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Coping with Climate Shocks: Food Security in a Spatial Framework

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Food Security in a Spatial Framework*

Prepared by Diogo Baptista, John Spray, and D. Filiz Unsal

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ABSTRACT: We develop a quantitative spatial general equilibrium model with heterogeneous house-holds and multiple locations to study households' vulnerability to food insecurity from cli-mate shocks. In the model, households endogenously respond to negative climate shocks by drawing-down assets, importing food and temporarily migrating to earn additional income to ensure sufficient calories. Because these coping strategies are most effective when trade and migration costs are low, remote households are more vulnerable to climate shocks. Food insecure households are also more vulnerable, as their proximity to a subsistence requirement causes them to hold a smaller capital buffer and more aggressively dissave in response to shocks, at the expense of future consumption. We calibrate the model to 51 districts in Nepal and estimate the impact of historical climate shocks on food consumption and welfare. We estimate that, on an annual basis, floods, landslides, droughts and storms combined generated GDP losses of 2.3 percent, welfare losses of 3.3 percent for the average household and increased the rate of undernourishment by 2.8 percent. Undernourished households experience roughly 50 percent larger welfare losses and those in remote locations suffer welfare losses that are roughly two times larger than in less remote locations (5.9 vs 2.9 percent). In counterfactual simulations, we show the role of better access to migration and trade in building resilience to climate shocks.

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1 Introduction

In 2021, 2.3 billion people suffered from moderate or severe food insecurity, a figure that has been steadily growing for the last decade (FAO, 2022). Insufficient food can lower individual productivity (Behrman et al., 1997; Cole and Neumayer, 2005), reduce the rate of human capital accumulation (Asfaw, 2016; Chakraborty and Jayaraman, 2019), and give rise to poverty traps through insufficient physical capital accumulation (Barrett and Carter, 2013; Kraay and McKenzie, 2014). A core determinant of this worsening trend is the increasing influence of climate change. Along with the rise in global temperatures, climate change is thought to increase the frequency and severity of extreme weather events which can cause large economic damages by lowering agricultural yields, destroying crops and damaging infrastructure.[1] While these shocks can have macroeconomic consequences, resilience to shocks is a function of individuals' climate and economic vulnerability, as well as economic integration. What is the impact of climate shocks on food security? Which types of households are most vulnerable? What factors build resilience, and what are the macroeconomic consequences of the coping strategies they adopt?

To answer these questions, we conduct three exercises. First, we document, in a climate-vulnerable developing country, that climate shocks are associated with significantly lower yields, farm income, and food security and that households responses include increased migration and reduced investment. Motivated by this empirical evidence, we design a quantitative spatial general equilibrium model which incorporates multiple locations and heterogeneous households to show the macroeconomic, welfare, and distributional impacts of climate shocks. The model assumptions capture key features of the economies of developing countries including subsistence requirements, income diversification through a combination of farm and off-farm income, and temporary migration. We calibrate the model to 51 districts in Nepal, which vary substantially in geographic connectedness, productivity, and food security. The model is used to quantify the local and macroeconomic impacts of climate shocks using historical district-level data on climate damages over a 12 year period. Furthermore, we study the role of economic integration in resilience to shocks through counterfactual simulations.

There are three main takeaways from this analysis. First, historical climate shocks have caused persistent and significant decreases in output, welfare and food security. Second, poverty and food insecurity exacerbate the impacts of climate shocks leading to more persistent and damaging aggregate impacts. Third, economic integration is an important source of resilience to climate shocks and improved transport infrastructure can substantially lower future climate damages.

We begin by providing empirical evidence on household and market-level responses to climate shocks in a developing country.[2] First, we show that climate shocks in Nepal are geographically dispersed and depend on geographic features of the district. Second, we show that at the household level, climate shocks correlate with significantly lower yields, lower farm income and increased food insecurity. The incidence of climate shocks is associated with the use of three key coping strategies: substitution away from non-food expenditure and towards higher food expenditure, increased migration, and lower savings and capital. The impacts are magnified among food insecure households, who disproportionately reduce their savings. Finally, we show that, at the market-level, climate shocks are associated with a significant increase in food prices which is approximately twice as large for remote regions. Collectively, these results indicate that the appropriate framework to study the aggregate impact of climate shocks is a model which incorporates heterogeneity across regions and households.[3]

Motivated by these empirical findings, we develop a quantitative spatial general equilibrium model with multiple locations and heterogeneous households. Households adopt endogenous response mechanisms to cope with the effects of shocks that have consequences for local markets

[1]See, for instance, Dell et al. (2009, 2012, 2014); Kahn et al. (2021); Nath (2022).

[2]We define a climate shock as the incidence of flood, landslide, drought, or storm which is recorded damages in the district by the Government of Nepal.

[3]By contrast, a framework which includes a representative agent would miss significant and important interlinkages across regions. Likewise, an empirical approach which was not able to capture general equilibrium forces may introduce bias and miss the interactions between regions.

as well as external regions through trade and migration linkages. Because of this, idiosyncratic climate shocks can have large and far-reaching aggregate implications. In the model, households endogenously limit reductions in food consumption when hit by a shock by utilizing four response channels: by shifting a larger share of their budget towards food consumption; selling off assets to finance current consumption at the expense of future consumption, diversifying income through labor migration, and importing additional food from other regions. The extent to which households utilize each channel depends on two sources of heterogeneity: household wealth and the size of spatial frictions (i.e. the costs of migrating and trading goods). Households living in geographically connected locations can import more food and use remittances from migrant household members in response to negative shocks, in contrast to those in more remote locations for whom these options are more costly. As a result, the latter will tend to endure larger increases in food prices and resort more to drawing down assets to attenuate the effects of shocks, with consequences for their future production.[4] Conditional on location, poorer households are more vulnerable to shocks since they are closer to subsistence. The latter implies they will hold a smaller capital stock buffer relative to their income, making them more vulnerable to shocks. Moreover, since their utility is more sensitive to reductions in consumption, they will dissave disproportionately more to avoid it.

Nepal is an ideal setting for this study given the pervasiveness of food insecurity among rural households, the importance of remittances in gross national income and as a social safety net, and the complex and diverse geography of the country as reflected in the spatial variation in agricultural suitability and number of people living in remote, difficult-to-access, mountainous regions (Barker et al., 2020; De Stefani et al., 2022). We calibrate the model for 51 districts[5] (accounting for roughly 78 percent of total Nepal population) using a variety of data sources including household panel surveys, censuses, and market price data. Much of the data used to calibrate our baseline economy were obtained from the Household Risk and Vulnerability Survey, a three-year longitudinal household survey administered by the World Bank covering 6,000 households and 400 communities in non-metropolitan areas of Nepal. The survey contains data on a wide range of household-level variables such as detailed food and non-food expenses, sources of farm and off-farm income, migration, assets and exposure to shocks, as well as community-level data on the market prices of several key consumption items. We use these data to estimate key exogenous parameters in the model such as local sectoral productivities and the size of trade and migration costs.

We measure damages from climate shocks using the Building Information Platform Against Disaster (BIPAD) database, containing a spatially-disaggregated historical record of natural disasters events in Nepal from 2011 to 2022 at the municipality-level which include earthquakes, floods, landslides, droughts, and storms. The dataset records the time and location of events as well as several measures of damages such as the number of fatalities, people affected, and estimated economic damages. Two features of this dataset make it particularly valuable for this paper. First, the spatial disaggregation allows the observation of the historical susceptibility of different districts to climate shocks. Second, the record of the date and duration of the shock allows the estimation of impulse response functions from the shock to local market prices. While this type of data is sometimes available at a national-level and annual frequency,[6] it is rare to have access to a detailed census of sub-national climate shocks, their scale, and the exact time and date.

We develop a novel methodology to convert coarse data on climate damages into productivity shocks by inferring the impact of climate shocks from movements in the local price of key food items. The latter is obtained from the World Food Programme (WFP) Global Food Prices Database which records monthly prices of key food items (rice and wheat) in 2001-2021 for 42 Nepalese markets spread across the country. The estimation procedure consists of three steps: first, we use the market price and disaster data to estimate an impulse response function of

[4]It is additional plausible that rural locations are also more prone to shocks which is another channel via which rural households can be more vulnerable. This is included in our calibration which includes recorded incidence of shocks at the district level.

[5]There is a total of 77 districts in Nepal, but data was only available for 51. We merge the districts of Kathmandu, Lalitpur and Bhaktapur into a single location, Kathmandu Valley, which is highly integrated.

[6]See for instance Kabundi et al. (2022)

local food prices to climate shocks occurrences, which provides us with estimates of the average price impact of a climate shock. Second, we use reported economic damages to inform us on the *relative* size of damages across climate shocks events reported in the BIPAD sample. The size of damages reported in BIPAD is likely an underestimation of the true magnitude of economic damages and so we divide the reported damages variable by its sample mean to obtain a measure of normalized damages. This is then multiplied by the average price impact from step 1 to obtain the estimated price impact of each climate shock. Finally, we convert the estimate changes in food prices into productivity shocks by estimating the elasticity between the two through model simulations of local idiosyncratic shocks in each district. This estimation procedure aims at mitigating issues of missing data and misestimation found in several disaster databases that measure economic damages from climate shocks.[7] Instead of relying on estimates of reported damages - which are missing for many observations and are likely under-reporting the full extent of economic damages - we measure losses through their effect on food production, which is manifested in price changes.

Our estimates show that climate shocks that occurred between 2011 and 2020 in Nepal generated annual welfare losses of 3.1 percent to the average rural household and raised the rate of undernourishment (defined as the share of individuals who consume less than 2,200 daily calories) by 2.8 percent above what it would have been in the absence of any climate shocks. In aggregate, rural GDP in Nepal is estimated to be 2.3 percent lower due to climate shocks. We find that the average annual aggregate impact of climate shocks over the sample period is relatively stable, but that there is substantial heterogeneity across districts. For instance, in 2019 the impact of climate shocks led the 95th percentile district to see almost 18 percent lower agricultural yields corresponding to a roughly 13 percent loss in welfare and 9 percent increase in undernourishment.

We highlight the importance of heterogeneity in geographic and household-level characteristics for household resilience to shocks. We show that geographic location and spatial frictions are key determinants of the impact of climate shocks with households in the top 30 percent most remote locations suffering average welfare losses of 5.9 percent and an increase of 4 percent in the rate of undernourishment. For undernourished households, the effects of shocks are deeper and longer-lasting, costing them 4.3 percent of annual welfare.

We show that three factors can mitigate the impact of climate shocks - higher agricultural productivity, access to migration and access to markets. This is shown to be more effective for undernourished households who are closer to their subsistence food consumption level and so benefit particularly from alternatives to reducing consumption or drawing down assets.

Finally, we show that policy which lowers trade and migration costs can substantially increase welfare, lower undernourishment, and build resilience to shocks, however, not all households will necessarily benefit. Under either 10 percent lower trade costs or 10 percent lower migration costs the welfare impact of shocks is reduced on average from 3.3 percent to approximately 2.7 percent (a reduction by a factor of 0.18).[8] Rates of undernourishment are reduced by a factor of almost a third falling from a 2.8 percent to a roughly 2 percent rise at the hands of climate shocks. While the aggregate effects are strongly positive, 18 percent of districts see an increase in undernourishment at the hands of lower trade costs while 16 percent see an increase at the hands of lower migration costs. This suggests these policies have important distributional effects even within districts, with poorer households potentially harmed by improvements in infrastructure. This may be partially induced by cross-district spillovers leading to both positive and negative effects on household vulnerability to external shocks. For instance, a negative climate shock in a district can lead to lower wages and higher food prices in neighboring districts when markets are more integrated.

Our paper is related to three strands of the literature. First, our paper is related to an extensive empirical literature in development economics on the coping mechanisms employed by

[7]See Tamrakar and Bajracharya (2020) for an overview of the issues associated with the estimation of economic damages and losses in BIPAD.

[8]Lowering trade and migration costs are key priorities for the Nepal authorities. Several major highways are under construction as part of the Nepal National Pride Projects while lowering migration costs have been targeted through migrant support centers in migrant destinations and provision of information to migrants (Ministry of Labour, Employment and Social Security, 2022; National Planning Commission, 2023)

households in response to adverse income shocks including internal migration and remittances (e.g. McKenzie and Yang (2014); McKenzie et al. (2014); Gröger and Zylberberg (2016)), selling off assets (e.g. Carter and Barrett (2007); Berloffa and Modena (2013)), and off-farm labor (e.g. Mathenge and Tschirley (2015)).[9] In contrast to much of the existing literature, we embed household decision-making within a general equilibrium framework. This allows us evaluating the aggregate effects of local shocks while accounting for spillovers across markets and space through price adjustments arising from shocks and households' endogenous responses. Moreover, using a rich model allows us to generate counterfactuals and structurally decompose the role of the various shock-coping mechanisms. We also contribute to this literature by shedding light on the quantitative role of spatial frictions for households' food security outcomes and coping mechanisms employed.

Secondly, our paper is related to a burgeoning quantitative spatial literature employing quantitative models with realistic geography with a focus on the agricultural sector. Previous literature has studied the effect of climate change on crop specialization patterns (Costinot et al., 2016), sectoral allocation (Nath, 2022) migration (Desmet and Rossi-Hansberg, 2015; Conte, 2022) and infrastructure (Balboni, 2019), the effects of trade on income diversification (Caselli et al., 2020) and farmers' crop portfolio choices (Allen and Atkin, 2022), the impact of railroad network expansions on the agricultural sector (Donaldson and Hornbeck, 2016), the role of trade costs and public investment in structural transformation (Adam et al., 2018; Gollin et al., 2014), and the general equilibrium effects of agricultural policy interventions (Bergquist et al., 2019; Asher et al., 2023). Similarly to this literature, we place economic agents in an environment with heterogenous geography in which regions can trade and households can move for work subject to spatial frictions. In contrast to much of this literature, which studies the long-run effects of changes in key model parameters (e.g. spatial frictions, policy, technology) we study the impact of temporary productivity shocks and how households respond to them through a variety of response mechanisms that are particularly relevant for low-income countries. Our approach is particularly well suited for the study of the spatial implications of climate shocks, which to the best of our knowledge, has not been studied in a similar framework.

Finally, our paper relates to the literature on food security. Previous research has analyzed the impact of food and nutrition on household income (e.g. Behrman et al. (1997)), economic development (e.g. Strauss and Thomas (1998), total factor productivity (e.g. Cole and Neumayer (2005), learning outcomes (e.g. Chakraborty and Jayaraman (2019)) and intergenerational effects (e.g. Asfaw (2016)). A different set of papers has developed statistical forecasting models with the aim of predicting future food crises and supporting early interventions (e.g. Seaman and Holt (1980); Mellor (1986); Okori and Obua (2011); Andree et al. (2020)).[10] Our paper focuses on quantifying the effect of climate shocks on food security outcomes in a spatially disaggregated economy where shocks, although localized in nature, can spill over across space and markets.

