Migration and Resilience during a Global Crisis

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Abstract

This study explores the relationship between migration and household resilience during a global crisis that eliminated the option to migrate. We link prior data from four populations in Bangladesh and Nepal to new phone surveys conducted during the early months of the COVID-19 pandemic. While earnings fell universally, pandemic-induced declines were 14–25% greater among previously migration-dependent households and urban migrant workers, with household remittance losses far exceeding official statistics. Heightened economic exposure during the pandemic erased prior gains achieved by transnational migrants and caused fourfold greater prevalence of food insecurity among domestic subsistence migrants. Economic distress spilled over onto non-migrants in high-migration villages and labor markets. We show that migration contributed to economic contagion independent of its role in disease transmission. Losing the option to migrate differentially increased the vulnerability of migration-dependent households during a crisis.

JEL Codes: G52, I15, J61, O15

1 Introduction

Economic migration is ubiquitous. An estimated 272 million people live outside their country of birth, of which 192 million come from regions classified as "less developed" (UNDESA, 2019). Direct remittances to low- and middle-income countries (LMICs) in 2018 reached nearly $500 billion, triple the flow of official development assistance and roughly 80% as much as foreign direct investment. Internal migration is even more prevalent with an estimated 763 million internal migrants worldwide, two-thirds of whom reside within LMICs (UNDESA, 2013). This mobility is closely tied to households' immediate financial prospects and long-term economic development.

In this paper, we demonstrate the importance of migration for household resilience to large-scale economic shocks using data from the COVID-19 pandemic. While the pandemic disrupted economies in many ways, it provides a unique opportunity to study the relationship between migration and economic distress because the global downturn was accompanied by severely curtailed geographic mobility. South Asia was no exception to the global trend, with numerous travel restrictions in place to slow contagion (see Hale et al., 2020). The region saw a mass return of international migrants at the onset of the pandemic (IOM 2021; OECD/ADBI/ILO 2021, e.g.) as well as comparably large within-country returns to rural places of origin (e.g. Roy and Agarwal, 2020).

We quantify the differential economic impact of COVID-19 on migrant populations in South Asia in the early months of the pandemic during the height of travel disruptions using new survey data. Surveys cover four distinct populations in Bangladesh and Nepal: in Bangladesh we surveyed former applicants for an international work visa, landless agricultural households in a high-migration rural region with predominantly domestic destinations, and casual day laborers at major urban markets; and in Nepal we surveyed low-income households in a high-migration rural region with destinations both within the country and in neighboring India. Survey samples were selected based on their prior involvement in ongoing research, and are therefore statistically representative of their underlying populations.

Income declined with the onset of the pandemic throughout our populations of study, but we find this decline to have been 14–25 percentage points more severe among households previously dependent on migration. A large fraction of this heightened impact was driven by loss of remittances, which fell 65 percent. These results complement existing studies showing economic contraction in OECD countries to be concentrated among occupations and industries high in migrant labor (Garrote Sanchez et al., 2020; Fasani and Mazza, 2020; Gelatt, 2020; Kerwin and Warren, 2020; Borjas and Cassidy, 2020; Shin, 2022), leading to a global reduction in official remittances Q2 2020 in the months immediately following the pandemic's spread (World Bank, 2020b). Our work extends previous findings along three dimensions. First, the use of household surveys enables us to reach populations often excluded from official statistics. Deaton (2005), among others, discusses shortcomings of official statistics when informal labor is common. Second, we focus on migrants traveling either domestically or to other developing regions rather than to OECD destinations. Third, our results relate previously documented labor market impacts of COVID-19 to household wellbeing. This study is informative about the extent to which migration-dependent households are insured against loss of migration income and economic shocks more generally.

Our analysis uncovers three novel facts about the nature of migrants' economic exposure. First, we document declines in remittance earnings far greater than those seen in official statistics. For example, among international migrants in Bangladesh, the estimated fall in remittance earnings in Q2 2020 in survey data exceeds that reported in the World Bank's KNOMAD database by more than 50 percentage points. Our findings stand in contrast to Dinarte et al. (2021) who report increases in remittances from the United States to Mexico following the pandemic, driven in part by a shift away from informal to formal remittance channels, and provide suggestive evidence of similar patterns in several countries. While our context differs, survey data indicate the decline in informal remittances far outpaced any offsetting gains in formal remittances. The discrepancy between official statistics and household surveys calls into question prominent reports from many nations that remittance flows recovered in Q3 2020 and beyond to above their 2019 levels. We urge caution in interpreting such data, especially in settings where informal remittances represent a substantial fraction of financial flows.

Second, we find the effect of lost migration income on household wellbeing varies with the type of migration involved. Transnational Bangladeshi migrants who received work opportunities in Malaysia by winning a visa lottery came from economically stable households and had enjoyed years of elevated earnings before the pandemic. COVID-19 wiped out all prior gains in this population, and lottery winners fared no better than lottery losers in terms of income or food security in the early months of the pandemic—the rate of food insecurity rose from 2% to 48% among both groups. This parity suggests that while migration can be a productive endeavor when available, it does not necessarily enable households to diversify production or build buffers that insure against the loss of migration opportunities.

In contrast, our rural survey populations in Bangladesh and Nepal primarily engaged in a form of "subsistence migration" to help cope with periods of deprivation in the rural area. Pre-pandemic income differences between migrants and non-migrants in these populations were minimal. A large gap in food insecurity emerged in the early pandemic months, and migration-dependent households were nearly 20 percentage points more likely to be food insecure than non-migrants. Among migrant households, food insecurity exceeded that of a typical lean season despite the pandemic arriving around a time of harvest. These magnitudes underscore the importance of migration as a tool to deal with economic shocks, and the resulting vulnerability of poor rural households when migration becomes unavailable.

Third, we show how migration linkages contribute to economic contagion from large-scale shocks. While migration has proven to be a vector of disease spread during the pandemic (Ahsan et al., 2020; Valsecchi, 2020), we present evidence it induced additional diffusion of economic contraction over and above its health effects. At the household level, migration-dependence better predicts economic distress in rural communities than the presence of COVID-19 symptoms. Moreover, for earners, disease prevalence at their destination labor market is a stronger predictor of pandemic earnings decline than disease prevalence at their native home or current residence. These household impacts also put a strain on local social networks, and even non-migrants faced elevated levels of food insecurity in villages and markets with high rates of migration dependence. Migration can drive a wedge between the epidemiological and economic impacts of the pandemic, and, as a result, the optimal targeting of resources for economic recovery may diverge from local pandemic severity.

The main empirical innovation in this paper is the use of household survey panel data containing pre- and post-pandemic outcomes. Linking to prior research enables a difference-in-differences study design that conditions on survey respondents' pre-COVID status. We define migration dependence based on household behavior before the pandemic, and then quantify how pandemic-induced changes in economic outcomes vary with migration dependence. The key identifying assumption is that differences in outcomes would have remained stable were it not for the global pandemic. In the case of the visa lottery sample, this empirical strategy identifies differences in pandemic impacts on households that were statistically identical before the lottery, a random subset of which enjoyed up to seven years of a migration earnings premium heading in to 2020. In two other populations—the rural samples from Bangladesh and Nepal—we present evidence of prior parallel trends in a monthly panel of household food security, and in the urban sample from Bangladesh we verify parity in pre-pandemic earnings. Where possible, we report year-on-year changes to account for seasonal variation.

A drawback of this study design is that post-COVID phone surveys were of limited duration to ensure completion, and the studies were unrelated before the pandemic. Phone questionnaires were adjusted by sample to maximize comparability to prior data, and hence, not all outcomes are harmonized or even available for all samples. In addition, due to the nature of the pre-existing research, we cannot construct comparison groups consisting of both workers at the migrants' destination and households at the migrants' origin for any survey population. We analyze the former in the urban worker sample from Bangladesh and the latter in the three household samples. Nevertheless, we present some of the only randomly sampled household-level data available from this period and region, and demonstrate a consistent pattern of heightened economic exposure among migration-dependent households.

This research sheds light on the relationship between migration and household economic stability. Prior work identifies migration as a form of self-insurance against community-level shocks such as natural disasters (Gröger and Zylberberg, 2016; Mbaye and Drabo, 2017) and seasonal fluctuations (Imbert and Papp, 2019; Molina-Millán, 2020; Lagakos et al., 2023), and has found this coping strategy to substitute with other types of social insurance (Munshi and Rosenzweig, 2016; Morten, 2019; Meghir et al., 2021). Such studies typically quantify the worker, household, and community impacts of shocks that induce a migration response. We analyze the inverse case of a shock that took away the option to migrate from those that had previously relied on it. In this regard, our investigation is most similar to Theoharides (2020); Cinque and Reiners (2022), who evaluate the closure of specific transnational migration channels. Cinque and Reiners (2022) find migration disruptions to be most damaging in the presence of another regional economic shock, consistent with our results.

Our findings more broadly contribute to estimates of the causal returns to migration. A small number of experimental evaluations find high earnings returns to both domestic and international migration, on the order of 50–250% (McKenzie et al., 2010; Bryan et al., 2014; Akram et al., 2017; Shrestha et al., 2020; Clemens and Postel, 2017; Barker et al., 2020). Other estimates using panel fixed-effects (Hendricks and Schoellman, 2017; Alvarez, 2020; Hamory et al., 2021; Lagakos et al., 2020) suggest observational returns may be more moderate after accounting for unobserved worker characteristics. Our data indicate that, in the context of a large-scale economic downturn, foregone migration income cannot easily be recovered in locally.

Our analysis highlights how, in conjunction with high returns, the risk of migration disruption can be a source of fragility. This risk compounds other ways in which migrants are economically and legally vulnerable, including exploitation by employers (Auwal, 2010; Hargreaves et al., 2019), exposure to macroeconomic shocks (Caballero et al., 2021; Gröger, 2021), and in the case of international migration, exchange rate fluctuations (Clemens, 2019; Yang, 2008). Such uncertainty can be particularly damaging given high up-front relocation costs, which cause households who invest in the migration of their productive members to be highly dependent on the income realization of the migrant (Bryan et al., 2014).

This study also contributes directly to research on the impact of COVID-19 in developing countries. Egger et al. (2021); Josephson et al. (2021) report ubiquitous declines in economic wellbeing across a number of LMICs using household survey data[1]. These economic impacts compound well-documented disparities in health outcomes during the pandemic, especially among low-income populations (e.g. Garg et al., 2020; Barnett-Howell and Mobarak, 2020). We extend existing findings by identifying a large subpopulation that is particularly economically vulnerable. An important related contribution is that of Gupta et al. (2021), who use financial transaction data to document sizable falls in income and food consumption, partially

[1]Some of the data in this paper also contributed to results presented by Egger et al. (2021)

driven by a fall in remittances, in a high-migration, rural region of India. Our two analyses reveal consistent patterns among similarly situated populations using different sources of data.

In Section 2 of this paper we describe the main methodology and various sources of data we draw on. Section 3 discusses our study samples in relation to migration globally. Section 4 presents our main findings on household economic impacts, and Section 5 explores how migration linkages affect the geography of economic transmission. We conclude in Section 6 by discussing broader implications.

2 Data and Methodology

This paper presents new evidence on how the migration disruptions caused by COVID-19 and associated lockdown policies differentially affected households that rely on migration income. For this exercise, we combine new phone survey data with existing records among three populations in Bangladesh and one in Nepal. All four samples were selected based on participation in prior research by the authors of this paper, and are statistically representative of their underlying populations. Pre-COVID data allow us to classify households by prior migration reliance and to control for pre-existing economic status. Data collection from each of these studies was either ongoing or complete by February 2020.

We re-contacted participants from each sample by phone in April–June 2020 with questions about recent travel, health symptoms, and earnings and financial distress. Surveys were restricted to twenty minutes to ensure completion. While this time constraint limited the scope of data collection, we present some of the only direct survey evidence generated by random sampling in this region during the early months of the pandemic.

The four study samples are summarized in Table 1, with further details in Appendix A:

Bangladesh–Malaysia Visa Lottery (G2G): The Government-to-Government (G2G) visa lottery study consists of Bangladeshi individuals who applied in 2013 for a visa to work in Malaysia. A random sample of 3,512 households representing lottery winners and losers were surveyed in person in August–December 2018, and we reached 3,233 of these by phone surveys conducted in April and June 2020[2] Migration-dependent households in this sample are defined as those that were awarded a visa in the lottery.

Migration enabled by the G2G lottery generally represents an expansion of economic opportunity for households that are already reasonably well off. Those that apply for work visas have the means to finance international travel. Correspondingly, the pre-pandemic incidence of poverty in this sample was nine percentage points below the national average. Visa holders migrate internationally for durations spanning several years and earn substantially more abroad than they would have domestically.

[2]We reached 2,557 (73%) in both phone surveys, 676 (19%) in one of the two waves, and 279 (8%) in neither wave.

Due to oversubscription, visas were awarded by lottery to around 30,000 of the nearly 1.5 million applicants in 2013. Households entering the lottery were identical prior to the allocation, and the lottery introduced experimental variation in the subsequent propensity to migrate. By 2018, lottery winners were 58 percentage points more likely to have had a member employed in another country, although many lottery losers also found ways to work abroad through alternate means. Shrestha et al. (2020) estimate income doubled for households in the G2G population enabled to migrate by the visa lottery. Among lottery-winning households, remittances comprised 33% of income on average in 2018 for the family in Bangladesh, and 63% when the visa holder was still abroad.

The primary impact of COVID-19 on this sample was loss of work at the migration destination. As of June 2020, only 2% of lottery applicants had returned from being away to Bangladesh in the window of time since February 2020, and this value did not differ by lottery status. Nevertheless, lottery-winning applicants experienced a 30 percentage point drop in whether they were working as of June 2020 relative to pre-pandemic, a 7 percentage point larger decline than for lottery losers. Our analysis in this sample evaluates whether the higher earnings enjoyed by migrant households over the prior seven years enabled them to build up assets or establish alternate sources of income to insure against this loss of migration earnings.

Nepal Rural Communities (NPL): The Nepal Seasonality (NPL) study consists of 1,820 households selected from the bottom half of the wealth distribution in multiple rural wards of the Western Terai region of Nepal. We construct a household panel of 1,419 households from six rounds of phone surveys conducted between August 2019 and June 2020, with the latter rounds including COVID-specific questions. We define migration-dependent households in this sample to be those that identified remittances as their primary source of earnings in 2019.

In contrast to the G2G population, NPL sample households engage more in subsistence migration than migration for economic opportunity, and migrant households were no better off than non-migrant households before the pandemic. The economy in rural parts of the Western Terai region is organized around a primary rice harvest in October and secondary wheat harvest in April. Seasonal patterns of food insecurity around this cycle are nearly identical for low- and high-remittance households prior to the pandemic.

Migrant workers in this population typically either remain within Nepal or travel to neighboring India, with which the country shared an open border. Travel is largely short-term and cyclical, with 75% of households having at least one migrant return home in the seven-month pre-pandemic data collection window. Migrants commonly return home in October–November for the rice harvest and in April–July for the wheat harvest and subsequent rice planting, and are away at other times of year.

The impact of COVID-19 on mobility can bee seen in migration rates among this population. In April–June 2019, roughly a quarter of NPL households had at least one adult male member away. By June 2020, this fraction had fallen to less than half its typical level, as shown in Figure 1. By contrast, migration in October–November remained largely consistent from 2018 to 2019. Money brought home by returning migrants during the October–November 2019 rice harvest made up 60% of household labor income in those months despite it being a time of high agricultural productivity. Our analysis investigates how households that lost access to this income in 2020 fared relative to comparable households with more local sources of earnings.

[Figure 1 about here.]

