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RESEARCH ARTICLE

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Covid-19 and agricultural labor supply: Evidence from the rural–urban interface of an Indian mega-city

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Abstract

This paper examines how India's national lockdown (March 25–May 31, 2020), in response to the spread of Covid-19, affected the on-farm family labor supply of 351 farm households in the rural–urban interface of Bangalore. We combine face-to-face survey data collected just before the start of the lockdown with phone survey data collected during the last 2 weeks of the lockdown. We find that 66% of farm households reduced their daily on-farm family labor supply during the lockdown, by on average almost 40% compared with prelockdown levels. Changes in on-farm family labor supply differed by key pre-Covid-19 household characteristics. Farm households that were engaged in crop marketing decreased their on-farm family labor supply by an average of 3–4 h/day. In turn, farm households that relied on off-farm income increased their on-farm family labor supply by on average 3–4 h/day [EconLit Citations: J22, J43, Q12, Q13, Q54].

Abbreviations: APMC, Agricultural Produce Market Committee; BPL, below-the-poverty-line; e.g., exempli gratia (for example); FAO, Food and Agriculture Organization; INR, Indian Rupee; IT, Information Technology; KMF, Karnataka Milk Federation; MNREGA, Mahatma Gandhi National Rural Employment Guarantee Act; OBC, Other Backward Castes; OLS, Ordinary Least Squares; OxCGRT, Oxford Covid-19 Government Response Tracker; PDS, public distribution system; PM-KSN, Pradhan Mantri Kisan Samman Nidhi; SC, Scheduled Castes; SHRUG, Socioeconomic High-Resolution Rural–Urban Geographic; SSI, Survey Stratification Index; ST, Scheduled Tribes; vs., versus; WTO, World Trade Organization.

KEYWORDS
agricultural households, agricultural markets, Covid-19, India, lockdowns, on-farm labor supply

1 | INTRODUCTION

The Covid-19 pandemic has affected countries all over the world. During the first wave of the pandemic in 2020, the direct health effects (e.g., death rates) have been less severe in low- and middle-income countries than in advanced economies.[1] However, the direct economic effects for developing countries have been devastating (Deaton, 2021; Egger et al., 2021; Ferreira et al., 2021). Across the world, governments responded to the spread of the Coronavirus by imposing lockdowns, with effects for employment, education, food security, nutrition, as well as the functioning of agriculture and food systems (Barrett, 2020; Devereux et al., 2020; Lele et al., 2020; Torero, 2020). Projections show that the pandemic could push millions of people into extreme poverty, particularly in sub-Saharan Africa and South Asia (Laborde et al., 2021). Empirical studies in several low- and middle-income countries document a reduction in total household income and household expenditures in response to lockdowns, whereas the evidence on decreasing food security and dietary diversity outcomes is more mixed (Amare et al., 2021; Jaacks et al., 2021; Janssens et al., 2021; Kansiime et al., 2021; Mahmud & Riley, 2021; Rönkkö et al., 2022).

In the agricultural sector, lockdowns disrupted supply chains, input markets, and rural labor markets, in particular wherever the latter rely on substantial numbers of internal migrants (Hammond et al., 2022; Laborde et al., 2021; Mahajan & Tomar, 2021; Nchanji & Lutomia, 2021; Ragasa et al., 2021; Rawal et al., 2020). These market disruptions, in turn, affected food prices and agricultural inputs, production, and marketing decisions (Ceballos et al., 2021; Rawal et al., 2020). In the aggregate, agriculture has been more resilient than other sectors (Beckman & Countryman, 2021; FAO, 2020), and trade in agricultural products has fared better than overall trade (WTO, 2020). Nevertheless, several studies have shown that on the microlevel, farm households were severely affected by the pandemic in terms of income, food security, and overall welfare (Amare et al., 2021; Gatto & Islam, 2021; Jaacks et al., 2021; Kansiime et al., 2021; Mahmud & Riley, 2021).

Smallholder households often diversify their livelihoods based on multiple income sources from the agricultural and off-farm sectors (Deichmann et al., 2009; Diao et al., 2019; Ellis, 1998; Fafchamps & Shilpi, 2003). Livelihood diversification can provide a buffer in times of shock, and adjustments to household labor allocation between sources of livelihood are one important strategy for smallholder households in developing countries to respond to shocks (Adams et al., 1998; Dercon, 2002; Morduch, 1995). However, while for example climatic shocks might lead farm households to increase their off-farm labor supply to compensate for agricultural income shortages (Blakeslee et al., 2020; Branco & Féres, 2021; Mathenge & Tschirley, 2015), or a financial crisis might result in additional household members entering the labor market (Frankenberg et al., 2003), lockdowns severely constrained such possibilities. Increasing household labor supply on the own farm, however, presents a coping strategy with relatively low entry costs (Dercon, 2002).

In the context of the Covid-19 pandemic, the literature suggests that households overall decreased their labor supplied to casual, salaried, and enterprise labor during lockdowns in different countries (Amare et al., 2021; Dang et al., 2023; Mahmud & Riley, 2021). However, the implications for on-farm labor allocation are less clear. While Mahmud and Riley (2021) find that farm households increased labor allocated to farm activities (crops and

[1]The direct health impacts of Covid-19 varied across regions of the developing world and over time. Latin America, for example, fared considerably worse than other regions. Moreover, some countries with relatively lower death rates in 2020 experienced major outbreaks in 2021 (e.g., India and Indonesia). Generally, the reported Covid-19 case numbers may be prone to an underestimation of actual infections (Wu et al., 2020). This is especially true in developing countries due to low testing capacity and imperfect record-keeping. Fewer travel activities and lower levels of international connectedness might have delayed the introduction of Covid-19 in low- and middle-income countries (Li et al., 2021).

livestock), Amare et al. (2021) find that lockdowns decreased the probability that households were engaged in farming activities. The latter finding is largely driven by households located in remote rural areas, as Amare et al. (2021) also show that engagement in farm activities became more likely when households were located in urban areas. They attribute this to a reallocation of labor resources towards farming to compensate for reduced nonfarm business and wage employment in urban areas. Opportunities for livelihood diversification are particularly pronounced in urban areas and both off-farm employment and agricultural commercialization can contribute to farm household income. However, it is not yet well understood how households with a diversified livelihood portfolio in urban areas responded to Covid-19-related lockdowns and what factors drive the differences in the outcomes for on-farm labor supply revealed in previous studies.

In this paper, we focus on changes in daily on-farm family labor supply in response to the Indian nationwide lockdown in a periurban setting in India. In India, both agricultural and off-farm labor markets were decisively disrupted by the lockdown (Reardon et al., 2020). The disruption of agricultural supply chains heavily affected the availability, sales, and prices of agricultural produce (Harris et al., 2020; Mahajan & Tomar, 2021). In particular, we test the hypothesis that the disruption of agricultural supply chains and marketing channels depressed on-farm labor supply of households who were integrated into agricultural markets pre-Covid-19, as they were unable to sell their output during the lockdown. Pre-Covid-19, the opportunity cost of on-farm labor was likely lower for these households due to higher income from farming. It is therefore expected that more family labor was allocated to the own farm that was not needed anymore once agricultural markets were closed and it was nearly impossible to reallocate this labor to other sectors. In contrast, we hypothesize that the lockdown suddenly made available household members who engaged in off-farm work pre-Covid-19. We thus hypothesize that a decrease in the opportunity cost of allocating time to farming and the likely loss of off-farm income had the opposite effect and increased agricultural labor supply at the household level.

Specifically, we focus on smallholder farmers in the rural–urban interface of Bangalore, a mega-city in the southern state of Karnataka. On March 25, 2020, in an effort to stop the first wave of Covid-19 infections, the Government of India imposed a 21-day nationwide lockdown. The lockdown, announced with only 4-h notice, was one of the strictest worldwide and was extended several times until May 31.[2] The rural–urban interface of a mega-city like Bangalore is especially interesting to study on-farm labor supply due to the large urban off-farm sector that, under normal conditions, provides various opportunities for farm households to diversify their income sources. Besides, urban markets attract (migrant) labor and present opportunities for farm households to engage in commercial agriculture.

In our empirical analysis, we take advantage of the combination of a face-to-face survey implemented shortly before the start of the national lockdown on March 25 and a phone survey of the same households during the last 2 weeks of the lockdown (May 18–June 2, 2020). The face-to-face survey included detailed information on agricultural production and marketing of 415 farm households located in the rural and periurban areas surrounding Bangalore. In the phone survey, we were able to reinterview 85% of the farm households. Hence, we have a dataset of 1152 individuals (age 15+) from 351 farm households to examine changes in on-farm labor supply due to the national lockdown.

