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Household Vulnerability to Income Shocks in Emerging and Developing Asia: the Case of Cambodia, Nepal and Vietnam

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ABSTRACT: We leverage survey data from emerging and developing Asia to highlight different aspects of household vulnerability to income shocks arising from the Covid-19 pandemic: occupation in Cambodia, self-insurance mechanisms in Nepal, and financial leverage in Vietnam. Occupation and ex-ante income levels emerge as the main drivers of vulnerability. We estimate that the pandemic could have placed an additional 6 to 9 percent of the population of each country in a vulnerable position, with the impact concentrated on urban, informal, and service sector workers. Government intervention and financial access emerge as key resilience-enhancing mechanisms.

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WORKING PAPERS

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Prepared by by Alessia De Stefani, Athene Laws and Alexandre Sollaci[1]

[1] We would like to thank Alejandro Badel, Era Dabla-Norris, Laura Jaramillo Mayor, Yasuhisa Ojima, Alasdair Scott, and participants in the APD/Developing Economies Group seminar for useful comments.

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Introduction

The Covid-19 pandemic represented a major disruption to livelihoods around the world, affecting not only health and safety but also households' ability to earn income. Yet, the impact of these events has been far from uniform, within individual countries. This paper exploits household-level survey data from three countries in emerging and developing Asia – Cambodia, Nepal and Vietnam – to assess various dimensions of household vulnerability and resilience to the income shock inflicted by the Covid-19 pandemic. Due to the different institutional and macroeconomic backgrounds across these three countries, we explore different aspects of vulnerability in each case: labor markets in Cambodia, financial access in Vietnam, and availability of income-smoothing mechanisms in Nepal. For ease of exposition, we treat each country individually, highlighting specific circumstances and policy interventions. However, a common thread emerges across the three case studies: occupation and ex-ante income levels are the main drivers of vulnerability to Covid-19. Furthermore, government policy and access to self-insurance mechanisms have key roles in dampening the effects of this aggregate shock.

We first turn to Cambodia, a key example of the role of policy intervention in mitigating income losses during the pandemic. As tourism collapsed by mid-2020, most Cambodian households suffered a large negative income shock. The government intervened promptly, issuing a broad cash transfer scheme aimed at the most vulnerable segments of the population. Applying a simple simulation exercise to survey data collected before the pandemic, we show that in absence of the cash transfer, the share of households living below the international poverty line would have climbed above 17 percent during the pandemic, undoing ten years of efforts towards poverty reduction. Thanks to the transfer, we estimate this share to be limited to 12.6 percent, instead, or a 2.6. p.p. increase from the baseline. Yet, many urban, service sector workers were likely to be excluded from the transfer scheme and may constitute a new pocket of poverty.

We then address Vietnam's case. Like Cambodia, Vietnam's economy was also severely impacted by Covid-19, but cash transfers were significantly smaller and did not reach a large proportion of the affected households. Instead, much of the population weathered the crisis by tapping into savings or taking debt. This raises two important concerns. First, what was the effect of the Covid-19 crisis on the financial health of households? Second, what role does financial access play in determining households' ability to cope with a shock of that magnitude? Our results indicate that access to financial services is strongly related to better financial health, but, as in many developing countries, remains an important constraint faced by a large share of households. We estimate that the pandemic could have placed over 10 percent of the population in a financially vulnerable position, with the impact concentrated on informal workers in the service sector.

Finally, we look to Nepal, a low-income country that is particularly vulnerable to climate shocks. Because of that, the 2016-18 Nepal Household Risk and Vulnerability Survey (HRVS) was conducted to capture data on the shocks that households are exposed to and the coping strategies that they use – which also allows us to anticipate how they might react to the Covid-19 pandemic. In any given year, 45 percent of households face at least one shock and 9 percent reduce their consumption in response, indicating imperfect consumption insurance.[1] We find that remittances and access to finance are effective mitigating strategies, reducing the probability that households have the reduce consumption. Simulated results estimate an additional 6 percent of households (15 percent in total) are forced to reduce consumption in response to Covid-19 employment effects.

[1] 'Shock' refers to a predefined list of adverse events in the HRVS, such as natural disasters, loss of health/life and financial shocks (job loss, bankruptcy etc). The full list of shocks can be found in Table C.2 in Appendix C.

Our paper has two main contributions. The first is to provide a descriptive analysis of household vulnerability to income shocks in developing Asia. Partly due to data availability, the vast majority of the literature on household income risk, financial distress and resilience has traditionally focused on advanced economies. The institutional context in developing Asia can be very different. The informal sector is often a predominant source of employment, excluding many workers from traditional social security schemes (Dabla-Norris et.al, 2005; 2020). The policy space available to governments is often limited, increasing the importance of self-insurance mechanisms (Townsend, 1995; Dercon, 2002). Finally, lack of access to financial services often limits households' capacity to smooth large income shocks, including aggregate ones (Kinnan and Townsend, 2012; Carlson et.al, 2015; Bellon et.al, 2020).

Second, we provide some quantitative estimates of the potential distributional implications of the Covid-19 pandemic in emerging and developing Asia. Compared to recent contributions focusing on the same region (Morgan and Thrin, 2020; World Bank, 2020a,b,c; 2021a,b) we highlight specific channels of transmission of this aggregate shock to households: availability of coping mechanisms, financial inclusion, and labor markets. Using household-level data, we highlight the distributional implications of aggregate shocks, focusing on the pandemic as a case study. Understanding these heterogenous effects is particularly relevant for EMEs, as limited fiscal space often requires effective policy support to be appropriately targeted (Coady et.al, 2004; Gerard et.al, 2020).

However, we add one important caveat: this paper relies on data collected *before* the pandemic, as more recent household-level data is yet unavailable. Thus, we cannot speak to the actual effects of Covid-19 on households' balance sheets, nor to the relative responses. We instead simulate the potential implications on the pandemic given ad-hoc assumptions on the relative distribution of the shock across households and derive implications for income poverty, financial distress, and spending. Despite the implicit limitations of this approach, we believe this exercise to be informative, as it highlights a high degree of within-country heterogeneity in the effects of the pandemic across households in the region.

The paper proceeds as follows. Section 2 describes the data used for each country. Section 3 discusses the analysis for Cambodia, including the impact of Covid-19 pandemic and the cash transfer program initiated by the authorities. Section 4 presents the Vietnam context, with the particular focus on financial vulnerability of households. Section 5 turns to Nepal, highlighting the coping strategies used by households in the face of shocks. Section 6 concludes with a summary and discussion of policy implications.

Data

Cambodia

The Cambodia Socio-Economic Survey (CSES) is a cross-sectional survey administered by the Cambodian Statistical Institute. The survey is conducted every two years and aims at being nationally representative, sampling around 10,000 households per year. One adult respondent per household reports a host of information on family composition and demographics, assets, liabilities, and detailed spending behavior. Crucially, the survey also reports the sector of employment and sources of income of each family member, which is a necessary precondition to model the effects of Covid-19 on household income. We employ the latest wave of the survey, conducted between the last quarter of 2019 and early 2020. Descriptive statistics are presented in Appendix Table A.1.

Vietnam

The analysis of financial vulnerabilities uses the 2018 vintage of the Vietnam Household Living Standards Survey (VHLSS), a representative survey of Vietnamese households conducted via face-to-face interviews.

The VHLSS contains information on income, expenditure, location, education level, family size, and other demographic variables for a subset of approximately 9,400 households.[2] Importantly, the VHLSS also provides data on all loans currently held by each household, which is used to construct three measures of financial vulnerability: savings rate, debt-to-income ratio (DTI), and financial margin (FMR). Details on the construction of each of those measures are discussed in Appendix B.1. The conclusions in this paper are based on common trends observed for all three measures, as each has different strengths and shortcomings that could bias our results.[3]

Nepal

The Nepal Household Risk and Vulnerability Survey (HRVS) is a three-year panel of 6,000 households and 400 communities in non-metropolitan Nepal from 2016-2018. Retention is high, with approximately 94% of households surveyed in all three waves. The geographic coverage is targeted at rural and semi-urban areas, and the Kathmandu Valley is excluded. The dataset includes standard household survey questions – such as demographics, employment, educational attainment, migrant work, consumption and agricultural activities. However, the emphasis of the survey is on household exposure and response to shocks, both ex ante and ex post. Extensive questioning on a broad range of shocks, their impacts on households, coping strategies used, and government and community support available provides a rich dataset from which to analyze household vulnerability.

Labor market vulnerability in Cambodia

A. Background

The pandemic inflicted a large negative shock on the Cambodian economy. Aggregate output is estimated to have declined by 3.1 percent in 2020, as the large contraction in tourism and related services compounded the drop in external demand for tradable goods. Firms experienced large sale and revenue losses, particularly concentrated in small and medium enterprises active in retail and the service sector.[4] As a result of the loss in employment opportunities, as many as 83 percent of Cambodian households reported suffering a decline in income in the first half of 2020.[5] About 50 percent witnessed their incomes declining further since then.[6]
This shocks nests into pre-existing labor market vulnerabilities. Retail and hospitality, the sectors most hard hit by the pandemic, employ around 20 percent of Cambodian workers (Figure 1, left-hand panel). This workforce is predominantly self-employed or working informally and may not be eligible for traditional social security, or furlough schemes (Figure 1, right-hand panel)

[2] The VHLSS surveyed 46,995 households overall, but only a subset of 9,399 households answered an extended questionnaire that includes detailed data on both income and expenditures. Detailed information on the 2018 VHLSS can be found in https://www.gso.gov.vn/en/data-and-statistics/2020/05/result-of-the-vietnam-household-living-standards-survey-2018/.

[3] The savings rate does not include debt services, which could underestimate the financial risk for indebted households. Conversely, the DTI offers limited insight into households with no financial access, which are typically constrained in the amount of debt they are able to take. Finally, the FMR includes both the savings rate and debt services, but includes variables that are not observed in our data. See Leika and Marchettini (2017) for an in-depth discussion on measures of household financial vulnerability and their data requirements.

