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

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The COVID-19 pandemic led to a huge surge in 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, 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.

JEL Codes: D14, E21, E66, H31

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1. INTRODUCTION

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 (Bachas *et al.*, 2020; Christelis *et al.*, 2020; Dossche and Zlatanos, 2020). In Italy, in 2020 the propensity to save increased by 7.6 percentage points (peaking at 15.8 percent) compared with the previous year, while income dropped 2.8 percent over the same period. On average, households have therefore compressed their consumption proportionally more than the reduction in disposable income.[1]

[1]Households' propensity to save is determined by a set of objective and subjective factors, which vary greatly among individuals with different socioeconomic characteristics (see Keynes, 1936, p. 108; Browning and Lusardi, 1996, p. 1798).

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During the phase in which the contagion containment measures were more severe, consumption dropped 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) amid growing concerns about the evolution of the pandemic and the timing of economic recovery. 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 percent 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. However, aggregate data do not provide an accurate picture of households' resilience to income shocks as liquidity is unevenly distributed across them. Indeed, according to the latest available data from the Bank of Italy's *Survey on Household Income and Wealth* (SHIW), in reference to 2016, 45 percent of the population did not have enough liquidity (bank and postal deposits) to avoid the risk of falling into poverty,[2] in the absence of income for at least 3 months.[3] This condition of vulnerability was also widespread among indebted households suggesting that the risk of illiquidity can easily translate into difficulty in repaying debts.[4]

Given the lack of more recent data on the distribution of the financial liquidity of Italian households, we use supervisory reports (SR) on bank and postal deposits divided into size buckets 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.

Our results show that the existing trend toward an increase in the degree of concentration of deposits has reversed in the aftermath of the COVID-19 outbreak. Yet, a lower concentration of liquidity does not necessarily imply an improvement of households' financial resilience, which instead depends on the absolute amount of liquid resources available at the bottom of distribution. To make the concept of financial resilience operational, we therefore 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

[2]The European Commission sets the at-risk-of-poverty threshold at 60 percent of national median equivalent disposable income. For a comprehensive discussion on the asset-based measures of poverty, see Brandolini *et al*., 2010. See also Brunetti *et al*., 2016 for a characterization of households' financial fragility/resilience.

[3]See also Bank of Italy (2018), p. 12. According to Gambacorta *et al*. (2021), this percentage drops to 40 percent when other financial assets 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.

[4]Indeed, 47 percent of indebted households were in conditions of liquidity poverty and about 44 percent of overall household debt was attributable to them. These shares remain large (42 and 37 percent, respectively), even when considering all financial assets and not only the most liquid ones.

released Federal Reserve's Distributional Financial Accounts (DFA) methodology. 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 percent of households).

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 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 toward low-income households.

There is, nonetheless, still a large share of liquidity-poor households who are vulnerable to unemployment and income shocks arising from a sustained economic downturn. Using data from a recent survey on Italian households, we find there is substantial heterogeneity across demographic and economic groups that could be differently hit by the crisis with, e.g., indebted households being much more likely to be liquidity-poor. 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. In addition to this, there is the risk 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 slow down the timing of the economic recovery, exacerbating adverse underlying trends already in place before the crisis (see Blanchard, 2020; Goy and End, 2020).

The remainder of the paper is structured as follows. Section 2 describes the data, provides descriptive evidence on liquidity growth in 2020, and presents the shifts in liquidity distribution during the COVID-19 crisis. Section 3 discusses the potential channels leading to the surge in the deposits at the bottom of the liquidity ladder. Section 4 provides estimates of the share of liquidity-poor households, while Section 5 presents evidence on heterogeneity in liquidity conditions across different groups. Section 6 concludes.

2. Data, Descriptive Evidence, and Liquidity Distribution Inequality Measures

Italian households' net financial wealth is structurally high by international standards, and a significant part of it is invested in liquid instruments.[5] Deposits are the most liquid form of savings as they can be readily used in case of need without

[5]At the end of 2020, Italian households' net financial wealth was equal to 3.3 times disposable income (2.7 times was the euro-area average) and around 40 percent of it was held in cash, bank, and postal deposits.

incurring any potential losses by liquidating other financial assets, especially in a period of crisis, in which sharp fluctuations in share prices and bond yields are recorded.[6]

To overcome the lack of high-frequency information on the distribution of households' liquidity, this work uses the Bank of Italy's SR on bank and postal deposits by size buckets. Data are provided every 6 months and report households' outstanding amounts and number of deposits at June 30 and December 31 of each year for each of the five size buckets (see Table 1 for the amounts defining the buckets).[7] The SR data statistical unit is the bank-province-size bucket cell, which is built aggregating information on bank–customer relationships. Therefore, 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.

