The Coronavirus Pandemic and Food Security: Evidence from West Africa*

Guigonan Serge Adjognon†

Jeffrey R. Bloem‡

Aly Sanoh§

September 9, 2020

Abstract

We document some of the first estimates of the effect of the coronavirus pandemic on food security in low- and middle-income countries. In this paper, we combine nationally representative pre-pandemic household survey data with follow-up phone survey data from Mali and exploit sub-national variation in the intensity of pandemic-related disruptions between urban and rural areas. These disruptions stem from both government policies aiming to slow the spread of the virus and also individual behavior motivated by fear of contracting the virus. We find evidence of increasing food insecurity in Mali associated with the pandemic. Difference-in-difference estimates show that moderate food insecurity increased by about 8 percentage points—a 33 percent increase—in urban areas compared to rural areas in Mali. Our estimates are substantially larger than existing predictions of the average effect of the pandemic on food security globally and therefore highlights the critical importance of understanding effect heterogeneity.

Keywords: COVID-19, Pandemic, Food Security, Mali, Sub-Saharan Africa

JEL Codes: Q18,O21, O55, I31, D63

*Authors are listed in alphabetical order and contributed equally to this paper. We thank Marc Bellemare, Steven Zahniser, and Cheryl Christensen for helpful feedback on initial drafts of this paper. The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent. Also, they should not be construed to represent any official US Department of Agriculture or US Government determination of policy. All remaining errors are our own. Please tell us about them.

†Agricultural Economist, World Bank Group, Email: gadjognon@worldbank.org

‡Research Economist, United States Department of Agriculture, Economic Research Service, MS9999, Beacon Facility, P.O. Box 419205, Kansas City, MO 64141, Email: jeffrey.bloem@usda.gov

§Poverty Economist, World Bank Group, Email: asanoh@worldbank.org

1 Introduction

The second United Nations Sustainable Development Goal calls for ending hunger and achieving food security for all people by 2030. Achieving this goal within the next ten years is now challenged by dramatic shocks to earned income, household expenditures, and agricultural value chains due to the coronavirus pandemic. Recent estimates suggest that the economic impact of the pandemic in sub-Saharan Africa specifically could be between a five and seven percent reduction in GDP (Djiofack *et al.*, 2020). Of course GDP is only instrumentally valuable and how the pandemic influences other micro-level outcomes—such as food security—remains largely unknown. Although predictions based on expected changes to income, prices, and food supply estimate that the coronavirus pandemic will dramatically increase the number of people suffering from food insecurity and undernutrition in low- and middle-income countries (Baqueano *et al.*, 2020; FAO *et al.*, 2020), these predictions have yet to be evaluated with real-time data.

In this paper we estimate the effect of the coronavirus pandemic on food security in Mali. We combine nationally representative data collected between October 2018 and July 2019 with follow up phone survey data collected between May and June 2020. The panel nature of these data allows us to control for important time-invariant household-level heterogeneity by including household fixed effects in our regression specifications. This is important because the effects of the pandemic may depend critically on geographic and household characteristics, such as existing vulnerabilities to income shocks (Amjath-Babu *et al.*, 2020; Bene, 2020; Devereux *et al.*, 2020). These features allows us to estimate nationally representative effects while also accounting for time-invariant differences between households.[1]

The coronavirus pandemic threatens food security in a number of ways. On the demand side, the pandemic has reduced earned income, increased poverty, and reduced household expenditures (Chetty *et al.*, 2020; Valensisi, 2020). On the supply side, the pandemic is particularly disruptive to post-farm agricultural value chains—such as wholesale and processing logistics enterprises (Reardon *et al.*, 2020). In the context of Mali, the coronavirus pandemic surged in March, in the midst of the off-season period of the agricultural cycle, thereby provoking minimal disruptions to crop production activities in rural areas.[2] Meanwhile, economic activities in urban areas were affected by government policies aiming to slow the spread of the virus and individual behavior motivated by fear of contracting the virus. These details, coupled with the biological dynamics of COVID-19 that spreads via close human contact, suggest that pandemic-related disruptions are likely more dramatic in Mali's urban and rural peri-urban areas than in remote rural areas.[3] We exploit this heterogeneity between urban and rural areas to calculate difference-in-differences estimates of the effect of the coronavirus pandemic on food security in Mali.

We estimate the effect of the *coronavirus pandemic* on food security, not the more specific effect of contracting the SARS CoV-2 (e.g., "COVID-19") virus on food security. This is an important point for

[1] Similar data have been collected in a number of countries by national statistical agencies, in partnership with the World Bank.

[2] As in other Sahel countries, Mali experiences one rainy season every year. For most farmers this facilitates only one crop production period, which typically spans from mid-June through mid-September.

[3] We will investigate and validate this claim in more detail in Section 2.

both the identification and interpretation of our estimates. Our empirical strategy exploits sub-national heterogeneity in pandemic-related disruptions between urban and rural areas in Mali. This strategy is similar to that employed by Ravindran and Shah (2020) who exploit sub-national heterogeneity in pandemic-related disruptions to estimate the effect of the pandemic on domestic violence in India. Our results do not rely on COVID-19 tests accurately identifying the true rate of infection in Mali.

Our paper is related to emerging work on the consequences of the coronavirus pandemic. Much of the existing research focuses on labor market outcomes in high-income countries (Adams-Prassl *et al.*, 2020; Alon *et al.*, 2020; Barrero *et al.*, 2020; Bartik *et al.*, 2020; Bui *et al.*, 2020; Chetty *et al.*, 2020; Coibion *et al.*, 2020; Cowan, 2020). A smaller set of studies focuses on low- and middle-income countries and we aim to add to this literature (Amare *et al.*, 2020; Arndt *et al.*, 2020; Djiofack *et al.*, 2020; Ceballos *et al.*, 2020; Gerard *et al.*, 2020; Jain *et al.*, 2020; Josephson *et al.*, 2020; Kerr and Thornton, 2020; Mahmud and Riley, 2020; Valensisi, 2020). To the best of our knowledge, Amare *et al.* (2020) is the only other paper that estimates the effect of the coronavirus pandemic on food security using real-time data in a nationally representative sample, however, Amare *et al.* (2020) are not able to make use of a complete food security measurement tool.[4] Complementary analysis of sub-national populations by Mahmud and Riley (2020) and Ceballos *et al.* (2020) document a dramatic decrease in food expenditures in rural Uganda and food security in two Indian states, respectively. Other researchers and analysts have raised serious concerns about the disruption of food systems (Reardon *et al.*, 2020) and food security (Arndt *et al.*, 2020; Mishra and Rampal, 2020; Narayanan and Saha, 2020; FAO *et al.*, 2020) but do not quantify the extent nor the effects of the disruption. Finally, existing predictions using expected changes to income, prices, and food supply support this serious concern for food security in low- and middle-income countries (Baqueano *et al.*, 2020; FAO *et al.*, 2020). Although these predictions provide valuable insight, they ultimately rely on expected changes rather than micro-level data measuring real-time-changes.

We make three core contributions. First, we provide self-reported descriptive evidence of how respondents themselves perceive that the coronavirus pandemic has influenced their food security. These results suggest the pandemic has had dramatic effects. For example, 50 percent of households report being worried that they will not have enough food to eat. Of those households, 65 percent identify the coronavirus pandemic as the most important cause of their food security worries. Moreover, despite higher incidence of food insecurity experience in rural areas, we find that respondents in urban areas more frequently identify the pandemic as the most important cause of their food security challenges. These self-reported descriptive results motivate a more sophisticated estimation approach to quantify the effect of the pandemic on food security.

Second, and most importantly, we document some of the first estimates of the effect of the coronavirus pandemic on food security outcomes in a low- and middle-income country in a nationally representative sample. We find evidence that the pandemic has led to a dramatic increase in food insecurity. House-

[4]For unknown reasons, the first round of the COVID-19 phone survey in Nigeria only included three out of the eight Food Insecurity Experience Scale (FIES) questions.

holds in urban areas are at least 33 percent more likely to experience moderate food insecurity. Given limitations of our empirical strategy, primarily due to the widespread disruption of the pandemic, we are careful to point out that these results likely represent an estimate of the lower bound of the effect of the coronavirus pandemic on food security. Despite this, we estimate economically meaningful effects that are substantially larger than existing predictions (Baqueano *et al.*, 2020; FAO *et al.*, 2020). This finding highlights the critical importance of understanding effect heterogeneity. Our results are important for understanding both the welfare loss due to the pandemic and, more specifically, the challenges of achieving the Sustainable Development Goals after the global spread of COVID-19 (Hoy and Sumner, 2020; Ravallion, 2020).