Since we base our analysis on within-household variation and include village trends and pre-Covid-19 socioeconomic controls, we are confident that changes in on-farm labor supply are attributed to short-run responses of households to the lockdown. Any participatory effects and other structural changes during the time of the lockdown are likely negligible and in light of the unexpected nature of the first Indian lockdown, anticipatory effects seem unlikely. Since household characteristics were only measured at one point in time before the lockdown, we however cannot entirely rule out other unobserved shocks occurring at the same time generating a similar response along pre-Covid-19 market integration or off-farm income.

[2]In the first lockdown phase, between March 25 and April 19, 2020, India achieved the maximum possible value (100) of the "Covid-19 Government Response Stringency Index," measured by the Oxford Covid-19 Government Response Tracker (OxCGRT) project. In the first semester of 2020 (January 21–June 30), only 13 out of 185 countries scored the maximum value. When considering the total number of days with a stringency score of 100 (the maximum) in the first semester of 2020, India, with 27 days, had the eighth most stringent lockdown out of 185 countries. For details on the OxCGRT project and database, see Hale et al. (2021).

The two hypotheses are confirmed by our analysis. We find that being integrated into agricultural markets before the lockdown is associated significantly with a reduction in their daily on-farm household labor supply during the lockdown. Relying on off-farm income sources before the lockdown is related to a substantial increase in the daily hours worked on the farm. Both findings are confirmed in individual-level regressions. Furthermore, there is a positive and robust relationship between changes in daily hours worked on farm and dairy and livestock activities, whose markets were much less disrupted than crop markets. This implies that the lockdown differentially affected households with different pre-Covid-19 livelihood strategies.

Our article contributes to the growing strand of literature on the implications of the Covid-19 pandemic for households in developing countries. Especially the unique periurban setting allows for new insights into the effects of lockdowns on on-farm labor allocation differentiated by disruptions in the on- as well as off-farm sectors. Understanding how on-farm labor supply is affected by Covid-19-related lockdowns is key to understanding their effects on household welfare. Agricultural activities are considered a fallback option for vulnerable households in times of crisis (Fallon, 2002), and our results indicate that agriculture provided a buffer to the lockdown for households with off-farm income before the pandemic, while this seems to not have been the case for market-integrated farm households.

It is also crucial to evaluate the microlevel social and economic effects of policies during the pandemic. The Covid-19 pandemic was an unprecedented experience so far, but scenarios of future health crises cannot be ruled out against the background of climate change, which increases the risk of vector-borne diseases and the zoonotic transmission of viruses and thereby the risk of future pandemics (Börner et al., 2015; Jones et al., 2013). Evidence that is generated in the context of the Covid-19 pandemic can thus inform policy making in response to future health crises.

The paper is structured as follows: In Section 2, we provide some context on Covid-19 in India and on our study area and present a conceptual framework. Subsequently, we describe the data collection for the pre-Covid-19 face-to-face and the Covid-19 phone surveys (Section 3). Section 4 introduces the empirical methodology. We then present the results in Section 5 and discuss them in Section 6. Section 7 concludes.

2 | CONTEXT

2.1 | Covid-19 in India and Bangalore

The first positive Covid-19 case in India was reported on January 30, 2020, in the state of Kerala. On March 9, the first positive cases were reported in Bangalore. The municipal Government reacted by implementing the first restrictions, for example, the closure of educational institutions, malls, and sports facilities, and a limitation of public gatherings (Ravi, 2020b). On March 22, Prime Minister Narendra Modi called for a “People's Curfew,” a voluntary 14-h lockdown in which people were urged to stay at home. On March 24, the Government of India announced a nationwide lockdown for 21 days with only 4-h notice. The lockdown was one of the most stringent worldwide. It was extended several times until May 31. As of June 1, a phased reopening of the country began (De, 2020). Nevertheless, Bangalore remained affected by local and regional lockdowns and restrictions after the end of the nationwide measure (Government of Karnataka, 2021). Figure 1 plots the evolution of new confirmed Covid-19 cases in India, between January 30 and June 15, 2020, and the timing of the two rounds of data collection (described in Section 2.2).

The first, and most stringent, phase of the national lockdown coincided with India's peak harvesting season for winter crops (Rabi) (Mohan, 2020). During the lockdown, farming was declared an “essential service” and agricultural markets were exempted from most restrictions.

Nevertheless, agricultural supply chains were hit due to closure of agricultural markets, the disruption of movement of vehicles (e.g., movement of trucks on roads and suspension of bus and train services), a lack of access to end buyers, and fluctuating demand (e.g., due to closure of hotels, restaurants and markets; fear of Covid-19 and social distancing causing empty markets), affecting farmers' ability to market their produce (Devaiah, 2020;

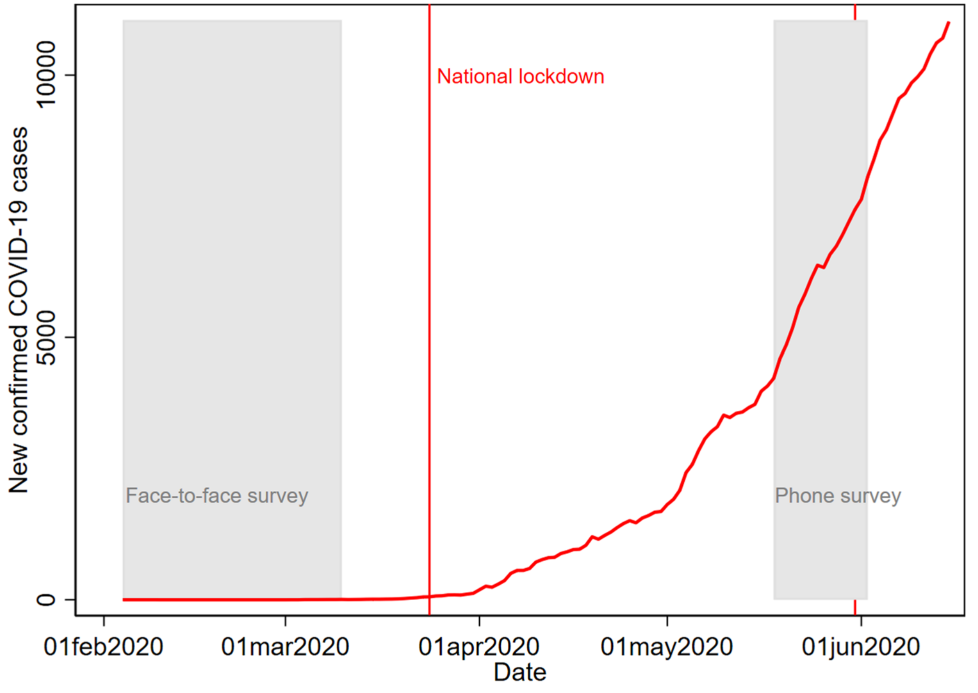

FIGURE 1 New confirmed Covid-19 cases in India: January 30–June 15, 2020. *Source*: Own calculations from Our World in Data (Ritchie et al., 2020). *Notes*: A 7-day moving average of new confirmed Covid-19 cases in India between January 30 and June 15, 2020. The timing of the face-to-face (pre-Covid) survey (February 4–March 10, 2020) and phone survey (May 18–June 2, 2020) is shown by the shaded gray areas. The timing of the national lockdown (March 25–May 31, 2020) is shown by the vertical red lines.

Gejji, 2020; Mahajan & Tomar, 2021; Mallikarjunan, 2020). Besides, farmers faced labor shortages due to migrant workers going back to their native villages (Bharadwaj et al., 2021). Figure 2 shows the total volume of agricultural commodities arriving each week at seven market yards (Mandis) run by the state's marketing board (Agricultural Produce Market Committee), in the districts of Bangalore Urban and Bangalore Rural. The data, compiled by the SHRUG COVID platform (Asher et al., 2019), reveal a sharp drop in the marketed volume immediately after the beginning of the lockdown. By June 15, the total volume was still 50% below the volume of the two previous years, 2018 and 2019.

2.2 | Bangalore's rural–urban interface

Bangalore is a growing mega-city. According to the latest Indian Censuses, the city's population grew from 5.8 million in 2001 to 8.7 million in 2011 (Directorate of Census Operations Karnataka, 2011b).[3] Bangalore has a booming IT sector (Narayana, 2011) and accommodates employment opportunities in various other off-farm sectors as well, like the banking and finance industries, biotechnology research centers, textile and automobile industries, and small-scale industries (Sudhira et al., 2007). However, for 49% of the labor force in the urbanizing region of Bangalore, agriculture still remains a

[3]These numbers are for the district Bangalore Urban. Recent unofficial projections suggest that the city's population has reached a population of more than 13 million in 2022 (https://www.census2011.co.in/census/district/242bangalore.html, accessed 24.01.2023; https://populationstat.com/india/bangalore, accessed 24.01.2023).