Bangladesh Landless Agricultural Workers (NLS): The No Lean Season (NLS) study population consists of landless agricultural workers in Northern Bangladesh. The NLS program offered migration loans around the region in 2018, and a random sample of 4,324 eligible households comprising both offered and non-offered workers were surveyed in person once in March and again in June 2019. We contacted a random sample of 292 households from among the non-offered participants by phone in 2020, stratified by prior migration status. Migration-dependence in this sample is defined as having a migrant away from the household in at least one of the previous three years.[3]

Migrants in the NLS sample most frequently travel seasonally in October–December around the primary Aman rice harvest in November, and again in April–May around the secondary Boro rice harvest in April. They typically head to destinations within Bangladesh and only remain away for 2–3 months on average. Like in the NPL sample, migration among NLS households is for subsistence, especially in the pre-harvest lean periods, and patterns of food security coincide between migrant and non-migrant households prior to the pandemic.

While we lack data on household members away in the COVID-19 months for this sample, there is evidence of elevated rates of return migration. In 2018 and 2019, around 5% of sample households per month had a short-term migrant return in March–April; in 2020, over 60% had a migrant return in one of those two months.[4] Our analysis investigates how this disruption differentially affected households that relied on migration as a source of earnings and a way to supplement income in the face of unanticipated shocks.

Bangladesh Urban Labor Markets (URB): The Urban Labor Market (URB) sample comprises workers

[3]Experimental variation generated by the migration loans could not be used in this paper because the program at scale had little effect on migration. See Mitchell et al. (2023) for evaluation details.

[4]These two values are not directly comparable because the 2018–2019 figure consists of only temporary migrants while the 2020 value includes all returning household members. Nevertheless, the magnitude of the difference is indicative of how COVID-19 disrupted migration in this population.

at over two hundred labor markets in nine major cities in Bangladesh. We identified 19,396 workers in September 2018 prior to the October–December migration season, conducted a followup survey with 8,490 of them by phone in April 2019, and contacted 2,682 of them by phone again in May 2020. Migrants in this population are defined as those who identified their native home to be a location outside the labor market sub-district, indicating they are recent arrivals to the city.

Respondents in this survey are urban residents found at spot markets awaiting solicitations for short-term labor, most commonly in the low-skill construction sector. Low-skill manual labor is a common destination occupation for short-term migrants and new urban arrivals. From October 2018–January 2019, migrants and non-migrants in the same market reported statistically similar wages, days worked, and monthly earnings.

The onset of COVID-19 spurred a mass migration away from urban centers. Sixty percent of our urban labor sample reported living in a sub-district outside their native home just prior to the lockdown in March 2020. Of these, 26% had returned to their native home by June 2020. Urban markets were selected from the most common destination cities and occupations for NLS migrants, so analysis in these two samples can be interpreted complementarily. In the NLS data we compare migrants to observably similar households in their place of origin, and in URB data we compare migrants to observably similar workers at their place of destination.

[Table 1 about here.]

2.1 Methodology

COVID-19 reached South Asia at the beginning of March 2020. We conduct difference-in-differences analysis around this point separately by study sample. The main estimating equation is

$$Y_{it} = \beta M_i \times C_t + \gamma_i + \delta_t + \epsilon_{it} \tag{1}$$

where Y_{it} represents an outcome Y for respondent i at time t, M_i is a dummy representing pre-COVID migration dependence, C_t is a dummy for post-COVID, and γ_i and δ_t represent respondent and time fixed effects, respectively. All analysis clusters standard errors at the household (worker for URB) level unless otherwise noted. The coefficient of interest β is the difference-in-differences estimate of the differential impact of COVID-19 on migration-dependent households or workers.

These research initiatives were unrelated before COVID-19, so outcomes are not harmonized or consistently available across samples. Earnings are measured at the household level in the G2G, NPL, and NLS samples, and for individual workers in URB. The NPL sample includes only household labor income, excluding agricultural output. In the G2G and NPL samples, we can further break down household earnings by source to isolate the impact of remittances.

As a more comprehensive measure of household wellbeing, we collect data on monthly self-reported food security in the G2G, NPL and NLS samples. Pre-pandemic food security was elicited at the time of the 2018 in-person survey in the G2G sample, in a 12-month retrospective survey during June 2020 in the NPL sample,[5] and during in-person surveys in March and June 2019 in the NLS sample. A full data description is provided in Appendix A.

Identification relies on the assumption that outcomes for migration-dependent respondents would have followed the same trend as those of non-migration-dependent respondents were it not for COVID-19. Evidence for this assumption is weakest in the G2G lottery, where migration-dependence was assigned randomly in 2013. By 2018, lottery winners clearly enjoyed greater earnings than lottery losers, and the gap remained stable from 2018 to 2019. We ascribe changes in this difference between lottery winners and losers by April and June 2020 to COVID-19, but it is unclear whether the earnings gap would have remained stable, grown, or shrunk in the absence of a global pandemic.[6]

In two other samples—NPL and NLS—we test the identifying assumption using data on food insecurity and show migrant and non-migrant households follow the same seasonal pattern in both trends and levels in pre-pandemic years, notably during lean-season periods of economic distress. In the URB sample, we establish a similar fact for monthly earnings in the four months from October 2018 to January 2019 and in pandemic recall of earnings in May 2019. We therefore attribute changes in the migrant–non-migrant gap after March 2020 primarily to the pandemic.

Where possible, we compare post-COVID outcomes to data from the same month in prior years to avoid confounding trends introduced by seasonality. This is possible to do for earnings in the three samples from Bangladesh because the COVID-19 phone survey asked specifically about one year prior, and the migration and food security data allow seasonally appropriate comparisons in the NPL and NLS samples. We lack data on income in the NPL sample from before August 2019, so we instead compare the early months of COVID-19, which fell during the wheat harvest, to the corresponding point in the preceding rice harvest. Unfortunately we have have no seasonally comparable data collected before the pandemic in the G2G and URB samples.

[5] Pandemic recall of pre-pandemic food security was validated against data from other households in the same region collected before the pandemic.

[6] If, for example, migrants to Malaysia experienced a negative income shock at the destination between our 2019 recall period and our 2020 phone surveys unrelated to COVID-19, we would improperly attribute the losses to pandemic-induced disruptions. We have no specific knowledge of other major migration-related shocks to the study samples in this time period; we believe it most plausible that the $M_i \times C_t$ term primarily captures the differential effect of COVID-19 on migrants.

Survey non-response poses a further threat to identification due to the difficulty of reaching respondents by phone during a period of crisis. Of those called, 92% responded in at least one of two waves in the G2G sample (82% in each of the April and June 2020 waves), 79% in the NPL sample, 76% in the NLS sample, and 74% in the URB sample during the post-COVID data collection. In Appendix Table S2 we show that post-COVID survey respondents roughly match their respective sampling frames on pre-COVID characteristics, and there is no differential attrition by migration status.

3 Background

Our four study populations represent migration types common around the world. The G2G sample in Bangladesh comprises primarily transnational migrants, with most lottery winners traveling to Malaysia. A small fraction of lottery losers also secure alternate work abroad in South Asia, Southeast Asia, or the Middle East. Such medium-term transnational migration is highly prevalent in the developing world. Of the estimated 192 million emigrants from less developed nations, just over half take up residence in other less developed nations and almost 60 million remain within their subregion of birth (UNDESA, 2019). It is important to understand how migration disruptions affect workers and households along these South-South migration channels.

By contrast, migration in the NPL and NLS samples in Nepal and Bangladesh is almost entirely short-term and seasonal. Migrants from the NLS households typically travel for two to three months, often during the agricultural lean season, and nearly all remain within the country. The majority of migrants in the NPL sample similarly either remain within Nepal or travel to neighboring India. This type of subnational and regional migration is estimated to be nearly three times as prevalent globally than transnational migration, with almost 500 million domestic migrants in less developed regions of the world (UNDESA, 2013).

Among domestic migrants in LMICs, short-duration seasonal travel is a fundamental component of household earnings. Figure 2 plots the annual share of households that participate in temporary migration—lasting under 12 months—for several populations where data are available. The calculations draw from multiple sources including both targeted research surveys and nationally representative samples collected by statistical offices, summarized in Appendix Table S1. Importantly, data include detailed information on episodes of short-term and circular migration, as well as cases where individuals migrate while the household remains behind.

Figure 2 illustrates three important features of short-term migration. First, it is extremely common in the LMIC countries for which we have data. Among populations in Asia, Africa, and Latin America, between one fifth and half of households send at least one member away for work temporarily. Where possible, we use national surveys to show such migrant households make up a substantial fraction of the national population. By contrast, the annual rate in the United States is below 0.2%.

Second, short-term migration within LMICs is concentrated among identifiable populations and regions, especially those that are poor and rural. In Nepal, India, and Uganda, where data on rates among the general population are available, we identify sub-populations for whom the rate of migration is up to fourfold the national average.[7] That is, identifiable locations and sectors are at even greater risk.

Third, short-term migration is frequently seasonal, especially among rural populations. The first three rows of Figure 2 report departure rates during the peak migration season in rural Nepal, Northern Bangladesh, and Central India.[8] Peak-season migration accounts for more than half of overall short-term migration in these populations.[9] This fact suggests that, in addition to targeting specific populations, economic policy for migrants should be appropriately timed throughout the year.

[Figure 2 about here.]

Finally, the URB sample in Bangladesh consists of urban residents employed in low-skill labor, the majority of whom migrated from rural areas in their lifetime. Rapid urbanization has been a recent trend throughout the developing world. The fraction of the population in LMICs living in urban areas has grown by 25% over the last twenty years (World Bank, 2020c), leading to a swell in urban workers with roots outside the city.

This newly urban population is characterized by frequent short-term mobility as well. Recent urban arrivals frequently move between markets to find short-term wage work, and often travel to visit extended family. Six months after the initial survey, more than half of URB respondents located in a new urban market, and 50% reported traveling to visit their native home at least once in October 2018–January 2018. Our research sheds light on how this segment of the labor force responds to economic downturns relative to their more established counterparts in the same labor market.

4 Economic Impacts by Household Migration Status

While COVID-19 was economically disruptive worldwide, its incidence was distributed unevenly. In this section, we report evidence of heightened economic exposure among migration-dependent households. Results are presented graphically here. In Appendix C we report the corresponding regression output,

[7] By contrast, in the U.S., short-term migration is not substantially more common than the national average among any region, education category, or any specific non-military industry or occupation.

[8] Data from the other sources do not indicate departure timing.

[9] By comparison, in the United States there is no single month where departures exceed ten percent of the annual rate; migration is distributed evenly throughout the year.

verify robustness to controlling for household fixed effects, and when possible use multiple different pre-COVID periods for comparison. Our analysis highlight how the elimination of migration as a coping mechanism left households with migrants uniquely vulnerable in the face of a global economic downturn.

4.1 Transnational Migration

We first investigate the relationship between migration and economic distress among transnational migrants in the G2G visa lottery. Households experienced a large fall in income in 2020 relative to pre-pandemic reference periods regardless of lottery status; and even lottery losers saw a 48% decline. The fall in income was larger for lottery winning households, however. Our point estimate of –\$40/month ($p< .01$) reflects a 14% larger drop compared to lottery losing households.

This difference effectively wiped out the earnings premium migrant households had built up over the prior seven years, as shown in Figure 3A, but was not large enough to cause a reversal in fortunes. Lottery-winning households did not report lower incomes than lottery-losing households in either COVID survey, and we cannot reject equality across lottery status after the onset of the pandemic. Findings indicate visa lottery winners previously enjoyed positive returns to migration, but had not managed to translate the accumulated gains into a diversified income portfolio robust to migration disruption.

[Figure 3 about here.]

Remittances account for the majority of lost income, especially among lottery winners, highlighting the importance of migration earnings as a source of exposure. Figure 3B shows the change in earnings by source from 2018 to 2020.[10] Among visa lottery winners, remittances make up 56% of the decline in income, as compared to 26% among the lottery losing sample. Appendix Table S7 provides a full decomposition of earnings changes by source.

Notably, our survey measure of household remittances reveals a decline far exceeding that documented in official statistics. We measure an average decrease of 61% across households in the G2G sample, compared to a 5% decline for Bangladesh in Q2 of 2020 relative to the prior year reported by the World Bank's KNOMAD database (2020b).[11] Because informal cash transfers make up a significant fraction of remittance earnings but rarely appear in aggregate statistics, official country-level measures are likely to be unreliable indicators of household economic status. As a result, indications of recovery in official statistics may be overly optimistic as long as informal networks remain disrupted.

[10] We lack granular data on source of income in April 2019.

[11] We lack the survey data to estimate a year-on-year decline. However, official remittances recorded by the Central Bank of Bangladesh were on average 12% greater in April than the prior August–December average in 2019 and 2018 after adjusting for inflation. Therefore, it is highly unlikely the discrepancy between pandemic-induced changes in official and informal remittances is caused by seasonality in measurement.

Self-reported food insecurity corroborates that, despite enjoying a lengthy period of higher earnings, migration-dependent households were no better positioned to weather an economic shock that disrupted migration ties. 98% of G2G households reported no experience of food shortage in the prior month in August–December 2018, while in June 2020 48% reported shortages in the prior week.[12] The portions of food insecure households among lottery winners and losers were nearly identical and statistically indistinguishable both before and during the pandemic, suggesting prior migration did not enable households to build consumption buffers against income loss. As a result, migrant households were no better off than their non-migrant counterparts once migration earnings were removed.

On net, migrant households were likely better off relative to a counterfactual of never having migrated. Visa lottery winners enjoyed greater earnings than an experimentally comparable reference group before the COVID-19 shock, and were no worse off after the shock on measures of income or food security. Nevertheless, our findings highlight the fragility of gains achieved through migration. The positive economic returns to transnational migration present in the pre-pandemic years were not converted into greater household resilience to disruption in this source of earnings.

4.2 Domestic and Intra-Regional Migration

Pandemic disparities in income are not as pronounced in the two household samples characterized by more local subsistence migration. Relative to the October 2019 rice harvest, household labor earnings during the April 2020 wheat harvest fell by 52% in Nepal. As shown in Figure 4A, households that reported remittances as their primary source of income in 2019 had slightly higher earnings at baseline but experienced a 14% greater drop during the pandemic, though neither difference is statistically significant. Income in NLS households in April 2020 also fell by nearly two thirds relative to a year prior, but due to the small sample size we can neither statistically distinguish between migrants and non-migrants nor rule out substantial earnings divergence.

[Figure 4 about here.]

Regardless, it is clear remittance earnings play a prominent role in the economic impact of the pandemic shock. Remittances account for the majority of lost labor income in the NPL data, comprising 72% of the decline in among households who identify remittances as their primary source of income 47% among those who identify a different primary income source.[13] By comparison, non-agricultural wages accounted for only 20% of lost labor income in migration-dependent households and 47% in the rest, and agricultural

[12] Food security was only assessed monthly in 2018 and weekly in 2020, and seasonally comparable pre-COVID data on food security is not available.

[13] We cannot report comparable measures in the NLS sample because earnings data are not appropriately disaggregated.

wages made up 10% and 9%, respectively. A full breakdown of earnings declines can be found in Appendix Table S9.

Lost remittance income can be attributed to both a lower rate of migration as well as depressed migrant earnings. Figure 4C plots the evolution of remittances over time, and Figure 4D shows remittances per migrant. Earnings per migrant remained stable across survey rounds in late 2019 but fell by 56% from $126 USD PPP to $55 USD PPP in April and May 2020. Both this statistically significant earnings difference ($p < .01$) and the depressed rate of migration shown in Figure 1 contribute to the fall in remittance income.

