COVID-19 through the Lens of Seasonal Agriculture in South Asia

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Abstract

75% of the world's poor reside in rural areas where the local economy is tied to agriculture. We interpret new panel data on COVID-19 from Nepal and Bangladesh in relation to agricultural seasonality. Conditions in April–June 2020 were comparable to a typical lean season even though the pandemic arrived at harvest time. Income losses stem from both depressed local employment as well as lower migration and remittances. We also document indirect adverse health impacts on nutrition and mental health. Findings are specific to the nature of economic activity at harvest, and effective pandemic policy must evolve with the agricultural season.

Keywords: COVID-19, seasonality, agriculture, nutrition, health, South Asia

JEL Codes: I15, Q12, O13, H12

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Introduction

The economic fallout from the COVID-19 pandemic has been felt around the world. Instability caused by the disease itself coupled with lockdown policies to contain its spread have led to universal declines in economic activity. The impacts fall especially hard on poor populations that live close to subsistence and lack the resources to insure against economic hardship (Egger et al., 2021; Josephson et al., 2021). With an estimated three quarters of the world's poor living in rural areas (Ravallion et al., 2007; Castañeda et al., 2016), it is imperative to understand how the effects of the pandemic interact with rural economies when interpreting data and designing policy around COVID-19 and future crises.

Seasonality has long been recognized as a salient feature of economic life in rural communities. More than a century ago Hill (1884) noted that deaths in India fell during peak agricultural months, and this pattern has persisted over the years (e.g. Becker, 1981; Becker and Weng, 1998). Still today, many countries in South and Southeast Asia and Sub-Saharan Africa suffer from pre-harvest "hungry" seasons of food deprivation among the rural poor, followed by post-harvest periods where agrarian production funds investment in the future (see Vaitla et al., 2009; Taylor and Charlton, 2018). In this paper we interpret household survey data from the early months of the pandemic in light of this predictable cycle.

Typically, distress during the agricultural lean season stems from a combination of high prices and little income. The period immediately before harvest is the time of year when local food stocks are lowest, and the restricted supply drives up prices in isolated regions. At the same time, limited agricultural labor demand keeps wages low. These two factors create a predictable, widespread decline in real income that many poor households are unable to insure against (Sen, 1981; Khandker and Mahmud, 2012; Gilbert et al., 2017). The COVID-19 pandemic created similar conditions by segmenting markets, barring supply of traded goods, and by dampening labor demand through the global recession (Hale et al., 2020). Thus, the crisis had the potential to depress harvest earnings and exacerbate lean season deprivation.

The pandemic placed particular strain on rural communities relative to other types of economic crises because migration restrictions are fundamental to disease containment. Rural households commonly turn to short-term labor migration as a method of self-insurance, especially in the face of community-wide shocks (Bryan et al., 2014; Rosenzweig and Udry, 2014; Morten, 2019; Barker et al., 2022). Without this option, vulnerable populations lose an important strategy to deal with economic distress.

In this article, we investigate how the early months of the COVID-19 pandemic interacted with the agricultural cycle in rural communities in Nepal and Bangladesh. We combine new phone survey data from 90 villages in Nepal and 79 villages in Bangladesh collected in April through June 2020, immediately after the pandemic reached the region, with existing survey data from prior years to construct a household panel. This panel, covering 2,023 households in Nepal and 294 households in Bangladesh, spans both lean and harvest seasons in prior years and allows us to compare conditions during the COVID-19 lockdown with the typical seasonal pattern.

The first contribution of this research is to document the depth of economic impact from COVID-19 in the context of the agricultural cycle. Even though COVID-19 reached our regions of study around a harvest season, we find economic wellbeing during the pandemic to be far worse than is typical. Employment and earnings both fell to below their regular lean season levels, resulting in a fourfold increase in household food insecurity. Food insecurity in the April and May 2020 harvest period reached levels near the usual lean season peak.

Our second contribution is to relate these outcomes to the nature of economic activity in the agricultural season. Specifically, we report evidence on labor migration and household remittance earnings. While return migration is common around an agricultural harvest, we measure returns in excess of a typical season. Moreover, household remittance earnings fell relative to the prior harvest season, and migration remained depressed post-harvest. Although limiting travel can promote public health during a pandemic, these lost opportunities may serve to extend economic distress past the initial crisis period by constraining a critical option that rural Nepalis and Bangladeshis commonly use to supplement their off-season earnings (Khandker and Mahmud, 2012).

More generally, economic distress during a harvest period can have long-term consequences because of household financial constraints. Our populations of study were previously selected for participation in seasonal loan programs, where high takeup rates reflect seasonal liquidity shortages (see Mobarak and Vernot, 2020; Bryan et al., 2019). Seasonality in household finances, common to rural populations around the world, leads such households to time their productive investments around agricultural harvests (e.g. Fink and Masiye, 2020; Dillon, 2020). Economic need during a harvest period can force households to forego such investment, depressing their expected future earnings even after the pandemic itself abates.

The third contribution of this research is to highlight the indirect public health consequences of COVID-19. Pre-pandemic, indicators of food insecurity and psychological distress are elevated during the agricultural lean season and fall with the subsequent harvest. During the April 2020 harvest, rates of food insecurity nearly reached their lean season peak. The prevalence of stress, depression, and irregular sleep in this period exceeded any prior lean or harvest season measurement. It is already documented that childhood nutrition in our regions of study regularly suffers during the agricultural lean season (e.g. Tetens et al., 2003; Hillbruner and Egan, 2008; Khandker, 2012). As the pandemic caused distress to persist into the harvest period, it is likely to impact child development (see Nandi et al., 2017; McGovern et al., 2017) and long-term economic decision-making (see Ridley et al., 2020).

Together, our results underscore the importance of accounting for agricultural seasonality when interpreting data and designing policy for rural areas during a pandemic. Economic wellbeing and health fluctuate predictably, and data must be benchmarked accordingly. Similarly, sources of household earnings vary by season, meaning the impacts of public health and safety net policies may differ over the course of a year. These lessons are important for policymakers trying to balance disease containment, short-term economic well-being, and long-term economic recovery.

The results in this paper are broadly relevant because seasonal poverty is prevalent around the world. Researchers document substantial increases in economic deprivation during the lean season in Burkina Faso (Gross et al., 2020), Ethiopia (Dercon and Krishnan, 2000), Kenya (Aggarwal et al., 2018), Madagascar (Dostie et al., 2002), Malawi (Ellis and Manda, 2012), Mali (Smale et al., 2019), Tanzania (Kaminski et al., 2016), Zambia Kumar (1988), Nicaragua (Macours and Vakis, 2010), Bangladesh (Khandker, 2012), India (Chaudhuri and Paxson, 2002), Indonesia (Basu and Wong, 2015), Thailand (Paxson, 1993), and inland China (Jalan and Ravallion, 2001), among others. The local name for the period before harvest roughly translates to "hunger" or "famine" season in many parts of the world including Malawi (Brune et al., 2011), Kenya, Nigeria, and Sudan (Swift, 1989), Bangladesh (Khandker, 2012), and Indonesia (Basu and Wong, 2015). In settings where agricultural seasonality is prevalent, negative economic shocks at harvest time are especially damaging to long-term economic prospects (e.g. Dercon and Christiaensen, 2011; Bellemare et al., 2013; Bacon et al., 2017; Guido et al., 2020; Pritchard et al., 2020), so public health policy must be sensitive to the local agricultural calendar.

Data and Methodology

We combine existing data from prior studies involving rural populations in Nepal and Bangladesh with new phone survey data collected shortly after the onset of COVID-19 in the region to construct household panels. In this section we describe the data and methodology for analysis.

Data from Nepal

Data from Nepal come from surveys among poor households in rural villages in the districts of Kailali and Kanchanpur in the Western Terai (plains) region. This sample resides in villages where we conducted a field experiment in partnership with the Nepali NGO *Backward Society Education* (BASE) that provided micro-loans during the pre-harvest lean season in summer 2019. Within each village, a group of community leaders were asked to assess household wealth, after which we randomly selected households from the bottom half of the wealth distribution for survey participation.

Between July 2019 and June 2020, we collected seven rounds of survey data from our study sample. Initial baseline surveys were conducted in-person in July 2019, followed by five rounds of phone surveys from August 2019-January 2020 and a sixth round of phone surveys conducted in April through June of 2020. In this paper we report only phone survey data, and split the final round in two based on the timing of responses relative to the harvest season.

Prior to the pandemic, phone surveys collected data on labor and wage income, food security, subjective wellbeing, migration and remittances, agricultural decisions, and output around the Fall 2019 Boro harvest. The final survey round conducted during the pandemic omitted the module on agricultural decisions and randomized between the food security and subjective wellbeing modules to shorten survey length, so the sample size for each outcome is smaller during the COVID-19 rounds.. In addition, the final round included a 12-month recall survey of food security in the prior year as well as recall questions of prior-year migration anchored to recognizable holidays.

