Economic Impacts of the COVID–19 Lockdown in a Remittance-Dependent Region

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The economic impacts of COVID-19 lockdowns on poor and vulnerable households living in rural areas of developing countries are not well understood due to a lack of detailed micro-survey data at the household level. Utilizing weekly financial transaction data collected from households residing in a rural region of India, we estimate the impacts of India's COVID-19 lockdown on household income, food security, welfare, and access to local loan markets. A large portion of households living in our study region is reliant on remittances from migrants to sustain their livelihoods. Our analysis reveals that in the month immediately after India's lockdown announcement, weekly household local income fell by INR 1,022 (US$ 13.5), an 88% drop compared to the long-term average with another 63% reduction in remittance. In response to the massive loss in earnings, households substantially reduced meal portions and consumed fewer food items. Impacts were heterogeneous; households in lower income quantiles lost a higher percentage of their income and expenditures, but government food aid slightly mitigated the negative impacts. We also find an increase in the effective interest rate of local borrowing in cash and a higher demand for in-kind loans, which are likely to have an adverse effect on households who rely on such services. The results from this paper have immediate relevance to policymakers considering additional lockdowns as the COVID-19 pandemic resurges around the globe and to governments thinking about responses to future pandemics that may occur.

Key words: COVID-19, financial diaries, lockdown, migration, poverty, remittances.

JEL codes: D14, O12, Q12.

As the world grappled with the novel coronavirus disease 2019 (COVID-19) pandemic since its first identification in December 2019, more than 100 countries had resorted to either full or partial lockdowns of their economy by the end of March 2020 (Dunford et al. 2020). Across the globe, controversy surrounded the "stay at home" orders, with rising unemployment in both developed and emerging economies. A recent surge in global research aimed at understanding the economic impacts of the COVID-19 pandemic and the subsequent lockdowns have relied mostly on aggregate data (Atkeson 2020; Fernandes 2020; Sumner, Hoy, and Ortiz-Juarez 2020; Van Lancker and Parolin 2020). There is relatively little micro-household-level research on how large-scale lockdowns affect the economic activity, income, and consumption of poor and vulnerable households.

A handful of previous research quantifies or predicts the macroeconomic impacts of past

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pandemics like the avian flu, HIV, and influenza (Meltzer, Cox, and Fukuda 1999; Arndt and Lewis 2001; Smith et al. 2009; Pike et al. 2014). Sumner, Hoy, and Ortiz-Juarez (2020) estimate the potential short-term economic impact of COVID-19 on global poverty. Their results suggest that global poverty increased for the first time since 1990, and the concentration of the new poor would occur in the poorest regions of the world, including South Asia. It is important to evaluate the impacts of the COVID-19 pandemic and the abrupt lockdowns imposed by many governments in the developing world on household welfare, but it is also essential to understand the coping strategies adapted by vulnerable households in some of the poorest parts of these countries.

This paper estimates the impacts of COVID-19 lockdowns on households residing within an economically poor region of a developing country. Using a novel high frequency weekly micro-survey data, which tracked households for over one year, we directly estimate the economic impacts of the COVID-19 lockdown on households residing in the Sundarbans region of West Bengal in India. Residents of the Sundarbans are generally impoverished and vulnerable to economic and weather shocks, which has led to high levels of migration out of the region to other parts of India (Sanyal and Routray 2016; Hajra et al. 2017; Sánchez-Triana, Ortolano, and Paul 2018). The recent lockdown has compounded livelihood issues in the region, with anecdotal accounts of households adopting various strategies to sustain their livelihoods. We find substantial heterogeneous impacts at the household level and provide insights into how residents and local markets coped with the crisis in the first month of the COVID-19 lockdown in India.

Background

The biggest COVID-19 lockdown was enforced in India starting on March 25, 2020. The prime minister of India announced the country's lockdown on national television the previous evening, giving notice of only four hours to its 1.3 billion citizens.[1] Immediately after the announcement of the first COVID-19 lockdown in India on March 25, police and local administration enforced the shelter-in-place order by restricting people from going outside for work or gathering in local marketplaces. Uncertainty surrounding the lockdown created panic as people rushed to stockpile food and other essential household items immediately after the announcement. Millions of migrants were stranded in major Indian cities and found themselves jobless overnight with no means of transportation back to their villages of origin. The gloomy images of migrants with infants and toddlers, trudging for days to cover hundreds of kilometers on their feet from far-off Indian cities back to their respective villages, made headlines in national and international media (Biswas 2020; Slater and Masih 2020).

Anecdotal evidence from news articles and other sources suggests that the poor people were the hardest hit by the COVID-19 lockdowns globally (Jamison 2020; Zargar 2020). Daily wage earners, such as those primarily engaged in agriculture, construction, and casual labor work, suddenly found themselves without a source of income and were unable to continue their work from home. Most poor households live at subsistence levels without any formal or informal savings to sustain their livelihood under an economic lockdown. Furthermore, those households with migrants could no longer rely on remittance to buffer against the negative income shock. Instead, migrants and landless workers returned to their villages without knowing when they could return to their migration destinations. Many of these younger migrants have difficulty obtaining local employment due to fewer jobs in their villages of origin, and small landholdings make it harder for their families to absorb them as subsistence farm labor (Narayanan and Saha 2020).

The COVID-19 lockdown has created uncertainty in markets and caused a widespread disruption of food supply chains in India. Disruptions to the food supply chain have negatively impacted the distribution of consumption goods, and the lack of an enclave of subsistence growers means there is little buffer to this disruption (Reardon et al. 2020). There is heterogeneity among Indian states in their farmers' ability to sell their harvest due to preexisting market infrastructures. Despite these heterogeneities, disruptions to the supply chain and income losses have contributed to smallholder farmers

[1]The Government of India initially decided on a roughly four-week lockdown from March 25 until April 14, later named Phase I lockdown, was extended until May 3 as Phase II. India eventually extended its Phase II lockdown to Phases III (until May 19) and IV (until May 31).

losing as consumers (Ceballos, Kannan, and Kramer 2020). Subsistence farming is a relatively common practice in the Sundarbans, but a recent cyclone, *Amphan,* in May has caused severe damage to existing crops and forced some households to evacuate to storm shelters, potentially reducing their ability to stay resilient and increasing their risk of contracting COVID-19 (Daniyal 2020). Although cyclone *Amphan* caused additional disruptions beyond the COVID-19 lockdown, coastal and tropical cyclones frequently occur in the Sundarbans region.

Recent studies have found that poverty and economic dislocation tends to lead to less compliance in lower income areas (Bargain and Aminjonov 2020; Wright et al. 2020). In a study with some parallel to ours, Buheji et al. (2020) highlight many issues regarding the impact of the lockdown on the poor in India. Specifically, the burden has fallen heavily on groups highlighted in our paper, including migrant laborers, daily earners, farmers, and children in communities that depend on school meals. In a study about microenterprise owners, Malik et al. (2020) find that sales and household income fell by 90% after the lockdown, and 70% could not repay their loan.

The heterogeneous impacts of the COVID-19 lockdowns along the income distribution could be quite dissimilar across developed and developing countries. Using transaction-level data from linked bank-accounts, Baker et al. (2020) find that households' in the United States increased spending immediately after the news of COVID-19, which was then quickly followed by a sharp decrease. However, they find little heterogeneity across income groups. Dang, Huynh, and Nguyen (2020) study the impact of COVID-19 on the different income groups in six countries (China, Italy, Japan, South Korea, the United Kingdom, and the United States). Their results, at least in the developed country context, indicate the pandemic has no impacts on household income losses for the different income quintiles, but the impacts are most noticeable in household savings.