Once again, surveys show larger falls in remittance earnings than official statistics. In fact, the KNOMAD database (2020b) recorded a 0% change in remittances to Nepal in Q2 of 2020 relative to the prior year, while survey data indicates a 65% decline.[14] Even this number likely understates the full financial impact of the pandemic over time because informal remittances typically peak as returning migrants bring back earnings by hand. Therefore, some of what we measure in April–June 2020 as remittance income may reflect displaced future earnings from migrants forced home unexpectedly early.

Despite similarly sized earnings losses between migrant and non-migrant households, data on self-reported food insecurity reveals a stark difference in the welfare impacts of the pandemic. Figure 4B plots monthly average values of an index of food insecurity in the late 2019 and early 2020 survey rounds compared to a "typical year" in the NPL sample. Food insecurity among migrants closely tracked that of non-migrants pre-COVID, with a small gap toward the start of the lean season months in July and August. By contrast, the rate of food insecurity among migrants in May–June 2020 resembled a typical lean season despite the post-harvest timing, and the gap between high- and low-remittance households exceeded two standard deviations. We reject that the post-COVID migrant–non-migrant difference is comparable to prior years ($p < .01$), to the October 2019 harvest ($p < .01$), to the November–December 2019 post-harvest ($p < .05$), and to the prior lean season peak ($p < .05$).

A comparably large gap in food security appeared between migrant and non-migrant households in the NLS sample after the outbreak of COVID-19. We plot the fraction of households reporting restricted food intake for more than half the month in Figure 5A, split by presence of a migrant in the previous three years. Prior to 2020, with data spanning January 2018 to June 2019, rates of food insecurity were nearly identical between households with and without migrants. The largest gap of 4–6 percentage points appears during the September–October lean season. Food insecurity in 2020 followed the seasonal pattern in January and February, but spiked among migrant households in March and April. Food insecurity among migrant

[14] We again lack the survey data to estimate a year-on-year decline. However, official remittances to Nepal recorded by the IMF were on average 2% greater in October than the prior April average after adjusting for inflation in 2015 and 2016, the latest years we could find monthly data. Therefore, it is again highly unlikely the discrepancy between pandemic-induced changes in official and informal remittances is caused by seasonality in measurement.

households in April 2020 exceeded 30%, surpassing the typical lean season peak of 25%. Increases among non-migrant households were much more modest, leading to an eighteen percentage point gap in food insecurity between migrant and non-migrant households during the pandemic period. We reject that the post-COVID migrant–non-migrant difference is equal to prior years ($p < .01$), to January and February 2020 ($p < .01$), and to the prior lean season peak ($p < .05$).

[Figure 5 about here.]

These differences in food security underscore the importance of migration as a mechanism for coping with economic shocks. Fallout from the global economic downturn is clearly present throughout our samples of study, and income disruptions are pervasive in both the NPL and NLS data. However, because the specific nature of the pandemic shut down transportation and mobility, households that had previously relied on migration as a source of income stabilization no longer had access to this outlet and therefore faced the greatest distress.

4.3 Urban Labor Markets

The preceding analysis shows how migration-dependent households fared worse than their peers in their place of origin during the early months of the COVID-19 pandemic. As a counterpart to this analysis, data on individual earnings from the URB sample indicate that migrant workers experienced greater income losses than peers in their labor market at their migration destination. Among urban spot-labor construction workers, earnings were nearly 74% lower in May 2020 relative to the prior year. However, the decline was 12% greater for workers who did not consider the labor market to be their native home ($p < .01$). This result, shown in Figure 5B, is robust to including worker fixed effects and to comparing against earnings from other times of year. This finding complements existing evidence that migrants are more likely to work in sectors that experienced greater economic contraction. We find that even within the same industry and occupation, migrant workers were more economically exposed than non-migrants.

5 Geographic Patterns of Economic Distress

In this section we explore how the specific vulnerability of migration-dependent households affects geographic patterns of economic distress. Prior research has shown migration to be a vector of disease transmission across communities and regions. We report evidence that migration linkages also contribute to economic contagion separately from their effect on infection rates, and that economic effects spill over onto non-migrants in high-migration areas.[15] Our findings identify migration as a unique and potentially underreported channel of economic exposure to global downturns.

5.1 Community-Level Economic Impacts

Household distress aggregates up to community-level vulnerability. In both the NPL and NLS data, households in villages with a high rate of migration-dependence fare worse regardless of the household's own migration status, and the same holds true across labor markets for workers in the URB data. Figure 6 breaks apart the evolution of food insecurity (earnings) among migrant and non-migrant households (workers) by village (labor market) migration prevalence. The solid lines and shaded markers represent survey respondents in low-migration areas while the dashed lines and hollow markers represent those in high-migration areas.

[Figure 6 about here.]

The highest increases in food insecurity were reported by migration-dependent households in villages with high migrant fractions. In the NPL data, shown in Figure 6A, food insecurity among this group had been on trend in the late 2019 survey rounds, but spiked to above lean season levels after the pandemic. In those village, even non-migrant households experienced comparable levels of distress, though they had been above trend in November–December 2019 so we cannot fully ascribe their heightened distress to COVID-19. By contrast, food security among both migrant and non-migrant households in low-remittance villages remained statistically indistinguishable from a typical year through June 2020.

Figure 6B reveals a similar pattern among NLS households. Food insecurity remained on trend through February 2020 before diverging in March and April. In March 2020, unseasonably high food shortages were only present among migrant households in high-migration villages, with food insecurity for this population already exceeding typical lean season peaks. In April, conditions for these households deteriorated even further. In addition, both migrant households in low-migration villages and, to a lesser extent, non-migrant households in high-migration villages began to deviate from the seasonal trend, though these deviations are estimated with substantial error due to the small sample size. Only non-migrant households in villages with low overall rates of migration were able to maintain typical food consumption through the early months of the pandemic.

Economic spillover within villages underscores the relationship between migration and local financial networks. For those that had previously turned to subsistence migration to stabilize income, COVID-

[15] This analysis excludes the G2G sample because households are geographically dispersed and we lack data on local heterogeneity in migration prevalence, and because migrant destinations are concentrated within Malaysia with little variation in migrant disease exposure.

19 simultaneously depressed economic opportunity and obviated a primary means of risk management. The combined consumption effect of this dual shock was especially strong when neighbors also lost their ability to mitigate risk, and placed strain on non-migrants within the same local social network. Inversely, households barred from migration as a form of self-insurance were less vulnerable when they could turn to neighbors with a diversified income portfolio.

Market-level contagion also appears among urban workers, shown in Figure 6C. Prior to the pandemic, markets where more than half of workers were local offered very slightly higher earnings than those composed of more than half migrants. The pandemic lowered labor demand countrywide, but earnings in high-migrant markets fell to less than half of the low-migration market level. Within-market effects on migrants are also present but substantially smaller in magnitude and statistically indistinguishable from zero.

These market spillovers are somewhat surprising because URB survey participants compete for spot labor contracts. Had COVID-19 only induced a relatively larger labor supply shock among migrants who returned to their native residence, we would expect to see positive earnings spillovers onto non-migrants seeking work in the same market. Instead, it seems high-migration markets were thinned out by enough to displace labor demand relative to low-migration markets. This induced demand effect hints at a potential complementary between migrants and workers in the same occupation that operate through market thickness.

5.2 Migration and Economic Contagion

The spillover effects of migration during the pandemic may have been caused by disease spread or economic contagion. Evidence of migration as a vector of infection appears in our household survey data in Bangladesh, which included syndromic surveillance of symptoms associated with COVID-19. The likelihood of self-reporting a COVID-19 symptom as identified by the WHO/CDC at the time of the survey—fever, dry cough, or fatigue—doubled from 7% to 14% in the G2G sample when an international migrant had returned in the previous two weeks, and was 20% greater in households with a recent domestic returnee in the NLS sample.[16] Labor migrants faced particularly high risk of exposure in transportation—over 95% of NLS migrants traveled on a high-density vehicle such as a bus or train—and housing—95% of NLS migrants shared sleeping quarters with at least three other individuals and 40% slept in rooms of ten or more at their place of work.

Nevertheless, we find migration linkages to be a strong predictor of economic outcomes independent

[16] These are simple differences, not difference-in-differences comparisons, and we cannot quantify whether return migrants have elevated disease symptoms during non-pandemic times.

of local disease prevalence. Table 2 presents results from a regression of URB workers' pandemic decline in earnings on disease prevalence[17] in their home and destination labor markets. The first column reports a weak negative relationship between economic distress and disease prevalence in a worker's place of residence in June 2020. However, the next three columns show this relationship disappears after controlling for disease prevalence at the individual's place of work in various pre-pandemic periods, and labor market infection rates are most strongly associated with distress. The final two columns confirm place of work to be the relevant location; disease prevalence at a worker's native home does not predict early pandemic distress. These results suggest that when the pandemic displaced workers from their place of work, they remained economically distressed even if the moved to avoid immediate health risks.

[Table 2 about here.]

NLS household outcomes provide further evidence of economic contagion through labor migration. Table 3 presents estimates from a regression of the change in self-reported food security from April 2019 to April 2020 on migration status and household presence of COVID-19 symptoms. Migration-dependence at both the household and village level remains an economically and statistically significant predictor of distress after controlling for household symptoms. It should be noted that syndromic surveillance is a noisy measure of true infection, so these estimates are subject to attenuation bias. Subject to this caveat, the available evidence is consistent with prior migration linkages transmitting economic distress over and above their epidemiological role.

[Table 3 about here.]

6 Discussion

In this paper we document how the economic centrality of migration left households and workers uniquely vulnerable when faced with the dual threat of a global downturn coupled with restricted mobility. Our findings underscore the difficulty in replacing migration as a source of income and tool to manage risk. When COVID-19 made this option unavailable, migration-dependent households were unable to make up lost capacity and, as a result, were more severely impacted in the early months of the pandemic than their non-migrant peers.

Vulnerability manifested differently for different types of migrants. Among relatively well-off households with members that had traveled in search of greater economic opportunity, the loss of migration income undid nearly a decade of progress. Those that had previously enjoyed years of extra income

[17] Data on district-level case rates are reported by the Institute of Epidemiology Disease Control And Research, Bangladesh.

boosted by the returns to migration became statistically indistinguishable from non-migrants in the absence of remittances at a time of crisis. In contrast, less wealthy rural households previously engaging in subsistence migration to stabilize income faced food insecurity exceeding even the most severe seasonal scarcity. The combined distress of these households put severe strain on local social networks in high-migration areas, while migrants in low-migration areas were not as severely affected.

The findings in this paper pertain to a large, correlated, and unanticipated economic shock. In such a context, the option to migrate serves as a form of self-insurance for those that cannot smooth consumption in other ways. Idiosyncratic migration disruptions may be less damaging when faced by individuals or households that can turn to communal risk sharing networks for support. Similarly, households may be able to make anticipatory adjustments to mitigate the shock if given advanced notice of a coming interruption.

In the midst of a large-scale shock, we reveal migration to be vector of economic contagion. Pandemic-related slowdowns at migrants' destination labor market translated into distress at their origin residence, and this type of linkage existed over and above any measured disease transmission. This finding has direct policy implications for pandemic recovery efforts. Migration connections may have decoupled economic distress from health risk, especially in rural areas where low population density curtailed infection rates. As a corollary, resources for economic recovery should be directed independently from epidemiological efforts. More generally, migration linkages can help identify vulnerable populations during times of crisis.

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List of Tables and Figures

Tables

Figures

Table 1: Primary Data Sources

Sample	Description	Migrant Type	COVID Shock	Original Survey Design
G2G (3,233 HHs)	Bangladeshi participants in a 2013 visa lottery for work permits in Malaysia	Opportunity	Loss of employment at destination leading to loss of household remittance earnings	In-person surveys of 3,512 households in Aug-Dec 2018 representing both lottery winners and losers
NPL (1,419 HHs)	Households in bottom 50 percentile of wealth in rural parts of Western Terai, Nepal	Subsistence	Half as many migrants away relative to a year prior leading to loss of remittance earnings	6 rounds of phone surveys between Aug 2019 and July 2020 with 1,820 rural households
NLS (294 HHs)	Landless rural households in Northern Bangladesh eligible for short-term migration loan	Subsistence	More than ten times as many returning migrants as in prior years	In-person surveys of 4,324 households in March and June 2019
URB (2,682 Wrkrs)	Urban laborers at over 200 spot markets for day labor, primarily in construction, in nine cities in Bangladesh	Urbanization	Fall in market labor demand, and one quarter of migrants return to native residence	In-person enumeration of 19,396 workers in September 2018 and phone survey with 8,490 respondents in April 2019

Table 2: Earnings Decline and Infection Rates in URB Sample

	Change in Household Earnings from May 2019 to May 2020					
	(1)	(2)	(3)	(4)	(5)	(6)
COVID-19 rate as of June 1 2020 in worker's district of:						
Residence	-11.909	40.666	19.612	6.872	-11.498	45.877
(July 2020)	(7.963)	(10.656)	(8.795)	(8.527)	(8.069)	(10.636)
Labor Market		-69.027				-43.703
(March 2020)		(9.001)				(10.063)
Labor Market			-60.404			-49.331
(April 2019)			(7.139)			(10.389)
Labor Market				-44.114		4.731
(Sept 2018)				(7.029)		(9.964)
Residence					-5.766	-8.507
(Native)					(25.236)	(25.654)
Constant	-324.631	-309.141	-295.943	-297.327	-324.227	-293.905
	(4.644)	(5.005)	(5.541)	(6.150)	(4.992)	(6.483)
R-Squared	0.00	0.02	0.03	0.02	0.00	0.04
Observations	2602	2598	2601	2602	2601	2596

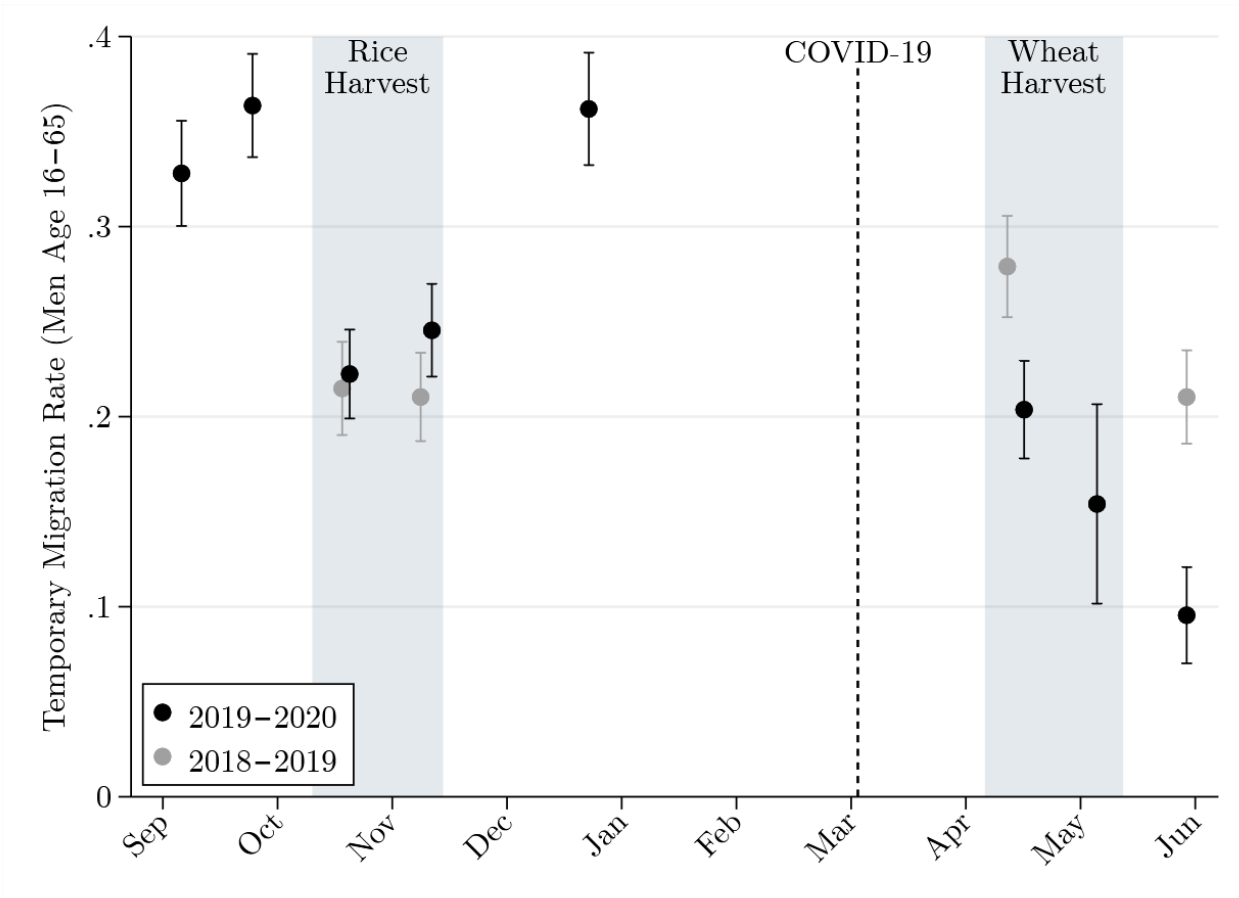
Notes: Change in self-reported worker earnings from May 2019 to May 2020 regressed on COVID-19 rates in districts of workers' history of residence. District-wise cumulative COVID-19 cases as reported by the Institute of Epidemiology, Disease Control and Research as of June 1, 2020. Heteroskedasticity-robust standard errors in parentheses.

