crisis a non-negligible part of the less affluent households deemed possible to increase their buffers of financial resources. This evidence corroborates the main finding of this paper, i.e. that during the financial crisis even a part of the less wealthy households were able in the first phase of the crisis to build up liquidity buffers to support their financial conditions in the coming months.

Multivariate Analysis

To better identify the underlying factors associated with liquidity poverty in the population, table A5 reports marginal effects of a multivariate probit analysis where the dependent variable takes the value of 1 if the respondent reported herself as liquidity poor, and 0 otherwise. This analysis controls for many demographic and economic characteristics where the specification adopted is comparable to prior studies (e.g. Clark et al. 2020).

Results show that being indebted increases the chance of being liquidity poor by 10.3 percentage points according to the marginal effect shown in table A5. This represents a 24.4 per cent rise in financial fragility relative to the mean level of fragility in the sample (42.2 per cent). The regression analysis also confirms several other findings from the univariate results regarding liquidity poverty. For example, in column 1 financial fragility declines strongly with education. A person with high school diploma has 13.1 percentage points lower likelihood of being liquidity poor compared with a mid-school or less educated person and the difference in likelihood rises to 21.9 percentage points for college graduates or PhDs. While it is likely that education captures differences in incomes, it seems likewise probable that higher education correlates with financial knowledge that, in turn, helps protect against financial insecurity.

As one would expect, holding part-time or temporary jobs greatly increases (13.4 percentage points) the likelihood of being liquidity poor compared with full-time permanent employment status while there are no statistically significant differences with the self-employed or retirees after controlling for key economic and demographic variables.

The intensity of the income shock due to the pandemic influences the likelihood of being liquidity poor. Respondents reporting having suffered moderate income shocks (up to 25

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they certainly could not or probably could not come up with $2,000 if an unexpected need arose within the next month. Adopting the same time span of one month, we find a similar share in the first survey wave, conducted in April and May 2020, since 17.1 per cent of the respondents declared having insufficient financial resources to cover essential household expenses.

per cent of their income) have a 9 percentage point lower probability of being financially fragile than those reporting severe income shocks (over 25 per cent of their income). Surprisingly, there are no statistically significant differences with households who did not experience declines in their income after the onset of the pandemic. This result is likely due to the presence in the sample of many low-paid households that were already liquidity poor before the pandemic and did not change their condition despite they did not suffer any financial strain after the Covid-19 outbreak. In line with this, columns 2 and 3 of table A5 reports a strong difference (around 23 per cent higher likelihood of being liquidity poor) between households reporting problems in making ends meet already before the crisis compared with those who do not.

Interestingly, while the univariate analysis suggested that financial fragility declines with age, the multivariate analysis finds no significant relationship between age and the poverty in liquidity. Hence, the difference in liquidity poor shares among age groups is related to other characteristics, including income shocks, holding a debt, and educational differences, rather than age per se. Differences among people living in different macro-areas or in cities of different size also vanish when demographic and economic characteristics are accounted for.

6. Sensitivity analysis: the DFA/Chow-Lin approach

In 2019, the Federal Reserve published its own statistics, the Distributional Financial Accounts (DFA), to measure the distribution of economic resources across households (Batty et al., 2020). Methodologically, the DFA start from the quarterly Financial Accounts aggregate and allocate these totals across the population, relying on the triennial Survey of Consumer Finances (SCF). More in detail, the DFA are constructed by: i) building a SCF analog for each component of aggregate household net worth in the Financial Accounts (*reconciliation*), ii) by interpolating and forecasting the SCF analogs between the triennial SCF observations, for each part of the wealth distribution (*benchmarking*), and iii) applying the distribution of the (interpolated) SCF analogs to the Financial Accounts aggregates each quarter (*estimates*). The benchmarking step is a temporal disaggregation problem of imputing higher-frequency data from lower-frequency observations, which is carried out by applying the Chow-Lin approach. By using the empirical relationship between the SCF, the Financial Accounts, and other macroeconomic data when all three are observed, the Chow-Lin procedure interpolates and forecasts the SCF data in quarters when only the Financial Accounts and macroeconomic data are available.