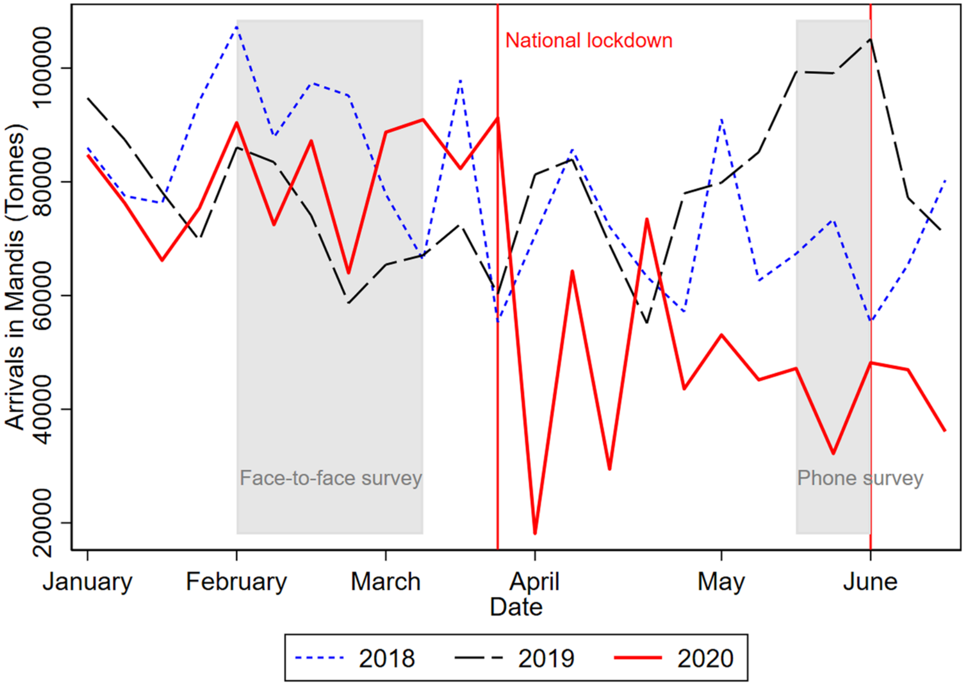

FIGURE 2 The impact of Covid-19 on Bangalore's agricultural markets. *Source*: Own calculations from the SHRUG COVID platform (Asher et al., 2019). *Notes*: Weekly arrivals of agricultural commodities in tonnes to markets (Mandis) between January 1 and June 15. Districts are Bangalore (urban) and Bangalore (rural). Mandis included are Bangalore, Binny Mill (F&V), Channapatana, Doddaballapura, Hoskote, Kanakapura, and Ramanagara. The timing of the face-to-face (pre-Covid-19) survey (February 4–March 10, 2020) and phone survey (May 18–June 2, 2020) is shown by the shaded gray areas. The timing of the national lockdown (March 25–May 31, 2020) is shown by the vertical red lines.

source of income (Directorate of Census Operations Karnataka, 2011a, 2011c).[4] Being located in relatively close proximity to an urban center presents opportunities for farm households to engage in diversified and commercial agriculture. Farmers have relatively good access to input and output markets, and urbanization is associated with a change in diets and preferences of urban residents, which increases the demand for high-value agricultural produce (Parthasarathy Rao et al., 2007). Despite this, given the large urban off-farm sector, farm households face high opportunity costs of intensifying agricultural production and allocating household labor to agriculture (Steinhübel & von Cramon-Taubadel, 2020). Since both agricultural and off-farm labor markets were heavily disrupted during the lockdown, the rural–urban interface of a mega-city like Bangalore is a particularly relevant setting to study the lockdown's implications on farm households' on-farm labor supply.

2.3 | Conceptual framework

The goal of our paper is to investigate the effect of the Indian nationwide lockdown on family labor allocation between the on- and off-farm sectors in an urbanizing environment. We conceptualize household decision-making

[4]This estimate covers the districts Bangalore Rural and Ramanagara, surrounding the city of Bangalore towards the North, South, and West, and in which our study area is located.

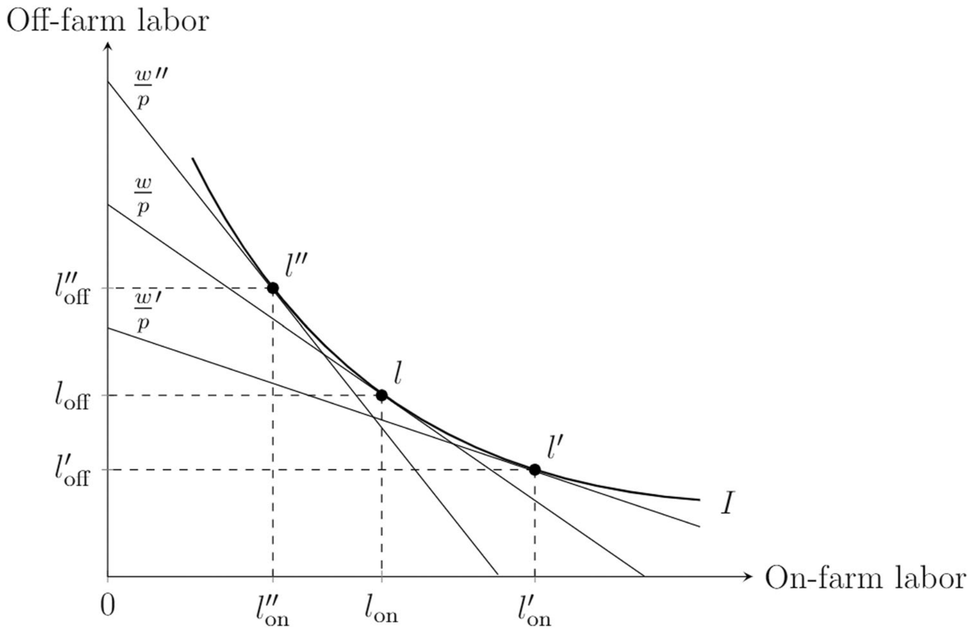

FIGURE 3 Family labor allocation between on- and off-farm sectors in response to the Indian nationwide lockdown. *Source*: Own illustration.

about labor allocation as an income maximization problem, graphically depicted in Figure 3. Thus, *I* represents an isoincome curve for potential combinations of on- and off-farm labor. The ratio of wage, *w*, and agricultural prices, *p*, determines the optimal allocation, *l*, of family labor into on- and off-farm work.

Let us assume that *l* represents the optimal labor allocation under pre-Covid-19 conditions. The effect of the lockdown can be represented by a change in the *w/p* ratio. Shutting down daily life, and thus most of the economy, will affect both wages and agricultural prices, but consequences for certain sectors, jobs, and value chains might be more severe than others (e.g., Bhatt et al., 2021; Van Hoyweghen et al., 2021). Also, restrictions on agricultural markets were lifted relatively quickly, while the shutdown of nonagricultural sectors continued (Government of India, 2020). Furthermore, household-specific shifts in *w/p* likely also depend on the crops produced and the level of commercialization pre-Covid-19, as well as on type and wages from off-farm employment. For example, Ceballos et al. (2021) and Mahajan and Tomar (2021) show that even though excluded from the lockdown, agricultural prices showed high and often crop-specific volatility.

We develop two scenarios that describe the effects of the lockdown on family labor allocation in the rural–urban interface of Bangalore:

Hypothesis 1. Households that strongly depended on off-farm employment and with household members who were able to realize good wages pre-Covid-19 are more likely to shift family labor to agricultural production during the lockdown. For them, the drop in *w* is more severe relative to the drop in *p* and thus the slope of *w/p* flattens (see [*w/p*]′ and *l*′ in Figure 3).

Hypothesis 2. Households with commercialized agricultural production and little or no income from the off-farm sector pre-Covid-19 (e.g., daily or informal labor) reduce family labor in agriculture because for them the reduction in *p* is larger relative to already low (or zero) levels in *w*. That means the slope of *w/p* becomes steeper (see [*w/p*]″ and *l*″ in Figure 3).

Note that for simplicity we assume that households can realize the same income pre-Covid-19 and during the lockdown, that is, only w/p changes during the lockdown but not I. In addition to the change in the slope of w/p, it is likely that the drop in both wages and agricultural prices due to the lockdown also causes a general shift of w/p towards the origin of the graph. As a result, there might be a shift of I to a lower income level as well. However, since we do not have information on income in our dataset, we do not focus on drivers of changes in income but only on labor allocation in this section.

