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COVID-19, information management by local governments, and food consumption

Vivek Pandey a, b, *, Shyam Singh a, b, Deepak Kumar c

a Institute of Rural Management Anand, India
b Verghese Kurien Policy Lab, IRMA, India
c Virginia Tech, USA

ABSTRACT

Federal and state governments in developing countries have tasked local governments with managing COVID-19 on the ground. The bottom-up approach is critical to ensuring household food security, especially in rural areas. We have utilized data from a panel of Indian households that participated in two rounds of a livelihoods survey. While the first round was fielded before COVID-19, the second round was conducted telephonically after the COVID-19-lockdown. We developed an Information Management Response Index (IMRI) to measure the strength of local governments’ information management initiatives. The difference-in-difference estimates show that local governments could partially mitigate the pandemic’s adverse effects on (a) level and distribution (adult-equivalent per-capita) of food and nutrition expenditure and (b) household vulnerability to food and nutrition poverty. For landless households, IMRI led to statistically significant and additional welfare effects. Three channels explain our empirical findings: (a) maintenance of essential commodities through fair-price shops, (b) access to paid employment and nutrition expenditure and (b) household vulnerability to food and nutrition poverty. For landless households, IMRI led to statistically significant and additional welfare effects. Three channels explain our empirical findings: (a) maintenance of essential commodities through fair-price shops, (b) access to paid employment and cash (income effect), and (c) disease management (substitution effect). The estimates have been adjusted for sample attrition and multiple-hypothesis correction. We conducted robustness checks with respect to index construction, instrumental variable estimation, and sub-group analysis.

1. Introduction

The rapid spread of SARS-CoV-2 and subsequent administrative efforts to contain the spread led to economic contraction and severe hardship for low-income households (Hsiang et al., 2020). The pandemic has intensified food insecurity and the inability to access medication and staple foods, making it difficult for households and communities in low-income areas to balance health outcomes and economic constraints. (Dey, 2020; Huang, et al., 2020; Josephson et al., 2021). To offset welfare losses some governments offered cash transfers and food grains to vulnerable citizens (Cuadrado, et al., 2020). However, the targeting and implementation gaps in such relief programs and subsequent exclusion of eligible populations from benefits (Cefala et al., 2020) have highlighted the critical role of local institutions in assisting national and international policy responses with implementation support (Dutta & Fischer, 2021). In some countries like India, federal and state authorities have asked local governments to manage the pandemic at a local level. With over 260,000 local governments and 3.1 million elected representatives, India has taken the lead in mobilizing what is probably the world’s largest number of local governments. The elected officials of local governments have been urged to strive toward (a) mitigating welfare losses for vulnerable populations by bolstering the execution of ongoing welfare programs and (b) limiting viral transmission and mortality by eliciting household participation in adhering to the COVID-19 protocol. The bottom-up approach to COVID-19 management is consistent with a JPAL survey’s findings, showing that 41% of male and 39% of female respondents trust the local governments’ messaging and preventive initiatives (Cefala et al., 2020). Almost 51% of respondents reported they would ‘most likely’ implement the preventive measures if local governments issued such advisories. However, the existing government recommendations for local governments lack clarity and policy emphasis in the absence of rich data and policy experiences of coordinating COVID-19 type events where local governance is essential. Vaccine roll-out had not begun at the time of the post-COVID-19 survey round in May 2020. Local governments, hence, were focused on disseminating COVID-19 protocols and coordinating with line departments to ensure adequate provisioning of essential commodities and income generation during the pandemic. This article

* Corresponding author at: Institute of Rural Management Anand, Faculty Room 107, IRMA Campus, Anand, Gujarat 388001, India.
E-mail addresses: vivek@irma.ac.in (V. Pandey), shyam@irma.ac.in (S. Singh), deepak21@vt.edu (D. Kumar).

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provides evidence on the extent to which the information management response (IMR) of local governments contributed to the mitigation of adverse impacts of the pandemic on household’s food and nutrition consumption and their exposure to future poverty (vulnerability) in Indian villages.

Rural communities generally suffer from high poverty rates (Mehta and Shah2013; Dercon 2009), irregular incomes, inadequate public safety nets (Morduch, 2004; Hallegatte et al., 2015), and weak food-supply networks. Many researchers, in the initial phase of the pandemic (Barrett, 2020; Reardon et al., 2020). In India, the Public Distribution System (PDS) is responsible for the distribution of staple food grains to impoverished households. As a relief measure, the Federal Government has announced the release of free food grains through PDS. The PDS implementation has been delegated to the GPs. We present evidence of the impact of IMR on the functioning of fair price shops (i.e., PDS) during the period of COVID-19-lockdown. Aside from food, rural households must maintain access to non-farm income generating activities to meet daily consumption requirements. The second channel is, therefore, related to GPs’ efforts to ensure that households continue to access labor markets, particularly the benefits of public works programs such as the Mahatma Gandhi National Rural Employment Guarantee Scheme (MGNREGS). The GP survey recorded information on whether elected representatives of local governments helped households access cash loans from informal sources during the pandemic. Access to cash and wage income is expected to mitigate the pandemic’s adverse effects on food and nutrition intake. The third channel is linked to the GP’s disease management efforts. Awareness of COVID-19 protocols can reduce the risk of being sick or hospitalized. Thus, the GP’s communication efforts may help mitigate the loss of wages and health costs associated with paying medical expenses (Abay et al., 2021). While the first two channels trigger income effects, the disease management channel can generate substitution effects because resources that would have been allocated to a counterfactual level of health expenditure may be now utilized to sustain food and nutrition levels.

While there is some evidence on the impact of lockdown measures on compliance to COVID-19 protocols elsewhere (Brodeur, 2020), the South-Asian evidence is slim. Few studies have investigated such initiatives and their welfare impacts, for example, Summerton (2020) highlights the importance of India’s welfare plan of USD 22.6 billion to supply free food material during the pandemic to poorer sections in the population. The state of Kerala in India implemented community kitchen programs to provide food to poor people during the lockdowns (Kumar et. al. 2021). Choudhary et. al. (2020) finds that the welfare and food security measures across the Indian states reduced the inter-state mobility by 12 percent. Das and Mishra (2020) show that the slum households in Delhi were able to take 2.5 meals per day and about 76 percent households of the study sample were able to take benefits of at least one welfare scheme worth Rs. 984 during the lockdown period. Anecdotal evidence suggest that local governments were instrumental in spreading awareness and providing work to poor families through the National Employment Guarantee Scheme and distributing food and other financial assistance during the lockdowns (UNICEF and IHD, 2021). There is little data and evidence on how governments can be more successful in responding to pandemics. In this context, this paper makes three contributions. To begin with, we contribute to a modest but growing literature on the effectiveness of local governments in managing pandemics in developing countries. Dutta and Fischer (2021) argue that local governments play a critical role in coordinating the pandemic response. According to an FAO survey in 20 African countries on local response to COVID-19, about 30% of local governments provided logistical support for food distribution (warehouse and coordination with food banks), while more than 50% monitored availability and prices in food markets. The Indian state of Odisha granted the GPs with magisterial powers to enforce lockdown measures. However, not much is known about the extent to which local governments’ efforts contributed to household welfare. Second, we examine the impact of IMR of GPs on vulnerability of rural households to food and nutrition poverty. Third, we identify mechanisms through which the benefits of IMR of GPs reach rural households. Our data allows us to present evidence on the impact of IMR on the channels during the pandemic.
previous round. The regions covered in the survey have traditionally struggled to access livelihood opportunities and as a result are vulnerable to pandemic’ adverse effects. We combine the panel nature of the data with the IMR of GPs to use difference-in-difference specification along with fixed-effects estimation. The identification approach allows us to control for a number of confounding variables.

The difference-in-difference estimates show that the monthly food and nutrition expenditure of rural households during the pandemic declined by Rs. 5959 (~USD 79) and Rs. 3902 (~USD 52), in that order. The information management response of GPs could partially offset the negative effect of the pandemic on food by Rs. 1919 (~USD 26) and nutrition by Rs. 1107 (~USD 15). While IMR reduced vulnerability to food poverty, the evidence on vulnerability to nutrition poverty is mixed. The sub-group analysis shows that IMR has a higher welfare effect on landless households. Our results are robust to possible non-random sample attrition, alternative measures of IMR, different estimation approaches, and multiple hypothesis test adjustments. The findings suggest that the IMR of GPs is positively related to the operation of fair price shops which ran on more working days (i.e., 1.20 days more) during the countrywide COVID-19-lockdown with a lower grain scarcity frequency (i.e., 24.7% less). Similarly, IMR increased the likelihood of payment of wages from MGNREGS to households (i.e., 10% more) while enabling cash availability for food and other essential commodities (i.e., 7% more). Our results highlight the criticality of local governments in pandemic and disaster management.

The paper has been organized as follows: section 2 provides a conceptual framework of the information management response (IMR) of local governments. Section 3 describes the livelihoods panel survey, construction of information management response index (IMRI) and outcomes variables. Section 4 describes the estimation strategy followed by presentation of results in section 5. In section 6, we conduct several robustness checks to assess the sensitivity of our empirical findings, and in section 7 we present evidence on channels. Policy implications are discussed section 8.

2. Conceptual framework

The discussion in this section highlights the criticality of local governments in managing COVID-19 through IMR. However, there is a dearth of pandemic-related data that can help us assess the effectiveness of local governments’ response to COVID-19 (Park, Thwaites, and Openshaw, 2020; Abay et al., 2021; Swinnen and Vos, 2021; Kokas et al., 2020). Hence, we leverage the disaster and risk mitigation and crisis communication literature to investigate whether information management may act as a fulcrum of the local government response to COVID-19.

Any disaster, irrespective of its coverage or intensity, is a local phenomenon because communities have to deal with such events primarily on their own and, to a limited extent, in conjunction with disaster & risk mitigation initiatives designed by local agencies (Killian 1994; O’Leary 2004; Reinhardt and Drennan 2019). Therefore, when IMR is developed at the local level, it generates civic engagement, strengthens disaster preparedness (Spialek, Czlapinski, and Houston 2016) and community resilience (Norris et al. 2008; Sakurai and Adu-Gyamfi 2020). While using a top-down approach to IMR design may enhance inter-agency cooperation, it may impede local information flow, leading to negative consequences (Schweinberger, Petrescu-Prahova, and Vu 1998; Okumura et al. 1998; Butts, Petrescu-Prahova, and Cross 2007).

Extant literature acknowledges the role of local governments in (a) risk-reduction and disaster management, (b) adaptation of mitigation strategies to local needs (Dutta and Fischer, 2021), and (c) institutional capacity development (Aoki, 2017; Jabar and Lamberte, 2017; Ruiz-Rivera and Melgar-Rodriguez, 2017; Chadaabal et al., 2020). Local governments respond to disasters by developing action plans based on scientific data, providing public goods and services, coordinating with line departments, and eliciting the trust and participation of citizens (Col, 2007). Among several initiatives, timely dissemination of critical information and its access by citizens has the potential to significantly mitigate losses. Fearnley and Dixon (2020) highlight the relevance of the ‘Early Warning Systems’ on natural disasters in avoiding social and economic losses during the pandemic. Local governments manage and coordinate a high volume of information generated by departments at local, state, and national levels (Bigdeli, Kamal, and Cesare 2013). Therefore, effective pandemic management requires local governments to establish and strengthen the information management eco-system that include (a) access to and dissemination of disaster-specific information to village-citizens (b) eliciting compliance from citizens, and (c) coordinating with line departments and public institutions to ensure access to essential commodities and services (Spialek, Czlapinski, and Houston 2016).