[4] World Bank, 2020a

[5] World Bank 2020b

[6] World Bank 2021a

Figure 1: Distribution of Cambodian Workforce by Sector

Source: Cambodia Socio-Economic Survey (2019/2020) and authors' calculations.

B. Policy response to the pandemic: a new cash transfer scheme

The social protection system was expanded significantly during the pandemic. Before June 2020, a mechanism called "Identification of Poor Households" (IDPoor) was used mainly to identify potential recipients for maternal and disability support, as well as scholarship programs. Public health and retirement pension schemes were limited to civil servants, which are also the only category covered by employment injury insurance. Unemployment insurance is absent.

In 2020, IDPoor's scope was expanded, as the government used it to target households eligible for the new Cash Transfer Program for the Poor and Vulnerable Households. This program aimed at tackling extreme poverty in response to the pandemic and had an initial budget of USD 300 mln for the first year (1 percent of 2020 GDP). Eligibility in the scheme, as well as the relative size of the monthly transfer, varied according to a complex system of thresholds. Households classified as being absolute priorities (PoorID1) or facing significant challenges (PoorID2) were approved to receive cash transfers.

About 710,000 households (2.8 million people) received the cash transfer in 2020. These households have received monthly subsidies worth 45 USD, on average, corresponding to about 33 percent of monthly household earnings at the 25th percentile of the distribution in 2019/2020. Cash is transferred directly from the Ministry of Social Affairs, Veterans and Youth Rehabilitation to recipients via electronic payments. Recipients are notified by SMS alerts to present ID cards and Equity Cards to the nearest Wing agent (a private bank partnered to the cash transfer program) which allows them to withdraw cash.

While support will eventually be rolled back as the economy recovers, the transfer provided support for an extended period of time, during the pandemic. Many recipients received the cash transfer until end-2020 (6-7 months on average); and parts of this scheme have been expanded into 2021. The relative design differs substantially from the one-off transfer commonly provided to households in advanced economies during the early months of the pandemic (Cobion, Gorodnichenko and Weber, 2021).

C. Simulation Analysis: Evaluating effectiveness of policy intervention

The distributional consequences of the cash transfer scheme can be approximated using household survey data. The CSES includes detailed information on the sector of operation of all working members of the households, including self-employed individuals. For self-employed individuals, total income includes monetary income in the year and any receipts from the sale of self-production (i.e., agricultural goods). To simulate the effects of Covid-19, we aggregate income at the household level and compute the distribution of household income before the pandemic (Figure 2, blue line). The simulation then shocks this distribution following two assumptions: first, households' income will decline by a factor directly proportional to the share of working members employed in retail, restaurants, logistics or the hospitality sector; second, workers operating in other sectors will maintain their income unchanged (Figure 2, red line).

These are admittedly strong assumptions. The size of the income shock we impose on service sector workers is arbitrary, while other workers are assumed to be completely unaffected by the pandemic. Either assumption is unlikely to be entirely realistic, since service sector workers may have not lost the entirety of their income during 2020, while workers in other sectors are indeed very likely to have experienced income losses. While these biases are likely to pull the results in opposite directions, the simulation estimates should be interpreted with caution, since they are likely to present a large margin of error (especially as we abstract from general equilibrium effects). With these caveats in mind, these estimations can shed some light on the counterfactual effects of pandemic in absence of government intervention.

Without the cash transfer, 17.3 percent of household would have seen their income fall below 1.9 USD per worker/day (PPP), a threshold frequently used to identify households in need in international comparisons.[7] This is a significant increase in relative adversity. In the baseline, only 10 percent of Cambodian households are estimated to live below this threshold. The income distribution becomes more left-skewed (Figure 2, red line), as more than a third of Cambodian households suffer some degree of income loss, in this scenario.

To approximate the effect of the cash transfer program, the simulation assumes that all workers below the 12th percentile of the baseline income distribution and/or in possession of an IDPoor card receive a transfer equivalent to 45USD per month (US$ 1.50 per day).[8]

Thanks to the transfer, the share of households living below the international poverty line is estimated to be only 12.6 percent, or a 2.6 percentage points increase from the pre-pandemic baseline. This large relative improvement compared a poverty rate of 17 percent simulated under the Covid-19 scenario, is evident from the significant shift to the right in the distribution of earnings (Figure 3, red line).

Furthermore, the cash transfer may have been able to lift 164,000 households out of income poverty, compared to the pre-pandemic baseline. Survey data collected during the pandemic confirms this. The percentage of households reporting some degree of food insecurity declined from 67 percent to 36 percent, between August and October 2020. Most of the transfers were spent on food and other necessities.[9]

[7] USD 1.9 per worker/day corresponds to the international poverty line defined by the UN/World Bank. See, for example World Bank (2020c).

[8] As the PoorID system relies on a complex system of indicators to determine eligibility into the cash transfer program, is not possible to precisely assign households to the recipient group using SES data. These numbers are chosen to match the aggregate numbers reported by the authorities: an average transfer size of 45 USD per month and about 710,000 recipient households in 2020.

[9] World Bank 2020a.

Figure 2: Simulating the Effects of the Pandemic on the Distribution of Income

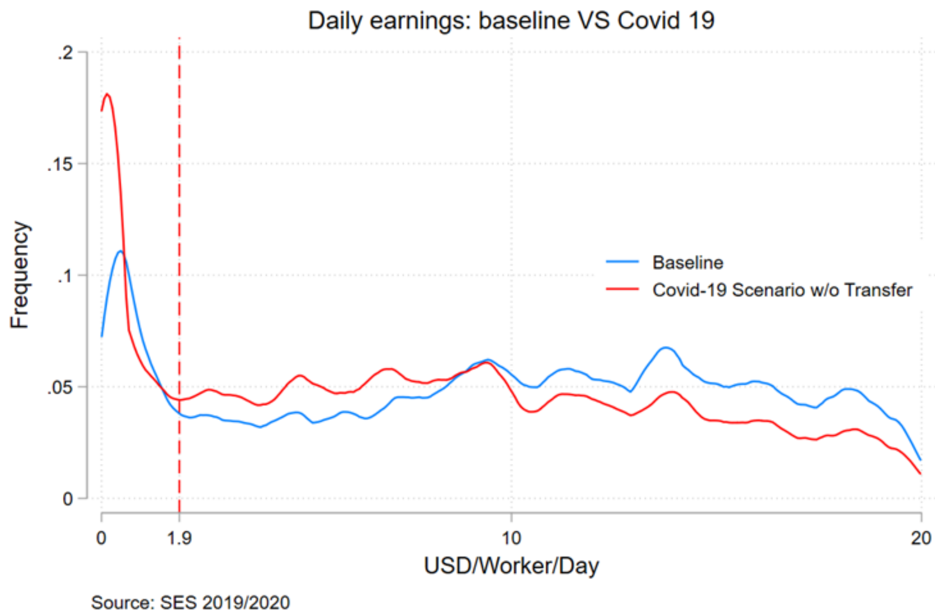
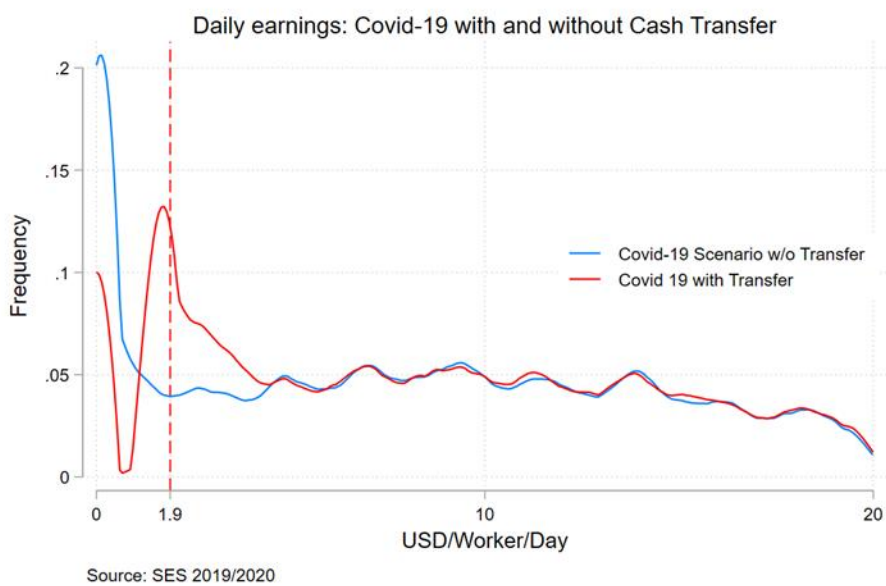


Figure 3: Simulating the Effects of the Cash Transfer



Source: Cambodia Socio-Economic Survey (2019/2020) and authors' calculations.

However, not all households affected by the pandemic are supported by the cash transfer scheme. According to the simulation, as many as 260,000 Cambodian households may have fallen below the US$ 1.90 threshold in 2020 but find themselves outside the spectrum of coverage of the cash transfer scheme.[10] These 'new poor' households constitute more than half of those estimated to be living below the poverty line in the aftermath of the pandemic (459,000).

The newly poor are typically urban and work in services. Under the assumptions of the simulation, cash transfer recipients are less likely to live in urban areas, compared to the general population and are significantly less likely to be employed in the hospitality sector (Figure 4). On the other hand, households who fall into poverty as a direct result of the pandemic and remain excluded from the cash transfer are disproportionately more likely to be living in cities and to be employed in services.

Figure 4: Demographics of Recipients vs New Poor

Source: Cambodia Socio-Economic Survey (2019/2020) and authors' calculations.