3 | DATA

3.1 | Pre-Covid-19 face-to-face household survey

Between February 4 and March 10, 2020, we collected household survey data from villages and urban neighborhoods in two transects in the North and the South of Bangalore city (see Figure 4 for a map of the transects). The survey was the second round of a panel of 1212 households who were first interviewed in 2016/17. Sampling of 61 villages/neighborhoods and households was done before the first round of the field survey in 2016/17 using a multistage stratified random sampling approach. As a proxy for urbanization, a Survey Stratification Index (SSI) was developed by Hoffmann et al. (2017). The SSI is calculated from the distance to Bangalore city center and the percentage of non-built-up area around the village/neighborhood. On the basis of the SSI, the area within the two transects was classified into six urban, periurban, or rural strata. Within the strata, 30 villages/neighborhoods in the Northern and 31 in the Southern transect were randomly sampled in proportion to the size of the stratum. A random sample of farm and nonfarm households was drawn proportionate to the size of the village based on lists obtained from mother and childcare centers.

In the second round of the survey in 2020, we planned to reinterview all 756 farm households from the previous round in 2016/17.[5] However, due to the outbreak of the Covid-19-pandemic, fieldwork was suspended on March 10, 2020, with only 422 households (partially) interviewed (56% of the sample); 41 households (5%) refused or could not be found, whereas 293 (39%) of the households had not yet been contacted by March 10. We were able to interview households from 50 out of 58 villages/neighborhoods,[6] and attrition rather occurred across than within villages/neighborhoods (see Supporting Information Table A2). Overall, at the household level, the likelihood of being reinterviewed in 2020 correlates positively with dairy activities (10 percentage points) and negatively with the number of owned land plots (−5 percentage points per extra plot) and belonging to a Scheduled Caste (−13 percentage points). None of the other household characteristics predicts attrition. For simplicity, we henceforth refer to the primary sampling areas as villages. The distance of each village's centroid to Bangalore's city center ranges from 8.8 to 44.4 km, with the distance from the average village being 27.3 km.

3.2 | Covid-19 phone survey

In the last 2 weeks of the nationwide lockdown, between May 18 and June 2, 2020, we contacted 415 farm households that were interviewed during the pre-Covid-19 household survey for a short phone interview.[7] We were able to complete phone interviews with 351 households, achieving a response rate of 85%. For nearly all

[5]Farm households are those who own or manage a farm or engage in any dairy or livestock activities. Out of the 1212 households surveyed in 2016/17, 756 (62%) are farm households.

[6]In three of the urban neighborhoods, there were no farm households sampled in 2016/17.

[7]Of the 422 farm households interviewed face-to-face in February–March 2020, seven had missing or invalid phone numbers.

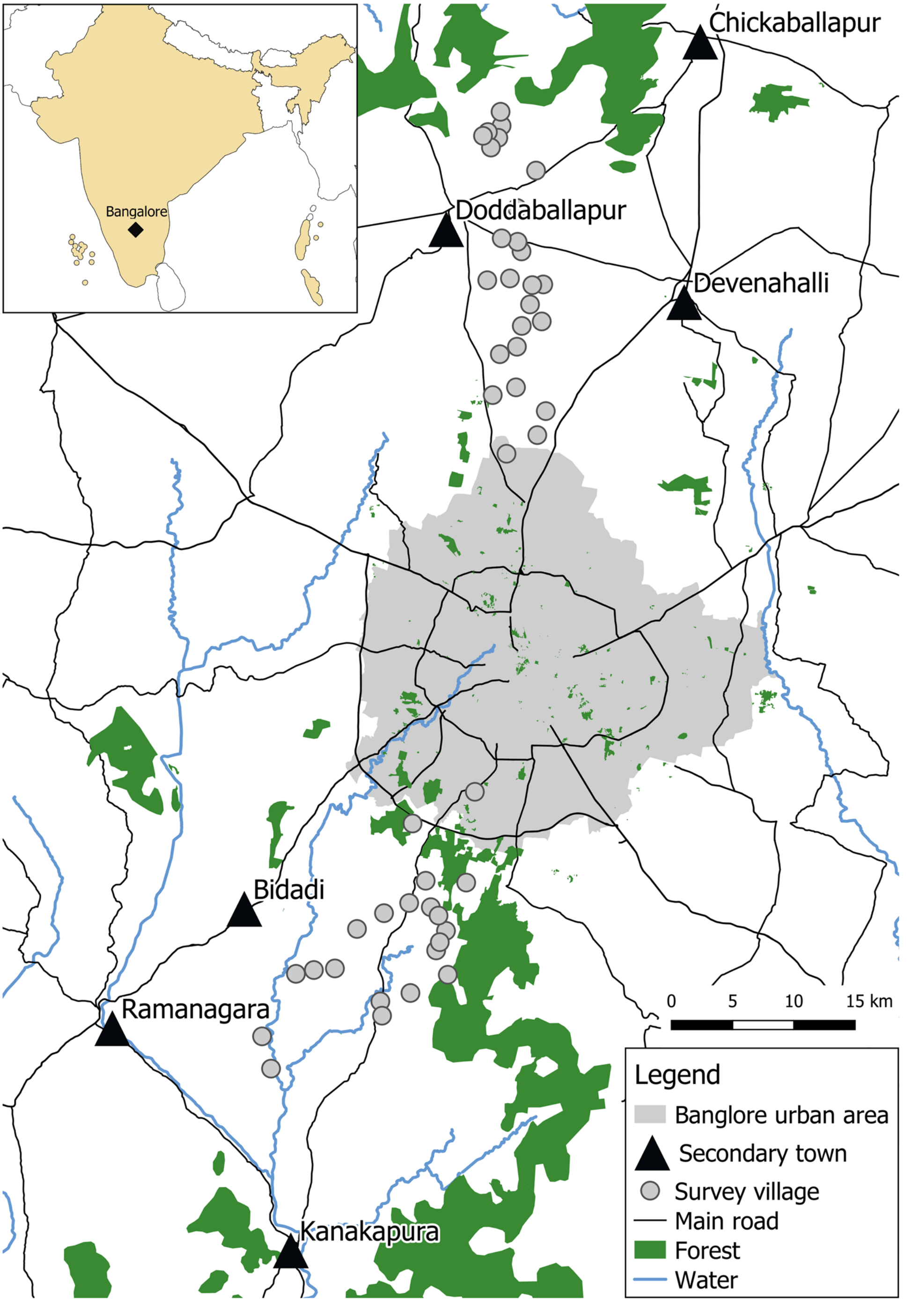

FIGURE 4 Study region in the Northern and Southern transects of Bangalore. *Source*: Own survey data.

households (93%), the interview could be conducted with the same respondent that was interviewed during the pre-Covid-19 household survey. All in all, we thus achieved a very high response rate.

This might have resulted from the in-person visits only a few weeks before the lockdown which implied that the respondents were familiar with the survey and the survey team. Only enumerators who were involved in the face-to-face survey conducted the phone interviews. The phone survey was administered in the last 2 weeks of the Indian nationwide lockdowns, when direct contact between respondents and enumerators was not possible. A phone survey therefore presented the only feasible way to contact the households and collect data from them. The advantage of this is that we were able to interview the households in real time and with a very short recall period of about 6–8 weeks. We could base our phone survey on an existing, largely representative, sampling framework and achieved a high response rate that raised no major concerns about selection bias (Ambel et al., 2021; Brubaker et al., 2021), which was facilitated by the widespread ownership of mobile phones of the sample households. Since we had conducted in-depth interviews with the same households only 1–2 months before the lockdown, we could develop our telephone survey module based on detailed information previously collected and thereby reduce the length of the questionnaire and the interview time to avoid response fatigue (Abay et al., 2021). Nevertheless, the shortening of the survey modules implies limitations, as we were not able to collect information in the same depth and detail as in the face-to-face survey. Changes in the types of wording of questions may reduce their comparability to the detailed information collected during the face-to-face survey (Gourlay et al., 2021). Since we relate our main outcome variable of interest, on-farm labor supply, to pre-Covid-19 household characteristics collected during the face-to-face survey, we are not concerned about comparability for the variables collected pre-Covid-19.

This differs for the main outcome variable of interest. In the phone survey, we asked the main decision-maker: "In case your household has a farm (including dairy and livestock), how many hours a day does [Household member age 15+] work on your farm, on a typical day?" This question was asked for every person aged 15+ who was a household member in the pre-Covid-19 survey, irrespective of their employment status or occupation. In contrast, in the face-to-face pre-Covid-19 survey, this question was only asked for individuals (15+) whose main or secondary occupation was own-farming (including dairy and livestock). For all other individuals (not working or working off-farm), we impute pre-Covid-19 on-farm hours work on a typical day as being zero. Clearly, this may underestimate prelockdown on-farm work done by household members sporadically, or, in the case of women, tasks that are not perceived as work (Dixon, 1982; Hirway & Jose, 2011). Accordingly, reductions in labor may be underestimated, whereas increases in labor may be overestimated. In our setting, on-farm hours worked were rather reduced between the two surveys. Hence, in case of a decrease in on-farm labor, our estimate can be considered a lower bound of the actual decrease in on-farm labor.