The initial sampling frame consisted of 15 sub-districts from which we randomly selected 33 of the 73 rural wards for study. In these wards we randomly chose 97 villages from the set of 227 villages, but seven were dropped from the study due to flooding at the time of baseline data collection, leaving a sample of 90 villages. The final sample consists of roughly thirty households per village, leading to a sample of 2,636 households. Of these, we were able to reach 2,023 in the post-COVID survey round.

Data from Bangladesh

Data from Bangladesh come from surveys among landless households in rural villages in the Rangpur division in the northern part of the country. This sample resides in an area where we conducted a randomized evaluation of a seasonal migration loan program in partnership with RDRS, a local microfinance organization, in 2017 and 2018. Households were deemed eligible for program and survey participation if they owned less then a half acre of land. In this article we report only data from households in the control arm of the evaluation, and in Appendix B verify that using the full data generates nearly identical results.

We collected two rounds of survey data in person in January and July 2019. We then followed up among a subset of households with a third round of phone surveys in May 2020, shortly after the beginning of the COVID-19 pandemic in Bangladesh.

In-person surveys collected detailed retrospective information on food security and migration history over the course of a year, which we use for comparison to the post-COVID economic situation in the same calendar month. In addition, we have data on pre-pandemic employment and earnings at a comparable period relative to the agricultural harvest. While data on other outcomes exist, the timing of the 2020 phone survey relative to the 2019 rounds prevents direct comparison because surveys are conducted at different parts of the seasonal agricultural cycle.

The initial sampling frame for in-person surveys consisted of villages in the catchment area of 100 RDRS branches participating in the study. One untreated village from each branch was randomly selected for surveying, making up the pre-COVID data used in this article. In each sample village, roughly twenty eligible households were identified via random walk sampling for survey. This strategy generated a sample of 1,891 households in the initial sample.

For the post-COVID survey, we randomly selected a subset of sample households to contact by phone, stratified by both treatment status and migration history. Among the untreated sample, we contacted 388 households out of which 294 were reached and consented to participate in the follow-up survey.

Sample Characteristics

Both study samples consist of low-wealth households that earn income from both their own cultivation and external wage labor. Agriculture and short-term migration both feature prominently in their economic livelihoods. In the sample from Nepal, 86% of households surveyed cultivate rice and 75% had a circular labor migrant that returned home at least once in the eight months of survey data. In Northern Bangladesh, 75% of households surveyed participate in agriculture on owned or rented land, and 47% had a regular household member that migrated for part of the year in 2018. These two activities are highly seasonal as the returns to agriculture are concentrated at harvest, and migration is more attractive at times of year when local labor returns are low.

Short-term migrants from our sample in Nepal typically either travel domestically or seek work in India, with which the country shared an open border. In the sample from Bangladesh, nearly all migration is domestic. Migrants most commonly do manual labor work, roughly half in agriculture at rural destinations, and primarily in the transportation (i.e. cycle rickshaw) and construction sectors in cities. Migrants generate income while away, but migration income is commonly realized into household earnings upon return as the migrant brings remittances home by hand.

More broadly, both study populations live in rural communities where economic activity is closely tied to the seasonal agricultural cycle. Local employment and earnings fluctuate according to agricultural labor demand, which peaks during times of plating and harvest. Local food prices follow a countercyclical seasonal pattern according to food availability, which reaches its maximum at harvest. These two patterns combine to place the most stress on households immediately before crop harvest when both food stores and labor demand are low.

Households in our study have low wealth, and therefore limited ability to self-insure against this seasonal cycle. In figure 1 we plot the monthly rate of food insecurity in both samples prior to the pandemic outbreak based on retrospective self-reports. As panel A shows, food insecurity in Nepal peaks in the months of August, September, and October, shortly before the November rice harvest. The seasonal cycle is slightly delayed in Northern Bangladesh, shown in panel B, where food insecurity peaks in the two months before the December rice harvest with a smaller spike just before the secondary harvest in April.

[Figure 1 about here.]

Both countries started to enact COVID-19 restrictions in March 2020. Policies included closure of international travel, notably to India from Nepal; barriers to internal travel; restricted public transit; and limitations on economic activity. Reported infection rates were low in both regions of study over the survey period. However, it is unclear whether infection rates were low because the pandemic was slow to reach isolated rural areas with sparse population density, or if reported case rates reflect underdiagnosis. In either case, uncertainty and fear of infection likely curtailed economic activity above and beyond official policy restrictions.

Methodology

In this article we compare the economic wellbeing of households surveyed during the COVID-19 pandemic to what we would expect in a typical agricultural cycle. Data collection during the pandemic took place in April through June 2020, coinciding with the secondary harvest in both areas of study. For outcomes relating to migration and food security, we compare 2020 values to their levels in the same calendar months of 2018 and 2019, which represent typical years to the best of our knowledge. For earnings and mental health, we unfortunately lack prior data from the same calendar month and instead compare the 2020 secondary harvest period to the comparable part of the 2019 primary harvest. We describe the available data in more detail in Appendix A.

All results are generated by fixed effect regressions of the form

$$Y_{it} = \alpha_t + \delta_i + \epsilon_{it} \tag{1}$$

where i indexes households or individuals and t indexes survey rounds or months. We report results for a given outcome Y as a series of period (α) fixed effects. The comparison of interest is the difference in outcome between pre-COVID and post-COVID periods, under the identifying assumption that outcomes after March 2020 would have followed the same pattern relative to the agricultural cycle were it not for the pandemic. We address issues of panel imbalance by including unit (household or individual) fixed effects (δ) so that all comparisons are made within household or individual across time. Standard errors are clustered at the household level with 95% confidence intervals depicted graphically.

Interpretation of regression coefficients suffers from three potential confounds. First, analysis of employment, earnings, and mental health in Nepal exploits the timing of surveys relative to the harvest cycle in different crop seasons. As a result, we cannot isolate the effect of COVID-19 from natural variation between the primary and secondary harvest. Nevertheless, results are consistent with other outcomes and indicate a level of economic deprivation that would be difficult to attribute to crop season alone.

Second, pre-pandemic data in Bangladesh was collected in person, and all post-pandemic data was collected over the phone. Therefore, we cannot separately identify the effect of COVID-19 from survey mode effects. However, post-pandemic phone survey responses to recall questions about food security in January and February 2020 closely align with in-person recall responses from prior years, suggesting little bias from changing survey mode.

Finally, there may be selective attrition of survey respondents during COVID-19. Response rates were between 75% and 80% for both samples during the COVID-19 phone survey. In Appendix A we show that the population reached during the pandemic closely matches the full study population on pre-pandemic household characteristics in each sample. However, we cannot rule out bias caused by selective attrition based on outcomes during the pandemic.

Results

In this section we report changes in employment and earnings, migration and remittances, food security, and mental health in the early months of COVID-19 relative to their pre-pandemic levels at comparable times in the agricultural cycle. Results are presented graphically as period fixed effects α_t from (1) net of household fixed effects. Regression tables are reported in Appendix B, as well as robustness checks limiting to a balanced panel and to omitting household fixed effects.

Labor and Earnings

Economic activity after the pandemic, during and immediately following the 2020 secondary harvest, fell well below its 2019 primary harvest level. Figure 2 plots economic activity by survey round in Nepal. Hours worked, shown in panel A, are lower in April and May 2020 than in any other survey period, especially for men who typically work outside the household. This decline comes from significant decreases in both non-farm work, including family-owned businesses, as well as farm work, including family agriculture and hired farm labor. Non-farm hours drop to below half of any prior period, and hours worked in agriculture also decline relative to the prior harvest season. The change in hours worked is indicative of a depressed local economy with limited capacity to substitute toward home production.

This decline in hours corresponds with lower household earnings during the pandemic, depicted in panel B. Non-farm income (including from agricultural wage labor) is significantly lower during the pandemic than in any other prior survey round, and 67% lower during the 2020 wheat harvest when compared to the 2019 rice harvest[1].

[Figure 2 about here.]

A similar pattern appears in employment and earnings in Northern Bangladesh when comparing the post-Boro harvest period in May 2020 to the post-Aman harvest period in January 2019. The fraction of households in which at least one member was employed for at least one day in the week prior to survey drops from 95% in the earlier survey to 49% during the COVID-19 period. Reported earnings also fall by 49% on average, with over half of households reporting no income from any source including remittances and outside assistance in the prior week compared to just 15% pre-pandemic.

Beyond participation and earnings in the local labor market, households in our sample experience a decline in migration and remittance earnings. Migration in the early part of the pandemic is below its expected level in both samples, as shown in figure 3. Panel A plots the fraction of households in Nepal with a male worker away in each round of survey. Prior to COVID-19, the migration rate during the 2019 rice harvest was above 25%, similar to the 2018 rice harvest. By contrast, the rate during the 2020 wheat harvest fell to less than 20%, well below its 2019 counterpart, and continued to decline post-harvest to around half its typical level.