The remainder of our paper is organized as follows: Section 2 presents a number of empirical relationships to inform the model; Section 3 lays out the model; Section 4 describes the calibration procedure; Section 5 shows the results from the quantitative exercises; Section 6 concludes.

2 Data and Empirical Relationships

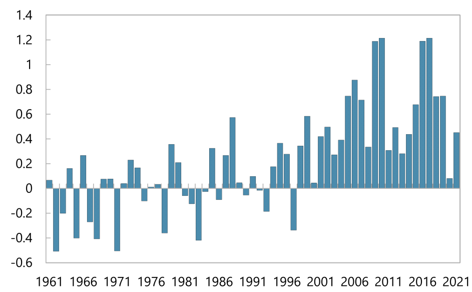
In this section we outline the primary data sources used in this paper, discuss the nature of climate shocks and food security in Nepal, and then present four empirical relationships which support our modelling approach.

[9] There is also an extensive literature relating agricultural outcomes and education in developing countries (Jacoby and Skoufias, 1997; Jensen, 2000; Kinda, 2010). Although this isn't directly a mechanism in our framework, it is closely related and especially if one is willing to interpret education as an asset which augments productivity.

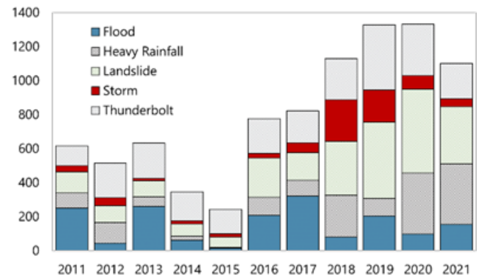
[10] A large and related literature studies the role of agriculture in development. See, for instance, Evenson and Gollin (2003); Gollin et al. (2014, 2007)

Figure 1: Weather Variability in Nepal

(a) Annual Temperature Deviation from baseline



(b) Number of Climate Related Incidents



Notes: BIPAD Government of Nepal

Notes:
Panel (A): FAO and IMF Climate Dashboard. Change in centigrade from a baseline of 1951-1980.
Panel (B): BIPAD Government of Nepal

2.1 Data

We compile two datasets at the household and district level in Nepal. Variable descriptions and summary statistics are provided in Tables 6 and 7.

To identify response mechanisms to climate shocks, we use household data from the Nepal Household Risk and Vulnerability Survey, a three-year longitudinal household survey administered by the World Bank covering 6,000 households and 400 communities in non-metropolitan areas of Nepal. The sample frame was all households in non-metropolitan areas per the 2010 Census definition, excluding households in the Kathmandu valley (Kathmandu, Lalitpur and Bhaktapur districts). To increase the concentration of sampled households, 50 of the 75 districts in Nepal were selected with probability proportional to the number of households. The survey contains data on a wide range of household-level variables such as detailed food and non-food expenses, sources of farm and off-farm income, migration, assets and exposure to shocks, as well as community-level data on the market prices of several key consumption items. We use the survey estimated measure of food insecurity which is compiled from a food insecurity index score.[11] The data is collected over three waves during 2016-2018 meaning the unit of observation is household-year.

To identify aggregate impacts from climate shocks we compile monthly district level market prices from the World Food Programme's (WFP) market price database which records the monthly price of key food items across 41 Nepalese districts in 2001-2021. This is combined with data on climate shocks from the Building Information Platform Against Disaster (BIPAD) database providing a historical record of natural disasters events in Nepal from 2011 to 2022 that include earthquakes, floods, landslides, droughts, and storms. The data records the time and location of events at the municipal level, as well as several measures of damages such as the number of fatalities, people affected, and estimated cost. We include all climate shocks (landslides, storms, cold, heavy rainfall, and floods) which have recorded a non-missing and positive value for estimated economic damages. This narrows down the sample to a total annual average of 125 shocks per year with a district-level probability of experiencing at least one shock of 34 percent in any given year.

We generate a district level variable for remoteness using the population-weighted average distance to all districts.[12] We define a dummy denoted *remote* if the district is in the top 30 percent of remoteness score.

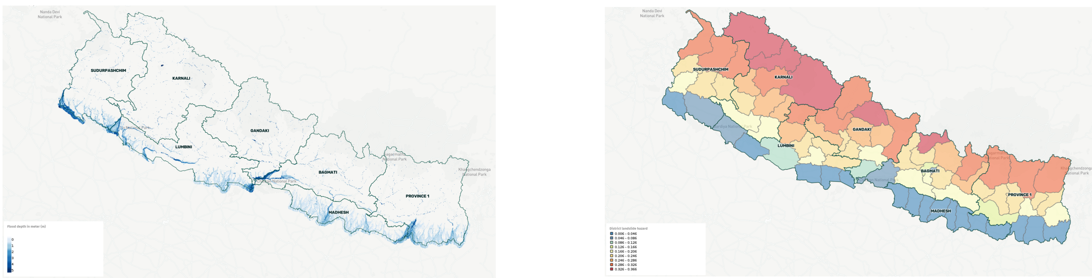
2.2 Context

Nepal is highly vulnerable to climate shocks and climate change. The average temperature in Nepal in the last decade is over 0.6 degrees Celsius higher than the baseline of 1950-1980

[11]Index generated by the World Bank based on methodology in Coates et al. (2007). The index assigns a value 0, 1, 2, or 3 points to each response in four categories, in order to arrive at a score out of 27. This is referred to as the Household Food Insecurity Access Scale.
[12]For more detail on variable construction see Section 4

Figure 2: Distribution of weather risk

(a) Flood Hazard (b) Landslide Risk



Notes:
Panel (A): BIPAD Government of Nepal and METEOR project, map exported on May 9, 2023. Data show the probability of experiencing a given water depth in meters within a single year over a 1000 year return period. Darker blue indicates larger risk. The data was produced by BIPAD using the Fathom global flood hazard-modelling framework (a development of Sampson et al. (2015) and Smith et al. (2015)).
Panel (B): BIPAD Government of Nepal. Map exported on May 9, 2023. Map shows landslide risk by ward. Dark red indicates larger hazard, blue indicates small risk.

(Figure 1a). The monsoon has become increasingly unpredictable, and the number of climate shocks related to floods, storms, and landslides has steadily risen (Figure 1b). These events can damage infrastructure, harm crops, and impact connectivity. This is particularly important in Nepal given the agricultural sector makes up 65 percent of total employment and 24 percent of GDP (ILO, 2020; Nepal National Statistics Office, 2023). In a severe climate change scenario, the World Bank estimate that GDP would be 7 percent lower (World Bank, 2022).

Shocks do not impact all areas of the country evenly. Figure 2 shows how excess rainfall can impact different regions in distinct ways. Figure 2a shows the location of highest flood risks, this is predominantly a concern in the flat lands of the south of the country because heavy rainfall in the mountainous regions can swell rivers, causing flooding in lower-lying areas. By contrast, Figure 2b shows landslide risk is a major concern in the hilly and mountainous regions of the north of the country where landslides induced by rainfall can wipe out roads, damage crops, and impact connectivity. This variation at the regional level, induced by geography, means that it is essential to not treat a country as one homogeneous entity, but instead a network of interconnected regions each subject to their own shocks and responses.

Matching global trends, the prevalence of moderate or severe food insecurity in Nepal has grown every year between 2015 and 2020. Food security currently affects more than one third of the population (Baptista et al., 2023). Recent shocks have continued to worsen food insecurity with 18 percent of the population reporting to not have consumed an adequate diet in October 2022 (World Food Programme, 2022).

A key household coping strategy is to rely on remittances from other districts of Nepal and abroad. Nepal is in the top 10 countries in the world in terms of remittance inflows with the latter accounting for 22.7 percent of GDP in 2020.[13] Despite being in the 10 least urbanised countries, Nepal has extremely high domestic and temporary migration with urbanisation rate in the top ten countries in the world (Barker et al., 2020; Bakrania, 2015). The remittances that follow this migration can act as a social safety net, allowing households to avoid more costly alternatives such as selling valuable assets or enduring large drops in consumption (Baptista et al., 2023; De Stefani et al., 2022).

2.3 Empirical Relationships

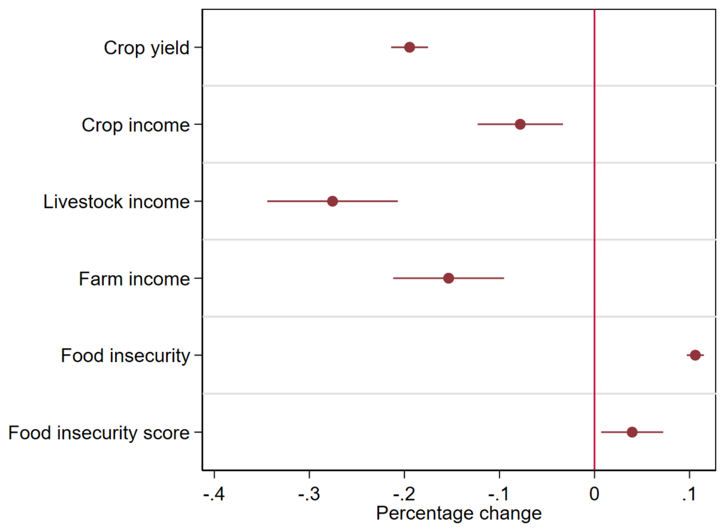
We use the data described above to establish four key empirical relationships. We show how households are affected by climate shocks; how they respond to them; the differential responses of food-insecure households; and how shocks affect remote vs. non-remote regions. The empirical relationships identified below inform the model assumptions made in the next section.[14]

[13] Data from World Development Indicators, World Bank.
[14] Note that while climate shocks are plausibly exogenous we are cautious to not interpret the results in this section to be causal estimates given households may anticipate climate variability and given climate shocks can have important spillovers across districts. This is exactly the reason we think the appropriate approach is to build a quantitative model which can capture rich interconnections across districts.

Fact 1. Households subject to an additional climate shock have lower yields, lower farm income and higher food insecurity.

We estimate a series of simple correlations via OLS between household-level outcomes and the number of district-level climate shocks. Figure 3 graphs these correlations and the 90 percent confidence interval. Each additional climate shock is correlated with statistically significant lower yields as well as lower crop, livestock and farm income. Additionally, a climate shock is correlated with an 11 percent increase in the likelihood of being food insecure and a higher food insecurity index score.[15][16]

Figure 3: Household impacts from climate shocks



Notes: This figure shows OLS correlations between household outcome variables and the number of climate shocks impacting the household. All variables are in logs except Food Insecurity which is a dummy variable.

Fact 2. Households subject to an additional climate shocks have (i) higher expenditure on food (ii) migrate and rely on remittance (iii) have lower savings and capital.

Figure 4 shows how different household coping strategies (consumption, migration, savings) correlate with incidence of climate shocks. First, households subject to an additional climate shock have statistically higher expenditure on food, and lower expenditure on non-food consumption. Overall, this is consistent with food prices increasing following climate shocks leading to higher food expenditure among households with subsistence food requirements. It is also consistent with households responding to shocks by shifting consumption towards food expenditure and away from non-essential non-food consumption. Second, households which are subject to a climate shock are more likely to migrate and have a higher number of migrants. They also rely more on remittances in their income. Third, households subject to shocks have lower savings and lower capital equipment. This is consistent with these households drawing down savings in response to shocks to make up for income shortfalls.

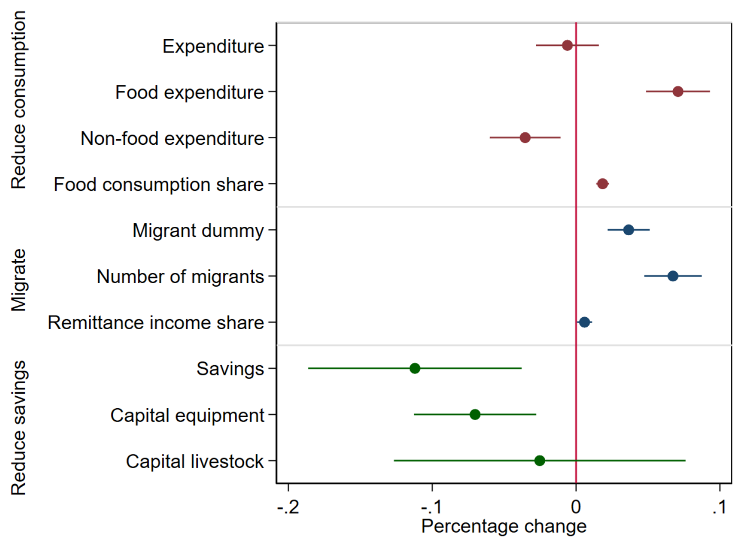
Fact 3. Households that are food insecure have lower savings rates when hit by a climate shock.

Figure 5 provides evidence that food insecurity may lead to differential savings rates following a shock. Among food insecure households the average savings rate is 5 percent lower for those subject to a climate shock. By contrast, food secure households subject to a climate shock do

[15]Index generated by the World Bank based on methodology in Coates et al. (2007). The index assigns a value 0, 1, 2, or 3 points to each response in four categories, in order to arrive at a score out of 27. This is referred to as the Household Food Insecurity Access Scale.

[16]We have also estimated the same model including district, household and time fixed effects. We find qualitatively similar results. We prefer the specification without fixed effects as it imposes the least structure on the data and our aim from this section is not to identify causality.

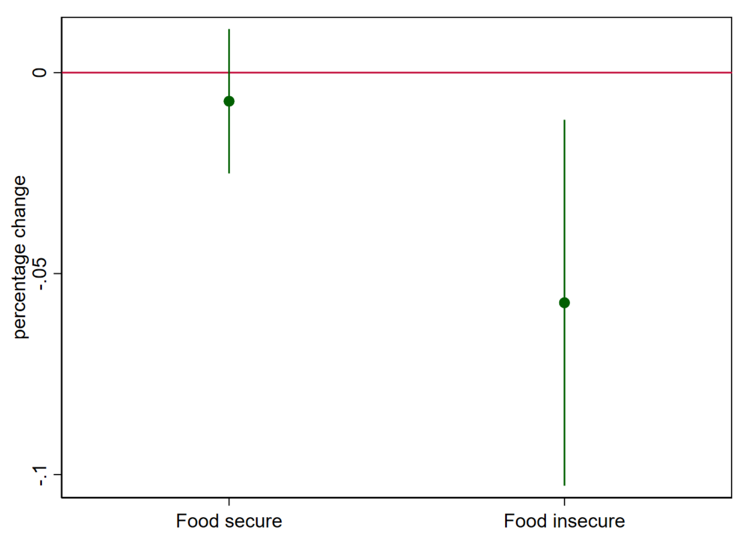
Figure 4: Household coping strategies to climate shocks



Notes: This figure shows OLS correlations between household outcome variables and the number of climate shocks impacting the household. All variables are in logs except Food Insecurity which is a dummy variable.

not have statistically different savings rates. This is suggestive evidence that households who are food insecure draw down savings in response to shocks to help maintain sufficient calories.