In total, 1455 household members were surveyed both in the pre-Covid-19 survey and in the phone survey. Ultimately, there are 1152 individuals with complete data (including imputed zeros) on on-farm labor supply that are matched across the pre-Covid-19 and phone surveys. Unfortunately, one of the enumerators only asked the question to individuals whose main occupation in the pre-Covid-19 survey was own-farming. As a result, 295 individuals have missing information on on-farm labor supply. Since the phone interviews were randomly distributed among enumerators, we are not worried about sample selection at the household level, but we introduce a variable ("number of adults with missing measurement of on-farm labor supply") to control for this in our estimations (see Section 4).[8] Because one of the main variables of interest—agricultural marketing—is defined at the household level, we aggregate the individual data at the household level to compute the difference between daily on-farm hours worked in the phone survey and daily hours worked in the pre-Covid-19 survey for 351 farm households. Later, we also estimate individual-level models.

4 | METHODS

To test our hypotheses, we estimate regressions of the following form:

$$\Delta Y_{hv} = \beta_1 Market_h + \beta_2 Off - farm_h + \delta \boldsymbol{X_h} + \theta \boldsymbol{H_h} + \alpha_v + \varepsilon_{hv}, \tag{1}$$

[8]See Supporting Information Table A3 for evidence that households with missing information on on-farm labor supply are balanced on pre-Covid-19 socioeconomic characteristics.

where ΔY_{hv} is the difference in household h's total on-farm daily hours worked between the lockdown (May/June) and the pre-Covid (February/March) periods. Agricultural market integration ($Market_h$) is a dummy taking a value of 1 if the household sold any crop in the market between January 2019 and January 2020.

Off-farm employment ($Off\text{-}farm_h$) is measured as the share of adult household members that worked off-farm pre-Covid-19. $\boldsymbol{X_h}$ is a vector of the characteristics of the household's decision-maker—gender, age, education, marital status, and whether he/she worked in the reference week—all measured pre-Covid-19. $\boldsymbol{H_h}$ is a vector of household socioeconomic characteristics—caste, religion, household size dairy or livestock farming activities, pesticide use (yes/no) in own farm, irrigation use (yes/no) in own farm, wealth decile fixed effects,[9] and the number of adults with missing measurement of on-farm labor supply—all measured pre-Covid-19, except for the number of adults with missing measurement of on-farm labor supply, which controls for an enumerator's skipping error in the phone survey. Lastly, α_v is a set of village dummies, with villages indexed by v. For some model specifications, we will replace the village dummies by the rural–urban index designed by Hoffmann et al. (2017) that captures the village's location in the periurban interface of Bangalore. ε_{hv} is the error term. For inference, standard errors are always clustered at the village level (49 villages). A summary and description of all variables used in the analysis is provided in Table A1 in the Supporting Information.

Note that all explanatory variables were measured before the lockdown and, importantly, before Covid-19 was a widespread public health concern in India. As a result, we do not expect the pre-Covid-19 measurements to be influenced by anticipation or uncertainty over Covid-19 or the looming lockdown.[10] Further, through the inclusion of village fixed effects, we allow for arbitrary differences in unobservable trends at the local level—for example, local spread of the virus, enforcement of lockdown rules, economic structure, and local informational and social support networks. Finally, by specifying our model with the first-differences in the outcome variables, we can implicitly absorb *level* effects by time-invariant household-specific unobservables. This follows from the idea that we can rewrite the model specified in Equation (1) as a panel fixed effect (within-estimator) model with interaction terms including a time trend (see, e.g., Wooldridge, 2010).[11] This also means that all coefficients in our model specification have to be interpreted as *trend* effects, which is what we are looking for in our research question. In short, our objective is to understand how the response of households to an unexpected massive shock relates to within-village variation in characteristics measured just before the shock occurred.

5 | RESULTS

5.1 | Descriptive statistics

Table 1 presents the socioeconomic profile of the average farm household, as of February/March 2020, before the lockdown. Around three out of four main decision-makers (who are also the primary survey respondents) are male,

[9]Wealth deciles are computed from the total per capita value of durable assets owned by the household. Data on durable assets were collected during the pre-Covid-19 face-to-face survey and covered 30 detailed asset types.

[10]We cannot entirely rule out anticipatory effects, but they seem unlikely due to the timing of our face-to-face survey. The face-to-face survey was administered between February 4 and March 10, 2020. Since the first positive case of a Covid-19 infection was detected in Bangalore only on March 9, we do not expect households to have anticipated a nationwide lockdown due to Covid-19 during our survey period, which took place before Covid-19 was even a major concern in the Bangalore area. The restrictions put in place by the local and national governments only happened afterwards. For example, the “People's Curfew” was announced on March 22 and the national lockdown was announced on March 24.

[11]In our two-period setting, Equation (1) is equivalent to the following panel fixed effect (within-estimator) specification:

$$Y_{hvt} = \omega_h + \varphi_t + \beta_1 Market_h \cdot t + \beta_2 Off - farm_h \cdot t + \delta X_h \cdot t + \theta H_h \cdot t + \alpha_v \cdot t + u_{hvt},$$

where, h, v, t are index households, villages, and time periods, respectively. ω_hs are household fixed effects; φ_ts are time fixed effects; X_h, H_h, and α_v are a main respondent and household controls and village dummies, respectively, all measured in period 1 (pre-Covid-19) and interacted with a time trend (t). In our two-period setup, by taking the first-differences {(t = 2) − (t = 1)}, we obtain

$Y_{hv2} - Y_{hv1} = (\omega_h - \omega_h) + (\varphi_2 - \varphi_1) + \delta X_h \cdot (2 - 1) + \theta H_h \cdot (2 - 1) + \alpha_v \cdot (2 - 1) + (u_{hv2} - u_{hv1})$, which simplifies our first-difference representation of the model (Equation 1): $\Delta Y_{hv} = \delta X_h + \theta H_h + \alpha_v + \varepsilon_{hv}$.

TABLE 1 Descriptive statistics of the estimation sample: Pre-Covid-19 household characteristics.

	Mean	SD	Minimum	Maximum	N
Decision-maker					
Male	0.77		0	1	351
Age	49.28	13.09	22	90	350
Education	6.25	5.01	0	20	348
Married	0.89		0	1	350
Worked	0.82		0	1	350
Household					
Dairy	0.71		0	1	347
Livestock	0.41		0	1	346
Pesticides	0.33		0	1	341
Irrigation	0.35		0	1	341
Caste					
General	0.52		0	1	347
SC	0.14		0	1	347
ST	0.06		0	1	347
OBC	0.24		0	1	347
Other	0.03		0	1	347
Hindu	0.96		0	1	348
Household size	4.99	2.54	1	24	347
Durable assets	30.99	55.93	0	570	341
Crop marketing	0.38		0	1	351
Off-farm employment	0.39	0.38	0	1	351
Rural–urban index	0.70	0.17	0	1	351

Notes: Durable assets are measured in thousand INR per capita. Off-farm workers are measured as the share of adult household members whose main occupation was off-farm in the pre-Covid-19 period. All variables are from the pre-Covid-19 household survey. For definitions of the remaining variables, see Supporting Information Table A1.

89% are married and 82% were working. The average decision-maker is 49 years old and has 6 years of education. Dairy and livestock activities are common, with 71% of households engaged in dairy and 41% engaged in livestock farming (other than dairy). Nearly all farm households are Hindu, with about half belonging to General Castes and the remaining half belonging to Scheduled Castes (SC), Scheduled Tribes (Tribes) or Other Backward Castes (OBC). The average household has five members.

Reflecting the large market for agricultural produce in and around Bangalore, 38% of households had sold at least one crop in the market in the year preceding the survey (January 2019–January 2020); and roughly a third of the households irrigated and applied pesticides to at least one crop. Beyond agriculture, 60% of farm households include at least one adult (15+) member working off-farm; on average, 39% of adult household members worked off-farm.

In the first weeks of the national lockdown, the plight of millions of stranded migrant workers across India was widely reported in the media (Slater & Masih, 2020). However, migration is not relevant in our study context.

TABLE 2 Change in household on-farm labor: Descriptive statistics.