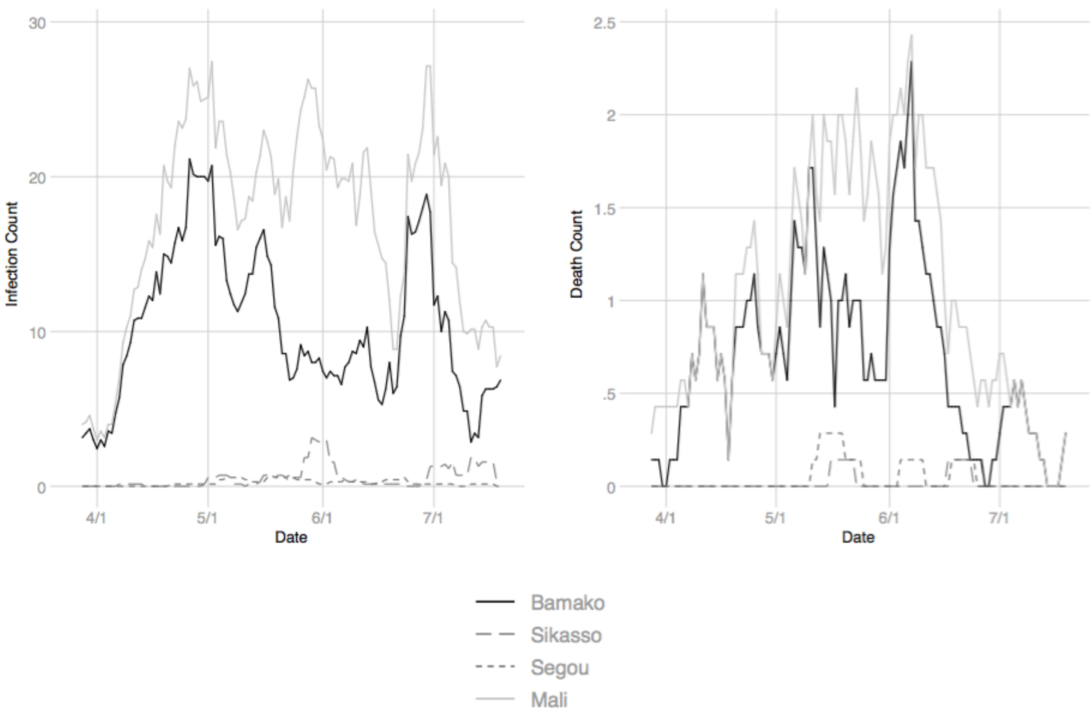
Third, we discuss and provide some descriptive insights on the potential mechanisms driving these results. Although we do not have access to data with sub-national variation in food prices for this analysis, we do have some information on recent behaviors and experiences of household members in the context of the coronavirus pandemic. We find that households in urban areas are more likely to take health-related safety precautions (e.g., wash hands more often, avoid greetings with physical contact, and avoid gatherings of more than 10 people), and report struggles to pay rent, access water or electricity, save money, and make investments in durable goods than households in rural areas. Despite this, we find no difference between urban and rural households in food-related behavior (e.g., stockpiling food, frequency of visits to food markets or grocery stores, or self-reported struggle to buy food). This suggests that reductions in food-related shopping behavior at the extensive margin do not fully explain our main effect estimates. However, relative price effects may still influence behavior at the intensive margin. More research is needed to fully understand these dynamics.

The remainder of this paper is organized as follows. The next section summarizes Mail's experience with the coronavirus pandemic. Section 3 discusses the data we use for our empirical analysis. Section 4 describes the empirical framework of this study and details our core identification strategy. Section 5 discusses the main results along with validity and robustness checks. Finally, section 6 concludes with a discussion of priorities for future work.

2 The Coronavirus Pandemic in Mali

On March 11, 2020, the World Health Organization (WHO) officially categorized the COVID-19 outbreak as a pandemic with consequences potentially reaching every country in the world. On March 18, as preventative measures, Mali suspended all flights traveling from affected countries to Mali, closed all public schools, and banned large public gatherings. On March 25 Mali confirmed its first two positive COVID-19 infections. The next day, upon two additional positive COVID-19 infections, Mali's President Ibrahim Boubacar Keita declared a state of emergency and implemented a curfew from 9 pm to 5 am in hopes of limiting the spread of the virus. Just two days later, on March 28 and after an additional 14 positive cases, Mali witnessed its first COVID-19 related death (WHO, 2020).

Figure 1: COVID-19 Infections and Deaths



Notes: These figures come from the Humanitarian Data Exchange (HDX) COVID-19 sub-national case data, supported by the United Nations Office for the Coordination of Humanitarian Affairs. They show the 7-day moving average of new daily COVID-19 infections and deaths for Mali and the three most populous urban areas: Bamako, Sikasso, and Segou.

Figure 1 shows a seven-day moving average of new daily COVID-19 infection and death counts in Mali, as well as in three of the largest urban centers—Bamako, Sikasso, and Segou—from April through July 2020. These data are collected by the United Nation's Office for the Coordination of Humanitarian Affairs (OCHA) and made available via the Humanitarian Data Exchange (HDE, 2020). Figure 1 highlights three important details about the coronavirus pandemic in Mali. First, and most important for our empirical approach, through about the middle of April 2020, almost all recorded COVID-19 infections and all COVID-19 deaths occurred in Bamako. It was not until the middle of May when the trends in both infections and deaths diverged between Mali and Bamako. Second, other relatively large urban centers—Sikasso and Segou—did not experience anything close to the number of COVID-19 infections or deaths recorded in Bamako. Aside from a small and short-lived increase in infections in Sikasso at the beginning of June, infections and deaths in Sikasso and Segou remained relatively flat from April through July 2020. Finally, the worst of the pandemic for Mali may be in the past, assuming of course no future wave of COVID-19 infections. By the end of July, daily infection counts are more than half of their peak in previous months and some days have zero recorded COVID-19 deaths.[5] Taken together, these data suggest that the coronavirus pandemic to date has been most disruptive in Bamako.

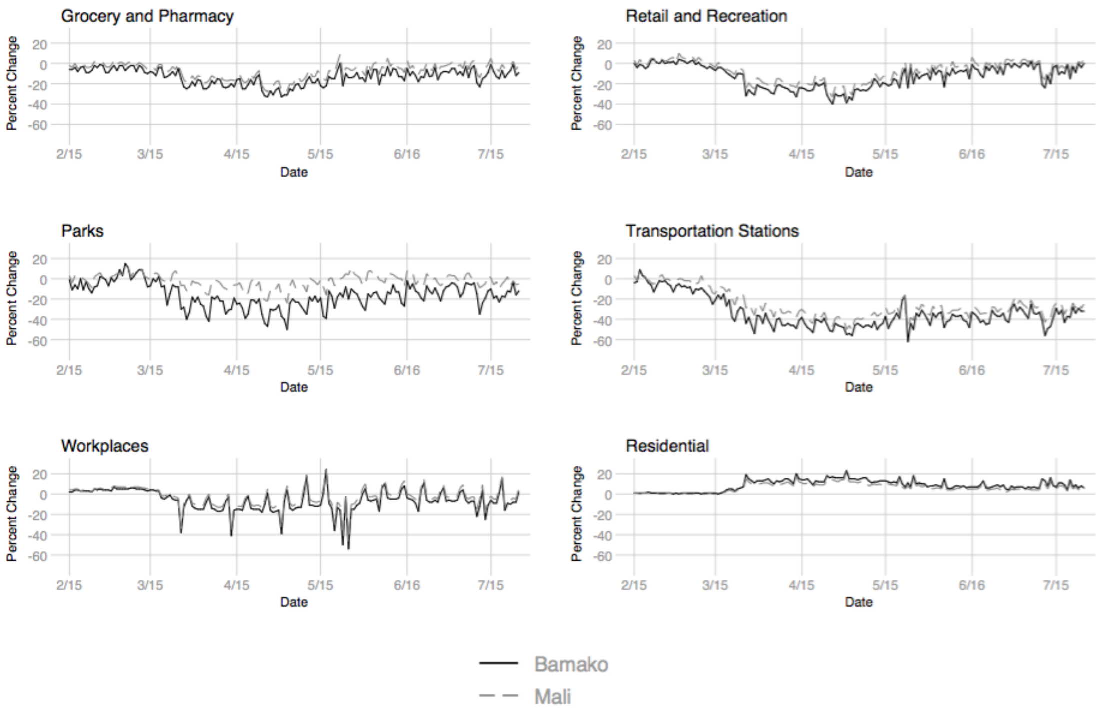
We observe that pandemic-related disruptions were more intense in Bamako and surrounding urban areas than in remote rural areas of Mali in three distinct sources of data. First, as shown in Figure 1 and discussed above, using data on *recorded* COVID-19 infection and death counts we observe that both of these indicators are dramatically skewed toward Bamako. Although these recorded infections and deaths likely underestimate the true incidence of infections and deaths, particularly outside of Bamako (UNICEF, 2020), they are indicators that influence containment policy efforts and motivate fear among individuals of contracting the virus in Bamako specifically. Therefore, for the purposes of our study, they support the observation that the intensity of pandemic-related disruptions was greater in urban areas than in rural areas in Mali.

We now turn to Google's Community Mobility Reports, our second source of information on the intensity of pandemic-related disruptions in Mali. For the purposes of contributing to an understanding of the consequences of the coronavirus pandemic, Google released anonymized and aggregated data from users who have turned on the location history setting of their Google account. These same data are used by Google Maps to predict real-time congestion. The Google Community Mobility Reports show daily changes in the amount of time spent at different places within a given geographic area. These data capture daily percent changes from February 15 through July 15 relative to a baseline representing the median value for the corresponding day of the week during the five-week period from January 3 through February 6, 2020.[6]

[5]To be clear, these data do not suggest that the coronavirus pandemic is no longer a critical concern for Mali. Indeed, these data only report *recorded* COVID-19 infections and deaths. Considering the likely limited COVID-19 testing and deaths monitoring capacity in Mali, especially outside of Bamako and other urban areas, these reported figures may dramatically underestimate the true incidence of infections and deaths (UNICEF, 2020). Moreover the long-term consequences of the coronavirus pandemic, not just in Mali but throughout the world, are sill unknown.