Building on the Federal Reserve's methodology, we apply to each size bucket the Chow-Lin approach to impute and forecast data on the number of deposit accounts and on the number of liquidity-poor households from the SHIW to semesters where it is not observed, exploiting the empirical relationship between the SHIW, the SR, and other macroeconomic data. The aim of this test is to provide a sensitivity analysis of the results presented in section 4 on the evolution in the share of liquidity-poor households by applying a different estimation procedure.

With respect to the DFA, we have the advantages of knowing a distribution in the higher-frequency data (the size buckets in SR) and that our lower frequency data are available biannually instead of triennially. On the other hand, we have the disadvantage that the time span in which both low and high frequencies data are available is shorter than for DFA (just three SHIW waves were conducted since 2012, the first year of SR data).

According to the reconciliation exercise presented, for the sake of brevity, in Appendix B, SHIW can reasonably approximates the number of accounts and the number of liquidity-poor households in the SR. The following step is to impute and forecast the reconciled SHIW accounts for semesters where SHIW measures are not available. To do

so, we apply the Chow-Lin (CL) approach following the DFA methodology. In particular, the CL method is a multivariable generalized least-squares regression approach for interpolation, distribution, and extrapolation of time series (for a formal description of the method please refer to Chow and Lin, 1971 or Annex 6.1.C in IMF 2014). As for the DFA, given the relatively few SHIW years available for estimating the high frequency (indicator) - low frequency (target) relationships, we parsimoniously choose the indicator series that measure quantities similar to the target series and/or capture important developments in the overall economy. Specifically, we use the corresponding SR series in every interpolation because these series and the aggregate reconciled SHIW series are closely related by construction, and the SR series is therefore likely to predict number of accounts levels for each size bucket we consider. Since flows of deposits are closely tied to interest rates, we also include bank interest rates on households' deposits in the regressions where the target series is the number of accounts. In the case of the direct predictions of the number of liquidity-poor households, we include as additional indicator series the total outstanding amounts of deposits in the lower size bucket. Table A.3 summarizes which indicator series are used for each low-frequency (target) series.

As a final step, we use the predictions from the CL method on share of the reconciled SHIW total number of deposits held in each size buckets each semester, and multiply these shares by the SR total number of deposits for each bucket.[30] This allows computing the share of liquidity-poor households based on the algorithm presented in section 4, but where the number of accounts is now the imputation and forecast result of the CL predictions. For the case of the direct CL predictions on the number liquidity-poor households, we simply project the SR data onto the reconciled SHIW liquidity poor shares without the need of applying the algorithm of section 4.

The results of the sensitivity analysis on the evolution in the share of liquidity-poor households using the DFA-CL approach are reported in figure 6. The predicted trends in the liquidity-poor households shares are estimated using i) the CL method on the number of deposit accounts (both for the upper and lower bounds of the estimates); ii) the CL method on the SR number of liquidity-poor households; iii) the baseline estimates reported in section 4 (the upper bound).

It is worth recalling that i) and ii) are computed on a restricted set of deposits while iii) on the full set. Therefore, in the latter case the absolute value of the liquidity-poor household share is necessarily lower (on average of about 5 percentage points) and this is the reason why we compare the trends for the different estimates. Results of the sensitivity analysis reported in figure 6 show a decreasing trend in the share of liquidity-poor households regardless of the estimation approach. This holds also true when it comes to the sharp reduction in the first half of 2020. Furthermore, the baseline estimates trend and the CL predictions on the number of liquidity-poor households follow an almost identical path, both indicating a decline of the share of liquidity-poor households of about 14 per cent between the end of 2013 and June 2020.

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[30] To do so, we define γ_t^j as the number of deposit accounts for stock bracket j, in semester t, and let Γ_t^j denote the corresponding line from the SR data. Define group j's number of accounts share in semester t as its share of the total reconciled SHIW number of accounts:

$$\omega_t^j = \frac{\gamma_t^j}{\sum_k \gamma_t^k}$$

To obtain the estimated number of accounts for stock bracket, we multiply these shares by the total SR number of accounts:

$$\bar{\gamma}_t^{j,p} = \Gamma_t^j \omega_t^{j,p}$$

This ensures that the estimated number of accounts aggregate to the SR totals.