A rigorous analysis of the economic impacts of lockdowns due to pandemics using primary data is challenging for five reasons. First, implementing "direct" enumerator-based surveys in remote rural areas are not feasible due to lockdowns, resulting in researchers relying on phone-based interviews (McKenzie 2020). Second, a proper assessment of pandemic-induced lockdowns on economic activity and household welfare requires pre-and-post lockdown data on the same panel households. Third, most analyses rely on annual aggregate survey data that mask time-sensitive economic fluctuations of any shock at a household level. Fourth, income and consumption vary seasonally for most poor households, inducing them to smooth their income and/or consumption. Finally, coincident negative covariate shocks along with the lockdown may confound the impacts of the lockdown and make them harder to identify.

Leveraging our high-frequency weekly micro-survey data, we can quantify the impact of the lockdown and compare it to long-term averages. Our study focuses on households' weekly financial activities for the first four weeks after India's lockdown announcement from March 25, 2020 to April 19, 2020. We compare weekly outcomes for a month after the lockdown announcement against two sets of baseline outcomes: one, on the same household from the same time-frame in the previous year (March 25, 2019 to April 19, 2019), and, two, for the same sample for the entire previous year (November 2018 to October 2019). The high-frequency data captured by financial diaries allow us to construct a more convincing counterfactual while controlling for temporal variation throughout the year.

Econometric analysis of weekly household-level panel data enables us to evaluate the impacts of COVID-19 lockdown on household local income, expenditure, consumption, remittance, and borrowing activities. The high-frequency weekly data also address any seasonality issues in income, consumption, and non-consumption expenditures, which are particularly prevalent in rural regions that rely on agriculture. To the best of our knowledge, during the first four weeks after the lockdown announcement, the households in the study sample were only coping with the negative shock of lockdown.[2]

We find that local income drops dramatically by 88%, while consumption goods spike upward immediately after the lockdown, then fall precipitously to less than half that of regular (non-COVID-19) weeks. We also find evidence that remittance income has dropped while in-kind borrowing has increased, with

[2]A key challenge would otherwise be to disentangle the impacts of lockdown from another coincidental covariate shock, like the landfall of cyclone *Amphan* in May 2020, which, fortuitously, is beyond the time frame considered in this paper.

rising effective interest rates. As households coped with their income losses, instances of households reporting reduced meal portions and fewer food items consumed increased. Additionally, our results uncover strong evidence of heterogeneous impacts, especially for poorer segments of the population and examine the role of local loan markets on household welfare.

The findings from this paper have potentially far-reaching policy implications beyond estimating the negative impacts in the first four weeks after the lockdown. Some of the immediate negative impacts on households' savings and borrowings may persist and potentially have longer term adverse effects on household welfare. Without the expansion of government social safety net, both in the short- and long-term, households may be pushed deeper into vicious poverty traps and may find it hard to escape if lockdowns extend for a considerable amount of time (Carter and Zimmerman 2000; Lybbert et al. 2004; Carter and Barrett 2006). Policies designed to help the economic recovery after COVID-19 must take into account these dynamics and how it might bring on persistent effects.

The rest of the paper is organized as follows: the next section introduces the study region with details of our baseline and financial diaries data before and after the COVID-19 lockdown in India, followed by our empirical strategies with details of econometric estimations using the panel data of financial diaries. The final three sections provide the impacts of the COVID-19 lockdown on household income, expenditure, remittance, consumption, and borrowing; robustness to alternative specifications and heterogeneous impacts discussed in the penultimate section; with the last section concluding the findings.

Data

We gathered survey data on household-level weekly financial activities of a representative sample of rural households in the Sundarbans region in West Bengal, India from November 2018 to October 2019. A similar survey instrument with some additional COVID-19 related questions was extended to the same households via phone calls after the announcement of the COVID-19 lockdown in India. Starting in mid-April 2020, we asked households to recall and record their financial activities in the four weeks during India's Phase-I lockdown announced on March 24, 2020. We also asked local community leaders a set of short questions about prices and supplies of essential commodities to understand how the COVID-19 pandemic and lockdown of economic activities have changed the daily lives of the people of their communities. The weekly impacts of the lockdown after its announcement are estimated by comparing the weekly outcomes to two baselines: first, a full baseline (November 2018 to October 2019), and second, a restricted baseline (March–April 2019).

A set of ten representative villages were randomly chosen from five administrative blocks in the Sundarbans. The households of the Sundarbans region of West Bengal are like other Indian rural poor in terms of their high levels of existing poverty (Ravallion and Datt 1999; Deaton and Dreze 2002; Pingali 2010). At baseline, about 34% of the households in our sample were below the Indian rural poverty line of INR 816 per month per person.[3] The incidence of poverty in the Sundarbans is similar to the rural areas of other poorer states like Uttar Pradesh and Chhattisgarh, where headcount ratios are 30.4% and 44.6%, respectively (Reserve Bank of India Publications 2013).

Despite its vicinity to Kolkata, the largest metropolitan city and commercial hub in eastern India, Sundarbans is remote and largely isolated. Out of 4,500 square kilometers of the inhabited area with over 3.9 million people, there are only 42 kilometers of railway and 300 kilometers of *pucca* (paved) road networks. Ninety-five percent of the population depend primarily on agriculture, who typically cultivate a single crop (usually *Aman* paddy) during the rainy season (July–October) in most parts of Sundarbans. Smallholder farmers usually sell their output to a handful of local middlemen and traders due to poor transportation infrastructure and inadequate connectivity, including facing local storage shortages (Hajra and Ghosh 2018). About half of these farmers can be classified as landless laborers. Some households are also entirely or partially engaged in catching fish or crab in the lean season.

Additionally, the Sundarbans delta region is frequented with devastating coastal cyclones,

[3] *Authors' calculations*: we use the 2011–12 poverty line from the Planning Commission of India.

making the households vulnerable to climate shocks (Mistri 2013; Zhu et al. 2018). In the last decade or so, this region has witnessed extremely severe tropical cyclones like *Sidr* (2007), *Aila* (2009), *Fani* (2019), *Bulbul* (2019), and *Amphan* (May 2020). A large proportion of agricultural land in the region has been rendered unproductive from previous coastal cyclones, leaving remittance income from domestic migration as one of the major income sources for a large proportion of households. Migration out of the Sundarbans, in the hope of better wages and to cope with failing agriculture, is a common phenomenon and prevalent in the other poorer states of India like Bihar, Jharkhand, Odisha, and Uttar Pradesh (De Haan 2002; Dubey, Palmer-Jones, and Sen 2006; Bhagat and Mohanty 2009).

Financial Diaries

Financial diaries are a unique way of capturing high-frequency data on household finances (Collins 2008; Kamath, Mukherji, and Ramanathan 2008; Morduch and Schneider 2017; Zhu et al. 2018). However, they are rarely used as survey instruments in development projects because of their high costs of implementation and monitoring (Hoogeveen et al. 2014; Headey and Barrett 2015). We have been tracking and collecting household-level data on the weekly financial activities of 305 randomly selected households in our study site.