[6]Additional detail about these data are available at `https://www.google.com/covid19/mobility/`. A few notes about these data are important. First, these data are not representative of the whole country. Google only reports on regions

Figure 2: Google Mobility Data



Notes: These figures come from Google's COVID-19 Community Mobility Data. With the same kind of aggregated and anonymized data used in Google Maps, these data show changes for each day in time spent at specific types of places relative to the baseline period. The Google Mobility Data use a baseline of the median value for the corresponding day of the week during the 5-week period of January 3 through February 6, 2020.

Figure 2 displays the Google Community Mobility data for both the entire country of Mali and for Bamako specifically. Google aggregates locations into six types of places: Grocery and Pharmacy, Retail and Recreation, Parks, Transportation Stations, Workplaces, and Residential. Overall, for the entire country of Mali, we observe a significant drop in time spent at all of these locations, except for places of residence, where we see a relatively small increase. This suggests that either the government containment policies or the risk of contracting the virus disrupted movement and economic activities in Mali.

Relative to the entire country, Bamako itself had a larger percent change in absolute value in the time spent at each of these places. Specifically, as reported in the Google Community Mobility Reports, for the period between June 13 and July 25, people in Mali spent two percent less time at grocery stores and pharmacies relative to the baseline period whereas people in Bamako specifically spent nine percent less time at grocery stores and pharmacies. A similar finding holds for other types of places. People in Mali spent five percent less time in parks, 25 percent less time at transportation stations, and four percent more time in residential spaces, relative to the baseline period. In comparison, people in Bamako specifically

if they have a sufficient number of observations over time to make credible estimates of mobility. Thus, these data exist for Mali and for Bamako specifically. No other regions within Mali are reported in Google's Community Mobility Reports. Second, Google data only rely on individuals who use Google applications and have turned on the location history setting in their Google account.

Figure 3: Coronavirus Pandemic Awareness, Beliefs, and Behavior

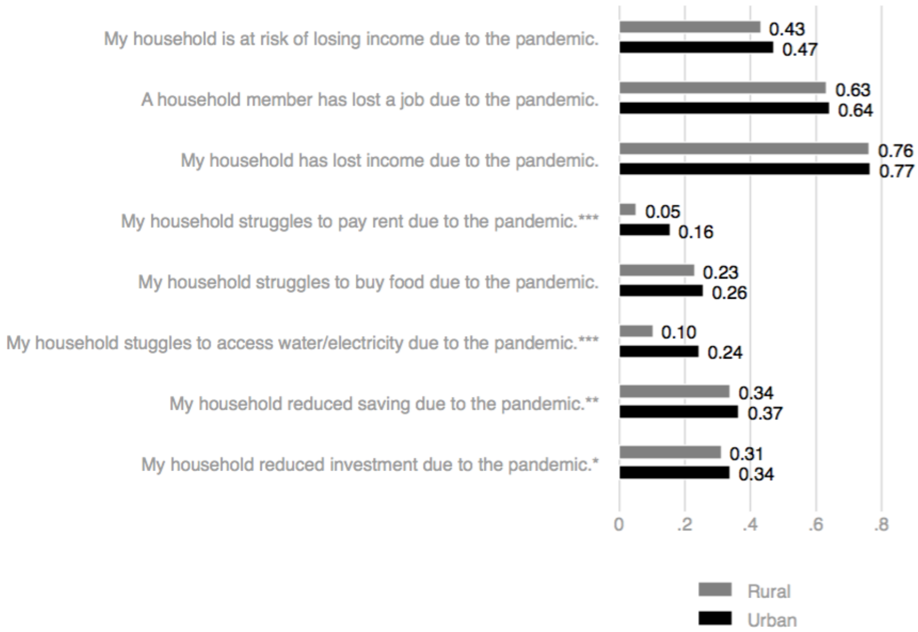
Notes: These descriptive statistics come from the World Bank's COVID-19 high-frequency survey from Mali. Missing and refused responses are excluded from these statistics. Standard errors are clustered at the sampling cluster level. ***, **, and *, in each graph's label indicate statistical significance at the 1, 5, and 10 percent critical level, respectively.

spent 12 percent less time in parks, 32 percent less time at transportation stations, and six percent more time in residential spaces relative to the baseline period. This highlights that the reduced mobility induced by the risk of contracting COVID-19 and government response to the pandemic was concentrated mostly in Bamako, and perhaps, in other urban areas. In rural areas, by contrast, such pandemic-related disruptions was not as noticeable. This supports the validity of our approach for investigating the effect of the coronavirus pandemic and Mali's containment policies on food security in Mali.

Finally, we use information from the COVID-19 phone panel survey, our third source of information used to investigate the intensity of pandemic-related disruptions within Mali. Figure 3 summarizes information about coronavirus-related awareness, beliefs, and behavior.[7] We see that approximately everyone in the sample, with no discernible difference between urban and rural areas, had previously heard of the coronavirus and received some information about social distancing. Although most respondents are, reportedly, satisfied with the Malian government's response to the coronavirus, those who live in rural areas are more satisfied on average than those who live in urban areas. Again, this supports our claim that the pandemic-related disruptions were more intense in urban areas compared to rural areas. Moreover, people living in urban areas are more likely to take extra health precautions due to the pandemic (e.g., wash their hands more than usual, avoid greetings with physical contact, and avoid gatherings with more than 10 people). However, and perhaps surprisingly, although most of the sample did reduce the number of times they went to the market or grocery store and were not able to stockpile more food than usual,

[7] Table A1 in the Supplemental Appendix, provides additional detail on the statistics reported in Figure 3.

Figure 4: Self-Reported Coronavirus Pandemic Impacts



Notes: These descriptive statistics come from the World Bank's COVID-19 high-frequency survey from Mali. Missing and refused responses are excluded from these statistics. Standard errors are clustered at the sampling cluster level. ***, **, and *, in the each graph's label indicate statistical significance at the 1, 5, and 10 percent critical level.

we do not see a discernible difference in these reported behaviors between urban and rural households. Although these descriptive insights highlight reasons why maintaining food security may be generally challenging in Mali, extensive margin changes in these behaviors do not explain differences in pandemic-related food security challenges between urban and rural areas. As documented in other contexts, and as suggested by the Google Mobility Data, price effects could influence behavior on the intensive margin. More research is needed to fully understand these dynamics.

Figure 4 shows self-reported estimates of the impact of the coronavirus pandemic on economic outcomes using information from our COVID-19 phone panel survey.[8] Most households, with no statistical difference between urban and rural areas, report that a household member has lost their job and report lost income due to the coronavirus pandemic. Slightly less than half of households, again with no statistical difference between urban and rural areas, feel at risk for losing more income in the future due to the pandemic. This highlights the magnitude and range of the economic shock associated with the pandemic. Roughly 16 percent of urban households, and only five percent of rural households experienced struggles to pay rent due to the pandemic. Although a similar pattern holds for accessing water or electricity, with 24 percent of urban households and ten percent of rural households reporting struggles due to the pandemic, we see no reported difference in struggles to buy food between urban and rural areas. This essentially mirrors the finding documented in Figure 3. In addition, we see relatively small

[8]Table A2 in the Supplemental Appendix, provides additional detail on the statistics reported in Figure 4.

but statistically significant differences in the ability to save money and invest in durable goods between urban and rural areas, with slightly more reported disruptions in urban areas.

Although we cannot be sure of the exact mechanism with our present data, our descriptive results suggest several possibilities. First, and as documented in Figure 4, although extensive margin changes in access to food does not explain the estimated differences in food security between urban and rural areas, it remains possible that intensive margin changes in food access and consumption explain the differential effects of the pandemic on food security between urban and rural areas. Future research, similar to the work of Narayanan and Saha (2020), should be completed in more contexts around the world. Second, according to our self-reported accounts, the coronavirus pandemic seems to have had a much more salient and direct effect on the ability to pay rent, access water or electricity, save money, and invest in durable goods than access to food in Mali's urban areas compared to rural areas. Despite this self-reported account and as we will discuss in Section 5, we find that households in urban areas experience more food insecurity due to the pandemic than households in rural areas based on a more detailed and specific measurement tool. Future research, using more detailed information on food prices in Mali, will do well to investigate the specific mechanisms that drive these differential effects.

3 Data

The primary data source for our analysis is the first round of the COVID-19 Panel Phone Survey of Households, collected by the Mali National Statistical Office, Institut National de la Statistique (INSTAT), in partnership with the World Bank.[9] The survey is part of a regional effort to generate high quality data on the coronavirus pandemic and its impacts in the West Africa Economic and Monetary Union (WAEMU) member countries. In Mali, the first round of the survey of Households was implemented between the end of May and early June 2020, and included 2,270 households. These households were drawn randomly from the *Enquête Harmonisée des Conditions de Vie des Ménages* (EHCVM) sample, which was conducted between October 2018 and July 2019 in a collaboration between INSTAT and the World Bank. The COVID-19 Panel Phone Survey of Households sample is nationally representative, representative of Bamako, and representative of both urban and rural areas.[10] The survey uses a relatively short instrument focusing on a subset of modules from the EHCVM and new modules on knowledge, perception, and behavior relating to the coronavirus pandemic. Data collection of additional rounds of the COVID-19 Panel Phone Survey of Households is ongoing and subsequent analysis can and should investigate the persistence of effects over a longer period of time.[11]

The EHCVM sample itself covered 8,390 households across Mali and is nationally representative,

[9]Publicly available at `https://microdata.worldbank.org/index.php/catalog/3725/study-description`.

[10]Since the COVID-19 Panel Phone Survey of Households relies on phone interviews, the sampled households include only those who reported a valid phone number during the 2018 EHCVM survey. In some contexts this could generate selection bias. In Mali however, mobile phone technology use is high. Roughly 90 percent of the households surveyed in 2018 provided at least one phone number.