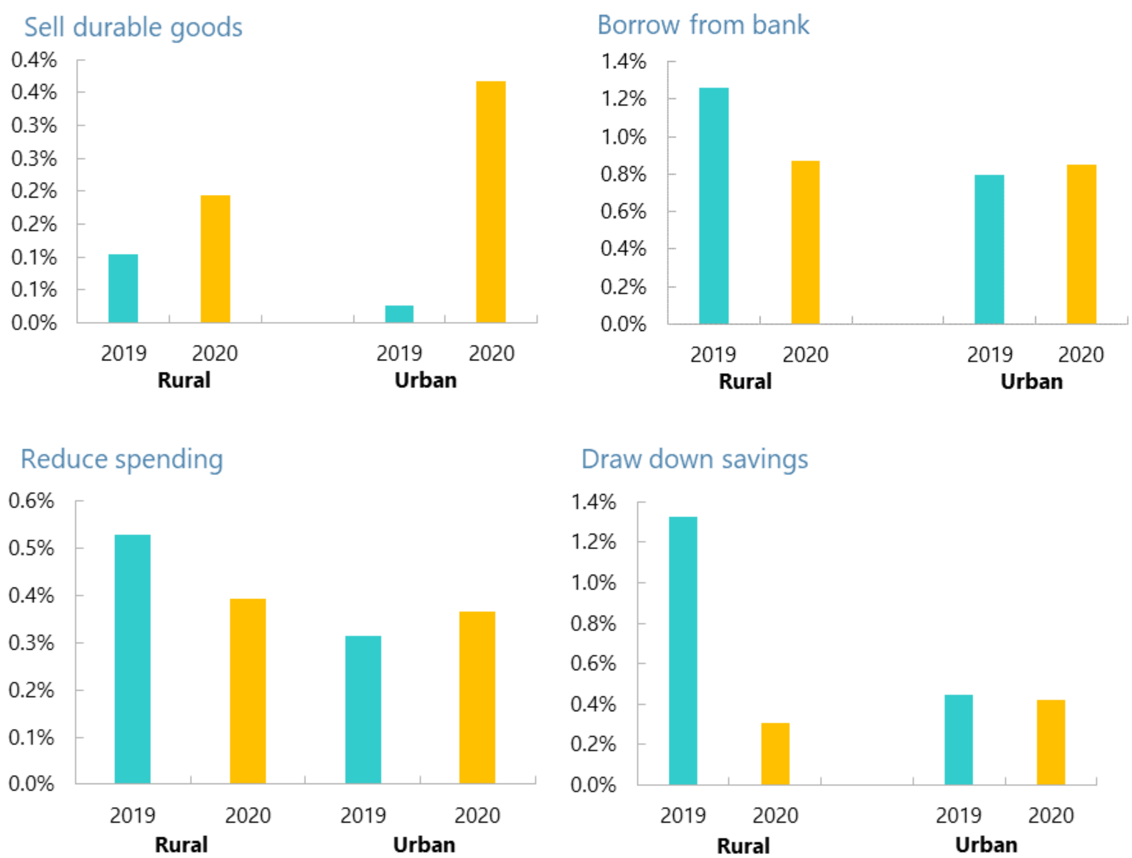
Survey data from the second quarter of 2020 validate these results, showing that urban households increasingly relied on private income smoothing mechanisms. The percentage of urban households who sold durable goods increased significantly in the first five months of 2020, compared to late 2019 (Figure 5). The propensity to reduce food spending also increased in this group, while reliance on savings drawdown and additional borrowing remained stable. The proportion of rural households doing the same declined, instead.

In contrast, rural households have *reduced* their tendency to rely on most income-smoothing mechanisms in 2020. This evidence is line with the predictions of the simulation, which indicates that rural households may have been less negatively affected by the 2020 shock. This is likely to be explained in part by lower exposure to the services sector, but also by the higher relative incidence of government support in rural regions.

[10] The simulation assumes that transfers are targeted to the bottom decile of the income distribution. Many urban, service sector workers are above these income thresholds, as the poorest households tend to be rural and living of subsistence agriculture.

In conclusion, the cash transfer scheme did very well in tackling the forms of extreme poverty which pre-dated the pandemic, by targeting households in the bottom deciles of the income distribution. However, many of these households tend to be rural and living out of subsistence farming, while income losses arising from the pandemic are likely to have be concentrated on urban and service sector workers. Many of these workers are likely to be left out of social protection and constitute a 'missing middle'. As recent income losses are unlikely to be fully recorded in real time and urban households tend to hold higher levels of illiquid wealth, service sector workers living in cities may have found themselves ineligible for IDPoor cash transfers. Most of these workers tend to be self-employed (Figure 1) and are not eligible for furlough schemes. Urban workers may constitute a new pocket of poverty, more likely to draw down on savings and borrow extensively in the aftermath of the pandemic.

Figure 5. Percentage of Households Resorting to Income-Smoothing Mechanisms



Source: Cambodia Socio-Economic Survey (2019/2020) and authors' calculations.

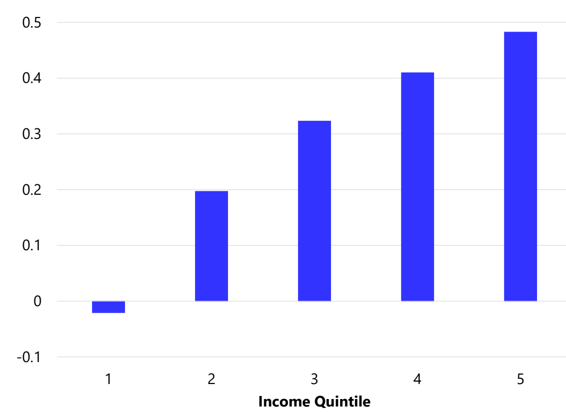
Financial vulnerability in Vietnam

A. *Background*

Despite rapid economic growth and significant improvement in living standards in the past decades, a large share of households in Vietnam are still mostly rural and have low incomes. In the VHLSS of 2018, the median household in Vietnam had a family of four members and an annual income of about USD 5,500 (using the exchange rate from Dec. 2018). Approximately 2 out of 3 households surveyed are located in rural areas and over half have at least one member working directly in agriculture.[11] Informality is also pervasive in the economy: over 45 percent of households in the sample operate as small businesses and 53 percent have at least one member that works informally (see also Dabla-Norris et al., 2020).[12] This issue becomes relevant in the context of financial vulnerability as it excludes workers from social insurance payments and could indicate that their income is more volatile than their formal counterparts.

On average, households save 23 percent of their income but there is significant heterogeneity. The savings rate increases sharply with income, as richer households save larger portions of their income. In addition, over 16 percent of households in the sample report negative savings (calculated as a flow, not a stock). On the expenditure side, food and other daily items comprise a larger share of total expenses for households in the bottom of the income distribution (68 percent for households in the lower quintile, versus 61 percent for households on the top quintile). Low-income households therefore have greater need, and less space, to cut expenses in order to increase savings.

Figure 6: Average Household Savings Rate



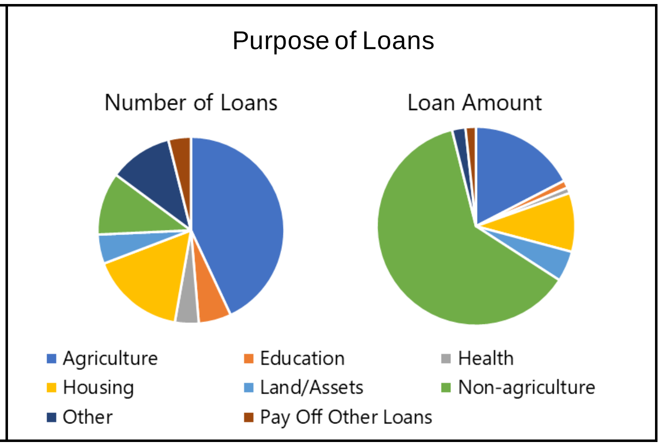
One quarter of Vietnamese households have outstanding debt. We measure household debt by adding up self-reported loans in the VHLSS. We find that nearly 25 percent of households in our sample have at least one outstanding loan (including both formal and informal lenders). Consistent with the income and demographic patterns described above, most households owe relatively small amounts (below USD 2,000) and the majority of loans are used for agricultural activities. At the top of the distribution, however, household debt can reach tens of thousands of dollars and loans are concentrated in non-agricultural businesses.

[11] The pace of urbanization has been rapid in Vietnam, with recent data from the General Statistics Office of Vietnam (GSO) showing that the share of rural households has fallen to about 50 percent.

[12] A worker is classified as informal when he/she does not have a labor contract and no access to social insurance. When this information is missing, we also classify self-employed individuals who work in household businesses as informal workers. Note that this is not the official definition of an informal worker, but it provides a reasonable approximation.

