Deep Impact: Geo-Simulations as a Policy Toolkit for Natural Disasters

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Abstract

Adverse post-natural disaster outcomes in low-income regions, like elevated internal migration levels and low consumption levels, are the result of market failures, poor mechanisms for stabilizing income, and missing insurance markets, which force the affected population to respond, and adapt to the shock they face. In a spatial environment, with multiple locations with independent but inter-connected markets, these transitions quickly become complex and highly non-linear due to the feedback loops between the micro individual-level decisions and the meso location-wise market decisions. To capture these continuously evolving micro-meso interactions, this paper presents a spatially-explicit bottom-up agent-based model to analyze natural disaster-like shocks to low-income regions. The aim of the model is to temporally and spatially track how population distributions, income, and consumption levels evolve, in order to identify low-income workers that are "food insecure". The model is applied to the 2005 earthquake in northern Pakistan, which faced catastrophic losses and high levels of displacement in a short time span, and with market disruptions, resulted in high levels of food insecurity. The model is calibrated to pre-crisis trends, and shocked using distance-based output and labor loss functions to replicate the earthquake impact. Model results show, how various factors like existing income and saving levels, distance from the fault line, and connectivity to other locations, can give insights on the spatial and temporal emergence of vulnerabilities. The simulation framework presented here, leaps beyond existing modeling efforts, which usually deals with macro long-term loss estimates, and allows policy makers to come up with informed short-term policies in an environment where data is non-existent, policy response is time dependent, and resources are limited.

Keywords: agent-based model, GIS, migration, food insecurity, Pakistan, earthquake

1. Introduction

According to the latest Global Assessment Report on Disaster Risk Reduction (UNISDR 2015), in the last three decades alone, over 1.6 million people have died as a result of natural disasters, of which 80% reside in low- and middle-income countries. Additionally, the total population displaced between 2008 and 2015 is estimated to be 26.4 million of which 95% live in low-income regions (IDMC 2015). 80% of the population in disaster-prone regions is considered food insecure and depends on agriculture as a main source of livelihood, a sector that is highly vulnerable to disaster-like shocks (FAO 2013; UNU-EHS 2015; WFP 2015; FAO 2015).

Adverse post-shock outcomes in low-income regions, like elevated internal migration levels, and low consumption levels are the result of market failures, poor mechanisms for stabilizing income, and missing insurance markets, which force the affected population to respond, and adapt to the shock they face (Kahn 2005; Kellenberg and Mobarak 2008; Noy 2009; Cavallo and Noy 2010; Schumacher and Strobl 2011). If individuals and markets are able to hedge against the shock, or policies are efficiently implemented, then vulnerabilities can be better managed and adverse post-shock outcomes can be contained (Dückers et al. 2015). Reasons for poor policy responses in low-income regions are the lack of, first, reliable pre- and post-natural disaster data on various disaster related indicators and, second, effective policy planning tools that allow for some reasonable prediction of post-natural disaster outcomes in the short-run (Okuyama 2007; Toya and Skidmore 2007; Noy 2009; Cavallo and Noy 2010).

Literature suggests that any tool that aims to analyze shocks scenarios, especially in the short-run, needs to address three key issues: time, geography, and feedback loops (Okuyama 2007). In order to construct a useful modeling framework, the processes following a natural disaster scenario need to be systematically understood and modeled. Natural disasters can have direct and indirect (or second-round) effects. The direct effects are the immediate losses resulting from the destruction of productive capital and loss of human life (Skoufias 2003). In a natural disaster setting, these immediate losses to output and labor, are not uniformly distributed across a region. The highest damage is near the epicenter, which dissipates as one moves away from the origin of the shock. Assuming markets exhibit stable trends pre-shock, a sudden, spatially-localized change in capital and labor ratios results in an immediate disequilibrium in one part of the region. As a consequence of these sudden losses, the regional economy enters into a second-round adjustment phase where labor and goods (assuming capital stock is fixed in the very short-run) respond to gaps created by the shock. Labor and goods respond to market signals from across the region, causing the economy to transition to a new equilibrium, and in the process, potentially cascading the shock to the rest of the region. As a result, new or additional vulnerabilities can be created, such as low consumption levels resulting from either low incomes caused by excess labor supply, or rising food prices caused by output losses, or a combination of both. In a spatial environment, with multiple locations with independent but inter-connected markets, these transitions quickly become complex, and highly non-linear, due to the feedback loops between the micro individual-level decisions and the meso location-wise market decisions.

To deal with these complex transitions, this paper presents an application of a spatially-explicit agent-based model (ABM), or a "geo-simulation", of spatial non-linear adjustment processes following a natural disaster-like shock scenario. The goal of this model is to allow policymakers to identify levels of displacement and spatial clusters of "food insecure" populations in low-income regions following a natural disaster-like shock scenario. This leaps beyond the existing modeling efforts on natural disasters that usually deal with macro aggregated loss estimates in the long-run.

Standard modeling tools, for example Input-Output models, CGE models, and Social Accounting Matrices (SAMs), lack the ability to analyze heterogeneous and spatial micro and meso level impact of shocks, and the short-run adjustment processes where vulnerabilities can emerge in short time span.

This paper builds on the agent-based model presented in Naqvi and Rehm (2014) where the interaction of six decision-making modules – *Production, Wages, Consumption, Buying, Selling, Migration* – form a complete economy with decentralized labor and goods markets with a focus on the decision making process of low-income workers. The original model is extended through two channels. First, market interactions are updated to allow for a more innovative search algorithm which allows supply networks to continuously adapt to a changing environment. Second, the model allows for a more dynamic migration decisions through endogenous location-wise probability assignments which go through several iterations to avoid completely arbitrary outcomes. In addition to updating the two behavioral rules, the model is extended to allow for incorporation of actual GIS data, bringing it one step closer to actual policy analysis.