Figure 5: Response of savings rate to climate shock



Notes: This figure shows OLS correlations between household savings rate and the incidence of a climate shock impacting the household for food secure and food insecure households. Savings rates are calculated as savings/income where values are truncated at 0 and 1.

Fact 4. Climate shocks raise prices, especially in remote areas, where the impact is also more persistent.

Figure 6 plots the results of local projection regressions (Jordà, 2005) for different forward horizons of the log of food prices on the incidence of a climate shock for a product i in a district s in month t

$$\text{Food price}_{is,t+h} = \sum_{l \in \{0,3,6,9\}} \beta_l \text{Climate shock}_{s,t-l} + \delta_t + \gamma_s + \alpha_i + u_{is,t} \tag{1}$$

where food price is the log of real food price in a Nepali district, climate shock is a dummy equal to one if the district experiences a flood, landslide, cold period or storm. Each regression includes three month lags of the shock variables, as well as a full set of fixed effects (district, food product, and time) as controls.[17] We run the regression for the full sample as well as separately for a sample of remote and connected districts.[18]

Panel (a) shows that climate shocks correspond to a statistically significant contemporaneous 1.9 percent increase in food prices which continues to rise over the subsequent 3 months to reach 3.3 percent. Following a shock, prices remain elevated for a total of 6 months. Panel (b) shows evidence that shocks are both more severe and have more persistent impacts in remote districts. Remote districts see a maximum increase in prices of 7 percent compared to 3 percent in connected districts. Similarly, in remote districts the shock causes prices to remain statistically above zero for 6 months after the shock, compared to 3 months for connected districts.

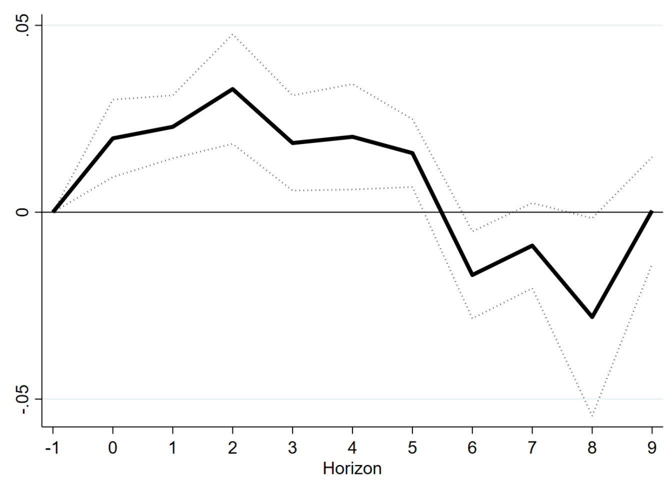
Taken together, the empirical relationships shown in this section suggest that climate shocks have significant impacts on agricultural outcomes, that these shocks vary across space and have heterogeneous impacts in different locations, and that household response mechanisms include migration and trade. These relationships suggest the impact of climate shocks on food insecurity will vary by location, income, and that resilience will depend on interlinkages across space. In the next section, we build a quantitative spatial model which can reproduce these facts as well as estimate the full general equilibrium impact of climate shocks and household response mechanisms.

[17] Note that this is a similar exercise to Kabundi et al. (2022) who use a cross-country approach to show the impact of climate shocks on national CPI inflation finding large and persistent effects.

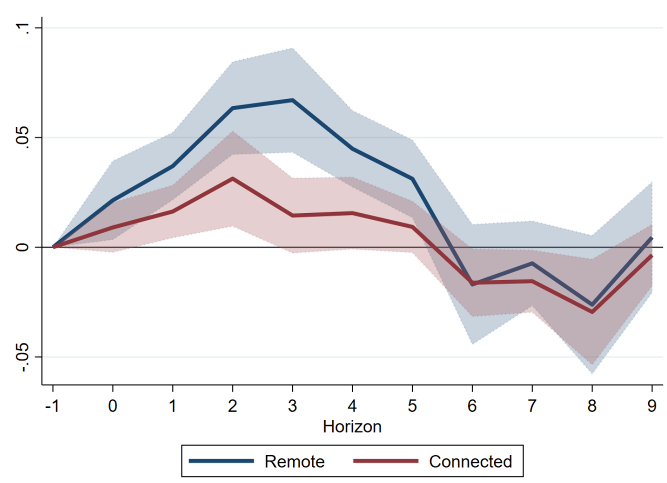
[18] Remote districts are defined as being in the bottom 30 percent of districts in terms of the population weighted driving time to all other Nepalese districts.

Figure 6: Local projection model for district level food prices following climate shocks

(a) All districts

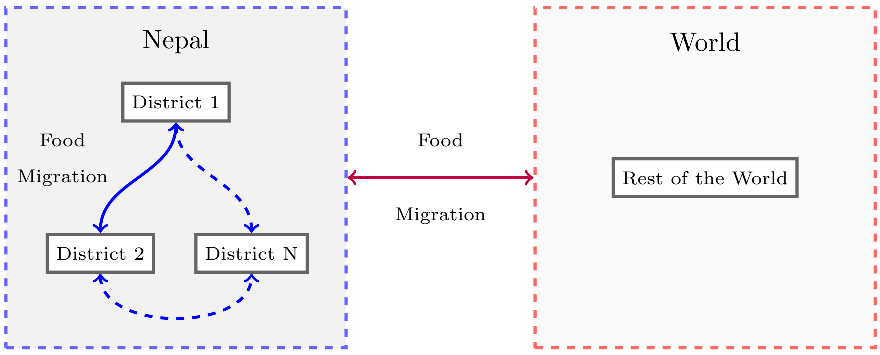


(b) Remote and connected districts



Notes: These figures plot the results of local projection regressions Jordà (2005) for different forward horizons of the log of food prices on the incidence of a climate shock (flood, landslide, cold, storm) for remote and connected districts and the 90 percent confidence interval. Each regression includes three month lags of the shock variables, as well as a full set of fixed effects (district, product, time) as controls. Panel (a) shows that climate shocks lead to a statistically significant contemporaneous 1.9 percent increase in prices which continues to rise over the subsequent 2 months and lasts for 6 months. Panel (b) shows that remote districts (defined as being in the bottom 30 percent of districts in terms of the population weighted driving time to Nepalese districts) experience a larger increase in prices when compared to connected districts (max: 7 percent vs. 3 percent) and have more persistent shocks (6 months vs. 3 months).

Figure 7: Model Environment



Districts: heterogeneous households working on owner operated farms, outside sector
Food security: subsistence food consumption, capital determined by invested earnings
Frictions: pairwise migration and trade costs
Policy: infrastructure, trade and migration costs

3 Model

3.1 Overview

The economy is made up of $n = 1, ..., N$ locations and is populated by a continuum of rural households $\omega \in \Omega$ of size L^R and a mass of size L^U of identical urban households. Households consume two types of goods: food and non-food.[19] Both goods can be traded between any pair of locations subject to trade costs. Each rural household owns and operates a farm in their residence location and chooses how much of their labor endowment to allocate to farm work and how much to allocate to supplying labor to firms in the non-food sector for a wage (off-farm labor). Urban households do not own farms and supply their labor exclusively to the non-food sector. Households cannot change their residence location and must supply farm labor in their residence location. Off-farm labor, on the other hand, may be supplied in a different location. In addition to the N locations in the domestic economy, there also exists a foreign economy (henceforth ROW) with which households can trade both food and non-food goods. Households can also migrate to ROW but ROW households cannot migrate to any of the N domestic locations.

Food goods are produced at farms using labor, land and capital. Each household has access to a plot of land where food goods are produced from crops and livestock. Households exhibit heterogeneity in human capital which determines their ability to generate income from farm production and wage labor. The productivity of land differs across locations due to differences in soil and climate suitability.[20] Districts can trade food goods subject to bilateral trade costs that vary across district pairs depending on the distance between them. The production of non-food goods is undertaken by perfectly competitive firms that hire labor from rural and urban households.

In each period, households decide how much to save and consume, how much to spend on food vs non-food goods, and where to supply wage labor to generate off-farm income. Households may decide to supply labor outside their residence location - i.e. migrate - and use transfers to equalize real consumption among its members. Migration is subject to bilateral movement costs which vary across location pairs. Households are not allowed to borrow and so all capital used for agricultural production must be financed through savings.[21] There is no money in the economy and prices are fully flexible, and so we abstract from exchange rates. Both trade and migration costs include not only monetary expenses such as tariffs and work

[19]The food sector should be equated to the agricultural sector as we abstract from the production of non-edible agricultural goods. The non-food sector should be seen as a residual sector that produces all other goods including manufacturing and services.

[20]We leave unspecified what foods or agricultural products households produce and may interpret it as a combination of staple and cash crops, as well as livestock.

[21]In many developing countries access to credit is limited especially in rural areas. In Nepal in 2021 there were 251 bank accounts at a bank or financial institution per 1000 population in rural municipalities (NRB, 2021).

visas but also any other costs that may limit the extent of bilateral flows such as those arising from search frictions or cultural and language barriers.

3.2 Consumption and Saving

A household of type $\omega \in \Omega$ in location i maximizes the utility function

$$u_{it}(\omega) = \left(c_{it}(\omega) - \overline{C}\right)^{\beta} k_{it+1}(\omega)^{1-\beta}, \text{ with } 0 < \beta < 1, \tag{2}$$

where $\overline{C}$ is a constant. According to this utility function, households derive utility from current consumption c_{it} and a capital bequest $k_{it+1}(\omega)$ for the following period. The household solves this problem sequentially in every period $t = 1, 2, ...$ and inherits the capital stock chosen as a bequest in the previous period. $\overline{C}$ is a consumption subsistence requirement that households must satisfy in each period. This represents a bundle of basic goods that is needed for survival such as a minimal caloric intake, shelter and access to health services. Households maximize the utility function above by choosing consumption and capital bequest subject to the per-period constraint $P_{it}c_{it} + P^k_{it}k_{it+1} = y_{it} + (1-\delta)P^k_{it}k_{it}$, where y_{it} is household income and $(1-\delta)k_{it}$ is the net of depreciation stock of capital carried over from the previous period, with $0 < \delta < 1$. We have dropped the subscript ω for simplicity. Optimally, households will choose current consumption

$$c_{it} = (1-\beta)\overline{C} + \beta\left(\frac{y_{it} + (1-\delta)P^k_{it}k_{it}}{P_{it}}\right) \tag{3}$$

and optimal bequest

$$k_{it+1} = -(1-\beta)\frac{P_{it}}{P^k_{it}}\overline{C} + (1-\beta)\left(\frac{y_{it} + (1-\delta)P_{it}k_{it}}{P^k_{it}}\right) \tag{4}$$

The inclusion of the subsistence term $\overline{C}$ creates a non-homotheticity in households' consumption-savings choice whereby the share of capital bequest in wealth $W_{it} = y_{it} + (1-\delta)P^k_{it}k_{it}$ is decreasing in wealth. From (4), the share of capital holdings $P^k_{it}k_{it+1}$ in wealth is given by

$$\frac{P^k_{it}k_{it+1}}{W_{it}} = -(1-\beta)\frac{P_{it}\overline{C}}{W_{it}} + (1-\beta)\ , \tag{5}$$

which implies the value of capital stock will make up a smaller portion of total wealth for poor households, i.e. those with lower W_{it}. This has two important consequences for poor households when hit by a negative shock. First, upon being hit by a negative shock, a poor households will have a lower capital stock buffer relative to their total wealth, implying they will suffer a larger drop in current wealth for a given decrease in current income. This will translate into lower current consumption and utility than their wealthier counterparts as they are less able to use their capital to absorb the shock. Secondly, poorer households will also reduce their capital-to-wealth ratio by relatively more in response to the shock. This can be seen by transforming equation (5) into relative changes as

$$\left(\widehat{\frac{P^k_{it}k_{it+1}}{W_{it}}}\right) = -\frac{P\overline{C}}{W - P_i\overline{C}}\widehat{W}^{-1} + \frac{W}{W - P_i\overline{C}}, \tag{6}$$

where hat denotes the ratio of future-to-current value, i.e. $\widehat{x} = x_{t+1}/x_t$ and where prices P and wealth W are initially at their steady-state values. Upon inspection, it can be concluded that the closer steady state wealth W is to subsistence spending $P\overline{C}$ the larger the response of the left hand-side to a change in current wealth $\widehat{W}$ due to an income shock. This in turn will also negatively impact poor households' ability to generate income in the future and will lead to a slower rebuilding of their capital stock over time with consequences for their current and future utility.