Panel B tells the same story in Northern Bangladesh. Between March 15 and May 15, 2020,

[1] Farm income is difficult to quantify because a large fraction of production is devoted to home consumption, and local prices are not well measured. However, wheat planting decisions were made prior to the outbreak of COVID-19 so there is limited capacity to replace lost non-farm income by increasing agricultural production.

65% of households reported a returning migrant. By contrast, only 10% had a return migrant over this two-month period in 2019. The rate of return during the pandemic exceeds the typical stock of outstanding short-term (under twelve months) migrants at this time of year, indicating that medium- to long-term migrants also left their place of work to return home. Remittance income, a crucial source of earnings for rural households during agricultural lean seasons, is likely to remain depressed as long as public health realities constrain mobility.

[Figure 3 about here.]

In a normal year, high return migration would generate a spike in remittance income as remittances are most commonly realized by migrants returning with cash in hand. This typical pattern is observable in the Nepal data as remittance income peaks at the start of the 2019 rice harvest in panel B of figure 2. By contrast, there is no corresponding spike at the start of the 2020 wheat harvest despite the abnormally high rate of returns, and remittances are 64% lower than their prior harvest level. The lack of a remittance spike suggests that recalling migrants is not a form a intertemporal substitution to bring home resources at a time of need, but rather reflects the loss of a household revenue stream.

Nutrition and Mental Health

Household survey data indicates that, in addition to the direct health threat posed by COVID-19, the pandemic has indirect public health impacts through the worsening of nutrition and mental health. As we show in figure 4, food insecurity rose to significantly above its typical post-harvest level. The two panels represent food insecurity in the Nepal and Bangladesh samples, respectively. The trend line in each represents prior years, while the plotted points represent survey responses in 2019 and 2020. In both samples, food insecurity follows the trend almost exactly until March

2020, when COVID-19 reached this region, after which it spikes up by more than 20 percentage points above trend in Nepal and nearly 15 percentage points above trend in Bangladesh.

[Figure 4 about here.]

Data on household food security confirms that the reported shocks to earnings represent real economic distress. If these shocks were a transitory function of temporal displacement of earnings, then we would expect to see households adjust resources to smooth consumption through the pandemic period.

The physical health impacts of the pandemic are accompanied by deterioration in mental health as well. In figure 5 we show how self-reported measures of mental health evolve across survey rounds in Nepal, each reported on a five point scale. Surveys focused on stress, depression, and irregular sleep, three indicators that have been linked to economic decision-making in ways that reinforce existing poverty (see Ridley et al., 2020).

The fraction of the population reporting high stress, shown in panel A, rose by 12 percentage points in May and June 2020 to nearly double its prior level. The fraction reporting high depression, panel B, similarly doubled from 14–16 percent in prior surveys to 29 percent during the pandemic. The frequency of irregular sleep, panel C, also rose with 15 percent of the population reporting irregular sleep in May and June.

In panel D, we combine the three indicators into a single index constructed as the average of standardized responses. There is a clear gap between the prior harvest and lean seasons, mostly driven by respondents moving from "Rarely" and "Never" to "Sometimes". The average decline in mental health was nearly twice as large in the April harvest season, post-COVID, when respondents are much more likely to report "Often" or "Always". The three indicators consistently show that deteriorating mental health may be an additional source of economic risk with lasting repercussions.

[Figure 5 about here.]

Discussion

In this paper we document declines in employment, earnings, migration, remittances, food security, and mental health among low-wealth households in two rural regions of Nepal and Bangladesh in the early months of the COVID-19 pandemic. We interpret this data in relation to the agricultural harvest cycle, which plays a central role in economic wellbeing in rural areas around the world. Our results are distressing precisely because the pandemic arrived in the regions of study during a post-harvest period when the local economy typically thrives. In normal times, harvest income facilitates household investment into future earnings capacity (Fink and Masiye, 2020; Dillon, 2020). The economic activity we observe in both samples in April–June 2020 is more comparable to a lean season than to a harvest period.

We draw specific attention to the effects of COVID-19 on migration and remittances. Short-term migration is extremely common in rural areas around the world and closely tied to the agricultural season. Many households send members to work in distant markets when earning opportunities are scarce, and realize remittance income as workers return to participate in the local harvest. The option to return or remit income early also provides insurance against unanticipated negative shocks during periods of scarcity.

Return migration at the start of COVID-19 was unseasonably high, but did not produce an influx of remittance income.[2] Over the short term, these observations indicate that households in our sample lost a valuable source of earnings and income stabilization that contributed to their economic vulnerability. Short-term migration in this region is highly dependent on informal relationships with employers (Lagakos et al., 2020), so prolonged mobility restrictions may cause these relationships

[2] A more thorough analysis of migration linkages and the labor market impacts of COVID-19 can be found in Barker et al. (2022).

to deteriorate to the point that migration networks are permanently damaged.

Limiting travel is a key component of pandemic response. However, our results show that this policy can exacerbate economic conditions in migration-dependent regions and at high-migration times of the year. Moreover, travel restrictions following a future disease outbreak may cause economic spillover even if the infection itself remains contained. Rural economic policy around a pandemic must account for foregone migration earnings and assist in re-establishing migration networks as a part of post-pandemic recovery.

Economic distress in the communities of study was accompanied by indirect public health impacts in the form of food insecurity and declining mental health. Our findings indicate that public health policy can complement economic support to help households stabilize through the global economic crisis. Specifically, there is need for both direct food aid to alleviate the nutritional deficits induced by loss of earnings as well as mental health services to help households manage the stress of the unanticipated economic shock. Many local organizations already incorporate counseling into their other activities (e.g. BRAC, 2020), and could adapt these programs with safe social distancing to assist households in their areas of operation.

Nutrition and mental health deficits can extend the persistence of economic shocks beyond the end of the pandemic. In addition to physical ailments directly caused by disease (e.g. Almond, 2006), poor nutrition can hinder child development with long-term repercussions. Food unavailability during the lean season regularly leads to measurable declines in energy intake for children in our area of study (Tetens et al., 2003; Khandker, 2012), so the fact that the current post-harvest level of food insecurity resembles a typical lean season raises the possibility that childhood undernutrition has similarly persisted past its normal duration. Nutrition throughout childhood has been linked to adult income and capacity (see Nandi et al., 2017; McGovern et al., 2017), so the economic shock caused by COVID-19 may be substantial enough to linger across generations.

Overall, the effect of a pandemic outbreak in rural communities is highly dependent on how the timing relates to the agricultural season. The results in this paper are specific to a setting where COVID-19 arrived at the start of a harvest season. It is possible that outcomes would have been even worse has the pandemic hit during a lean season, when households had even less available resources to manage hardship. Alternately, the economic fallout may not be as severe at times of the year when there is little economic activity to disrupt. In either case, it is clear that the nature of economic activity and household need in rural areas evolves with the agricultural cycle. As the timing of harvest seasons vary around the world, so too will the economic impacts of a pandemic. As a crisis unfolds, it is important for governments and other organizations to be sensitive to seasonality in determining how to allocate resources for a response.

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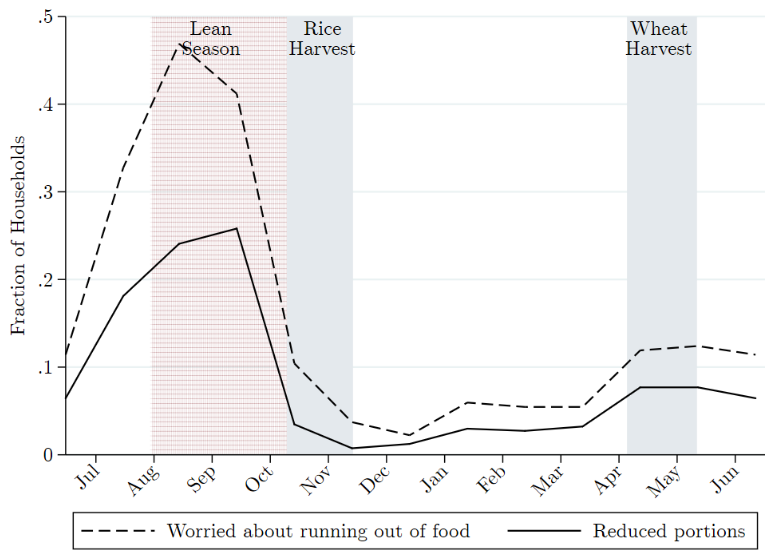
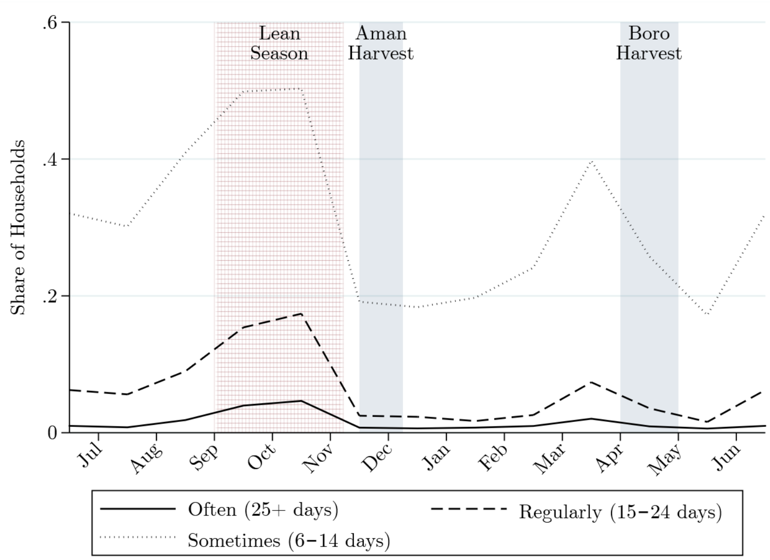
Figure 1: Seasonality in food security in Western Terai, Nepal and Northern Bangladesh