The model framework is applied to the 2005 earthquake in Pakistan which resulted in a massive loss of output and human life. A large fraction of the population was displaced while majority of the inhabitants in the region were left "food insecure" within weeks of the earthquake shock (ADB-WB 2005; ERRA-UN 2006). The region required immediate policy response to target vulnerable populations especially those facing food insecurity, but lacked reliable data for evidence-based policy planning. This region is selected for two reasons. First, the region is fairly closed, both geographically and economically, comprising a large rural agrarian sector with simple economic dynamics and decision-making rules which are easy to implement in an agent-based modeling environment. Second, baseline data on population ratios, income, and consumption levels for pre-shock trends exists allowing for model calibration. Additionally, the event was an isolated large-scale natural disaster incident in 2005 which received unprecedented attention in the aftermath from local and international organizations. Given the focus on the region, the level of aid disbursed, and the involvement of various national and international disaster management institutions in this "best-case" scenario response, the effectiveness of policy response is still being debated a decade after a earthquake.[2]

The model is set up using actual GIS data on village and city locations, and road networks. Using the actual location of the fault line, the spatially-defined artificial economy is subjected to a calibrated earthquake-like shock to determine loss of output and labor. Model results are spatially and temporally tracked on demographic changes, and on changes in income and consumption patterns which allow for identification of food insecure populations in the short-run. The results show how geo-simulations can provides one plausible way of replicating natural disaster-like shock scenarios in a lab like setting for a more informed policy planning in a short-run setting where data is non-existent, policy response is time dependent, and resources are limited.

The remaining paper is structured as follows. Section 2 discusses relevant literature and the role of geo-simulations in the analysis of natural disasters. Section 3 presents stylized facts from the 2005 earthquake affected region of northern Pakistan. Section 4 describes the model framework and behavioral rules in detail. Section 5 presents the simulations setup and Section 6 gives the results of the earthquake experiment. Section 7 concludes.

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[2]See, for example, a recent 2016 newspaper article: "Remembering Oct 8, 2005: The day the earth shook", URL: http://www.dawn.com/news/1211695.

2. Literature

Two broad strands of literature are discussed in this section. The first strand discusses existing modeling efforts of natural disasters and the related empirical literature, both of which focus on a long-period analysis. The second strand summarizes the literature on micro household adaptation strategies in the face of natural disaster-like shocks. The last subsection provides a rationale for using geo-simulations as a modeling tool that can fill in the short- to medium-run gap for disaster related policy planning.

2.1. Models of natural disasters and long-period analysis

Existing modeling frameworks on natural disasters focus on long-run loss estimations using three popular techniques; Input-Output (I-O) models, Computational General Equilibrium (CGE) models, and Social Accounting Matrices (SAMs). I-O models of natural disasters stem from the pioneering work of Dacy and Kunreuther (1969) and focus on long-run direct and indirect loss estimations. While the initial I-O models focused mainly on western high-income economies (Cochrane 1974; Wilson 1982; Rose and Benavides 1998; Cho et al. 2000), focus quickly shifted to other parts of the world (for example, the 1995 Kobe earthquake and the 2004 Indian Ocean Tsunami Okuyama (2004, 2007)). These models were later expanded to accommodate inter-regional dependencies as more data became available (Okuyama and Santos 2014). I-O models have been criticized on restrictive assumptions of linearity, and lack of sensitivity to parameter changes. As a result they assume very little adaptation in behavior to shock-like scenarios and tend to over-estimate economic losses (Rose 2004).

To overcome some of these limitations, Computational General Equilibrium (CGE) models were introduced in the 2000s and have been extensively used in disaster analysis at the national (Ueda et al. 2001; Rose and Guha 2004; Rose and Liao 2005) and at the regional level (Tsuchiya et al. 2007; Hallegatte and Ghil 2008; Hallegatte and Dumas 2009). CGE models in their standard formulation of optimizing firms and households assume a long-run steady-state equilibrium which is achieved through smooth transitions based on agile reactions. Therefore, the models tend to estimate rather minimal losses. The issue, of whether households and firms even optimize in a highly uncertain environment, has been raised several times in literature (Rose 2004; Okuyama 2007).

To further advance modeling efforts, a third wave of models based on Social Accounting Matrices (SAMs) were developed to bring in some of the structural aspects of economies which dealt with inter-sectoral interactions, for example between households and firms (Cole 1995, 1998, 2004). While SAMs handle distributional aspects of natural disasters better than earlier modeling tools, they also suffer from fixed parameters bounding estimates at the upper end, and do not factor in supply side constraints, which tend to restrict estimates (Okuyama 2007; Okuyama and Sahin 2009).

Analysis of disaster affected regions has been further boosted due to a growing consensus to push for more research on disaster-affected low-income regions (Toya and Skidmore 2007; Cavallo et al. 2013), and due to the availability of standardized longitudinal data sets which makes systematic empirical analysis possible (for example, the widely used CRED database EM-DAT 2016). Furthermore, the development of the modeling literature introduced several hypotheses for further testing which has resulted in a growing body of empirical literature in the last two decades. For example, Albala-Bertrand (1993) introduces three key hypotheses that have been extensively tested. First, the impact of natural disasters is small in the aggregate but sufficiently large at the

regional level. Second, the magnitude of the shock, its impact, and the level of social vulnerability are heterogeneous, and spatially and temporally distributed. Third, the shock impacts the most vulnerable parts of the economy – the low-income unskilled workers and low-quality productive capital – the most.