Table 3: Migration Dependence and COVID-19 Symptoms in NLS Data

Outcome:	Change in Food Insecurity April 2019–April 2020				
	(1)	(2)	(3)	(4)	(5)
Migrant Household	0.201	0.201			0.137
	(0.091)	(0.090)			(0.086)
High Migration Village			0.233	0.233	0.184
			(0.094)	(0.094)	(0.091)
COVID Symptoms		-0.009		0.003	-0.014
		(0.168)		(0.181)	(0.178)
R-Squared	0.04	0.04	0.05	0.05	0.06
Observations	146	146	146	146	146

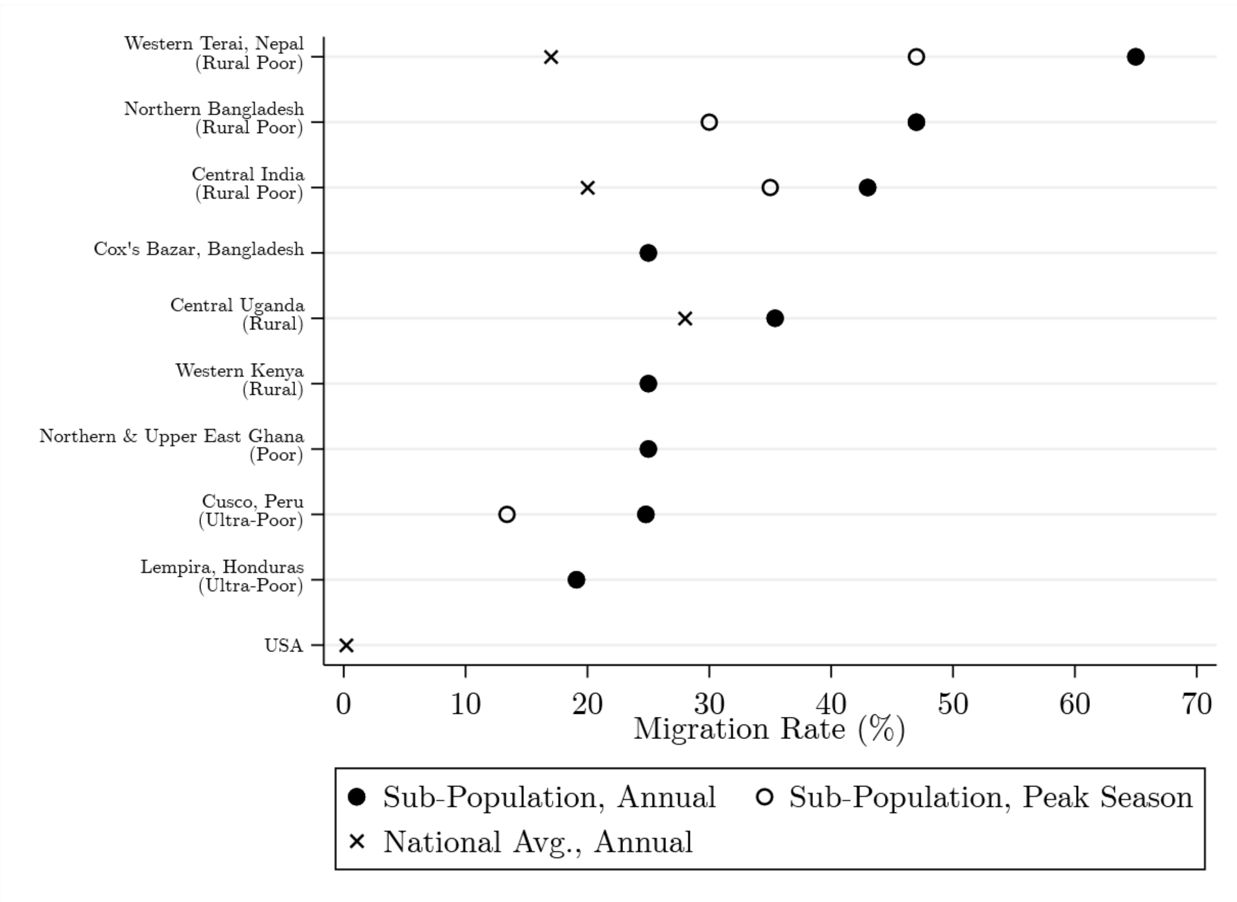
Notes: Change in self-reported household food insecurity from April 2019 to April 2020 regressed on household migration status, village migration intensity, and presence of COVID-19 symptoms in household. Migrant household defined as having at least on member migrate in prior three years. High-migration village defined as having above-median fraction of migrant households. COVID-19 symptoms include fever, dry cough, and fatigue. Heteroskedasticity-robust standard errors in parentheses.

Figure 1: Temporary Migration Rates in NPL Data



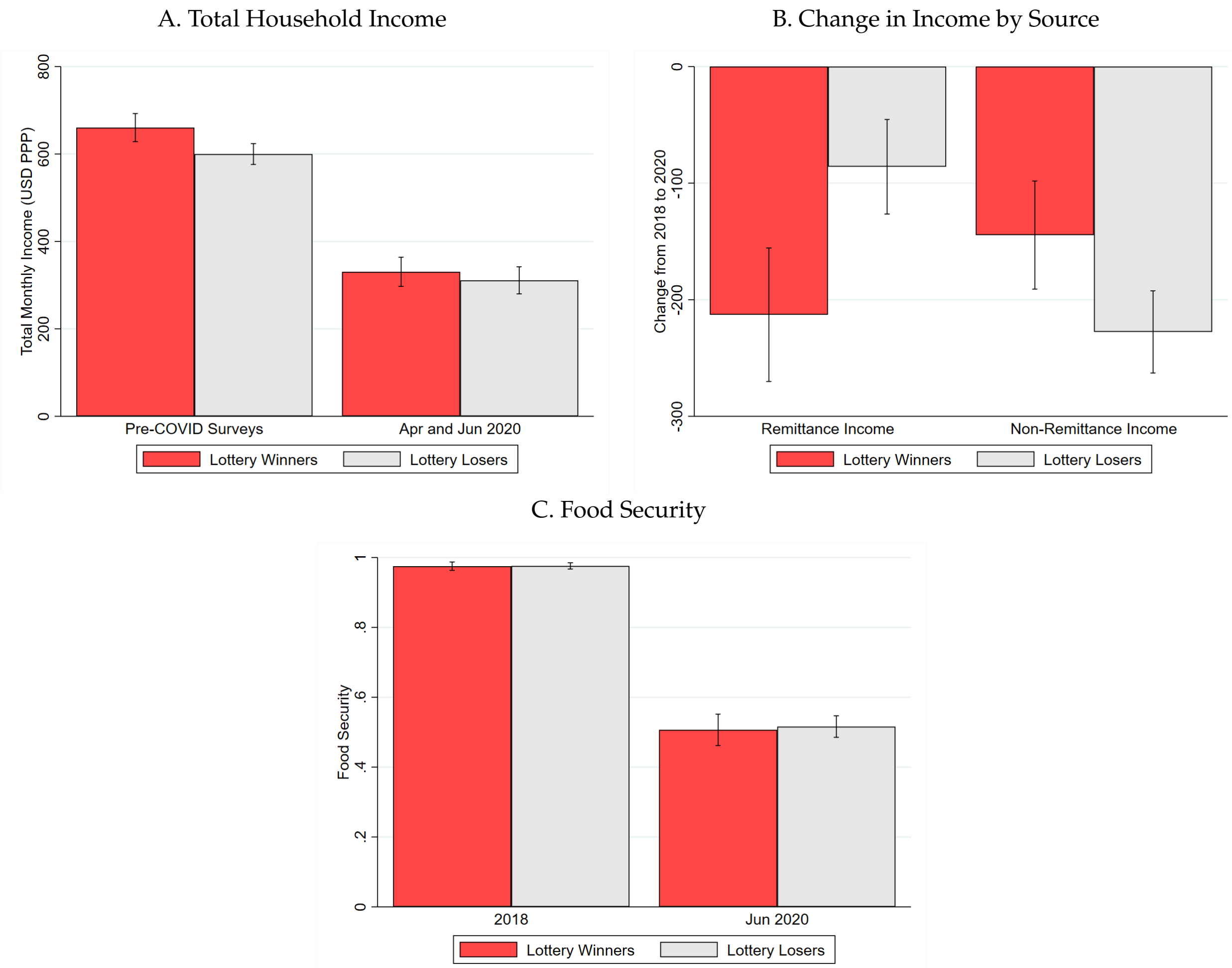
Notes: Means and 95% confidence intervals. Figure plots fraction of households that report having at least one male member away by time. 2019–2020 data elicited in contemporaneous phone surveys, and 2018–2019 data elicited from recall around major national holidays asked in April 2020 phone survey round. Confidence intervals computed from standard errors clustered at the household level. A version of this figure was presented in Kharel et al. (2022).

Figure 2: Short-Term Migration Rates in Multiple Populations



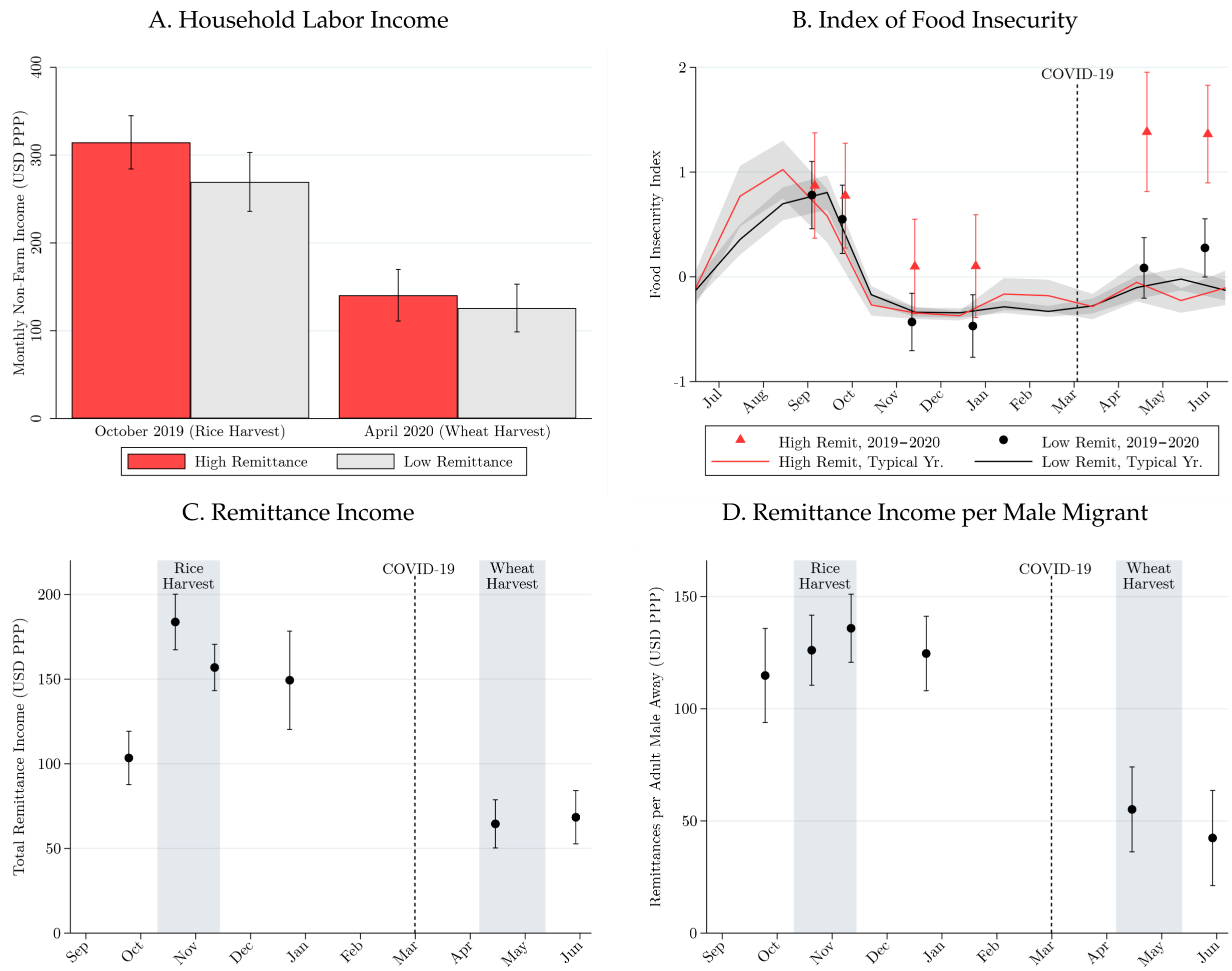
Notes: Fraction of households with a departing migrant who returns in under 12 months in select samples. Sub-Population refers to population selected for survey data. Peak season refers to 1–2 calendar months with greatest rates of migration. National average computed from national surveys when available. See Table S1 for details on data sources.

Figure 3: COVID-19 Impacts on G2G Households



Notes: Means and 95% confidence intervals. Migration status determined by 2013 visa lottery outcome. A. Average sum of monthly earnings from wages, business, remittances, capital, NGOs, friends and family, and home production, comparing pre-COVID periods (August–December 2018, April 2019) to post-COVID periods (April and June 2020). B. Average change in earnings from remittances and from all other sources between August–December 2018 to April and June 2020 (the three waves for which we have detailed income breakdowns) by lottery outcome. C. Fraction of households with no reported instances of food insecurity over the past month in August–December 2018 and no instances over the past week in June 2020. Confidence intervals computed from standard errors clustered at the sub-district (union) geographic level.