	Mean	SD	Minimum	Maximum	N
Panel A: Full sample					
Household on-farm labor (hours/day)					
Lockdown (May–June)	6.64	4.58	0	27	351
Prelockdown (February–March)	10.86	7.98	0	64	351
Difference	−4.22	8.70	−56	18	351
Panel B: Difference lockdown – prelockdown					
By crop marketing					
No crops sold	−2.87	7.85	−34	18	216
At least one crop sold	−6.39	9.56	−56	13	135
Panel C: Difference lockdown – prelockdown					
By off-farm employment					
No household member employed off-farm	−5.67	9.09	−56	18	141
At least one member employed off-farm	−3.25	8.32	−34	15	210

Notes: All figures refer to total household daily hours worked on-farm. Lockdown (May–June) data are measured from the phone survey conducted during the national lockdown. Prelockdown (February–March) data are measured from the pre-Covid-19 face-to-face household survey. All differences refer to simple difference between Lockdown (May–June) and Prelockdown (February–March) figures. Crop marketing (panel B) and off-farm employment (panel C) are measured prelockdown (February–March) from the face-to-face survey.

Due to the close proximity to Bangalore, most of the off-farm workers in the study villages commute, rather than migrate, to urban areas.[12] In-migration is also very rare, since most migrants settle within Bangalore's metropolitan area, rather than in the surrounding villages. To be sure, during the phone interview, we asked about changing household composition since the start of the lockdown. No household members had left, and only 8% of households reported that relatives or friends came to permanently live with them during the lockdown period. In addition, we also probed respondents' knowledge of emergency social support policies set up during the lockdown. Knowledge was generally high, and virtually all households also benefited from at least one policy scheme.[13]

5.2 | Change in on-farm labor supply

Among households with on-farm household labor before the lockdown, 66% reduced their daily on-farm labor supply during the lockdown. Compared with before the lockdown, households worked, on average, 4.2 daily hours less on-farm (Table 2). There is substantial variation in the change, with a standard deviation of 9 h (Figure 5).

[12]The average household in our sample lives in a village whose centroid is only 29.4 km away from Bangalore's city center.

[13]The five main emergency social support policies are: (i) 500 INR transfers to all female Jan Dhan accounts for 3 months (86% know, 50% have used); (ii) topping-up Pradhan Mantri Kisan Samman Nidhi transfers by 2000 INR for 3 months (96% know, 80% have used); (iii) raise of MNREGA wage rates from 108 to 202 INR (54% know, 11% have used); (iv) scaling up of public distribution system allocations for all below-the-poverty-line (BPL) households for 3 months (1 kg pulses per household and 5 kg wheat or rice per individual; 100% know, 99% have used); and (v) home delivery of food ingredients for children's midday-meal by Anganwadis (women and child care centers) or public schools (28% know, 9% have used). The average household knows about 3.5 policies, and has benefited from 2.3. All households had heard of at least one social policy, and all but two households had benefited from at least one policy.

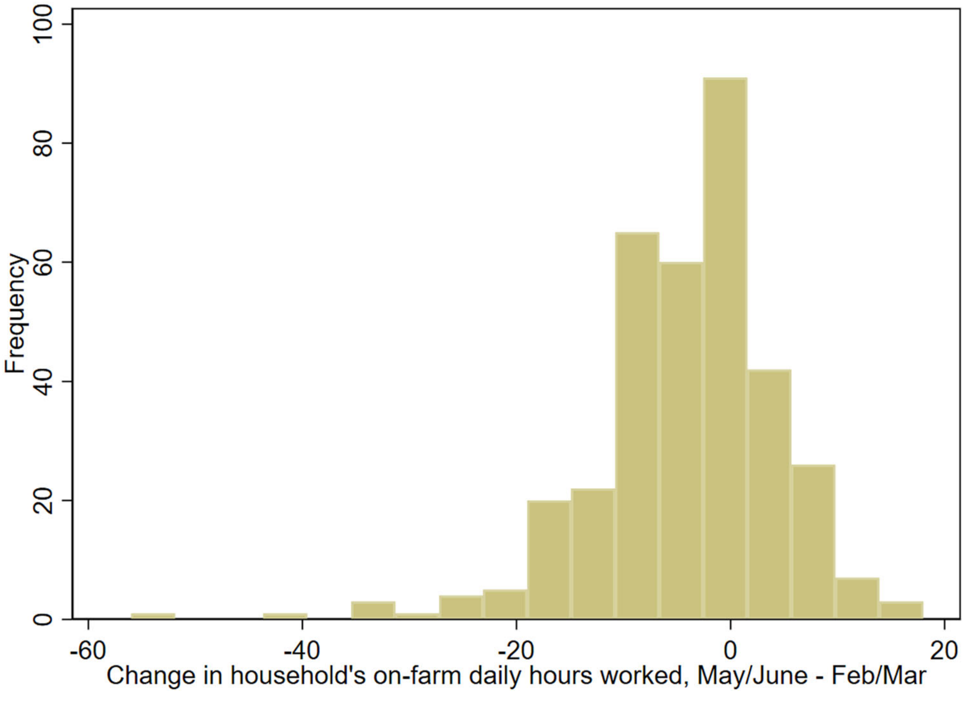

FIGURE 5 Change in total household on-farm labor (daily hours): lockdown (May/June) versus prelockdown (February/March). *Source*: Own calculations from phone survey (lockdown) and household survey (prelockdown). *Notes*: Unit of observation is the household. $N = 351$. The variable "change in on-farm household labor" measures the difference between the sum of hours worked on the farm by all adult (15 years+) household members during and before the lockdown. Households without on-farm household labor before the lockdown are not included.

We now test the two main hypotheses of this article: (a) daily on-farm household labor supply is negatively affected by agricultural market integration; and (b) daily on-farm labor supply is positively affected by the availability of adults that were employed off-farm pre-Covid-19. In Table 2, we present the mean change in on-farm daily hours worked by market integration (panel B) and off-farm employment. We find that, on average, all groups reduced on-farm hours worked. As shown in panel B, the average reduction in hours worked is larger for households that sold at least one crop pre-Covid-19 (−6.4 daily hours) than for households that did not market any crop (−2.9 daily hours). With respect to off-farm employment, panel C shows that households where at least one adult member worked off-farm pre-Covid-19 reduce hours worked by a smaller amount (−3.3 daily hours), on average, than households where no adult was employed off-farm (−5.7 daily hours).

Table 3 reports the estimates of Equation (1).[14] Market-integrated households experience a larger reduction in daily on-farm household labor supply during the lockdown. Households that sold at least one crop in the market before Covid-19 work, on average, 3.7 daily hours less on-farm relative to those households that did not market their crops (Table 3, column 1). The second hypothesis is also confirmed. Column (2) of Table 3 shows that off-farm employment has a strong positive effect on the change in daily on-farm household labor supply: a 10-percentage point increase in the share of adult household members with off-farm income pre-Covid-19 increases on-farm household labor by 0.6 daily hours. Column (3) tests the marketing and off-farm employment channels jointly. Both channels remain highly significant, albeit of slightly reduced (absolute) magnitude.

[14]Supporting Information Table A5 shows coefficient estimates for the control variables.

TABLE 3 Correlates of change in household's on-farm labor supply: Agricultural marketing and off-farm work.

	ΔHousehold on-farm daily hours worked		
	(1)	(2)	(3)
Dairy	2.494**	2.759*	2.685*
	(1.235)	(1.416)	(1.442)
Livestock	2.802**	2.356**	2.503**
	(1.283)	(1.141)	(1.162)
Crop marketing	−3.742**		−3.529**
	(1.506)		(1.487)
Off-farm employment		6.329***	6.176***
		(1.771)	(1.724)
Decision-maker controls	Yes	Yes	Yes
Household controls	Yes	Yes	Yes
Village dummies	Yes	Yes	Yes
N	327	327	327
R^2	0.379	0.405	0.423
Adjusted R^2	0.197	0.230	0.251

Notes: Ordinary Least Squares estimates reported with robust standard errors clustered at the village level shown in parentheses. The outcome variable is the change in the total household on-farm daily hours worked between May–June (national lockdown) and February–March (pre-Covid-19) 2020. "Crop marketing" is a dummy variable that equals one if any crop was sold in the market before the lockdown and zero otherwise. "Off-farm employment" is the share of adult household members (aged 15+) with an off-farm job pre-Covid-19. "Decision-maker controls" are all measured pre-Covid-19 and include gender, age, years of education, being currently married, and having worked. "Household controls" include the pre-Covid-19 variables: caste, religion, household size, pesticide use (yes/no) on own farm, irrigation use (yes/no) on own farm, and wealth decile fixed effects. It also includes the number of adults with missing measurements of on-farm labor supply. For variable definitions, see Supporting Information Table A1. For coefficient estimates of the control variables, see Supporting Information Table A5.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

Individual-level data reveal that the increase in on-farm labor supply is driven by household members working off-farm before the lockdown (as hypothesized). Table 4 shows the estimates of the individual-level regressions, where, in addition to all the household-level control variables of Equation (1), we control for individual age, gender, and years of schooling. Among the individuals who were working before the lockdown, those working off-farm spend 4 daily hours more on on-farm labor relative to those working on-farm before the lockdown. This estimate is remarkably robust in magnitude and significance, even when we control for household fixed effects in column (4).