[11]Although recent political events in Mali (See here) might confound any effects captured with later rounds of COVID-19 phone surveys.

representative of Bamako, and representative of both urban and rural areas. The survey relies on a multi-module instrument covering topics including a household's socio-economic characteristics, time-use, production activities, and welfare indicators such as consumption expenditure and food security. We use sampling weights derived from the 2018 EHCVM sampling frame and adjusted for response rates in the COVID-19 Panel Phone Survey of Households. These sampling weights are applied both in our descriptive statistics and regression estimates.

3.1 Measuring Food Security

The United Nations Food and Agriculture Organization (FAO) defines food security as existing, "when all people, at all times, have physical, social, and economic access to sufficient, safe, and nutritious food that meet their dietary needs and food preferences for an active and healthy life" (FAO, 1996, 2009). Although this definition is widely accepted, consistently measuring food security based on this definition is a considerable challenge (Carletto *et al.*, 2013).

In this study, we use the FAO's Food Insecurity Experience Scale (FIES) as primary outcome of interest. The FIES aims to measure food security based on the direct experiences of people relating to food security (Ballard *et al.*, 2013; Smith *et al.*, 2017). This experienced-based measure of food security offers more precision than model-based measures relying on national-level food supply (Coates, 2013; Smith *et al.*, 2017). The FIES is constructed based on respondents' responses to eight questions about experience in various domains of food insecurity:

- FS1: "Household members have been worried that they will not have enough to eat?"
- FS2: "Household members have been worried that they can not eat nutritious foods?"
- FS3: "Household members had to eat always the same thing?"
- FS4: "Household members had to skip a meal?"
- FS5: "Household members had to eat less then they should?"
- FS6: "Household members found nothing to eat at home?"
- FS7: "Household members have been hungry but did not eat?"
- FS8: "Household members have not eaten all day?"

Both the EHCVM sample and the COVID-19 phone survey include each of the eight FIES questions, allowing us to get a measure of food insecurity for both periods. As long as the data generated via these questions align with the Rasch measurement model's assumptions (Rasch, 1960), food security status can be measured by summing the number of affirmative responses to the FIES questions to produce the raw FIES score. We use the raw FIES score as a primary outcome as well as the food insecurity severity classifications developed by Smith *et al.* (2017) as follows: (a) We define "mild food insecurity" with a raw FIES score greater than zero. This definition aligns closely with the FAO's definition of food security as having "physical, social, and economic access to sufficient, safe, and nutritious food [...] at all times" (FAO, 2009). (b) We define "moderate food insecurity" with a raw FIES score greater than three. Finally, (c) we define "severe food insecurity" with a raw FIES score greater than seven—or answering affirmatively to each of the eight FIES questions.

4 Estimation Strategy

Our estimation relies on a difference-in-differences empirical framework based on the presence of sub-national variation in the intensity of pandemic-related disruptions. Consistent with existing predictions highlighting the primarily post-farm disruption of the coronavirus pandemic on food systems (Reardon *et al.*, 2020), the fact that the pandemic peaked prior to the beginning of the agricultural season in Mali, and the biological dynamics in which COVID-19 spreads via close human contact, we claim that urban areas experienced more intense pandemic-related disruptions than rural areas in Mali. We validate this claim with data on recorded COVID-19 infections, Google mobility data, and the COVID-19 phone survey. Therefore, in our core regression specification, we compare the difference in food security measures between urban and rural areas before the peak of the coronavirus pandemic to the same difference after the peak. We estimate the following linear regression:

$$y_{cht} = \alpha_t + \gamma_{ch} + \beta \cdot \mathbf{1}\{ch = Urban\} \cdot \mathbf{1}\{t = Post\} + \epsilon_{cht} \quad (1)$$

In equation (1), y_{cht} is an indicator of food security measured with the FIES within sampling cluster c, in household h, in time t. This outcome variable takes several forms throughout our analysis. First, we report the raw FIES score which is simply the sum of responses to the eight FIES questions each capturing a different component of experienced food insecurity at the household level. We standardize this variable so that this scale has a mean of zero and standard deviation of one in each survey wave. We take this approach because the baseline EHCVM food security indicator questions use a 12-month reference period and the COVID-19 phone survey use a 30-day reference period. By standardizing the outcome within each survey wave the data represent deviations from the within-wave mean and therefore mitigate complications with inconsistent reference periods. Additionally, this standardization process allows for easier interpretation of our estimated coefficients in terms of standard deviations instead of a unitless score.[12] Second, we report dichotomous indicators of different levels of food insecurity severity following the methods of Smith *et al.* (2017) and discussed above. These dichotomous variables represent "mild food insecurity," "moderate food insecurity," and "severe food insecurity" based on the raw FIES score.

On the right-hand-side of equation (1), α_t is survey wave or time fixed effect, and γ_{ch} is a household

[12] We show results without this standardization procedure in the Supplemental Appendix. The estimates are qualitatively consistent.

fixed effect. The coefficient β represents the difference-in-differences estimate on the interaction between a dichotomous variable $\{ch = Urban\}$ indicating the household resides in an urban area (or in Bamako, in alternative specifications) and a dichotomous variable $\{t = Post\}$ indicating a post-pandemic outbreak survey wave. Finally, ϵ_{cht} is the error term.

This empirical strategy relies on the claim that disruptions due to the coronavirus pandemic have been much more severe in urban areas than in rural areas in Mali. We validate this claim with observations from three different sources of information. First, according to the United Nations' Office for the Coordination of Humanitarian Affairs (OCHA) and shown in Figure 1, despite the fact that Bamako is home to roughly 12 percent of Mali's population, over 60 percent of Mali's COVID-19 infections were located in Bamako, as of the end of July 2020 (HDE, 2020). Although this statistic likely represents easier access to COVID-19 testing in Bamako relative to other parts of Mali and positive cases of COVID-19 likely do exist in rural areas, it does show that the recorded distribution of the prevalence of COVID-19 in Mali is dramatically skewed toward Bamako. Second, insights from Google's Community Mobility Reports, shown in Figure 2, suggest that individuals living in Bamako have experienced large changes in the time spent at various types of places relative to a baseline period in early 2020. Consistent with our claim, these changes in Bamako are larger than reported changes for individuals in all of Mali. Third, as documented in Figure 3 and Figure 4, according to our COVID-19 phone panel survey data individuals in urban areas are more likely to report taking health-related precautions and negative economic impacts due to the coronavirus pandemic than individuals in rural areas. As predicted by Reardon *et al.* (2020), this evidence highlights the reality that although the coronavirus pandemic increased challenges related to food security everywhere, the pandemic is much more disruptive in urban areas than in to rural areas in Mali.

The difference-in-differences identification strategy rests on the assumption of parallel counterfactual trends in latent food security between households in urban and rural areas (or, in some specifications, between households in Bamako and all else) in the absence of the coronavirus pandemic. While this identifying assumption cannot be tested directly, we argue that if bias exists in our empirical strategy, then equation (1) generates estimates of the lower bound effect of the pandemic on food security. We perform a number of robustness and sensitivity checks on our results. First, in each table reporting regression results we show two variations of our core specification: one that does not include household fixed effects and one that does include household fixed effects. The household fixed effects allow us to account for time-invariant omitted heterogeneity between households which may bias our results. Second, in the Supplemental Appendix, we show results that exclude all households in Bamako from the regression specification and therefore estimates differences between urban and rural areas outside of Bamako. Although these estimates suffer from limited statistical power, we find results that are qualitatively similar to our core results.

5 Results

In this section we report three sets of results. First, we report descriptive results which come directly from the COVID-19 phone survey, targeted at understanding the responses to and socio-economic effects of the coronavirus pandemic. While these results do not specifically quantify the effect of the coronavirus pandemic on food security, they do provide insight of how individuals in Mali perceive the effect of the pandemic in their own lives. Second, we report estimation results based on variations of the regression specification in equation (1). These results provide some of the first estimates of the effect of the coronavirus pandemic in low- and middle-income countries. As we have previously discussed, we see these results as estimates of the lower bound of the effect of the pandemic on food security. Third, we discuss and implement several robustness tests.

5.1 Descriptive Results

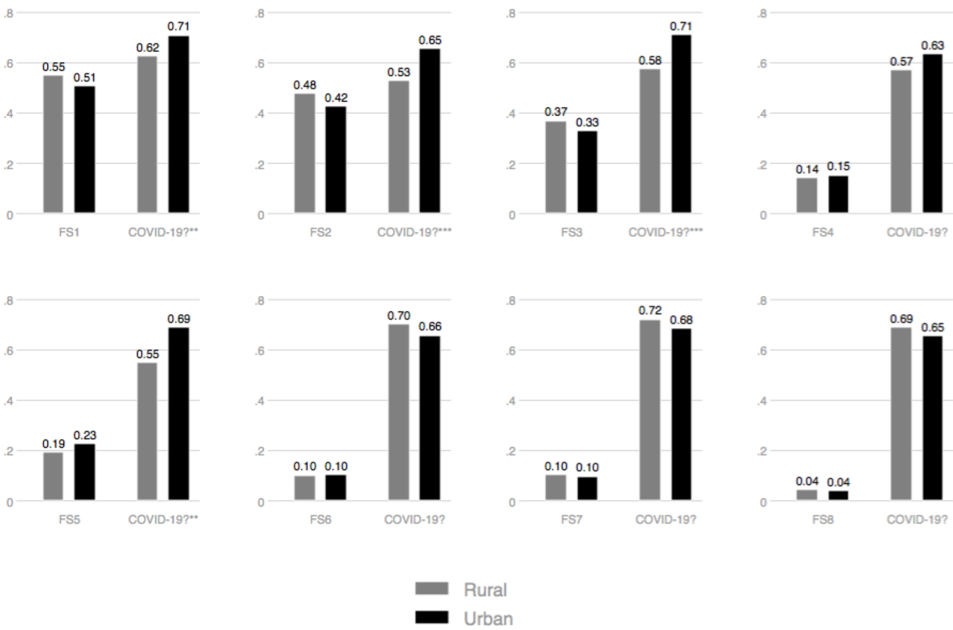
These descriptive results provide insight by directly asking respondents if indicators for food insecurity are due "specifically to the COVID-19 crisis." This allows for a self-reported causal statement, which is not necessarily equivalent to causal identification in the statistical use of the phrase. Nevertheless, these descriptive results highlight how respondents understand changes in their life in the time of the coronavirus pandemic.