The Indian Constitution mandates local governments to plan and implement basic welfare services. Evidence shows that the citizen-led local government institutions have improved the quality of welfare measures and enhanced the accountability of implementers (Nagarajan, et al., 2014; Munshi & Rosenzweig, 2008; Banerjee et al., 2007). Local governments are the first point of contact for citizens to reach out for assistance and seek solutions (Bardhan et al., 2011). Local governments’ proximity (reachability) to citizens improves their ability to disseminate information and, consequently, make efficient resource-allocation decisions (Besley et al., 2008). The local governments can leverage this proximity to manage disasters.

In light of the above, we have proposed a conceptual framework that describes the GP’s responsibility in information management while ensuring the provision of basic services in order to mitigate the adverse impact of COVID-19. We refer to PAHO (2012) to develop the conceptual framework of information management response (IMR) of local governments to COVID-19. The framework is based on four dimensions (a) communicating about the virus to check its spread, (b) coordinating with public agencies and departments, (c) information dissemination to relevant stakeholders after curation, and (d) resource mobilization to elicit public trust and compliance. Effective communication (precision and timeliness) has been shown to increase public compliance to regulations and advisories. Local governments are expected to strengthen inter-departmental coordination, which is critical for accessing new information, monitoring the pandemic’s spread, and ensuring the delivery of basic services to citizens (Abraham and Reddy 2010; WHO 2020). Leaving information dissemination to the public may lead to false rumours and disinformation (Cui, Shen, and Wang 2020). Therefore, local governments should not only access relevant information but also curate and disseminate information to citizens. If local governments mobilize human and financial resources during the pandemic, their efforts will be more credible, and citizen’s confidence will be strengthened (Krumay and Brandtweiner 2015).

We posit that if local governments design and implement high quality IMR then the welfare loss of households during the pandemic in such constituencies will be relatively less.

3. Data

3.1. The livelihoods panel survey

We created a panel dataset of households to assess the impact of Gram Panchayats’ information management response on household welfare during the pandemic. The first round was completed between June and September 2019 – before the first incidence of COVID-19 in India- as part of a livelihoods survey. The second round was fielded in May 2020 through phone surveys after the nation-wide COVID-19-lockdown. Hence, the pre-COVID-19 livelihoods survey served as a sample frame for the phone surveys, which were designed to be regionally representative. During the first round, community and household surveys were conducted in three states (Bihar, Madhya Pradesh, and Gujarat), 175 villages, and 2213 households. The nearest-
neighbor matching method was used to select the village sample. The selection model used demographic and socio-economic covariates from Census 2011 and Socio-Economic and Caste Census (SECC 2012). Following village selection, 12 to 13 households were selected at random from the SECC 2012 list in each village. The nearest-neighbor matching technique was used to pick the village sample.

While we included all the villages from the first round in the second round, we randomly selected and tracked six to seven households in each village from the list of households surveyed in the first round. The panel sample comprised of 12 districts, 175 villages, and 1075 households. Since the second round was mounted on a livelihoods survey of poor and vulnerable rural households, the households in our sample are representative of deprived sections in the population on account of caste, landlessness and access to basic services is relatively higher as compared to other households in the village. The household sample primarily recorded consumption behavior of poor and vulnerable households conditioned on social and economic safety nets that GPs may provide. The strategy was useful for conducting sub-sample analysis based on household deprivation status. Fig. 1 shows the study area.

Out of 2213 households questioned in the first round, 1075 were surveyed again during the second round. Due to nationwide travel restrictions and a shortage of key human resources during India’s lockdown period, a smaller sample of households was used for the follow-up phone survey. Despite the fact that the second-round households were randomly sampled, the partial coverage of the first-round households caused concern due to observed and unobserved heterogeneities. If the panel households (those questioned in the second round as well) were systematically less vulnerable than those surveyed in the first round, the welfare estimates were likely to be inconsistent. Therefore, we tested for the balance between panel and non-panel households by using a number of covariates from the first round.

The distribution of demographic and economic characteristics in panel and non-panel samples is similar, according to Table 1. We found no statistical disparities in the age and education of the household’s head. The size of the household, dependency ratio, intensity of household-level financial inclusion, and access to amenities such as drinking water are also statistically non-different. The vulnerability status of households did not vary statistically in panel and non-panel samples. Therefore, the findings indicated that the limited coverage of households during the second round did not create systematic biases that may have had implications for the consistency of the welfare estimates. The exogeneity of sample attrition conditioned on baseline observables seem to suggest that coverage of all 175 villages in both survey rounds and random selection of households for the second-round surveys contributed to attaining balance between panel and non-panel households.

The household roster was used to capture each household member’s phone number as part of the 2019 survey. According to the initial set of survey data, every household had access to at least one mobile phone. We used this information to conduct the second survey on 1075 households in 2020. While the obvious advantage of the telephonic surveys is that it could be implemented during the invasive COVID-19 pandemic, there are some disadvantages that are important to recognize. The most significant limitation of telephonic surveys is that they are exposed to very high levels of attrition rates on account of survey length and inaccuracies in telephone information. However, the collection of household data via phone calls is reliable in our case for three main reasons. First, all the respondents were drawn from an earlier sample of a rural livelihoods survey. Therefore, the team of enumerators were acquainted with the surveyed households. We leveraged these linkages by maintaining the enumerator-household pair, in almost all cases, from the previous round. Second, the timing of the survey reduced our reliance on recall method of questioning. The telephonic round was conducted during the COVID-19 induced lockdown period and the consumption section focused on food and nutrition expenditures during the same period. Third, we kept the telephonic survey short (Swinnen and Vos, 2021). The identifying assumptions associated with the panel structure of the data influenced the survey design and its length. All time fixed variables (gender, adult education, etc.) were excluded in the phone survey round as well as structurally stable variables including location, size of household, etc. We also excluded those sections in the follow-up round that were not related with the study objectives and instead focused on getting accurate information on household food consumption. The survey instrument consisted of four primary sections. The first section collected identification information. The second section asked about household food consumption in last one week. The third and fourth section collected information on food security and use of digital financial services during the pandemic.

We mitigated non-response during the phone survey round by deploying several techniques: (a) multiple call attempts during the day and the subsequent day in the event of initial non-response, (b) allowing for multiple calls to the same household in the event that all survey questions could not be canvassed in a single call (such households were called within three hours to complete the survey), (c) in order to prevent survey fatigue, the survey duration was restricted to 30 min, while the actual median survey length was 27 min, and (d) in order to account for enumerator-fixed-effects households were surveyed by the same set of enumerators who had interacted with them during the previous round’s face-to-face interview. Around 75% of the sampled households responded to the first call and 97% to the second one. The response rate improved following the second round of phone calls because we telephoned and requested the neighbouring household(s) to ensure that the sampled household is available for the telephonic survey when we called the household next time. Only six out of 1075 households did not respond despite repeated attempts2, giving us a response rate of more than 99% in the second round. The second round was finally implemented on 1069 households.

As discussed, and shown above, the panel and non-panel households are comparable across a number of observables (Table 1); nevertheless, there is still concern about the validity of employing uniform sample weights when performing estimation using survey data. Hence, we accounted for sample attrition by predicting the probability of a panel household. We constructed sample weights as the inverse of the predicted probability of the panel household using a logistic specification (see Appendix Table A1). We used the sampling (attrition) weights in all the estimations.

3.2. Information Management Response Index

Our analysis explores variations in the information management response (IMR) of local governments during the pandemic and its impact on household welfare. Hence, we developed an Information Management Response Index (IMRI) based on using PAHO (2012) Information management framework for pandemic response during epidemics and

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1 The telephone and/or mobile phone coverage has reached almost all the rural households owing to mandatory linking of Aadhar card (unique identification number) and telephone number, required for government’s direct benefit transfer schemes. The introduction of cheap mobile handsets and steep decline in tariffs due to stiff competition for market share has further intensified the mobile phone coverage in India. Therefore, one telephone per household was a plausible assumption while mounting the second round of survey.

2 Out of six households, the phone numbers of four households were no longer in service, while two did not respond. All the households who responded to the phone call agreed to participate in the phone survey.
Fig. 1. Location of study villages are marked in red, with the first sub-figure (top left corner) show three Indian states: Bihar, Gujarat, and Madhya Pradesh, where the two rounds of surveys were conducted.
other disasters’. The PAHO framework encourages local governments to design their information management initiatives along four dimensions: (a) communication, (b) coordination, (c) information dissemination, and (d) resource mobilization. The GP schedule recorded information on all four dimensions which were contextualized to reflect extant scientific evidence on COVID-19.

The four dimensions of IMRI comprised 17 indicators and 73 binary sub-indicators (see Appendix Table A2). The IMR composite index was computed as a linear combination of the sub-indicators as extensively utilized in the literature (e.g., Freudenberg 2003; OECD 2008). Under the communication dimension, GPs were asked to inform whether they had communicated to households about social distancing, hand hygiene, face mask usage, public gathering norms, symptoms of COVID-19, and accessing public health facilities. Further examination of the information content of GP communications was conducted to assess their accuracy. Appendix Table A2 shows that while all the GPs communicated about the need for maintaining social distancing during public interactions, there was a significant variation in the accuracy of the information provided by local governments. For instance, only 45% Gram Panchayats provided accurate information on social distancing as per COVID-19 guidelines. Approximately one-third of GPs communicated that plain water was an effective sanitizer, while 6% relied on sand and ash. At the same time, 35% GPs were not against public meetings. The composite score penalized the GPs’ aggregate communication scores to account for the lack of accuracy in information on COVID-19 preventive measures.

Under the coordination dimension, GPs were encouraged to work with relevant line departments that include food-distribution, healthcare, public works, police, and civil administration. While coordination with public distribution system of food grains and public works department could ensure availability of food grains and timely payment of wages during the pandemic, access to healthcare and police services were critical to prevent the spread of infection, provide treatment, secure hospitalization and maintain law and order within villages.

The information dissemination dimension considered three aspects of GP’s initiatives: (a) number of sources from which Panchayat leaders accessed COVID-19 related information1, (b) methods adopted to curate such information2, and (c) number of media channels through which information was disseminated to citizens. GPs primarily relied on television (92%), social media (76%), and government websites (45%) for information. Only 8% GPs contacted health professionals, while one-third used the Aarogya Setu application, a digital service platform developed by the Ministry and Electronics and Information Technology department could ensure availability of food grains and timely payment of wages during the pandemic, access to healthcare and police services were critical to prevent the spread of infection, provide treatment, secure hospitalization and maintain law and order within villages.

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The alternative methods include newspaper, television, social media, internet, friends and acquaintances, Whatsapp, Aarogya-Setu application, and health professionals.

COVID-19 related information accessed from centralized and other sources may require further deliberation with other Panchayat members, community leaders, or block development teams, before it is made available for public consumption.

Information can be shared with households through village-wide Whatsapp groups, Panchayat notice board, and public announcements.

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Notes: Sample from the first round of survey is comprised of 176 villages and 2213 households. In the second (i.e., post-COVID-lockdown) round, 6 to 7 households (out of 13 households from the first round) were surveyed in each village. One village was dropped because the members of Gram Panchayat were not available for the local government survey. Therefore, the second survey round covered 175 villages and 1075 households. These are termed as panel households and the remaining 1138 households that were not covered in the second round constitute the non-panel households. This table exhibits the statistical balance between panel and non-panel households. The balancing test makes use of household and village-level variables as well as outcome variables from the baseline survey. The estimates suggest that the panel and non-panel households are not systematically different from each other. Therefore, we infer that the non-panel households are ‘missing at random’ from the second round. *** p < 0.01, ** p < 0.05, * p < 0.1.