Figure 4: COVID-19 Impacts on NPL Households

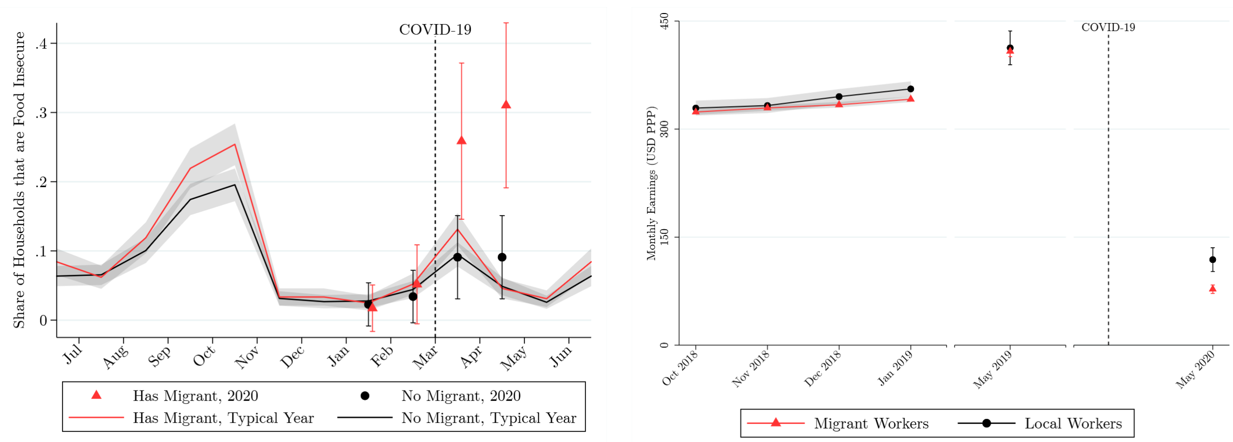


Notes: Means and 95% confidence intervals. Migration status determined by identifying remittances as primary source of income in baseline survey. A. Average sum of monthly earnings from wages, remittances, and informal labor in October 2019 and April 2020 by migration status. B. Average of responses from an index of three questions on food shortage. 2019–2020 data elicited in contemporaneous phone surveys, and "Typical Year" data elicited from monthly recall asked in April 2020 phone survey. C. Average monthly earnings from remittances across all households in late 2019 and early 2020 elicited in contemporaneous phone surveys. D. Average across all households of monthly remittances (as reported in Panel C) divided by number of adult males away (as reported in Figure 4) in late 2019 and early 2020. Confidence intervals computed from standard errors clustered at the household level.

Figure 5: COVID-19 Impacts on NLS Households and URB Workers

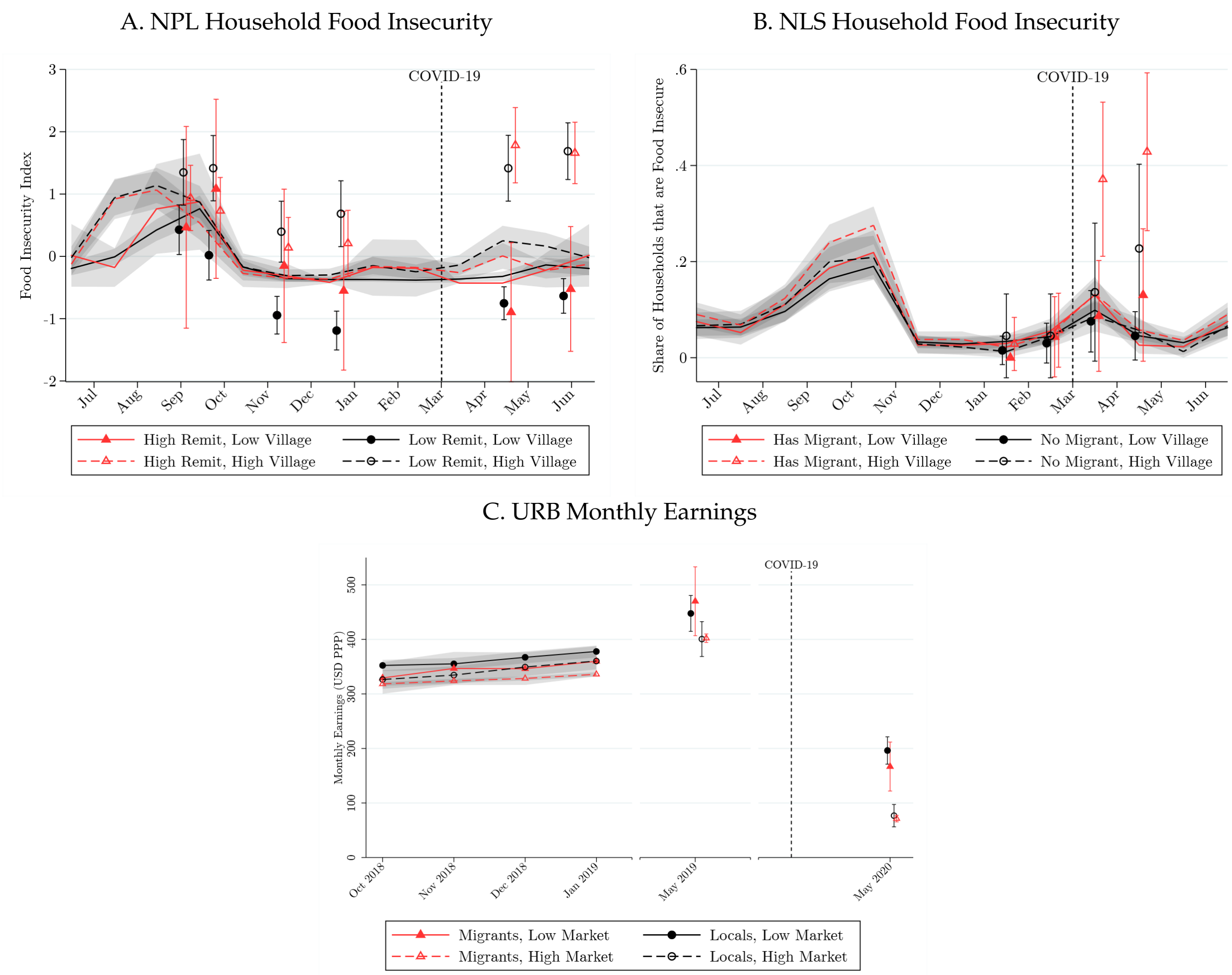
A. Food Insecurity among NLS Households

B. Monthly Earnings among URB Workers



Notes: Means and 95% confidence intervals. Migration status in NLS data determined by having a household member migrate in prior three years. Migration status in URB data determined by identifying a native home in different district than survey labor market. A. Fraction of households reporting restricting food intake for at least 15 days in a month. 2020 data elicited from monthly recall in April 2020, and ”Typical Year” data elicited from monthly recall over prior 12 months in March 2019 and June 2019. B. Average monthly wage earnings. October 2018–January 2019 data elicited from monthly recall in April 2019 phone survey; May 2019 and May 2020 elicited in May 2020 phone survey. Confidence intervals computed from standard errors clustered at the household level for NLS and worker level for URB.

Figure 6: Household and Community-Level Migration Exposure



Notes: Means and 95% confidence intervals. Household migration status as previously defined by remittances in NPL data, prior migration in NLS data, and native home away from labor market in URB data. Village status denotes above/below median fraction of migrant households in the village for NPL and NLS, and labor market status denotes above/below 50% migrant workers in September 2018 market enumeration. Market status for workers in URB data is defined by original market in the September 2018 baseline. Line and marker color identify household or worker migration status; line pattern and marker fill identify village/market migration status. Confidence intervals computed from standard errors clustered at the household level for NPL and NLS, and at the worker level for URB.

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All data collection was approved by the Yale University IRB.

The order of author names is alphabetical as all authors contributed to data collection, analysis, and writing. Naguib and Reimão were employed by Evidence Action, the implementing partner for the No Lean Season experiment, from 2016 to 2019. Mitchell's position at Y-RISE from 2019–2021 was also funded by Evidence Action. No institution had the right to review results before publication. The remaining authors declare we have no conflicts of interest.

Supplementary Appendix for
“Migration and Resilience during a Global Crisis”
For Online Publication Only

A Data

A.1 Study Samples

The analysis in this paper primarily uses four COVID-19 specific phone surveys that sample from participants in existing studies and took place in April–June, 2020.

Government-to-Government (G2G): The G2G sample, conducted in Bangladesh, consists of individuals who applied for a visa lottery in 2013, intermediated by the Government of Bangladesh, for a temporary work program in the palm sector in Malaysia. The Government of Bangladesh determined via lottery (conducted independently by the Bangladesh University of Engineering and Technology) which 30,000 individuals would receive work visas of the 1.43 million who applied. This study aims to understand the impact on households of winning the work visa lottery, and more generally, to estimate the returns to short-term international migration. Details of the evaluation are discussed by Shrestha et al. (2020).

In 2018 the project tracked and administered surveys to lottery applicant households, including both lottery winners and losers, in 49 subdistricts in the two largest divisions of Bangladesh—Chittagong and Dhaka—via an in-person survey. The population is representative of lottery applicant households in Dhaka and Chittagong Divisions; in practice this sample should roughly be thought of as middle-class Bangladeshis since the poorest households in the country are unlikely to be able to afford the expenses needed to travel abroad.

For our COVID-19-specific phone survey we attempted to contact 3,512 study participants, stratified by lottery outcome, out of which 3,233 were found and consented to participate in at least one of the post-COVID waves.

Western Terai, Nepal (NPL): NPL data comes from an existing phone panel of 1,820 rural households in the districts of Kailali and Kanchanpur, two of the poorer districts in the country. This sample was constructed in June, 2019, by randomly selecting 30 wards from 17 of 20 subdistricts, and then selecting a random 90 villages from within those wards. The households surveyed come from the bottom half of the wealth distribution in these villages as estimated by a participatory wealth ranking exercise with members of the village. A substantial fraction of income for these households comes from remittances from migrants in India or elsewhere in Nepal. Initial baseline data were collected in-person in July 2019, and five rounds of phone survey data were collected between August 2019 and January 2020. Details of the planned evaluation are documented by Mobarak and Vernot (2020).

Our COVID-19 specific phone survey constituted the most recent round of the ongoing panel with all 1,820 study participants, out of which 1,419 were reached and consented to participate.

No Lean Season (NLS): The NLS study consists of several rounds of data collection in Northern Bangladesh from

2008 to 2019. The study is a randomized evaluation of a short-term zero-interest migration loan offered during the agricultural lean season to landless agricultural households. The first two rounds of study, from which we report estimates of the causal return to migration, included 1,900 households in 2008 and 3,600 in 2014. Full details from these studies are discussed by Bryan et al. (2014) and Akram et al. (2017), respectively.

In 2017 and 2018, the loan program was expanded to a large scale with 158,014 loans made in 2017 and 143,721 in 2018. For evaluation, the project surveyed a subset of 4,428 eligible households in May 2018 and 4,324 households in June 2019. Details of the evaluation at scale are discussed by Mitchell et al. (2023).

For our COVID-19 specific phone survey we attempted to contact 388 study participants from the 2019 round of evaluation, selected from among the control group and stratified by prior migration experience, out of which 294 consented to participate.

Urban Labor Markets (URB): The URB sample was initially drawn in conjunction with the No Lean Season study. Survey sites were selected to represent all spot labor markets for manual construction labor in the nine most common destination cities for migrants in the NLS study area. At each site, a census of workers was conducted on a random day in September 2018, shortly before the migration season. This census generated a sampling frame of 19,396 workers at 200 spot labor markets in 9 Bangladeshi cities. We then conducted follow-up phone surveys with 8,490 of these workers in April 2019 to track their labor market progress over the 2018–2019 migration season.

For our COVID-19 specific phone survey, we attempted to contact 3,746 of the workers from the April 2019 endline, out of which 2,682 consented to participate. We reached out by phone to an additional 1,930 workers from the initial census who were not surveyed in April 2019, but this group had a response rate below 20% and are excluded from study. All results are robust to including respondents from this subsample.

Data on Migration Rates: The national migration rates in Figure 2 are calculated using nationally representative datasets. Data for Nepal come from the 2010–2011 round of the Nepal Living Standards Survey (NLSS). Ugandan data come from the 2009 and 2011 waves of the Uganda National Panel Survey (UNPS). Migration rates in the United States are computed from the 1996, 2001, 2004, and 2008 rounds of the Survey of Income and Program Participation (SIPP). Remaining values were reported in the sources cited, detailed in Appendix Table S1.

[Table S1 about here.]

A.2 Survey Attrition

Appendix Table S2 compares respondents from our COVID-19 phone surveys to the population from which they are sampled. The first three rows report the average age, gender, and education level of the household head; the fourth row reports household size; and the fifth reports monthly income prior to COVID-19. Standard errors of the mean are reported in parentheses.

We evaluate representativeness in the COVID sample by treating the original study participants as the underlying population, and then testing the null hypothesis that the COVID sample mean equals the known population mean. p-values from this test are presented in square brackets. In the G2G and NPL samples, COVID survey respondents closely match the study population and we fail to reject equality on any dimension. In the NLS sample, we reject equality in completion of secondary school at the 10% level, but fail to reject equality in any other measure. In the URB sample, we only have data on pre-COVID monthly earnings. The COVID sample earns more on average than the full study sample, significant at the 1% level, but the difference is quantitatively small at less than 5% of total earnings.

The final two rows of report survey response rates by migration status. Response rates are generally high, ranging from 74% to 92%. Moreover, nonresponse to the phone survey is nearly exactly balanced between migrants and non-migrants in all four surveys. Although we cannot rule out selective attrition based household outcomes during the pandemic period, these results indicate that any bias caused by selective attrition according to migration status or pre-COVID characteristics is likely to be small.

[Table S2 about here.]

A.3 Available Data

The four survey samples in this study were part of unrelated research prior to the onset of the pandemic. As a result, not all outcomes are available for all samples. Appendix Table S3 provides a detailed description of each variable that is observed in each sample and when it was collected. Some pre-pandemic outcomes were reported retrospectively during the post-pandemic phone survey while others were recorded during contemporaneous pre-pandemic surveys. Where possible, we verify that results are consistent between pre- and post-pandemic recall data.

[Table S3 about here.]

B Mobility Restrictions in Bangladesh and Nepal

The pandemic is informative about migrant populations because they face heightened risk from both the global economic slowdown as well as travel disruptions caused by the disease and policy response. Multiple studies document how migrant-heavy sectors in OECD countries, such as transportation and hospitality, experienced the largest contractions at the onset of the pandemic (Garrote Sanchez et al., 2020; Fasani and Mazza, 2020; Gelatt, 2020; Kerwin and Warren, 2020; Borjas and Cassidy, 2020). Further economic exposure stems from mobility restrictions that featured prominently in initial public health policy. To limit personal contact, nearly every country in the world incorporated social distancing into its COVID-19 response. Measures included restrictions on gatherings, stay-at-home orders, and mandatory curfews. Importantly, most nations have adopted restrictions on domestic and international travel to slow the geographic diffusion of the illness. In a March 26 audit of 1,596 national border crossings, the IOM (2020a) recorded that 1,372 crossings had imposed limitations on mobility. By April 17, 161 of 190 countries evaluated had instituted barriers to internal mobility in their pandemic response (IMF, 2020). Even without explicit mobility restrictions, uncertainty and concerns about safety raised mobility costs.

Barriers to mobility were prominent in social distancing efforts in our study areas of Bangladesh and Nepal. As of May 16 and 28, respectively, both countries had implemented a variety of measures including curtailing public transport, barring non-essential travel, and limiting internal movement. Additionally, Bangladesh banned international arrivals from some regions while Nepal imposed a complete border closure (Hale et al., 2020). Appendix Table S4 describes mobility restrictions in these countries more thoroughly. In this paper we evaluate how the diminished prospects for migration employment and income have affected household resilience to a crisis.