We then extend the empirical analysis in five additional directions (Table 5). First, is the change in daily on-farm labor related to farm size? In column (1), we control for the log of farm size (in acres) and find a positive but insignificant association. Second, we investigate whether government policies during the lockdown, such as handouts to farmers pradhan mantri kisan samman nidhi (PM-KSN transfers), depressed on-farm work. In column (2), we control for whether the household has reported receiving the government top-up of PM-KSN by 2000 INR for the three lockdown months (April–June), and, in column (3), we control for the number of social policies taken up by the household. Both coefficients are statistically insignificant, although the PM-KSN transfer coefficient is negative, as expected. Third, the lockdown might have generated a surge in local labor supply, incentivizing farmers to substitute household labor with hired labor. Unfortunately, we did not collect information on hired on-farm labor

TABLE 4 Correlates of change in individual on-farm labor supply.

	ΔOn-farm daily hours worked			
	(1)	(2)	(3)	(4)
Crop marketing	−0.533**	−0.732**	−0.680*	
	(0.255)	(0.346)	(0.378)	
Individual-level variables				
Employed off-farm	4.003***	4.161***	4.384***	4.594***
	(0.242)	(0.344)	(0.349)	(0.486)
Age		0.103*	0.139**	0.059
		(0.062)	(0.061)	(0.063)
Age squared		−0.001	−0.001	−0.000
		(0.001)	(0.001)	(0.001)
Male		0.239	0.104	0.438
		(0.300)	(0.298)	(0.316)
Years of schooling		0.061*	0.077**	0.009
		(0.036)	(0.037)	(0.044)
Household baseline controls		Yes	Yes	
Village dummies			Yes	
Household fixed effects				Yes
N	688	609	609	686
R^2	0.251	0.258	0.355	0.743
Adjusted R^2	0.249	0.226	0.273	0.497

Notes: Ordinary Least Squares estimates reported with robust standard errors shown in parentheses. The outcome variable is the change in individual on-farm daily hours worked between May–June (national lockdown) and February–March (pre-Covid-19) 2020. The sample includes individuals working pre-Covid-19. "Crop marketing" is measured at the household level and is a dummy variable that equals one if any crop was sold in the market before the lockdown and zero otherwise. "Household baseline controls" include the pre-Covid-19 variables: caste, religion, household size, pesticide use (yes/no) on own farm, irrigation use (yes/no) on own farm, and wealth decile fixed effects. It also includes the number of adults with missing measurements of on-farm labor supply. For variable definitions, see Supporting Information Table A1.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

during the phone survey, so we cannot test this hypothesis directly. As an approximation, we use pre-Covid-19 measures of hired labor. In column (4), we introduce an indicator for whether the household hired on-farm (nonhousehold) labor for at least one crop between January 2019 and January 2020, and, in column (5), we include the (log) total hired labor days, across all crops and plots, in the same time period. Both variables have small and insignificant coefficients.

Fourth, the variation in daily on-farm labor supply responses may be explained by variations in cropping patterns across farmers (e.g., due to crop-specific seasonality in labor inputs). In column (6), we introduce dummies for seven crop categories (cereals, pulses, vegetables, fruits, flowers, fodder/grasses, and nonfood commercial crops). Contrary to the seasonality hypothesis, the model with crop categories generates very limited additional explanatory power (adjusted R^2 of 26.2% vs. 25.1% for the model without crop categories of Table 3, column 3).

TABLE 5 Correlates of change in household's on-farm labor supply: Extended models.

	ΔHousehold on-farm daily hours worked						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dairy	2.374	2.673*	2.753*	2.945**	2.646*	2.409*	2.725*
	(1.494)	(1.472)	(1.467)	(1.342)	(1.430)	(1.300)	(1.412)
Livestock	2.274*	2.376**	2.474**	2.249*	2.310*	2.572**	2.413**
	(1.345)	(1.165)	(1.126)	(1.198)	(1.292)	(1.193)	(1.190)
Crop marketing	−4.082**	−3.445**	−3.556**	−3.544**	−3.298**	−2.988*	−3.460**
	(1.686)	(1.525)	(1.496)	(1.498)	(1.524)	(1.554)	(1.521)
Off-farm employment	6.267***	6.132***	6.172***	6.145***	5.765***	5.214***	6.057***
	(1.804)	(1.721)	(1.721)	(1.775)	(1.792)	(1.713)	(1.768)
Log farm size (acres)	0.898						
	(0.832)						
PM-KSN transfer: used		−0.738					
		(1.431)					
Social policies: number used			0.047				
			(0.808)				
Hired on-farm labor (pre-Covid)				−0.074			
				(1.981)			
Log hired on-farm labor (days)					−0.316		
					(0.461)		
Crop categories						Yes	
Extended sociodemographic							Yes
Decision-maker controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	291	326	325	324	285	327	327
R^2	0.423	0.424	0.425	0.427	0.412	0.447	0.428
Adjusted R^2	0.236	0.248	0.249	0.251	0.216	0.262	0.244

Notes: Ordinary Least Squares estimates reported with robust standard errors clustered at the village level shown in parentheses. The outcome variable is the change in the total household on-farm daily hours worked between May–June (national lockdown) and February–March (pre-Covid-19) 2020. "Dairy" is a dummy variable that equals one if the household owned at least one dairy cow before the lockdown and zero otherwise. "Livestock" is a dummy variable that equals one if the household owned at least one other livestock animal before the lockdown and zero otherwise. "Crop marketing" is a dummy variable that equals one if any crop was sold in the market before the lockdown and zero otherwise. "Off-farm employment" is the share of adult household members (aged 15+) with an off-farm job pre-Covid-19. "Decision-maker controls" are all measured pre-Covid-19 and include gender, age, years of education, being currently married, and having worked. "Household controls" include the pre-Covid-19 variables: caste, religion, household size, pesticide use (yes/no) on own farm, irrigation use (yes/no) on own farm, and wealth decile fixed effects. It also includes the number of adults with missing measurements of on-farm labor supply. "Crop categories" are indicators for crops grown between January 2019 and January 2020: cereals, pulses, vegetables, fruits, flowers, fodder/grasses, and nonfood commercial crops. "Extended sociodemographic" are pre-Covid-19 household-level variables: whether the household has a below-the-poverty-line ration card, mean years of education (adults), number of children ages 6–14, and number of elderlies (ages 60+). For variable definitions, see Supporting Information Table A1.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

More importantly, the negative effect of marketing and the positive effect of off-farm employment retain size and statistical significance.

Fifth, and finally, we control for several additional sociodemographic characteristics of the household: the number of school-age children (6–14), who, since schools were closed, could have substituted adult labor supply (we do not measure child labor directly); the number of members age 60+ (which could proxy for how concerned a household is about Covid-19); mean years of education (as a proxy for access to information and health knowledge); and a BPL ration card dummy (as a proxy for access to targeted social policies during the lockdown). None of these additional sociodemographic characteristics has independent explanatory power or affects the estimates of crop marketing and off-farm employment. Supporting Information Table A4 reports descriptive statistics for all the additional covariates described above.

To sum up, none of the new (group of) variables is significant, either in economic or statistical terms. Reassuringly, the negative effect of market integration and the positive effect of off-farm employment remain robust across specifications, confirming our two initial hypotheses.

We perform several robustness checks to ensure that our results are not sensitive to specification choice (Table 6). In columns (1)–(5), we show that the results do not depend on how the village's location is modeled. In column (1), no village-level control is used. In column (2), the (log) distance to Bangalore's city center is included. In column (3), the covariate is, instead, the percentage of built-up area in the village (measured via remote sensing in 2016). Column (4) uses, alternatively, the rural–urban index introduced by Hoffmann et al. (2017). The baseline specification, with village fixed effects, is reported in column (5) for comparison. The coefficient estimates of marketing and off-farm employment remain robust throughout. Lastly, in column (6), (phone survey) interviewer fixed effects are introduced; once again, the main findings remain qualitatively unchanged.

6 | DISCUSSION

Our analysis generates two main results. As hypothesized, we find that market-integrated farm households have experienced a significant drop in daily on-farm household labor supply during the lockdown. This can likely be explained by the movement, transportation, and marketing restrictions that affected crop marketing. Although agricultural activities were officially exempted from the lockdown in India, access to input and output markets was disturbed by the disruption of transportation networks, and farmers faced difficulties finding buyers for their crops (Devaiah, 2020; Gejji, 2020). Especially the supply and demand for perishable crops fell, as the lockdown negatively affected many people's employment and income situation, and limited capacity for (cold) storage made it difficult to store harvested perishable crops (Alam & Khatun, 2021; Cariappa et al., 2021; Hari et al., 2020; Harris et al., 2020; Mahajan & Tomar, 2021; Rawal et al., 2020). Furthermore, while transport costs surged, farm-gate prices decreased substantially, which, according to several media reports, led some farmers to destroy their output or prevented them from harvesting their crops at all (Bharadwaj et al., 2021; The Times of India, 2021). Volatile prices and uncertainties related to marketing opportunities thus increased risks for farmers and might have led them to reduce their labor allocation to cropping activities altogether.