The empirical literature based on these models usually discusses the extent of the negative impact of natural disasters on output and growth (Toya and Skidmore 2007; Noy 2009). However, several studies show that the impact is restricted to certain regions and do not necessarily affect the overall economy (Horwich 2000; Strobl 2012; Loayza et al. 2012), or are just limited to short-run variations without having a significant long-run impact (Raddatz 2007; Felbermayr and Gröschl 2014). Some studies also claim that natural disasters allow for positive long-run growth due the "creative destruction" process where policy planners can reconfigure the economy to achieve higher growth trajectories in the future (Skidmore and Toya 2002; Hallegatte et al. 2007; Hallegatte and Dumas 2009).

This ambiguity of the impact of natural disasters on economies, both in the long-run and at the national level, has prompted for a more refined analysis at the micro level where individual behavioral decision-making and meso level institutions need to be studied further to understand which factors exacerbate losses or allow regions to be resilient towards natural disasters.

2.2. Micro adaptation studies

Several micro empirical studies have looked at *ex-post* household income and consumption smoothing strategies (Morduch 1995) following a natural disaster like scenario based on Friedman's (Friedman 1957) permanent income hypothesis (PIH) (see Auffret 2003 for a comprehensive review of literature on post-disaster coping strategies). The literature tests the conditions under which the PIH hypothesis holds especially in the absence of formal insurance mechanisms. Three short-term household strategies are prominent within this literature; precautionary money savings, holding food inventories, and internal regional migration.

Precautionary money savings are key to consumption smoothing in the absence of formal financial services and can provide quick liquidity in the short-run (Deaton 1991; Paxson 1992; Udry 1995). These can also take the form of investment in productive assets, for example livestock (Townsend 1994), and are preferred over informal loans with high interest rates (Chaudhuri and Paxson 2002). Several studies also highlight the role of food inventories in areas with poorly functioning food markets (Townsend 1994; Lim and Townsend 1998). Literature also highlights this as an imperfect mechanism for consumption smoothing that only allows households to hedge against minor shocks in the short-run (Auffret 2003; Kazianga and Udry 2006; Park 2006).

A third strategy discussed in literature is internal regional migration to ensure income and consumption smoothing. The standard "push–pull" model of migration (Harris and Todaro 1970; Todaro 1980) suggests that real income differences across locations incentivizes workers to move around equalizing real income levels in the absence of barriers. Short-run internal migration has been highlighted in literature as a coping mechanism to ensure a continuous income stream (Rosenzweig and Stark 1989; Borjas 1994; Beegle et al. 2011) especially in a post-shock scenario when households might not have enough resources to move outside the region (Halliday 2006).

2.3. Why geo-simulations?

Meso and macro outcomes emerges through the interaction of individuals which then feedback on individual decisions. The result of this process is a complex adaptive system which exhibits path dependency and non-linearity (Schelling 1978; Holland and Miller 1991). In the type of spatial

economy that is presented in this paper, multiple locations feature their own decentralized goods and labor markets, and interact with each to form a complete economic system. Therefore changes in one part of the region can have repercussions on the rest of the system resulting in complex adjustment processes.

ABMs allow for easy incorporation of such feedback mechanisms at the micro, meso, and the macro level which entails a bottom-up approach where agents iteratively solve complex non-linear economic problems using simple decision making rules in a way that might not be possible using optimization techniques (Axtell 2000; Borrill and Tesfatsion 2011). Such a framework provides a powerful tool for conducting a natural disaster-like shock experiment. The lab setting allows establishing counter-factual scenarios that can help general probabilistic post-shock outcomes that can inform policy especially in the absence of any reliable data. Additionally, a salient feature of ABMs is their ability to incorporate a spatial dimension to understand how patterns unfold across various parts of an economy (Axtell 2000; Farmer and Foley 2009). They are a powerful tool that allows simulating out-of-equilibrium states in a spatially defined decentralized multi-market framework (Schelling 1978; Epstein and Axtell 1996; Epstein 1999; Tesfatsion 2006; Farmer and Foley 2009). Integration of geographical information systems (GIS) makes it possible to use actual locations and road networks to represent a real world setup. Such a model can be calibrated using baseline data to validate it against empirical benchmarks. If it is found to replicate actual outcomes accurately, it can then be used to investigate the process through which outcomes in disaster scenarios might emerge and, thus, what could be entry points for policy responses.

3. Stylized Facts from the 2005 Pakistan Earthquake

In October 2005, the northern region of Pakistan was hit by a massive earthquake measuring 7.6 on the Richter scale. Figure 1 shows the detailed geographical setup of the earthquake affected region. Large dots represent three major cities – Muzaffarabad, Mansehra, Abbottabad – in the selected region, small dots represent villages, while major road networks are shown as lines networks.

The shock originated along the fault line between the Eurasian and Indian tectonic plates which spans 300 kilometers in a south-east direction (shown as the thick line in Figure 1). The fault line passes along a major city, Muzaffarabad, which had a population of 90,000 in 2005. Shock waves generated by the earthquake spread in both directions of the fault line causing massive destruction within a 10 km buffer with the intensity of the shock dissipating as one moved further away. Since the epi-center of the earthquake was a straight fault line, locations equidistant from the fault line faced the same magnitude of the shock.

In 2005, the estimated population of the region was 5.7 million, of which approximately 84% were classified as rural.[3] The region had a very low annual per capita income of around USD 360 in 2005, that is, less than a dollar per day. This compares to the national average of USD 693 (ERRA-UN 2006).[4] Economic activity is mostly rural subsistence farming, and a small service sector in cities, mostly providing health, schooling, small businesses, and tourism. As a result of low income levels, approximately 80-90% of income is spent on food and other essential items like health and schooling, resulting in low savings (FBS 2011). Due to a large dependance on agrarian production for income and food, and due to weather variability, households hold food inventories

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[3]The regional population was 3.5% of total country population estimated at 160 million for 2005.