Overall, similar patterns in the share of liquidity-poor households are obtained whether we start from the SR data and apply the distribution of accounts observed in SHIW (the baseline scenario of section 4) or we start from SHIW households' balance sheet and we interpolate and forecast them in semesters when only the SR and other macroeconomic data are available.

Figure 6 – Chow-Lin predicted trends in the share of liquidity-poor households

(index numbers, 2013H2=100)
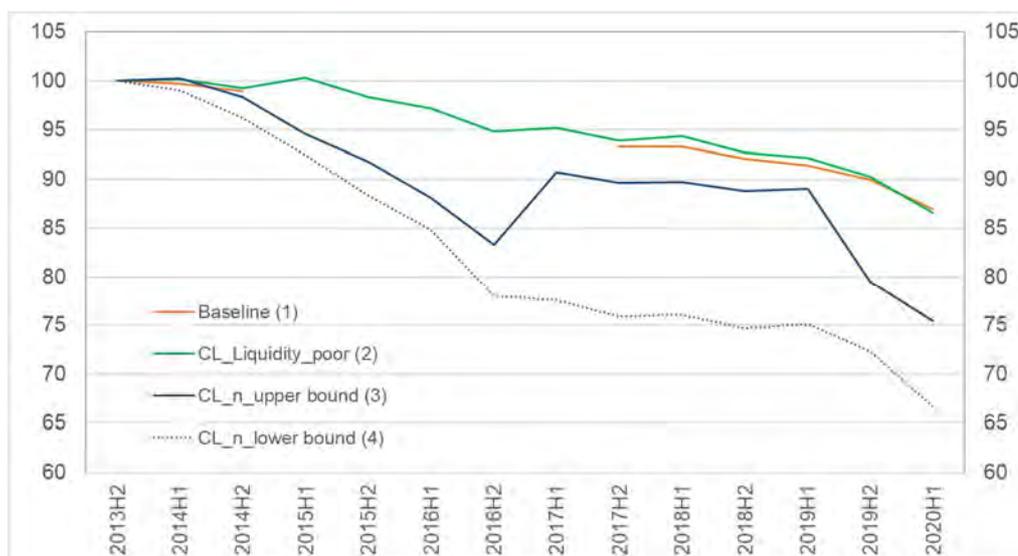
Liquidity-poor households calculated using: (1) all SR deposits according the algorithm presented in section 4 (upper bound); (2) CL predictions of the number of SR liquidity-poor households (upper bound) excluding postal savings deposits and bonds; (3) CL predictions of the number of SR accounts (upper bound) excluding postal savings deposits and bonds; (4) CL predictions of the number of SR accounts (lower bound) excluding postal savings deposits and bonds.

7. Conclusions

Household financial buffers – in the form of liquid asset holdings – are a key driver of households' financial resilience, that is, their capacity to continue servicing their debt while maintaining reasonable levels of consumption when hit by an income shock. After the Covid-19 outbreak, alongside the sharp rise in saving rates, deposits have grown at a record pace. However, little is known about the distribution of such a rise.

This paper has overcome this lack of data by using supervisory data on deposits divided into size buckets, proposing a new approach to estimate the trend in liquidity distribution and the percentage of liquidity-poor households.

Our analysis shows that the increase in liquidity was stronger at the lower end of the liquidity ladder and the degree of deposit concentration decreased in 2020. We find that the number of liquidity-poor households also dropped, which implies a larger share of financially resilient ones. Arguably, this is due in part to government action to protect workforce income from the sharp downturn. According to the suggestive evidence presented in Section 3, policy interventions - such as short-time working allowances, temporary income-support schemes for self-employed workers, and debt moratoriums - have also allowed households at the bottom end of the liquidity ladder to save out of their declining income, which is a result in line with the findings of Bachas et al. (2020) for the US.