At the end of 2020, bank and postal deposits of Italian households amounted to €1,138 billion, up by about €74 billion 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.

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; see Table 1). Yet, the average amount deposited in each size bucket increased only for the lower size bucket (up to €12,500), while it shrank for the upper three size buckets and remained stable for the second-last one. The surge in the average amount of deposits in the lower bucket (+7.1 percent) is remarkable because it reversed the (overall) previous decreasing trend (see column 2 of Table 2, panel A) and the opposite happened in the upper size buckets (see column 2 of Table 2, panel B). Exploiting the variability in the average balance among bank-province cells of SR data, such distributional shifts are also observable in other points of average amount distributions in the different size buckets (Table 2 reports the median and the 90 percentiles).[8]

The percentage change in the outstanding amount of deposits by size buckets can be further 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 recorded in 2020 in the lower bucket did not stem from an outflow of deposits from the adjacent bucket.

[6]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 these assets from the analysis. Nevertheless, our results are not significantly affected because they represent only a negligible fraction of the financial wealth of Italian households (below 1 percent at the end of 2019).

[7]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.

[8]In Section 4, we show that the average amounts of SR deposit holdings by percentiles approximate reasonably well the distribution of average deposit amounts by percentiles in SHIW.

TABLE 1
Italian household deposits

Liquidity Bucket	Numbers (Thousands)	Share on the Total Number	Outstanding Amounts (Millions of Euros)	Share on the Total Outstanding Amount	Average Outstanding Amounts (Euros)
At the end of 2020					
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
€250,000–500,000	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
At the end of 2019					
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
€250,000–500,000	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.

TABLE 2

Changes in the distribution of deposits by size buckets

Year	Growth Rate (2)	Average Amount (3)	P50 of Distribution (4)	P90 of the Distribution (5)
Panel A: deposits in the lower size bucket (<€12,500) (1)				
2013		2,278	2,542	4,880
2017	−9.7	2,057	2,559	4,949
2018	1.9	2,095	2,548	4,935
2019	−1.0	2,074	2,578	5,043
2020	7.1	2,221	2,719	5,196
Panel B: deposits in the upper size buckets (>€12,500) (1)				
2013		52,395	80,784	560,003
2017	6.6	55,834	84,803	575,989
2018	1.6	56,740	85,514	589,332
2019	2.9	58,359	87,663	605,380
2020	−0.9	57,824	85,153	578,034

Source: Supervisory reports, end of period data. (1) Due to the inconsistencies in the reports of postal saving deposits and bonds between December 2014 and June 2017, it is not possible to compute figures on total deposits during this time span. (2) Average amount annual growth rate except for the 2017 where it expresses the growth rate between 2017 and 2013. (3) Average amount of outstanding deposits in the size bucket. (4) Median of the average amount distribution in the size bucket. (5) 90 percentile of the average amount distribution in the size bucket.

TABLE 3
Comparison of deposit distributions in SHIW and SR data

Size Bucket[a]	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
€250,000–500,000	1.93	0.4	0.4	360,975	326,084
Over €500,000	3.21	0.2	0.1	891,533	994,389

Source: Survey on Household Income and Wealth 2016 and Supervisory reports.

[a]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 to have a comparable distribution between SHIW and SR.