We implemented the weekly survey instrument in November 2018 for a full year, after collecting a wave of baseline data through a standard survey.[4] During the baseline interview, enumerators trained the sampled households to fill out the financial diaries that would capture their weekly household income, remittance, borrowing, lending, and expenditure on consumption and non-consumption items. The households received two more rounds of training and instructions in the following two weeks before they started independently recording their financial activities in pre-printed diaries handed out to them. Our field team collected four weeks of filled-out financial diaries during their monthly visit and provided support via phone calls to ensure proper recording of weekly data. Following the COVID-19 lockdown announcement, financial diaries with some Supplementary COVID-19 related questions were extended to the same households via phone calls. We use the forty nine-week data from November 2018 to October 2019 as our baseline and construct a pre- and post- lockdown dynamic panel on our sampled households with the financial diaries of the first four weeks post lockdown starting from March 25 to April 19, 2020.[5]

Baseline Household Characteristics

Table 1 presents the baseline demographic characteristics of our sample, collected at the beginning of the study in 2018. Most of the household heads are male (about 91%), with an average age of about fifty years. The typical household size is about four to five members. The average educational attainment of a household head is around five years, which is representative of the national average for males' completed years of schooling (Pratap 2013). About 65% of our sampled households have at least one migrant member working as an agricultural worker or a non-farm casual labor in a major Indian city or another part of the country (table 1).

Outside of migratory work, primary livelihood activities within the Sundarbans consist of farming, foraging (including catching fish/shrimp), fishing, and casual labor. Prior to the lockdowns, the income of households from local (non-remittance) sources is about INR 1,160 (approx. US$ 15) in an average week. Remittances constituted about 16% of total household income in the baseline, which was INR 227 (US$ 3) per week (table 2, column 1).

The summary comparisons show that local income post lockdown decreased from INR 1,160 to INR 163 (US$ 2) in the first four weeks of lockdown. Consequently, households reported that average consumption and non-consumption expenditures in a typical week decreased from INR 749 (US$ 9.9) to

[4]The baseline survey in November 2018 gathered data on household demographics, assets, landholding, economic activities, past shocks, and migration.

[5]Our field team could not connect with twenty-nine households after the COVID-19 lockdown resulting in an attrition rate of 9.5% from the 2018–19 baseline. In online supplementary appendix Table A1, we test for attrition using a probability model of attrition on the baseline household characteristics (Hausman and Wise 1979; Moffit, Fitzgerald, and Gottschalk 1999). We fail to reject the null at a 5% level of significance that attritted households are not systematically different from non-attritted households. So, we include the attritted households in the baseline to gain additional information from those observations and more degrees of freedom for the analysis.

Table 1. Summary of Household Demographics

Variables	Mean	Standard deviation
HH head age	49.74	*13.05*
HH head years of education	5.33	*3.77*
Female headed household	0.09	*0.28*
HH size	4.53	*1.83*
Number of children	1.08	*1.02*
Proportion of HH with migrant	0.65	*0.48*
Proportion of HH involved in agriculture	0.66	*0.48*
Proportion of HH with businesses	0.12	*0.33*
Land owned (in kathas)	31.72	*50.37*
Proportion of HH below the Indian poverty line	0.34	*0.47*
N	305	

Source: Authors' calculations from the baseline data.
Notes: Table 1 shows the summary statistics (mean and standard deviation) of the listed variables collected during the baseline household survey in November 2018. The standard deviations of variables are italicized.

Table 2. Summary of Financial Diaries

Variables	Full baseline (Nov '18-Oct '19)	Restricted baseline (Mar '19-April '19)	Post-lockdown (Mar '20-April '20)
Local income (INR)	1,159.7 (*1706.9*)	1,280.5 (*1826.9*)	162.9 (*883.7*)
Remittance income (INR)	227.0 (*1705.3*)	342.1 (*4132.9*)	48.5 (*759.7*)
Proportion of HH who borrowed	0.22 (*0.42*)	0.20 (*0.40*)	0.31 (*0.46*)
Loan size (INR)	1707.1 (*2929.4*)	2114.1 (*3397.4*)	2338.3 (*3058.6*)
Consumption (INR)	748.5 (*768.0*)	785.5 (*1217.6*)	500.6 (*612.8*)
Non-consumption expenditure (INR)	1,222.8 (*3736.0*)	1,263.7 (*2601.3*)	435.3 (*2351.8*)
N × T	14,622	1,189	1,104

Source: Authors' calculations from the financial diaries.
Notes: Standard deviations appear (*in italics*) in parentheses. The sample mean of variables are reported for the three time periods: full baseline, restricted baseline, and post-lockdown, respectively. The sample sizes reported are $(N \times T)$ for each column, where N is the number of panel households and T is the number of weeks in each period. The currency reported for the variables is Indian Rupees (INR). The standard deviations of variables are italicized.

INR 501 (US$ 6.6) and INR 1,223 (US$ 16.2) to INR 435 (US$ 5.7), respectively. Households do not report paying higher interest rates after lockdown despite loan sizes increasing from INR 1,707 (US$ 22.6) to INR 2338 (US$ 31) on an average (table 2); however further analysis reveals an increase in the markup (effective) interest rate on some loans.

Post COVID-19 Lockdown Responses

In our phone call surveys during the first four lockdown weeks, we asked households a set of lockdown-related questions, in addition to our financial diary questions, to understand how they were coping with the economic shutdown. About 86% of the sampled households reported that at least one member lost a job, and about 16% lost employment from the local Mahatma Gandhi National Rural Employment Guarantee Act (MNREGA) job schemes (table 3, panel (a)). During the time of our surveys, the households were in the middle of *Rabi* (winter) crop harvest, and about 20% of them reported income losses related to agriculture because of their inability to reach the traders and, vice versa, due to the lockdown.

About 24% of households reported losing remittance income because migrant members were stranded and jobless in their migrant destinations. Some households sent money to their migrant members in destinations to help them cope with their daily livelihoods (table 3, panel (c)). Of those migrants stuck in their respective destinations, 42% reported losing jobs temporarily, 9% lost jobs permanently, and only 9% kept their jobs (table 3, panel (c)).[6]

[6]These are household-reported information on their migrant members. Forty percent of the households could not answer whether the migrant had their jobs at the destination or not.

Table 3. Summary of Household-Level Loss of Income Sources, Adjustments, and Migrant Members after Lockdown

Variables	Mean	Standard deviation
(a) Loss of income sources		
Proportion of HH…		
With local job loss	0.86	*0.35*
With loss of agricultural income	0.20	*0.40*
With loss of remittance income	0.24	*0.43*
With loss of MNREGA income	0.16	*0.36*
(b) Adjustments on consumption and assets		
Proportion of HH who…		
Increased consumption from own production	0.82	*0.39*
Foraged	0.62	*0.49*
Postponed buying essential household items	0.30	*0.46*
Sold assets	0.07	*0.25*
N	276	
(c) Migrant members		
Has work	0.09	*0.29*
Lost jobs temporarily	0.42	*0.50*
Lost jobs permanently	0.09	*0.29*
Money amount from HH to migrant (INR)	217.95	*975.64*
N	78	

Source: Authors' calculations from phone-call surveys during the COVID-19 lockdown.
Notes: This table shows the sample proportions (mean and standard deviation) of households for the listed variables collected during the phone-call surveys during the COVID-19 lockdown. The currency in the last reported variable in panel (c) is Indian Rupees (INR), which is the amount of money households had sent their migrant members at the time of our phone-call surveys. The sample size of panels (a) and (b) is 276 and of panel (c) is 78. The standard deviations of variables are italicized.