[Table S4 about here.]

C Regression Results

Tables S6–S11 present regression results on the differential effect of COVID-19 on household earnings and food security by prior migration dependence in the G2G, NPL, NLS, and URB samples, respectively. These regressions correspond to the results presented in the text and figures in Section 4.

[Table S5 about here.]

[Table S6 about here.]

[Table S7 about here.]

[Table S8 about here.]

[Table S9 about here.]

[Table S10 about here.]

[Table S11 about here.]

Table S12 presents regression results on the differential effect of COVID-19 on food security and monthly earnings by prior household (worker) and village (market) migration status in the NPL, NLS, and URB samples corresponding to the results presented in Figure 6.

[Table S12 about here.]

C.1 Robustness of difference-in-differences analyses to violations of parallel trends

In this supplementary analysis, we apply the method developed by Rambachan and Roth (2023) to evaluate whether results in Appendix C, Tables S8 and S10 are sensitive to violations of parallel trends.

To conduct this sensitivity analysis, we first estimate a standard event study specification for both the NLS and NPL samples:

$$Y_{it} = \gamma_i + \delta_t + \sum_{s \neq t^*} \mathbf{1}[s = t] \times D_i \times C_t + \varepsilon_{it} \tag{2}$$

where i indexes households, t indexes time period, γ captures household fixed effects, δ captures time period fixed effects, t^* correspond to the final pre-treatment period, D is an indicator for treated households, and C is an indicator for time periods. Standard errors are clustered by household in all event study results shown below. Note that the event study coefficients differ from those presented in Tables S8 and S10 for several reasons, including that Equation 2 uses the last pre-treatment survey wave as the comparison period.

The Rambachan and Roth (2023) method then uses pre-treatment deviations from parallel trends, or transformations thereof, as alternative counterfactuals to the usual assumption of parallel trends. The ultimate result of this exercise is a confidence interval for the causal effect of treatment, accounting for hypothesized deviations from parallel trends and statistical uncertainty in the event study estimation.

C.1.1 No Lean Season

The event study coefficients show no evidence of differential pre-trends. Figure S1 shows estimates from Equation 2 in the NLS sample. In this sample, t^*, the omitted final pre-treatment period, is defined as February, 2020 and D_i is an indicator for migrant-sending households. The outcome is food insecurity. Harvest periods are shaded in blue while the lean season is shaded in red. No pre-treatment coefficients are statistically different from zero, and they do not show any long-run trends.

[Figure S1 about here.]

In Figure S2, we show the results of the most stringent application of the Rambachan and Roth (2023) method to our data. Specifically, considering all 19 pre-treatment periods, we identify the largest differential trend between any 2 sequential pre-treatment periods, i.e. $\delta_{s+1} - \delta_s \ \forall s \leq t^* - 1$. Then, we construct confidence intervals relaxing the typical assumption of post-treatment parallel trends, i.e. $\delta_{t+1} - \delta_t = 0$, instead assuming $\delta_{t+1} - \delta_t \leq \max_{s \leq t^*-1} |\delta_{s+1} - \delta_s| \times \bar{M}$ for $\bar{M} \in \{0.5, 1, 1.5, 2\}$ and $\forall t \geq t^*$. Rambachan and Roth (2023) refer to this approach as "bounding relative magnitudes."

This approach is stringent in several senses. First, by considering 19 pre-treatment periods and taking the maximum, this sensitivity analysis is more likely to be based on measurement error or other idiosyncratic forces generating a pre-treatment differential trend that is not informative about the post-treatment counterfactual. Second, we impose no sign or seasonal restriction. Consistent with our intuition about seasonal poverty in this setting, the estimates in

Figure S1 suggest that migrant-sending households tend to experience relatively less food insecurity during harvest seasons and more during lean seasons. This sensitivity analysis does not incorporate any data or contextual knowledge about seasonal patterns, even though our primary difference-in-differences result show a marked departure from them. Finally, when constructing the Rambachan and Roth (2023) confidence intervals, we include and equally weight both post-treatment periods, allowing $\max_{s \leq t^*-1} |\delta_{s+1} - \delta_s| \times \bar{M}$ to be applied consecutively.

As Figure S2 shows, our main results remain significant at the 5 percent level for $\bar{M} = 0.5$ but are not significant at that level for $\bar{M} = 1$. That is, if we allow the post-treatment differential trend to be as large as the maximum pre-treatment differential trend, the Rambachan and Roth (2023) confidence interval includes zero. The confidence interval excludes zero at a significance level of roughly 12.4 percent.

[Figure S2 about here.]

We can incorporate information about seasonal patterns through a straightforward modification to Equation 2; in doing so, our main results remain significant for $\bar{M} = 1$ at the 10 percent level. In particular, if we replace the time period fixed effects with separate calendar month and year fixed effects, the Rambachan and Roth (2023) confidence interval excludes zero for a confidence level of 10 percent. The results from the revised event study specification, shown in Figure S3, are qualitatively unchanged. The Rambachan and Roth (2023) confidence intervals are presented in Figure S4.

[Figure S3 about here.]

[Figure S4 about here.]

C.1.2 Nepal

Some event study coefficients are statistically significant, which we believe is explained by seasonal patterns, but there is no consistent long-run trend in the pre-treatment period. Figure S5 shows estimates from Equation 2 in the NPL sample. In this sample, t^*, the omitted final pre-treatment period, is defined as July, 2019 and D_i assumes a value of 1 for high-remittance households and a value of 0 otherwise. The outcome is food insecurity. Harvest periods are shaded in blue while the lean season is shaded in red. Food insecurity tends to increase for high remittance households, relative to other households, after the harvests. However, there is no clear long-run trend.

[Figure S5 about here.]

In Figure S2, we repeat the stringent Rambachan and Roth (2023) "relative magnitudes" approach using the NPL data. Here, our main results are no longer significant at the 5 percent level even for $\bar{M} = 0.5$. The confidence interval for $\bar{M} = 1$ excludes zero at a significance level of roughly 47.7 percent.

This approach is stringent for the reasons listed in Section C.1.1. In particular, note that this approach includes no data or contextual knowledge regarding seasonality. Our main results, based on outcomes measured during and immediately after a harvest, stand in contrast to the patterns in the observed 2018 and 2019 harvests.

[Figure S6 about here.]

Again adjusting by replacing the time period fixed effects with separate calendar month and year fixed effects, the confidence intervals shrink, excluding zero for a confidence level of 10 percent and $\bar{M} = 0.5$. However, the confidence interval for $\bar{M} = 1$ still includes zero. See Figure S8 for details. Figure S7 shows that, as above, the event study coefficients are qualitatively unchanged.

[Figure S7 about here.]

[Figure S8 about here.]

Table S1: Secondary Data Sources

Function	Data Source	Population	Sample
Descriptive statistics on national migration rates	(NLSS) Nepal Living Standards Survey	Nepal	5,988
	(UNPS) Uganda National Panel Survey	Uganda	1,237
	(SIPP) Survey of Income and Program Participation	United States	237,711
	Morten (2019)	Rural India	440
Descriptive statistics on migration rates in specific sub-populations	Banerjee et al. (2015)	Ultrapoor in Lempiras, Honduras	654
		Ultrapoor in Cusco, Peru	669
	Barker et al. (2020)	Rural Northern & Upper East Ghana	2,975
	Baseler (2023)	Rural Western Kenya	485
	Imbert and Papp (2020)	Rural poor in India	2,224
Descriptive statistics on migration rates during a peak migration period	Banerjee et al. (2015)	Ultrapoor in Cusco, Peru	669
	Imbert and Papp (2020)	Rural poor in India	2,224

Table S2: Summary Statistics for Original Sample and COVID Phone Subsample by Study

	G2G		NPL		NLS		URB	
	COVID	Original	COVID	Original	COVID	Original	COVID	Original
Observations	3,233	3,512	1,419	1,820	294	4,324	2,682	8,490
HH Head Age	45.7	45.7	43.1	43.3	45.8	45.2		
	(0.3)	(0.3)	(0.3)	(0.3)	(0.7)	(0.2)		
	[0.83]		[0.59]		[0.33]			
HH Head Male	0.80	0.80	0.08	0.10	0.93	0.94		
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)		
	[0.50]		[0.11]		[0.19]			
HH Head	0.17	0.16	0.31	0.30	0.09	0.05		
Secondary Educ.	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)		
	[0.47]		[0.43]		[0.01]			
HH Size	5.76	5.74	5.06	5.02	4.57	4.53		
	(0.04)	(0.04)	(0.05)	(0.04)	(0.08)	(0.02)		
	[0.71]		[0.56]		[0.61]			
Pre-COVID Income	628.27	620.96	194.40	200.97	203.23	203.90	359.30	343.04
(USD PPP/Month)	(50.64)	(46.71)	(5.47)	(6.90)	(24.97)	(8.20)	(2.74)	(1.50)
	[0.92]		[0.45]		[0.98]		[0.00]	
Migrant Response Rate	0.91		0.78		0.760		0.74	
Non-Migrant Response Rate	0.92		0.78		0.760		0.75	

Notes: Group means with standard errors in parentheses and p-value for difference in square brackets. p-value treats the original sample as the population, and tests the null hypothesis that the mean in the COVID sample drawn from that population equals the true population mean. Demographic data unavailable for URB sample.

Table S3: Available Data on Pre-COVID Outcomes by Sample

Sample	Outcome	Outcome Date	Survey Date	Details
G2G	Household Earnings	August 2018 to December 2018	August 2018 to December 2018	Broken down by source
		April 2019	April 2020	Aggregate Only
	Food Security	August 2018 to December 2018	August 2018 to December 2018	
NPL	Household Earnings	September 2020 to January 2021	September 2020 to January 2021	Broken down by source
	Food Security	Typical Year	April 2020	Index of 3 questions; Recall over 12 months
		September 2020 to January 2021	September 2020 to January 2021	Index of 3 questions
	Members Away	October 2018 to June 2019	June 2020	Around major holidays
		September 2020 to January 2021	September 2020 to January 2021	
NLS	Household Earnings	April 2019	April 2020	
	Food Security	March 2018 to June 2019	March 2019 and June 2019	Recall over 12 months
		January 2020 to February 2020	May 2020	
URB	Individual Earnings	October 2018 to January 2019	April 2019	Recall over 4 months
		May 2019	May 2020	
	Native Place		September 2018	
	Employed District	September 2018	September 2018	
		April 2019	April 2019	
		March 2020	May 2020	Pre-pandemic location

Table S4: COVID-19 Government Mobility Policies in Bangladesh and Nepal

	Bangladesh as of May 16	Nepal as of May 28
School Closing	All schools closed	All schools closed
Work place closing	Closing/work from home, some sectors	Closing/work from home, some sectors
Cancel public events	Required cancelling	Required cancelling
Restrictions on gatherings	Restrictions on gatherings of 10 people or less	Restrictions on gatherings of 10 people or less
Close public transport	Require closing (or prohibit most citizens from using it)	Require closing (or prohibit most citizens from using it)
Stay home requirements	Require not leaving house with exceptions for daily exercise, grocery shopping,and 'essential' trips	Require not leaving house with exceptions for daily exercise, grocery shopping,and 'essential' trips
Domestic travel restrictions	Internal movement restrictions in place	Internal movement restrictions in place
Foreign travel restrictions	Ban arrivals from some regions	Ban on all regions or total border closure

Source: (Hale et al., 2020)

Table S5: First Stage Effects of COVID-19 on G2G Sample

Outcome:	Applicant Returned Home, March 2020 or later	Applicant abroad as of June 2020
Migrant	0.003	0.365
	(0.01)	(0.02)
Lottery Loser Mean	0.02	0.13
N	1,935	1,935
R-squared	0.04	0.19

Notes: Migration dependence defined by visa lottery status. Data comes from phone survey conducted in June 2020. Regressions include controls for upazila (subdistrict geographic unit larger than union) fixed effects. Standard errors are clustered at the union (subdistrict geographic unit smaller than upazila) level.

Table S6: Differential Impact of COVID-19 by Migration Dependence in G2G Sample

Outcome:	Total Household Income		Applicant Currently Working		Food Security	
Pre-Period(s):	2018, 2019		2018		2018	
Post-Period(s):	Apr 2020, Jun 2020		Jun 2020		Jun 2020	
Migrant × post	-40.9	-39.6	-0.068	-0.060	-0.009	-0.003
	(17.0)	(20.4)	(0.025)	(0.042)	(0.023)	(0.034)
Post	-288.9	-299.6	-0.229	-0.238	-0.460	-0.466
	(15.8)	(19.7)	(0.017)	(0.029)	(0.016)	(0.023)
Migrant	60.5		-0.020		-0.000	
	(16.4)		(0.009)		(0.01)	
HH FEs		X		X		X
Lottery Loser Pre-Pandemic Mean	599.9		0.96		0.98	
N	8,194	8,194	3,762	3,762	4,305	4,305
R-squared	0.09	0.42	0.15	0.66	0.31	0.68

Notes: Regression results correspond to data presented in Figure 3. Migration dependence defined by visa lottery status. Pre-COVID data from August–December 2018 elicited in contemporaneous survey, and from April 2019 in COVID recall survey. The relatively low number of observations in columns 3 and 4 (relative to 5 and 6) reflect the relatively high rates of ”Don't Know” responses for whether the applicant is working. Food security is defined as 0 if individuals ever had to skip meals, cut their meal size, or substitute towards cheaper foods instead of their normal meals, and 1 if none of those conditions are met. Pre-COVID food security is asked about prior month, while post-COVID is asked about prior week. Therefore the coefficient on ”Post” is not directly interpretable, but the interaction term still captures differential changes by migration status. All regressions include upazila (subdistrict geographic unit larger than union). Income regressions include round fixed effects, and ”Post” quantifies change from August–December 2018 to June 2020 among non-migrants. Standard errors clustered at the upazila (subdistrict geographic unit smaller than upazila) level.

Table S7: COVID-19 Income Decomposition, G2G Sample

Outcome:	Income from Remittances		Income from Wages		Income from Microenterprises		Income from Home Production	
Migrant × post	-124.1	-125.0	25.19	23.89	42.07	46.12	4.9	11.3
	(13.9)	(18.4)	(12.1)	(15.4)	(17.6)	(23.9)	(8.5)	(10.9)
Post	-84.0	-84.0	-66.1	-67.3	-150.4	-160.9	-19.9	-24.4
	(8.8)	(11.8)	(9.3)	(11.9)	(13.6)	(18.8)	(7.2)	(8.9)
Migrant	177.1		-47.1		-51.7		-10.2	
	(13.8)		(10.9)		(18.5)		(5.8)	
Non-Migrant Pre-Pandemic Mean	112		150		219		103	
HH FEs		X		X		X		
N	6,266	6,266	6,266	6,266	6,266	6,266	6,266	6,266
R-squared	0.12	0.574	0.02	0.52	0.04	0.51	0.043	0.49

Notes: Migration dependence defined by visa lottery status. Data in the "pre" period comes from in-person data conducted in 2018. Data in the "post" periods come from data collected via phone surveys in April and June 2020. Regressions include controls for upazila (subdistrict geographic unit larger than union) fixed effects and round fixed effects. "Post" quantifies change from pre-COVID to June 2020 among non-migrants. Standard errors are clustered at the union (subdistrict geographic unit smaller than upazila) level.