A. Share of food insecure households in Western Terai, Nepal



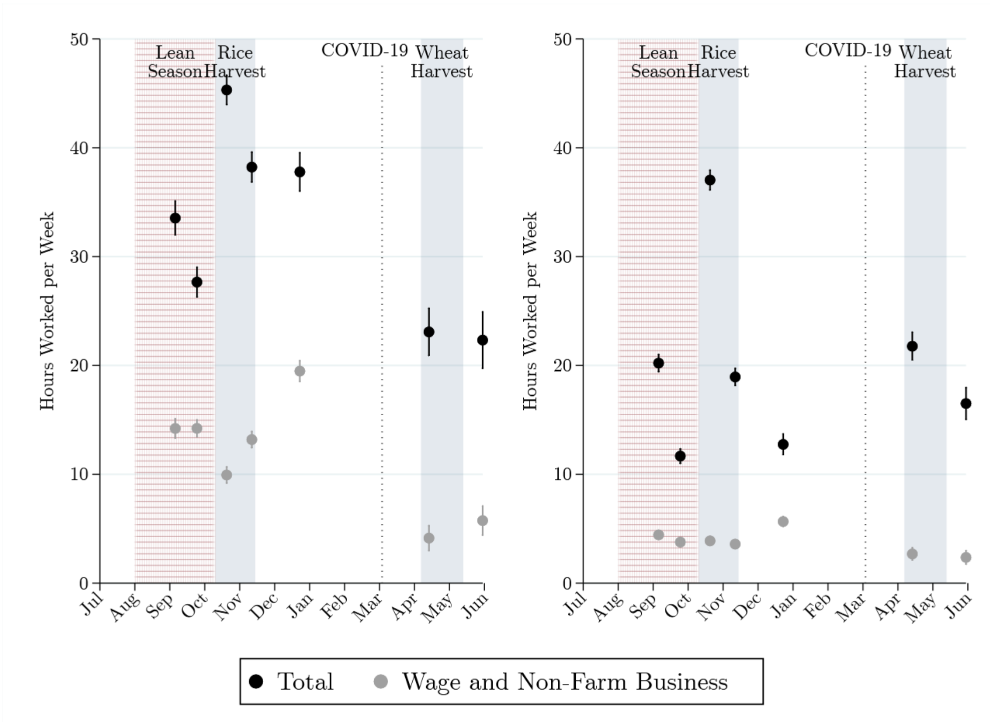
B. Share of households reducing portion sizes in Northern Bangladesh



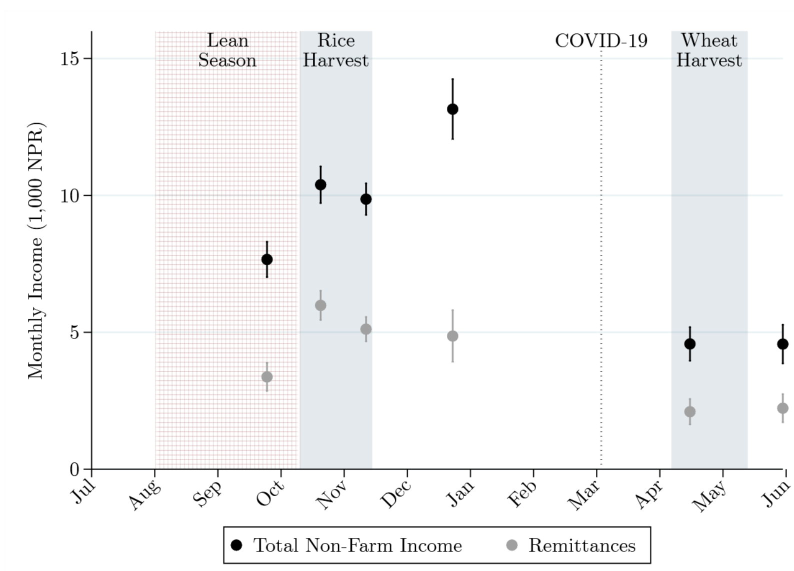
Notes: Rates of food insecurity around the seasonal agricultural cycle in a typical year. A. Data collected during the sixth phone survey round asking about a typical year. B. Data collected during the two in-person survey rounds asking retrospectively by month.

Figure 2: Economic activity in Western Terai, Nepal

A. Hours worked by survey round and gender



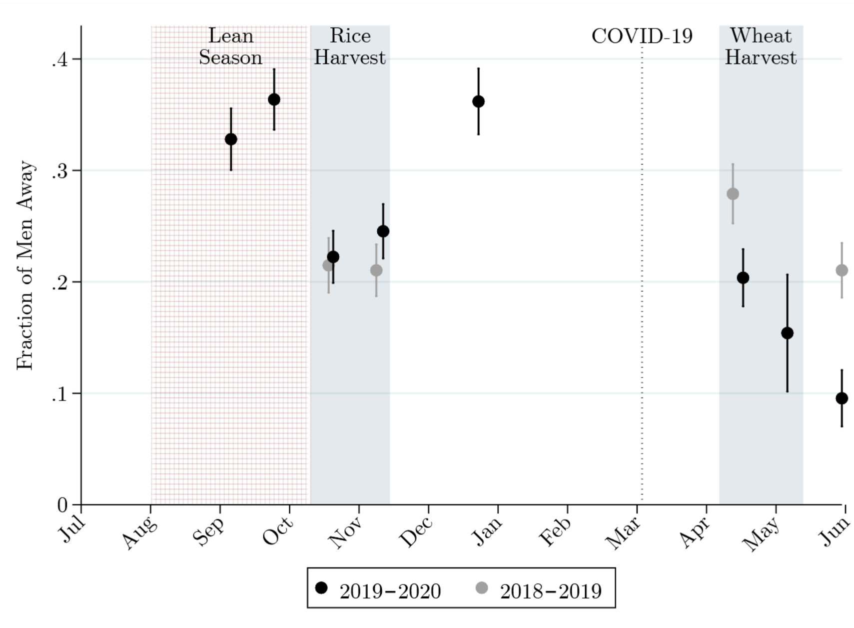
B. Household earnings by survey round



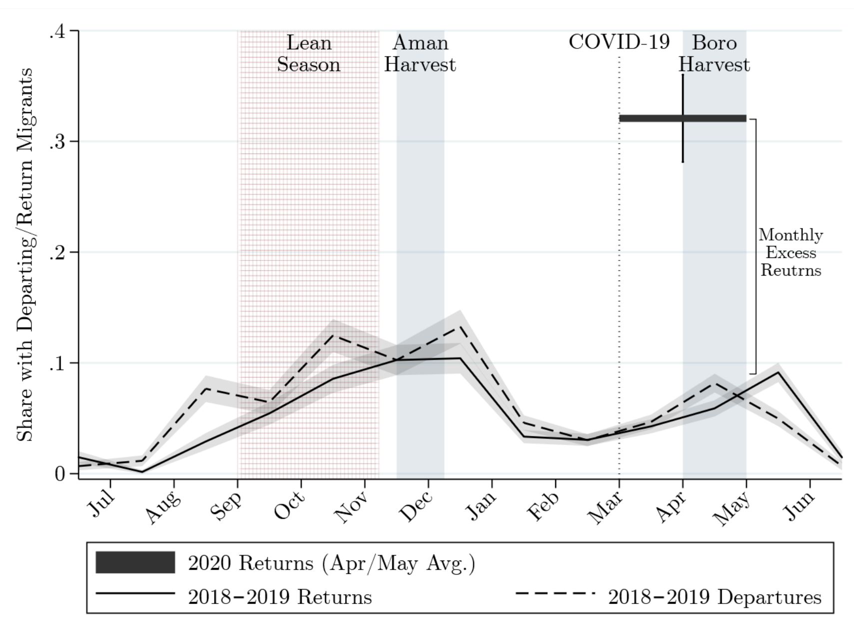
Notes: Hours worked and household earnings in Western Terai, Nepal. Regression estimates of period fixed effects from (1) with 95% confidence intervals. A. Hours worked for male adults in left panel, female adults in right panel. B. Household non-farm earnings. A version of remittance data from panel B appears in Barker et al. (2022).