When asked about how households were coping with the income losses during lockdown weeks (table 3, panel (b)), 82% reported having increased consumption of food items from their own production, and 62% engaged in foraging leafy vegetables and small freshwater fish. About 30% postponed the purchase of essential non-food items to save money for food consumption and the uncertain future weeks of lockdown. About 7% reported selling household assets in the first four weeks after the COVID-19 lockdown announcement. The scope of this study restricts us to estimating only the short-term effects of how households coped with the lockdown situation, with longer run ramifications yet to be understood in due course and with future research.

The negative impact of idiosyncratic shocks (e.g., loss of employment) for an individual household can, in theory, be mitigated to a large extent through income smoothing. Although the proportion of households taking out a cash loan remains largely unchanged, the average size of loans is nearly doubled along with a markup, measured as the difference between the amount borrowed and the amount required to pay back the loan (table 4, panel (a)). The duration of the loan has also increased by roughly 50%, allowing more time for repayment. However, the net effect has been a substantial increase in the effective interest rate of loans when borrowing in cash.

In addition to cash loans, the financial diaries also requested households to record in-kind borrowing. Household members were asked to estimate the monetary value of what they had borrowed. Instances of borrowing in-kind have increased (from 12% to 20% in table 4, panel (b)), with the source of the loans being primarily from stores/business owners (i.e., borrowing goods/produce with a promise to pay back later). The estimated value of in-kind loans and the duration have almost doubled. Given the informal nature of borrowing in-kind from local grocery shops, the markup is relatively small.

Empirical Strategy

Our econometric strategy of estimating the impacts of the lockdown utilizes the full forty nine-weeks in 2018–19 as one (full) baseline, and a restricted data on the same four weeks in March–April 2019 as an alternative (restrictive) baseline for comparison. Although the first baseline using the full data compares the financial activities and economic outcomes of the households during the lockdown weeks to an annual average of the previous year controlling for any seasonality during the March–April weeks, the second (restricted) baseline compares the outcomes in the lockdown weeks to the same four weeks last year. We present results based on both baseline samples to perform our econometric analysis of the comparison of outcomes before and after the COVID-19 lockdown announcement.

Our preferred specification for estimating the impacts of COVID-19 lockdown is equation (1), where Y_{it}, the dependent variable, is the outcome of interest. The indicator variable

Table 4. Summary of Local Borrowing and Loans

Variables	Full baseline (Nov '18-Oct '19)	Restricted baseline (Mar '19-April '19)	Post-lockdown (Mar '20-April '20)
		(a) Cash loans	
Probability of getting a cash loan	0.13 (*0.33*)	0.12 (*0.33*)	0.14 (*0.35*)
Loan size	2758.56 (*4696.39*)	3200.22 (*4611.75*)	4332.43 (*5347.03*)
Markup	165.10 (*541.13*)	150.80 (*572.53*)	329.81 (*862.67*)
Duration (days)	60.71 (*82.61*)	67.41 (*94.77*)	99.10 (*58.22*)
		(b) In-kind loans	
Probability of getting an in-kind loan	0.12 (*0.33*)	0.10 (*0.30*)	0.20 (*0.40*)
Loan size	574.96 (*752.36*)	574.78 (*844.35*)	989.00 (*943.91*)
Markup	0.05 (*0.94*)	0.00 (*0.00*)	0.00 (*0.00*)
Duration (days)	67.35 (*95.72*)	51.04 (*78.46*)	96.26 (*52.90*)
N × T	14,622	1,189	1,104

Source: Authors' calculations from the financial diaries.
Notes: Standard deviations appear (*in italics*) in parentheses. The sample mean of variables are reported for the three time periods- full baseline, restricted baseline, and post-lockdown, respectively. The sample sizes reported are ($N \times T$) for each column, where N is the number of panel households and T is the number of weeks in each period. The standard deviations of variables are italicized.

$COVID_t$ takes the value of 1 for the weeks post lockdown announcement (March 25 to April 19) in 2020. We include three sets of other factors in specification (1) to control for potential bias. First, an indicator variable $MarchApril_t$ for the same weeks in 2019 and 2020 to control for seasonality in the weeks of March and April. Second, two trend variables, one before ($PreCOVID_t$) and one after ($PostCOVID_t$), allowing for a break in the trend. Third, we estimate (1) controlling for household-specific fixed effects δ_i for all households.[7]

$$(1) \quad Y_{it} = b_0 + b_1 COVID_t + b_2 MarchApril_t + b_3 PreCOVID_t + b_4 PostCOVID_t + \Sigma_i \delta_i + \varepsilon_{it}$$

The pre-and post-lockdown trends allow for two independent linear trends to fit the outcome variables in 2018–19 weeks in the baseline and the four weeks after lockdown. We leverage the panel structure of our data to estimate a within-household estimator using household fixed effects. All standard errors are clustered at the village level to help account for correlation of the error terms within each village.

The sum of the estimates on coefficient b_1 and b_2 gives the impact of COVID-19 lockdown on our outcome variables of interest compared to the full baseline of 2018–19. For comparison to the restricted sample of March and April, we exclude the indicator variable $MarchApril_t$ and the time-trends from equation (1). Tables 5 and 6 give the estimates of levels and percentage comparisons to full and restricted baselines of the outcome variables of interest.

The gap in the data after the end of one full year of weekly financial diaries (November 2018 to October 2019) until before the announcement of lockdown on March 24, 2020 precludes the use of regression discontinuity in our estimation strategy. Owing to large discrepancies between annual and seasonal income (and expenditures) in developing country poor and agrarian households, we prefer to include both the comparisons of full annual baseline and restricted (March–April 2019) baseline.

Three robustness checks to support the results of equation (1) are performed in the penultimate section: first, with an alternative specification replacing the linear time trend with a more parsimonious week fixed-effects to control and adjust for weekly fluctuations; second, with another alternative specification similar to our preferred specification but separating the weeks post lockdown into two months' (March and April 2020) indicator variables; and, finally, estimating the model as a dynamic panel allowing for lags of dependent variables as independent variables in the respective estimation of the outcomes using an Arellano-Bond instrumental variable approach (Arellano and Bond 1991). Our estimates of the magnitude of losses are largely robust to the alternative specifications and estimation strategies.

[7] $PreCOVID_t$ is a time index and $PostCOVID_t$ is the time index interacted with the $COVID_t$ indicator.

Table 5. Marginal Impacts of COVID-19 Lockdown on Local Income, Total Expenditure, and Remittance Income

Compared to	Changes in	Local income (INR)	Total expenditure (INR)	Remittance income (INR)
Full baseline (Nov '18-Oct '19) $N \times T = 15{,}726$	Levels	−1,021.65*** (105.60)	−1,344.99*** (212.03)	−142.41* (75.18)
	Percentage	*−88%*	*−68%*	*−63%*
	Baseline Mean	1,159.71	1,971.27	227.02
	R^2 (*within*)	0.031	0.007	0.001
Restricted baseline (Mar '19-April '19) $N \times T = 2{,}293$	Levels	−1,109.81*** (58.08)	−1,111.28*** (105.53)	−319.73** (131.88)
	Percentage	*−87%*	*−54%*	*−93%*
	Baseline Mean	1,280.51	2,049.19	342.06
	R^2 (*within*)	0.160	0.049	0.003

Notes: The first column indicates the comparison sample of the post-lockdown data per week at a household level and the sample size of the panel data used in the regressions. The changes from the baselines are reported in levels and percentages. The percentages (*in italics*) are calculated as proportional changes to the respective baseline values of a variable. Also, the table reports the baseline means of the comparison samples, and the R^2 *(within)* from each fixed-effects estimation. Standard errors are reported in parentheses, which are clustered at the village level. Regressions control for a linear time trend, which breaks before and after the lockdown. The percentage change from baseline values of outcome variables are italicized.
*$p < 0.10$.
**$p < 0.05$.
***$p < 0.01$.