Table S8: Differential Impact of COVID-19 by Migration Dependence in NPL Sample

Outcome:	Labor Income		Remittance Income		Food Insecurity	
Comparison Period:	Sep–Dec 2019		Sep–Dec 2019		Typical Year	
Source:	Survey		Survey		Recall	
Migrant × COVID-19	-1.880	-15.343	-43.075	-49.144	0.768	1.211
	(26.843)	(35.493)	(21.974)	(28.787)	(0.150)	(0.302)
COVID-19	-196.997	-203.722	-75.713	-84.246	-0.019	0.295
	(16.353)	(20.531)	(12.211)	(15.301)	(0.069)	(0.143)
Migrant	-7.937		73.568		0.043	
	(20.653)		(16.982)		(0.044)	
HH FEs		X		X		X
Time FEs	Season	Season	Season	Season	Month	Month
Prior Mean	336.38	336.38	160.27	160.27	160.27	160.27
R-Squared	0.02	0.34	0.01	0.30	0.05	0.51
Observations	11920	11920	12038	12038	8298	8298

Notes: Regression results corresponding to data presented in Figure 4 and associated text. Migration dependence defined by identifying remittances as primary source of income before COVID-19. Income data elicited in contemporaneous phone surveys, and labor income computed as sum of wages and remittances. Regressions with income run using data from Oct–Dec 2019 and Apr–June 2020. Survey rounds cover harvest and post-harvest periods, and regressions include a dummy for harvest season in Oct–Nov 2019 and Apr 2020. Food insecurity in typical year elicited in May 2020 phone survey, and values computed from index of three questions. Regressions with food insecurity run on data from both contemporaneous phone survey rounds and "typical year" recall data, and include calendar month fixed effects. COVID-19 identifies data from after March 2020. Prior mean reported across all households and time periods. Standard errors clustered by household in parentheses.

Table S9: COVID-19 Labor Income Decomposition, NPL Sample

Outcome:	Remittance		Ag. Wage		NonAg. Wage		Misc. Labor	
Migrant × COVID-19	-43.1	-49.1	-2.1	-3.6	42.8	38.5	-2.7	-3.0
	(22.0)	(28.8)	(6.5)	(8.1)	(9.2)	(11.8)	(7.4)	(9.0)
COVID-19	-75.7	-84.2	-14.6	-14.5	-76.2	-75.7	5.7	4.7
	(12.2)	(15.3)	(3.5)	(4.2)	(6.6)	(8.1)	(5.3)	(6.4)
Migrant	73.6		1.6		-68.6		-16.4	
	(17.0)		(5.0)		(8.3)		(3.9)	
HH FEs		X		X		X		X
Time FEs	Season	Season	Season	Season	Season	Season	Season	Season
Prior Mean	160.27	160.27	40.24	40.24	108.54	108.54	25.63	25.63
R-Squared	0.01	0.30	0.00	0.31	0.03	0.41	0.01	0.34
Observations	12038	12038	11644	11644	11644	11644	12038	12038

Notes: Changes in household labor income by source. Migration dependence defined by identifying remittances as primary source of income before COVID-19. Misc. Labor refers to informal labor exchange. All data elicited in contemporaneous phone surveys, and regressions run using data from Oct–Dec 2019 and Apr–June 2020. Survey rounds cover harvest and post-harvest periods, and regressions include a dummy for harvest season in Oct–Nov 2019 and Apr 2020. COVID-19 identifies data from after March 2020. Prior mean reported across all households and time periods. Standard errors clustered by household in parentheses.

Table S10: Differential Impact of COVID-19 by Migration Dependence in NLS Sample

Outcome:	HH Food Insecurity			
Comparison Period:	2017–2019		Jan–Feb 2020	
Source:	Survey		Recall	
Migrant × COVID-19	0.178	0.180	0.188	0.188
	(0.062)	(0.070)	(0.062)	(0.072)
COVID-19	0.019	0.025	0.063	0.062
	(0.028)	(0.031)	(0.027)	(0.031)
Migrant	0.016		0.006	
	(0.006)		(0.022)	
HH FEs		X		X
Month FEs	X	X		
Prior Mean	0.08	0.08	0.03	0.03
R-Squared	0.07	0.38	0.11	0.50
Observations	22984	22984	584	584

Notes: Regression results corresponding to data presented in Figure 5. Migration dependence defined by having at least one member migrate in prior three years. 2017–2019 data elicited in March 2019 and June 2019 in-person surveys. Jan–Feb 2020 data elicited in May 2020 phone survey. Regressions with 2017–2019 data include calendar month fixed effects. COVID-19 identifies data from after March 2020. Prior mean reported across all households and time periods. Standard errors clustered by household in parentheses.

Table S11: Differential Impact of COVID-19 by Migration Dependence in URB Sample

Outcome:	Monthly Earnings			
Comparison Period:	Oct 2018–Jan 2019		May 2019	
Source:	Survey		Recall	
Migrant × COVID-19	-31.350	-27.033	-36.462	-36.381
	(9.337)	(11.715)	(12.449)	(17.280)
COVID-19	-223.174	-230.077	-294.084	-294.084
	(8.825)	(10.977)	(11.737)	(16.291)
Migrant	-10.570		23.273	
	(6.420)		(14.334)	
Market FEs	X		X	
Worker FEs		X		X
Prior Mean	332.34	332.34	419.71	419.71
R-Squared	0.32	0.78	0.56	0.81
Observations	35101	35101	5258	5258

Notes: Regression results corresponding to data presented in Figure 5. Migration dependence defined by self-reported native place in different district from labor market. Oct. 2018–Jan. 2019 data elicited in April 2019 phone survey. May 2019 data elicited in May 2020 phone survey. COVID-19 identifies data from after March 2020. Prior mean reported across all workers and time periods. Standard errors clustered by worker in parentheses.

Table S12: Differential Impact of COVID-19 by Household and Community Migration Status

Outcome:	Food Insecurity		Food Insecurity		Monthly Earnings	
Sample:	NPL		NPL		URB	
	(1)	(2)	(3)	(4)	(5)	(6)
COVID-19×Migrant	-0.177	-0.067	0.043	0.051	-22.487	-13.274
	(0.283)	(0.314)	(0.060)	(0.066)	(25.216)	(29.747)
COVID-19×High Mkt.	0.510	0.808	0.116	0.104	-104.550	-107.160
	(0.135)	(0.143)	(0.078)	(0.075)	(15.416)	(18.262)
COVID-19×Migrant×High Mkt.	0.546	0.305	0.157	0.160	36.580	27.027
	(0.345)	(0.378)	(0.123)	(0.128)	(27.526)	(32.629)
COVID-19	-0.081	0.148	-0.011	-0.004	-168.739	-180.401
	(0.072)	(0.096)	(0.026)	(0.027)	(11.121)	(12.956)
Migrant	0.344		0.005		8.314	
	(0.128)		(0.009)		(13.305)	
High Mkt.	0.632		0.005		73.885	
	(0.069)		(0.010)		(7.966)	
Migrant×High Mkt.	-0.328		0.013		-19.452	
	(0.154)		(0.014)		(15.368)	
Month FEs	X	X	X	X		
HH FEs		X		X		X
R-Squared	0.07	0.47	0.08	0.34	0.19	0.72
Observations	18491	18491	23276	23276	37730	37730

Notes: Regression results corresponding to data presented in Figure 6. Migrant indicates household identifying remittances as primary source of income in NPL, having a member migration in prior three years in NLS, and naming a native place away from labor market in URB. "High Mkt." refers to villages with above-midean fraction of migrants in NPL and NLS, and to labor market with more than 50% migrants in URB. Regressions include all available rounds of data, and COVID-19 identifies data from after March 2020. NPL and NLS regressions include calendar month fixed effects. Standard errors clustered by household/worker in parentheses.

Figure S1: NLS Event Study Estimates

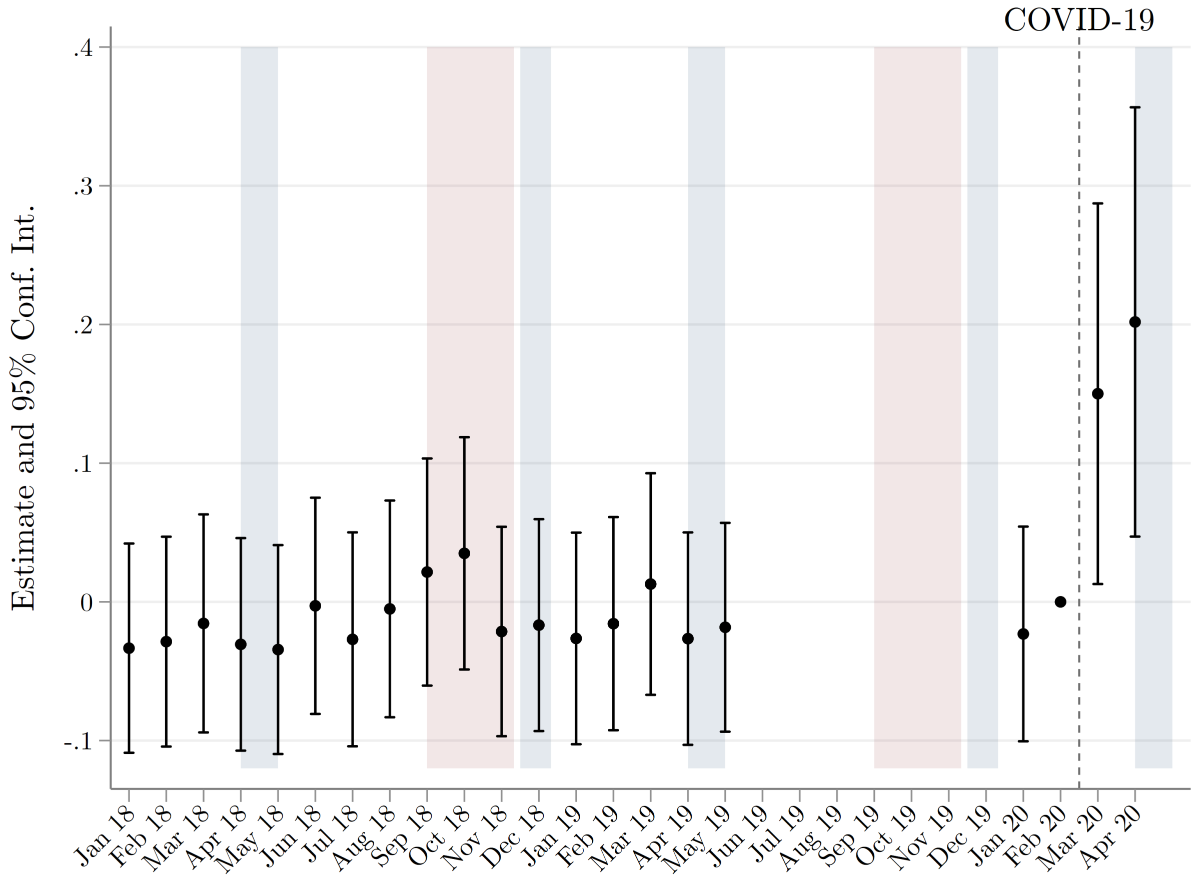

Figure S2: Rambachan and Roth (2023) Confidence Intervals

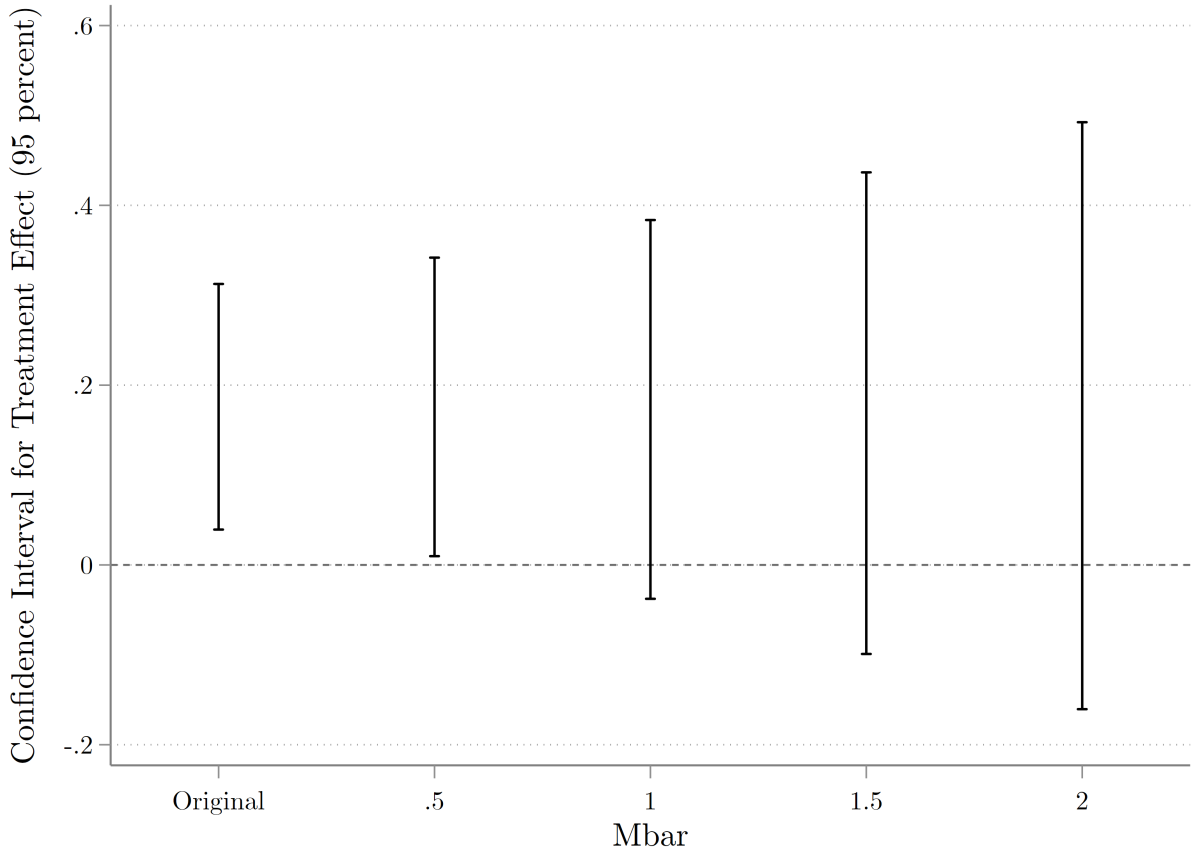

Figure S3: NLS Event Study Estimates (separate calendar month and year fixed effects)