While market-integrated farm households appear to have reduced their daily on-farm work, a higher share of adults with off-farm income before the lockdown is ceteris paribus associated with an increase on average daily hours worked. It could be that these households replaced hired labor with family labor due to the additional availability of family labor and the out-migration of daily laborers. Plausibly, households that missed income from off-farm sources attempted to substitute lacking income with increased crop or livestock activities to meet subsistence demands. This likely did not increase their revenues from crop production as crop markets were largely closed, but produce might have been intended for own consumption or stored (e.g., staple crops) (Jaacks et al., 2021). Our result relates to findings by Mahmud and Riley (2021) and Amare et al. (2021), who found that households that relied on off-farm income before the lockdown increased on-farm activities during the lockdown.

TABLE 6 Correlates of change in household's on-farm labor supply: Robustness.

	ΔHousehold on-farm daily hours worked					
	(1)	(2)	(3)	(4)	(5)	(6)
Dairy	2.516**	2.617**	2.407**	2.660**	2.685*	2.893*
	(1.103)	(1.156)	(1.092)	(1.159)	(1.442)	(1.504)
Livestock	2.027**	1.915**	2.073**	1.991**	2.503**	2.318*
	(0.878)	(0.919)	(0.901)	(0.875)	(1.162)	(1.219)
Crop marketing	−2.819**	−3.007**	−2.708**	−3.099**	−3.529**	−3.161**
	(1.205)	(1.192)	(1.177)	(1.174)	(1.487)	(1.483)
Off-farm employment	6.517***	6.681***	6.363***	6.727***	6.176***	5.652***
	(1.447)	(1.437)	(1.451)	(1.426)	(1.724)	(1.690)
Distance to Bangalore (log km)		1.774				
		(1.904)				
Built-up area (%)			0.060			
			(0.049)			
Rural–urban index				4.583		
				(3.806)		
Decision-maker controls	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes
Village dummies					Yes	Yes
Interviewer dummies						Yes
N	327	327	327	327	327	327
R^2	0.249	0.252	0.253	0.255	0.423	0.439
Adjusted R^2	0.182	0.182	0.183	0.185	0.251	0.263

Notes: Ordinary Least Squares estimates reported with robust standard errors clustered at the village level shown in parentheses. The outcome variable is the change in the total household on-farm daily hours worked between May–June (national lockdown) and February–March (pre-Covid-19) 2020. "Dairy" is a dummy variable that equals one if the household owned at least one dairy cow before the lockdown and zero otherwise. "Livestock" is a dummy variable that equals one if the household owned at least one other livestock animal before the lockdown and zero otherwise. "Crop marketing" is a dummy variable that equals one if any crop was sold in the market before the lockdown and zero otherwise. "Off-farm employment" is the share of adult household members (aged 15+) with an off-farm job pre-Covid-19. "Decision-maker controls" are all measured pre-Covid-19 and include gender, age, years of education, being currently married, and having worked. "Household controls" include the pre-Covid-19 variables: caste, religion, household size, pesticide use (yes/no) on own farm, irrigation use (yes/no) on own farm, and wealth decile fixed effects. It also includes the number of adults with missing measurements of on-farm labor supply. For models without village dummies, an intercept term is also included. For variable definitions, see Supporting Information Table A1.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

Although Amare et al. (2021) find that, generally, households decreased their on-farm activities during the lockdown in Nigeria, when differentiating by the location of the household, their results show that households in urban areas reduced only nonfarm business and wage-related work but increased on-farm activities, thereby reallocating household labor to alternative economic activities.

We also find a robust positive association between dairy farming (pre-Covid-19) and daily on-farm hours worked during the lockdown. One explanation for this increase might be that, other than crop marketing, the milk supply chain operated under the auspices of the Karnataka Cooperative Milk Producers' Federation (KMF) functioned relatively smoothly despite the lockdown (Jayasimha, 2020). In contrast to crop markets, farmers commonly supply milk to collection centers within the village and no transportation outside of the village is required. Although the demand for dairy products by some buyers (e.g., restaurants, hotels, and temples) dropped, private demand might have increased as people spent more time at home (Jayasimha, 2020). Further, the collection and supply of milk by the KMF during the lockdown remained at prelockdown levels, likely also due to the procurement of milk by the Karnataka state government (Akshatha, 2020; Ravi, 2020a). This might have incentivized farmers to focus more on dairy activities. Finally, cattle and other livestock are also an asset that is permanently available to the household. During the lockdown, households that experienced loss from either crop market closures or off-farm employment might have used these assets as a buffer to smooth income shocks (Ali, 2015).

We do not find any significant relationship between the change in daily on-farm labor and farm size, the household's receipt of government support programs, the availability of hired labor, and cropping patterns. It thus seems that the change in agricultural labor supply was mainly driven by restrictions in crop marketing and off-farm employment opportunities during the lockdown, with diverging effects for households with differing livelihood portfolios before the lockdown.

7 | CONCLUSION

We examined the household-level response to one of the most stringent lockdowns implemented in response to the outbreak of the Covid-19 pandemic, the Indian national lockdown between March 25 and May 31, 2020. Using face-to-face survey data collected before the pandemic and data collected in a phone survey in the last 2 weeks of the lockdown, we analyzed the association between several household characteristics measured pre-Covid-19 and the change in households' daily on-farm family labor supply for farm households in the rural–urban interface of Bangalore, India. Given the urbanizing setting, we particularly focused on the relationship between the change in on-farm family labor and households' engagement in crop marketing and off-farm employment before the outbreak of the pandemic. We find that 66% of the farm households reduced their daily on-farm labor supply during the lockdown, by on average almost 40%/day compared with prelockdown levels. The results of our regression analysis suggest that prelockdown market integration is associated with a reduction in on-farm family labor supply by on average 3–4 h/day during the lockdown period. However, we find a positive association between a higher share of household members with an off-farm income before the lockdown and on-farm family labor supply during the lockdown. The latter finding possibly indicates that households with a higher dependence on off-farm income before the lockdown compensated for lacking income from off-farm employment by increasing on-farm activities. Increasing their own production might have enabled these households to save food expenditure previously covered by off-farm incomes. We also find a significant association between prelockdown dairy cow and livestock ownership and daily on-farm hours during the lockdown period. This might be explained by the availability of cattle and other livestock as an asset to the household that was already available as an income source and by the relative stability of the dairy value chains in comparison to crop markets during the lockdown. Our findings thus indicate that farm households' response to the lockdown in terms of on-farm family labor supply differed by certain key pre-Covid-19 household characteristics.

Although we cannot make direct welfare inferences, we believe that our findings are relevant for policy makers in several ways. First, our results reveal short-term agricultural labor supply responses in a rapidly urbanizing area where both off-farm labor markets and crop markets were severely disrupted by the lockdown. Second, for households with off-farm workers, our results demonstrate that the agricultural sector acted as an informal safety net during the lockdown, playing a relevant role in their livelihood diversification strategies. Third, for market-integrated farming households, our results reflect the importance of keeping value chains operating during the lockdown, as also suggested by the differing findings for crop and dairy markets. Finally, our results illustrate that households adapt to lockdowns in different ways along identifiable dimensions, such as off-farm work, market-orientation, and farm activities. Understanding these different responses is crucial for targeting future relief policies more effectively. Specifically, future policies should ensure the functioning of agricultural supply chains in the event of future health crises and recognize the importance of agriculture as a safety net for households with a diversified income portfolio.

It is important to point out that the findings of this paper relate to the first, short-term, nationwide lockdown that hit India at a time when the number of Covid-19 cases was still relatively low. In India, the number of Covid-19 infections strongly increased later in 2020 and especially throughout the first half of 2021, accompanied by additional local restrictions and lockdowns. Therefore, beyond the short-term effects of the first nationwide lockdown, future research should examine the medium- to long-term implications of the Covid-19 pandemic on on-farm labor supply and farm households' coping strategies with this major shock.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ETHICS STATEMENT

Ethical approval was obtained from the ethical review committee of Göttingen University before the survey. There were no objections by the committee concerning the implementation of the data collection.

PEER REVIEW

The peer review history for this article is available at https://www.webofscience.com/api/gateway/wos/peer-review/10.1002/agr.21893.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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