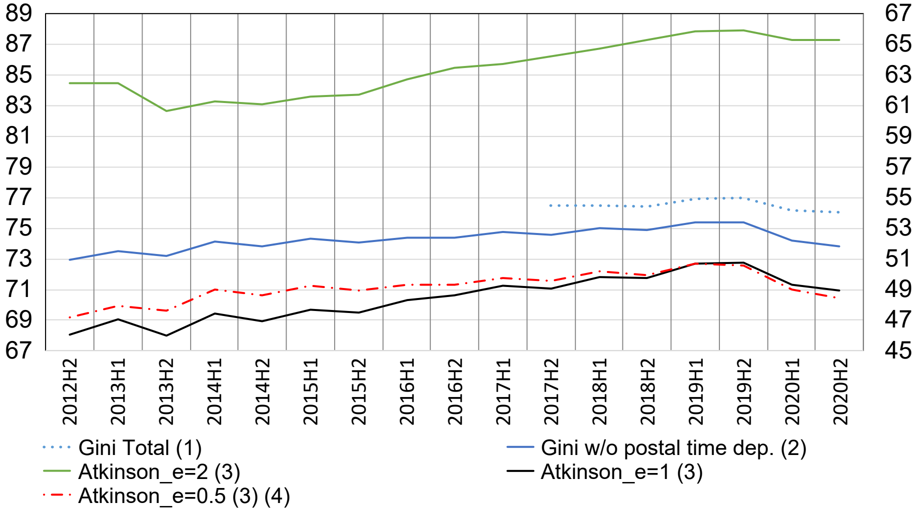

Figure 1. Different Measures of Deposit Concentration

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, and 2. (4) Right-hand scale. [Colour figure can be viewed at wileyonlinelibrary.com]

At the end of 2020, 77 percent 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). 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 percent 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 A1 in the Appendix). Even though the number of accounts held on average by a household grows rapidly as its liquidity increases, it also hinges on households' characteristics such as 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 ladders. To consider this issue, in column 1 of Table 3 we show the distribution of the regression-adjusted[9] average number of deposits by size buckets in 2016.

Obviously, the unit of observation in SR statistics (individual accounts) differs from the one in SHIW (households accounts), because in the former different

[9]In Table 3, 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, the working status, and the education of the head of the household. The estimations are run on SHIW household-level data and are weighted using SHIW sampling weights, and standard errors are corrected for heteroscedasticity. In Table A1, we report the regression-adjusted number of accounts (and the corresponding underlying regressions) for each SHIW wave and, differently from column 1 of Table 3, including the full set of deposits.

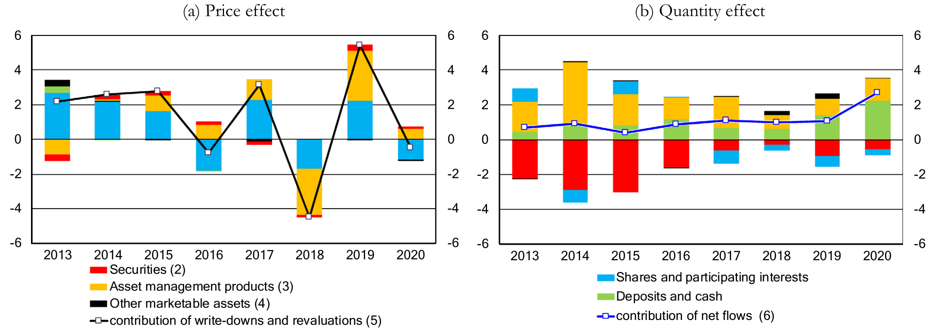

Figure 2. Contributions to Changes in Gross Financial Wealth (1) (Percentage Points)
Source: Authors' elaborations on Bank of Italy, Financial Accounts. (1) End-of-period data for consumer households, producer households, and non-profit institutions serving households. (2) Public sector, bank, and corporate bonds. (3) Investment fund units, life insurance, pension funds, and supplementary pension funds, excluding severance pay (TFR). (4) Commercial loans, TFR, and other minor items. (5) Total contribution of write-downs and revaluations of financial assets. (6) Total contribution of net flows of investments and divestments of financial assets.[Colour figure can be viewed at wileyonlinelibrary.com]

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 Section 4. 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).

To take a step further in the study of the distribution of liquid assets among households after the COVID-19 outbreak, we provide a synthetic index that measures the concentration of deposits relying on the Gini coefficient.[10] Figure 1 shows that, in the months following the COVID-19 emergency, the Gini coefficient for deposits by size buckets has decreased, lowering to 73.8. Despite being still a very high value,[11] the index reduction was marked since it returned to the values recorded

[10]The available data allow us to know only the values at certain intervals of the Lorenz curve. Appendix B describes the procedure adopted to compute the Gini coefficient in case of grouped data. 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 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.

[11]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 Gini coefficient of deposits was almost equal to the same index computed on SHIW data 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.

at the end of 2014. The decreasing trend in 2020 is also confirmed for all bank and postal deposits, observable only since the end of 2017.