Households with insufficient liquidity buffers remain, nevertheless, a significant share of the population so that an economic recovery weaker than the one indicated by the latest

macroeconomic forecasts could still weigh on their debt repayment capacity. Evidence drawn from the special surveys of Italian households in 2020 shows, in fact, that over half of indebted households with problems supporting consumption over one quarter with their financial assets, including less liquid ones, also highlighted difficulties in meeting their financial obligations.

The Covid-19 pandemic outbreak led to an immediate and large decline in consumer spending and an increase in households' aggregate saving rates in many countries affected by the virus. The results of our analysis may shed some light on the ongoing debate as to whether or not this reluctance to spend, alongside soaring deposits, is likely to slow down the timing of the economic recovery.[31] This depends on whether the money represents pent-up consumer demand that will quickly be spent as lockdowns are lifted (or the pandemic is over), or a safety net put aside by households to insure against uncertain times ahead. This precautionary behaviour, should it take firm root, would slow the recovery and, possibly, exacerbate the downturn. If households continue to hoard their incomes, a vicious circle of weak expenditure, slower recovery and higher unemployment may occur which would add to corporate bankruptcy threats. This paper, by showing that the growth in liquidity has also affected less wealthy households, who on average have a lower propensity to save (see, for instance, Kaldor, 1966), suggests that spending patterns could rebound once confidence about the economic outlook is restored.

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[31]Monetary authorities recently cited a surge in household bank deposits as reason for caution on the speed of the economic recovery. See, for instance, Christine Lagarde, president of the European Central Bank, 2020 Northern Light Online Summit organised by the European Business Leaders' Convention – participation in discussion on "World Economy: What will the recovery look like?", 26 June 2020. Also reported in *Financial Times* article "Europe's recovery will be 'restrained', Christine Lagarde warns".

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Regression-adjusted number of deposits by size buckets

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
	2016		2014		2012	
Number of accounts		#accounts predicted values		# accounts predicted values		# accounts predicted values
1. Deposit size bucket	Reference category	**1.407**	Reference category	**1.393**	Reference category	**1.413**
2. Deposit size bucket	0.333***	**2.047**	0.355***	**2.048**	0.241***	**1.974**
	(0.036)		(0.030)		(0.033)	
3. Deposit size bucket	0.677***	**2.579**	0.668***	**2.542**	0.454***	**2.384**
	(0.080)		(0.076)		(0.069)	
4. Deposit size bucket	0.642**	**2.662**	1.048	**3.031**	0.564***	**2.605**
	(0.327)		(0.773)		(0.145)	
5. Deposit size bucket	1.697**	**3.784**	2.302***	**4.355**	1.818**	**3.976**
	(0.825)		(0.884)		(0.871)	
Number of earners	0.355***		0.315***		0.286***	
	(0.025)		(0.020)		(0.021)	
Log of eq. income	0.000*		0.000		0.000*	
	(0.000)		(0.000)		(0.000)	
Retired	-0.110***		-0.131***		-0.078***	
	(0.026)		(0.026)		(0.025)	
Unemployed	0.019		-0.075		-0.076*	
	(0.047)		(0.048)		(0.039)	
Self-employed	0.123**		0.118***		0.064	
	(0.057)		(0.043)		(0.041)	
Middle school	-0.006		-0.008		-0.003	
	(0.026)		(0.026)		(0.025)	
High school	-0.026		0.044		0.089***	
	(0.033)		(0.032)		(0.030)	
University	0.007		0.057		0.056	
	(0.050)		(0.044)		(0.046)	
Single bank	-1.047***		-1.085***		-1.138***	
	(0.042)		(0.034)		(0.034)	
N	6865		7536		7513	
R^2	0.497		0.503		0.491	

Notes: In columns (2), (4) and (6) we report the number of deposit account predicted values for each liquidity bucket from the linear regressions in columns (1), (3) and (5), respectively. All regressions include a constant term, are estimated using sampling weights and differently from results reported in table 1, refer to all deposit accounts (including postal savings deposits). Deposit size buckets are in ascending order where 1. Deposit size bucket indicate deposits up to €12,500 and so on. Reference categories: education = elementary school; employment status= employee. Single bank relationship is a dummy variable equal to 1 when the household held all its deposits in one bank. Coefficients are reported with robust standard errors in parenthesis. ***, **, and * denote significance at 1, 5, and 10 per cent, respectively.