Note that in contrast to a more standard maximization problem where an agents maximizes over a sequence of future consumption streams, here, household savings enter directly into utility instead of indirectly via their effect on future production. Although formally unspecified, the preference for capital/savings accumulation may be interpreted as a combination of a desire to generate more future income and a desire to hold precautionary savings. The choice of this parsimonious specification offers at least two advantages. First, it avoids having to model forward-looking agents who form expectations of endogenous equilibrium variables, which would add substantial complexity to the model. This complexity would be further aggravated by household's inability to borrow as it would give rise to occasionally binding constraints. Second, it is able to generate with few assumptions, i.e. only that of the existence of a consumption subsistence requirement, an asset holdings-to-wealth ratio in steady-state that is increasing in wealth. In other words, in a steady-state, poorer households will exhibit lower wealth-to-income ratios making them more vulnerable to negative income shocks.[22]

3.3 Final Goods Consumption and Food Security

The final good C_{it} is made up of the consumption of a food and a non-food good. We use a non-homothetic CES demand specification following Comin et al. (2021) in which food is a necessity good and non-food is a luxury good. According to this specification, preferences for the final good C_{it} are defined implicitly as

$$\Omega_F^{\frac{1}{\rho}} C_{it}^{\frac{\varepsilon_F}{\rho}} c_{Fit}^{\frac{\rho-1}{\rho}} + \Omega_N^{\frac{1}{\rho}} C_{it}^{\frac{\varepsilon_N}{\rho}} c_{Nit}^{\frac{\rho-1}{\rho}} = 1 \; . \tag{7}$$

Parameters (Ω_F, Ω_N) are sectoral taste parameters for food and non-food goods, respectively, ρ is the price elasticity of substitution between food and non-food goods, and $(\varepsilon_F, \varepsilon_N)$ are utility elasticities that govern the responsiveness of sectoral consumption to changes in utility for given relative prices. The household chooses the optimal bundle of sectoral goods by maximizing the implicitly defined C_{it} above subject to the constraint $p_{Fit}c_{Fit} + p_{Nit}c_{Nit} = P_{it}C_{it}$. The optimal share of spending on food ω_F is given by

$$\omega_f \equiv \frac{p_F \cdot c_F}{P \cdot C} = \Omega_F \left(\frac{p_F}{P}\right)^{1-\rho} C^{\;\varepsilon_F-(1-\rho)} \; , \tag{8}$$

where we have dropped the location and time subscripts for simplicity and where the average cost index P satisfies

$$P = \left(\left(\Omega_F p_F^{1-\rho}\right)^{\frac{1-\rho}{\epsilon_F}} \left(\omega_F (P{\cdot}C)^{1-\rho}\right)^{\frac{\epsilon_F-(1-\rho)}{\epsilon_F}} + \left(\Omega_N p_N^{1-\rho}\right)^{\frac{1-\rho}{\epsilon_N}} \left((1-\omega_F)(P{\cdot}C)^{1-\rho}\right)^{\frac{\epsilon_N-(1-\rho)}{\epsilon_N}} \right)^{\frac{1}{1-\rho}} . \tag{9}$$

As can be seen in equation (8), the share of spending on food will fall as consumption C rises, since $0 < \varepsilon_F < 1$ (necessity good), while that of non-food will rise, since $\varepsilon_N > 1$ (luxury good).

In order to characterize consumption in terms of food security we assume a relationship between real food consumption c_F and calorie intake $kcal$. As has been extensively documented in the literature (Subramanian and Deaton, 1996), as food spending rises households tend to purchase foods with higher cost-per-calorie so that calorie consumption rises slower than food consumption with income. For example, while the bulk of food expenses among poor households tend to go towards grains and cereals like rice and wheat which have a high caloric content per dollar amount spent, wealthier households allocate larger shares of their budget to less calorie-effective goods like meat, oils and beverages. To capture this pattern we assume calorie consumption is a constant elasticity function of real food consumption

$$kcal_{it}(\omega) = \eta_0 c_{it}^F(\omega)^{\eta_1} \; , \; \eta_0 > 0 \; , \; 0 < \eta_1 < 1 \; .$$

[22]Note this would not be the case if the utility function were, for example, of the form $U = \sum_{t=1}^{N} u(C_t - \overline{C})$ as it would not guarantee an increasing wealth-to-income ratio in steady-state. In fact, under, for example, a Cobb-Douglas production function with decreasing marginal returns to capital, this ratio would be constant across households.

The fact the elasticity parameters η_1 is between 0 and 1 ensures calories rise slower than food consumption. We define a threshold calorie consumption level $\overline{kcal}$ below which a household is said to be undernourished. We use this as our key measure of food insecurity to the extent it captures households' ability (or inability) to satisfy a minimum energy level requirement needed to live a healthy life. We define the prevalence of food insecurity in a district as the share of households who are undernourished.[23]

3.4 Household Heterogeneity

Each rural household is endowed with human capital $z(\omega)$ that determines their ability to generate income from farm and off-farm activities. The distribution of $z(\omega)$, whose cdf we denote $F(\cdot)$, is iid across households and districts. Letting y_{it}^F and y_{it}^N denote farm and off-farm income generated with one unit of human capital $z(\omega) = 1$, respectively, household income of type ω, $y_{it}(\omega)$, is given by

$$y_{it}(\omega) = z(\omega)\big(y_{it}^F + y_{it}^N\big) \ .$$

In other words, human capital $z(\omega)$ scales both sources of income by the same proportion which keeps sector income shares constant across households. A more general model would allow for sector-specific household human capital that could give rise to household sectoral specialization patterns, but we abstract from this labor allocation margin. Human capital $z(\omega)$ may be interpreted as differences in effective labor hours which determine the overall productivity of a worker. Households with higher human capital are able to both grow a higher volume of crops with the same inputs (e.g. better farming knowledge and technique) and earn a higher wage in the non-food sector with the same labor hours.

This source of household heterogeneity gives rise to a non-degenerate distribution of outcomes at the district level. Importantly, there will be a threshold $\overline{z}_i$ below which household will not be able to generate enough income to optimally choose food consumption with a caloric content of at least 2200 calories, thereby making them undernourished. This threshold varies across districts depending on local productivities and existing frictions as well as over time as districts are hit by shocks. A negative shock (e.g. flood) would push this threshold up and lead to an increase in the share of undernourished households.

3.5 Food Markets

The supply chain of food distribution is made up of three agents: farms, wholesalers, and retailers.[24] First, in each location a continuum of heterogeneous rural households produce food goods that are differentiated by location but homogeneous within them. Households exhibit heterogenous levels of output that depend on their type ω and sell all output to a perfectly competitive local wholesaler at price p_i^F which they take as given. The wholesaler takes the sum of local agricultural output (denoted intermediate food good) and sells it to retailers around the country. The retailers, also competing in a perfectly competitive environment, aggregate intermediate goods from all wholesalers into a final food good according to an Armington aggregator[25]

[23] In our framework we primarily use the term undernourishment instead of food insecure, although there is a close link between the two. This is because food security is often defined as a multidimensional index. For instance, the FAO defines food security along four dimensions - access, availability, utilization and stability (FAO, 1996). We have experimented with including all four of these dimensions in the model. Our current definition links closest to access - the household has sufficient income to purchase adequate calories at market prices. Availability can be approximated by the level of food production in the country plus net imports. Food utilization can be included in our framework via a measure of the nutritious quality of food. This is currently approximated in our framework via the functional form we impose on calorie consumption. Finally, sustainability can be included in the model via the probability of becoming food insecure under a typical series of shocks. This can be included in our framework by repeated simulations of the economy and observing resilience. We have experimented with this approach and see it as a future extension of our work.

[24] The inclusion of three distinct agents in the food supply chain is needed to accommodate the simultaneous presence of household heterogeneity, Armington assumption, and trade across regions. The wholesaler aggregates homogeneous food products produced by local farms with heterogenous productivities into a differentiated local variety. Retailers then aggregate the differentiated products assembled by wholesalers from different locations

[25] Note that according to the Armington assumption goods from the same sector produced in different regions are perceived by retailers (or consumers, ultimately) as heterogeneous goods. This is arguably an unreasonable

$$C_i^F = \left(\sum_{n=1}^{N} c_{in}^{F\ \frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} , \text{ with } \sigma > 1 \ , \tag{10}$$

where c_{in}^F denotes food goods imported into i from the wholesaler in location n. After having sourced intermediate goods from wholesalers around the country, the retailer sells final food goods to local households at the CES price index

$$P_i^F = \left(\sum_{i=1}^{N} (p_{in}^F)^{1-\sigma} \right)^{\frac{1}{1-\sigma}} ,$$

where p_{in}^F is the price of sourcing food goods from location n into i. Shipping intermediate goods from location n into i incurs an iceberg trade cost τ_{in} for any pair n, i with $\tau_{in} \geq 1$ and $\tau_{ii} = 1$ for all i, n. We make the assumption that it never pays off to ship goods indirectly via a third location, i.e $\tau_{in} \leq \tau_{m,n}\ \tau_{i,m}$, for $m \neq n$ and $m \neq i$. We denote the rest of the world with an asterisk and assume the price of importing food from abroad, p_*^F, is given exogenously. The net price of goods imported into i from n will equal factory gate prices in n plus a transportation cost τ_{in}

$$p_{in}^F = \tau_{in}\ p_n^F \ .$$

One can show that the wholesaler will optimally choose to source goods according to the import share equation

$$\pi_{in} \equiv \frac{p_{in}^F c_{in}^F}{X_i^F} = \frac{(\tau_{in} p_n^F)^{1-\sigma}}{\sum_{n'=1}^{N} \left(\tau_{in'} p_{n'}^F\right)^{1-\sigma} + \left(\tau_{i,*}\ p_*^F\right)^{1-\sigma}} = \left(\frac{\tau_{in} p_n^F}{P_i^F} \right)^{1-\sigma} , \tag{11}$$

where π_{in} is the share of expenditures X_i^F spent on purchasing goods from origin n and $\tau_{i,*}$ is the cost of importing goods from abroad into i. The share of imports falls with farm-gate price p_n^F and shipping cost τ_{in} and rises with the CES price index P_i^F. In other words, more is purchased from origin n whenever sourcing goods from there becomes cheaper relative to the cost of final food goods bundle C_i^F. The latter bundle is non-tradable so that all households must buy their final food goods from their local retailer at the CES price index P_i^F.

3.6 Food Production

Households $\omega \in \Omega$ have access to a plot of land of size $h(\omega)$ which they use to produce food. The household has access to the constant returns to scale farm production function

$$q_{it}^F(\omega) = z(\omega) A_{it} h(\omega)^{\alpha_h} \left[k_{it}(\omega)\right]^{\alpha_k} \left[l_{it}^F(\omega)\right]^{\alpha_L} \ ,$$

where A_{it} is average district farm productivity and captures the suitability of local climate and soil to grow crops and livestock, l_{it} is farm labor, and k_{it} is farm capital. Capital should be interpreted in a broad sense so as to include a wide range of productive inputs like fertilizer, seeds, tools, machinery, and irrigation. The land endowment is fixed and assumed to be proportional to human capital with $h(\omega) = \chi\ z(\omega)$, with $\chi > 0$.

Households endogenously select how to optimally allocate their time endowment - which we normalize to 1 - between farm labor $l_{it}^F(\omega)$ and off-farm labor $l_{it}^N(\omega)$. In particular, they

assumption for specific staple foods such as rice and wheat for which households are less likely to either perceive or value differences in goods produced across different locations. An extensive literature provides a treatment of models of spatial price equilibrium with homogeneous goods based on spatial arbitrage and proposes solution algorithms using quantitative methods (e.g. Samuelson (1952); Takayama and Judge (1973); Nagurney et al. (1996)). Unlike these, the Armington model yields tractable closed-form solution that are amenable to analytical characterisation and that dispense with the need of more computationally-intensive solution methods. We also note that we model a single agricultural good so that one may interpret the food good produced in each region as composed by different specific food items that households do perceive as being differentiated.

will supply farm labor supply $l_{it}^F(\omega)$ until the marginal product of farm labor is equal to the marginal return on off-farm labor, which is the wage rate w_{it} offered by non-food sector firms. Thus, labor l_{it}^F satisfies

$$l_{it}^F = \left(\frac{\alpha_l p_{it}^F A_{it} K_{it}^{\alpha_k}}{w_{it}} \right)^{\frac{1}{1-\alpha_l}} . \tag{12}$$

Moreover, the return on capital r_{it} is given by

$$r_{it} = z\alpha_k p_{it}^F A_{it} \frac{q_{it}^F}{k_{it}} .$$

Farms only use land and labor supplied by the owner of the farm and so we refrain from introducing a farm wage or land rental rate since these factor payments will constitute no more than a transfers within the household.

3.7 Non-food Sector

In each location a perfectly competitive firm produces non-food goods by hiring labor supplied by households according to the production function

$$Q_{it}^N = A_i^N \Big(\psi L_{it}^U + L_{it}^R (1 - l_{it}^F) \int_\omega z(\omega) dF(\omega) \Big) \quad , \qquad > 1$$

where A_i^N is TFP and L_{it}^U and L_{it}^R are the mass of urban and rural household labor supply in i, respectively. We assume urban households supply their entire labor endowment of 1 to the non-food sector. Urban households are more productive than rural households in producing non-food goods as captured by the term $\psi > 1$. Non-food goods are also traded across districts with the structure of trade following the same as that of food goods (including the same elasticity of substitution σ), as described in section 3.5.

Households earn wage rate w_{it} for supplying labor. In equilibrium, firms make zero profits or, equivalently, the marginal revenue product of labor is set equal to the wage rate with

$$w_{it} = p_{it}^N z_i^N , \tag{13}$$

where p_{it}^N is the price of non-food goods. After observing their farm productivity realisation, rural households decide where to supply labor for a wage, which may include the foreign economy offering an exogenous wage rate w^*. We assume the existence of idiosyncratic migration costs $\kappa_{in}(\omega)$ that only allow households to keep a share of their total wage earnings.[26] Migration costs $\kappa_{in}(\omega)$ are assumed to follow an extreme value distribution following McFadden (1974). In particular, $\kappa_{in}(\omega)$ are drawn from independently distributed Frechet distributions with scale parameter $D_{i|n}$ controlling the average size of migration costs for migration from n to i, and with share parameter λ, common across all district pairs, regulating the dispersion of migration costs across households. We set the normalization $D_{n|n} = 1$ for all n.