However, the Gini coefficient is sometimes criticized as being too sensitive to relative changes around the mode of the income distribution (see, for instance, Atkinson, 1970; Cowell and Jenkins, 1995). Adopting as a measure of inequality the Atkinson indices, which are more sensitive than Gini coefficient to differences in different parts of the distribution, 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 is 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.

3. Mechanisms Behind the Surge in Deposits for the Lower end of the Liquidity Ladder

Different factors contributed to the increase in deposits during the COVID-19 pandemic, including pent-up consumer demand and higher precautionary savings. A potential competitive explanation 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 purely savings motives. However, by analyzing the net flows reported in Financial Accounts, we can rule out such a "flight-to-safety" view.

Indeed, the financial wealth of producer and consumer households increased by 2.2 percentage points in 2020. The negative contribution of asset prices to financial wealth growth (−0.5 percent, Figure 2A) was largely offset by the sharp increase in net savings (+2.7 percent, Figure 2B). Increase in deposits was the main source of wealth change because the total net flows of savings amounted to over €126 billion and the 83 percent of it was concentrated in cash and deposits. Moreover, during 2020 negative flows in securities and shares accounted only for 39 percent of the positive flows in deposits and less than a quarter of the increase in total assets recording positive flows (mainly deposits and asset management products; Figure 2B). This implies that the reallocation of risky investments was not the main source of the flow of funds into deposits.

The unusual growth of savings invested in deposits during the crisis may be then the result of (a combination of) different potential reasons: (i) a consumption drop because of lockdown measures (*forced*); (ii) an infection-concern motive that caused consumers to refrain from many purchases where a physical proximity is

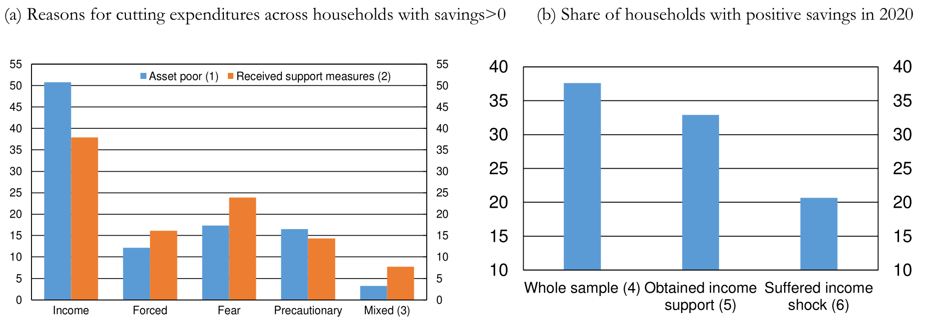

Figure 3. The Effect of Income Support Measures on Savings (Percentage Points)
Source: Bank of Italy Special Survey of Italian Households—waves second to fourth. Data are weighted using survey weights. Panel (A) presents the prevalent reason for cutting consumption in the month preceding the interview in the third wave (December 2020) across households with positive savings in 2020 and (1) who declare having financial assets below the at-risk-poverty threshold or (2) who were recipients of one form in income support in the 9 months before. (3) Households where the respondent assigns equal weights to at least two motivations for cutting expenditures. Panel (B) presents the share of households reporting positive savings in 2020: (4) on the total panel component in the three waves (1,781); (5) among those who received some form of income support in the 9 months preceding the interview; (6) among those who in the last month earned an income lower than one normal earned before the pandemic and who did not receive some form of income support in the 9 months preceding the interview.[Colour figure can be viewed at wileyonlinelibrary.com]

involved (*fear*); (iii) precautionary reasons arising from the increased uncertainty caused by the pandemic (*precautionary*); (iv) a drop in income to which households reacted by reducing consumption more than proportionally (*income*). The surge in deposits for the lower end of the liquidity ladder can also be traced back to those motives but, for such households, a crucial role may have also been played by the increased ability to save, thanks to government support measures (*support*) that (partly) protected the income of households that suffered falls in earnings (Carta and De Philippis, 2021).