Figure 3: Household migration in Western Terai, Nepal and Northern Bangladesh

A. Temporary migration in Western Terai, Nepal



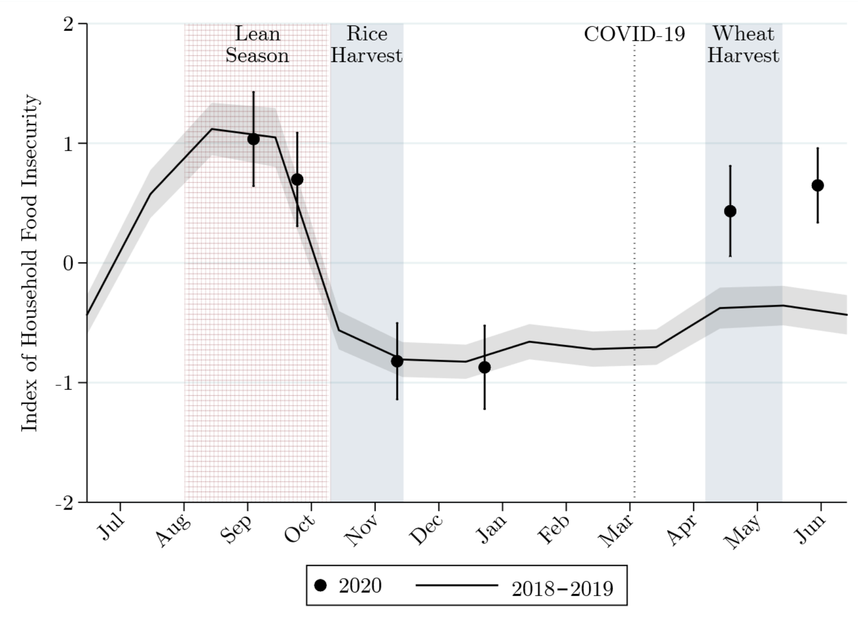
B. Migration departures and returns in Northern Bangladesh



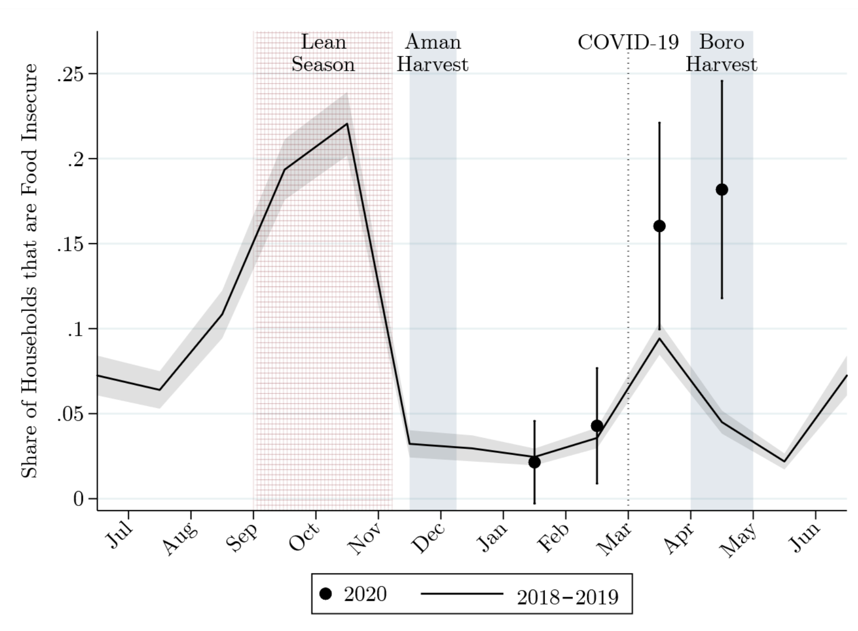
Notes: Rates of short term migration. Regression estimates of period fixed effects from (1) with 95% confidence intervals. A. Fraction of households with a male aged 18–65 currently away but considered a household member by survey round. B. Migration departures and returns by month. 2018–2019 data collected during the two in-person survey rounds asking retrospectively by migration episode. 2020 value represents the monthly average for the two months from March 15 to May 15, and the gap represents the monthly excess returns for each of two months. A version of data from panel A appears in Barker et al. (2022).

Figure 4: Food insecurity in Western Terai, Nepal and Northern Bangladesh

A. Food insecurity in Western Terai, Nepal

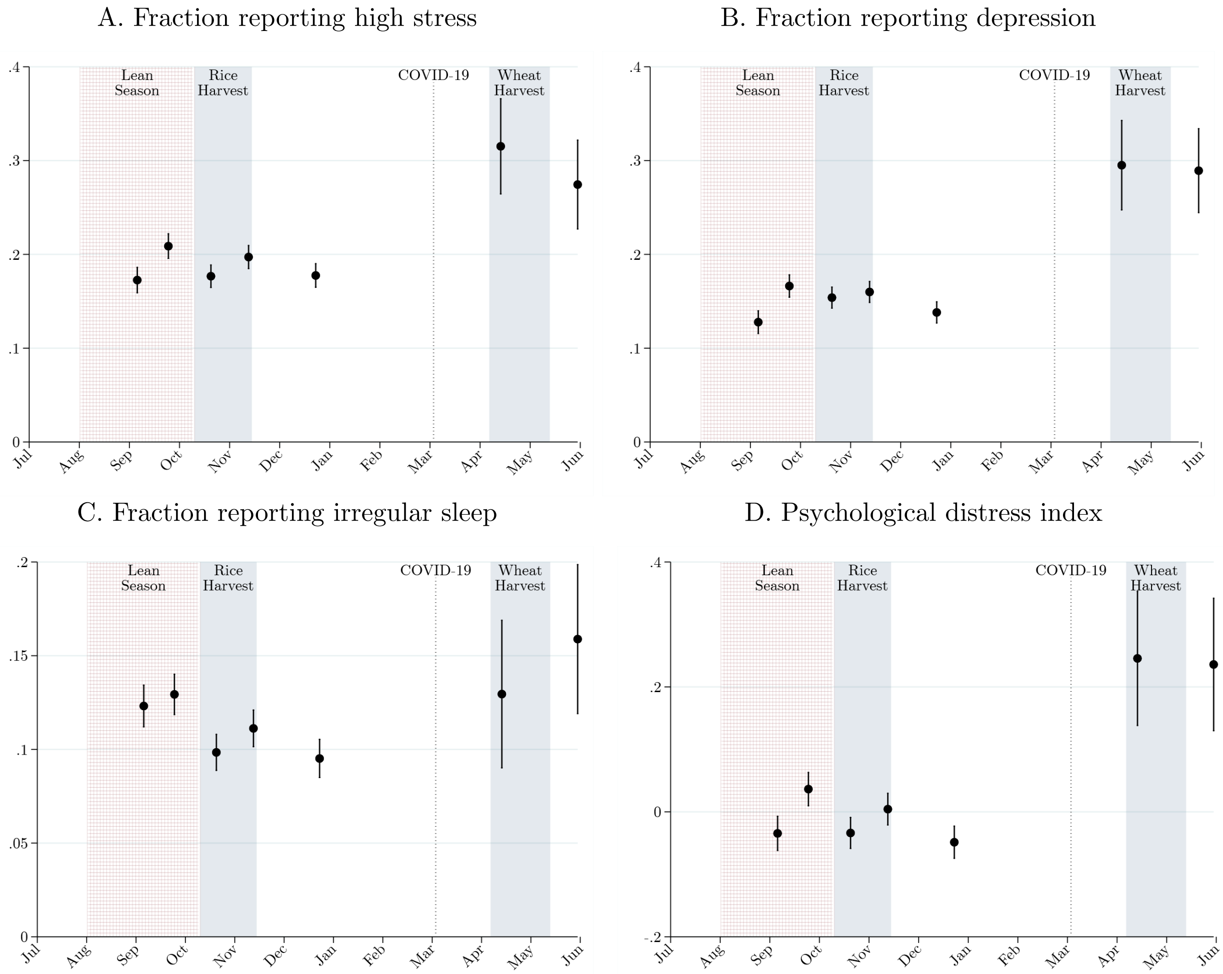


B. Food insecurity in Northern Bangladesh



Notes: Rates of food insecurity around the seasonal agricultural cycle in a typical year. Regression estimates of period fixed effects from (1) with 95% confidence intervals. A. Average of standardized responses to three qualitative questions on food scarcity. Typical year data collected during the sixth phone survey round asking about a typical month. 2019–2020 data collected during contemporaneous phone survey rounds. B. Fraction of households reducing portions for at least 15 days in a month. 2018–2019 data collected during the two in-person survey rounds asking retrospectively by month. 2020 data collected in phone survey asking retrospectively by month. A version of data from both panels appears in Egger et al. (2021).

Figure 5: Mental health indicators in Western Terai, Nepal



Notes: Indicators of mental health. Regression estimates of period fixed effects from (1) with 95% confidence intervals. A–C. Fraction reporting "Always" or "Often" as opposed to "Sometimes", "Rarely", or "Never" for stress, depression, and poor sleep. D. Standardized rating across all three indicators.