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A global panel database of pandemic policies, the Oxford Stringency Index (OSI), has been developed to calculate the strictness of government policies during the pandemic. The focus of OSI is on lockdown measures and includes nine items: (i) school closures, (ii) workplace closures, (iii) cancellation of public events, (iv) restrictions on public gatherings, (v) closures of public transport, (vi) stay-at-home requirements, (vii) public information campaigns, (viii) restrictions on internal movements, and (ix) international travel controls. The OSI tracks the strictness of policies and does not measure the efficacy of country’s response; in contrast, the IMR index used in this study tracks the extent of information management response on the basis of information management initiatives of local governments.

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1 The alternative methods include newspaper, television, social media, internet, friends and acquaintances, Whatsapp, Aarogya-Setu application, and health professionals.

2 Information can be shared with households through village-wide Whatsapp groups, Panchayat notice board, and public announcements.
result, the Resource Mobilization dimension tracked GPs’ attempts to raise funds for the distribution of face masks, hand sanitizers, sanitization of public spaces, and community kitchens. We can see from Appendix Table A2, that large number of Gram Panchayats mobilized resources to facilitate the distribution of face masks (82%), hand sanitizers (60%), and sanitization of public spaces (83%). In addition to using GP money, the elected officials solicited contributions and assistance from local businesses.

Data associated with four dimensions on information management response was used to construct the IMRI. We computed IMRI for the $j^{th}$ dimension as:

$$\text{IMRI}_j = \sum W_{ij} S_{ij}$$

where $S_{ij}$ is the score obtained on the $i^{th}$ sub-indicator for the $j^{th}$ dimension element of one of the four dimensions as explained earlier. $W_{ij}$ is the weight attached to the $i^{th}$ sub-indicator in the $j^{th}$ dimension, which is expressed as:

$$W_{ij} = \frac{1}{\sum r_{ij}}$$

where $r_{ij}$ is the maximum score of the $i^{th}$ sub-indicator in the $j^{th}$ dimension.

Finally, overall IMRI is, therefore, expressed as:

$$\text{IMRI} = \sum W_j GRI_j$$

where $W_j (= \sum r_j)$ is the weight attached to $j^{th}$ dimension.

The value of IMRI ranges between 0 and 1, and we rescaled it to measure how the household food consumption is distributed among its members. Therefore, we imputed individual consumption from household data by making assumptions about intra-household food distribution. We used FAO’s adult male consumption equivalents (AMEs) to measure the distribution of food and nutrition, assuming that such a distribution is positively related with the individual’s energy requirements (Haddad et al., 1996; Berti, 2012). We calculated their AMEs with the help of member-level information from the household roster, which included age and gender. We assigned a weight of 1.2 for adult males, 0.9 for adult females, 1.0 for adolescents (age 12–21 years), 0.8 for children aged 9–12, 0.7 for children aged 7–9, 0.6 for children aged 5–7, 0.4 for children younger than 3, and 0.78 for anyone older than 60 (Deininger and Liu, 2019; Gopalan et al., 2004). Individual AMEs were added to calculate household-level AME. We calculated per-capita adult equivalent of food expenditure by dividing monthly food consumption expenditure by household AME. Similarly, we computed per-capita adult equivalent of nutrition expenditure.

### 3.3. Household welfare outcome variables

Food consumption expenditures in rural India are typically low, and this is likely to worsen during the epidemic. We examined a number of welfare outcomes linked to food intake.

#### 3.3.1. Household food and nutrition expenditure

First, we focussed on the levels of household food and nutrition consumption during the pandemic. The decline in the level of household expenditure on food is indicative of food insecurity and widespread hunger. So, we investigated whether local government’s information management initiatives (as measured by IMRI) are likely to reduce the pandemic’s adverse effects on household food consumption. Household Consumption and Expenditure Surveys (HCES) were used to estimate food consumption expenditure (Beegle et al., 2010). Cereals, pulses, sugar (refined and jaggery), edible oils, spices, dairy products, fruits, nuts, and confectionery goods were all included in the food items. Nutrition consumption was defined as expenditure on dairy products, fish, poultry, meat, green leafy vegetables, and pulses.

#### 3.3.2. Adult equivalent per-capita food and nutrition expenditure

We looked at the impact of IMRI on the distribution of food and nutrition within households during the pandemic, in addition to the level of household food and nutrition spending. However, HCES does not measure how the household food consumption is distributed among its members. Therefore, we imputed individual consumption from household data by making assumptions about intra-household food distribution. We used FAO’s adult male consumption equivalents (AMEs) to measure the distribution of food and nutrition, assuming that such a distribution is positively related with the individual’s energy requirements (Haddad et al., 1996; Berti, 2012). We calculated their AMEs with the help of member-level information from the household roster, which included age and gender. We assigned a weight of 1.2 for adult males, 0.9 for adult females, 1.0 for adolescents (age 12–21 years), 0.8 for children aged 9–12, 0.7 for children aged 7–9, 0.6 for children aged 5–7, 0.4 for children younger than 3, and 0.78 for anyone older than 60 (Deininger and Liu, 2019; Gopalan et al., 2004). Individual AMEs were added to calculate household-level AME. We calculated per-capita adult equivalent of food expenditure by dividing monthly food consumption expenditure by household AME. Similarly, we computed per-capita adult equivalent of nutrition expenditure.

### 3.3.3. Vulnerability as expected food and nutrition poverty

Next, we examined the impact of IMRI of GPs on the vulnerability status of rural households. The pandemic had placed rural households at risk of future food poverty. We measured vulnerability as a probability of consumption loss in the near future ($t + s$) for a household $h$ at the time $t$ (Chaudhuri et al., 2002).

$$V_{hs} = Pr(\ln C_{h,i+s} \leq \ln Z)$$

where $C_{h,i+s}$ is defined as household welfare in terms of adult equivalent per capita food consumption expenditure at time $t + s$; $\ln Z$ is the natural log of the relevant food poverty line. We used state-specific poverty lines using GOI (2014)$^{15}$. Chaudhuri et al. (2002) measure of VBP has been widely used in the development literature (e.g., Gunther & Harrtgen, 2009; Cahyadi & Wailbe, 2015; Zereyesus et al., 2017). The underlying assumption is that the estimated residual from the household consumption regression explains uncertainties associated with idiosyncratic shocks that a household is likely to experience shortly. Other unobservable sources of variation were assumed to be time-invariant. Therefore, the residual obtained from the consumption function is the only source of inter-temporal variation at the level of consumption for observationally similar households.

We first estimated the consumption function by expressing food consumption expenditure of the household $h$ in terms of observed household characteristics and an error term that captures idiosyncratic factors:

$$\ln C_h = \gamma X_h + \varepsilon_h$$

where $\ln C_h$ is the natural log of per capita food consumption expenditure for household $h$, $X_h$ is a vector of household characteristics such as the dependency ratio, age and education of the household head, and household assets. $\gamma$ is a vector of parameters, and $\varepsilon_h$ is the error term that captures idiosyncratic shocks with mean zero and normal distribution. Further, we assume the variance of $\varepsilon_h$ (i.e., $\sigma_{\varepsilon_h}^2$) is correlated with observable household characteristics:

$$\sigma_{\varepsilon_h}^2 = \alpha X_h + \varepsilon_h$$

The OLS specification of equation (3) gives an unbiased but inefficient estimate because it assumes homoskedasticity across households. However, the error term captures the impact of shocks on household consumption. Therefore, to address heteroskedasticity, we use Amemiya’s (1977) three-step feasible generalized least squares (FGLS) to estimate $\gamma$ and $\alpha$.

To apply FGLS, we first estimate equation (2) using OLS. The estimated error term is then used to estimate equation (4) using OLS:

$$\tilde{\sigma}_{\varepsilon_h}^2 = \alpha X_h + \varepsilon_h$$

The predicted $\alpha$ from equation (4) is used to transform equation (4):
The transformed equation (4) is estimated using simple OLS which gives \( \hat{\sigma}_{FGLS} \), which is asymptotically efficient. \( \hat{\sigma}_{FGLS} \) is an efficient estimate of \( \sigma_{hh} \), the idiosyncratic variance component of household consumption. Using \( \hat{\sigma}_{FGLS} \), we measure the standard error:

\[
\hat{\sigma}_{hh} = \sqrt{\hat{\sigma}_{FGLS}^{2}X_{h}}
\]

We use \( \hat{\sigma}_{hh} \) from equation (6) to transform equation (2):

\[
\frac{(\ln C_{h})}{\hat{\sigma}_{hh}} = \eta \left( \frac{X_{h}}{\hat{\sigma}_{hh}} \right) + \epsilon_{h} \tag{7}
\]

We get \( \hat{\gamma}_{FGLS} \) from the OLS estimation of equation (7), which is asymptotically consistent and efficient. We then use \( \hat{\gamma}_{FGLS} \) and \( \hat{\sigma}_{FGLS} \) to estimate expected per capita food consumption expenditure (log) for household \( h \) (equation 8) and its variance (equation (9)):

\[
E[X_{h}] = \hat{\gamma}X_{h}, \quad \beta_{FGLS} \tag{8}
\]

\[
Var(VFP_{h}) = \alpha \left( \frac{X_{h}}{\hat{\sigma}_{hh}} \right) + \varepsilon_{h} \tag{9}
\]

Finally, assuming that food consumption is log-normally distributed, we use equations 8 and 9 to estimate vulnerability level as:

\[
\hat{V}_{h} = \hat{\gamma}_{FGLS}(X_{h}) = \phi \left( \frac{lnZ - \hat{\gamma}X_{h}}{\sqrt{\hat{\sigma}_{hh}}} \right) = VFP
\]

where \( \phi(.) \) denotes the cumulative density of the standard normal.

From equation (10), we compute the household’s VFP (i.e., \( \hat{V}_{h} \)), which predicts the latter’s likelihood of being poor in the future, i.e., extended poverty. The value of \( \hat{V}_{h} \) is between 0 and 1 where \( \hat{V}_{h} = 0 \) implies that the household is not at all vulnerable, while \( \hat{V}_{h} = 1 \) indicates that it is most vulnerable.

Chaudhuri et al. (2002) propose a VFP measure that assumes a risk-free environment with no likelihood of macroeconomic shocks. However, the macroeconomic climate is expected to change significantly between the pre-COVID and COVID-19 eras. In fact, dynamic covariate shocks are likely to push comparatively less vulnerable households below the poverty line. These households are particularly vulnerable to shocks (Lipton, 1983; Fujii, 2016). So, we used extended poverty lines to assess VFP, which incorporates minimum welfare consumption and the cost of insurance against shocks (Caferio & Vakis, 2006). This approach identifies the state’s propensity to target vulnerable populations in response to macroeconomic shocks. Mathematically, the new poverty gap may be expressed as:

\[
G_{h} = (Z \pm l_{h}) - C_{h} \tag{11}
\]

where \( G_{h} \) is the poverty gap for household \( h \) and \( l_{h} \) is the insurance value against the immediate uncertainty arising out of shocks. \( Z \) and \( C_{h} \) have been defined already. The sum of \( Z_{x} \) represents the extended poverty line for household \( h \). However, the extent of uncertainty on household welfare due to shocks varies across households as, does the insurance value. Yet, the nature of cross-sectional data does not allow us to estimate insurance value \( l_{h} \) for the targeted population \( N \). In other words, it does not allow us to calculate the \( N \) number of the extended poverty lines. The ideal solution for this problem is to construct a confidence interval by adopting the universal value of \( l_{h} \) in terms of the current poverty line as follows:

\[
G_{h} = (Z \pm \theta Z) - C_{h} \tag{12}
\]

\[
G_{h} = Z - C_{h} \tag{13}
\]

where \( \theta \) ranges from 0 to 1, and \( Z \) represents the extended poverty line. Vulnerability at the extended poverty line can be re-defined as:

\[
\tilde{V}_{h} = \hat{F}_{P}(X_{h}) = \phi \left( \frac{lnZ - \hat{\gamma}X_{h}}{\sqrt{\hat{\sigma}_{hh}}} \right) \tag{14}
\]

Following Jha et al. (2011), we use 0.2 as the value of \( \theta \), that is, 20% of the current poverty line \( Z \).