Figure 5 shows descriptive results using the May-June 2020 phone survey from Mali. The results suggest that the coronavirus pandemic has dramatically reduced the food security of households in Mali.[13] Overall, 50 percent of the full sample is worried that they will not have enough to eat. Of those households, 65 percent report that this worry is specifically due to COVID-19. This finding, that a substantial share of households identify COVID-19 as an important cause of food security challenges, is largely driven by households in urban areas. Specifically, we see an 11 percentage points difference, between urban and rural areas, in those who identify COVID-19 as the source of their worry that they will not have enough to eat. Similar findings persist for most of the remaining FIES questions. Across seven of eight food security indicators, the exception being FS8 which is only experienced by less than 4 percent of households, a larger share of households living in urban areas than in rural areas report food security challenges due to COVID-19. In five out of eight food security indicators the difference between urban and rural areas in reporting of food security challenges due to COVID-19 is statistically significant at conventional levels.

These findings are striking for at least two reasons. First, specifically in the context of Mali, food security is on average more challenging in rural areas. Despite this, urban households tend to be more likely than rural households to identify COVID-19 as the most important cause of their food security challenges. In particular, 48 percent of rural households, compared to 42 percent of urban households, indicate being worried that they cannot eat nutritious foods. However, 53 percent of rural households, compared to 65 percent of urban households, indicate that this is primarily due to COVID-19— this

[13] Table A3 in the Supplemental Appendix, provides additional detail on the statistics reported in Figure 5.

Figure 5: The Coronavirus Pandemic and Food Security Challenges—Descriptive Results



Notes: These descriptive statistics come from the World Bank's COVID-19 high-frequency survey from Mali. Missing and refused responses are excluded from these statistics. Within each panel, the left-most two columns represent mean responses to each of the eight FIES questions. FS1 = "Household members have been worried that they will not have enough to eat?" FS2 = "Household members have been worried that they can not eat nutritious foods?" FS3 = "Household members had to eat always the same thing?" FS4 = "Household members had to skip a meal?" FS5 = "Household members had to eat less then they should?" FS6 = "Household members found nothing to eat at home?" FS7 = "Household members have been hungry but did not eat?" FS8 = "Household members have not eaten all day?" The right-most two columns represent mean responses to the question, "Was this due to the COVID-19 crisis?" Standard errors are clustered at the sampling cluster level. ***, **, and * in each graph's label indicate statistical significance at the 1, 5, and 10 percent critical level, respectively.

Table 1: The Coronavirus Pandemic and Food Insecurity—Raw FIES Score

	(1)	(2)	(3)	(4)	(5)	(6)
	First-Difference		Urban-Rural DID		Bamako-Else DID	
After COVID started	0.141**	0.146*	0.0859	0.0916	0.121*	0.127
	(0.0552)	(0.0787)	(0.0754)	(0.108)	(0.0629)	(0.0898)
Urban			-0.227***			
			(0.0663)			
After COVID started × Urban			0.189**	0.186		
			(0.0854)	(0.121)		
Bamako					-0.226***	
					(0.0640)	
After COVID started × Bamako					0.150*	0.144
					(0.0868)	(0.122)
Observations	3532	3532	3532	3532	3532	3532
R^2	0.015	0.605	0.020	0.606	0.018	0.605
Household FEs	No	Yes	No	Yes	No	Yes
Missing Control	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Mean	0.09	0.09	0.16	0.16	0.12	0.12

Notes: The outcome variable is the raw score of the Food Insecurity Experience Scale (FIES) standardized to have a mean of zero and standard deviation of one in each period. Standard errors clustered at the sampling cluster level *** p<0.01, ** p<0.05, * p<0.1.

difference is statistically significant at conventional levels. Second, this highlights the validity of previous predictions that the coronavirus pandemic would be more disruptive to food systems in dense urban and rural peri-urban areas (Reardon *et al.*, 2020). Additionally, as previously discussed, this finding helps support our identification strategy where we exploit sub-national variation in the intensity of the disruption of the coronavirus pandemic.

5.2 Estimation Results

We now turn to discussing results from estimating variations of equation (1). In this sub-section we discuss four sets of results: first considering the full raw FIES score and the remaining three considering increasingly severe levels of food insecurity.

Table 1 shows estimates when using the raw FIES score standardized to have a mean of zero and standard deviation of one in each survey wave. The first two columns show simple first-difference estimation results. These results highlight that, relative to a pre-pandemic baseline, households in Mali report an increase in the raw FIES score of roughly 0.14 of a standard deviation. Comparing the estimates in columns (1) and (2) shows that this trend in time is robust to the inclusion of household fixed effects. The last four columns of Table 1 report variations on our main difference-in-difference estimation specification. Columns (3) and (4) exploit differences in the coronavirus pandemic's shock to the food system between urban and rural areas. Column (3) reports the results from a simplified difference-in-difference estimation specification which includes a single dichotomous variable indicating a household resides in an urban area, rather than household fixed effects. Column (4) reports the results from our main difference-in-difference estimation with household fixed effects. Both columns show that, relative to the pre-pandemic baseline, the raw FIES score increased more in urban areas than rural areas by about 18 percent of a standard deviation; though estimating this effect with household fixed effects increases the standard error around

Table 2: COVID-19 and Mild Food Insecurity—Raw FIES Score > 0

	(1)	(2)	(3)	(4)	(5)	(6)
	First-Difference		Urban-Rural DID		Bamako-Else DID	
After COVID started	0.0457*	0.0464	0.0238	0.0239	0.0321	0.0328
	(0.0245)	(0.0346)	(0.0337)	(0.0476)	(0.0280)	(0.0396)
Urban			-0.122***			
			(0.0320)			
After COVID started × Urban			0.0757*	0.0768		
			(0.0392)	(0.0548)		
Bamako					-0.144***	
					(0.0312)	
After COVID started × Bamako					0.101**	0.0997*
					(0.0394)	(0.0550)
Observations	3532	3532	3532	3532	3532	3532
R^2	0.014	0.578	0.022	0.579	0.020	0.579
Household FEs	No	Yes	No	Yes	No	Yes
Missing Control	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Mean	0.59	0.59	0.63	0.63	0.61	0.61

Notes: The outcome variable is dichotomous indicating mild food insecurity if the raw score > 0 (Smith et al. 2017). Standard errors clustered at the sampling cluster level *** p<0.01, ** p<0.05, * p<0.1.

this estimate. Finally, in columns (5) and (6), when only considering differences between Bamako and elsewhere in Mali, the observed differential change in the raw FIES score falls slightly to about 15 percent of a standard deviation. This slightly smaller effect estimate is consistent with the idea that other urban or peri-urban areas are now included in the comparison and therefore bias the estimate toward zero.

Table 2 shows estimates using a dichotomous dependent variable indicating at least "mild food insecurity" defined as equal to one if the raw FIES score is greater than zero (Smith *et al.*, 2017). These estimates are helpful for at least two key reasons. First, they provide a more intuitive assessment of effect magnitude than estimates reported in Table 1. The outcome variable identifies if a household responds affirmatively to any of the eight FEIS questions. Second, the definition of the dichotomous outcome variable used in Table 2 aligns more closely with the FAO's definition of food security (FAO, 1996, 2009). This is because the FAO's definition views food security as existing "when all people, at all times, have physical, social, and economic access to sufficient, safe, and nutritious food that meet their dietary needs and food preferences for an active and healthy life," which we measure if an individual does not answer affirmatively to any of the FIES questions.

The first two columns of Table 2 show a simple first-difference estimation. These results highlight roughly a 4 percentage-point increase in the probability of being food insecure, relative to the pre-pandemic period. The last four columns report variations on our main difference-in-difference estimation specification. Columns (3) and (4) show that the coronavirus pandemic increased food insecurity by about 8 percentage points in urban areas relative to rural areas. Again, although the inclusion of household fixed effects increases the standard error around this estimate the estimated average effect remains stable. Finally, columns (5) and (6) focus on differences between Bamako and the rest of Mali, and show qualitatively similar results to those reported in columns (3) and (4). The results indicate that the coronavirus pandemic increased urban food insecurity by roughly 10 percentage points, results that are

Table 3: COVID-19 and Moderate Food Insecurity—Raw FIES Score > 3

	(1)	(2)	(3)	(4)	(5)	(6)
	First-Difference		Urban-Rural DID		Bamako-Else DID	
After COVID started	-0.0298	-0.0288	-0.0536*	-0.0529	-0.0388	-0.0377
	(0.0220)	(0.0314)	(0.0298)	(0.0425)	(0.0249)	(0.0356)
Urban			-0.0792***			
			(0.0253)			
After COVID started × Urban			0.0821**	0.0821*		
			(0.0339)	(0.0482)		
Bamako					-0.0823***	
					(0.0251)	
After COVID started × Bamako					0.0664*	0.0651
					(0.0360)	(0.0504)
Observations	3532	3532	3532	3532	3532	3532
R^2	0.012	0.572	0.016	0.574	0.014	0.573
Household FEs	No	Yes	No	Yes	No	Yes
Missing Control	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Mean	0.22	0.22	0.24	0.24	0.23	0.23

Notes: The outcome variable is dichotomous indicating moderate food insecurity if the raw score > 3 (Smith et al. 2017). Standard errors clustered at the sampling cluster level *** p<0.01, ** p<0.05, * p<0.1.

robust across specifications. These effect estimates show meaningful increases in mild food insecurity. Considering a baseline mean of 0.61, in columns (5) and (6), our estimates show that the coronavirus pandemic increased mild food insecurity in Bamako by 16 percent relative to the rest of Mali.