More formally, households choose the location with the highest net real wage $V_{nt}(\omega)$, which satisfies

$$V_{nt}(\omega) = \max_i \kappa_{in}(\omega) \frac{w_{it}}{P_{it|n}} ,$$

which also includes the foreign destination. Note the net real wage $V_{nt}(\omega)$ depends on the price index $P_{it|n}$ which combines the price indices of origin and destination destination location according to $P_{it|n} = P_{it}^{\phi} P_{nt}^{1-\phi}$ with $0 < \quad < 1$. We employ this migration-adjusted price index

[26] We choose to treat migration costs as a monetary costs although, in reality, they are likely a combination of the monetary and non-monetary costs like utility costs associated with being away from relatives or from differences in local amenities. Migration costs have been typically modelled as direct utility costs in the quantitative spatial literature (Allen and Arkolakis, 2014; Caliendo et al., 2018; Miyauchi et al., 2021) with some exceptions like Caliendo et al. (2019) who model them as fixed, additive, monetary costs. The lack of data on explicit monetary costs prevents us from being able to distinguish between monetary and non-monetary costs and we choose to interpret the migration costs exclusively as the former. This is not expected to have a significant quantitative effect on our results as is mostly a matter of interpretation

to account for the role of remittances. We assume all members of the household pool their income and use transfers to equalize real consumption with migrant members of the household buying goods at the destination price index P_{it} and the remaining at the origin price index P_{nt}. Parameter ψ governs the relative consumption expenditure at the two locations which we equate to the share of migrant household members. To ensure real consumption is equalized across members of the household the level of remittances rmt_{ni} sent from destination i to origin n is $rmt_{ni} = z(\omega)\phi_n\big(\psi P_n w_i - (1-\psi)P_i w_n\big)/\big(\psi P_n + (1-\psi)P_i\big)$

Households drawing a low κ_{it} for a given destination will be more likely to exploit spatial differentials in real wages by seeking employment in that location. For some households, the costs of migration to all $i \neq n$ will be so high that they may keep their members in the residence location even if there exist other locations with higher gross real wages. The dispersion parameter λ measures the degree of heterogeneity in idiosyncratic migration costs, with $\lambda \to \infty$ representing the extreme case where costs are fully homogeneous across all households. Lower values of λ correspond to more heterogeneity in migration costs. Using the properties of the Frechet distribution, one can show that the probability of sending migrants from n to i, ξ_{int}, is

$$\xi_{int} = \frac{D_{i|n}\big(\frac{w_{it}}{P_{it|n}}\big)^{\lambda}}{\sum_{m=1}^{N+1} D_{m|n}\big(\frac{w_{mt}}{P_{mt|n}}\big)^{\lambda}} \ . \tag{14}$$

With the existence of a continuum of rural households, the law of large numbers implies that bilateral migration flows match the probability above, i.e. $\xi_{it|n} = L^R_{it|n}/L^R_{nt}$, where $L^R_{it|n}$ is the mass of households in n who decide to send migrants to i. Seen through the expression above, parameter λ therefore governs the elasticity of migration flows with respect to real wages: a lower λ implies that an increase in wages in i will generate a smaller inflow of migrants into that location. In the extreme case of $\lambda \to \infty$, the elasticity of migration is infinite and net real wage $V_{nt}(\omega)$ is equalized for all households. This will not be the case for other values of λ and so net real wages will in general not be equalized across locations.

Moreover, one can derive the expected net real wage $\mathrm{E}[V_{nt}]$ earned by a household which is given by

$$\mathrm{E}[V_{nt}] = \left(\sum_{i=1}^{N+1} D_{i|n}\left(\frac{w_{it}}{P_{it|n}}\right)^{\lambda}\right)^{\frac{1}{\lambda}} , \tag{15}$$

where the plus one in the summation operator denotes the foreign economy.

3.8 Market Clearing

In this section we close the model by providing market clearing conditions. To ensure market clearing in final goods, we impose the condition that total sales Y_i^j must equal the sum of domestic and international exports across all destinations for $j = A, N$. We first assume that exports to the rest of the world $X^j_{*,n}$ are given by a constant elasticity function of prices with elasticity $1-\sigma$, where σ is the same as the variety elasticity of substitution defined above. Thus,

$$X^j_{*,n} = b^j \cdot \left(\tau_{*,n}\ p_n^j\right)^{1-\sigma} \ , \text{ for } j = F, N \ , \tag{16}$$

where b^j is a constant capturing the size of demand for exports. Then, we can impose market clearing for intermediate goods through the condition

$$Y_i^j = \sum_{n=1}^{N} \pi_{ni} X_n^j + X^j_{*,i} \ , \text{ for } j = F, N \ .$$

Since final goods producers are perfectly competitive, sales must equal expenditures so that

$$p_i^j Q_i^j(\omega) = \sum_{n=1}^{N} \pi_{ni} X_i^j + X_{*,i}^j \ , \ \text{for } j = F, N \ , \quad (17)$$

which pins down equilibrium prices. Given trade shares π_{ni} and exports $X_{*,i}^F$, this equation provides the vector of equilibrium prices $\{p_i^j\}_{i=1}^N$ that are consistent with market clearing. For the non-food sector, labor market clearing implies

$$w_{it}(\psi L_{it}^U + L_{it}^R) = \sum_{n=1}^{N} \pi_{ni} X_i^N + X_{*,i}^N \ ,$$

which pins down service sector wages w_{it}. Finally, we need to impose that the share of local rural supply of service labor L_{it}^R is consistent with wage work location shares so that

$$L_{it}^R = \sum_{n=1}^{N} \phi_n \xi_{it|n} L_{nt}^R \ .$$

4 Calibration and Model Simulation

In this section we discuss data sources used to externally calibrating the model and then the approach used for parameters internally calibrated in the model. The calibration is performed for a steady-state equilibrium in which all household-level capital stocks are constant, i.e. $k_{it}(\omega) = k_{it-1}(\omega) = k_i(\omega)$ for all households. To solve the model, we first simulate independent human capital draws for 1000 households in each location and set capital stock levels to an arbitrary initial value. We then solve for the economy's equilibrium, update capital stocks based on households' optimal choices and iterate until all household-level capital converge to a steady-state. We calibrate model parameters to ensure our steady-state equilibrium matches key targeted data moments. We outline our approach to approximate the magnitude of historical climate shocks. We validate the model through observing the determinants of the prevalence of undernourishment in model simulated data. Finally, we demonstrate model mechanisms via simulating responses to a geographically isolated normalised climate shock.

4.1 External Calibration

4.1.1 Preferences

We use a value of 6 for the variety elasticity of substitution σ which is consistent with the range of parameter estimates in Eaton and Kortum (2002) which would translate to a range of values between 4.6 and 13.86. We set the migration elasticity parameter λ equal to the estimate in Monte et al. (2018) who estimate a value for λ equal to 3.4. Estimates for the non-homothetic CES utility function defined in equation (7) are based on Comin et al. (2021) for their non-OECD sample. Their framework considers three sectors - agriculture, manufacturing, and services - while our model features only two. We take weighted averages between manufacturing and service sector parameters to obtain estimates for the non-food sector and directly use agriculture parameter estimates for the food sector. Thus, we set the parameters regulating the income elasticities of demand $\varepsilon_F = 0.2$ and $\varepsilon_N = 1.19$, and price elasticity of substitution γ equal to 0.48. We assume an elasticity of calorie intake with respect to food consumption of 0.4 which is in line with the estimates found in Subramanian and Deaton (1996) in the range 0.3-0.5. Calorie intake threshold for undernourishment $\overline{kcal}$ is set to 2,200 calories, which is the minimum average adequate requirement set by the Government of Nepal.[27]

4.1.2 Population

We use the 2019 Nepal Statistical Year Book to measure the sizes of rural and urban population across districts. The dataset provides information on population size of each sub-administrative regions within each district - metropolitan cities, sub-metropolitan cities, municipalities, and

[27] See World Food Programme (2013) and CBS (2011)

rural municipalities. We assign urban status to any sub-administrative region with a population of more than 120,000 and rural status to all other regions. After aggregation, we end up with 80.6 percent rural population across all 77 districts in Nepal which is very close to the share reported by the World Bank of 79.4 percent in 2020. We calibrate the model for 51 districts where data is available from the HHRV (accounting for roughly 78 percent of total Nepal population).[28] If we only include the 51 Nepali district used in our calibration and assign urban status to all households in the Kathmandu Valley area, the rural population share falls only slightly to 78.4 percent. Across the 51 districts, 38 are entirely rural, 12 are mixed contain both rural and urban population and 1 (Kathmandu Valley) is entirely urban, containing 35.3 percent of all urban population in our sample.

4.1.3 Farm Production

We use data from the Nepal Household Risk and Vulnerability Survey (HRVS) 2016-18 to estimate local average agricultural yields.[29] The survey contains detailed household-level information on the type of crops grown, the size of land allocated to each crop, volume harvested, selling price for any farm output sold in the market, sales and purchases of livestock, and costs associated with farming activities. For each district and crop, we compute the volume-weighted average selling price and multiply this by production volume to obtain nominal crop revenues for each household. We then sum across crops to obtain total household crop revenues. We add to this any reported net revenues associated with selling livestock and subtract any costs associated with hired labor and inputs that include seeds, fertilizer and farming tools, machinery and equipment. We then divide this combined figure by land x labor hours to obtain total household-level farm profits. After aggregating at the district level, we obtain our estimate of average district farm productivity. We use farm production share values based on estimates from Bergquist et al. (2019) for what they define as the modern agricultural sector in Uganda. Taking the average across the nine crops considered in their paper[30] and interpreting what they classify as intermediate inputs as capital inputs in our model, we obtain estimates $\alpha_h = 0.5$, and $\alpha_k = 0.15, \alpha_l = 0.35$.[31] We assume capital depreciates at rate $\delta = 0.05$.

Household human capital $z(\omega)$ is assumed to follow a log-normal distribution with $\log z(\omega) \sim \mathcal{N}(0, \sigma^2_{z_i})$ iid across households. Note we allow the the level of variation in human capital to vary across districts as some districts may exhibit more inequality than others. As human capital is unobservable, we rely on differences in real consumption outcomes as proxies for the underlying variation in human capital. Thus, we calibrate the level of dispersion in human capital σ^2_z to match the observed variance of real consumption among rural households in the HRVS data. More specifically, we add up all sources of food and non-food expenses recorded in the survey for each household and divide by a local price index constructed from price data information to obtain a measure of real consumption. We take the log, compute the cross-sectional variance in each district and use this as our estimate for σ^2_z. Our estimates vary between 0.24 and 1.07 for the least and most unequal districts, respectively, with the median district with an estimate of 0.55.

Table 1: Externally Calibrated Parameters

Parameter	**Description**	**Source**
Preferences		
$\sigma = 6$	Elasticity of Substitution	Standard

[28] The districts included are Taplejung, Ilam, Jhapa, Morang, Sunsari, Dhankuta, Bhojpur, Solukhumbu, Okhaldhunga, Khotang, Udayapur, Saptari, Dhanusha, Mahottari, Sarlahi, Sindhuli, Dolakha, Sindhupalchok, Kabhrepalanchok, Nuwakot, Dhading, Makwanpur, Bara, Parsa, Gorkha, Lamjung, Tanahun, Syangja, Myagdi, Baglung, Gulmi, Palpa, Nawalparasi, Rupandehi, Rolpa, Rukum, Dang, Banke, Surkhet, Dailekh, Jajarkot, Jumla, Kalikot, Bajura, Bajhang, Achham, Doti, Kailali, Baitadi,Darchula, and Kathmandu Valley. There is a total of 77 districts in Nepal. We merge the districts of Kathmandu, Lalitpur and Bhaktapur into a single location, Kathmandu Valley, which is highly integrated.

[29] For more detail see section 2.

[30] These are Beans, Cassava, Coffee, Groundnuts, Maize, Matooke, Millet, Sorghum, and Sweet Potatoes

[31] In a future version of the paper, we plan to estimate farm production shares based on data on land usage and farm input spending from the HRVS dataset.

$\lambda = 3.4$	Migration Dispersion Param.	Monte et al. (2018)
$\varepsilon_F = 0.2$	Income Elasticity of Demand	Comin et al. (2021)
$\varepsilon_N = 1.19$	Income Elasticity of Demand	Comin et al. (2021)
$\gamma = 1.4$	Price Elasticity of Substitution	Comin et al. (2021)
Production		
Z_i	Local Farm Productivity	HRVS
$\sigma^2_{z_i}$	Dispersion of Human Capital	HRVS
$\delta = 0.05$	Depreciation Rate	Standard
$\alpha_h = 0.50$	Farm Land Share	Bergquist et al. (2019)
$\alpha_k = 0.15$	Farm Capital Share	Bergquist et al. (2019)
$\alpha_l = 0.35$	Farm Labor Share	Bergquist et al. (2019)
Trade		
$\zeta = 0.31$	Distance Decay Rate	Disdier and Head (2008)
Nutrition		
$\eta = 0.4$	Elasticity of Kcal wrt Food	Subramanian and Deaton (1996)
$\overline{kcal} = 2200$	Undernourishment Threshold	Government of Nepal

4.2 Internal Calibration

4.2.1 Consumption Preferences

We calibrate β to match a capital stock value to wealth ratio for the average household of 0.5. The subsistence requirement $\overline{C}$ is calibrated to 80 percent of the 5th percentile of consumption level C_i across households in the baseline economy. We use the 5th percentile as a reference for extreme poverty consumption and choose a level of consumption 20 percent below in order to approximate a threshold for human survival. We refrain from using consumption below the 5th percentile as our extreme poverty baseline to avoid picking up anomalously low consumption levels that may result from our simulation procedure.[32] Consumption weights Ω_F, Ω_N in non-homothetic CES utility function are calibrated to match the average share of household budget spent on food across rural and urban households which is estimated at 0.58 based on data from the Central Bureau of Statics (CBS) for 2015-16.[33]

4.2.2 Trade Costs

We parameterize trade costs as a constant elasticity of substitution function of distance so that $\tau_{ni} = a_n \; dist^{\zeta}_{ni}$ with $a_n > 0, \zeta > 0$. We measure distances $dist_{ni}$ as the driving distance between pairs of locations which we estimate using the distance Matrix API from Google Maps for the 51 Nepalese districts in our sample.[34] We set the distance with own-district $dist_{nn}$ equal to 0.25 times the smallest bilateral distance that n has with other locations $i \neq n$. We set $a_n = dist^{-\zeta_1}_{nn}$ so as to impose the normalization $\tau_{nn} = 1$ for all n.

The value of the distance decay rate ζ is chosen so that it is in range with the values implied by typical estimates of the elasticity of trade flows with respect to distance - in our model this corresponds to $-\zeta(1-\sigma)$. The meta analysis of Disdier and Head (2008) finds a central estimate of -0.9 for this elasticity with 90 percent of estimates lying between -0.28 and -1.55. This would imply a range for ζ between 0.056 and 0.31 given our choice of $\sigma = 6$ for the variety elasticity of substitution. The highly mountainous geography of Nepal likely implies exceptionally high costs of traversing space and we set the decay rate ζ equal to the upper bound estimate of 0.31.

We calibrate import food and non-food price from ROW by matching the 2019 share of imports in total food expenditures that is consistent with World Bank data on import flows

[32]Note Adam et al. (2018) use a value of $\bar{C}$ equal to 90 percent of baseline consumption which is in a similar range to the approach we choose.
[33]https://cbs.aw/wp/index.php/2015/09/
[34]The district's most populous town is used as the that district's centroid

and sectoral consumption shares. Similarly, we calibrate export demands X_*^j in order to match observed export shares.