Comparison between SHIW and SR deposit percentiles in the lower bucket (1)

```
                                  SHIW
-------------------------------------------------------------
      Percentiles     Smallest
 1%     111.4347      1.41844
 5%     274.2696      6.80944
10%     398.3602      7.296541      Obs                 2,280
25%     1059.731      7.329909      Sum of Wgt.         2,280
50%     2332.579                    Mean            2765.717
                      Largest       Std. Dev.       2097.132
75%     3953.719      12408.06
90%     5608.708      12410.34      Variance         4397963
95%     6953.111      12411.72      Skewness         1.01467
99%     8510.638      12430.68      Kurtosis        4.034002
-------------------------------------------------------------
                                   SR
-------------------------------------------------------------
      Percentiles     Smallest
 1%     119.8511          100
 5%     224.8968          100
10%     423.3333          100       Obs                22,849
25%     1186.299          100       Sum of Wgt.        22,849
50%     2217.625                    Mean            2559.345
                      Largest       Std. Dev.       2049.106
75%         3203         12492
90%     4949.412         12498      Variance         4198837
95%         6598         12499      Skewness         1.82821
99%        10556         12499      Kurtosis        7.522953
```

(1) SHIW data refer to 2016 wave and are obtained dividing the amount of deposits declared by households by their number of accounts. SR data refer to 2017H2 (first available date including postal saving deposits and bonds after the 2013H2-2017H1 break).

**Summary of Indicator Series Used in
Interpolating and Forecasting SHIW Household Balance Sheets**

	SR number of accounts series	SR deposit outstanding amounts series	SR liquidity poor households series	Bank interest rates on households' deposits
Number of accounts	X			X
Number of liquidity-poor households		X	X	

Table A4: Demographics and Liquidity Poor Descriptive Results (1)

Variable	Observations	Overall%	Non-Liquidity Poor %	Liquidity Poor %
Age				
Age 18-39	1,181.19	22.91	60.91	39.09
Age 40-49	923.35	17.91	55.38	44.62
Age 50-59	1,027.70	19.93	55.50	44.50
Age 60-69	868.88	16.85	58.79	41.21
Age 70 and up	1,154.88	22.40	57.92	42.08
Gender				
Male	2,829.05	54.87	57.96	42.04
Female	2,326.95	45.13	57.64	42.36
Education level				
Middle School or Less	2,632.14	51.05	50.23	49.77
High School	1,747.35	33.89	62.83	37.17
Some College or above	776.52	15.06	72.23	27.77
Employment Status				
Works full-time, permanent contract	1,389.21	26.94	62.80	37.20
Works part-time and/or temporary contract	527.20	10.22	47.36	52.64
Not working	1,039.21	20.16	55.66	44.34
Self-employed	517.67	10.04	58.89	41.11
Retired	1,682.72	32.64	57.97	42.03
Macro-region				
North-West	1,432.28	27.78	62.52	37.48
North-East	991.31	19.23	62.25	37.75
Center	1,037.13	20.12	57.81	42.19
South	1,057.27	20.51	54.47	45.53
Islands	638.01	12.37	45.91	54.09
City-size				
Up to 5,000 inhabitants	755.53	14.65	55.34	44.66
5,000 – 10,000 inhabitants	746.63	14.48	54.53	45.47
10,000 – 30,000 inhabitants	1,193.42	23.15	59.49	40.51
30,000 – 100,000 inhabitants	1,130.70	21.93	57.25	42.75
Over 100,000 inhabitants	1,329.73	25.79	60.03	39.97
Indebted				
No	2,903.33	56.31	61.04	38.96
Yes	2,252.67	43.69	53.65	46.35
Income shock				
Suffered Severe Income Shock	1,377.95	26.73	50.83	49.17
Suffered Moderate Income Shock	937.11	18.18	65.07	34.93
No Income Shock	2,840.94	55.10	58.81	41.19
Make Ends meets				
No	2,598.85	50.40	42.66	57.34
Yes	2,557.15	49.60	73.22	26.78
Expected Savings				
Positive savings	1,901.78	36.88	68.49	31.51
No savings	2,646.29	51.32	54.29	45.71
Dissaving	607.93	11.79	39.75	60.25
Total	**5156**	**100.00**	57.81	42.19