Table 3 reports results using a dichotomous dependent variable indicating "moderate food insecurity" defined as equal to one of the raw FIES score is greater than three (Smith *et al.*, 2017). Although columns (1) and (2) show no evidence of an increasing time trend of moderate food insecurity in Mali associated with the pandemic, our difference-in-difference estimates in columns (3) and (4) highlight that in urban areas moderate food insecurity increased by 8 percentage points more than in rural areas. This represents a 33 percent increase in moderate food insecurity in urban areas relative to rural areas. These results represent the strongest estimates in this paper. This is important because existing research using the FIES across a variety of contexts consider this measure of "moderate food insecurity" as the primary measure of food insecurity (Smith *et al.*, 2017). This measure, which identifies "moderate food insecurity" if a household responds affirmatively to at least three out of the eight FIES questions, more accurately represents the multidimensional reality of experienced food insecurity for households. Finally, we find qualitatively similar results on average in columns (5) and (6), when considering differences between Bamako and the rest of Mali, though these effects are less precisely estimated.

Finally, Table 4 reports the results using a dichotomous dependent variable indicating "severe food insecurity" defined as equal to one if the raw FIES score is greater than seven (Smith *et al.*, 2017). This definition therefore requires that households have indicated affirmative responses on all eight of the FIES questions and is commonly associated with individuals experiencing physiological hunger (Nord, 2014). Perhaps unsurprisingly, due to the relative infrequency of this extreme level of food insecurity, these estimates suffer from low statistical power. We estimate effects with substantial magnitudes but that remain statistically indistinguishable from a null result. Specifically, severe food insecurity increased

Table 4: COVID-19 and Severe Food Insecurity—Raw FIES Score > 7

	(1) First-Difference	(2)	(3) Urban-Rural DID	(4)	(5) Bamako-Else DID	(6)
After COVID started	-0.0116 (0.0121)	-0.0108 (0.0170)	-0.0187 (0.0166)	-0.0179 (0.0235)	-0.0125 (0.0139)	-0.0117 (0.0196)
Urban			-0.0192 (0.0139)			
After COVID started × Urban			0.0244 (0.0181)	0.0242 (0.0256)		
Bamako					-0.00707 (0.0132)	
After COVID started × Bamako					0.00679 (0.0168)	0.00699 (0.0238)
Observations	3532	3532	3532	3532	3532	3532
R^2	0.002	0.498	0.003	0.499	0.002	0.498
Household FEs	No	Yes	No	Yes	No	Yes
Missing Control	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Mean	0.03	0.03	0.04	0.04	0.03	0.03

Notes: The outcome variable is dichotomous indicating severe food insecurity if the raw score > 7 (Smith et al. 2017). Standard errors clustered at the sampling cluster level *** p<0.01, ** p<0.05, * p<0.1.

by roughly 60 percent in urban areas relative to rural areas. Therefore, the results reported in Table 4 should be interpreted with extreme caution. Severe food insecurity remains relatively uncommon in Mali, experienced by roughly three percent of the population prior to the coronavirus pandemic.

Existing predictions, based on modeling the expected changes to income, prices, and food supply, suggest that the coronavirus pandemic may increase the number of undernourished people in the world by between 10 and 16 percent in 2020 (Baqueano *et al.*, 2020; FAO *et al.*, 2020). Our estimates suggest that these aggregate global estimates may hide important heterogeneity. In the context of urban Mali the short-term effect of the coronavirus pandemic on mild food insecurity is *at least* as large as the average global effect and likely larger. Heterogeneity also exists in the level of severity of food insecurity. In urban Mali we find that the pandemic increased "moderate food insecurity" by at least 33 percent. This is an important finding for at least two reasons. First, existing research uses this "moderate food insecurity" measure as the primary measure of experienced food insecurity globally (Smith *et al.*, 2017). Second, this estimate is substantially larger than existing predictions of the effect of the pandemic globally (Baqueano *et al.*, 2020; FAO *et al.*, 2020). Taken together, this implies that future work should focus on measuring the extent of heterogeneity in the effect of the coronavirus pandemic on food security in a variety of contexts around the world. Understanding this heterogeneity is important for understanding how to best design, implement, and target policies and programs aimed at assisting those harmed most by the pandemic.

5.3 Robustness

We conduct several robustness checks to test the sensitivity of our results. First, in Table A4 in the Supplemental Appendix, we show results where the raw FIES score is not standardized to have a mean of zero and standard deviation of one in each survey wave. Although we prefer the results using the standardized dependent variable, this robustness check shows that our core findings are not driven by our standardization procedure. Specifically, the difference-in-differences estimates shown in the last four columns of Table A4 are qualitatively similar to the core results reported in Table 1.

Second, in Table A5 in the Supplemental Appendix, we show results that exclude households in Bamako from the sample. This tests if our results are strictly driven by the effect of the pandemic within Bamako. To the contrary, we find qualitatively similar results outside of Bamako, although the difference-in-difference estimates are not robust to the inclusion of household fixed effects, largely due to limited statistical power. We continue to find evidence of worsening food security outcomes, on average and at every level of severity, in urban areas relative to rural areas outside of Bamako.

The analysis in this paper is not without limitations. First, and most generally, although the coronavirus pandemic has disrupted life in every country around the world, we study only one country. The effects of the pandemic on welfare may vary substantially across countries, largely due to the specific non-pharmaceutical policy response of each country. We argue, however, that the situation in Mali may resemble that in many other parts of sub-Saharan Africa where public health measures intended to slow the spread of the virus are difficult to implement effectively, but were generally more disruptive in urban areas. The work of Amare *et al.* (2020) in Nigeria and Mahmud and Riley (2020) in Uganda provide complementary analysis highlighting the substantial effect of the pandemic on food security in sub-Saharan Africa.

Second, and specifically relating to our empirical strategy, our difference-in-difference estimates likely underestimate the effect of the coronavirus pandemic on food security in urban Mali. The lack of a truly unaffected comparable population challenges our ability to estimate an unbiased effect. Although we show that pandemic-related disruptions in Mali's urban areas likely outweigh disruptions in rural areas, the pandemic likely had non-negligible disruptions in rural areas. Nevertheless, these challenges likely bias our estimates toward zero and despite this reality, we estimate effects with substantial and meaningful magnitudes.

Third, our estimates only represent the short-term effects of the coronavirus pandemic on food security. As the spread of the virus began in Bamako, and therefore initial containment policies were most intense in the capitol city, the short-term effect of the pandemic is more directly felt by urban households. As time progresses, and the agricultural season gets underway, it is plausible, and in fact likely, that rural households will be increasingly affected by the consequences of the pandemic (Amjath-Babu *et al.*, 2020). Future research which specifically examines the medium- and long-term effects of the coronavirus pandemic, in both rural and urban areas, is absolutely essential.

Finally, we are unable to credibly identify mechanisms that explain our main findings. Research in India suggests that food prices in urban areas have increased which could lead to challenges relating to food security, especially for households that have lost a primary source of income due to pandemic-related disruptions (Narayanan and Saha, 2020). It is plausible that this mechanism persists in Mali, however, we do not have the data to examine this empirically. We do show some descriptive evidence suggesting that the pandemic has reduced the frequency of visits to the market or grocery store, but there is very little difference between households in urban and rural areas. Therefore, this type of extensive margin behavior change does not seem to explain our main results in a meaningful fashion. Future research should focus on identifying the mechanisms that explain these results as to help inform effective policy responses.

6 Conclusion

We add to the emerging research which estimates the effect of the coronavirus pandemic on food security in low- and middle-income countries (Amare *et al.*, 2020; Ceballos *et al.*, 2020; Mahmud and Riley, 2020). Using nationally representative pre-pandemic household survey data and a follow-up phone survey from Mali, our difference-in-difference estimates highlight a dramatic increase in food insecurity. These difference-in-difference estimates rely on sub-national variation in the intensity of pandemic-related disruptions between urban and rural areas. Although we aim to validate our understanding of the variation in intensity of these disruptions with data on recorded COVID-19 infections, Google mobility data, and our phone survey data, it remains likely that the pandemic also disrupted food systems in rural areas. Therefore, our results in this paper are likely an estimate of the lower bound of the effect of the pandemic on food security in Mali. Despite this limitation, we estimate effects with meaningful magnitudes that are substantially larger than existing predictions of the effect of the coronavirus pandemic on food security globally.