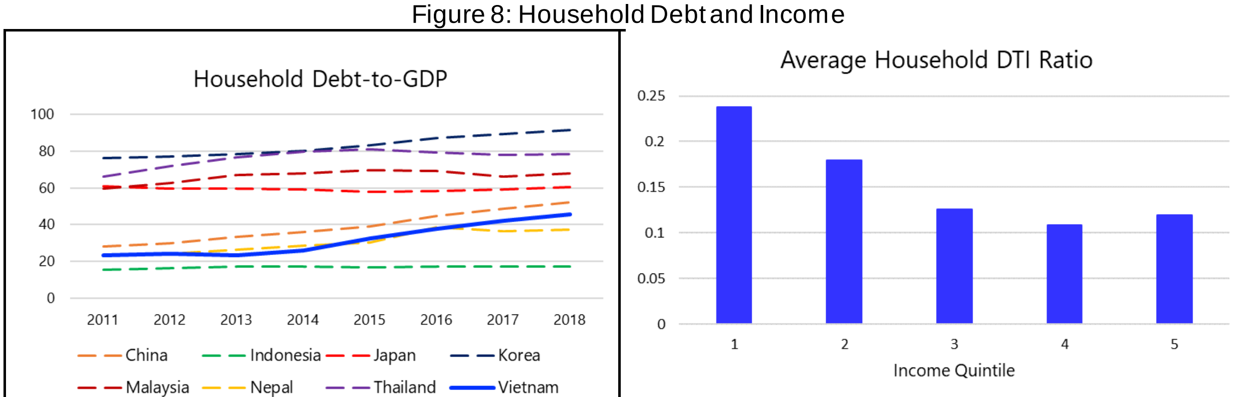
Figure 7: Debt Value Distribution and Purpose of Loans

PERCENTILE	DEBT VALUE (USD)
1	107.78
25	862.20
50	1810.62
75	4311.00
99	64665.00
MEAN	9223.45
SD	117977



The household debt-to-GDP ratio in Vietnam remains lower than most AEs and EMDEs in South-East Asia, but has risen rapidly in recent years. Household debt-to-GDP ratio was relatively low and stable (around 25 percent) between 2011 and 2013. After 2014, as economic growth picked up and interest rates were lowered, household debt-to-GDP grew at a fast pace, reaching a level similar to China's. Calculating the DTI at the household level from the VHLSS data, we find that the average ratio is around 23 percent. This difference can be partly explained by the fact that three-quarter of households in our data do not have any outstanding loans. In addition, we again see considerably heterogeneity across households, with the DTI ratio for households at the bottom quintile of the income distribution being almost twice as large as the ratio for households at the top.

Figure 8: Household Debt and Income

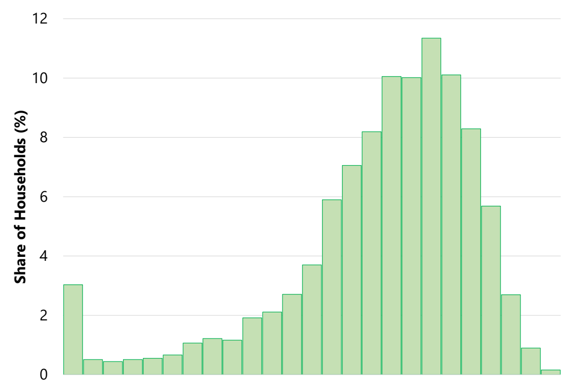


Source: SBV and IMF Datamapper.

Approximately 1 out of 5 households in the VHLSS sample are in a financially unsustainable position, as measured by a financial margin (FMR) below zero. The financial margin measures the amount of income left to a household after discounting expenditures and debt service (as a share of the household's income). Because we do not observe liquid assets, the measure of the FMR used in this note does not necessarily indicate financial distress. Instead, it is a signal of a financially unsustainable position, as it cannot be maintained indefinitely.[13] In the VHLSS, 19 percent of all households have a negative FMR, increasing to 37 percent if only consider households that hold outstanding debt (loans).

There is significant heterogeneity among households with a negative FMR. For some households, the FMR is only marginally below zero, suggesting that their financial situation is manageable or requires few adjustments. Around 3 percent of households are very likely to be in financial distress, having expenditures and estimated debt payments that are several times greater than their annual income (FMR < -1).

Figure 9: Financial Margin Distribution

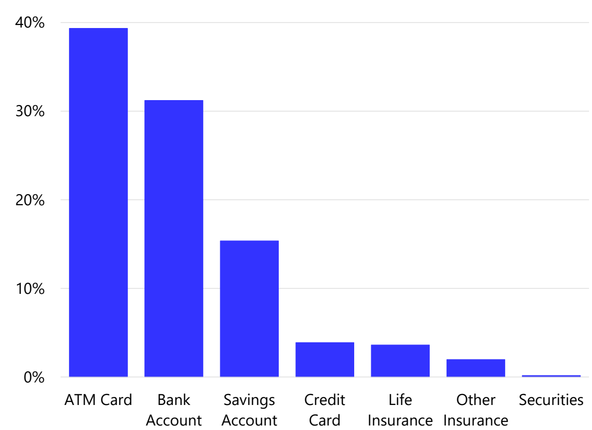


Note: FMR is truncated at -1 for plotting

A.1 Access to Financial Services

Most households in the VHLSS do not report use of financial services such as bank accounts, credit cards, or have insurance. This observation can be partly explained by the demographic distribution of households in the data, where approximately 2/3 of households are located in rural areas. These regions tend to be underserved by commercial banks and other traditional financial institutions.

Figure 10: Financial Services Currently Used



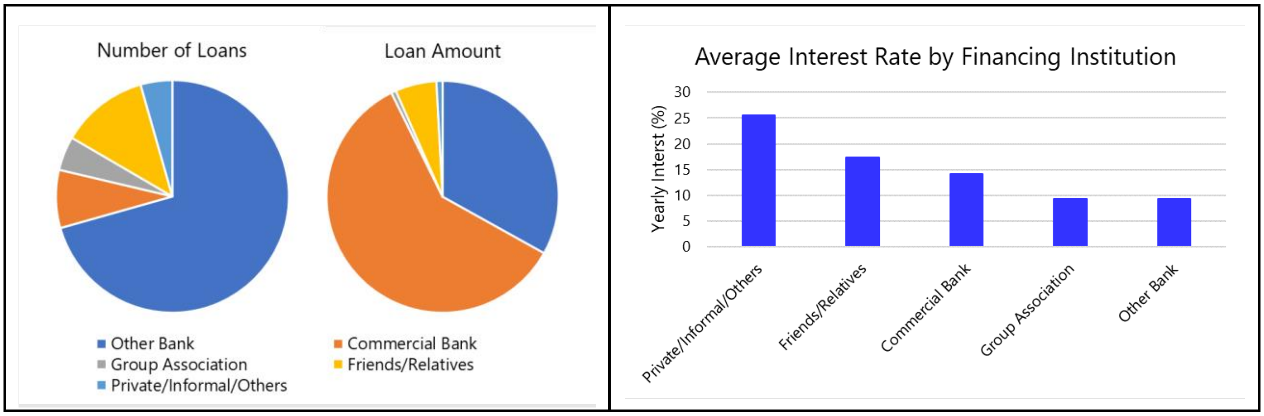
Households without access to commercial banks can still take debt from other financial institutions such as social or development banks, microcredit institutions, etc. To illustrate this argument, we classify each of the financing sources listed by households in our data into five categories: (1) commercial banks (private and state-owned commercial banks); (2) other banks (Social Policy Bank, Bank of Agriculture and Rural Development, People's Credit Funds, local government, other credit institutions); (3) group associations (famer's association, veteran's association, women's association); (4) friends and relatives; and (5) private or informal (businessmen, private lenders, informal credit, others).

Many of the non-commercial financing institutions impose constraints on the type or amount of the loans that they provide. "Other banks", for example, own almost two-thirds of all loans to households in the data, but only about one-third of the loan value. This suggests that these institutions only provide smaller loans, which in

[13] The FMR is typically measured as the result of savings plus liquid assets minus debt payments, generally normalized by net income for comparisons across households. In the VHLSS, we do not observe liquid assets, and thus do not include them in the calculation of the FMR. As such, the interpretation of this number is subject to caveats. For example, that 16 percent of households in the sample have negative savings; without liquid assets, this necessarily means that they will have FMR < 0 as well (note that this also means that only 3 percent of households have a negative FMR and positive savings). As mentioned before, these households might be in financial distress, or simply tapping into their stock of assets to finance part of their current expenses.

many cases come with additional requirements on purpose for which the loan is used. Informal sources of financing tend to charge prohibitively large interest rates or have other types of constraints in place.

Figure 11: Total Loan Value and Interest Rate by Source of Finance



B. *Identifying Vulnerable Households*

This section attempts to identify which households are the most vulnerable to financial. We start with the simplest research design, where the probability that a household has an unsustainable financial position (indicated by FMR < 0) is modeled as a function of household characteristics, including income, education, urban/rural status, employment status, informality, and financial access.[14] For ease of interpretation, the impact of each variable is estimated using a linear probability model (logit specifications produce qualitatively similar results). We also analyze how household characteristics impact each of our three measures of financial vulnerability (savings rate, DTI and FMR) on a continuous scale. This is done by estimating a similar model to the one described above, changing only the dependent variable in each regression.

Each of the regression models and their results are discussed in greater detail in appendix B. We also note that, due to measurement error and potential endogeneity concerns, the coefficients discussed here might not reflect causal relationships between variables.

Income is the most important determinant of an unsustainable financial position and has the largest impact on all financial vulnerability measures employed in the analysis. The estimation results suggest that, all else equal, a 1 percent increase in household income decreases the probability of financial distress by 0.26 percentage points. Households with higher income are also less likely to take loans, save a higher portion of the income, have less debt relative to their income, and have a higher financial margin. Quantitatively, those effects are considerably larger than for other characteristics.

Financial access decreases financial vulnerability, particularly for low-income households. Granting financial access to households can drastically reduce the probability that their financial margin is negative. In addition, the coefficient on the interaction between *financial access* and *log(income)* is positive, which means that the effect is greater for poorer households. The results are similar when looking at the measures of financial

[14] Financial access is defined as a dummy that equals 1 members of the household claim to currently use at least one of the following services: ATM card, bank account, savings account, credit card, life (or other) insurance, or if it owns securities. This acts a proxy for access to commercial banks that does not rely on directly observing loans between households and commercial banks – that is, it includes households that choose not to take a loan, even if they had the choice to do so. Less than 1 percent of households without financial access have loans with commercial banks.

vulnerability themselves: financial access reduces DTI and increases FMR (the coefficient on the savings rate is also positive, but not significant). Once again, the effect is higher for households with lower income.