4. Methods

4.1. Identifying variation in information management response of local governments

Villages offer historical and political contexts for local government operations and can also influence the quality of their governance (Protik et al., 2018). Hence, exogeneity of IMRI is not a tenable assumption to begin with. Local government effort during COVID-19 is endogenous to several observable and unobserved village-level characteristics. Villages with a higher degree of citizen awareness, for example, are anticipated to develop and execute more extensive and accurate information management initiatives. Indeed, we find considerable heterogeneity in the quality and accuracy of Gram Panchayat communication and coordination efforts as well. Therefore, citizen awareness and activism determine the quality and extent of the local governments’ pandemic response. Additionally, Panchayat officials’ lack of knowledge about the nature of issues and potential solutions could result in inefficient governance overall (Dal Bo & Finan, 2016), particularly during natural disasters (Hong et al., 2018). Therefore, the quality of GP leadership and its level of awareness about local issues may also result in endogenous information management response of GPs during the pandemic.

In the absence of COVID-19, village-level awareness of the COVID-19 pandemic can be safely assumed to be non-existent, in the initial round of the survey. This implies that unobserved heterogeneity with respect to local government information management response is primarily on account of a generic level (ex-ante) of rural household awareness, activism, and participation in governance processes. Given that the nature and evolution of citizen-local government interactions are dependent on local history and cultural norms (Protik et al., 2018), our main identifying assumption is that citizen awareness and activism are time-invariant between the two survey rounds. Additionally, it is plausible to argue that even though the elections to GPs do not take place based on party symbols, most of the contestants to the GP elections are affiliated with state or national political parties (Rajasekhar et al., 2017). Therefore, omission of political affiliation with central or state governments can confound the IMRI effects. However, no state in our sample elected new GP council members or a state government between the two survey periods. Therefore, the quality of leadership, awareness of local issues and problems and political affiliations during the same regime, are assumed to be time-fixed for a given village for the course of the two rounds of survey.

However, it is important to qualify and underscore some of the potential issues associated with assuming time-invariant unobserved heterogeneity in local governments’ capacity for learning and adaptation, citizen awareness and their propensity to participate in and influence

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7 The extended poverty line defined for relatively vulnerable households during pre-COVID and post-COVID lockdown are: \( E/IP < VFP < 0.5IP_{pre-COVID} = Rs. 1125.52E/IP < VFP < 0.5IP_{post-COVID-Lockdown} = Rs. 1064.60 \) where IP is actual incidence of poverty defined as the proportion of households consuming below food poverty line. As we see that the average changes in the monthly food consumption for relatively vulnerable group falling from pre-COVID period to COVID period pushing the group to higher vulnerability.

8 While 100% of GPs communicated about the need to follow social distancing norms, only 45% did so using correct information. Similarly, 29.30% of GP leaders informed the village citizens that water or ash, are as effective as hand sanitizers.
local governance processes. If we consider the theoretical perspectives of organizational learning by Crossan et al. (1999), then the learning of local governments (in terms of communication, coordination, information dissemination, and resource mobilization), should be regarded as a concurrent, multi-level, and dynamic process. Such linkages are expected to exist in the case of GPs that were recently exposed to natural catastrophes such as floods and droughts. This implies that recalling prior knowledge (feedback) will be correlated with the absorption of new learning (feed-forward). In such situations, we must exercise caution while inferring precise causal relationships from the results. Without a randomized allocation of information management initiatives at the level of GPs or a natural experiment to ensure exogeneity of information management response, we have used time-invariant village and household-level unobserved heterogeneities to identify the welfare impacts of IMRI during the pandemic.

Next, we offer some suggestive evidence on correlation between household and village observables and the local government information management response to the pandemic. To this end, we classified GPs into two groups: (i) GPs with an IMRI value above the median and (ii) GPs with IMRI below the median value in the sample. We regressed several household and village covariates from the baseline on the binary variable above-median which equals 1 for GPs with IMRI values greater than the median and 0 otherwise.

Table 2 provides summary statistics and compares the sample means of key variables from the above-median and ‘below-median’ groups using the baseline characteristics of households, villages, and GPs. According to the statistics in Table 2, the average age of household heads is about 45; they have completed around five years of schooling. Within households, the average dependency ratio is 0.60 while 78% of household heads own a bank account. Additionally, the data indicates that households in above-median and below-median categories have statistically comparable access to facilities including piped water and toilets. We did not notice any statistically significant difference in the reservation status of GPs for women in accordance with the 73rd constitutional amendment. The likelihood of observing a female reserved GP is about 51% across all groups, indicating that randomized allocation of female agency at the GP level does not co-vary with IMRI.

In terms of outcomes variables of interest, Table 2 indicates that during the baseline period (i.e., before the COVID-19 spread), per-capita adult equivalent food expenditure is somewhat higher for households in the above-median group than for households in the below median group (959 versus 938). The difference, however, is not statistically significant. The magnitude of per-capita adult equivalent nutrition expenditure is comparable across groups above and below the median IMRI (517 versus 516). Once again, the difference in sample mean is not statistically significant. Other factors, such as caste diversity and village vulnerability to droughts, are shown to be balanced in GP groups above and below the median IMRI.

Table 2 shows that the information management response index (i.e., IMRI) is not correlated with household and village observables in the pre-COVID phase. We next present the econometric specification based on our main identifying assumption- unobserved heterogeneities such as citizen awareness, leadership quality and understanding of local problems on the part of Panchayat council members are time invariant.

### 4.2. Estimation strategy

The panel structure of our data enables estimation of the welfare effects of IMRI designed and implemented by GPs between the two rounds of livelihoods survey. We looked specifically at the relationship between local governments’ information management responses and patterns in: (i) food and nutrition expenditure, (ii) the distribution of such expenditures within households as measured by per-capita adult equivalent of food and nutrition expenditure, and (iii) vulnerability to food and nutrition poverty.

We used difference-in-difference (D-I-D) approach to compare the welfare effects of IMRI. As discussed, our identification approach employed the fixed-effects assumption (in terms of unobserved household and village characteristics that may be associated with IMRI) to estimate within-household variations in food and nutrition spending. Our main models of IMRI impact on food consumption and vulnerability status of rural households in India are linear fixed effects D-I-D specification. We denote the outcomes as \( Y_{it} \) where \( i \) identifies the household and \( v \) and \( s \) are location variables indicating the village and state in which the household is located. \( PostCovid \) represents whether a household is observed before or after the COVID-19 rollout. \( IMRI_{it} \) is the information management response index measured at village-level. We then estimate the following specification:

| Variable                      | Mean Difference |
|-------------------------------|-----------------|
| Age of Household (HH) head    | 44.77 to 44.86  |
| Education of HH head          | 5.75 to 5.18    |
| Whether HH head has bank account? | 0.78 to 0.79  |
| Dependency Ratio              | 0.63 to 0.21    |
| Whether HH has access to piped water? | 0.14 to 0.18  |
| Per-capita adult equivalent food expenditure (INR) | 959.00 to 937.80  |
| Per-capita adult equivalent food expenditure (INR) | 526.95 to 519.46  |
| Whether village exposed to covariate-shock during previous two years | 0.16 to 0.13  |
| Whether Gram Panchayat is reserved for female? | 0.517  |
| Caste diversity in Gram Panchayat | 0.225 to 0.226  |

Notes: The data used for checking the balance in the table is from the pre-COVID phase (i.e., first round of survey). Local governments (Gram Panchayats) were categorized on the basis of their IMRI score during the COVID-19 lockdown. The Gram Panchayats that received index score (i.e., IMRI) above the median value were grouped together, while those below the median score formed the second group. Age, education, and bank account pertains to the household head. Dependency ratio is defined as the ratio of number of household members in the productive age group who access labor markets to household size. Piped water and toilet are dummy variables that equal to one if a household has access to these amenities during the sample period and zero otherwise. Land is defined as the sum of irrigated and unirrigated land. Per-capita adult equivalent food and nutrition consumption is calculated by using the calorie requirements of individual household members and total energy (calories) available for the household to consume conditioned on expenditure on food and nutrition items. Caste diversity is the ratio of number of unique caste individuals to the size of the Gram Panchayat council. For columns 1 and 2, standard deviations are in parentheses. *** \( p < 0.01 \), ** \( p < 0.05 \), * \( p < 0.1 \).
$Y_{street} = \gamma_{t} + \alpha_{1}IMRI_{t1} + \alpha_{2}PostCovid_{t} + \delta(IMRI)_{t1}$
\[ \times PostCovid_{t} + \sum p_{k}X_{ivst} + \epsilon_{st} \] (15)

$\alpha_{2}$ is used to assess overall time-trends (specifically trends for villages with low-levels of IMRI). $\delta$ coefficient on the interaction of IMRI and Post-Covid measures the welfare impacts of IMRI for rural households.

We cannot directly test the parallel trends assumption because we lacked access to data on either actual or retrospective household level welfare outcomes from the pre-baseline period. Instead, we used the village-level nighttime lights data to conduct an alternative test for parallel trends. Nighttime light intensity tracks economic activity and have been employed in various research including the impact of demonetization (Beyer, Chhabra, Galdo, and Rama, 2018). The parallel trends test based on the nighttime lights intensity data was conducted using the following specification:

$NL_{st} = \pi_{0} + \pi_{1}IMRI_{ivs} + p(above_{ivs} \times Baseline_{ivs}) + \epsilon$ (16)

where $NL_{st}$ is the ratio of nightlights to village area; $above_{ivs}$ is a dummy variable with value 1 to indicate GPs with above-median IMRI scores, 0, otherwise; $Baseline_{ivs}$ takes value 1 for baseline period, and 0, for pre-baseline period. The coefficient of the intersection term $p$ will be statistically insignificant if parallel trends assumption hold, that is, the difference in economic activity as measured by nightlights (citation) in above and below median IMRI GPs is parallel over time.

We conducted two more tests to assess the validity of our identification assumption. The first was a placebo specification that exploited a fake treatment strategy. We argue that if $\delta$ in equation (15) measures the impact of local governments’ IMR on consumption and household vulnerability during the pandemic, then IMR associated to COVID-19 management should have no effect on household welfare in the absence of pandemic. We use the following specification, which involves regressing baseline welfare outcomes are regressed on (a) baseline covariates, and (b) IMRI measured from the post-COVID round of survey:

$Y_{vst} = \tau_{0} + \tau_{1}IMRI_{t1} + \sum p_{k}X_{ivst} + \theta$ (17)

where $Y_{vst}$ is a welfare outcome obtained from the baseline survey, and $IMRI_{t1}$ is the information management response index measured from the second round of survey. $\tau_{1}$ is the placebo effect and its statistical significance is used to assess the validity of our identifying assumption. In addition to the placebo test we used a matching approach to first balance the above-median and below-median GP groups using pre-COVID-19 covariates before applying the difference-in-difference method to the matched data to control for time-invariant residual biases. In the absence of a direct parallel trends test, matching on pre-COVID-19 variables helped improve the balance, particularly with respect to unobserved confounders (Stuart et al. 2014).

5. Results

We compare temporal changes in welfare outcomes to examine the effect of IMRI on household food and nutrition expenditures as well as exposure to food and nutrition poverty during COVID-19. We begin by discussing the impact of the IMRI on household-level welfare outcomes before presenting findings from the placebo and other identification tests.