Existing predictions of the effect of the coronavirus pandemic on food security globally—based on expected changes to income, prices, and food supply—point to an increase in the number of undernourished people in the world of 10–16 percent in 2020 (Baqueano *et al.*, 2020; FAO *et al.*, 2020). Our estimates document important heterogeneity in this global aggregate prediction. In Mali our difference-in-difference estimates show that moderate food insecurity increased in urban areas by *at least* 8 percentage points, which is equivalent to about a 33 percent increase—more than double the predicted global aggregate percent change. These results are important for informing short-term policy responses aiming to limit the welfare loss from the coronavirus pandemic.

Our work in this paper only represents the beginning of the necessary research needed to better understand the micro-level welfare implicates of the coronavirus pandemic. Throughout this paper, we highlight many avenues for future research and encourage interdisciplinary approaches to address existing questions. These future research topics include a more detailed investigation of the mechanisms driving these relatively short-term effects and subsequent analysis of the medium-term effects which consider household-level resiliency to the dramatic health and economic shock of the coronavirus pandemic.

References

Adams-Prassl, A., Boneva, T., Golin, M. and Rauh, C. (2020). Inequality in the impact of the coronavirus shock: Evidence from real time surveys. *Working paper*.

Alon, T., Doepke, M., Olmstead-Rumsey, J. and Tertilt, M. (2020). The impact of covid-19 on gender equality. *NBER Working Paper, No. 26947*.

Amare, M., Abay, K. A., Tiberti, L. and Chamberlin, J. (2020). Impacts of covid-19 on food security: Panel data evidence from nigera. *PEP Working Paper No. 21.*

Amjath-Babu, T., Krupnik, T., Thilsted, S. and McDonald, A. (2020). Key indicators for monitoring food system disruptions caused by the covid-19 pandemic: Insights from bangladesh toward effective response. *Food Security*, **12**, 761–768.

Arndt, C., Davies, R., Gabriel, S., Harris, L., Makrelov, K., Robinson, S., Levy, S., Simbanegavi, W., van Sventer, D. and Anderson, L. (2020). Covid-19 lockdowns, income distribution, and food security, an analysis for south africa. *Global Food Security*, **26**.

Ballard, T. J., Kepple, A. W. and Cafiero, C. (2013). The food insecurity experience scale: development of a global standard for monitoring hunger worldwide. *Rome: FAO*.

Baqueano, F., Christensen, C., Ajewole, K. and Backman, J. (2020). International food security assessment, 2020–30. *GFA–31, U.S. Department of Agriculture, Economic Research Service.*

Barrero, J., Bloom, N. and Davis, S. (2020). Covid-19 is also a reallocation shock. *NBER Working Paper, No. 27137*.

Bartik, A., Bertrand, M., Cullen, Z., Glaeser, E., Luca, M. and Stanton, C. (2020). How are small businesses adjusting to covid-19? early evidence from a survey. *NBER Working Paper, No. 26989*.

Bene, C. (2020). Resilience of local food systems and links to food security: A review of some important concepts in the context of covid-19 and other shocks. *Food Security*.

Bui, T., Button, P. and Picciotti, E. (2020). Early evidence on the impact of covid-19 and the recession on older workers. *NBER Working Paper, No. 27448*.

Carletto, C., Zezza, A. and Banerjee, R. (2013). Towards better measurement of household food security: Harmonizing indicators and the role of household surveys. *Global Food Security*, **2** (1), 30–40.

Ceballos, F., Kannan, S. and Kramer, B. (2020). Impacts of a national lockdown on smallholder farmers' income and food security: Empirical evidence from two states in india. *World Development*, **136**.

Chetty, R., Friedman, J., Stepner, M. and the Opportunity Insights Team (2020). How did covid-19 and stabilization policies affect spending and employment? a new real-time economic tracker based on private sector data. *Working Paper.*

Coates, J. (2013). Build it back better: Deconstructing food security for improved measurement and action. *Global Food Security*, pp. 188–194.

Coibion, O., Gorodnichenko, Y. and Webber, W. (2020). Labor market during the covid-19 crisis: A preliminary view. *NBER Working Paper, No. 27017.*

Cowan, B. (2020). Short-run effects of covid-19 on u.s. worker transitions. *NBER Working Paper, No. 27315.*

Devereux, S., Bene, C. and Hoddinott, J. (2020). Conceptualizing covid-19's impacts on household food security. *Food Security*, **12**, 769–772.

Djiofack, C., Dudu, H. and Zeufack, A. (2020). Assessing covid-19's economic impact in sub-saharan africa: Insights from a cge model. *COVID-19 in Developing Countries*, (ed. Djankov, S. and Panizza, U.).

FAO (1996). Declaration on world food security and world food summit plan of action. world food summit. *World Food Summit, Rome: FAO.*

— (2009). Declaration of the world summit on food security. *World Summit on Food Security, Rome: FAO.*

—, IFAD, UNICEF, WFP and WHO (2020). The state of food security and nutrition in the world: Transforming food systems for affordable healthy diets. *Rome, FAO.*

Gerard, F., Imbert, C. and Orkin, K. (2020). Social protection response to the covid-19 crisis: Optionis for developing countries. *Policy Brief: Economics for Inclusive Prosperity.*

HDE (2020). Mali: Coronavirus (covid-19) subnational cases. *Humanitarian Data Exchange, United Nations Office for the Coordination of Humanitarian Affairs.*

Hoy, C. and Sumner, A. (2020). Growth with adjictives: Global poverty and inequality after the pandemic. *Center for Global Development Working Paper.*

Jain, R., Budlender, J., Zizzamia, R. and Bassier, I. (2020). The labor market and poverty impacts of covid-19 in south africa. *CSAE Working Paper.*

Josephson, A., Michler, J. and Killic, T. (2020). Microeconomic impact of covid-19 in africa. *Working Paper.*

Kerr, A. and Thornton, A. (2020). Essential workers, working from home and job loss vulnerability in south africa. *Working Paper.*

Mahmud, M. and Riley, E. (2020). Household response to an extreme shock: Evidence on the immediate impact of the covid-19 lockdown on economic outcomes and well-being in rural uganda. *Working Paper.*

Mishra, K. and Rampal, J. (2020). The covid-19 pandemic and food insecurity: A viewpoint on india. *World Development.*

Narayanan, S. and Saha, S. (2020). Urban food markets and the lockdown in india. *Working Paper.*

Nord, M. (2014). Introduction to item response theory applied to food security measurement: Basic concepts, parameters, and statistics. *Rome: FAO.*

Rasch, G. (1960). Probabilistic models for some intelligence and achievement tests. *Copenhagen: Danish institute for Educational Research.*

Ravallion, M. (2020). Sdg1: The last three percent. *Center for Global Development Working Paper.*

Ravindran, S. and Shah, M. (2020). Unintended consequences of lockdowns: Covid-19 and the shadow pandemic. *NBER Working Paper, No. 27562.*

Reardon, T., Bellemare, M. and Zilberman, D. (2020). How covid-19 may disrupt food supply chains in developing countries. *IFPRI Blog Post.*

Smith, M. D., Rabbitt, M. P. and Coleman-Jensen, A. (2017). Who are the world's food insecure? new evidence from the food and agriculture organization's food insecurity experience scale. *World Development*, **93**, 402–412.

UNICEF (2020). Mali: Covid-19 situation report. *UNICEF, Situation in Numbers.*

Valensisi, G. (2020). Covid-19 and global poverty: A preliminary assessment. *COVID-19 in Developing Countries*, (ed. Djankov, S. and Panizza, U.).

WHO (2020). Coronavirus disease (covid-19) situation report—102. *World Health Organization.*

Supplemental Appendix

This Supplemental Appendix provides additional information supporting the results in the main manuscript.

- Table A1 reports descriptive results on coronavirus awareness, beliefs, and behavior in tabular form. These results report the underlying information used when generating Figure 3 in the main manuscript.
- Table A2 reports descriptive results on self-reported coronavirus pandemic impacts. These results report the underlying information used when generating Figure 4 in the main manuscript.
- Table A3 reports descriptive results on the coronavirus pandemic and food security challenges in tabular form. These results report the underlying information used when generating Figure 5 in the main manuscript.
- Table A4 shows a robustness test on the results reported in Table 1 in the main manuscript. Instead of standardizing the raw FIES score to have a mean of zero and standard deviation of one in each survey wave, the dependent variable in Table A4 is left as the raw non-standardized FIES score. These results show that the estimates in Table 1 of the main manuscript are not driven by this standardization procedure.
- A5 shows a robustness test on the results reported in Tables 2 through 4 in the main manuscript. Specifically, households in Bamako are intentionally omitted from the results reported in Table A5. These results show that the results reported in Tables 2 through 4 in the main manuscript are not primarily driven by the effect of the coronavirus pandemic in Bamako, but qualitatively persist when excluding Bamako from the estimation specification.