[4]The exchange rate in 2005 was USD 1 = PKR 60.

Figure 1: Map of the Affected Region
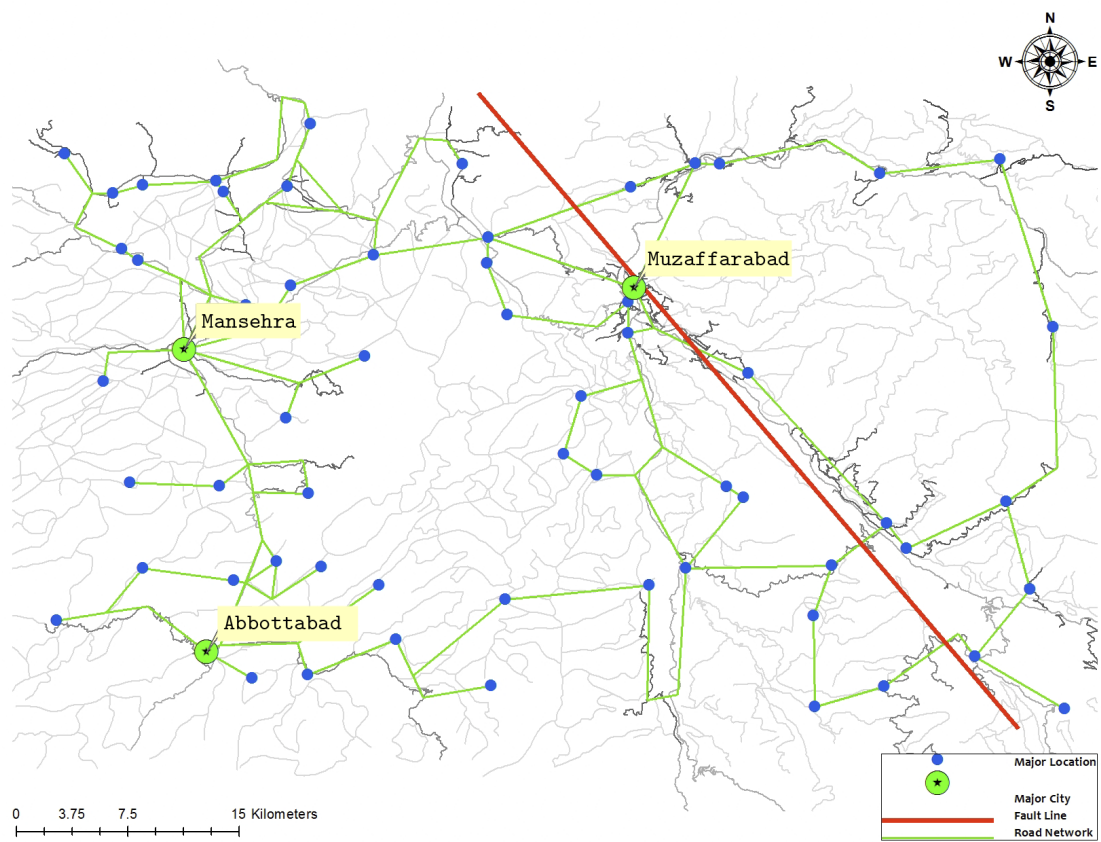
to smooth out consumption across employment and seasonal variations (Morduch 1995; ERRA-UN 2006). Financial institutions are minimal, private sector insurance mechanisms are virtually non-existent, and public social safety nets are similarly poorly developed, forcing the population to adapt to income variability locally. Due to a high number of low-income jobs across the region, and a socially and culturally homogenous landscape, there is high rural-urban mobility within the region (ERRA-UN 2006).

The 2005 earthquake caused major physical damage and a large loss of human life. Landslides destroyed crops and rendered many farms non-functional while cities saw a significant collapse of production facilities. The immediate death toll of the shock was estimated to be over 73,000 individuals (1.3% of the regional population), while 70,000 individuals (1.2%) were estimated to be seriously injured. Muzaffarabad, the city on the fault line, reported over 80% of all physical structures as damaged and over 70% of lives lost. The other two cities, Mansehra and Abbottabad, faced relatively minor losses as they were further away from the fault line. Approximately 3.5 million people (61%) were directly affected by the shock and 2.3 million (40%) were left "food insecure" (ERRA-UN 2006). In the first few days alone approximately 300,000 individuals (5.2% of regional population) were displaced (ADB-WB 2005), mostly to cities and to the east away from the fault line. From an economic perspective, GDP of this region was about USD 2.3 billion (2.6% of 2005 national GDP). Total damage was in the range of USD 3.5 billion, that is 150% of regional GDP but only 4% of the 2005 national GDP (ADB-WB 2005). Therefore, the economic impact of the earthquake was restricted to the regional level with a minimal impact at the national level.[5]

The earthquake caused a major distributional shock both as a result of damage to capital stock and population displacement. Since sparse pre-shock baseline data existed on this region, the effectiveness of the relief efforts was difficult to assess. However, levels of food vulnerability remained high and livelihoods remained disrupted despite the aid spent on the region (ADB-WB 2005; ERRA-UN 2006). One reason for the poor response was a lack of knowledge as to where markets were non-functioning, where there were food shortages, or where clusters of vulnerable populations existed. Most of the aid went to major cities due to better road access and better communication networks, even though a lot of the vulnerable population was located in remote areas with poor, or no access to any form of aid (ADB-WB 2005; FAO 2009). Therefore, a modeling tool that could help pinpoint potential vulnerability hotspots might have made a big difference to the relief efforts which focused mostly on urban cities leaving out most of rural villages.