Acknowledgements and Declarations

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All data collection was approved by the Yale University IRB.

The authors declare we have no conflicts of interest, and no institution had the right to review results before publication.

Supplementary Appendix for "COVID-19 through the Lens of Seasonal Agriculture in South Asia" For Online Publication Only

A Data

Data from Nepal comes from the Western Terai region of Nepal. Official statistics report an urbanization rate of 66% for the nation and 76–91% for our region of study, though these values overstate the true level of urbanization by misclassifying households living in rural parts of administrative jurisdictions designated as urban. The poverty rate in rural Western Terai is estimated to be 24%, nearly identical to the national rate[3]. Households participating in this study were drawn from the bottom half of the wealth distribution in rural villages as identified in a participatory wealth ranking exercise with prominent members of the community.

Data from Bangladesh comes from a survey of rural households in the Rangpur Division in northern Bangladesh. In the 2011 census, this region had an urbanization rate just under 15%, compared to 28.1% for the full nation. Among the rural population of Rangpur, 48% of households were classified as moderately or extremely poor in 2016, compared to only 24% for the country overall. Households participating in this study were drawn from among rural households owning less than 0.5 acres of land, which constitutes around two thirds of rural households in the Rangpur region.

In Table S1 we present summary statistics describing baseline characteristics of the study population prior to the pandemic and the subsample we reached by phone during the pandemic. The table verifies that there was no selective attrition by pre-pandemic household characteristics. However, we cannot rule out bias caused by selective attrition based on outcomes during the pandemic. The table also compares our samples to the national average reported by the Living Standards Measurement Study (LSMS).

[Table S1 about here.]

In Table S2 we summarize the available data from each sample.

[Table S2 about here.]

B Regression Results

Tables S3–S13 present regression estimates corresponding to the paper's main results. We verify that estimation is robust to restricting to a balanced panel, to omitting household fixed effects,

[3]Nepal Central Bureau of Statistics. "Small Area Estimation of Poverty," published June 2013.

and for Bangladesh to including the full sample rather than restricting to the prior experimental control group.

[Table S3 about here.]

[Table S4 about here.]

[Table S5 about here.]

[Table S6 about here.]

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[Table S8 about here.]

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[Table S13 about here.]

Table S1: Baseline Characteristics of Pre- and Post-COVID Samples

	Sample average (COVID) (1)	Survey average (pre-COVID) (2)	National average (LSMS) (3)
Nepal (Response rate = 0.79)			
Share rural	1.00	1.00	0.79
Household size	5.03	5.03	4.80
Female respondent	0.45	0.42	0.54
Secondary school completion	0.30	0.29	0.29
Monthly HH income (USD PPP)	191	186	457
Bangladesh (Response rate = 0.76)			
Share rural	1.00	1.00	0.73
Household size	4.81	4.74	4.06
Female respondent	0.29		0.50
Secondary school completion	0.10	0.05	0.20
Monthly HH income (USD PPP)	237	219	510

Notes: Mean baseline characteristics from the subsample of phone respondents during the COVID period, the full pre-COVID sample, and the national LSMS for comparison. Table values were also reported in the Appendix to Egger et al. (2021).

Table S2: Available Prior Data for Each Outcome from Each Sample

Outcome	Country	Measure	Pre-COVID Comparison Period
Employment	Nepal	Hours worked by gender	2019 rice harvest
	Bangladesh	Employed in prior week	2019 Aman harvest
Earnings	Nepal	Income excluding own farm	2019 rice harvest (Not asked in August)
	Bangladesh	Income including own farm	2018 Aman Harvest
Migration	Nepal	Fraction of men away	2019 rice harvest 2018–2019 holidays (post-COVID recall)
	Bangladesh	Migrant departures and returns	2018–2019 monthly (pre-COVID recall)
Remittances	Nepal	Household remittance income	2019 rice harvest
Food Security	Nepal	3-question index	2019 rice harvest 2018–2019 monthly (post-COVID recall)
	Bangladesh	Days missed or reduced meals	Early 2020 (post-COVID recall) 2018–2019 monthly (pre-COVID recall)
Mental Health	Nepal	3 indicators and index	2019 rice harvest

Notes: Comparison period data comes from contemporaneous surveys unless otherwise noted. Pre-COVID surveys in Nepal were conducted by phone, and in Bangladesh were conducted in person.

Table S3: Male hours worked (Nepal)

	Total Hours			Wage and Business Hours		
	(1)	(2)	(3)	(4)	(5)	(6)
August 2019	33.54***	36.54***	33.81***	14.21***	15.76***	14.53***
(Base Period)	(0.801)	(1.078)	(0.933)	(0.455)	(0.623)	(0.553)
September 2019	-5.881***	-5.631***	-5.445***	0.0112	0.349	0.0299
	(1.039)	(1.405)	(1.047)	(0.595)	(0.829)	(0.600)
October 2019	11.77***	12.73***	10.87***	-4.274***	-4.453***	-4.896***
	(1.177)	(1.603)	(1.139)	(0.660)	(0.926)	(0.633)
November 2019	4.684***	5.633***	3.727**	-1.022	-0.705	-1.859**
	(1.204)	(1.670)	(1.178)	(0.670)	(0.942)	(0.655)
December 2019	4.239**	2.893	3.957**	5.273***	4.449***	4.879***
	(1.343)	(1.798)	(1.334)	(0.745)	(1.002)	(0.735)
April 2020	-10.46***	-10.92***	-9.673***	-10.07***	-10.89***	-9.495***
	(1.447)	(1.819)	(1.316)	(0.808)	(1.030)	(0.714)
May–June 2020	-11.21***	-12.41***	-11.94***	-8.467***	-9.375***	-9.295***
	(1.673)	(2.063)	(1.520)	(0.894)	(1.122)	(0.773)
Individual Fixed Effects	X	X		X	X	
Balanced Panel		X			X	
R-Squared	0.0533	0.0621	0.0310	0.0621	0.0712	0.0382
Observations	11845	5664	11845	11825	5621	11825

Notes: Regression estimates of period fixed effects with standard errors in parentheses. Columns 1 and 4 follow the regression specification in (1) and are plotted in figure 2, panel A. Columns 2 and 5 restrict to a balanced panel of households. Columns 3 and 6 drop household fixed effects. Coefficients reported relative to base period.

Table S4: Female hours worked (Nepal)

	Total Hours			Wage and Business Hours		
	(1)	(2)	(3)	(4)	(5)	(6)
August 2019	20.22***	20.82***	20.04***	4.435***	4.315***	4.449***
(Base Period)	(0.402)	(0.511)	(0.487)	(0.196)	(0.248)	(0.246)
September 2019	-8.544***	-9.442***	-8.390***	-0.664*	-0.659	-0.765**
	(0.536)	(0.677)	(0.531)	(0.268)	(0.351)	(0.267)
October 2019	16.82***	17.12***	17.03***	-0.553	-0.597	-0.554
	(0.681)	(0.835)	(0.681)	(0.317)	(0.391)	(0.317)
November 2019	-1.273*	-1.039	-0.900	-0.848**	-0.676	-0.798**
	(0.632)	(0.777)	(0.626)	(0.298)	(0.376)	(0.298)
December 2019	-7.469***	-8.812***	-6.832***	1.223***	0.967*	1.430***
	(0.691)	(0.850)	(0.700)	(0.346)	(0.420)	(0.352)
April 2020	1.550	0.807	1.320	-1.752***	-1.787***	-1.930***
	(0.838)	(0.931)	(0.805)	(0.383)	(0.413)	(0.353)
May–June 2020	-3.712***	-4.045***	-4.114***	-2.073***	-1.904***	-2.379***
	(0.890)	(0.973)	(0.885)	(0.391)	(0.427)	(0.367)
Individual Fixed Effects	X	X		X	X	
Balanced Panel		X			X	
R-Squared	0.126	0.133	0.0854	0.00752	0.00691	0.00622
Observations	18791	11719	18791	18773	11670	18773

Notes: Regression estimates of period fixed effects with standard errors in parentheses. Columns 1 and 4 follow the regression specification in (1) and are plotted in figure 2, panel A. Columns 2 and 5 restrict to a balanced panel of households. Columns 3 and 6 drop household fixed effects. Coefficients reported relative to base period.