5.1. Can Gram Panchayats mitigate adverse effects on food and nutrition consumption?

Tables 3 and 4 present difference-in-difference estimates of the temporal evolution of welfare outcomes under COVID-19, while controlling for time invariant household and village characteristics. We report linear fixed effects regression results with and without the sampling weights because unweighted D-I-D even with MAR attrition tend to over-reject the null of no effect. We have already discussed the procedure for calculating the sampling weights. The first four columns of Table 3 show results for monthly household food and nutrition expenditure, while columns 5–8 report results for per-capita adult equivalent food and nutrition expenditure. Columns 1, 3, 5, and 7 are based on unweighted fixed-effects estimation, while columns 2, 4, 6, and 8 make use of the weighted fixed-effects estimation. Table 4 provides estimates of the impact of IMRI on household vulnerability to food and nutrition poverty. While columns 1 and 3 are based on unweighted fixed-effects model, columns 2 and 4 account for sampling weights in the D-I-D estimation. The weighted regressions are the preferred specifications. Given the use of panel data in estimation, all the standard errors presented in Tables 3 and 4 are bootstrapped to account for the clustering of household errors within GPs as well as serially correlated household errors.

Several important findings emerge from the results in Table 3. First, in the absence of any information management response from GPs, the monthly household food consumption would have declined by Rs. 5959.50 (79 USD) during nine-month period consisting of 2019 survey and the second round of post-COVID-19 survey in May 2020 (Table 3, Column 2). Household monthly nutrition expenditure (Column 4) would have declined by Rs. 3902.20 (52.60 USD). Second, as expected, the decline in the levels of food and nutrition expenditure is accompanied by a negative impact of the pandemic on the distribution of food and nutrition within the household: in the absence of an information management response, monthly per-capita adult equivalent food, and nutrition expenditures (Columns 6 and 8, respectively) would have declined by Rs. 1305.90 (17 USD) and Rs. 868.80 (11.70 USD), respectively.

Third, the intention-to-treat estimates show that the information management response contributed significantly to the offsetting of COVID-19’s adverse impacts on household welfare. In column 2, the magnitude of D-I-D estimate $\delta$ shows that a unit increase in the natural log of IMRI will offset monthly food expenditure loss by Rs. 1919.09 (26.11 USD) during the pandemic. By adding coefficients $\alpha_{2}$ and $\delta$, we find that monthly food expenditure declined by Rs. 5959.50 for households residing in GPs with low IMRI scores and by Rs. 4040.41 (=5959.50–1919.09) for households in GPs with relatively high IMRI. Similarly, the information management response of local governments could restrict the decline in monthly nutrition expenditure to Rs. 2795.13 (=3902.20–1107.03) during the pandemic. Adding coefficients $\alpha_{2}$ and $\delta$ for column 6 shows that per-capita adult equivalent food expenditure declined by Rs. 862.31 (=1305.90–443.59) for households with higher IMRI GPs, whereas it decreased by Rs. 1305.90 for households in low IMRI GPs. Similarly, from column 8, the per-capita adult equivalent nutrition expenditure declined by Rs. 614.93 (=868.833–253.90) for higher IMRP GP households, whereas it decreased by Rs. 868.833 for households in low IMRI scoring GPs.

Fourth, econometric estimates of the extent to which local governments’ IMR countered the negative effects of the pandemic are robust to the standardized D-I-D regressions (i.e., we normalized IMRI and used the z-scores). Column 1 in Appendix Table A3(i) shows that having a GP with a standard deviation higher IMRI can increase the monthly household food expenditure by Rs. 1581.8 (21.30 USD), and nutrition expenditure (column 2) by Rs. 943.66 (12.72 USD). The estimates suggest that a standard deviation increase in IMRI virtually offsets the entire loss of nutrition expenditure during the pandemic. Similarly, GPs with a standard deviation higher IMRI led to Rs. 327.963 (4.42 USD) increase in the per-capita adult equivalent food expenditure and Rs. 180.06 (2.43 USD) increase in the per-capita adult equivalent nutrition expenditure.

9 The range of the raw IMRI score is 22–60 while maximum score possible is 80. The range of natural log of IMRI is 3.113 to 4.09. Therefore, a unit increase in the natural log of IMRI is equivalent to approximately three times the increase in the raw IMRI score.
Clustered at the village level. *** p < 0.001, ** p < 0.01, * p < 0.05, * p < 0.1.

Table 3
Difference-in-difference estimates of the impact of IMR on food and nutrition expenditure.

| Variables | (1) Food Expenditure | (2) Food Expenditure | (3) Nutrition Expenditure | (4) Nutrition Expenditure | (5) Per-Capita Adult Equivalent Food Expenditure | (6) Per-Capita Adult Equivalent Food Expenditure | (7) Per-Capita Adult Equivalent Nutrition Expenditure | (8) Per-Capita Adult Equivalent Nutrition Expenditure |
|-----------|----------------------|----------------------|--------------------------|--------------------------|-----------------------------------------------|-----------------------------------------------|-----------------------------------------------|-----------------------------------------------|
| Post COVID-19 | -7,044.701* (3,798.901) | -595.489*** (2849.146) | -4,913.986*** (2,182.072) | -3902.179*** (1,800.259) | -1,429.914* (910.538) | -1305.893* (906.738) | -994.685** (471.014) | -868.833* (496.154) |
| IMR * Post COVID-19 | 2,150.022** (1,022.120) | 1919.091** (773.587) | 1,344.121** (588.252) | (486.709) | (219.222) | (244.781) | (127.282) | (133.6705) |

Notes: Estimates are from linear D-I-D regressions controlling for household fixed effects. The dependent variable in columns 1–2 is the level of monthly household food expenditure. The dependent variable in columns 3–4 is the level of monthly household nutrition expenditure. The dependent variable in columns 5–6 is per-capita adult equivalent food expenditure and in columns 7–8, the dependent variable is per-capita adult equivalent nutrition expenditure. The odd numbered columns report estimates from unweighted regressions, while even numbered columns are based on weighted fixed effects regression. IMRI is the information management response index (with regards to COVID-19) calculated at the village level. In pre-COVID-19 phase, the value of IMRI is zero for all the villages. The standard errors are clustered at the village level. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 4
Difference-in-difference estimates of the impact of IMR on Vulnerability to Food and Nutrition Poverty.

| Variables | (1) VFP-100 | (2) VFP-100 | (3) VNP-100 | (4) VNP-100 |
|-----------|------------|------------|------------|------------|
| IMR * Post COVID-19 | -0.164*** (0.046) | -0.0618** (0.0297) | -0.113*** (0.040) | -0.028 (0.0310) |
| Post COVID-19 | 0.285* (0.1558) | 0.0544 (0.1017) | 0.236* (0.1373) | 0.0491 (0.1072) |
| Household Fixed Effect | Yes | Yes | Yes | Yes |
| Sampling weights applied | No | Yes | No | Yes |
| Observations | 1069 | 1069 | 1069 | 1069 |

Notes: Estimates are from linear D-I-D regressions controlling for household fixed effects. The dependent variable in columns 1–2 is household vulnerability to food poverty in a risk free state (i.e., VFP-100). VFP-100 and VNP-100 are based on state specific poverty lines. Columns 1 and 3 report estimates from unweighted regressions, while columns 2 and 4 are based on weighted fixed effects regression. IMRI is the information management response index (with regards to COVID-19) calculated at the village level. The standard errors are clustered at the village level. *** p < 0.01, ** p < 0.05, * p < 0.1.

5.2. Can Gram Panchayats mitigate adverse effects on household vulnerability?

Table 4 provides estimates of the impact of IMR on household vulnerability to food (VFP-100) and nutrition (VNP-100) poverty. Columns 1 and 2 indicate that the pandemic increased household’s vulnerability to food poverty. The magnitude of the difference-in-difference estimate δ in column 1 suggests that an increase in IMRI reduced the likelihood of household food poverty by 0.16%. When the sample (attrition) weights are included in Column 2, the magnitude is reduced to 0.062%, however. Column 5 in Appendix Table A3 shows similar findings; having a GP with a standard deviation higher IMRI will reduce VFP-100 by 0.23%.

The findings of VNP-100 are fairly varied. While the unweighted regression estimates in column 3 of Table 4, suggest that IMRI reduced exposure to nutrition poverty (VNP-100) by 0.113%, the weighted regression shows a much smaller and statistically insignificant decline of 0.03%. The standardized difference-in-difference results in column 6 of Appendix Table A3 show that having a GP with a standard deviation higher IMRI reduces VNP-100 by 0.12%.

Table 4 shows the estimates of the impact of IMR on household vulnerability during the pandemic based on the assumption that the economy will continue to expand at its current rate. Table 5 shows vulnerability estimates for two more scenarios to consider: (a) the economy shrinks (VFP-120 and VNP-120), and (b) the economy grows (VFP-80 and VNP-80). Columns 1 and 3 provide vulnerability estimates for first scenario, in which the economy shrinks, while columns 2 and 4 present findings for the second scenario in which the economy grows. The D-I-D estimates suggest that IMR reduces household vulnerability to food and nutrition poverty regardless of the state of the economy. According to column 1, if the economy shrinks, IMR contributes to a 0.15% reduction in VFP-120 but if the economy expands, IMR contributes to a 0.16% decrease in VFP-120 (see column 2). Columns 3 and 4 indicate that the contribution of IMR to anticipated nutrition poverty is greater

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USD) increase in the per-capita adult equivalent nutrition expenditure.

Fifth, econometric estimates of the extent to which local governments’ IMR countered the negative effects of the pandemic are robust to the logarithmic D-I-D specification (i.e., we use logarithm of food and nutrition expenditures as well as the logarithm of the per capita adult equivalent of food and nutrition expenditure). In column 2 of Appendix Table A3(ii), the magnitude of D-I-D estimate δ shows that a percentage increase in IMRI will offset monthly food expenditure loss by 0.389% during the pandemic. This then implies that the monthly food expenditure declined by 1.395% for households residing in GPs with 1% lower IMRI score and by 1.006% for households residing in 1% higher IMRI score. From columns 3, 5, and 7, we show that the D-I-D estimates of IMRI elasticity of nutrition expenditure, and per-capita adult equivalent food and nutrition expenditure is positive and statistically significant.

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10 As discussed earlier, VFP-100 is the measure of the likelihood that household’s monthly per capita food consumption expenditure is below the extent the poverty line. Similarly, we interpret VNP-100.
when the economy contracts (0.114%) than when the economy grows (0.10%).

5.3. Parallel trends, matching with D-I-D and placebo test

As previously stated, our panel dataset lacks pre-baseline information on the welfare outcomes of interest; thus, we used village nighttime lights intensity from the baseline and pre-baseline period for testing the parallel trends assumption. Appendix Table A5 shows that, before the pandemic, the village-level nighttime lights intensity in above-median and below-median IMR GPs for the May 2018 and May 2019 were similar. We provided two additional suggestive evidence with regards to the parallel trends assumption:

(a) We used a matching method to first balance the above-median and below-median IMRI GPs based on pre-COVID-19 covariates and outcomes before applying the D-I-D to control for time-invariant residual biases in the matched data (Abadie, 2005; Heckman et al. 1997). Matching on pre-COVID-19 outcomes is particularly helpful for improving the balance in terms of unobserved confounding variables (Stuart et al. 2014). The application of D-I-D estimation on matched data can help address the problem of residual imbalances (Neill et al. 2016). Appendix Tables A6 and A7 show estimates from the propensity score weighted D-I-D model, where the weights are the inverse probability of belonging to the above-median IMRI group 

\[ \text{weights} = \frac{1}{\text{Propensity Score}^{\text{above-median}}} \]

According to Appendix Table A7, having a GP with a standard deviation higher IMRI reduced the increase in VFP-100 and VNP-100 (Column 2) by 8.50% and 1.10% (Column 4). In line with main results in Table 4 (see Column 4), the impact of IMRI on VNP-100 is not statistically significant.