Table 6. Marginal Impacts of COVID-19 Lockdown on Consumption Variables

Compared to	Changes in	Total consumption expenditure (INR)	Variety of food items consumed	Indicator for reduced meal portions
Full baseline (Nov '18-Oct '19) $N \times T = 15{,}726$	Levels	−88.65 (100.54)	−4.00*** (0.27)	0.92*** (0.01)
	Percentage	*−12%*	*−56%*	-
	Baseline mean	748.47	7.20	0.04
	R^2 *(within)*	0.028	0.252	0.681
Restricted baseline (Mar '19-April '19) $N \times T = 2{,}293$	Levels	−279.94*** (49.84)	−3.80*** (0.11)	0.96*** (0.01)
	Percentage	*−36%*	*−54%*	-
	Baseline mean	785.45	7.04	0.03
	R^2 *(within)*	0.024	0.557	0.934

Notes: The first column indicates the comparison sample of the post-lockdown data per week at a household level, and the sample size of the panel data used in the regressions. The changes from the baselines are reported in levels and percentages. The percentages (*in italics*) are calculated as proportional decrease to the respective baseline values of a variable. Also, the table reports the baseline means of the comparison samples, and the R^2 *(within)* from each fixed-effects estimation. Standard errors are reported in parentheses, which are clustered at the village level. Regressions control for a linear time trend, which breaks before and after the lockdown. The percentage change from baseline values of outcome variables are italicized.
*$p < 0.10$,
**$p < 0.05$,
***$p < 0.01$

Results

We present the results from the econometric analysis of weekly data to show how households were affected in the first four weeks after the lockdown announcement. About 34% of households in our sample live below the Indian rural poverty line of INR 816 (US$ 10.8) per person per month, making them more vulnerable to economic shocks. They rely heavily on income generated locally from economic activities within the region and

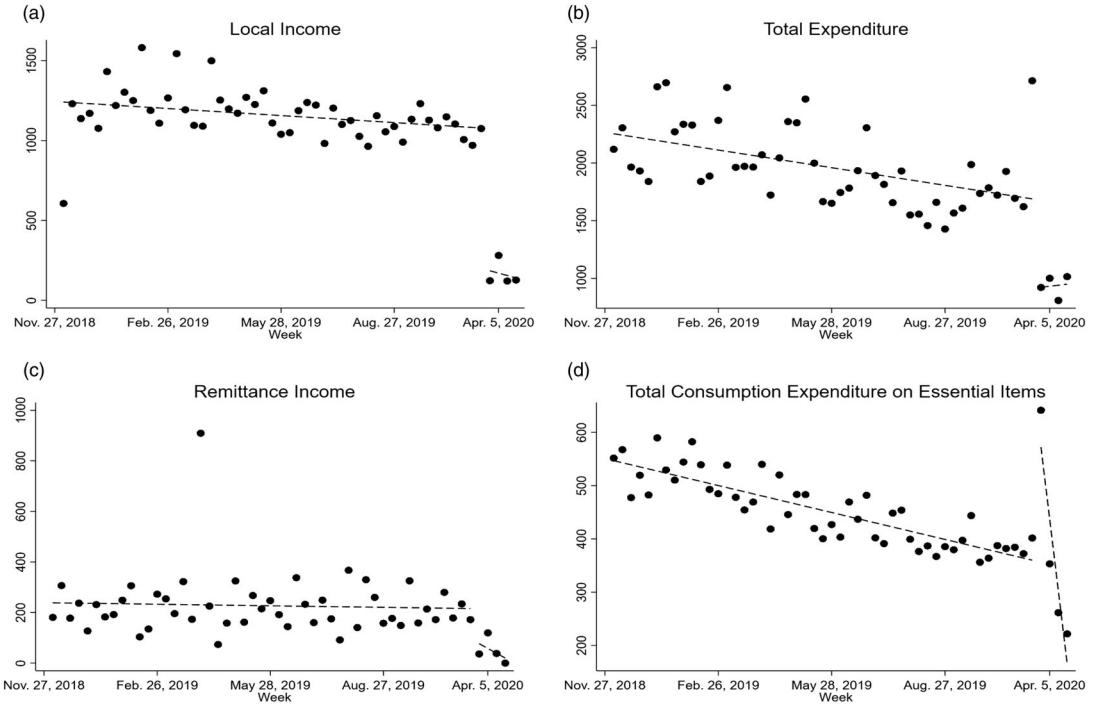

Figure 1. Weekly average plots of all variables at the household-level against time (in weeks)

Note: The pre-lockdown weekly data are from November 2018 to October 2019, and post lockdown four weeks are from March 25 to April 19, 2020.
Source: Authors' calculations.

remittances from migrants in other parts of India. A substantial and significant decrease in both local and remittance income after the lockdown announcement has reduced households' ability to purchase essential food and non-food items to sustain their livelihoods.

The four panels (a)–(d) in figure 1 show averages of weekly local income, total expenditure, remittance income, and consumption expenditure on essential items, respectively, against time measured in weeks. The households' average local income, total expenditure, and remittance income reduced drastically after the lockdown, compared to their respective averages last year. Household consumption expenditure on essential items did not decline immediately in the first week of lockdown, indicating that households spent their money on stockpiling food and other consumption items. They mainly purchased rice, grains, other cereals, and vegetables. However, in subsequent weeks, consumption expenditure on essential items fell (figure 1, panel (d)).

A panel fixed effects model, as described in equation (1), is utilized to evaluate the impacts of the lockdown on consumption diversity (number of different food items consumed in a week) and food security (reduced meal portions) in addition to the variables described in figure 1. We present estimated outcomes of the lockdown to both our baselines, full and restricted. The results of our econometric estimations are presented in tables 5 and 6. For our discussion throughout the rest of the paper, we only use the comparison to the full baseline.

Impacts on Household Income, Expenditures, and Remittances

About 86% of households report that at least one household member became unemployed. Around 16% of those previously employed were unable to continue their work as a casual laborer under the MNREGA, a government employment scheme that ensures 100 days of employment for the rural poor.[8] We find that average household weekly local income fell

[8]See Table 3 for a detailed summary of household losses post COVID-19 lockdown.