While it is difficult to do a formal test of the relative importance of the various channels leading to an increase in savings, it is worth noting that the welfare and policy implications differ substantially depending on which mechanism is operable. Households' welfare declines if households reduce consumption due to forced, fear, precautionary, and income motives but households' welfare increases if they can save more as a result of government support measures. As for policy implications, if *forced* was the main reason of savings, households, especially low-income households, would increase their consumption and curtail their saving as contagion containment measures are relaxed or eliminated. By contrast, if *fear* and *precautionary* mechanisms are operable, future trends in consumption and savings will depend on how households' concern about the course of the pandemic can be attenuated. Yet, policies aimed at stimulating consumption are not likely to be effective until uncertainty and fear of contagion persist. Finally, if *support* mechanism is operable, the discontinuation of government support measures will lower the incomes of low-income households and reduce both their consumption and their savings (unless the economy recovers sufficiently).

Using two different surveys both Immordino *et al*. (2021) and Guglielminetti and Rondinelli (2021) find that, apart from any economic reasons, in Italy spending was held back more by fear and precautionary than by forced motives. To shed some light on the channels leading to the increase in deposits at the bottom of the liquidity ladder, we use data from Bank of Italy's *Special Surveys of Italian Households*.[12] Figure 3A shows that, among households with positive savings in 2020, both asset-poor households and households who received some form of income support indicate *income* as the prevailing motive for consumption reduction. Yet, as one would expect, support measures lower greatly the share of households who increased savings by reducing consumption more than proportionally to the income drop. Across other motives the evidence is less clear-cut, but *fear* seems to have also played a relevant role, especially among households who received income support. However, this should be taken as cautious evidence because households respond reporting savings over all the 2020 while they indicate reasons for drop in consumption in the month preceding the interview. Figure 3B allows us to explore further the role of support measures in boosting savings. Indeed, nearly one-third of households who were recipient of at least one form of income support were also able to save out of their income in 2020 (32.9 percent of them compared with 37.6 percent of the whole sample; Figure 3, panel B), over 12 percentage points more than households reporting a lower income than the one normally earned before the pandemic (and that were not recipients of support measures). Figure A2 in the online Appendix shows that support measures as wage supplementation schemes, unemployment benefits, and temporary income for self-employed workers played a larger role in fostering the savings ability of their recipients with respect to minimum income scheme, emergency income, and debt holidays. Overall, according to the suggestive evidence presented in this section, support measures allowed a large number of households to save even in the face of declining incomes, a result in line with Bachas *et al*. (2020) who find that in the US the initial impact of the pandemic on household wealth was a shift in households' liquid-balances distribution toward low-income households. Such a shift reflects the fact that stimulus checks and expanded unemployment insurance benefits provided a disproportionate increase in income for low-income households.

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. This depends crucially on the reasons behind the increase in deposit held by those households located at the bottom end of the liquidity distribution who on average have a higher propensity to consume (see, for instance, Kaldor, 1966). Although the mechanism leading to the increases in their liquidity is hard to identify precisely, from this analysis it is reasonably possible to conclude that support measures played a relevant role. It follows that if government support were significantly scaled down before the economy recovers sufficiently, the incomes of low-income households will be

[12]For a description of the survey characteristics and methodology, see Neri and Zanichelli (2020).

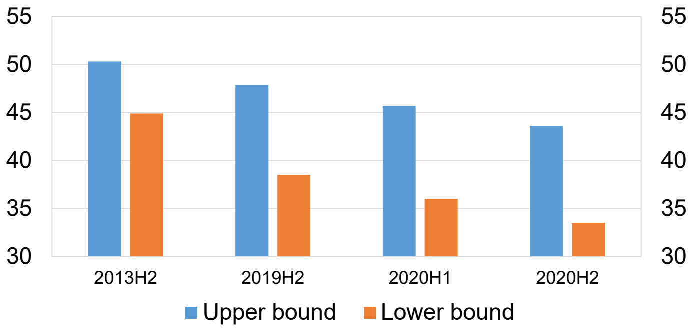

Figure 4. Share of Liquidity-Poor Households (Percent). [Colour figure can be viewed at wileyonlinelibrary.com]

lowered, and they may reduce both their consumption and their saving with the risk of slowing down further the timing of the economic recovery.

4. Liquidity-Poor Households

In Section 2 we have shown that measures of concentration of deposits decreased during the crisis. Yet, a lower concentration of liquidity does not necessarily imply a decrease in the share of households unable 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 distribution. To this end, we define as liquidity-poor those households having deposits holdings lower than a quarter of the threshold that identifies the risk of poverty (60 percent of the median equivalent income; see footnote 2).