C. *The Covid-19 shock in Vietnam*

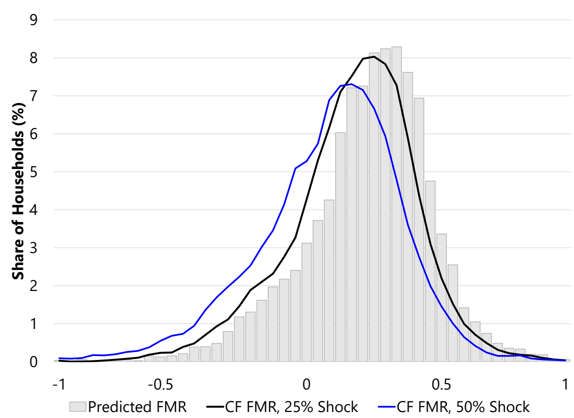
Leveraging the results from the estimation above, the analysis suggests that COVID-19 could have increased the share of financially vulnerable households by 3 – 10 percentage points. This result is obtained by treating COVID-19 as an exogenous income shock that primarily affects informal workers (who do not have access to social insurance) and those in the service sector (whose jobs are more likely to be disrupted by social distancing restrictions). In this scenario, household h's income is modelled as

$$y_h(\varepsilon) = y_h(0) \times \left(1 - s_h^i \varepsilon - 0.4\, s_h^f \varepsilon\right)$$

where $y_h(0)$ is household h's observed income (pre-COVID-19), s_h^i is the share of adults[15] working informally in the service sector, s_h^f is the share of adults with formal jobs in the service sector, and $\varepsilon \in \{0.25, 0.50\}$ is the size of the income shock. We differentiate between formal and informal workers because formal workers that lost their jobs were eligible for a benefit equal to 60 percent of their income (World Bank, 2021b). The size of the shock, ε, can be interpreted as the duration of the Covid crisis: $\varepsilon = 0.25$ indicates that the crisis lasts for one quarter (e.g., Q3 of 2021, when strict lockdowns were imposed). We also allow for a longer duration $\varepsilon = 0.50$ to capture lingering effects on worker's income.

Plugging in $y_h(\varepsilon)$ into regression model with the FMR as the dependent variable gives the counterfactual distributions, which are compared to the predicted FMR. While this approach allows for controlling for a number of household characteristics when estimating the effect of the income shock, note that the predicted FMR fails to capture the relevant mass of households with an FMR smaller than -1 (compare this figure with the distribution of the FMR shown above). In appendix C, an alternative method to calculate the impact of COVID-19 on household vulnerability is adopted, which yields even stronger results.

Figure 12: Predicted and Counterfactual FMR



Value of income shock, ε	*0 (baseline)*	*0.25*	*0.5*
Share of households with FMR < 0 (%)	12.23	15.11	22.56
Difference relative to baseline		2.88	10.33

[15] We exclude any household member that cites "young/studying", "retired", or "sick" as the reason for not working.

Coping strategies and resilience in Nepal

A. Background

The Nepal data (HRVS) dedicate considerable efforts to understanding how households have adapted to shocks they have faced in the prior 12 months. Households are asked about the shocks they faced in, and the survey responses contain a mix of natural disasters, health, economic and political shocks. In any given year, 9 percent of household had to reduce consumption in response to a shock, and 45 percent of households faced at least one shock. The 2016 data is dominated by damage from the previous year's earthquake. Disease and death of a family member make up over a quarter of observed shocks over the three years, while other natural disasters such as drought, hail, pests, and floods comprise another quarter. The average financial loss was 64,844NRs, with earthquakes, other natural hazards, and family member death generating the greatest financial loss. Further details of the type of shocks and frequencies are displayed in Table C.2 in the Appendix.

Households also reported the coping strategies used in response to shocks, and the results show a striking lack of financial access. Table 1 below shows the responses of households to shocks they faced in the previous year. Over three quarters of households relied on savings following the shock, and another 15 percent borrowed from friends and families. Borrowing from money lenders (aka money sharks) was the next most common. Very few households accessed formal finance. Over 80 percent of households used only one copin g strategy, either because the first was sufficient or due to lack of access to a second.

Households were also asked how they would anticipate responding to a shock, ex ante, and results similarly showed a reliance on savings with very little financial access. Table C.3 in the appendix shows the breakdown of expected coping strategies in detail. When asked how they would respond to a shock of NRs25,000 (about USD210), very few indicated they would access formal, financial channels. Far more indicated they would be likely to borrow from friends and family than those facing shocks did. As for the ex-post responses, the breakdown shows a strong lack of access to finance in responding to shocks.

Table 1: Percentage of HHs Using Each Coping Strategy Following a Shock in the Preceding 12 Months

Coping strategies (% respondents)	(1) 2016	(2) 2017	(3) 2018
Spent Savings	78.1	79.3	80.3
Borrowed from friends/family	15.2	15.3	11.6
Pawned the house or land	0.5	0.7	0.8
Pawned farm animals/equipment	0.2	0.1	0.1
Pawned other properties	0.4	0.2	0.0
Sold the house or land	0.3	0.9	1.8
Sold farm animals/equiment	7.6	1.9	2.6
Sold other properties	0.5	0.4	0.5
Borrowed from moneylenders/sharks	11.5	10.7	13.1
Borrowed from a private bank	0.6	0.5	0.7
Borrowed from a government bank	0.7	0.8	0.5
Borrowed from a co-op/savings group	5.0	6.8	6.3
Other	0.0	0.0	1.6
Observations	4970	1999	995

Percentage of households responding a shock with the above coping strategies. Some households respond with multiple coping strategies, thus column totals are greater than 100%.

B. Baseline distribution of vulnerabilities and resilience in Nepal

We now turn to identifying vulnerability at the household level to shocks and insurance mechanisms that mitigate impacts. Equation 1 displays the core specification. Household i's outcome in time t is regressed on the number of shocks faces and a vector X_{it} of time varying household characteristics.[16] Variables capturing potential coping strategies, such as remittance receipt, government support receipt and access to savings/credit are included as required. Outcomes are financial loss (in Nepali Rupees, NRs) and binary variables indicating whether households were forced to reduce consumption or not.[17] Household fixed effects are included to control for unobservable time-invariant household characteristics that may generate several endogeneity issues, including being located in areas more exposed to natural disasters. Time fixed effects are also included to remove aggregate shocks such as the 2015 earthquake and blockade shocks captured in the 2016 survey wave. Household level weights are used, constructed based on survey weights in the original data. Standard errors are robust to heteroskedasticity.

$$Y_{it} = \beta_0 + \beta_1 Number\ Shocks_{it} + \beta_2 X_{it} + \beta_3 Rem_{it} + \beta_4 Gov_{it} + \beta_5 Credit_{it} + d_i + d_t + \epsilon_{it} \quad \text{(Eq 1)}$$

Table 2 displays the financial loss and consumption impacts of shocks, regressed on the central variables. Column one of Table 5 regresses the household's financial loss of the current year's shocks, in Nepali Rupees, and columns two through four on the binary variable that the household reduced consumption. Columns two through four are displayed as linear probability models, however the results are robust to probit and logit specifications. Unsurprisingly, the more shocks a household faces, the greater the combined reported financial loss (30,000 rupees per additional shock) and the greater likelihood of reduced consumption (~13 percentage points per additional shock). Of the household characteristics, we see that the number of children, number of elderly, and vulnerable employment status (daily waged or self-employed in agriculture) are associated with a smaller financial loss. The reduced loss is possibly due to these households being poorer, on average, and thus have fewer assets or income to lose. Households self-employed in agriculture are, however, 1.3 percentage points more likely to reduce consumption, indicating their heightened vulnerability.

Remittance receipt provides effective mitigation against consumption loss, while government assistance is not effective in this context. Remittance receipt is associate with a 2.3 percentage point reduction in the probability of reducing consumption. Columns three and four split the consumption loss into food and non-food consumption and show that the results are strongest for non-food consumption. Government assistance has no statistical impact on the probability of reducing overall consumption in this dataset. However, caution should be taken: at the time of the survey, government assistance programs were very minimal, and the result with more robust support structures may be more significant. Relatedly, the positive association between government assistance receipt and financial loss is likely to due to reverse causality from support to (high loss) earthquake affected households.

Savings and credit access mitigate the consumption impacts of shocks, but not through net wealth channels. Table 3 incorporates measures of savings (total savings in columns 1,2,4, separated into bank and cash

[16] Time invariant household characteristics, such as geographic location, will be covered by the household fixed effect. The core set of household characteristics are: number of children, elderly, education level, type of employment (e.g. hourly paid employment), and an indicator for self-employment in agriculture.

[17] Our preferred measure of shock impact is a household reduction in consumption following a shock, as i) this is less subject to measurement error (compared to self-reported financial loss), ii) financial loss often reflects pre-shock affluence, and iii) reduced consumption indicates imperfect consumption insurance, i.e., heightened vulnerability.

savings in column 3), loan access (all loans in columns 1,2,3, loans separated into formal finance loans and money shark loans in column 4) and net assets (savings minus loans in column 5). As we can see, access to savings or credit does not affect the financial loss faced from shocks, but does substantially impact the flow on consequences to consumption.

For every 100,000 Nepali Rupees in savings, households are 0.3 percentage points less likely to reduce consumption. When separated by savings type (column 3) we see that it is bank accounts, not cash holdings, that provide this insurance. Access to loans is also associated with a two percentage point reduction in the probability of losing consumption. Most loans come from friends or family. Column four shows that those with loans from financial corporations (private banks, development banks, cooperatives) are able to smooth consumption slightly more. Money lenders, also known as loan sharks, provide no consumption values, possibly because these are the most vulnerable individuals. Column five shows that net assets (savings minus loans) are not associated with weakened consumption impacts. This would imply that loans and savings results are not simply working through a wealth channel.

Results are robust to a range of specifications and controls. These include incorporating the value of variables such as government assistance and remittances rather than indicators, controlling for the financial shock loss in linear probability models, the type of shock faced (particularly controlling for natural hazards like earthquakes). As mentioned above, the results from the linear probability models are qualitatively similar when probit and logit specifications are run.