Source: Bank of Italy *Special Survey of Italian Households* April - May 2020. (1) Entries show per cent of each variable by liquidity poor condition. Data are weighted using survey weights.

Table A5: Probit marginal effects – Liquidity-poor households

VARIABLES	(1) Liquidity-poor hh	(2) Liquidity-poor hh	(3) Liquidity-poor hh
Debt (Base no debt)			
Indebted	0.103***		
	(0.019)		
Mortgage		0.037*	
		(0.021)	
Consumer Credit		0.067***	
		(0.020)	
Age (Base Age < 39)			
Age 40-49	0.016	-0.005	0.001
	(0.031)	(0.029)	(0.029)
Age 50-59	0.013	-0.003	-0.006
	(0.030)	(0.028)	(0.028)
Age 60-69	-0.037	-0.048	-0.054
	(0.037)	(0.035)	(0.034)
Age 70 and up	-0.054	-0.055	-0.068*
	(0.041)	(0.039)	(0.038)
Gender (Base Male)			
Female	0.023	0.011	0.006
	(0.020)	(0.019)	(0.019)
Education (Base Middle School or Less)			
High School	-0.131***	-0.085***	-0.080***
	(0.022)	(0.020)	(0.020)
Some College or above	-0.219***	-0.146***	-0.144***
	(0.027)	(0.026)	(0.026)
Employment Status (Base Works full-time, permanent contract)			
Works part-time and/or temporary contract	0.134***	0.098***	0.087***
	(0.032)	(0.032)	(0.032)
Not working	0.065**	0.041	0.025
	(0.029)	(0.027)	(0.027)
Self-employed	0.043	0.018	0.005
	(0.037)	(0.034)	(0.033)
Retired	0.051	0.035	0.025
	(0.034)	(0.032)	(0.032)
Income Shock (Base Severe income shock)			
Moderate Income Shock		-0.090***	-0.091***
		(0.025)	(0.025)
No Income Shock		0.001	-0.009
		(0.023)	(0.023)
Make Ends meets (Base No)			
Yes		-0.224***	-0.232***
		(0.019)	(0.019)
Expected savings (Base no savings)			
Positive savings		-0.069***	-0.072***
		(0.019)	(0.019)
Dissaving		0.089***	0.096***
		(0.031)	(0.030)
N	5156	5156	5156

Notes: The table reports marginal effects (and associated standard errors) from a probit regression used to model the probability of being liquidity poor. Marginal effects are expressed at the mean value of the independent variables and, for factor levels, indicate the discrete change from the base level. The regression includes 5 geo (Macro-areas: NW, NE, Center, South, Islands) and 5 city-size (see table A4) indicators. Coefficients are reported with robust standard errors in parenthesis, which are clustered at household level. ***, **, and * denote significance at 1, 5, and 10 per cent, respectively.

Appendix A – Contributions to size-buckets growth

The percentage change in the outstanding amount of deposits by size buckets can be broken down into percentage changes in the number of deposits and the average amount deposited (plus a residual due to the interaction between the two components).

In 2020, the growth in the amount of deposits in the lower bucket is attributable to the increase in average stocks (+7.1 per cent) which more than offset the reduction in the number of deposit accounts (-2.3 per cent; fig. A1). While this result suggests a reduction in the concentration of liquidity, some concerns may arise. First, one may argue that depositors in the adjacent bucket drained liquidity to face the crisis, mechanically increasing deposits in the lower bucket. However, since the number of deposits increased in the second lower bucket (fig. A1), we can reasonably assume that the surge in average stocks in the lower bucket did not stem from an outflow of deposits from the adjacent bucket. Secondly, one may be worried that for the lower bucket the negative contribution of number of accounts to deposit growth means many households closed their accounts due to the crisis. On the basis of available data, we deem more likely that declining incomes prevented inflows of new accounts rather than triggering households to suddenly close existing accounts (even if the downturn absorbed most of their funds) after just few months of crisis.