4.2.3 Non-food Sector Productivities

We calibrate non-food sector productivities in order to match observed district-level farm labor shares. The HRVS provides information at the individual level on the number of hours spent on wage and self-employment in and outside agriculture during a year. We add up the total amount spent by all households members on agriculture vs non-agriculture (irrespective of being wage or self-employment) and take the share of labor hours spent on agriculture as our observed farm labor share l_{it}^F. Non-food productivity A_i^N is then set as the productivity value that rationalizes observed labor allocation choices in the model. Based on equations (12) and (13) this implies that

$$A_i^N = \frac{\alpha_l p_{it}^F A_{it}^F K_{it}^{\alpha_k}}{p_{it}^N} \left(l_{it}^F\right)^{\alpha_l - 1}$$

Thus, conditional on prices, farm productivity and capital, a smaller farm labor share l_{it}^F must be rationalized by higher productivity in the non-food sector A_i^N. Conversely, holding farm labor share constant, increases in farm productivity or food prices would increase the marginal product of farms so that maintaining the same farm labor share would only be consistent with a higher non-food sector productivity. The relative productivity of urban households ψ is calibrated so as to match the urban-rural wage gap.

4.2.4 Migration

We leverage data on district-to-district and international migration flows from HRVS to estimate scale parameters $D_{i|n}$ regulating average bilateral migration costs. The HRVS records household residence location, whether there are any migrant households members and, if so, what their destination is. This enables the construction of a migration flow matrix where each entry provides the share of households choosing each of the available destinations as their migration choice. The diagonal terms of this matrix correspond to the share of households who choose to work in their residence district, i.e. non-migrants. We calibrate the matrix of parameters $D_{i|n}$ so that the model-implied bilateral migration flows given by equation (14) match their empirical counterparts. For international migration, we use estimates from the HRVS for nominal wages for the top 3 most common international destinations. These are India, Gulf Region and Malaysia. We pool all three destinations into one destination (ROW) giving us a total of 52 potential migration destinations.

Table 2: Internally Calibrated Parameters

Parameter	Description	Source	Targeted Moment
Preferences			
β	Consumption-Saving Weight		Capital-to-Wealth Ratio
$\overline{C}$	Subsistence Consumption	HRVS	80% of 5th Percentile Consumption
Ω_F, Ω_N	Consumption Weights	HRVS	Average Food Share
Trade			
X_*	ROW Demand	WITS	Export Shares
p_*	Import Price	WITS	Import Shares
Production			
A_i^N	Non-food Sector TFP	HRVS	Farm Labor Shares
Migration			
$D_{i\|n}$	Migration Costs	HRVS	Bilateral Migration Shares

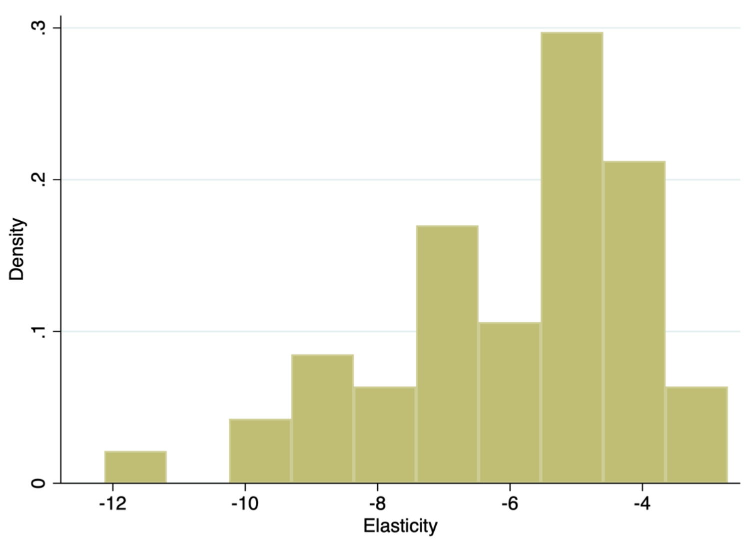
4.3 Climate shocks

As seen in Section 2, large climate shocks (including floods, landslides, cold weather, and storms)[35] as recorded by the Government of Nepal have a significant negative correlation with food prices in impacted districts, lower crop yields, and lower farm income.

While the government of Nepal does record a measure of economic damage from these shocks, this is limited in its scope to the direct effect e.g. cost of lost infrastructure, damaged crops etc. What is not recorded is the wider impact on production and prices. Instead, we infer the impact of climate shocks on agricultural productivity from price responses.

To do this, we first estimate the impact of an average large climate shock using the exercise in Section 2.3 to obtain the average treatment effect of a climate shock on food prices based on the BIPAD data. We take the value of the average treatment effect across all districts at its peak (2 months after the shock) which corresponds to a 3 percent increase in local food prices. Because the different districts operate as open economies there will not be a one-to-one relationship between the effect on prices and productivity. In general, the associated impact on productivity will be larger than that on prices since households buy goods not only from their own district but also from other districts that were not hit by the shock. To obtain a relationship between prices and productivity, we simulate a random $T = 100$ series of local idiosyncratic productivity shocks in each district,[36] feed them into the calibrated model, estimate the implied change in prices, and compute the average elasticity of productivity with respect to prices across simulated values in each district. Figure 8 shows the distribution of productivity-price elasticities across all of the districts in our sample. In the median district, a 1 percent increase in local prices is associated with a 5.4 percent drop in productivity. This means the average climate shock in our sample corresponds to a 16.2 percent reduction in productivity in the median district. Note there is substantial heterogeneity across districts with some exhibiting elasticities higher than 12 percent - more than twice that of the median district. These differences reflect spatial variation in the degree of trade openness and agricultural productivity along with other local characteristics.

Figure 8: Distribution of District-level Productivity-Price Elasticities



Notes: This figure shows model simulated elasticities of productivity with respect to prices across the 50 districts calibrated in the model.

Second, we estimate a panel of climate damages for all 50 districts measured in TFP percent annual loss. We take monthly climate shock observations from BIPAD for the period 2011-2022 and consider only large climate events, i.e. those that record damages larger than zero. To

[35]We define a large shock as any shock with a recorded value of damages greater than zero. This is because smaller shocks are less likely to receive an estimate of damage recorded by the Government of Nepal. The reason for including just this sample, is that smaller shocks may not have a measurable impact on prices, making our approach infeasible.

[36]Specifically, we simulate decreases of $x\%$ in agricultural productivity relative to the baseline economy with x drawn from a log-normal distribution with $\log x \sim \mathcal{N}(0, 0.1^2)$

make damages comparable across districts, we divide the size of damages by district population so as to obtain damages per capita. Although the damage variable is unlikely to be an accurate measure of the total extent of economic damages, we use it to obtain a measure of the *relative* magnitude of shocks across districts and time. Thus, we set the TFP loss of an event with the average damage per capita (37 Nepalese Rupees per capita) equal to the a TFP loss equivalent to the 3 percent price average treatment effect. Then, we divide per capita damages for all shocks by the average per capita damages and multiply this by the median TFP loss of 16.2%. Finally, we aggregate all monthly TFP damages recorded in any given year by compounding TFP losses throughout the year.

4.4 Determinants of food security in calibrated model

Having estimated the steady-state economy, we now establish which district-level variables correlate with the prevalence of undernourishment in the absence of climate shocks. This helps to validate the calibration as well as to identify core parameters which determine undernourishment. To do this we run a series of regressions of the district-level proportion of undernourished on a vector of district-level characteristics in steady-state. We do so using model-simulated data for the 51,000 households across 51 districts.

The first column of Table 3 shows that districts with 1 percent higher agricultural yields have on average 0.26 percent fewer undernourished households. Column 2 shows that more remote regions are also significantly more undernourished. Column 5 shows that both remoteness and agricultural productivity are independently important in determining district level undernourishment and together explain 73 percent of the variation. In a similar vein, Columns 3 and 4 show that regions with greater trade and migration access also have a lower prevalence on undernourishment (although not statistically significant in the case of migration access). However, when there are controls for agricultural yields (column 6) these both variables are statistically significant at the 1 percent level. In other words, controlling for low yields, households coping strategy of importing and migration are strongly effective in lowering undernourishment. A key takeaway is that, even in the absence of climate shocks, remoteness and agricultural productivity are important for determining the level of undernourishment.

4.5 Model simulation in response to shocks

The non-linear nature of the model prevents the derivation of closed-form solutions for the endogenous variables. In order to obtain a sense of the magnitude of the effects of productivity shocks we turn to simulations. We do this also to highlight how household human capital affects the impact of shocks on welfare and food consumption and the intensity with which each response margin is utilized. For each district, we simulate a 10 percent temporary negative shock lasting one period while keeping all other districts' productivity at their estimated baseline levels. This is meant to capture the effect of an isolated climate shock like a flood or landslide that reduces that district's harvest by 10 percent.

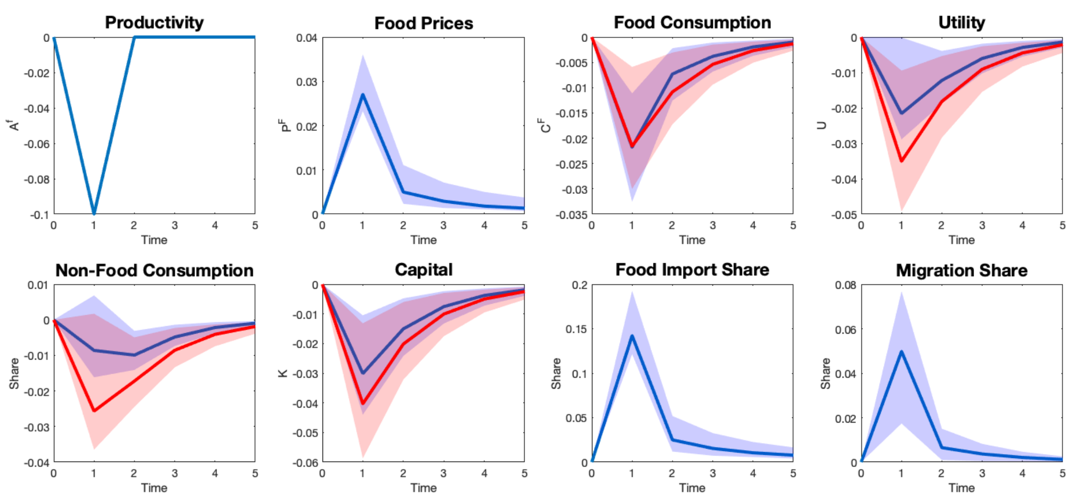
Figure 9 reports the impact of the one-off shock on some key variables for both the average household and undernourished households from the steady-state baseline economy. The blue solid line shows that in the average district, the 10 percent reduction in productivity raises food prices by 3.8 percent on impact, with considerable variation across districts. Districts that import a larger share of their food will tend to experience smaller increases in food prices since a smaller share of their food consumption bundle is affected by the shock. Moreover, conditional on the food import share, it is also the case that less remote districts are able to more easily substitute their source of food supply to other, unaffected districts, which mitigates the extent of the price increase. In reaction to the shock, the average district increases the share of food imported from other regions by almost 15 percent.

Food consumption falls on average by only 2.2 percent (or a 0.88 percent fall in calorie consumption) which is relatively small when compared to the 10 percent negative shock. This is because households employ coping strategies that aim at mitigating utility losses from food consumption. The effects of the shock are particularly pronounced for undernourished households who suffer larger overall consumption losses. Note that the fall in food consumption would have been larger for the undernourished were they not able to shift away from consumption of non-food goods as seen in the bottom-left figure.

The larger welfare losses for the undernourished (3.5 vs 2.1 percent) seen in the top-right figure can be explained by two effects. First, undernourished households spend a larger share of their budget on food and so are more sensitive to changes in food prices. Secondly, the non-homotheticity introduced by the subsistence term implies undernourished households hold a smaller capital stock buffer relative to their income before the shock and so their current resources (income plus capital stock value) will fall by relatively more, as will consumption.[37]

The shock also has the effect of lowering real non-food sector wages due to both the increase in food prices and because it depresses local demand for non-food goods. Household respond by sending additional household members to migrate, as a result the share of migrants in the household rises by 5 percent on average. Similarly to prices and the food import share, the observed variation across districts is a reflection of differences in remoteness with districts exhibiting lower costs of migration to high-wage destinations experiencing smaller decreases in income.

Figure 9: Impulse Response Functions for a -10% Productivity Shock: Average Household (Blue) vs Undernourished (Red)



Notes: Solid blue lines represent the response of the average household in the average district to a normalized shock. Solid red lines represent the response of the average undernourished household in the average district. Graphs include 5-95th percentile bans to show cross-district heterogeneity.

5 Economic Impact of Historical Climate Shocks

In this section we conduct three empirical exercises using the calibrated model. First, we feed historical climate shocks into the model to identify the average annual impact of climate shocks in Nepal. Second, we assess the role of variation in household characteristics and geography in determining the impact of shocks and the response mechanisms. Third, we simulate policy counterfactuals to estimate the effect of reductions in trade and migration costs in reducing the impact of climate shocks.

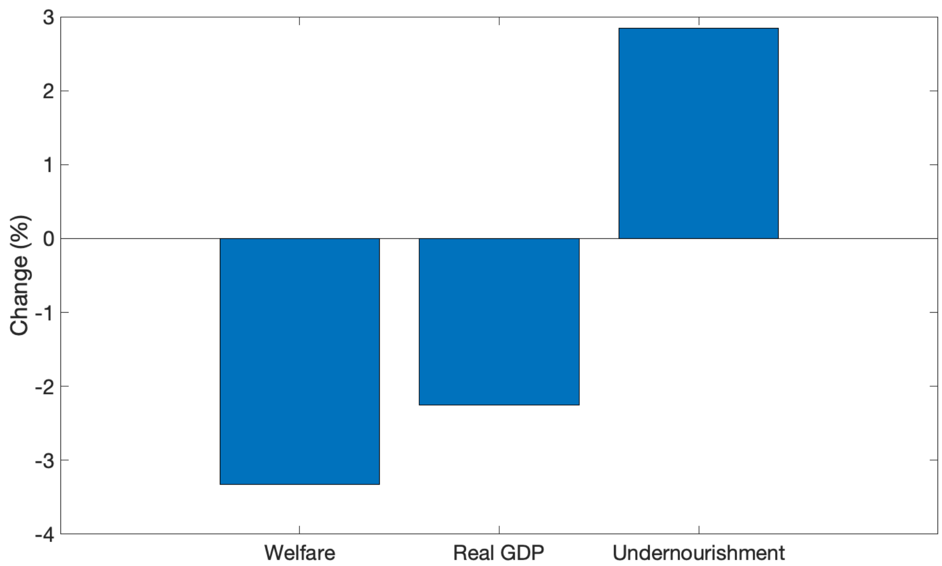
5.1 Annual Climate Damages

Figure 10 shows the average annual impact of climate shocks between 2011 and 2022 in Nepal. The figure shows the economy's values relative to the calibrated steady-state baseline economy

[37]Note this is similar to having a precautionary savings motive that is increasing in wealth. Although our intertemporal preferences specification makes no attempt to formally capture this the inclusion of the subsistence term can be seen as creating a tension between satisfying current consumption needs and saving resources for the future for the purposes of achieving higher future production but also as a precautionary savings motive. Wealthier households, by being further away from the current subsistence constraint will therefore allocate more resources towards precautionary savings under this interpretation. A formal precautionary savings motive could be added to the model with the introduction of forward-looking intertemporal preferences with, for example, a CRRA utility function.

in which district farm productivities are set to their estimated averages.[38] Due to climate shocks, agricultural yields are 5.75 percent lower on average annually across all districts with a maximum average impact of -11 percent in 2019. This translates into an average annual loss of 2.1 percent to GDP and average welfare losses of 3.1 percent. This is relatively similar to the average annual loss of 2.65 percent due to floods reported in the United Nations' WESR Risk Platform.[39] On food consumption impacts, we see a rise in the rate of undernourishment of 2.8 percent due to climate shocks over the last decade.