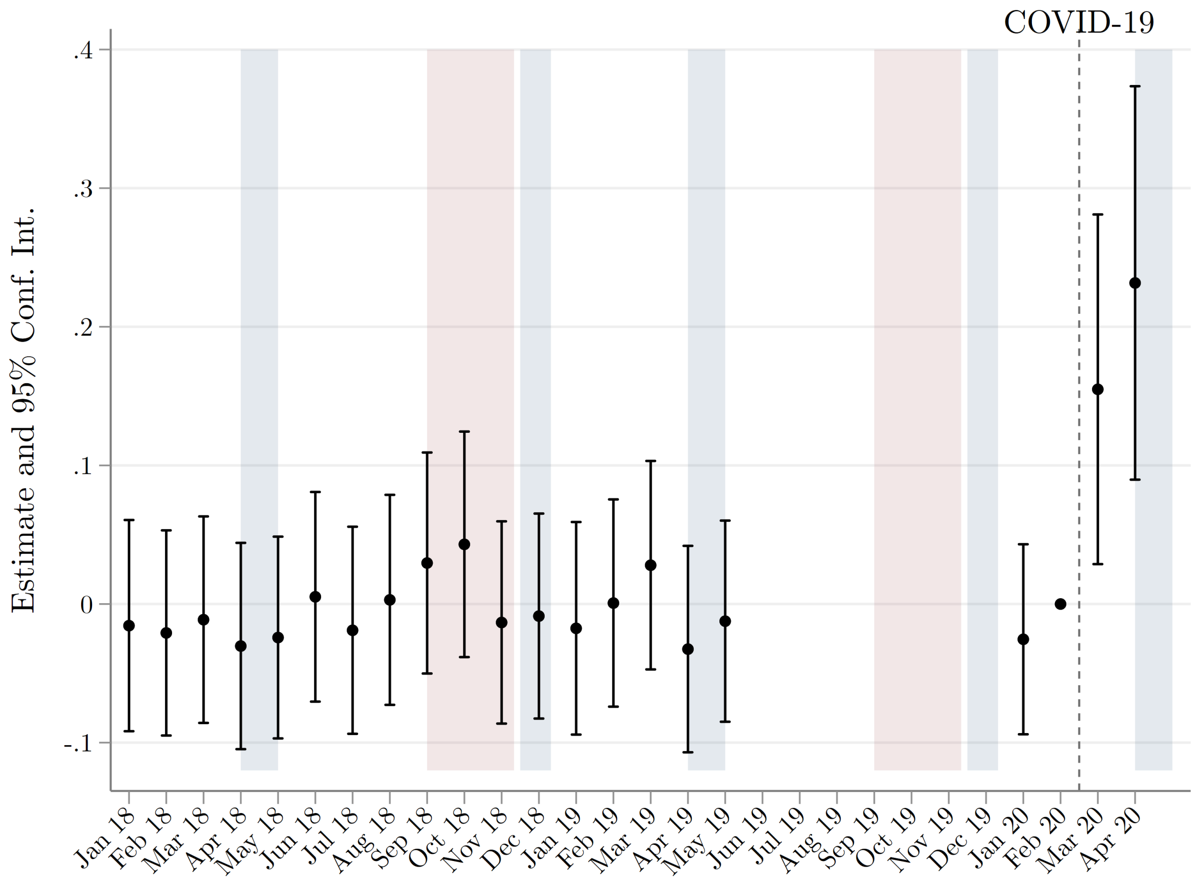

Figure S4: Rambachan and Roth (2023) Confidence Intervals (separate calendar month and year fixed effects)

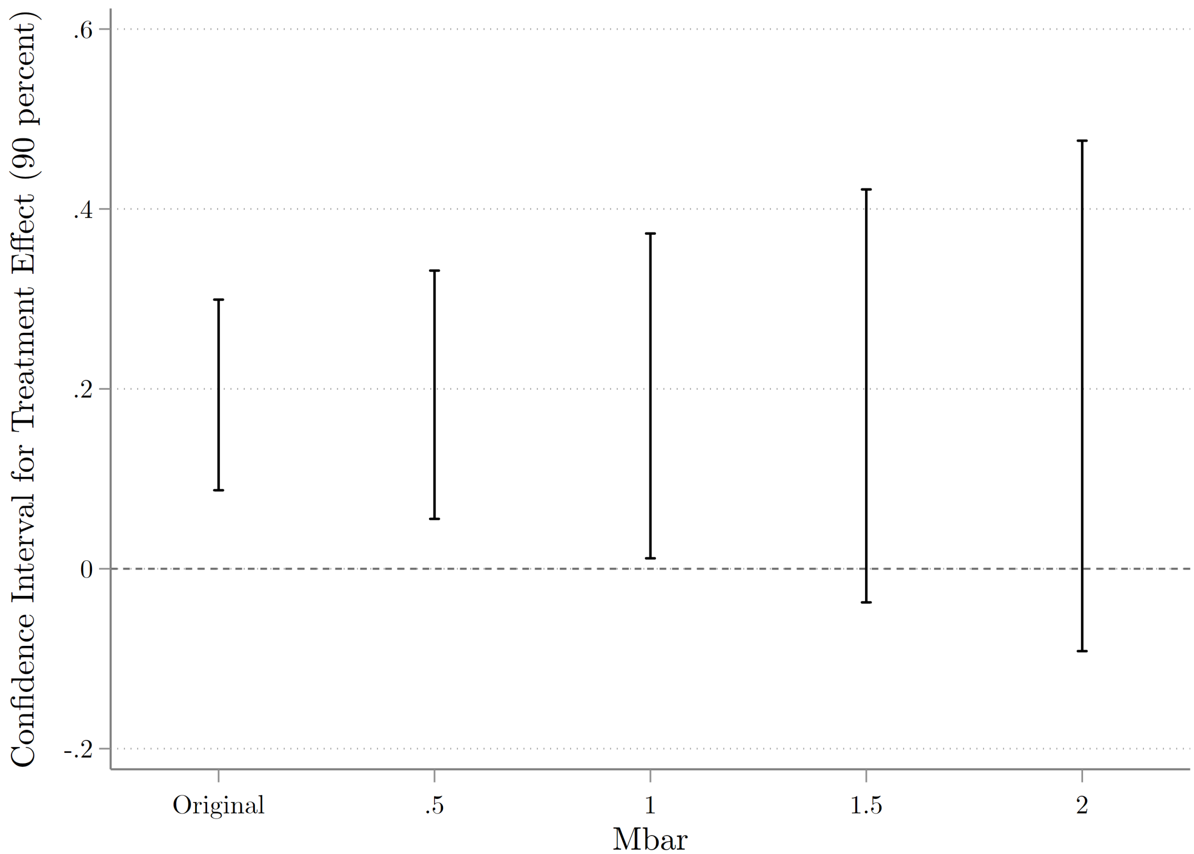

Figure S5: NPL Event Study Estimates

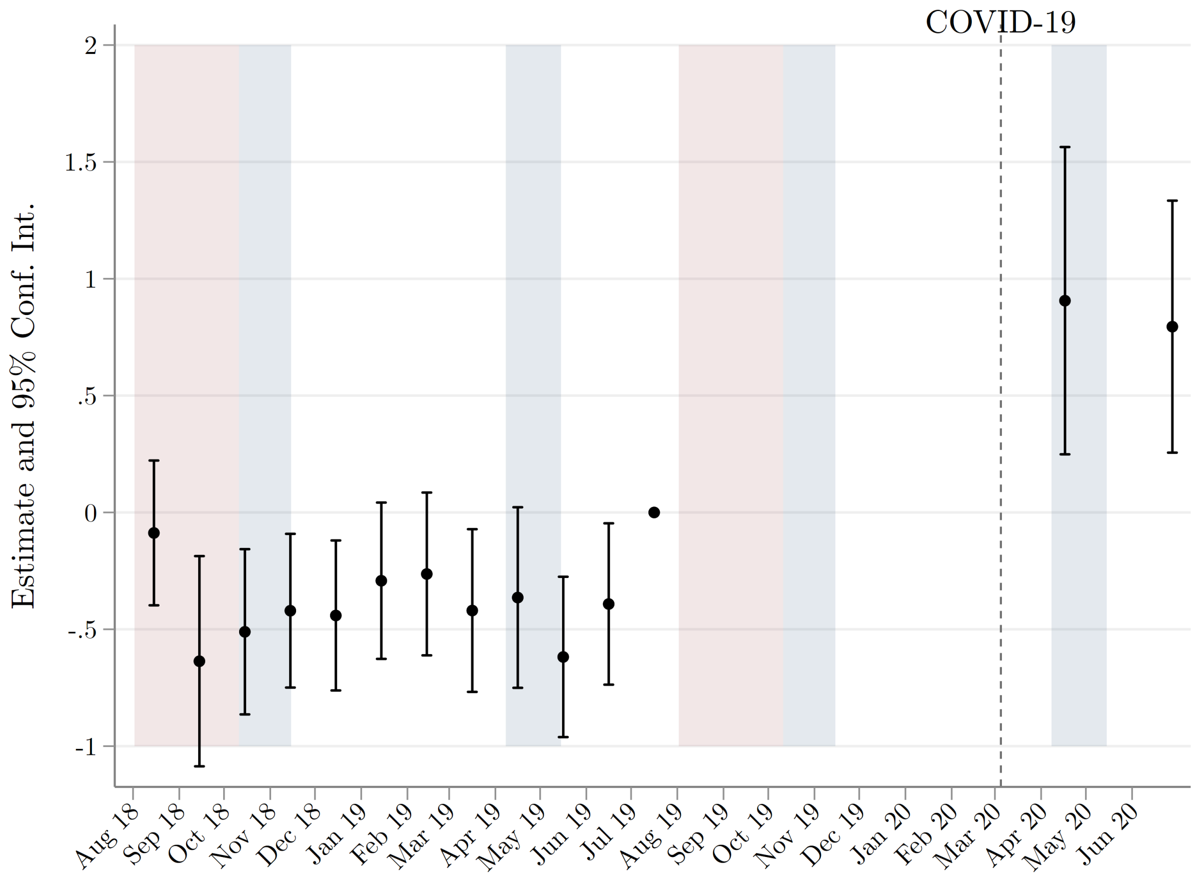

Figure S6: Rambachan and Roth (2023) Confidence Intervals

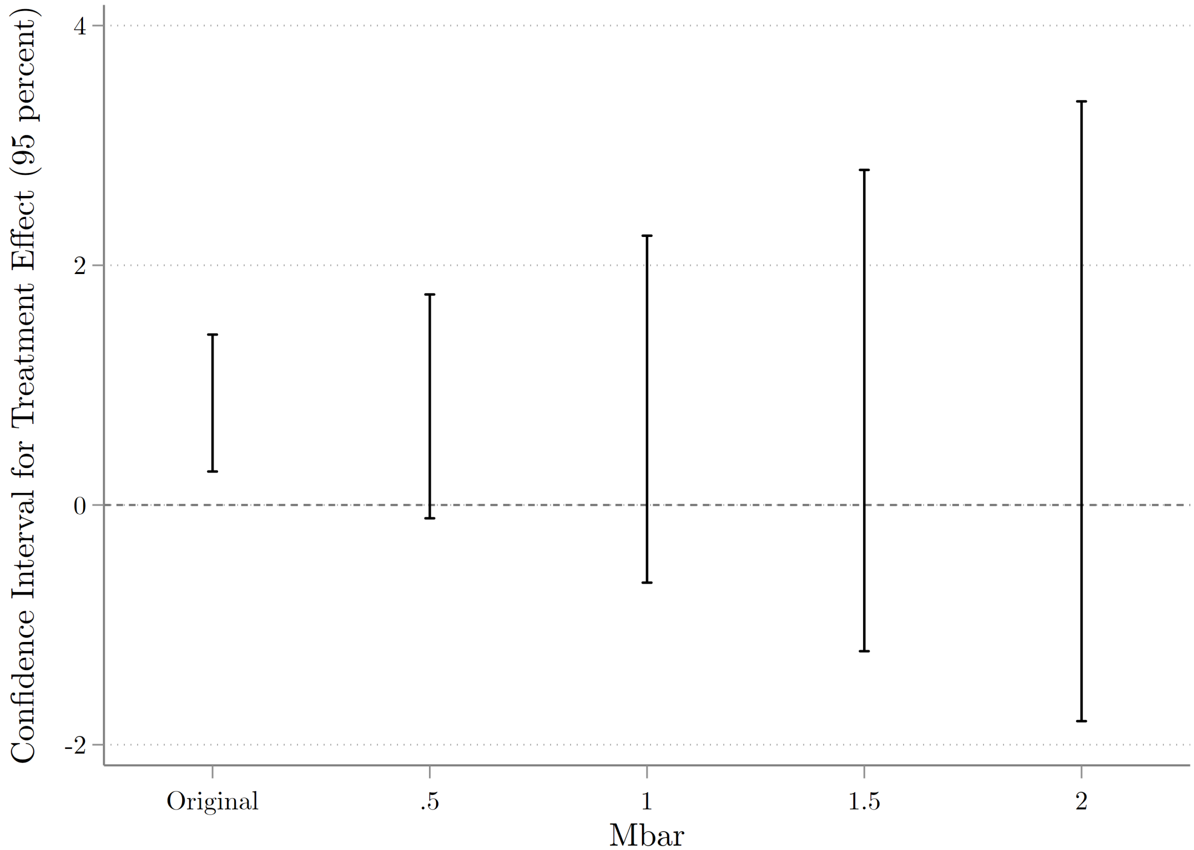

Figure S7: NPL Event Study Estimates (separate calendar month and year fixed effects)

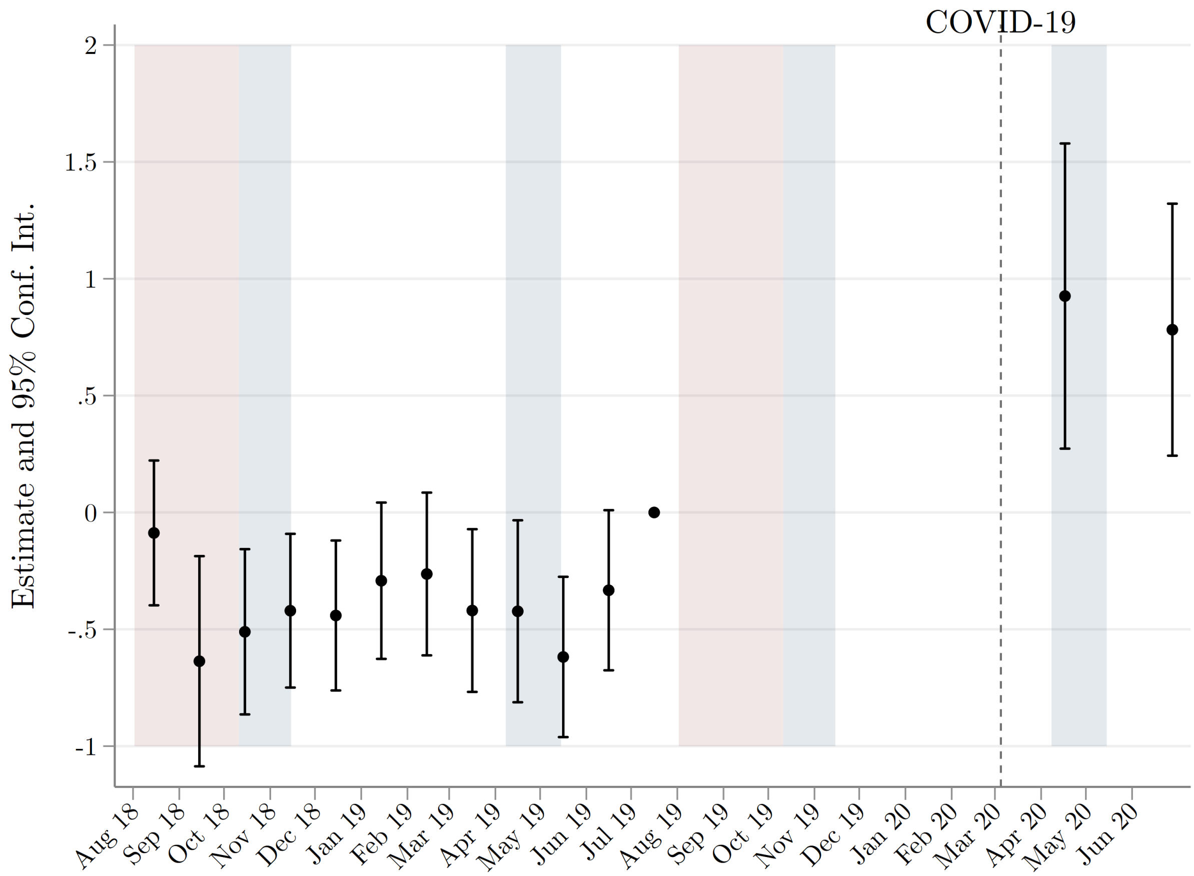

Figure S8: Rambachan and Roth (2023) Confidence Intervals (separate calendar month and year fixed effects)