(b) We next present estimates from a placebo specification (equation (17)). As previously stated, the fake treatment by construction should have no effect on household welfare for the placebo test to be valid. Therefore, if we treat GPs with their respective IMRI from the post-COVID-19 period (i.e., fake treatment) in the baseline, then the estimated impact of fake treatment \( (\tau_1) \) on welfare outcomes should be statistically insignificant. The results in Appendix Table A8 (columns 1–8) show that \( \tau_1 \) is not statistically significant. The coefficient of \( \tau_1 \) in column 2 of Appendix Table A9 is nevertheless statistically significant; the fake treatment increased the VFP-100 in the absence of the pandemic. The overall findings from parallel trends, matching with D-I-D estimates and placebo tests offer substantial evidence on identification and consistency of the IMR’s welfare effects on rural households during the pandemic.

5.4. Multiple hypothesis testing and adjustments

The standard D-I-D specification results in over-rejection (false) of null hypotheses because it overlooks the multiplicity of the testing framework (Clarke et al., 2019). In this section we examined whether the statistical significance of the welfare coefficients is robust to family wise error rate (FWER) adjustments. We re-computed p-values for each independent variable using the Westfall and Young (1993) and Romano-Wolf algorithms, along with the Bonferroni-Holm, and Sidak-Holm methods. The outcomes are grouped into two families: (a) food and nutrition outcomes (both levels and distribution), and (b) household vulnerability outcomes. Table 6 shows that the p-values for both families’ outcomes are robust to adjustments for multiple hypothesis testing. Although, the coefficient of VNP-100 is significant across all the adjustments, it is only marginally significant for the Romano-Wolf adjustment and not statistically significant for the Westfall and Young correction.

We adjusted across all outcomes in addition to adjusting for multiple hypotheses by family (Petek and Pope, 2021). Table 7 shows that the statistical significance of household food and nutrition expenditure, the per-capita adult equivalent of food and nutrition expenditures, and VFP-100 are similar to p-values after adjusting within the family. While VNP-100 is no longer significant under the Romano-Wolf and Westfall and Young corrections \( (p_{-RW} = 0.89 \text{ and } p_{-WT} = 0.11) \), the p-values for Bonferroni-Holm, and Sidak-Holm procedures are statistically significant. In general, these results suggest that the welfare effects of local government’s response to the pandemic (i.e., IMRI) are positive and statistically significant, and that the estimates are unaffected by the testing of multiple hypotheses.

6. Sensitivity analysis

We performed three sets of robustness checks: (a) we used alternative aggregation and weighing approaches to construct IMRI and re-estimate the D-I-D models, (b) we used instrumental variable models to estimate the welfare impacts, and (c) we re-estimated the D-I-D models by distinguishing between landless households from the rest of the sample.
Table 6
Effect of IMR on household welfare: adjust for multiple hypothesis testing across by outcome variable family.

| Output   | (1) Food Expenditure | (2) Nutrition Expenditure | (3) Per-Capita Adult Equivalent Food Expenditure | (4) Per-Capita Adult Equivalent Nutrition Expenditure | (5) VFP-100 | (6) VNP-100 |
|----------|----------------------|---------------------------|--------------------------------|---------------------------------------------------|--------|--------|
| β        | 2829.426             | 1599.000                  | 586.8335                        | 253.894                                           |        |        |
| SE       | 1131.886             | 775.063                   | 239.668                         | 133.67                                            |        |        |
| p-value  | 0.012                | 0.017                     | 0.018                           | 0.022                                             |        |        |
| p-RW     | 0.0396               | 0.0297                    | 0.0594                          | 0.0396                                            |        |        |
| p-WY     | 0.06                 | 0.052                     | 0.072                           | 0.06                                              |        |        |
| p-Bonf   | 0.0035               | 0.0049                    | 0.0141                          | 0.0141                                            |        |        |
| p-Sidak  | 0.0035               | 0.0049                    | 0.0140                          | 0.0140                                            |        |        |

Notes: The sample includes panel of households and the unit of observation is a household’s consumption in the past one month at the time of survey. This table reports the impact of IMR of GPs on household food, nutrition, and vulnerability status (see Table 3). Standard errors clustered at the level of village are reported in the parentheses. P-values are reported and are calculated using clustered standard errors, the Romano Wolf correction (p-RW), the Westfall Young algorithm (p-WY), the Bonferroni correction (p-Bonf), and the Sidak-Holm correction (p-Sidak). The families are the levels and per-capita adult equivalent food and nutrition consumption, and vulnerability to food and nutrition poverty.

Table 7
Effect of IMR on household welfare: adjust for multiple hypothesis testing across all outcomes.

| Output   | (1) Food Expenditure | (2) Nutrition Expenditure | (3) Per-Capita Adult Equivalent Food Expenditure | (4) Per-Capita Adult Equivalent Nutrition Expenditure | (5) VFP-100 | (6) VNP-100 |
|----------|----------------------|---------------------------|--------------------------------|---------------------------------------------------|--------|--------|
| β        | 2829.426             | 1599.000                  | 586.8335                        | 253.894                                           |        |        |
| SE       | 1131.886             | 775.063                   | 239.668                         | 133.67                                            |        |        |
| p-value  | 0.012                | 0.017                     | 0.018                           | 0.022                                             |        |        |
| p-RW     | 0.0198               | 0.0198                    | 0.0594                          | 0.0396                                            |        |        |
| p-WY     | 0.044                | 0.034                     | 0.072                           | 0.06                                              |        |        |
| p-Bonf   | 0.003                | 0.004                     | 0.0088                          | 0.002                                             |        |        |
| p-Sidak  | 0.003                | 0.004                     | 0.0088                          | 0.0019                                            |        |        |

Notes: The sample includes panel of households and the unit of observation is a household’s consumption in the past one month at the time of survey. This table reports the impact of IMR of GPs on household food, nutrition, and vulnerability status (see Table 3). Standard errors clustered at the level of village are reported in the parentheses. P-values are reported and are calculated using clustered standard errors, the Romano Wolf correction (p-RW), the Westfall Young algorithm (p-WY), the Bonferroni correction (p-Bonf), and the Sidak-Holm correction (p-Sidak). The families are the levels and per-capita adult equivalent food and nutrition consumption, and vulnerability to food and nutrition poverty. Instead of adjusting for multiple hypothesis tests by family, we instead adjust across all outcomes.
6.1. Alternative approaches to compute IMRI

The concern with constructing the IMRI (and hence the welfare estimates during the pandemic) is that the composite index can be sensitive to a specific aggregation and weighting method or the inclusion or exclusion of one of the dimensions of information management framework. As a robustness check, we therefore evaluated IMRI’s sensitivity to alternative aggregation and weighting methods as well as the inclusion and exclusion of IMRI’s dimensions (Saisana & Tarantola, 2002).

The linear aggregation method is used to develop the base IMRI\(^{13}\). The additive utility approach assumes preferential independence between the dimensions. The compensatory approach of linear aggregation is based on the premise of full trade-off between the dimensions. As a result, a low score in one of the IMRI dimensions can be compensated for by relatively higher scores in other dimensions. For example, if GPs do poorly on the communication dimension, they can compensate by improving on other dimensions. It is plausible to suggest that including some degree of non-compensability among the dimensions would be a more realistic approach towards measuring IMMRI during the pandemic. Because it implies decreasing trade-offs and reduced marginal compensability across dimensions, the geometric aggregation technique is more suited for such an undertaking. The expression for computing IMRI based on geometric aggregation is:

\[
IMRI = \left( \prod_{j=1}^{s} W_j^{w_j} \right)^{\frac{1}{\sum w_j}} \exp \left( \frac{\sum w_j \frac{W_j - \text{IMRI}_j}{w_j}}{\sum w_j} \right).
\]

Appendix Tables A10 and A11 present results based on the geometric mean aggregation method. We observe that while all the D-I-D estimates are statistically significant or have become more efficient, some of the magnitudes are now smaller. While the effect of linear-aggregation-based-IMRI (i.e., base IMRI) on VNP-100 during the pandemic is –0.02 and statistically insignificant (see Column 4, Table 4), the impact of geometric-aggregation-based-IMRI on VNP-100 is higher (-0.08) and statistically significant at <1% (see Column 4 in Appendix Table A11). Similarly, the geometric mean aggregation method yields a bigger and more efficient estimate of the impact of IMRI on VNP-100 (see Column 2, Appendix Table A11).

Next, we consider the possibility that in the construction of base IMRI, score of one of the individual dimensions exerts significantly larger effect on composite IMRI than other dimensions. We recalculated IMRI by omitting one of the four dimensions at a time to see whether the welfare estimates are sensitive to extreme value indicators. In Appendix Tables A12 and A13, the resource mobilization dimension is excluded while re-computing IMRI. Similarly, the information dissemination dimension has been excluded from Appendix Tables A14 and A15, as has the coordination dimension from Appendix Tables A16 and A17 and the communication dimension from Appendix Tables A18 and A19. Appendix Tables A12-A19 demonstrate that removing IMRI dimensions one at a time from the main analysis has no effect on the D-I-D estimates of household welfare during the pandemic. We continue to report results for both unweighted and sample weighted specifications. The impact of IMRI on household and per-capita adult food and nutrition consumption remains intact and statistically significant, but the magnitude of the impact is smaller compared to the main results in Tables 3 and 4. The results are consistent with respect to the vulnerability estimates; however, the sample weighted estimates are no longer statistically significant.

Appendix Tables A18 and A19 show the most significant deviations from the main result. When we exclude the communication dimension and re-compute IMRI, the estimates of all welfare effects associated with food and nutrition consumption, as well as household vulnerability to food and nutrition poverty, are statistically insignificant. This suggests that the welfare effects of IMRI are affected by the communication dimension. The sub-indicators of communication dimension measure the GP’s information management efforts to disease management in the village. The findings in Appendix Tables A17 and A18 ties back to the conceptual framework, that identifies disease management as an important channel linking the information management response of local governments to household welfare and exposure to poverty.

The final robustness check for IMRI construction is to utilize Principal Component Analysis (PCA) to determine weights for IMRI computation. Standard PCA is appropriate for continuous data where the assumption of normality is reasonable; hence its application is limited in our case since we deployed discrete variables. Instead, we used the polychoric PCA (Kolenikov and Angeles, 2009) which is an improvement over the first principal component approach of Filmer and Pritchett (2001). The polychoric PCA assumes that there is a latent continuous variable underlying the observed binary variable and estimates the polychoric correlation matrix for latent continuous variables. The first component from the analysis is taken as a proxy for the index. The maximum likelihood function is used to estimate the weights used by polychoric PCA. For the construction of the IMRI index, all 17 indicators from four dimensions were considered (see Appendix Table A22). However, four sub-indicators were dropped due to perfect collinearity. The first component for 13 variables explains 23% variance, which we then rescaled between 0 and 1. Estimates of the main results are of similar magnitude and more often statistically significant when we use weights from the polychoric PCA (Appendix Tables A20 and A21). The estimates for VFP-100 and VNP-100 are larger and more efficient when alternative weights are used, as shown in Appendix Table A21.