Figure 10: Average Annual Impact of Historical Climate Shocks, 2011-2022



Notes: This figure shows model simulated average annual climate damages, the impact on welfare, undernourishment based on historical climate shocks reported by the Government of Nepal.

The first row in Figure 11 shows the impact in each year for the period 2011-2022. The figure contains a blue line representing the median household and a shaded area for the impact range for districts between the 5th and the 95th percentile. The average impact on agricultural yields is relatively stable over time with a maximum annual impact on the median household of 8 percent in 2019 and a minimum impact of 2 percent in 2012. This translates into relatively stable losses in welfare and higher levels of undernourishment. However, while the average is stable the impact on the most impacted districts varies substantially. For instance, in 2019 the impact of climate shocks led the 95th percentile district to see almost 18 percent lower agricultural yields corresponding to a roughly 13 percent loss in welfare and 9 percent increase in undernourishment.

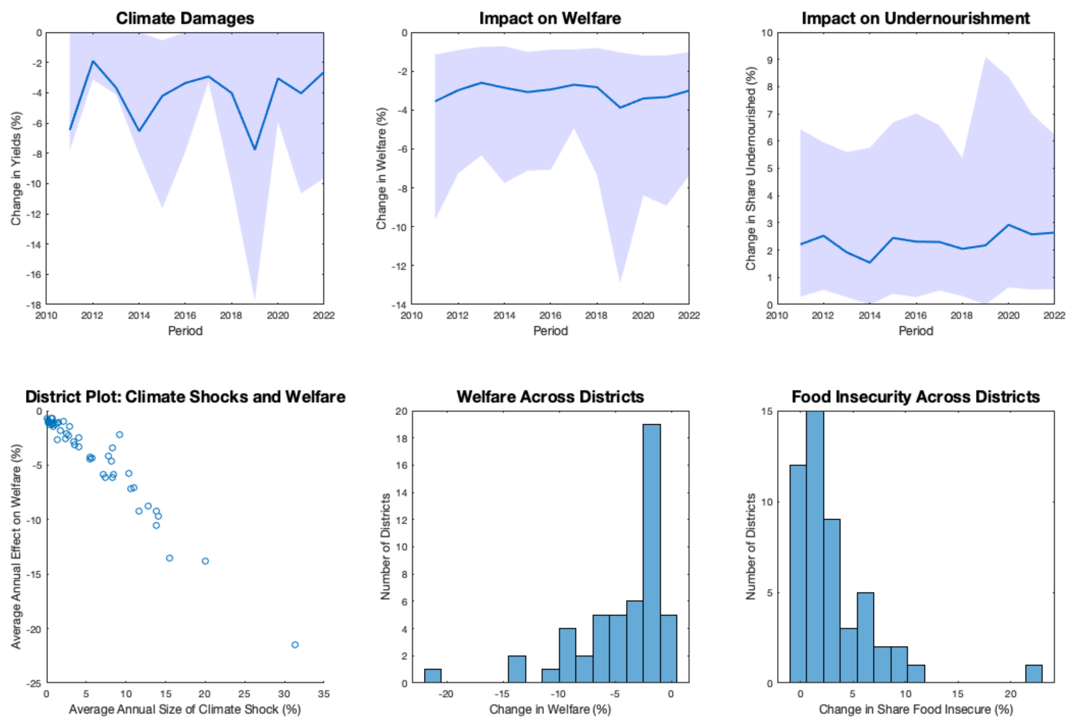
The second row shows the heterogeneity across districts in the impact of climate shocks on welfare and undernourishment. The far left chart shows a scatter plot, for each district, of the average annual size of climate shocks and the model-estimated welfare loss. It can be seen that some districts are much more exposed to climate shocks than others with 11 districts estimated to suffer average annual farm productivity losses of more than 10 percent. As one would expect, there is a very strong correlation between size of district-level climate shocks and the estimated district welfare losses. Regardless of location, a larger climate shocks will tend to cause larger damages to productivity, lower farm incomes, and larger increases in prices. However, the correlation is not perfect; some districts are able to better cope with climate shocks and suffer lower welfare losses compared to other districts with the same level of exposure to shocks. We explore the determinants of this resilience further in the next section. The chart on the far right,

[38]We acknowledge that our estimates for average farm productivities used in our baseline economy should themselves reflect the effect of climate shock occurrences. This means our loss estimates are best seen as a lower bound.

[39]This platform was developed in partnership with UNEP-Geneva. Average annual loss is a measure developed by the UN Global Assessment Report on Disaster Risk Reduction (GAR) that shows losses in terms of a probabilistic risk metric. As stated in the platform: "the average annual loss (AAL) accounts for a long-term overview of disaster risk by being the expected loss, averaged on an annual basis, that considers the occurrence of small, medium and extreme events". Although this only accounts for floods, the latter are one of the main source of climate damages in Nepal and are often associates with landslides too.

shows the district-level impact on undernourishment from historical climate shocks. Although many districts see relatively small changes in their rate of undernourishment a large number of them appear to be highly vulnerable with increases in undernourishment rates of more than 5 percent in roughly a quarter of districts. The presence of significant district heterogeneity is important as it highlights that food security and climate vulnerability can vary significantly at a sub-national level and emphasises the need for a framework which incorporates geographic variation.

Figure 11: Impact of Historical Climate Shocks across Districts and Time, 2011-2022



Notes: This figure shows model simulated climate damages, the impact on welfare, undernourishment, and the distribution of damages across districts based on historical climate shocks reported by the Government of Nepal. The solid blue line indicates the average impact across districts. Graphs include 5-95th percentile bans to show district heterogeneity.

5.2 Determinants of Vulnerability

This section explores the key determinants of shock vulnerability using the model simulated data. We begin by showing the overall welfare effects of climate shocks in Figure 12 distinguishing between undernourished and food secure households, and between remote and non-remote districts. We define remoteness as the population-weighted average distance to other districts. More formally, remoteness in district n is

$$remoteness_n = \sum_{i \neq n} dist_{ni} L_i$$

which is meant to capture a district's general level of access to other locations which is meant to capture both the ability to trade and migrate to the extent the costs of the latter increase with distance. A district is defined as remote if it exhibits a level of remoteness in the 30 percent of districts. As seen in Figure 12, households in remote districts suffer welfare losses at the hands of climate shocks that are 2.04 times that of non-remote districts. Undernourished individuals are also in a more vulnerable position with welfare losses of 4.3 percent, which are 1.54 times those of food secure individuals.

Note that the variation in welfare losses combines variation in both the magnitude of local climate shocks and in households' ability to cope with shocks. It may be the case, for example, that more remote and undernourished households are more exposed to climate shocks and this is what is driving differences in welfare losses. In order to control for average climate shock size and investigate how undernourishment and remoteness affect household vulnerability we consider the following regression specification for household h in district c at time t via OLS

$$\Delta \log(U_{hct}) = \alpha \Delta \log(A_{ct}) + \Gamma' \Delta \log(A_{ct}) \cdot \mathrm{D}_c + \Lambda' \Delta \log(A_{ct}) \cdot \mathrm{H}_h + v_{ict} \tag{18}$$

where D_c is a vector of district-level variables and H_{it} is a vector of individual-specific characteristics which are interacted with the change in productivity due to climate shocks $\Delta \log(A_{ct})$. The regression aims at understanding the factors that determine the responsiveness of welfare to changes in local agricultural productivity. Higher responsiveness indicates more vulnerability holding fixed exposure to climate shock. We include in our vector of district-level variables D_c local agricultural productivity, remoteness, trade access, and migration access. Importantly, all these variables are invariant to productivity shocks so they should be seen as baseline characteristics of districts.

In order to attempt to separate the effects of trade and migration costs we define market access and migration access, respectively, based on the model's equilibrium equations. Based on the model, and following Redding and Sturm (2008), we define market access as

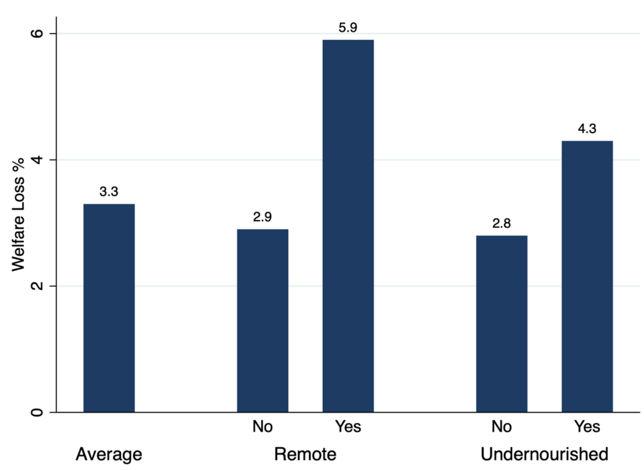
$$marketaccess_n = \sum_{i=1}^{N+1} \tau_{ni}^{1-\sigma} (P_i^F)^{\sigma-1} X_i^F \ .$$

The market access variable is similar in spirit to the remoteness variable above in that it is a weighted average of bilateral distances. Here, instead, we apply a decay rate to distances based on the estimated elasticity of trade flows $\zeta(1-\sigma)$ and account for the degree of multilateral resistance as captured in $(P_i^F)^{\sigma-1}$ (Anderson and Van Wincoop, 2004). We also weigh distances by food expenditures rather than population. Note that we also include the rest of the world in the summation. In a similar fashion, we define migration access as

$$migrationaccess_n = \left(\sum_{i \neq n}^{N+2} B_{i|n} \left(\frac{w_i}{P_i} \right)^{\lambda} \right)^{\frac{1}{\lambda}} .$$

which is the same as the expected net wage earned by a household living in district n while excluding the option to remain in the district to work. Thus, it attempts to capture the expected net wage earned conditional on migration. The summation includes migration to the foreign economy. Both market and migration access are fixed throughout the sample and they are computed for the baseline economy.

Figure 12: Welfare Loss from Climate Shocks by Remoteness and Undernourishment, 2011-2022



Notes: This figure shows model simulated average annual welfare loss from climate damages discriminating between households living in remote vs non-remote areas, and between households who are undernourished in the baseline economy and those who are not. Estimates based on historical climate shocks reported by the Government of Nepal.

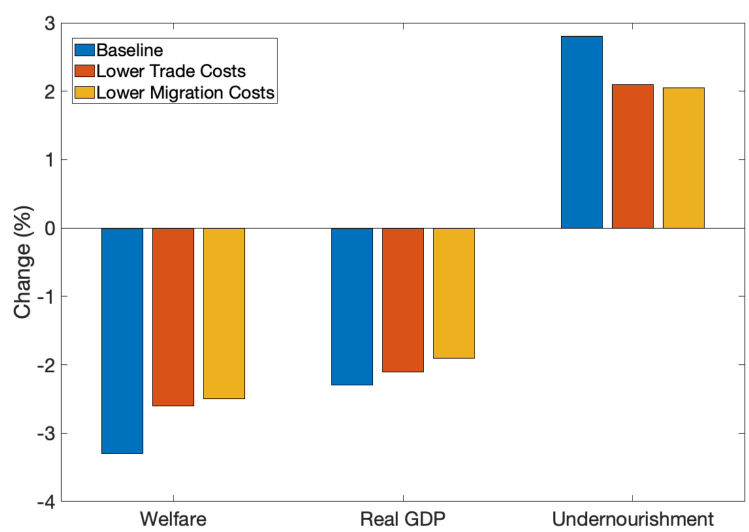
For household-level variables H_h, we use a dummy denoting whether or not the household is undernourished in the baseline economy.

Table 4 shows the regression results and confirms that both undernourishment status and remoteness significantly raise vulnerability. The table shows that conditional on the size of the shock, being in an undernourished status increases the responsiveness of log utility to the shock from -0.013 to -0.020, a 54 percent increase in magnitude. Similarly, households in remote districts exhibit a responsiveness of -0.023 which is 54 percent larger that their counterparts in non-remote districts. By contrast, agricultural productivity reduces the magnitude of the shock as households have larger buffers and so do not need to resort to more damaging mitigation strategies.

Table 5 extends the previous table to show how different coping strategies - trade access, migration access, agricultural productivity - interact with a dummy variable for being undernourished. In all three instances, undernourished households benefit more than food secure households from access to these coping mechanisms. The reason for this is that these households have lower capital buffers to absorb the shock, meaning access to other coping strategies are particularly important in order to avoid further cutting consumption or drawing down assets.

5.3 Policy counterfactuals

Figure 13: Effect of Improved Infrastructure on Welfare Losses from Climate Change



Notes: This figure shows model simulated average annual climate damages, the impact on welfare, undernourishment based on historical climate shocks reported by the Government of Nepal under baseline and under two counterfactual scenarios - lower trade costs and lower migration costs.

In this section, we utilize the calibrated model to consider three different policy counterfactuals which have been proposed as methods to mitigate food insecurity and the damage from climate shocks. First, we model the impact of 10 percent reduction in migration costs $D_{i|n}$ for all migration destination in Nepal and abroad in every district. This could be achieved through improved transport infrastructure, provision of information to migrants, reducing the costs of sending remittances, or via providing migrant support centers in migrant destinations.[40] Second, we model the impact of lower trade costs by reducing iceberg trade costs τ_{in} by 10 percent for all pairs (i, n) of Nepali districts. This could be achieved through, for instance, improved road, air, or rail infrastructure and has been a focus of the Nepal government (National Planning Commission, 2023).[41]

The average annual impact of the two policies is shown in Figure 13. Note that both these policies generate two types of effects. First, they generate changes in the baseline economy. By lowering trade costs and/or migration costs, real incomes rise for any given productivity level which pushes households away from subsistence consumption and more of their budget

[40]The Nepal government has undertaken many of these reforms, see Ministry of Labour, Employment and Social Security (2022) for details.