Figure A1 – Contributions to deposits growth by size buckets

(June 2020 on December 2019, percentage points)
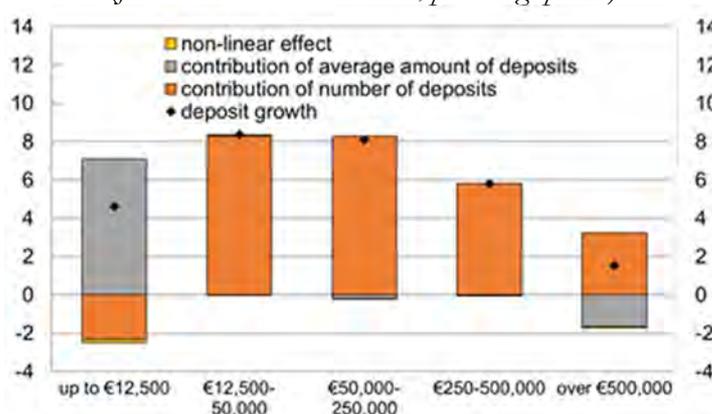
Source: Supervisory reports.

Appendix B – Methodology adopted to compute the Gini coefficient

In order to calculate the Gini coefficient of the distribution it is necessary to know its Lorenz curve. Data on deposits by size buckets depict sparse points of the Lorenz curve since only values at certain intervals are given. Hence, to estimate inequality measures, it is essential to define a method to link such points. In such circumstances, the Gini coefficient can be calculated by interpolating the missing values of the curve. More in detail, if the Lorenz curve is approximated in each interval as a line between two consecutive known points, then the area below the Lorenz curve (conventionally referred to as area B) can be approximated with trapezoids according to the following formula:

$$G1 = 1 - \sum_{k=1}^{n} \llbracket (N_k - N_{k-1})(Y_k + Y_{k-1}) \rrbracket$$

where (N_k, Y_k) are the known points on the Lorenz curve, with $(N_{k-1} < N_k)$, indexed in increasing order, so that:

- N_k is the cumulated proportion of the number of deposits, for $k = 0,...,n$, with $N_0 = 0$, $N_n = 1$.
- Y_k is the cumulated proportion of the amount of deposits, for $k = 0,...,n$, with $Y_0 = 0$, $Y_n = 1$.

and G1 is the resulting approximation for the Gini coefficient G used in this work.[32]

Appendix C – The reconciliation exercise in detail

The first step of the DFA-CL approach is reconciling the types of deposits used in the SR and the SHIW. This would be an easy task since the deposit types included in the SR are closely aligned with the information reported by SHIW respondents. However, due to the inconsistencies in the SR reporting of postal savings deposits and bonds between December 2014 and June 2017, we have to rule out such form of deposits from the reconciliation exercise. Only the data relating to bank (checking, time and saving) and postal (checking) deposits can be therefore used in time series during the time span 2012-2020. Despite this means excluding the 23 per cent of total SR deposits, we will show that if we distribute the reconciled deposits rather than the full deposit totals, the trend in the share of liquidity-poor households over time is almost unchanged.

After constructing measures that are conceptually aligned, we assess the degree to which the national aggregates implied by the SHIW are numerically similar to those from the SR. While close empirical matches are ideal, to make the Chow-Lin work it is enough aiming for similarity in magnitude more so than a precise match (Batty et al., 2020). Table A6 summarizes the results of the SHIW-SR reconciliation exercise by showing, for each wave of the SHIW since 2012, the ratio of the two measures for both the number and total outstanding amounts of deposits as well as the SR number of liquidity-poor households estimated in section 4. A ratio of 100 per cent would indicate that the two series match exactly, while lower (higher) percentages indicate that the reconciled SHIW understates (overstates) the SR total. For reference, the figure also shows the level of the SR and SHIW series in 2016 in millions of euros for deposit amounts and in millions of deposit accounts number.