4. Setting up a Simulation Framework

In order to create a geo-simulation framework that can replicate natural disaster-like outcomes in low-income regions, three inputs are required. First is the spatial layout of the region where clustering of locations, road connectivity, and distance from the fault line can play a role in determining post-shock outcomes. The spatial layout also plays a crucial role in migration and selling decisions. For example, if individuals need to decide between two locations at different distances offering the same level of income, they will chose the closer one (in spirit of Hotelling's rule (Hotelling 1929)). Similarly, it is cheaper to transport goods to nearby locations. Second, the economic setup of the region is important to understand how the market for labor and goods (food and non-food tradeable items) function, how wages are determined, and market demand and supply

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[5]Annual GDP growth rates in Pakistan were 7.7% and 6.2% in 2005 and 2006 respectively.

are generated. Third, an understanding of behavioral responses to a crisis situation is necessary to capture region specific cultural and sociological variations. This, for example, can include how an individual will adapt income and consumption decisions in the face of a highly uncertain and rapidly changing environment. The interaction of these three inputs produces a spatially defined regional economy where population and goods markets engage in exchanges that lead to stable long-run population distributions, and income and consumption trends. Each of the three inputs for the 2005 earthquake-affected region are discussed below.

4.1. GIS Data

The baseline map (Figure 1) is used to extract useful location and road information to represent the region in the simulations. For the 2005 earthquake, data for all 53 villages and three cities is extracted from Figure 1 as location nodes.

In the next step, road networks are coded as links shown as straight lines in Figure 1. While the road network data in Figure 1 is fairly detailed, ranging from paved roads to dirt tracks, only the information on major paved roads is used. The decision to just use major roads is made for two reasons. First, unpaved dirt roads and trails were destroyed or disrupted due to landslides and landscape changes and thus were not the obvious choice for mobility following the 2005 earthquake (ADB-WB 2005). Second, a simpler road network is computationally easier to handle for behavioral rules dealing with selling goods and migration decisions carried out by a large number of agents over a large set of location destinations. A larger road network, which is possible to construct in the simulation framework, can quickly result in computational bottlenecks especially when calculating optimal paths for migration and selling across a large set of agents.

Modeling the fault line

In order to replicate the damages caused by an earthquake, two loss functions are used in the model. First is the productive capital loss function which determines damage to output. Second, is the human life loss function which determines lives lost affecting availability of productive labor. The extent of damage caused by the shock is a function of the Euclidean distance to the fault line (Figure 2). Mathematically it is calculated as the perpendicular distance from a village or city node to the fault line. These are highlighted by the dotted lines in Figure 2.

The intensity of the earthquake shock, which resulted in capital and labor losses, is defined as a logistic function which falls exponentially as distance increases. To calibrate the damage functions, estimates are used from the 2009 census of earthquake affected districts in Pakistan analyzed in Andrabi and Das (2010) and summarized in Figure 3.

Andrabi and Das (2010) show an exponential decline in property and human loss relative to the fault line (Figure 3a). The lines representing "House Destroyed" and "Someone Died" are used for estimating the capital stock and labor losses in the model, respectively. The lines shown in Figure 3a follow a generic inverse logistic function of the form:

$$Loss_j = 1 - \frac{1}{\alpha_1 + \alpha_2 e^{-\beta \hat{d}_j}} \tag{1}$$

where $\hat{d}_j$ is the normalized Euclidean distance to the fault line from a location j. Normalization converts distances from kilometers to a $\{0,1\}$ scale. The furthest location from the fault line in terms of the Euclidean distance, is used as a normalizing factor for distances for all other locations. The parameter values α_1, α_2, β are calibrated to replicate the original curves resulting in Figure

Figure 2: GIS Fault line
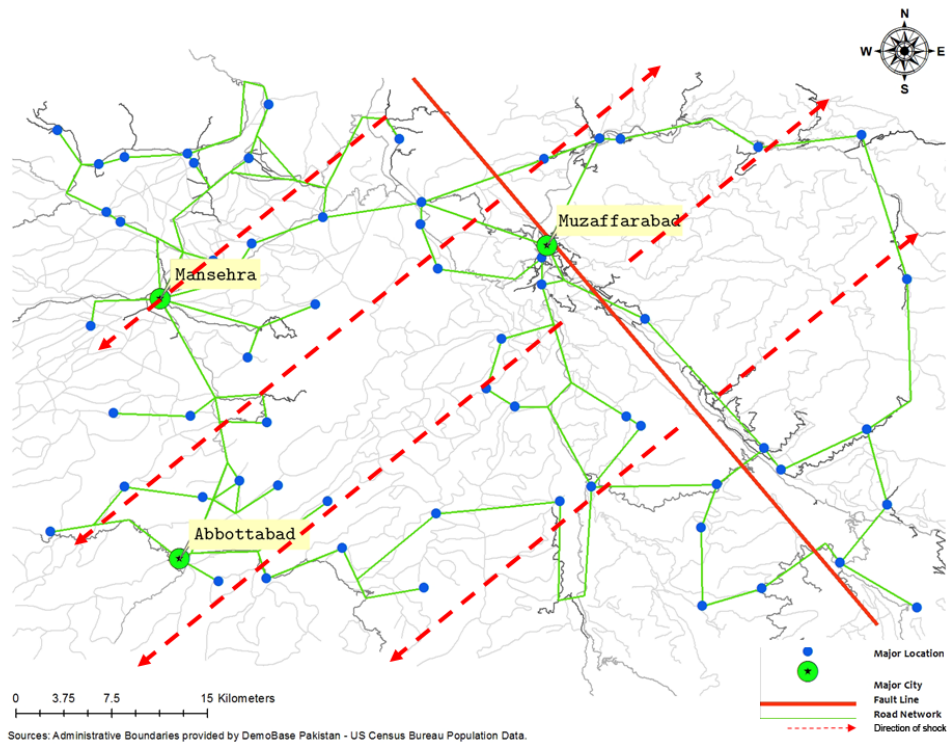
Figure 3: Empirical loss estimates