Table S5: Household earnings and remittances (Nepal)

	Total Non-Farm Income			Remittances		
	(1)	(2)	(3)	(4)	(5)	(6)
September 2019	7661.2***	7873.3***	7565.1***	3370.4***	3388.4***	3342.4***
(Base Period)	(328.9)	(388.7)	(348.1)	(262.2)	(308.0)	(278.2)
October 2019	2728.4***	2736.8***	2723.2***	2612.4***	2743.5***	2561.6***
	(506.5)	(606.0)	(499.6)	(401.7)	(479.9)	(396.0)
November 2019	2202.6***	2110.1***	2192.3***	1745.0***	1799.1***	1668.4***
	(459.4)	(536.0)	(454.9)	(361.8)	(420.3)	(356.9)
December 2019	5489.4***	5645.6***	5490.7***	1492.8*	1515.6*	1455.4*
	(733.7)	(879.3)	(727.1)	(633.1)	(756.4)	(626.5)
April 2020	-3085.9***	-3094.9***	-2904.6***	-1270.3***	-1241.2**	-1138.8***
	(477.8)	(514.4)	(450.5)	(357.5)	(385.9)	(339.3)
May–June 2020	-3092.2***	-3127.3***	-2803.1***	-1142.9**	-1116.5**	-1002.8**
	(515.7)	(547.3)	(485.5)	(371.0)	(395.4)	(363.7)
HH Fixed Effects	X	X		X	X	
Balanced Panel		X			X	
R-Squared	0.0267	0.0273	0.0193	0.00914	0.00931	0.00635
N	14347	12119	14347	14514	12384	14514

Notes: Regression estimates of period fixed effects with standard errors in parentheses. Columns 1 and 4 follow the regression specification in (1) and are plotted in figure 2, panel B. Columns 2 and 5 restrict to a balanced panel of households. Columns 3 and 6 drop household fixed effects. Coefficients reported relative to base period.

Table S6: Household employment (Bangladesh)

	Any HH member employed in previous week			
	(1)	(2)	(3)	(4)
Aman 2019	0.954***	0.972***	0.952***	0.935***
(Base Period)	(0.00311)	(0.0216)	(0.00493)	(0.00158)
Boro 2020	-0.490***	-0.490***	-0.466***	-0.453***
	(0.0430)	(0.0432)	(0.0416)	(0.0310)
HH Fixed Effects	X	X		X
Balanced Panel	X			
Treated Sample				X
R-Squared	0.476	0.476	0.195	0.427
Observations	2016	286	2016	5759

Notes: Regression estimates of period fixed effects with standard errors in parentheses. Column 1 follows the regression specification in (1). Columns 2 restricts to a balanced panel of households. Column 3 drops household fixed effects. Column 4 includes the full sample of experimentally treated and control households. Coefficients reported relative to base period.

Table S7: Household earnings (Bangladesh)

	Household earnings incl. own farming			
	(1)	(2)	(3)	(4)
Aman 2019	2010.1***	1831.9***	2025.2***	1934.4***
(Base Period)	(15.08)	(104.6)	(86.69)	(8.075)
Boro 2020	-975.6***	-975.6***	-1184.1***	-1259.3***
	(208.2)	(209.2)	(162.0)	(158.2)
HH Fixed Effects	X	X		X
Balanced Panel	X			
Treated Sample				X
R-Squared	0.133	0.133	0.00707	0.181
Observations	2016	286	2016	5759

Notes: Regression estimates of period fixed effects with standard errors in parentheses. Column 1 follows the regression specification in (1). Columns 2 restricts to a balanced panel of households. Column 3 drops household fixed effects. Column 4 includes the full sample of experimentally treated and control households. Coefficients reported relative to base period.

Table S8: Fraction of men away (Nepal)

	Away from housheold (males)		
	(1)	(2)	(3)
October 2018	0.215***	0.213***	0.216***
(Base Period)	(0.0125)	(0.0127)	(0.0158)
November 2018	-0.00448	-0.00279	-0.00438
	(0.00813)	(0.00822)	(0.00812)
April 2019	0.0642**	0.0622**	0.0642**
	(0.0196)	(0.0200)	(0.0196)
June 2019	-0.00448	-0.00712	-0.00438
	(0.0186)	(0.0190)	(0.0187)
August 2019	0.113***	0.111***	0.113***
	(0.0209)	(0.0212)	(0.0210)
September 2019	0.149***	0.149***	0.148***
	(0.0211)	(0.0213)	(0.0211)
October 2019	0.00759	0.00768	0.00735
	(0.0194)	(0.0197)	(0.0194)
November 2019	0.0306	0.0314	0.0287
	(0.0193)	(0.0193)	(0.0193)
December 2019	0.147***	0.144***	0.147***
	(0.0221)	(0.0223)	(0.0221)
April 2020	-0.0112	-0.0159	-0.0116
	(0.0188)	(0.0189)	(0.0188)
May 2020	-0.0608*	-0.0620*	-0.0542
	(0.0297)	(0.0299)	(0.0294)
June 2020	-0.119***	-0.117***	-0.119***
	(0.0189)	(0.0191)	(0.0189)
Indiv. Fixed Effects	X	X	
Balanced Panel		X	
R-Squared	0.0511	0.0504	0.0304
N	7849	7665	7849

Notes: Regression estimates of period fixed effects with standard errors in parentheses. Column 1 follows the regression specification in (1) and is plotted in figure 3, panel A. Column 2 restricts to a balanced panel of households. Column 3 drops individual fixed effects. Coefficients reported relative to base period.

Table S9: Migration departures and returns (Bangladesh)

	Departures			Returns		
	(1)	(2)	(3)	(4)	(5)	(6)
Monthly rate in 2018–2019:						
January	0.0460***	0.0276***	0.0569***	0.0334***	0.0206*	0.0408***
(Base Period)	(0.00288)	(0.00808)	(0.00191)	(0.00275)	(0.00969)	(0.00173)
February	-0.0157***	-0.00346	-0.0194***	-0.00292	6.51e-16	-0.00192
	(0.00404)	(0.0125)	(0.00264)	(0.00377)	(0.0121)	(0.00246)
March	0.000798	0.0242	-0.00795**	0.00931*	0.0277*	0.00146
	(0.00426)	(0.0142)	(0.00267)	(0.00397)	(0.0137)	(0.00248)
April	0.0359***	0.0381*	0.0325***	0.0255***	0.0346*	0.0303***
	(0.00487)	(0.0164)	(0.00308)	(0.00445)	(0.0161)	(0.00276)
May	0.00372	0.00346	-0.00128	0.0580***	0.0519**	0.0630***
	(0.00451)	(0.0135)	(0.00286)	(0.00496)	(0.0162)	(0.00305)
June	-0.0390***	-0.0137	-0.0499***	-0.0186***	-0.0135	-0.0232***
	(0.00396)	(0.0138)	(0.00245)	(0.00404)	(0.0120)	(0.00248)
July	-0.0342***	-0.0206*	-0.0421***	-0.0318***	-0.0203*	-0.0390***
	(0.00405)	(0.00964)	(0.00260)	(0.00308)	(0.00968)	(0.00197)
August	0.0308***	0.0479*	0.0337***	-0.00434	0.0139	-0.00802**
	(0.00639)	(0.0203)	(0.00414)	(0.00476)	(0.0169)	(0.00298)
September	0.0186**	0.0274	0.0280***	0.0210***	0.0139	0.0256***
	(0.00613)	(0.0194)	(0.00407)	(0.00575)	(0.0183)	(0.00364)
October	0.0789***	0.0959***	0.0971***	0.0522***	0.0687**	0.0595***
	(0.00767)	(0.0264)	(0.00492)	(0.00665)	(0.0252)	(0.00420)
November	0.0567***	0.0548*	0.0622***	0.0692***	0.0687**	0.0900***
	(0.00703)	(0.0235)	(0.00447)	(0.00714)	(0.0252)	(0.00462)
December	0.0869***	0.0753**	0.0938***	0.0708***	0.0687**	0.0764***
	(0.00761)	(0.0250)	(0.00480)	(0.00717)	(0.0252)	(0.00445)
Two-month rate in 2020:						
March–April				0.618***	0.624***	0.626***
				(0.0404)	(0.0421)	(0.0280)
HH Fixed Effects	X	X	X	X	X	X
Balanced Panel		X				X
Treated Sample			X			X
R-Squared	0.0249	0.0233	0.0297	0.0537	0.290	0.0453
Observations	32042	2467	94415	32188	2613	94709

Notes: Regression estimates of period fixed effects with standard errors in parentheses. Columns 1 and 4 follow the regression specification in (1) and are plotted in figure 3, panel B. Pre-COVID data includes full sample of study participants. Columns 2 and 5 restrict to a balanced panel of households that responded to COVID-19 phone survey. Columns 3 and 6 include the full sample of experimentally treated and control households. Coefficients reported relative to base period.