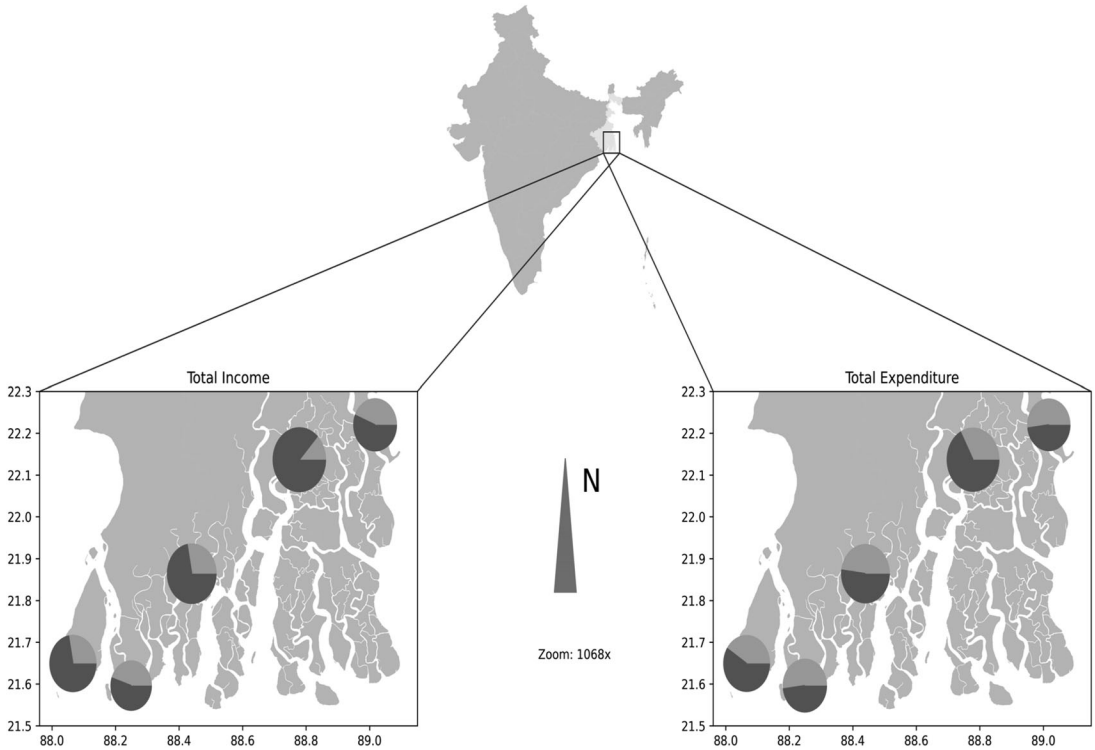

Figure 2. Income and expenditure loss by cluster

Notes: The light-gray area in the circle represents the average household income (expenditure) post-lockdown, while the dark-gray area shows the reduction in income (expenditure) from the pre-lockdown period, respectively. The size of the circle in each case shows the relative pre-lockdown average in each administrative block.
Source: Authors' calculations from estimations in Table 7.

by 88% when compared to their annual average weekly local income last year (table 5, column (1)). Figure 2 (left panel) shows the estimated reduction in weekly total income (local and remittance) from their annual averages in the previous year for each of the five administrative block clusters in our sample. The size of the circles represents the relative pre-lockdown average income in each administrative block. The light-gray area in the circle represents the average household income post-lockdown, and the dark-gray area shows the percentage reduction in income from the pre-lockdown period.

Households in the Sundarbans, typical of a poor region with substantial migration, also rely on migrant remittances for their daily subsistence. About 65% of our sample in the baseline had at least one migrant member working as a casual laborer in a major Indian city or other parts of the country. We find that remittance income reduced significantly by 63% after the announcement of nationwide lockdown as the migrants lost their employment in their destinations (table 5, column (3)). Our phone call surveys revealed that households, on average, sent INR 218 (US$ 3) to their migrant members during these four weeks post lockdown, conditional on the migrants remaining at the destinations during the time of the survey.[9]

In an average week, rural households frequently purchase both consumption and non-consumption goods. The typical consumption basket includes staples like rice, wheat, pulses, vegetables and fruits, and protein items like dairy products, eggs, fish, and meats. Non-consumption expenditures vary weekly depending on the items purchased, like clothes, personal non-durables, or paying utility bills and buying household durables. The map in figure 2 (right panel) shows the

[9]See Table 5 for detailed summary statistics on households' migrant members.

Table 7. Marginal Impacts of COVID-19 Lockdown on Borrowing and Non-Consumption Expenditure Using Main Specification

Compared to	Changes in	Indicator for borrowing in cash	Indicator for borrowing in kind	Non-consumption expenditure (INR)
Full baseline	Levels	−0.04 (0.04)	0.11*** (0.04)	−1,256.33*** (174.70)
(Nov '18-Oct '19)	*Percentage*	*−29%*	*92%*	*−103%*
$N \times T = 15{,}726$	Baseline mean	0.13	0.12	1,222.80
	R^2 *(within)*	0.018	0.007	0.004
Restricted baseline	Levels	0.02 (0.02)	0.11*** (0.01)	−831.34*** (92.32)
(Mar '19–April '19)	*Percentage*	*13%*	*110%*	*−66%*
$N \times T = 2{,}293$	Baseline mean	0.12	0.10	1,263.74
	R^2 *(within)*	0.001	0.030	0.035

Notes: The first column indicates the comparison sample of the post-lockdown data per week at a household level, and the sample size of the panel data used in the regressions. The changes from the baselines are reported in levels and percentages. The percentages (*in italics*) are calculated as proportional decrease to the respective baseline values of a variable. Also, the table reports the baseline means of the comparison samples, and the R^2 *(within)* from each fixed-effects estimation. Standard errors are reported in parentheses, which are clustered at the village level. Regressions control for a linear time trend, which breaks before and after the lockdown. The percentage change from baseline values of outcome variables are italicized.

*$p < 0.10$.

**$p < 0.05$.

***$p < 0.01$.

estimated reduction in average total household expenditures post COVID-19 lockdown in the different clusters. We find that total household weekly expenditures plummeted by 68% in the first four weeks after the announcement of the lockdown (table 5, column (2)).

Impacts on Consumption and Food Security

Although total spending on all items declined significantly, the average weekly reduction in consumption good expenditure was by 12% (table 6, column (1)) and that of non-consumption items was by 103%, respectively (table 7, column (3)).[10] The point estimate on consumption expenditure is not statistically significantly different from the baseline due to the panic purchase in the first week of lockdown immediately after its announcement (see figure 1, panel (d)). However, after the first week, consumption expenditures declined significantly compared to the baseline weeks by INR 260 to 375 (US$ 3.4 to 4.9).[11] Expenditures on non-food items essentially collapsed to zero during the post-COVID-19 period as households preserved their remaining cash for purchasing food items.

Households coped during the first four weeks of lockdown by reducing the number of food items they typically consume or limiting the portion size of meals altogether. The instances of reduced-size meals in a week increased by twenty-three times that of the baseline, that is, from about 4% to over 90% (table 6, column (3)). We also find households cut down the diversity of consumed items by 56% after the lockdown (table 6, column (2)).

The effect of the lockdown on food consumption was slightly mitigated by the food aid provided to all households through the Indian public distribution system (Roy, Boss, and Pradhan 2020). The government announced a provision of 5 kilograms of rice or wheat and a kilogram of pulses free for a month, per person. Of the 83% of households that procured their food aid, they reported receiving 14 kilograms of rice and wheat in total per family, along with 3 kilograms of potatoes.[12] About 25% of the households also received INR 603 (US$ 8) through a direct cash-based transfer to women beneficiaries with a *Jan Dhan* account, a Government of India initiative that started in 2014 for the expansion of financial inclusion (*Economic Times* 2020).

[10]Reductions over 100% imply that the drop in non-food expenditure is higher than the average expenditures in the baseline.

[11]The regression results are presented in online supplementary appendix table A9.