To make this definition operational, we need to determine the amount of resources needed to support essential consumption. For the sake of brevity, we show in Appendix C that the poverty threshold at 3 months for median household equals €5,000. Indeed, according to SR data 77.1 percent 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; see Table 1), it would not exceed the poverty threshold of €5,000 for the median household.[13] On the contrary, the remaining 22.2 percent of the accounts have deposit stocks above €12,500, i.e., significantly above the poverty line.

To assess the change in adequacy of household liquidity stocks, we should therefore estimate the number of liquidity-poor households. Because 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

[13]This holds true even for different compositions of the reference household (see Appendix C).

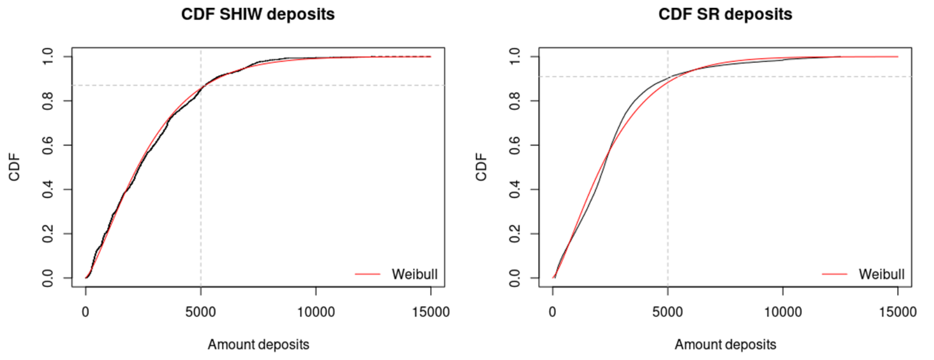

Figure 5. Comparison between Empirical and Fitted Distributions. [Colour figure can be viewed at wileyonlinelibrary.com]

estimates of the distribution of accounts that households have on average for each size bucket (presented in Table A1—see also Table 3 for reference).

For the upper bound case, we assume that all households (including financially resilient ones) have at least one account in the lower size bucket. To determine the number of households that have also 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 those buckets (see Table A1) minus one (because 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:

(1) $$\mathrm{NLP}_{\min} = \sum_{i=2}^{5} \frac{N_i}{(n_i - 1)},$$

(2) $$\mathrm{LP}_{\max} = 1 - \frac{\mathrm{NLP}_{\min}}{\mathrm{NH}_{\mathrm{tot}}},$$

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 A1); $\mathrm{NLP}_{\min}$ is the estimate of the minimum number of households that are not in a condition of liquidity poverty (i.e., they are financially resilient); $\mathrm{LP}_{\max}$ is the corresponding upper bound to the share of liquidity-poor households, and $\mathrm{NH}_{\mathrm{tot}}$ 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:

$$\text{NLP}_{\max} = \sum_{i=2}^{5} N_i, \tag{3}$$

$$\text{LP}_{\min} = 1 - \frac{\text{NLP}_{\max}}{\text{NH}_{\text{tot}}}, \tag{4}$$

where the meaning of the notation can be easily deduced from above. It is worth nothing that a corollary of the adopted algorithm is that households with no deposits are always included among liquidity-poor households because by construction the latter are obtained as a difference from those who are certainly not.[14]

According to these estimates, the percentage of liquidity-poor households at the end of 2020 was between 33.5 and 43.6 percent: both values are lower from those at the end of 2019 (between 38.5 and 47.8; Figure 4). Data indicate that the decrease began in the first half of 2020. In comparison with 2013, the last year of crisis preceding the current one, the percentage of liquidity-poor households fell by about 11 (7) percentage points for the lower (upper) end of the estimate range. Therefore, 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 improved the financial resilience of Italian households.

One may argue that we are overestimating the share of liquidity-poor households because some of them may have accounts with a balance above poverty threshold (between €5,000 and €12,500) 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 (because, 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 in the Appendix shows that the average amounts of SR deposit holdings by percentiles approximate reasonably well the distribution of average deposit amounts by

[14]It is worth noting that the assumptions behind the construction of the upper and lower bounds imply 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 in line with the SHIW figures reported in Section 2).