(a) Empirical

Destruction
Pakistan Earthquake 2005

- - - - - Someone Died   — — House Damaged or Destroyed
———— House Destroyed

Distance to Faultline in km

Source: Earthquake Districts Household Census 2009
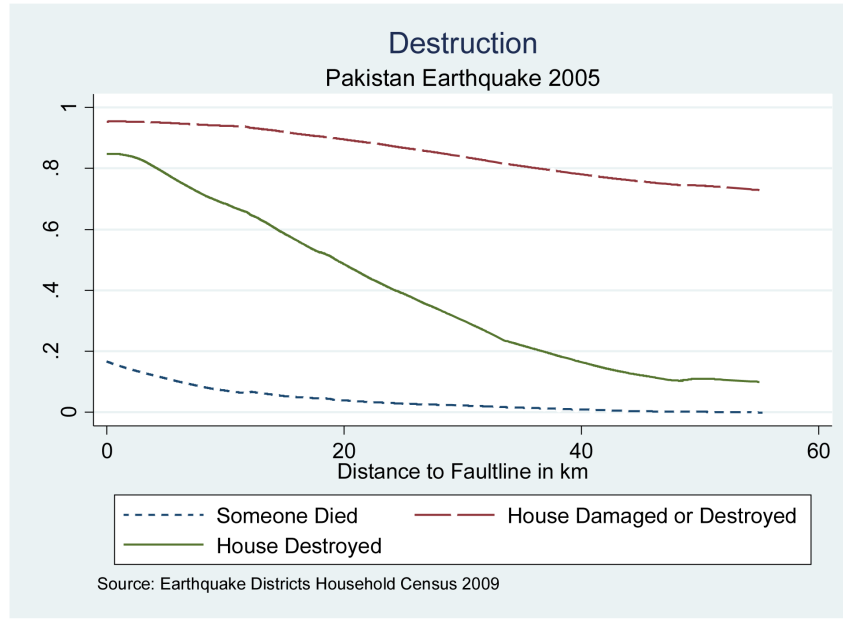
Notes: Distance from the fault line is calculated using the 2009 District Household Census and digital maps of the Himalayan Frontal Thrust provided by NESPAK. The mortality data are from the 2009 District Household Census short form (28,297 households) and the destruction and damage data from the 2009 District Household Census long form (6455 households).

Source: Andrabi and Das (2010) Figure 2a: p. 47.

(b) Simulated
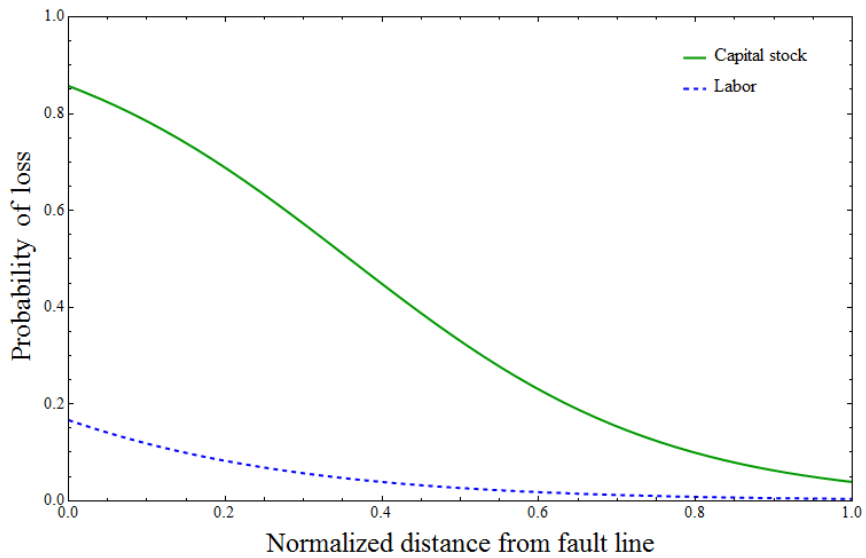
3b. For loss of output parameters take on the following values: $\alpha_1^{output} = 1, \alpha_2^{output} = 6, \beta^{output} = 5$. For loss of life, parameters equal: $\alpha_1^{life} = 1, \alpha_2^{life} = 0.2, \beta^{life} = 4$. The two loss functions are shown in Figure 3b.

According to Figure 3, capital stock damage equals almost 85% on the fault line while workers have an approximately 18% chance of losing their lives. The unequal treatment of loss of capital and labor together with spatially heterogeneous distribution of locations and road network implies that a natural disaster-like shock will lead to complex adjustment processes as each location deals with its remaining stock of production capacity and workforce.

4.2. Economic setup

The 2005 earthquake-affected region, is characterized by relatively homogenous "villages" engaged in agrarian production. Workers in villages produce food in exchange for subsistence levels of income. A large number of villages are connected to "cities" which produce non-food tradeable goods demanded within the region. Tradeable goods, for example, can include schooling, healthcare, clothing, or jobs paying daily wages like construction work. Low-income workers move around responding to real income signals across the region to ensure higher income and saving levels implying better consumption smoothing opportunities. Assuming free mobility of workers within a region, in the long-run worker population distributes itself across the region to stabilize real income levels resulting in a long-run stable rural-to-urban population ratio.