Table S10: Food insecurity (Nepal)

	Index of food insecurity					
	(1a)	(2a)	(3a)	(1b)	(2b)	(3b)
	Monthly index in 2018–2019			Monthly index in 2019–2020		
June (Base Period)	-0.433*** (0.0840)	-0.487*** (0.0897)	-0.428*** (0.0727)			
July	1.009*** (0.126)	1.060*** (0.132)	1.009*** (0.126)			
August	-0.0450 (0.0669)	-0.0614 (0.0702)	-0.0450 (0.0669)			
September	1.482*** (0.145)	1.521*** (0.152)	1.482*** (0.145)	1.468*** (0.236)	1.561*** (0.251)	1.453*** (0.236)
October	-0.129 (0.0919)	-0.0801 (0.0947)	-0.129 (0.0919)	1.131*** (0.238)	1.156*** (0.246)	1.151*** (0.240)
November	-0.374*** (0.0771)	-0.352*** (0.0766)	-0.374*** (0.0771)	-0.388 (0.211)	-0.335 (0.225)	-0.393 (0.212)
December	-0.392*** (0.0751)	-0.372*** (0.0741)	-0.392*** (0.0751)	-0.439* (0.222)	-0.466* (0.233)	-0.423 (0.224)
January	-0.225* (0.0882)	-0.204* (0.0904)	-0.225* (0.0882)			
February	-0.287*** (0.0849)	-0.284*** (0.0840)	-0.287*** (0.0849)			
March	-0.270*** (0.0803)	-0.265** (0.0818)	-0.270*** (0.0803)			
April	0.0560 (0.0938)	0.0977 (0.0985)	0.0560 (0.0938)	0.866*** (0.228)	1.014*** (0.240)	0.839*** (0.231)
May	0.0770 (0.0671)	0.0946 (0.0713)	0.0770 (0.0671)	1.081*** (0.0840)	1.218*** (0.0897)	1.035*** (0.0727)
HH Fixed Effects	X	X		X	X	
Balanced Panel		X			X	
R-Squared	0.0677	0.0705	0.0528			
Observations	7707	7134	7707			

Notes: Regression estimates of period fixed effects with standard errors in parentheses. May 2020 coefficient spans late May and June. Columns 1a and 1b represent a single regression following the specification in (1) and are plotted in figure 4, panel A. Columns 2a and 2b restrict to a balanced panel of households. Columns 3a and 3b drop household fixed effects. Coefficients reported relative to base period. Regressions broken into two columns for ease of display.

Table S11: Food insecurity (Bangladesh)

Missed/reduced meals for at least 15 days	(1)	(2)	(3)	(4)
Monthly rate in 2018–2019:				
January	0.0245***	0.0274**	0.0247***	0.0262***
(Base Period)	(0.00255)	(0.00932)	(0.00253)	(0.00162)
February	0.0112***	0.00346	0.0112***	0.0162***
	(0.00325)	(0.0125)	(0.00325)	(0.00200)
March	0.0697***	0.0484**	0.0697***	0.0896***
	(0.00501)	(0.0166)	(0.00501)	(0.00321)
April	0.0205***	0.0277	0.0205***	0.0243***
	(0.00382)	(0.0154)	(0.00382)	(0.00235)
May	-0.00266	-0.00346	-0.00266	0.00347
	(0.00306)	(0.0115)	(0.00306)	(0.00196)
June	0.0480***	0.0208	0.0477***	0.0515***
	(0.00603)	(0.0182)	(0.00602)	(0.00365)
July	0.0395***	-0.00655	0.0393***	0.0518***
	(0.00570)	(0.0120)	(0.00570)	(0.00364)
August	0.0840***	0.0619*	0.0837***	0.0916***
	(0.00724)	(0.0244)	(0.00723)	(0.00434)
September	0.169***	0.172***	0.169***	0.208***
	(0.00903)	(0.0329)	(0.00902)	(0.00564)
October	0.196***	0.185***	0.196***	0.247***
	(0.00948)	(0.0338)	(0.00947)	(0.00593)
November	0.00780	-0.0134	0.00753	0.00458
	(0.00423)	(0.0138)	(0.00423)	(0.00249)
December	0.00516	0.00714	0.00489	0.00634**
	(0.00381)	(0.0154)	(0.00381)	(0.00233)
Monthly rate in 2020:				
January	0.00337	-0.00655	-0.00418	0.0117
	(0.0143)	(0.0155)	(0.0120)	(0.0107)
February	0.0239	0.0140	0.0164	0.0185
	(0.0181)	(0.0195)	(0.0167)	(0.0115)
March	0.140***	0.130***	0.133***	0.121***
	(0.0317)	(0.0320)	(0.0303)	(0.0202)
April	0.161***	0.151***	0.153***	0.185***
	(0.0334)	(0.0336)	(0.0318)	(0.0235)
HH Fixed Effects	X	X		X
Balanced Panel	X			
Treated Sample				X
R-Squared	0.0632	0.0659	0.0518	0.0827
Observations	32626	3051	32626	95591

Notes: Regression estimates of period fixed effects with standard errors in parentheses. Column 1 follows the regression specification in (1) and is plotted in figure 4, panel B. Pre-COVID data includes full sample of study participants. Column 2 restricts to a balanced panel of households that responded to COVID-19 phone survey. Columns 3 drops household fixed effects. Column 4 includes the full sample of experimentally treated and control households. Coefficients reported relative to base period.

Table S12: Mental health indicators pt. 1 (Nepal)

	High Stress			Sadness or Depression		
	(1)	(2)	(3)	(4)	(5)	(6)
August 2019	0.173***	0.185***	0.177***	0.128***	0.123***	0.135***
(Base Period)	(0.00691)	(0.0110)	(0.00744)	(0.00616)	(0.00962)	(0.00665)
September 2019	0.0362***	0.0322*	0.0276**	0.0385***	0.0521***	0.0282**
	(0.0104)	(0.0164)	(0.0100)	(0.00933)	(0.0146)	(0.00907)
October 2019	0.00412	-0.00260	-0.000311	0.0262**	0.0341*	0.0194*
	(0.0100)	(0.0155)	(0.00961)	(0.00912)	(0.0138)	(0.00881)
November 2019	0.0246*	0.00966	0.0146	0.0322***	0.0331*	0.0221*
	(0.0105)	(0.0160)	(0.00997)	(0.00934)	(0.0145)	(0.00897)
December 2019	0.00492	-0.00680	0.00412	0.0104	0.0205	0.00584
	(0.0106)	(0.0164)	(0.0100)	(0.00947)	(0.0144)	(0.00894)
April 2020	0.143***	0.186***	0.136***	0.167***	0.235***	0.143***
	(0.0281)	(0.0373)	(0.0248)	(0.0264)	(0.0341)	(0.0238)
May–June 2020	0.102***	0.113**	0.0949***	0.162***	0.184***	0.152***
	(0.0264)	(0.0358)	(0.0230)	(0.0249)	(0.0330)	(0.0232)
Individual Fixed Effects	X	X		X	X	
Balanced Panel		X			X	
R-Squared	0.00719	0.0161	0.00486	0.0129	0.0290	0.00822
Observations	13456	4944	13456	13454	4946	13454

Notes: Regression estimates of period fixed effects with standard errors in parentheses. Columns 1 and 4 follow the regression specification in (1) and are plotted in figure 5, panels A and B. Columns 2 and 5 restrict to a balanced panel of households. Columns 3 and 6 drop household fixed effects. Coefficients reported relative to base period.

Table S13: Mental health indicators pt. 2 (Nepal)

	Trouble Sleeping			Psychological Distress Index		
	(1)	(2)	(3)	(4)	(5)	(6)
August 2019	0.123***	0.136***	0.123***	-0.0344*	-0.0123	-0.0244
(Base Period)	(0.00568)	(0.00929)	(0.00639)	(0.0139)	(0.0223)	(0.0156)
September 2019	0.00621	-0.00583	0.00489	0.0709***	0.0641*	0.0537**
	(0.00852)	(0.0134)	(0.00832)	(0.0207)	(0.0323)	(0.0204)
October 2019	-0.0247**	-0.0228	-0.0231**	0.000630	0.00252	-0.00845
	(0.00826)	(0.0129)	(0.00785)	(0.0205)	(0.0313)	(0.0198)
November 2019	-0.0119	-0.0273*	-0.0137	0.0388	0.00850	0.0187
	(0.00852)	(0.0134)	(0.00807)	(0.0213)	(0.0330)	(0.0206)
December 2019	-0.0280**	-0.0350*	-0.0257**	-0.0142	-0.0249	-0.0170
	(0.00870)	(0.0140)	(0.00818)	(0.0214)	(0.0332)	(0.0206)
April 2020	0.00637	0.0205	0.0123	0.280***	0.391***	0.260***
	(0.0219)	(0.0288)	(0.0185)	(0.0595)	(0.0777)	(0.0533)
May–June 2020	0.0357	0.0370	0.0387*	0.270***	0.299***	0.261***
	(0.0221)	(0.0299)	(0.0191)	(0.0589)	(0.0792)	(0.0534)
Individual Fixed Effects	X	X		X	X	
Balanced Panel		X			X	
R-Squared	0.00364	0.00470	0.00226	0.00903	0.0195	0.00569
Observations	13463	4949	13463	13408	4928	13408

Notes: Regression estimates of period fixed effects with standard errors in parentheses. Columns 1 and 4 follow the regression specification in (1) and are plotted in figure 5, panels C and D. Columns 2 and 5 restrict to a balanced panel of households. Columns 3 and 6 drop household fixed effects. Coefficients reported relative to base period.