Table A6

The Ratio of the Reconciled SHIW Household Balance Sheet to SR (1)

Deposits	Ratios in SHIW Years				Recent Levels (million)	
	2012	**2014**	**2016**	**Average**	**SR 2016H2**	**SHIW 2016**
Number	100	83.4	83.5	89.0	48.7	40.7
Amount	41.8	40.0	46.1	42.6	727,914	335,673
Liquidiy-poor hh (2)	85.5	88.5	90.0	88.0	14.5	13.1

Sources: Authors' elaborations on data from SR and SHIW. (1) The reconciliation exercise includes all deposits types excluding postal savings deposits and bonds which are not available in the period 2014-2017 in SR data. (2) Liquidity-poor households upper-bound in SR calculated according to the algorithm presented in section 4.

Overall, we find that the deposit account numbers from our reconciled SHIW balance sheet are quite similar to those from SR. For example, averaging across SHIW waves, aggregate SHIW accounts number is very close (at 89 per cent) to SR accounts number.

Differently, the SHIW measure of total outstanding amounts of deposits is consistently below the SR measure, historically ranging around 40-46 per cent of the SR total (see table

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[32] It is worth noting that estimates on grouped (banded) data neglect liquidity differences within brackets, introducing, therefore, a potential source of measurement error. Indeed, they assume that all individuals within a particular bracket have the same level of liquidity, which may underestimate the actual level of inequality. As a result, relative inequality measures estimated within this framework are lower bound estimates. Therefore, to obtain reliable estimates of inequality measures, we minimize such a potential measurement error by augmenting the variability of the data within shares by computing the Gini coefficient on data grouped at province-bank-stock bracket level. On estimation of inequality indices from grouped data, see e.g. Cowell and Mehta, 1982.

A6). For reference the Federal Reserve's DFA low-frequency data reconciles about 57 per cent of the high-frequency total deposits amounts in year 2016 (see table 2 in Batty et al., 2020). One reason for the discrepancy may be that, like all household surveys, the SHIW relies on self-reported information and suffers from small sample sizes at the top of the income distribution. In the latest wave of the survey, about 7,400 households were sampled (still a limited number even though much larger than the 6,200 households sampled in the US SCF when compared with the reference population). Non-sampling errors might also be a cause of the differences between SHIW and SR deposit amount aggregates: some of the rich respondents who agree to participate in the SHIW might under-report their assets. Both potential sampling and non-sampling errors act in the same direction, i.e. underestimating the full extent of wealth at the top end of the scale.[33] To investigate potential sampling and non-sampling errors, it is useful to compare the differences between SHIW and SR deposit amount aggregates for each deposit bucket. It turns out that the two data sets align reasonably well for the lower bucket where the reconciled SHIW deposit amounts range around 74-79 per cent of the SR total for the same size bucket. The discrepancy increases for higher buckets and it reaches a maximum for the third and fourth size buckets, suggesting that both sampling and non-sampling errors are at work.

We also perform a reconciliation exercise directly on the number of liquidity-poor households calculated in SHIW and with the SR data (the latter according the algorithm presented in section 4) but limiting in both cases the deposits included in computations to those that are consistent along the whole time series (i.e. excluding postal savings deposits and bonds). Table A6 shows that the numbers of liquidity-poor households from our reconciled SHIW are quite similar to those obtained from SR, historically ranging around 86-90 per cent of the SR total.

Overall, the reconciliation exercise shows that the SHIW can reasonably approximate the number of accounts and the number of liquidity-poor households in the SR.

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[33] To overcome such limitations Saez and Zucman (2016) adopt a different methodology from DFA for estimating the distribution of financial accounts among percentiles of wealth (the capitalization method). Such a methodology is not applicable to Italian households due to the lack of individual tax records on wealth. However, as pointed in Saez and Zucman (2020), the DFA method and their capitalization approach give similar distributional results at least for the US case.