6.2. Sub-group analyses

Landless households are likely to be disproportionately affected by the pandemic. The first round of household surveys recorded information on land ownership. An important mandate of GPs is to protect the well-being of the vulnerable and deprived groups in the villages. In addition, vulnerable households (for example, landless) compared to generic ones, are more likely to reach out to village institutions for essential commodities and services. Therefore, if village local governments are effective in providing landless households with suitable channels to access such benefits during the shock, the magnitude of welfare is expected to be higher for vulnerable dwellings compared to landed households. Also, it may be possible that the welfare distribution of landless households may not exhibit first order stochastic dominance over landed households conditioned on IMRI. In fact, the three-way interaction of IMRI, Post COVID-19, and Landless can suggest that the magnitude of the difference in welfare between landed and landless households is less when compared to welfare gap in lower IMRI villages. We, therefore, re-estimated our models to distinguish between landless households and land-owning households. The new specification includes all the variables from the D-I-D equation as well as an additional triple-difference term (IMRI * Post COVID-19 * Landless) to estimate the heterogeneous effect of IMR of GPs on welfare. Two findings emerge from the sub-group analysis in Tables 8 and 9. First, IMR has a positive welfare impact. While some of the estimates of the double interaction term (δ1) (i.e., IMRI*Post COVID-19) round) are statistically insignificant when we use sampling weights, the magnitudes and the signs are intact as reported in the main results. Second, the coefficient of the triple interaction term (δ2) (i.e., IMRI*Post COVID-19*Landless) indicates that IMRI has an additional positive effect on food (Rs. 351) and nutrition expenditure (Rs. 210). The per-capita adult equivalent food and nutrition consumption follows a similar trend. Estimates from Table 9 show that IMRI reduced landless households’ vulnerability to food and nutrition poverty. All the triple difference coefficients in Columns 1–4 are negative and statistically significant. The findings in Tables 8 and 9 confirm that, in the absence of IMR, the pandemic’s adverse impact on welfare of rural households could have

13 Base IMRI is the index used in Tables 3 and 4 (i.e., equation (15)).
been more severe. We also report heterogeneous IMR effects for bank account owning households (see Appendix Table A22a). The coefficient of the three-way interaction term: (IMRI\* Post COVID-19\* Bank), estimates the impact of IMR on the welfare of landless households during post-COVID lockdown phase. Results show that IMR of GPs lead to additional positive impact on the food and nutrition expenditure of landless households. Decline in vulnerability to food and nutrition poverty was also larger for this sub-group in the sample. The variable ‘Landless’ is dropped in the D-D because it is time fixed during the duration within which the two survey rounds were fielded. The standard errors are clustered at the village level. *** p ≤ 0.01, ** p ≤ 0.05, * p ≤ 0.1.

### 6.3. IV models for endogenous information management response of local governments

We analysed the sensitivity of our main results to an alternative identification assumption as well. Our last robustness check included using instrumental variable models to account for endogenous placement of IMR in GPs during the pandemic. GP elections are organized by respective state governments. Thus, the time remaining (in months) for the next the GP election, among other things, is determined by the year in which the state government enacted the State Panchayati Raj act and any subsequent amendments to it. For example, both Gujarat and Bihar accepted the recommendations of the 73rd Constitutional Amendment in 1993, while Bihar introduced a new set of amendments in 2006. Therefore, the elections cycle varies across states. We exploited this variation and instrumented the IMRI using the time to next GP elections. The model incorporates the same set of controls that were used in the logit specification for sampling weights estimation, except that we could not include household-fixed effects, since our instrument is at the village-level and the IV specification is estimated using information from the post-COVID-19 round. According to the descriptive analysis of the data, the mean time until the next election in the above-median IMRI group of GPs is 16.63 months, as against 36.22 months for the below-median group. Appendix Tables A23 and A24 show the results from the IV specification. The first stage results in panel B from Appendix Tables A23 and A24 show that the time until the next election has a negative and statistically significant effect on IMRI. These findings are consistent with the extant evidence on the positive relationship between upcoming elections and electoral gains for incumbents who responded effectively to an adverse shock (Bechtel & Hainmueller, 2011). We have presented the second stage estimates with and without the sample weights. Panel A in Appendix Table A23 shows that findings from the main results remain intact. However, since we did not account for the time-trend and household fixed effects, the magnitudes in the IV specification are larger than the D-D estimates. Appendix Table A24 shows that the vulnerability effects are not statistically significant.

We used the falsification specification to test instrumental exogeneity. We checked whether the instrument (i.e., time to next election)
could directly influence household welfare in the post-COVID-19 phase in the absence of IMR. Because the IMRI value was non-zero in the post-COVID phase for all the GPs, we conducted the falsification test on a group of GPs that constituted the lowest 25% of the IMRI. We demonstrate in Appendix Tables A25 and A26 that the direct association between the instrumental variable (i.e., time until next election) and all the outcome variables is statistically insignificant. In addition, the magnitude of the relationship is very small. The result provides evidence for instrumental validity.

We performed three types of robustness tests in all, and the results were qualitatively consistent with the primary findings.

7. Channels

The primary findings suggest that, during the pandemic, the food, nutrition, and vulnerability status of rural households, among other things, depends on the quality of information management response of local governments. In this section we hypothesize that the primary results are consistent with three channels. The first is maintenance of essential food services such as the distribution of food grains through fair price shops under the public distribution system (PDS). The second channel is concerned with ensuring that rural households continue to access and benefit from rural employment programs such as Mahatma Gandhi National Rural Employment Guarantee Scheme (MGNREGS), as well as access funds and cash during the pandemic. The third channel involves disease management by GPs based on four critical aspects of the COVID-19 protocol: social distancing, hand hygiene, public gathering norms, and use of mobile application (Aarogya Setu App) for self-reporting and tracking. We acknowledge that this project was not designed to estimate causal links between change in the quality of essential services delivery and household consumption during the pandemic and therefore only correlational evidence is presented here. We have analysed simple correlational regressions in two ways (a) by classifying local governments based on whether they have an above or below median IMRI value and (b) by using standardized IMRI values.

7.1. PDS channel

We began by exploring the first channel, viz., the impact of information management response on the delivery of essential services during the pandemic. Public Distribution System (PDS) oversees food supply. The federal and state governments, together, provide food grains to beneficiaries. GPs strive to enhance PDS efficiency by identifying and verifying beneficiaries, monitoring the operation of fair price shops, and ensuring that the price and availability of essential commodities are displayed to the village population. Table 10 shows a significant and positive correlation between IMR and the operation of PDS shops during COVID-19, both with and without the sampling weights. Panel A shows that fair price shops (PDS) located in ‘above-median IMRI’ GPs are 26.90% (see Column 2) more likely to function during the pandemic than in GPs in the below median group. In accordance with this finding, we show that the fair price shops in above-median Gram Panchayats functioned for an additional 1.58 days per week compared to the base group. Compared to below-median GPs, the above-median GPs are 4.70% less likely to experience a scarcity of essential commodities (i.e., rice, wheat, sugar, pulses, kerosene, and edible oil) during the pandemic. In Panel B, we have reported standardized coefficients that support the correlational evidence that essential services provide a critical channel through which local governments’ IMR can reduce the negative impacts of the pandemic on household welfare.

7.2. MGNREGS channel (Income Effect)

Next, we explored the employment and cash channels. MGNREGS has been mandated to offer at least 100 days of wage employment to rural households. GPs provide administrative support to the program.

### Table 9

**Heterogeneous effect for landless households: impact of IMR on household vulnerability.**

| Variables | (1) | (2) | (3) | (4) |
|-----------|-----|-----|-----|-----|
| IMRI* Post-COVID-19** | -0.036*** | -0.031*** | -0.039*** | -0.036*** |
| Landless (δ₂) | (0.004) | (0.004) | (0.004) | (0.004) |
| IMRI* Post-COVID-19 (δ₁) | -0.154*** | -0.057 | -0.099** | -0.021 |
| Post COVID-19 | 0.273* | 0.052 | 0.212 | 0.050 |
| (0.147) | (0.152) | (0.131) | (0.138) |
| Control for time to next Panchayat election | YES | YES | YES | YES |
| Household Fixed E | YES | YES | YES | YES |
| Sampling Weights applied | No | Yes | No | Yes |
| R-squared | 0.617 | 0.71 | 0.373 | 0.471 |
| Observations | 1059 | 1026 | 1058 | 1025 |

Notes: Estimates are from linear regression controlling for household fixed effects. The dependent variable in columns 1–2 is vulnerability to food poverty and the dependent variable in columns 3–4 is vulnerability to nutrition poverty. The odd numbered columns report estimates from unweighted regressions, while even numbered columns are based on weighted fixed effects regression. IMRI is the information management response index (with regards to COVID-19) calculated at the village level. In pre-COVID-19 phase, the value of IMRI is zero for all the villages. The coefficient of the three-way interaction term: (IMRI* Lockdown* Landless), estimates the impact of IMR on the welfare landless households during post-COVID lockdown phase. Results show that the decline in vulnerability to food and nutrition poverty is larger for landless households. We also conducted regressions for the extended poverty lines (not shown here) and the heterogeneous effect for landless households continues to hold. The variable ‘Landless’ is dropped in the D-I-D because it is time fixed during the duration within which the two survey rounds were fielded. The standard errors are clustered at the village level. *** p < 0.01, ** p < 0.05, * p < 0.1.

Local governments receive applications for MGNREGS participation; they issue job cards, assess demand for work, and maintain accounts and utilization certificates. While the survey instrument did not collect detailed information on household program participation, it did ask the GP leaders to report whether they had facilitated the payment of outstanding wages and demanded more work for rural households under MGNREGS during the pandemic. The results are reported in Table 11. In Column 2 of Panel A, we show that the above-median GPs are 9.2% more likely than below-median GPs to demand work and facilitate payment of pending MGNREGS wages. The involvement of GPs in MGNREGS is essential during the pandemic since rural households are reported to financially strapped. Public works programs like MGNREGS help disadvantaged families get access to the job market while simultaneously providing liquidity for essentials such as food and nutrition. Moreover, the same group of above-median GPs are 17.5% more likely than below-median GPs to demand work and facilitate payment of pending MGNREGS wages. The involvement of GPs in MGNREGS is essential during the pandemic since rural households are reported to financially strapped. Public works programs like MGNREGS help disadvantaged families get access to the job market while simultaneously providing liquidity for essentials such as food and nutrition. Moreover, the same group of above-median GPs are 17.5% more likely than below-median GPs to demand work and facilitate payment of pending MGNREGS wages. The involvement of GPs in MGNREGS is essential during the pandemic since rural households are reported to financially strapped. Public works programs like MGNREGS help disadvantaged families get access to the job market while simultaneously providing liquidity for essentials such as food and nutrition. Moreover, the same group of above-median GPs are 17.5% more likely than below-median GPs to demand work and facilitate payment of pending MGNREGS wages.