Table 2: Baseline Indicators for Vulnerability and Resilience

	(1)	(2)	(3)	(4)
	Finance loss	Cons. loss	Food loss	Non-food loss
Unit:	NRs	Prob	Prob	Prob
Number of shocks	30300.8***	0.135***	0.127***	0.0973***
	(1845.3)	(0.00317)	(0.00319)	(0.00325)
Children under 16	-6830.6**	0.00460	0.00448	0.00728
	(3021.3)	(0.00595)	(0.00538)	(0.00527)
Adults over 60	-13435.0**	-0.0154	-0.00260	-0.00436
	(5936.2)	(0.0120)	(0.0111)	(0.0102)
Higher educ	3706.3	0.000151	0.000204	-0.00668
	(3747.0)	(0.00788)	(0.00718)	(0.00702)
Paid Employment	-9694.1***	0.00700	0.00944	-0.00415
	(2755.7)	(0.00668)	(0.00605)	(0.00567)
Self employed in agri	-7380.3***	0.0132**	0.00780	0.0195***
	(2677.2)	(0.00558)	(0.00506)	(0.00483)
Remittance receiving	5623.6	-0.0233**	-0.0126	-0.0206**
	(4269.2)	(0.00994)	(0.00897)	(0.00887)
Public assistance	33330.3***	0.00907	0.00957	0.0125
	(4483.0)	(0.00924)	(0.00856)	(0.00806)
Household FEs	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes
Constant	44609.5***	0.0348**	-0.00671	0.0162
	(7062.3)	(0.0142)	(0.0130)	(0.0126)
Observations	17709	17709	17709	17709
R^2	0.084	0.287	0.270	0.227

Standard errors in parentheses, robust to heteroskedasticity. Time and household fixed effects included. Columns two through four are linear probability models with a binary outcome variable (1 for lost consumption, 0 for no lost consumption).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Impacts of Financial Access on Shock Outcomes

	(1) Finance loss (NRs)	(2) Cons. loss (Pr)	(3) Cons. loss (Pr)	(4) Cons. loss (Pr)	(5) Cons. loss (Pr)
Remittance receiving	3766.4	-0.0171*	-0.0173*	-0.0217**	-0.0235**
	(4635.0)	(0.00996)	(0.00996)	(0.00999)	(0.00994)
Public assistance	33329.6***	0.00909	0.00909	0.00876	0.00901
	(4476.3)	(0.00924)	(0.00924)	(0.00924)	(0.00923)
Total savings	310.3	-0.00385***		-0.00383***	
	(1014.8)	(0.00137)		(0.00136)	
Loans	8411.1	-0.0263***	-0.0265***		
	(5937.6)	(0.00517)	(0.00517)		
Bank savings			-0.00449***		
			(0.00158)		
Cash holdings			0.00996*		
			(0.00576)		
Finance loans				-0.0339***	
				(0.00739)	
Money lender loans				-0.00213	
				(0.00755)	
Net wealth					-0.00118*
					(0.000707)
Household characteristics	Yes	Yes	Yes	Yes	Yes
Household & Time FEs	Yes	Yes	Yes	Yes	Yes
Constant	39584.6***	0.0519***	0.0513***	0.0419***	0.0345**
	(9049.4)	(0.0146)	(0.0146)	(0.0143)	(0.0142)
Observations	17709	17709	17709	17709	17709
R^2	0.085	0.290	0.290	0.289	0.288

Standard errors in parentheses, robust to heteroskedasticity. Household characteristics include: number of children in the household, number of adults over 60 years old in the household, education level, type of employment (hourly paid employment), indicator if self-employed in agriculture. Household and time fixed effects are included. Columns two through five are linear probability models with a binary outcome variable (1 for lost consumption, 0 for no lost consumption)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C. The Covid-19 shock in Nepal

Similar to the methodology for the Cambodia and Vietnam case studies, we identify households at direct risk of Covid-19 job disruption based on occupation. The HRVS occupation data is more limited, so we identify such households as those working in services (dominated by tourism) and construction industries (subject to lockdowns). 43 percent of households are employed or self-employed in these industries. The average expected loss for an additional shock for these households would be 53,671 NRs (~US$450).

We estimate an additional 6 percent of households are expected to reduce their consumption in direct response to Covid-19 job disruption (a total of 15 percent of households). We construct a hypothetical shock scenario whereby those in Covid-19 exposed industries are subject to an additional shock. All other households are not exposed to the shock. These are strong assumptions: full employment effects for occupation exposed households and no indirect effects (e.g. recession) for other households. Simulating the baseline regression model with the shock scenario yields an additional 6 percent of households, or 15 percent in total, forced to reduce consumption.

Despite the data and methodology limitations, the magnitude of the estimates lines up with direct survey data on the Covid-19 shock. Egger et al (2021) surveyed Nepali households in 2020 and found that 40 percent of households lost income, 20 percent lost jobs and 11 percent missed or reduced meals in Nepal. The HRVS data is very effective at identifying vulnerability and coping responses, but less useful for quantifying aggregate effects. It is reassuring that direct survey evidence provides a quantitatively similar and compelling result.

Summary and policy implications

The pandemic inflicted a large negative shock on emerging Asia, a region highly dependent on tourism and exports. Despite the aggregate nature of this shock, the effects were not homogenously distributed across the population. Our results highlight how low-wage workers, more likely to be employed informally and to work in the services sector were the most affected. These workers have little means to smooth consumption when faced with negative income shocks as their stock of savings tends to be limited and they often lack access to financial services, or to other self-insurance mechanisms.

For many vulnerable households, adequate and timely intervention of the public sector was key to weather the storm of the pandemic. We provide the example of Cambodia, where we estimate that the newly enacted cash transfer scheme may have kept 5 percent of the population out of income poverty, compared to a counterfactual where households were left to face the pandemic without government support. These results highlight how creating appropriate fiscal room for well-targeted social spending is a crucial component of building resilience to shocks in low-income and developing economies.

The experiences of Nepal and Vietnam highlight another key area of policy intervention: fostering consumer access to a formal and adequately regulated financial services sector. Ensuring access to traditional banking services may not only improve self-insurance towards idiosyncratic shocks, but may also reduce reliance on informal lending, a likely root cause of a mounting household leverage problem in the region.

As we focus on three countries in a vast and very diverse region, we claim no general validity of our estimates and results. Yet, one basic principle should hold across many LICs and EMEs: understanding heterogenous responses to aggregate events is crucial to ensure adequate and equitable policy responses. Knowledge of heterogeneity informs appropriately designed targeting, maximizing the impact of scarce fiscal resources. This knowledge can be used to improve efficiency, fiscal sustainability and adequacy of policy support, all of which are macro-critical in LICs and EMEs with limited fiscal space.

References

Bellon, Matthieu; Pizzinelli, Carlo; Perrelli, Roberto (2020). Household Consumption Volatility and Poverty Risk: Case Studies from South Africa and Tanzania IMF Working Paper No. 20/51.

Carlson, Stacy; Dabla-Norris, Era; Saito, Mika; Shi, Yu (2015). Household financial access and risk sharing in Nigeria, IMF Working Paper No. 15/169.

Coady, David; Grosh, Margaret; Hoddinott, John (2004). Targeting of Transfers in Developing Countries, World Bank Publishing.

Cobion, Olivier; Gorodnichenko, Yuriy; Weber, Michael (2021). How Did U.S. Consumers Use Their Stimulus Payments? NBER Working Paper Series, 27693/2020.

Dabla-Norris, Era; Gradstein, Mark; Inchauste, Gabriela (2005). What Causes Firms to Hide Output? The Determinants of Informality, IMF Working Paper No. 05/160.

Dabla-Norris, Era; Ganelli , Giovanni; Nguyen, Anh Thi Ngoc Nguyen; Nguyen, Mai Thi Thanh ; Vu, Thuy Thi Thu (2020). Role of Individual Characteristics and Policies in Driving Labor Informality in Vietnam, IMF Working Paper 2020/273.

Dercon, Stefan (2002). Income Risk, Coping Strategies, and Safety Nets. The World Bank Research Observer, Volume 17, Issue 2, September 2002, Pages 141–166.

Gerard, François; Imbert, Clément; Orkin, Kate (2020). Social protection response to the COVID-19 crisis: options for developing countries, Oxford Review of Economic Policy, Volume 36, Issue Supplement_1, 2020, Pages S281–S296.

Egger, Dennis et al. (2021). Falling living standards during Covid-19 crisis: Quantitative evidence from nine developing countries. Science Advances 7(6).

Kinnan, Cynthia; Townsend, Robert (2012). Kinship and Financial Networks, Formal Financial Access, and Risk Reduction, American Economic Review 102(3), pp. 289-93.

Townsend, Robert (1995). Consumption Insurance: An Evaluation of Risk-Bearing Systems in Low-Income Economies. Journal of Economic Perspectives 9(3).

Morgan, Peter; Trinh, Long (2021). Impacts of COVID-19 on Households in ASEAN Countries and Their Implications for Human Capital Development, ADBI Working Paper Series 1226/2021.

World Bank (2020a). Cambodia Economic Update, November.

World Bank (2020b). The Socioeconomic impact of Covid-19 on Households in Cambodia, n.2 November.

World Bank (2020c). Reversals of Fortune: Poverty and Shared Prosperity, World Bank Group, 2020.

World Bank (2021a). The Socioeconomic impact of Covid-19 on Households in Cambodia, n.3 February.

World Bank (2021b). The Labor Market and the COVID-19 Outbreak in Vietnam: Impacts and Lessons Learned for Social Protection, World Bank Publishing.