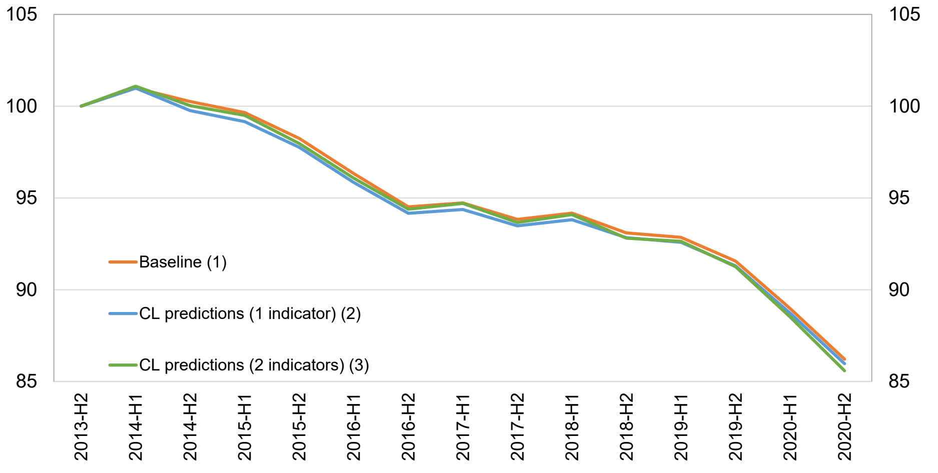

Figure 6. Chow–Lin Predicted Trends in the Share of Liquidity-Poor Households (Index Numbers, 2013H2 = 100)

Notes: Liquidity-poor households calculated using: (1) baseline estimates according to the algorithm presented in Section 4 (upper bound); (2) CL predictions of the number of SR liquidity-poor households, using as a single indicator series the upper bound SR estimates; (3) same as in (2) but using as an additional indicator series the outstanding amounts of deposits in the lower size bucket.[Colour figure can be viewed at wileyonlinelibrary.com]

percentiles in SHIW data up to the poverty threshold of €5,000, 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.[15] More in detail, the share of households with deposits in the lower size bucket and with an outstanding amount below the poverty line is 87 percent in SHIW, while the correspondent share of accounts in SR data is 91 percent. 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 percent) 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 percent in 2020H2 and 42.3 percent in 2019H2, both values in line with the corresponding estimated ranges of Figure 4.

To estimate the shares of liquidity-poor households, we have started from the SR data and applied the distribution of accounts observed in SHIW. Building on the DFA approach, we now reverse the estimation procedure by starting from SHIW households' balance sheet and interpolating and forecasting them in semesters when only the SR data are available. This test provides a sensitivity analysis on the evolution in the share of liquidity-poor households.

[15]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.

In particular, we adopt the Federal Reserve's DFA approach to measure the distribution of economic resources across households starting from the quarterly Financial Accounts aggregate and allocating these totals across the population, relying on survey data (Batty *et al.*, 2021). The three steps (reconciliation, benchmarking, and estimates) required to construct the DFA are illustrated for the sake of brevity in Appendix D. According to the reconciliation exercise (see Appendix D1), SHIW can reasonably approximate the number of accounts and the number of liquidity-poor households in the SR. The benchmarking step is a temporal disaggregation problem of imputing higher-frequency data from lower-frequency observations. In our case, this means imputing and forecasting data on the number of liquidity-poor households from the reconciled SHIW series for semesters where SHIW measures are not available, exploiting the empirical relationship between the SHIW, the SR series, and other macroeconomic data using the Chow–Lin (CL) approach.[16] As for the Federal Reserve's DFA, given the relatively few SHIW years available for estimating the high frequency (indicator)–low frequency (target) relationships, we parsimoniously choose the indicator series.[17] Specifically, we use the corresponding liquidity-poor 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 them. As additional indicator series we include the total outstanding amounts of deposits in the lower size bucket. To avoid the risk of over-fitting the model, we also adopt another specification with the SR number of liquidity-poor households as a single indicator. As a final step, we simply project the SR data onto the reconciled SHIW liquidity-poor shares.