Villages and cities exchange food and tradeable goods which allows supply networks to form across the region based on distances, demand, and price signals. If food production is insufficient in a location, it is imported from other locations. Similarly, cities, which are much larger in size, import all their food from villages. Since all sellers are considered homogenous, they compete for sales across locations based on expected profits. Fewer sellers in the neighborhood result in the formation of local monopolies while competitive prices emerge if many sellers are catering to few locations. If sellers have excess stock, that is not sold in regional markets, it is exported outside the region at competitive prices.

In the model, all workers are assumed perfectly homogenous in their productivity levels and their access to information. Similarly all locations produce homogenous type of goods; perfectly substitutable food items in villages, and goods in cities. This simplifying assumption serves two purposes. First, it is not far from reality that low-income regions have a large stock of low-income unskilled or semi-skilled workers which are easily able to substitute jobs, for example, between farm labor in villages and factory work in cities with roughly similarly daily wage rates. Second, homogeneity of agents helps presenting the results, such that the emergence of distributions, and heterogeneity in outcomes is driven by variations in the level of shock faced by spatially-distributed locations rather than adjustment processes of heterogeneous workers. A fully heterogeneous model, which is possible to execute in the current setup, will make it hard to untangle the direct distributional effects of natural disasters.

The dual circulation of population and goods, summarized in Figure 4, forms a circular flow semi-closed economy. The economy comprises multiple autonomous decision making locations – villages and cities – that evolve their own labor and goods markets.

Each location is assumed to own a stock of workers and goods which it can exchange with other location based on market signals. Locations are inter-connected through road networks with varying distances which also play a role in decision-making processes. Locations further away have a negative weight on migration and selling decisions while higher income gains and profits have a

Figure 4: A multi-market circular flow economy with distances
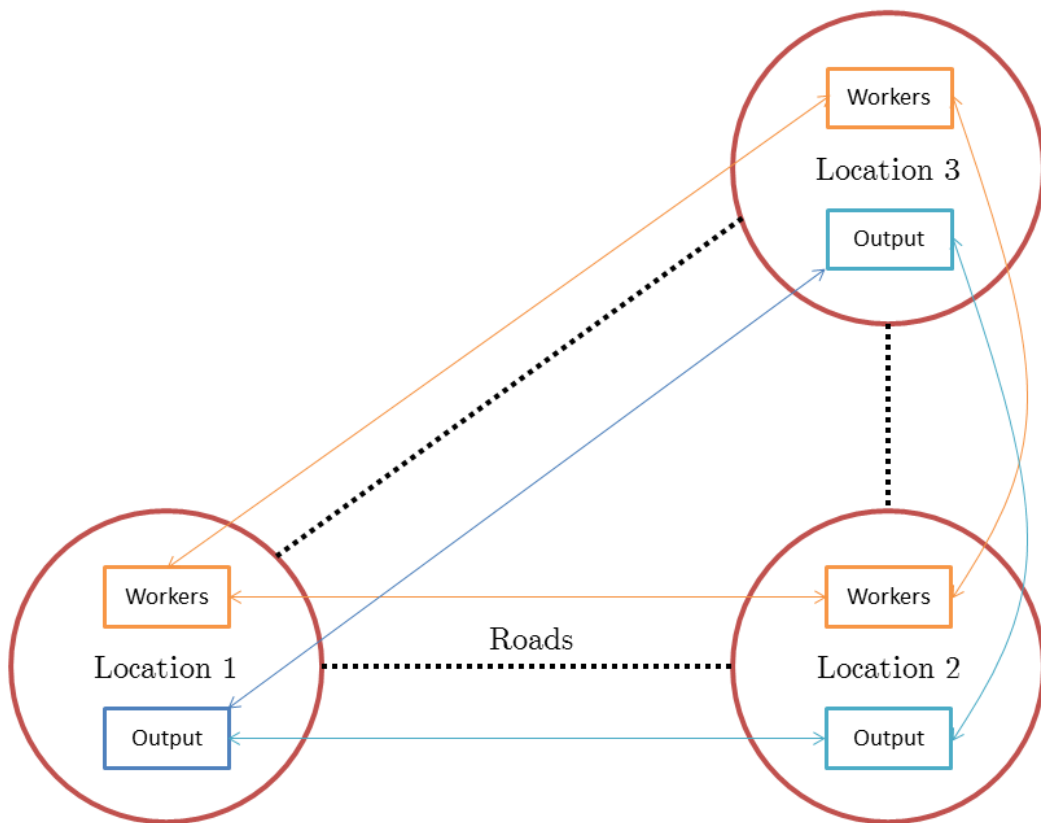
positive weight. These trade-offs between distance and welfare gains are continuously evaluated by agents in the model.

The model is driven by the migration and market selling procedures which act as stabilizing mechanisms across the region. Rising prices in one location imply lower real incomes forcing workers to find work in other locations. An out-migration from a location reduces its demand resulting in a reduction of prices. This, in-turn, also affects real incomes, and subsequently demand and supply decisions to this location. This endogenous micro-meso adjustment process allows for observing cascading effects of the type that are typical in a natural disaster like scenario. If one location is affected, it sets in motion a sequence of adjustment processes across the region where incomes and prices continuously and endogenously adjust to equalize disparities across locations.

4.3. Behavioral setup

The primary goal of low-income workers is to ensure at least a minimum level of subsistence food consumption, below which, they are considered starving or "food insecure". Consumption is tracked at the individual worker level and a minimum consumption line is used to check if an agent is starving or not. Consumption levels are assumed to be non-linear in their relation to income. This non-linear relationship is summarized in Figure 5.