Appendix A: Details for Cambodia

Table A.1.: Descriptive Statistics; Income Distribution Under Different Scenarios

	(1) Urban Share	(2) Self-employed Share	(3) Workers per HH Count
Mean	37%	41%	2.4

Income distribution (USD/worker/day)

	(1) Baseline	(2) Covid-19 w/o transfer	(3) Covid-19 w/transfer
Mean	21.4	16.8	17.1
p50	14.3	10.8	11.1
p10	1.6	0.03	1.5
p90	37.9	31.7	31.8
Poverty rate	10%	17.3%	12.6%
Observations	10,075	10,075	10,075

Source: Cambodia Socio-Economic Survey, 2019/2020.

Appendix B: Details for Vietnam

B.1 Measures of financial vulnerability

Savings Rate

The savings rate is calculated as the ratio of savings (net income – total expenditure) to net income. Using data from the VHLSS, we compute net income as the sum of:

- All revenue from employment, including wages, bonuses, subsidies, and other revenues;
- Revenue from education and healthcare aid, and from rental of properties;
- Sales of crops, and revenues from land, animal husbandry, hunting, agriculture, aquaculture, forestry and other non-farm activities, **net of their respective costs of production**.

Similarly, total expenditure includes the sum of:

- Expenditures of education, healthcare and festive occasions;
- Recurrent expenditures such as food and daily-use items;
  - These items are measured on a monthly basis, and thus are multiplied by 12 for the computation of total yearly expenditures.

Expenditure on non-food items (yearly), durable goods and housing.

  - Durable goods are assumed to have an average lifespan of 10 years, and housing expenditures are assumed to have a lifespan of 30 years. In each case, expenditure values are divided by their lifespan to construct yearly expenses.

Debt-to-Income Ratio

The debt-to-income ratio is defined, as the name suggests, as the ratio of a household's total debt to its net income. Net income is measured as above, while each household's total debt is computed by summing the outstanding amount of each loan (i.e., total loan amount minus principal payments already made) taken by the household. In the VHLSS, loans and their respective amounts are self-reported by households, and other forms of debt are not observed. Both factors can lead to an underestimation of the total financial obligations owed by households.

Financial Margin

For each household in our sample, we define the financial margin as

$$\mathrm{FMR}_h = \frac{\text{net income}_h - \text{total expenditure}_h}{\text{net income}_h} - \mathrm{DSTI}_h, \quad \text{if net income}_h > 0,$$

where net income and total expenditure are defined as above, and DSTI_h is the household's yearly debt service to income ratio. Note that this definition differs from the "usual" FMR (e.g., Leika and Marchettini, 2017), which would also add the stock of liquid assets to the expression above. We do not include liquid assets in our definition due to data constraints.

Assuming households make equal amortization payments each year, debt service-to-income is

$$\mathrm{DSTI}_h = \frac{1}{\text{net income}_h} \sum_{j=1}^{N_h} \left(\frac{L_j}{d_j} + L_j r_j \right),$$

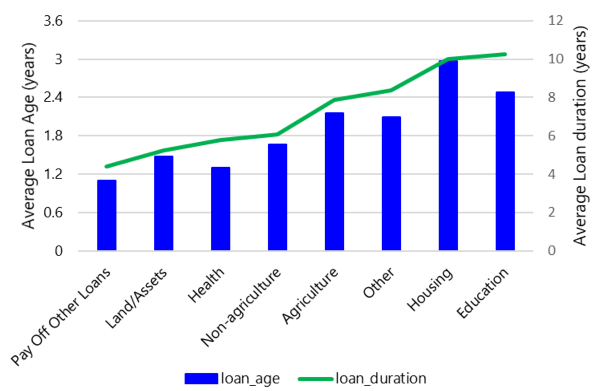
where N_h is the number of loans that household h has, L_j is the value of loan j, r_j is the annual interest rate paid on that loan, and d_j is its duration in years.

We do not observe the duration/maturity of each loan in our data. However, we can construct a loan's age (i.e., the difference between the current date and the date when the loan was first given to the household), which we use to estimate its maturity. The idea behind the process is that old loans in our sample should have longer maturities, otherwise they would have already been paid off by the household. Thus, if we determine the characteristics that determine loan age, we can extrapolate them to impute maturity.

We regress *log*(loan age) on *log*(interest rate), as the maturity of the loan should affect the interest rate; dummies for the institution that gave the loan, since this can affect the interest rates charged (see the discussion on household financial access on the main text); and dummies for the purpose for which the loan was taken, for example to buy/build housing or to pay for living costs – which could affect the likelihood that the household taking the loan has collateral or other factors that change the type of loan or the conditions under which it is taken.

Having estimated this model, we use it to predict loan age based on the characteristics above, and finally rescale the predicted loan age so that the average mortgage loan has a maturity of 10 years (see figure B.1). Once this is done, we can simply plug in loan duration into the formula for DSTI and calculate the FMR for each household.

Figure B.1: Loan Age and Predicted Duration



B.2 Regression analysis

We start by modelling the probability that a household has debt and the probability that it is in an unsustainable financial position (indicated by FMR < 0) as a function of the household's net income, education attainment and gender of the household head, family size, share of working-age members that are employed and the share that works informally, the household's region,[18] whether it is located in an urban or rural area, whether members have access to the internet, and whether they have financial access. An interaction term between the household's income and financial access is also included.

As mentioned in the main text, we favor a linear probability model due to its ease of interpretation, but our results are qualitatively consistent with alternative non-linear models as well (e.g., logistic regression). Coefficients are estimated via OLS and shown in table B.1. Column (1) shows the probability that a household has an FMR < 0, while column (2) shows the same probability excluding households that do not have any outstanding debt/loans. Because access to financial institutions can be an issue for many households in Vietnam, we also analyze how household characteristics affect their probability of having debt in column (3).

Results:

Estimation results suggest that a 1 percent in a household's income, all else equal, decreases the probability that a household has a negative FMR by 0.26 percentage points, with an even stronger impact if the household holds debt. We also find that households with higher income have outstanding loans with lower probability. Financial access seems to drastically decrease the probability that a household is in an unsustainable financial position, although the effect that we estimate might not be causal due to unobserved variables that could increase both financial access and the FMR. We also find that the coefficient on the interaction between having financial access and log(income) is positive, meaning that low income households benefit more from having financial access. Financial access does not have a statistically significant impact on the probability of debt,

[18] Vietnam is divided into 6 macro-regions: North Midlands and Mountains, Red River Delta, North and Coastal Central, Central Highlands, Southwest, and Mekong River Delta. Dummies for each of those regions, along with a urban/rural dummy, are included to control for different levels of urbanization across the country.

likely due to the fact that social banks and other credit institutions provide loans to households without financial access.

Larger families have a higher probability of taking loans and of being in a more vulnerable financial position, likely due to extra expenses with children or elderly members. The same appears to be true for families with a higher share of working-age individuals that are employed, although the estimates are less precise. In contrast, households with a larger share of members working informally have a lower probability of having a negative FMR. One possible explanation is that, because informal workers do not have access to social insurance, they might be more prone to building up savings, in case of a negative shock. They might also simply have less access to taking on debt, as they lack a formal job.

More educated households and those with access to the internet are more likely have debt and a negative FMR (however, note that the effect of education is not monotonic). In part, this result could be related to access to more sophisticated financial services (e.g., online banking) that decrease the cost of financial transactions, such as taking loans. More educated individuals could also face fewer constraints to take debt (and thus are more likely to have larger loans), which can contribute to the higher probability of financial distress.

Table B.1: Probability of Debt and Financial Distress

	(1)	(2)	(3)
Dependent Variable	Prob($FMR < 0$)	Prob($FMR < 0$ | Debt > 0)	Prob(Debt > 0)
Log(income)	-0.264***	-0.316***	-0.0478***
	(0.0135)	(0.0277)	(0.0150)
Financial Access	-0.914***	-1.903***	-0.360
	(0.235)	(0.527)	(0.231)
Financial Access × Log(income)	0.0772***	0.158***	0.0285
	(0.0195)	(0.0441)	(0.0196)
Highest Educ. (HH head)			
Secondary	0.0526***	0.100***	-0.0110
	(0.0172)	(0.0346)	(0.0188)
College+	0.0823***	0.172***	-0.0199
	(0.0210)	(0.0507)	(0.0255)
Share employed	0.0468**	0.0583	0.0493**
	(0.0206)	(0.0511)	(0.0194)
Share informal	-0.0341**	-0.0520	0.0452**
	(0.0165)	(0.0428)	(0.0194)
Family Size	0.0303***	0.0260***	0.0224***
	(0.00419)	(0.00985)	(0.00508)
Female head of HH	-0.0117	0.00201	-0.0113
	(0.0125)	(0.0321)	(0.0146)
Urban	0.0110	0.0322	-0.111***
	(0.0128)	(0.0351)	(0.0146)
Uses Internet	0.0638***	0.0925***	0.0524***
	(0.0154)	(0.0319)	(0.0181)
Observations	4,663	1,320	4,663
R-squared	0.187	0.182	0.093

Standard errors in parentheses, robust to heteroskedacity. Region fixed effects are included.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

We also analyze how household characteristics impact each of our three measures of financial vulnerability (savings rate, DTI and FMR) on a continuous scale. To do that, we estimate a similar model to the one described above, changing only the dependent variable on the regression. The coefficients from this model are displayed in table B.2, where columns (1) – (3) show the coefficients on the full sample, and columns (4) – (6) only include households that have some amount of debt.

Results:
Once again, we find that income is a strong determinant of household vulnerability. Households with higher income save a higher portion of their proceedings, have less debt relative to their income, and have a higher financial margin. Those results hold both in the overall population and when restricted to only households that have outstanding loans.

Financial access reduces household's DTI and increases their FMR. The impact on the savings rate is not statistically significant, but this could be due to the fact that households without access to financial services save a higher share of their income as insurance (since they face borrowing constraints and might not be able to take debt if they are hit by a negative shock). As before, we find that the effects of financial access for low-income households are greater than the effects for high-income households, as measured by the coefficient on the interaction between 'financial access' and 'log(income)' (positive for DTI, and negative for FMR).