7.3. Disease management channel (substitution effect)

Finally, we examined the third channel on disease management by GPs during the pandemic. The survey tracked the GP’s communication initiatives on four aspects of COVID-19 protocol to check the spread of virus: (a) social distancing, (b) hand hygiene, (c) public gathering norms, and (d) use of mobile application (Aarogya Setu App) for self-
According to the conceptual framework, effective disease management by GPs allows households to maintain food and nutrition intake while avoiding resource diversion to COVID-19 related health expenditures. The results are reported in Table 12. The disease management initiatives are measured using five binary variables: (a) a dummy for whether the GP provided correct information with regards to prescribed social distancing norm of six feet, (b) a dummy whether the GP communicated importance of regular hand wash, (c) a dummy for whether the GP provided correct information with regards to duration of hand washing, (d) a dummy for whether GP asked village households to avoid public gatherings, (e) a dummy for whether the GP encouraged households to use the Aarogya Setu application to self-report COVID-19

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**Table 10**

PDS Channel.

| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
|-----------|-----|-----|-----|-----|-----|-----|
| PDS open (0/1) | PDS open (0/1) | PDS Operate Week-days | PDS Operate Week-days | PDS shortage (1/0) | PDS shortage (1/0) |
| **Panel A: Using Above Median IMRI** | | | | | | |
| IMRI | 1.333*** | 1.237*** | 1.751*** | 1.579*** | −0.543*** | −0.682*** |
| (0.145) | (0.374) | (0.165) | (0.442) | (0.227) | (0.247) |
| Marginal effects | 0.294*** | 0.269*** | 1.751*** | 1.579*** | −0.039*** | −0.047*** |
| (0.030) | (0.0785) | (0.165) | (0.442) | (0.015) | (0.016) |
| Household fixed effect | Yes | Yes | Yes | Yes | Yes | Yes |
| Sampling weights applied | No | Yes | No | Yes | No | Yes |
| R-squared | 0.0589 | 0.0468 | 0.091 | 0.0799 | 0.0383 | 0.0551 |
| Observations | 1069 | 1026 | 1069 | 1026 | 1069 | 1026 |

**Panel B: Using Standardized IMRI**

| IMRI | 2.963*** | 2.956*** | 2.605*** | 2.736*** | −1.335*** | −1.718*** |
| (0.215) | (0.587) | (0.152) | (0.414) | (0.364) | (0.372) |
| Marginal effects | 0.643*** | 0.644*** | 2.605*** | 2.736*** | −0.807*** | −0.105*** |
| (0.043) | (0.124) | (0.152) | (0.414) | (0.020) | (0.0189) |
| Household fixed effect | Yes | Yes | Yes | Yes | Yes | Yes |
| Sampling weights applied | No | Yes | No | Yes | No | Yes |
| R-squared | 0.154 | 0.147 | 0.134 | 0.153 | 0.0656 | 0.0987 |
| Observations | 1069 | 1026 | 1069 | 1026 | 1069 | 1026 |

**Notes:** The dependent variables include two dummy variables: a dummy for functioning of fair price PDS shops (see columns 1 and 2) and a dummy for grain shortage in PDS shops (see columns 5 and 6). The dependent variable in columns 3 and 4 is number of days in a week the PDS shop operated. Columns 1, 2, 4, and 6 have used logistic specification and the marginal effects have been reported separately in row 2 of the results. The odd numbered columns report estimates from unweighted regressions, while even numbered columns are based on weighted fixed effects regression. IMRI in Panel A is a binary variable: whether the GP is from the above median or below median group. In Panel B, the z-score of IMRI is used. The independent variables include time remaining for next GP election and the whether the GP is reserved for women president. The standard errors are clustered at the village level. *** p < 0.01, ** p < 0.05, * p < 0.1.

**Table 11**

Public works program and cash channels.

| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) |
|-----------|-----|-----|-----|-----|-----|-----|
| MGNREGA (1/0) | MGNREGA (1/0) | COVID fund (1/0) | COVID fund (1/0) | Cash (1/0) | Cash (1/0) |
| **Panel A: Using Above Median IMRI** | | | | | | |
| IMRI | 0.739*** | 0.991** | 2.000*** | 2.264** | 0.056* | 0.068** |
| (0.184) | (0.492) | (0.390) | (0.979) | (0.030) | (0.031) |
| Marginal effects | 0.079*** | 0.092* | 0.178*** | 0.175*** | 0.056* | 0.068** |
| (0.0215) | (0.0499) | (0.0282) | (0.0732) | (0.030) | (0.031) |
| Sampling weights applied | No | Yes | No | Yes | No | Yes |
| R-squared | 0.129 | 0.158 | 0.102 | 0.134 | 0.0458 | 0.061 |
| Observations | 1069 | 1026 | 1069 | 1026 | 1069 | 1026 |

**Panel B: Using Standardized IMRI**

| IMRI | 1.562*** | 2.030*** | 2.315*** | 2.503*** | 0.115*** | 0.122*** |
| (0.307) | (0.634) | (0.283) | (0.844) | (0.035) | (0.037) |
| Marginal effects | 0.156*** | 0.175** | 0.204*** | 0.173*** | 0.115*** | 0.122*** |
| (0.0305) | (0.0746) | (0.0229) | (0.0554) | (0.035) | (0.037) |
| Sampling weights applied | No | Yes | No | Yes | No | Yes |
| R-squared | 0.158 | 0.201 | 0.114 | 0.140 | 0.0521 | 0.07 |
| Observations | 1069 | 1026 | 1069 | 1026 | 1069 | 1026 |

**Notes:** The dependent variables include three dummy variables: a dummy for access to MGNREGA wages (see columns 1 and 2), dummy for village level COVID-fund for food distribution (see columns 3 and 4), and a dummy variable for household access to cash during the pandemic (see columns 5 and 6). Columns 1–6 have used logistic specification and the marginal effects have been reported separately in row 2 of the results. The odd numbered columns report estimates from unweighted regressions, while even numbered columns are based on weighted fixed effects regression. IMRI in Panel A is a binary variable: whether the GP is from the above median or below median group. In Panel B, the z-score of IMRI is used. The independent variables include time remaining for next GP election and the whether the GP is reserved for women president. The standard errors are clustered at the village level. *** p < 0.01, ** p < 0.05, * p < 0.1.

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As reported earlier, all 176 GPs communicated about the importance of observing social distancing; however, there is significant variation in precision of the information content.
Table 12
Disease management channel.

| VARIABLES | (1) Social Distancing (1/0) | (2) Social Distancing (1/0) | (3) Hand wash (1/0) | (4) Hand wash (1/0) | (5) Duration of Hand wash (1/0) | (6) Duration of Hand wash (1/0) | (7) Avoid Public gathering (1/0) | (8) Avoid Public gathering (1/0) | (9) Aarogya Setu Application (1/0) | (10) Aarogya Setu Application (1/0) |
|-----------|-----------------------------|-----------------------------|---------------------|---------------------|-------------------------------|-------------------------------|----------------------|----------------------|-------------------------------|-------------------------------|
| Panel A: Using Above Median IMRI | | | | | | | | | | |
| IMRI      | 0.729*** (0.149) | 0.686* (0.391) | 0.563* (0.335) | 0.905 (0.824) | 0.988*** (0.145) | 0.893** (0.3922) | 1.655*** (0.162) | 1.727*** (0.457) | 2.388*** (0.233) | 3.05*** (0.561) |
| Marginal effects | 0.174*** (0.167) | 0.04* (0.0741) | 0.241*** (0.241) | 0.218** (0.365) | 0.370*** (0.609) | 0.61*** (0.61) |
| Sampling weights | (0.0349) | (0.094) | (0.024) | (0.0671) | (0.0339) | (0.092) | (0.0327) | (0.087) | (0.029) | (0.082) |
| R-squared | 0.232 | 0.486 | 0.158 | 0.067 | 0.06 | 0.506 | 0.086 | 0.083 | 0.263 | 0.261 |
| Observations | 1069 | 1026 | 1069 | 1026 | 1069 | 1026 | 1069 | 1026 | 1069 | 1026 |

Panel B: Using Standardized IMRI

| VARIABLES | (1) Social Distancing (1/0) | (2) Social Distancing (1/0) | (3) Hand wash (1/0) | (4) Hand wash (1/0) | (5) Duration of Hand wash (1/0) | (6) Duration of Hand wash (1/0) | (7) Avoid Public gathering (1/0) | (8) Avoid Public gathering (1/0) | (9) Aarogya Setu Application (1/0) | (10) Aarogya Setu Application (1/0) |
|-----------|-----------------------------|-----------------------------|---------------------|---------------------|-------------------------------|-------------------------------|----------------------|----------------------|-------------------------------|-------------------------------|
| IMRI      | 1.216*** (0.192) | 1.093** (0.517) | 1.775*** (0.324) | 2.047** (0.868) | 1.003*** (0.178) | 0.86** (0.470) | 2.308*** (0.220) | 2.658*** (0.586) | 3.644*** (0.242) | 3.05*** (0.561) |
| Marginal effects | 0.295*** (0.268) | 0.107*** (0.324) | 0.149*** (0.149) | 0.25*** (0.178) | 0.212** (0.407) | 0.521*** (0.220) | 0.595*** (0.586) | 0.623*** (0.242) | 0.611*** (0.561) |
| Sampling weights | (0.0468) | (0.127) | (0.0178) | (0.0543) | (0.044) | (0.110) | (0.0485) | (0.126) | (0.0874) | (0.082) |
| R-squared | 0.158 | 0.04 | 0.125 | 0.11 | 0.05 | 0.041 | 0.103 | 0.125 | 0.361 | 0.261 |
| Observations | 1069 | 1026 | 1069 | 1026 | 1069 | 1026 | 1069 | 1026 | 1069 | 1026 |

Notes: The dependent variables include five binary variables; a dummy for whether the GP provided correct information with regards to prescribed social distancing norm of six feet (see columns 1 and 2), a dummy whether the GP communicated information of regular hand wash (see columns 3 and 4), a dummy for whether the GP provided correct information with regards to duration of hand wash (see columns 5 and 6), a dummy for whether GP asked village households to avoid public gatherings (columns 7 and 8), and a dummy for whether the GP encouraged households to use the Aarogya Setu application (columns 9 and 10). We have used logistic specification across columns 1–9 and the marginal effects have been reported separately in row 2 of the results. The odd numbered columns report estimates from unweighted regressions, while even numbered columns are based on weighted fixed effects regression. IMRI in Panel A is a binary variable: whether the GP is from the above median or below median group. In Panel B, the z-score of IMRI is used. The independent variables include time remaining for next GP election and the whether。

8. Policy implications

This paper documents the relationship between the local government’s information management response and household food and nutrition intake, as well as their vulnerability status, in India’s post-COVID-19-lockdown period. Using a panel data on households and information management activities of GPs, we found a positive and statistically significant impact on the consumption and vulnerability status of rural households in India. The impact is persistent and somewhat more pronounced for landless and bank-account holding households. Additionally, we have presented suggestive evidence showing that GPs with higher IMRI were able to: (a) maintain household access to staple food grains via coordination with fair price shops, (b) enable access to paid employment under MGNREGS and cash, and (c) communicate about disease management and COVID-19 protocols.

Effective information management is likely to enhance the trust between citizens and local governments, resulting in greater compliance and welfare prospects during the pandemic. The current literature also provides credence to the findings of the paper. For instance, in the absence of effective communication about an adverse event and its potential impact could well affect the adoption strategies of local governments (Goidel et al., 2019). As a result, local-level communication and coordination efforts based on information collection and sharing are anticipated to build confidence between citizens and local institutions (Windsor et al. 2019, Balts, 2021). Our empirical findings are consistent with the extant literature, which highlights the efficacy of information management efforts in strengthening community and household resilience during shock occurrences (Goidel et al., 2019). However, some limitations continue to persist in our work. The two survey rounds made use of different methods to collect the data. While, the first round was conducted as ‘in-person’ interviews, the second round was telephonic. We adopted several strategies to reduce biasness and inefficiency on account of attrition and response bias during the telephonic round, however we cannot completely eradicate its possibility if the ‘in-person’ and telephonic surveys were to trigger distinct data generating processes or induce further measurement errors. In addition, the fixed effects assumption is tenable in a limited way and relies significantly on the assumption that the systematic differences among GPs continue to persist and evolve at the same rate, both before and during the pandemic. It would be critical, both from the empirics and policy-making perspective to induce certain capacities in GPs following a pandemic. It would be critical, both from the empirics and policy-making perspective to induce certain capacities in GPs following a pandemic.
Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.foodpol.2022.102278.

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