Table A1: Coronavirus Pandemic Awareness, Beliefs, and Behavior

Variable	(1) Urban N/[Clusters]	(1) Urban Mean/SE	(2) Rural N/[Clusters]	(2) Rural Mean/SE	(3) Total N/[Clusters]	(3) Total Mean/SE	T-test Difference (1)-(2)
Have you heard of coronavirus?	1219 [214]	0.997 (0.001)	547 [228]	0.991 (0.004)	1766 [442]	0.993 (0.003)	0.006
Have you received information about social distancing and self-isolation measure	1214 [214]	0.963 (0.007)	542 [227]	0.951 (0.010)	1756 [441]	0.954 (0.007)	0.012
Are you satisfied with the government's response to the coronavirus?	1170 [214]	0.811 (0.014)	515 [227]	0.870 (0.016)	1685 [441]	0.853 (0.012)	-0.059***
Last week, did you wash your hands more often than usual?	1218 [214]	0.934 (0.008)	547 [228]	0.867 (0.016)	1765 [442]	0.887 (0.012)	0.067***
Last week, did you avoid shaking hands or other greetings with physical contact?	1218 [214]	0.926 (0.008)	547 [228]	0.814 (0.019)	1765 [442]	0.846 (0.014)	0.111***
Last week, did you avoid gatherings of more than 10 people?	1219 [214]	0.861 (0.014)	547 [228]	0.811 (0.020)	1766 [442]	0.825 (0.015)	0.050**
Last week, did you cancel any travel plans?	1218 [214]	0.706 (0.013)	546 [228]	0.691 (0.022)	1764 [442]	0.695 (0.016)	0.015
Last week, did you stockpile more food than usual?	1219 [214]	0.290 (0.016)	547 [228]	0.285 (0.022)	1766 [442]	0.287 (0.016)	0.004
Last week, did you reduce the number of times you went to the market or grocerty	1219 [214]	0.676 (0.016)	547 [228]	0.672 (0.024)	1766 [442]	0.673 (0.017)	0.004
Last week, did you reduce the number of times you went to a place of worship?	1219 [214]	0.641 (0.015)	547 [228]	0.607 (0.025)	1766 [442]	0.617 (0.018)	0.033

Notes: These descriptive statistics come from the World Banks's COVID-19 high frequency survey from Mali. Missing and refused responses are excluded from these statistics. Standard errors clustered at the sampling cluster level. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent critical level.

Table A2: Self-Reported Coronavirus Pandemic Impacts

	(1) Urban		(2) Rural		(3) Total		T-test Difference
Variable	N/[Clusters]	Mean/SE	N/[Clusters]	Mean/SE	N/[Clusters]	Mean/SE	(1)-(2)
My household is at risk of losing income due to the pandemic.	1036	0.473	486	0.433	1522	0.444	0.040
	[214]	(0.018)	[223]	(0.027)	[437]	(0.020)	
A household member has lost a job due to the pandemic.	1219	0.286	547	0.270	1766	0.274	0.017
	[214]	(0.015)	[228]	(0.021)	[442]	(0.015)	
My household has lost income due to the pandemic.	1219	0.536	547	0.529	1766	0.531	0.007
	[214]	(0.016)	[228]	(0.025)	[442]	(0.018)	
My household struggles to pay rent due to the pandemic.	1219	0.311	547	0.108	1766	0.167	0.203***
	[214]	(0.017)	[228]	(0.021)	[442]	(0.016)	
My household struggles to buy food due to the pandemic.	1219	0.515	547	0.462	1766	0.478	0.053
	[214]	(0.022)	[228]	(0.027)	[442]	(0.020)	
My household stuggles to access water/electricity due to the pandemic.	1219	0.490	547	0.207	1766	0.289	0.283***
	[214]	(0.019)	[228]	(0.030)	[442]	(0.022)	
My household reduced saving due to the pandemic.	1219	0.734	547	0.678	1766	0.694	0.056**
	[214]	(0.015)	[228]	(0.024)	[442]	(0.017)	
My household reduced investment due to the pandemic.	1219	0.681	547	0.624	1766	0.641	0.057*
	[214]	(0.017)	[228]	(0.024)	[442]	(0.018)	

Notes: These descriptive statistics come from the World Banks's COVID-19 high frequency survey from Mali. Missing and refused responses are excluded from these statistics. Standard errors clustered at the sampling cluster level. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent critical level.

Table A3: The Coronavirus Pandemic and Food Security Challenges—Descriptive Results

Variable	(1) Urban N/[Clusters]	(1) Urban Mean/SE	(2) Rural N/[Clusters]	(2) Rural Mean/SE	(3) Total N/[Clusters]	(3) Total Mean/SE	T-test Difference (1)-(2)
(FS1) ... have been woried that you will not have enough to eat?	1217	0.507	544	0.550	1761	0.537	-0.043
	[214]	(0.018)	[228]	(0.022)	[442]	(0.016)	
...Was this specifically due to COVID-19?	601	0.707	287	0.623	888	0.646	0.084**
	[190]	(0.020)	[179]	(0.035)	[369]	(0.026)	
(FS2) ... have been woried that you could not eat nutritious foods?	1215	0.424	541	0.476	1756	0.461	-0.052
	[214]	(0.019)	[228]	(0.026)	[442]	(0.019)	
...Was this specifically due to COVID-19?	494	0.653	260	0.528	754	0.562	0.125***
	[187]	(0.024)	[165]	(0.036)	[352]	(0.027)	
(FS3) ... had to eat always the same thing?	1217	0.328	546	0.367	1763	0.356	-0.039
	[214]	(0.019)	[228]	(0.026)	[442]	(0.019)	
...Was this specifically due to COVID-19?	381	0.711	191	0.575	572	0.611	0.136***
	[179]	(0.023)	[135]	(0.042)	[314]	(0.031)	
(FS4) ... had to skip a meal?	1216	0.151	545	0.139	1761	0.143	0.012
	[214]	(0.015)	[228]	(0.019)	[442]	(0.014)	
...Was this specifically due to COVID-19?	171	0.632	69	0.569	240	0.588	0.063
	[112]	(0.039)	[60]	(0.063)	[172]	(0.045)	
(FS5) ... had to eat less than they should?	1215	0.227	545	0.190	1760	0.200	0.037
	[214]	(0.016)	[228]	(0.018)	[442]	(0.014)	
...Was this specifically due to COVID-19?	257	0.688	103	0.547	360	0.594	0.141**
	[145]	(0.030)	[88]	(0.053)	[233]	(0.037)	
(FS6) ... found nothing to eat at home?	1217	0.103	543	0.100	1760	0.101	0.003
	[214]	(0.011)	[228]	(0.017)	[442]	(0.012)	
...Was this specifically due to COVID-19?	124	0.656	48	0.699	172	0.686	-0.044
	[91]	(0.046)	[39]	(0.078)	[130]	(0.056)	
(FS7) ... been hungy but did not eat?	1215	0.096	545	0.102	1760	0.100	-0.006
	[214]	(0.011)	[228]	(0.017)	[442]	(0.012)	
...Was this specifically due to COVID-19?	115	0.683	52	0.720	167	0.710	-0.037
	[85]	(0.042)	[44]	(0.062)	[129]	(0.046)	
(FS8) ... not eaten all day?	1217	0.040	542	0.042	1759	0.041	-0.002
	[214]	(0.007)	[228]	(0.011)	[442]	(0.008)	
...Was this specifically due to COVID-19?	46	0.653	20	0.688	66	0.678	-0.035
	[41]	(0.084)	[19]	(0.120)	[60]	(0.088)	

Notes: These descriptive statistics come from the World Banks's COVID-19 high frequency survey from Mali. Missing and refused responses are excluded from these statistics. Standard errors clustered at the sampling cluster level. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent critical level.

Table A4: Robustness—Raw FIES Score (DV Not Standardized)

	(1)	(2)	(3)	(4)	(5)	(6)
	First-Difference		Urban-Rural DID		Bamako-Else DID	
After COVID started	-0.0209	-0.0106	-0.141	-0.131	-0.0662	-0.0549
	(0.115)	(0.163)	(0.156)	(0.224)	(0.130)	(0.186)
Urban			-0.489***			
			(0.143)			
After COVID started × Urban			0.414**	0.410		
			(0.176)	(0.250)		
Bamako					-0.487***	
					(0.138)	
After COVID started × Bamako					0.336*	0.324
					(0.179)	(0.251)
Observations	3532	3532	3532	3532	3532	3532
R^2	0.010	0.602	0.015	0.604	0.013	0.603
Household FEs	No	Yes	No	Yes	No	Yes
Missing Control	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Mean	1.91	1.91	2.05	2.05	1.98	1.98

Table A5: Robustness—Excluding Bamako

	First-Difference		Urban-Rural DID	
Panel A: Standardized Raw FIES Score				
After COVID started	0.120*	0.126	0.0856	0.0912
	(0.0629)	(0.0902)	(0.0755)	(0.108)
Urban			-0.194**	
			(0.0779)	
After COVID started × Urban			0.190**	0.192
			(0.0924)	(0.132)
Baseline Mean	0.12	0.12	0.16	0.16
Panel B: Mild Food Insecurity (Raw Score > 0				
After COVID started	0.0315	0.0317	0.0235	0.0230
	(0.0279)	(0.0396)	(0.0336)	(0.0476)
Urban			-0.0870**	
			(0.0376)	
After COVID started × Urban			0.0448	0.0482
			(0.0429)	(0.0601)
Baseline Mean	0.61	0.61	0.63	0.63
Panel C: Moderate Food Insecurity (Raw Score > 3)				
After COVID started	-0.0387	-0.0377	-0.0534*	-0.0528
	(0.0249)	(0.0357)	(0.0297)	(0.0426)
Urban			-0.0655**	
			(0.0294)	
After COVID started × Urban			0.0819**	0.0832
			(0.0364)	(0.0520)
Baseline Mean	0.23	0.23	0.24	0.24
Panel D: Severe Food Insecurity (Raw Score > 7)				
After COVID started	-0.0125	-0.0116	-0.0187	-0.0178
	(0.0139)	(0.0196)	(0.0166)	(0.0235)
Urban			-0.0258*	
			(0.0142)	
After COVID started × Urban			0.0345*	0.0338
			(0.0196)	(0.0276)
Household FEs	No	Yes	No	Yes
Missing Control	Yes	Yes	Yes	Yes
Baseline Mean	0.03	0.03	0.04	0.04