Larger households save less, which also reduces their FMR. Consistent with our previous results, this could be the effect of additional expenses with children or elderly relatives. As above, households with a higher share of working-age members that are employed appear to save less and have a lower FMR, while households with more informal workers behave in the opposite way. The standard errors around these coefficients are, however, much higher, and in most instances are not statically significant.

Urban and more educated households, as well as those with access to the internet, tend to be more financially vulnerable, all else equal. As mentioned above, these observations could be related to access to more sophisticated financial services (not observable in our data) and/or the possibility of taking bigger loans from commercial banks. These households are also more likely to have other sources of income or wealth (assets, capital, property), which we do not observe. This introduces a downward bias on our measure of the financial margin.

Table B.2: Determinants of Household Vulnerability

Dependent Variable	(1) Savings Rate	(2) DTI	(3) FMR	(4) Savings Rate (Debt > 0)	(5) DTI (Debt > 0)	(6) FMR (Debt > 0)
Log(income)	0.371***	-0.0761***	0.394***	0.447***	-0.189***	0.477***
	(0.0125)	(0.0199)	(0.0155)	(0.0263)	(0.0433)	(0.0313)
Financial Access	0.326	-1.065***	0.825***	0.566	-3.553***	1.960***
	(0.205)	(0.326)	(0.252)	(0.409)	(1.053)	(0.648)
Financial Access × Log(income)	-0.0307*	0.0871***	-0.0728***	-0.0496	0.296***	-0.167***
	(0.0171)	(0.0277)	(0.0212)	(0.0345)	(0.0893)	(0.0546)
Highest Educ.						
Secondary	-0.0547***	0.0323*	-0.0682***	-0.0907***	0.119***	-0.128***
	(0.0134)	(0.0166)	(0.0158)	(0.0249)	(0.0417)	(0.0336)
College+	-0.113***	0.0222	-0.125***	-0.166***	0.139*	-0.229***
	(0.0170)	(0.0263)	(0.0206)	(0.0325)	(0.0805)	(0.0496)
Share employed	-0.0300*	0.0405**	-0.0419**	-0.0170	0.00383	-0.0166
	(0.0174)	(0.0205)	(0.0194)	(0.0387)	(0.0821)	(0.0513)
Share informal	0.0231	-0.0106	0.0249	0.0291	-0.139**	0.0592
	(0.0142)	(0.0193)	(0.0167)	(0.0307)	(0.0572)	(0.0411)
Family size	-0.0457***	0.00642	-0.0466***	-0.0420***	-0.0300*	-0.0304***
	(0.00338)	(0.00550)	(0.00401)	(0.00665)	(0.0157)	(0.00876)
Female head of HH	0.0219**	0.00719	0.0150	0.0402*	0.0304	0.0117
	(0.0101)	(0.0158)	(0.0119)	(0.0221)	(0.0500)	(0.0304)
Urban	-0.0654***	-0.0785***	-0.0440***	-0.0387*	-0.0451	-0.0203
	(0.00967)	(0.0148)	(0.0111)	(0.0204)	(0.0517)	(0.0280)
Uses Internet	-0.103***	0.0715***	-0.113***	-0.151***	0.107***	-0.157***
	(0.0129)	(0.0174)	(0.0149)	(0.0228)	(0.0407)	(0.0292)
Observations	4,560	4,610	4,561	1,277	1,267	1,275
R-squared	0.369	0.068	0.329	0.447	0.104	0.350

Standard errors in parentheses, robust to heteroskedacity. Region fixed effects are included.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

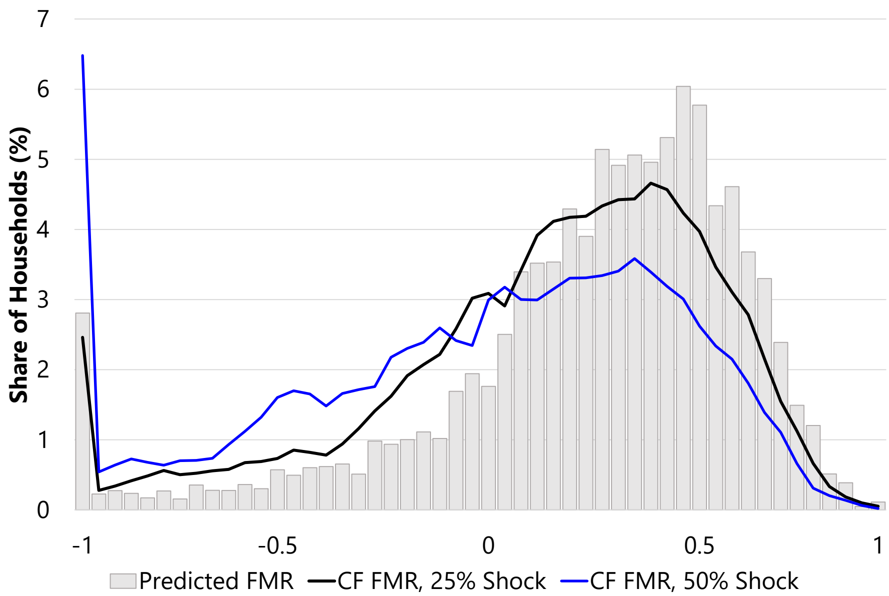
B.3 Alternative Computation of the impact of COVID-19

An alternative way to estimate the impact of the COVID-19 income shock is to "re-compute" each of our measures of financial vulnerability, including the FMR, using the post-shock income, $y_h(\varepsilon)$. Assuming that debt and other expenditures remain constant,[19] the share of households whose financial margin falls below zero is given by

Value of income shock, ε	*0 (baseline)*	*0.25*	*0.5*
Share of households with FMR < 0 (%)	19.00	30.67	46.21
Difference relative to baseline		11.67	27.21

[19] While it is unlikely that households do not adjust expenditures after an income shock of that magnitude, the elasticity of expenditures with respect to income for most households is likely small: 66 percent of the total yearly expenditure of the median household in our sample consists of food and other daily essential items.

Figure B.2: FMR Density After COVID-19 Income Shock



Note: FMR is truncated at -1 for plotting

Appendix C: Details for Nepal

Household level descriptive statistics for the HRVS are presented below in Table C.1. Table C.2 provides a breakdown of the shocks households face in the previous year, by survey year and type. The 2016 data is dominated by the 2015 earthquakes and border blockades with India. Table C.3 is the ex-ante analogue to Table 5.1 in the main text, asking households how they anticipate they would respond to a hypothetical shock. The table shows the responses of households to the question 'How would you respond to a shock of NRs25,000 (approx. USD210)?" Households were able to provide multiple responses, and therefore the percentage of households identifying each strategy sum to more than 100%. By far the most anticipated coping strategies were relying on savings and borrowing from friends/family. Very few households anticipated using formal financial loans, yet more evidence of minimal financial access.

Table C.1: Household Descriptive Statistics for Nepal's Household Risk and Vulnerability Survey (HRVS)

	(1) 2016 mean	(2) 2017 mean	(3) 2018 mean
Urban (%)	31.1	31.1	31.1
Rural (%)	68.9	68.9	68.9
Mountain region (%)	8.5	8.5	8.5
Tarai region (%)	50.9	50.9	51.0
Hills region (%)	40.6	40.6	40.5
Children (Number)	1.6	1.1	1.1
Elderly (Number)	0.5	0.5	0.5
Women (Number)	1.7	1.7	1.7
Men (Number)	1.5	1.5	1.4
Paid jobs (Number)	0.6	0.6	0.7
Savings (NRs)	46924.7	40558.7	38180.6
Self-employed agriculture (%)	55.5	56.4	60.4
Remittances (%)	30.0	35.2	36.0
Public assistance (%)	31.7	30.0	35.2
Observations	6000	6005	6051

Table C.2: Types of Shocks Faced by Households in Nepal's HRVS

	(1) 2016 Count	(2) 2017 Count	(3) 2018 Count	(4) Total Count
Earthquake	2237	0	0	2237
Flood	190	41	105	336
Landslide	151	39	7	197
Drought	1134	226	87	1447
Fire	23	7	2	32
Hail/Lightening	188	384	119	691
Pests and Plant Diseases	332	137	246	715
Post Harvest Loss	22	4	4	30
Forced Displacement	2	1	0	3
Riots/Blockage	1240	0	0	1240
Death of Family Member	109	128	141	378
Disease or injury of family member	771	1395	631	2797
Loss of a regular job of a household member	24	6	2	32
Failure or bankruptcy	11	10	4	25
Theft	61	8	6	75
Break up of family	10	3	5	18
Loss of contract or default by creditor	12	3	3	18
Withdrawal of government assistance	1	0	0	1
Fuel Shortage	127	0	0	127
Unexpected Higher Prices	1082	7	0	1089
Livestock Loss	245	228	131	604
Total	7972	2627	1493	12092

Table C.3: Household ex-ante coping strategies:
"How would you respond to a shock of NRs25,000 (approx. US$210)?"

	(1)	(2)	(3)
Coping strategies (% respondents)	2016	2017	2018
Own Savings	32.5	21.4	31.0
Relatives/Friends without interest	30.8	24.1	20.4
Relatives/friends with interest	51.5	52.2	47.9
Bank Loan	4.7	3.6	2.0
NGO/CBO loan	1.8	2.5	0.1
Savings Group	16.5	20.3	31.5
Money Lender	29.4	32.9	36.8
Shopkeeper	9.0	7.9	6.3
Other	0.2	0.1	0.2
Pawn the house/land	0.0	2.3	1.4
Pawn farm animal/equipment	0.0	2.0	0.7
Pawn other properties	0.0	0.7	0.1
No source	0.8	0.4	0.0
Observations	5999	6005	6051

Percentage of households flagging each coping strategy in response to the question "How would you respond to a shock of NRs25,000?" (approx USD210). Some households respond with multiple coping strategies, thus column totals are greater than 100%.

PUBLICATIONS

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