[12]Households in the Sundarbans received potatoes instead of pulses.

Impacts on Borrowing and Loans

There was a reduction in household borrowing in cash, largely due to a lack of lenders' willingness to lend money (table 7). However, this reduction was statistically insignificant when compared to the pre-lockdown baseline.[13] Borrowing in-kind increased substantially by 92% because many households were cash strapped (table 7, column (2)). The local groceries lent out food items in the first week after lockdown but stopped doing so in subsequent weeks.[14] Anecdotal conversations with community leaders suggest that some households resorted to selling their vegetables and grains reserved for future self-consumption at lower than usual prices. A complete inability to export goods outside of their village has contributed to some reductions, rather than increases, in the prices of some consumption goods such as vegetables. Responses from a community questionnaire reveal that although prices of staples remained more or less stable pre- and post-lockdown, the price of cooking oil, which is imported from outside the region, increased, while the prices of vegetables that were locally produced declined.[15] The households also exchanged agricultural labor for crop harvest and sold vegetables from their garden plots to their neighbors within the community while maintaining social distancing.

The purpose of the loan has also changed post-COVID-19 lockdown. Whereas previously, around 65% of loans (either cash or in-kind) were primarily taken out to purchase consumption goods, that number has now increased to 92% (online supplementary appendix table A2). Access to funds for the purchase of food items has become a priority. This has potentially long-term implications for the households in this region as purchases of inputs and assets for agricultural production have fallen to the wayside, lowering future household incomes. Loan payback is another concerning issue as previously around 10% of borrowing was for the express purpose of paying off a previous loan. That number has dropped to 1% during the lockdown (online supplementary appendix table A2). It is highly unlikely that households collectively paid off their loans before the lockdown. Thus, the lockdown may push households further into debt, especially because most cash loans are taken out from other households, which may suffer should the debtor fail to pay back their loans.

To help assess the impact of the lockdown on local borrowing patterns, we additionally asked households how much they would have needed in loans for each of the four weeks recorded. We see a spike in the amount of loans desired in the first week after the lockdown and then a steady reduction, meanwhile actual loans as a percentage of the loans the household would like to take out remains fairly constant (online supplementary appendix table A3). Although we take this as evidence that some liquidity remains in these local communities, it is important to note that this information is only available for the month immediately after lockdowns. The current state of local loans is unknown and has likely deteriorated.

Heterogenous Impacts, Alternative Specifications, and Robustness Checks

We describe our preferred specification for estimating the impacts of COVID-19 lockdown in equation (1). This section presents results from three sets of robustness checks to compare against the findings from the estimation of equation (1).

First, we employ a model with a more parsimonious time trend to check for the robustness of our results and if they are being driven by our simplified assumption of a linear time trend, pre-and-post lockdown. Second, we perform another robustness check with the linear time (week) trend but separating the weeks post COVID-19 lockdown into March and April 2020 weeks by creating two indicator variables for the two months, respectively. Finally, we modify equation (1) to be estimated via a dynamic panel model to address potential endogeneity issues with the dependent variables.[16] The dynamic panel model with longer time lags also doubles as a

[13]In the COVID-19 supplemental questionnaire, we ask household members, "Did you try to get a cash loan this week?" to which 14% answered yes. This is not significantly different from the 13% average percent chance of borrowing during the pre-COVID-19 sample.

[14]See online supplementary appendix Tables A2 and A3 for detailed summary statistics on borrowing and loans.

[15]Online supplementary appendix Figure A1 provides a time-series plot of weekly prices of consumption good post lockdown.

[16]Our primary concern is the endogeneity of lagged dependent variables (omitted from the base model) and the error term. For example, households who purchased a lot of rice last week would likely reduce subsequent purchases the following week.

check for the robustness of our standard errors under serial correlation.

The linear time-trend breaks in equation (1), captured by the two trend variables $PreCOVID_t$ and $PostCOVID_t$, despite being a useful simplifying assumption, may not capture the full extent of non-linear seasonal fluctuations throughout our panel, which could result in biased estimates. First, an nth degree polynomial (upwards of fifth degree) allowing for a more non-linear time trend was estimated to similar results.[17] Next, to allow the most parsimonious time trend, an alternative specification replacing the time trend variable with time (week) fixed-effects was estimated for comparison. The resulting transformed equation that we estimate is described in equation (2),

$$(2) \quad Y_{it} = b_0 + b_1 COVID_t + b_2 MarchApril_t + \sum_{t \in T} \gamma_t + \sum_{\forall i} \delta_i + \zeta_{it}$$

Like equation (1). (2) additionally consists of household-specific fixed effect δ_i and an indicator variable $MarchApril_t$ to control for any seasonality for weeks in March and April. γ_t are weekly dummies over the entire sampling time frame. The estimated results of (2) appear in panels (a) of online supplementary appendix tables A4 and A5, and are similar to those under our primary specification.

We perform another robustness to our preferred specification in equation (1) by replacing the post COVID-19 weeks indicator variable, $COVID_t$, and the indicator for March and April weeks in 2019–20, $MarchApril_t$, with separate month indicators for March 2020 and April 2020, $Mar2020_t$ and $Apr2020_t$, respectively, in equation (3). This alternative specification in equation (3) checks if our results are robust to any month-to-month seasonal variation in March and April 2020.

$$(3) \quad Y_{it} = b_0 + b_1 Mar2020_t + b_2 Apr2020_t + b_3 PreCOVID_t + b_4 PostCOVID_t + \sum_{\forall i} \delta_i + \vartheta_{it}$$

Like equations (1)–(2), equation (3) additionally consists of household-specific fixed effect δ_i. The estimated results of (3) appear in panels (b) of online supplementary appendix tables A4 and A5 and are largely similar to those in our primary specification.

Next, we employ an Arellano-Bond dynamic panel model to check the robustness of the estimated coefficient on $COVID_t$, which may suffer from potential endogeneity in a static panel model. We modify equation (1) to fit a dynamic panel by including lagged levels of the dependent variable, instrumented with the lagged dependent variable. The transformed equation is shown in (4):

$$(4) \quad Y_{it} = b_0 + \sum_{k>0} \rho_k Y_{i,t-k} + b_1 COVID_t + b_2 MarchApril_t + b_3 PreCOVID_t + b_4 PostCOVID_t + \alpha_i + \xi_{it}$$

where $Y_{i,\,t-k}$ is the lagged dependent variable for k lags and α_i is a time-invariant household fixed effect. In practice, we test the crucial assumption of serially uncorrelated errors ξ_{it}, a necessary condition for implementation of the Arellano-Bond estimator for each equation.

Estimates from (4) using the Arellano-Bond instrumental variables approach are shown in panels (a) and (b) in online supplementary appendix table A6 (Arellano and Bond 1991; Cameron and Trivedi 2009; Roodman 2009). The estimated impacts as changes in levels and percentages from the Arellano-Bond estimation are also presented in online supplementary appendix table A6 with heteroskedastic-consistent estimates of the variance–covariance matrix clustered at the village level. We find that the dynamic panel estimates are significant and comparable in magnitudes to our main specification in equation (1).

An extension of our base model using quantile regressions, presented in online supplementary appendix table A7, shows that impacts are not evenly distributed among different quantiles of the outcome variables. Percentage reductions in income and total expenditures are substantially higher for households at lower income and expenditure percentiles. Poorer households are hit harder by the lockdown in terms of a percentage of their income and expenditures, though they lose less in absolute terms. Reductions to consumption expenditures are larger for poorer households, coupled with a dramatic increase in reduced meals raising concerns over short-term food security in the region.