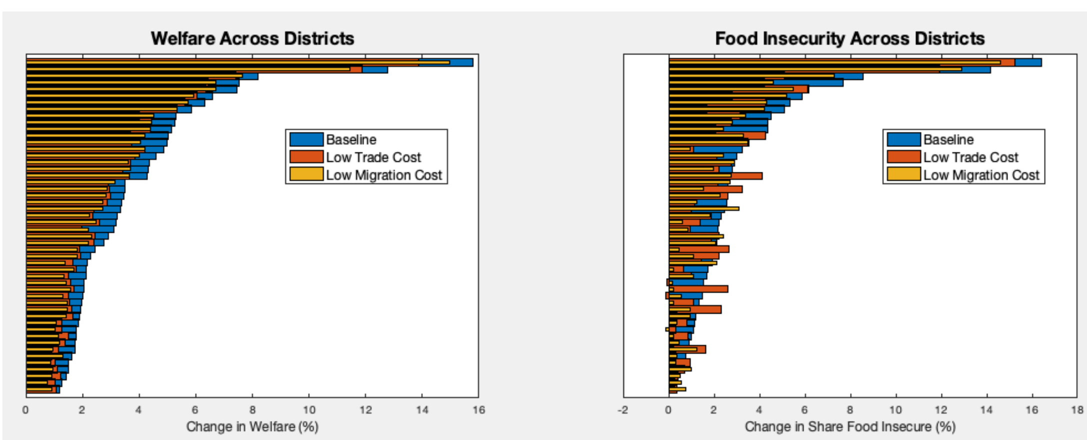
[41]In an accompanying policy paper we also considered the impact of cash transfers in Nepal showing that well targeted cash transfers following shocks can significantly mitigate the damage and persistence of climate shocks (Baptista et al., 2023). In a seperate related paper we also considered the impacts of irrigation and access to finance (Baptista et al., 2022)

towards non-food purchases which reduces their vulnerability to climate shocks. Second, the lower trade and migration costs change the way households are affected by shocks by reducing the cost of accessing alternative sources of income (migration) and goods (trade). Importantly, it is also possible that reductions in spatial frictions raise the vulnerability of some households to climate change. This is because districts may become more exposed to external shocks with the integration of goods and labor markets. In particular, districts that are not directly exposed to large climate shocks but that trade intensely with highly affected districts are at higher risk of experience welfare losses from trade integration

The results reported in Figure 13 represent the combination of these two effects. The two policy interventions have quite similar effects on average outcomes. Under either 10 percent lower trade costs or 10 percent lower migration costs the welfare impact of shocks is reduced on average from 3.3 percent to approximately 2.7 percent (a reduction by a factor of 0.18). Rates of undernourishment are reduced by a factor of almost a third falling from a 2.8 percent to a roughly 2 percent rise at the hands of climate shocks.

In Figure 14 we also show how the impact of the infrastructure improvements are distributed across districts. All districts experience smaller welfare losses although some see larger relative reductions than other, likely as a function of their initial level of openness to trade and migration. Rates of undernourishment, on the other hand, do not fall in all districts. In fact, 18 percent of districts see an increase in undernourishment at the hands of lower trade costs while 16 percent see an increase at the hands of lower migration costs. This suggests these policies have important distributional effects even within districts, with poorer households potentially harmed by improvements in infrastructure. This may be in part due to increased risk exposure induced by cross-district spillovers that make households more vulnerable to external shocks. Since more food-insecure households spend a larger share of their budget on food, they will be more sensitive to such cross-border spillovers.

Figure 14: Effect of Improved Infrastructure on Welfare Losses from Climate Change by District



Notes: This figure shows model simulated average welfare losses from climate shocks by district based on historical climate shocks reported by the Government of Nepal under baseline and under two counterfactual scenarios - lower trade costs and lower migration costs.

6 Conclusion

Climate change is set to permanently increase the prevalence and severity of weather shocks which will inevitably inhibit the world's ability to produce and distribute food and will lead to large and persistent impacts on poverty, food insecurity and growth. Understanding the magnitude of the issue, which households are the most vulnerable and how household response mechanisms can lead to large macroeconomic outcomes is therefore essential.

We develop a new quantitative spatial framework which allows us to incorporate two important sources of heterogeneity - household and remoteness. Using the calibrated model we show that (i) climate shocks are already having large negative impacts on GDP, nutrition and welfare, (ii) these impacts are disproportionately harming those households which are remote and food insecure, (iii) poverty and food insecurity exacerbates the impact of shocks. We go on to show that policy to lower the cost of trade and migration can lower the impact from climate shocks by allowing households alternative sources of income and affordable food. However, not all households will benefit due to the complex price and income effects induced by changes in spatial frictions.

From a broader perspective, our paper studies the impacts of climate shocks on food insecurity and welfare in a framework where households can trade, migrate and send remittances across regions. Distinct from much of the existing literature, we study not only the steady-state responses to changes in parameters but also the effects of temporary shocks. In this way, we can study the damage and persistence of climate shocks over time and space. A potential avenue for future research would be to extend this framework to multiple countries to study the resilience gained through open and regional trade and the dangers from countries adopting trade restrictions in food products.

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A Empirical Appendix

Table 3: Determinants of Prevalence of Undernourishment

	(1) Undernourished	(2) Undernourished	(3) Undernourished	(4) Undernourished	(5) Undernourished	(6) Undernourished
Agricultural productivity	-0.162***				-0.148***	-0.130***
	(0.0147)				(0.0147)	(0.00977)
Remoteness		0.0881***			0.0389***	
		(0.0234)			(0.0142)	
Trade access			-0.109***			-0.0655***
			(0.0156)			(0.00785)
Migration access				-0.0471		-0.0402***
				(0.0449)		(0.0148)
N	50	50	50	50	50	50
r2	0.717	0.227	0.504	0.0224	0.756	0.900

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Regression uses model-simulated data for each of the districts in the sample. All variables are in steady-state at the district-level. The outcome variable is the proportion of undernourished, agricultural productivity is the log of farm productivity, remoteness is the population weighted-distance to all other Nepali districts, trade access is a weighted-distance to other Nepali districts including a decay rate of distance based on the elasticity of trade, migration access is the expected net wage earned by a household living in district n if they were to migrate.

Table 4: Which Factors Impact Climate Vulnerability?

	(1)	(2)	(3)	(4)
	Utility	Utility	Utility	Utility
Climate shock	-0.0129***	-0.0150***	-0.0415***	-0.0394***
	(0.0000725)	(0.0000573)	(0.000157)	(0.000188)
Undernourished=1 × Climate shock	-0.00691***			-0.00364***
	(0.000118)			(0.000114)
Climate shock × Remoteness		-0.00808***		0.000167
		(0.000109)		(0.000116)
Climate shock × Agricultural productivity			0.0312***	0.0304***
			(0.000177)	(0.000199)
HouseholdFE	Yes	Yes	Yes	Yes
N	351000	351000	351000	351000
r2	0.724	0.725	0.747	0.747

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Regression uses model-simulated data for each of the 1000 households in each of the 51 districts over each of year 2010-2022 in the sample. The outcome variable is the household utility at time t, climate shock is the household change in productivity due to climate shock in period t, undernourished is a dummy equal to 1 if the household is below the calorie threshold for being undernourished, agricultural productivity is the log of farm productivity, remoteness is the population weighted-distance to all other Nepali districts, trade access is a weighted-distance to other Nepali districts including a decay rate of distance based on the elasticity of trade, migration access is the expected net wage earned by a household living in district n if they were to migrate.

Table 5: How Does Being Undernourished alter Effectiveness of Coping Strategies?

	(1) Utility	(2) Utility	(3) Utility	(4) Utility
Climate shock	-0.0370***	-0.0130***	-0.0137***	-0.0342***
	(0.000212)	(0.0000701)	(0.0000744)	(0.000268)
Undernourished=1 × Climate shock	-0.00904***	-0.00389***	-0.00625***	-0.00717***
	(0.000316)	(0.000117)	(0.000120)	(0.000403)
Climate shock × Agricultural productivity	0.0276***			0.0248***
	(0.000230)			(0.000310)
Undernourished=1 × Climate shock × Agricultural productivity	0.00670***			0.00580***
	(0.000366)			(0.000475)
Climate shock × Trade access		0.0106***		0.00562***
		(0.000105)		(0.000118)
Undernourished=1 × Climate shock × Trade access		0.00373***		0.00142***
		(0.000174)		(0.000199)
Climate shock × Migration access			-0.0108***	0.00594***
			(0.000250)	(0.000288)
Undernourished=1 × Climate shock × Migration access			0.00846***	0.00300***
			(0.000389)	(0.000427)
HouseholdFE	Yes	Yes	Yes	Yes
N	351000	351000	351000	351000
r2	0.748	0.741	0.725	0.753

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Regression uses model-simulated data for each of the 1000 households in each of the 51 districts over each of year 2010-2022 in the sample. The outcome variable is the household utility at time t, climate shock is the household change in productivity due to climate shock in period t, undernourished is a dummy equal to 1 if the household is below the calorie threshold for being undernourished, agricultural productivity is the log of farm productivity, remoteness is the population weighted-distance to all other Nepali districts, trade access is a weighted-distance to other Nepali districts including a decay rate of distance based on the elasticity of trade, migration access is the expected net wage earned by a household living in district n if they were to migrate.

Table 6: Variable Description

	Description
Crop yield	Natural log of household crop yield
Crop income	Natural log of household income from crops
Livestock income	Natural log of household income from livestock
Food insecure dummy	=1 if household is categorised by World Bank as food insecure
Food insecurity score	Index of food security which assigns a value between 0 and 3 on four categories. High number indicates less secure.
Expenditure	Natural log of total household expenditure
Food expenditure	Natural log of household food expenditure
Non-food expenditure	Natural log of household food expenditure
Food expenditure share	Food expenditure divided by total expenditure
Migrant dummy	=1 if any household member is a migrant in the sample period
Number of migrants	Count of migrants in household
Remittance share of income	Remittances divided by total income
Savings	Natural log of savings
Capital equipment	Natural log of farm equipment holdings
Capital Livestock	Natural log of livestock holdings
Savings rate	Savings divided by income
Price	Natural log of price in NPR
Climate shock	=1 if district has recorded flood, heavy rainfall, landslide, or storm in month

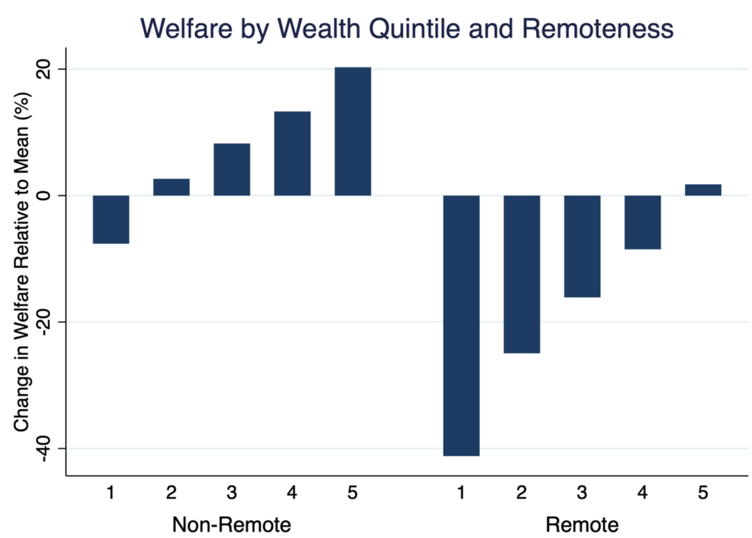
Table 7: Descriptive Statistics

	Mean	SD	Min	Max	N
Household-level					
Crop yield	2.02	0.73	-4.53	9.28	13,977
Crop income	8.70	1.35	-2.75	15.51	9,890
Livestock income	9.53	1.28	2.08	14.81	3,407
Food insecure dummy	0.14	0.35	0.00	1.00	16,951
Food insecurity score	0.69	2.10	0.00	24.00	16,951
Expenditure	11.17	0.83	7.76	16.18	16,951
Food expenditure	9.58	0.83	5.56	13.60	16,774
Non-food expenditure	10.83	0.94	7.28	16.18	16,951
Food expenditure share	0.26	0.17	0.00	0.94	16,951
Migrant dummy	0.46	0.50	0.00	1.00	16,951
Number of migrants	0.35	0.52	0.00	2.89	8,380
Remittance share of income	0.10	0.18	0.00	1.00	16,276
Savings	10.59	1.45	0.75	15.50	5,452
Capital equipment	7.91	1.28	1.61	14.65	9,442
Capital Livestock	8.73	1.45	3.40	14.00	2,305
Savings rate	0.48	0.25	0.00	1.00	5,452
District-level					
Price	4.50	0.84	1.95	6.91	14,394
Climate shock	0.14	0.35	0.00	1.00	14,394

B Interaction of Remoteness and Undernourishment

We also report in Figure 15 how household wealth and district remoteness interact in determining resilience to shocks. The figure shows the welfare impact of historical climate shocks on different remote and non-remote wealth quintiles relative to the mean change in welfare. For instance, the bar on the far left of the figure shows that the bottom wealth quintile of non-remote households has on average 8(?) percent larger decline in welfare than the average household. This is because wealth is a key buffer which allows households to avoid more damaging coping strategies such as selling off assets which impacts future production. All other non-remote household's perform better than the average household.[42] This is because being connected allows the household to use alternative coping strategies including accessing trade and migration and avoiding more damaging responses. By contrast, quintiles 1-4 among remote households all have larger welfare losses than the average. Those households which are both the most remote and poorest see, on average, 40 percent larger losses in welfare than the average in the whole sample, compared to the poorest households in non-remote districts.

Figure 15: Relative welfare impact by wealth and remoteness



Notes: This figure shows model simulated average changes in welfare due to climate shocks relative to the mean change in welfare among different wealth quintiles disaggregated in the top XX percent of remoteness districts. For example, the bar on the far left shows that the bottom wealth quintile in non-remote districts were more negatively impacted than the average household in the country, whereas the next four quintiles in non-remote districts were less negatively impacted than the average household in the country.

[42]Note these households still see a decline in welfare in absolute values.

PUBLICATIONS

Coping with Climate Shocks: Food Security in a Spatial Framework

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