In Figure 6 are reported the predicted trends in the liquidity-poor households shares estimated using the CL method on the SR number of liquidity-poor households controlling for (i) one indicator series or (ii) two indicators series, (iii) according to the algorithms (1) and (2) reported above (the upper bound). The results show that the baseline estimates trend and the CL predictions on the number of liquidity-poor households follow an almost-identical path, all indicating a decline in the share of liquidity-poor households of about 14 percent between 2013 and 2020, regardless of the estimation approach (Figure D2 in Appendix shows that using the lower bound SR series—instead of the upper bound ones—produces qualitatively similar results).[18] A large part of this reduction in the share of liquidity-poor households (over 5 percentage points out of 14) was recorded during the pandemic in 2020.

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 estimates of Figure 4), or we start from SHIW households'

[16]For a formal description of the method, refer to Chow and Lin, 1971 or Annex 6.1.C in IMF, 2014.

[17]Only three SHIW waves were conducted since 2012, the first year of SR data.

[18]It is worth noting that all the series are computed on a restricted set of deposits (i.e., excluding postal savings deposits and bonds), while estimates reported in Figure 4 are 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.

TABLE 4
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 above	−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	5,156	5,156	5,156

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 five geo (macro-areas: NW, NE, Center, South, and Islands) and five city-size (see Table A3) indicators. Coefficients are reported with robust standard errors in parenthesis, which are clustered at household level. ***, **, and * denote significance at 1, 5, and 10 percent, respectively.

balance sheet and we interpolate and forecast them in semesters only when the SR and other macroeconomic data are available.[19]

5. Which Households Are Liquidity-Poor?

To explore differences in liquidity conditions across demographic and economic groups that could be differently hit by the crisis, we use data from the Bank of Italy's *Special Surveys of Italian households in 2020*.[20] 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 respondents who stated that they could not cover 3 months' expenses or less as liquidity-poor.[21] According to the descriptive evidence reported in Table A3 in the Appendix, 42.2 percent of respondents reported themselves to be liquidity-poor, which is a figure within our estimate range and closer to its upper bound, most likely because of the inclusion of service of debt among expenses. The liquidity poverty condition is more spread among indebted households (46.4 percent compared with 39 percent of households with no debt). Furthermore, almost 60 percent of indebted households who were also liquidity-poor highlighted difficulties in meeting their financial obligations. Being short in liquid assets can therefore easily translate into difficulties in repaying debts in a period during which many households are experiencing declining incomes. Interestingly, nearly one-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.

To better identify the underlying factors associated with liquidity poverty in the population, Table 4 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. The results show that being indebted increases the chance of being liquidity-poor by 10.3 percentage points. This represents a 24.4 percent rise in financial fragility relative to the mean level of fragility in the sample (42.2 percent). The regression analysis highlights other dimensions of heterogeneity across demographic and economic groups. For example, in column 1 financial fragility declines strongly

[19]Because there are so few observations where the SHIW and SR overlap, it may be helpful to test the predictive power of the SR data points in estimating the objects calculated from the SHIW. In Appendix D, we present results from an exercise where we use data from the SHIW only through 2014 and forecast the number of liquidity-poor households for 2016H2 using indicator series observations through this semester. Even with so few observations, we find that our CL forecast successfully predicts the quantitative patterns in the actual SHIW data (see Figure D1).

[20]We use the first and third waves of the survey that was administered to 5,156 individuals aged over 18 (3,079 in the April–May 2020 wave and 2,077 in the December 2020 wave).

[21]This question has proven to be a good indicator of respondents' financial resilience (see Clark *et al*., 2020).

with education. 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.

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 percent of their income) have a 9 percentage point lower probability of being financially fragile than those reporting severe income shocks (over 25 percent 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 4 report a strong difference (around 23 percent higher likelihood of being liquidity-poor) between households reporting problems in making ends meet already before the crisis compared with those who do not. Finally, we find no significant relationship between age and the poverty in liquidity. Therefore, the difference in liquidity-poor shares among age groups in the raw data is related to other characteristics rather than age per se.

6. Conclusions

Household financial buffers—in the form of liquid asset holdings—are a key driver of households' financial resilience, i.e., 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 information 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, implying greater households' financial resilience. Arguably, this is due in part to government action to protect workforce income from the sharp downturn. According to the suggestive evidence, policy interventions 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 and expenditure patterns. Indeed, the COVID-19 pandemic outbreak led to an immediate and large 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. 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 behavior, 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, suggests that spending patterns could rebound once confidence about the economic outlook is restored provided that government support is not significantly scaled down before the economy recovers sufficiently.

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