[17]The results of non-linear time trends are available upon request.

Table 8. Conditional Correlations of Percentage Reduction in Total Income and Total Expenditure from Baseline

Variables	Dependent variables (% reduction from baseline)	
	Total income	Total expenditure
Total expenditure (in full baseline)	-	0.0001* (0.00004)
Total income (in full baseline)	0.00004 (0.0001)	-
Dummy if aid package received	0.043 (0.119)	0.115 (0.151)
Dummy if HH in bottom 50th percentile (in full baseline)	−0.215** (0.095)	0.093 (0.089)
Household characteristics		
HH size	−0.015 (0.016)	0.003 (0.019)
Female headed HH	0.177 (0.125)	0.085 (0.083)
HH with migrant	0.082 (0.149)	0.151 (0.117)
HH involved in agriculture	0.069 (0.112)	−0.136 (0.082)
HH with business	0.04 (0.103)	0.153** (0.076)
Impacted income sources		
Loss of local employment	0.198 (0.146)	−0.249*** (0.075)
Loss of agricultural income	0.005 (0.09)	10.045 (0.110)
Loss of remittance income	0.133* (0.077)	0.009 (0.112)
Loss of business income	0.045 (0.141)	−0.053 (0.097)
Loss of MNREGA income	−0.289 (0.228)	0.064 (0.144)
Constant	0.597*** (0.217)	0.292 (0.199)
N	276	276

Notes: Standard errors are reported in the parentheses. The dependent variables (total income and total expenditure) are percentage reduction in the lockdown weeks compared to the full baseline (Nov'18-Oct'19). Total income is defined as the sum of local and remittance incomes. The percentage change from baseline values of outcome variables are italicized.

*$p < 0.10$.

**$p < 0.05$.

***$p < 0.01$.

We utilize information from the post lockdown supplementary questionnaire to examine the heterogeneous impacts of the lockdown. Impacts of the lockdown in terms of losses to income sources are severe enough such that they have had a negative effect on income differentials between households. Thus, the gap between poorer and wealthier households has closed. Prior to the lockdown, the difference in average weekly income and expenditure between the top and bottom 50th percentile of households was around INR 1,328 (US$ 17.6 and INR 1,169 (US$ 15.5), respectively (see online supplementary appendix table A8). Post lockdown, the gap in income sources is no longer significant, although expenditures remained relatively higher for the top 50th percentile, with the difference being INR 430 (US$ 5.7). This result corroborates local reports that nearly all economic activity has ceased in the area, thus wealthier households that previously had more/higher sources of income have lost more in absolute terms. The lockdown has essentially made households more equal in terms of income and expenditures, albeit in a regressive way.

In addition, we explore the relationship between household characteristics and how they were impacted by the lockdown. Table 8 presents the results of the reduction in income and expenditures (calculated as a percentage reduction over pre-lockdown average income/expenditures) regressed over a vector of household characteristics and self-reported loss of income by the household. Our results here should not be interpreted as causal but rather as conditional correlations due to the potential endogeneity of the explanatory variables like income and expenditure. Households with a higher average expenditure during the baseline experience a slightly larger percentage reduction in their weekly income; we observe a similar impact on incomes, albeit not significant. Receipt of the government food aid package has no statistically significant impact on spending because the food aid was universally distributed. A large percentage of our sample (about 86%) received aid from the government or non-government organizations (NGOs) at the time of the survey. Most aids were delivered in-kind, usually in the form of rice, wheat, or potatoes. We only find

a significant correlation between the business operations of a household on average spending. Households who own and operate a business can draw down their stores, resulting in a larger spending departure from their pre-lockdown average spending.[18]

Finally, in our follow-up survey (post-lockdown), we asked households to self-report income-generating activities impacted by the lockdown. We find that losing remittance incomes is positive and significantly correlated with a larger reduction in average weekly income. The shutting down of remittances due to the massive loss of migrant income has negatively impacted many households who rely on transfer income. Surprisingly, we find that losing a local job (non-migrant job) is negatively correlated with spending reductions, meaning households with some members who lost a local job reduce their spending less than those who do not. Although initially perplexing, conversations with households in our sample reveal that this is largely driven by the need to provide food to an additional person in the household now that they no longer receive meal benefits, a common form of compensation, on the job. This result highlights the value of microeconomic studies in understanding the complex impacts that the lockdown may have.

Conclusions

The findings from this paper provide estimates and a glimpse into the extent to which poor households are affected by the largest lockdown due to the COVID-19 pandemic. The results have immediate relevance to policymakers considering additional lockdowns as the pandemic resurges around the globe and to governments thinking about responses to future pandemics that may occur. Using high-frequency weekly household-level data before and after the lockdown from a relatively poor region in India with high out-migration, we find that households lost 88% local income and 63% remittance income. Households coped with their income losses in the first four weeks of the lockdown by reducing purchases of non-consumption items, consuming less diverse food items, and cutting down on meal portions. Most of these households also increased consumption from self-production and relied on foraging leafy vegetables and small freshwater fish. Many migrant members of our surveyed households, who were still stranded in their migrant destinations at the time of our surveys, lost their jobs and relied on local aid in the cities and other parts of India for their subsistence. In some instances, households sent money to migrant members to support them during the lockdown. Although the first week post-lockdown witnessed panic purchases of food items, particularly staples, we found that households spent less on essential food items in subsequent weeks.

Our paper utilizes extremely detailed weekly data to focus on the immediate short-run impacts of the COVID-19 lockdown on poor and vulnerable households. However, this once-in-a-century covariate shock in the form of a pandemic and, consequently, nation-wide lockdowns, is likely to have severe longer term ramifications for the well-being of the impoverished and the vulnerable households living in some of the poorest rural parts of the world. On the brink of food insecurity, rural households may smooth consumption in the immediate aftermath of lockdowns but possibly may have to revert to various income smoothing mechanisms such as selling off productive assets and livestock should income sources shrink with prolonged lockdowns.

Dealing with this economic crisis for the poor may call for interventions by the government and other local agencies in the rural areas of developing countries. Such responses could include cash transfers to the poor and vulnerable households, expansion of existing social safety nets, and ensuring assistance in harvesting and selling of crops in rural areas as relief to distressed farmers (Gerard, Imbert, and Orkin 2020; Mishra and Rampal 2020). In the Indian context, the national government provided food aid of essential staples and cash transfers to women beneficiaries of *Jan Dhan* account holders. The Government of India also extended the MNREGA employment support starting in May 2020 (Ministry of Rural Development, Government of India 2020). However, disbursement of such relief programs cannot possibly be instantaneous. The long-term effects of COVID-19 remain to be seen, but it is important to keep in mind that such prolonged negative shocks can lead to persistent poverty trap dynamics.

[18]It should be noted that business input purchases were not recorded. Thus, this cannot reflect a reduction in input purchases.

Some of the sustained negative impacts of lockdowns for the rural poor may be mitigated or prevented by timely and continuous support in the form of government interventions. This paper shows how high-frequency data can provide insight into the immediate short-run impacts of large shocks on rural poor households and emphasizes the importance of future research to investigate the longer term impacts of severe pandemics like COVID-19 on the poor and the vulnerable.

Supplementary Material

Supplementary material are available at American Journal of Agricultural Economics *online.*

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