According to Figure 5, beyond a certain income level, labeled as Y^{min}, at which the minimum consumption bundle C^{min} is affordable, workers consume a fixed fraction of their income. If income falls below Y^{min}, such that the minimum consumption bundle C^{min} becomes unaffordable, two decision rules are triggered. First, workers search for other locations offering them higher real income gains. Migrating to other locations, if a preferable option exists, allows workers to sustain higher levels of consumption. Second, if income cannot be increased, all income is directed towards purchasing food. If income is insufficient, workers run down their savings to allow the consumption to stay at the minimum consumption level. As savings run out, workers' consumption fall below the minimum consumption threshold C^{min} forcing them to starve. The aim of the model is to identify the time and place the populations that fall below the minimum consumption line. As indicated in Figure 5, the region to the right of Y^{min} allows for the build-up of food inventories and savings, while the region to the left of Y^{min} results in a run down of food inventories and savings causing vulnerabilities to arise.

The formal logical sequence of behavioral rules as used in the model is summarized in the box below.

Figure 5: Workers' consumption decision
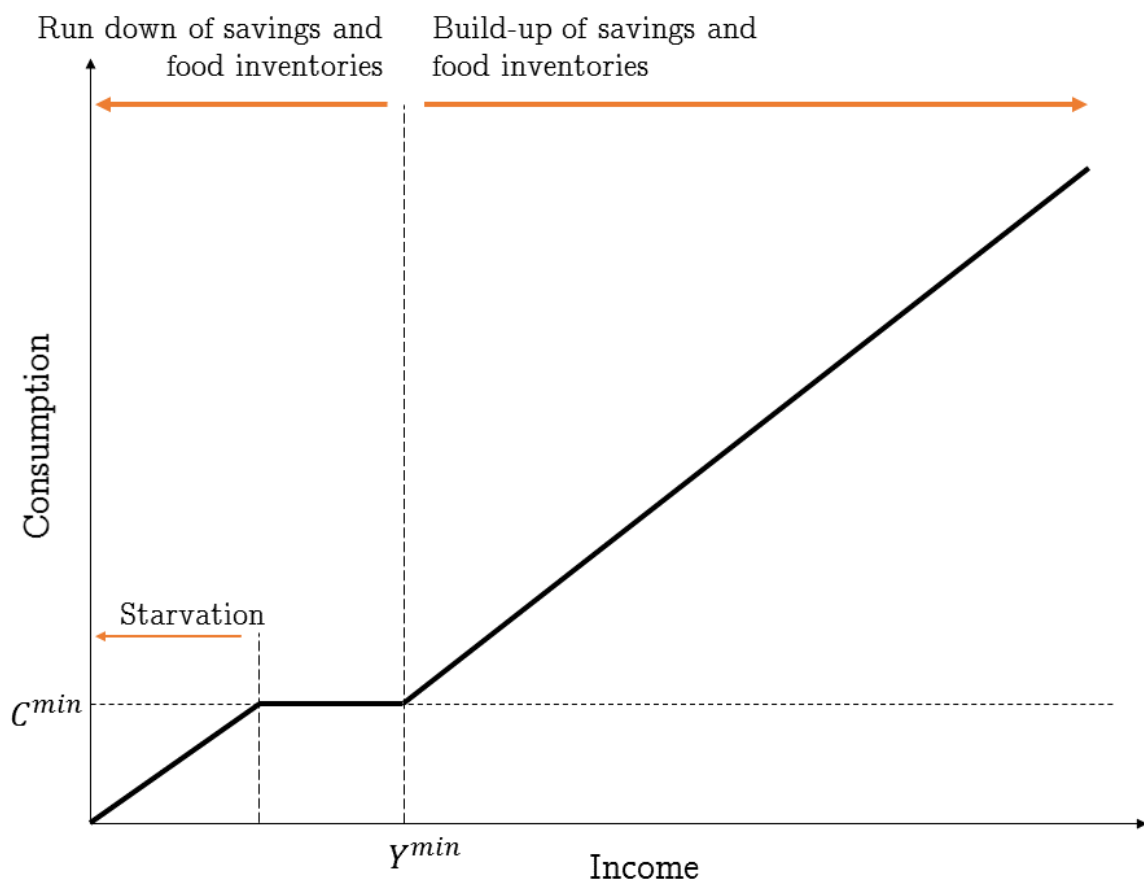
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Earning income?
     → Produce goods, earn income
     → Check for other locations offering higher real income
          → If a favorable location exists then migrate

Has sufficient food inventories?
→ Check for income relative to cost of minimum consumption bundle
     → Income > Minimum consumption cost
          → Buy food = MPC Income
          → Increase food inventories for desired number of days
          → Increase money savings
          → Consume a fraction of food inventories
     → Income = Minimum consumption cost
          → Buy food = Income
          → Consume at least the minimum food bundle
     → Income < Minimum consumption cost
          → Buy food = Income
          → Check savings
               → Savings ≥ Minimum consumption cost
                    → Spend savings to ensure minimum food bundle
                    → Consume the minimum food bundle
               → Savings < Minimum consumption cost
                    → Spend all savings on food
                    → Consume all the food in stock
```

According to the box above, each time period two independent checks are made by workers simultaneously. The first check "Earning income?" determines relative real income levels. A higher real income will always guarantee higher food consumption. Workers, therefore constantly evaluate locations in the region to find work offering a higher real income gain. If real income differences across locations are minimal, workers stay at their current location. The second sequence is the food consumption decision, where several condition checks are used. These include checking whether sufficient income exists to purchase food, how much of it should be spent on food, and if it is insufficient how much of savings should be redirected towards purchasing food. If food inventories exist, then a fraction of inventories are consumed, otherwise workers try to ensure that workers consume at least the minimum consumption bundle. If workers run out of all options, they fall below the minimum consumption line and are labeled as starving.

Decision-making rules

The behavioral rules are adapted from Naqvi and Rehm (2014) which are characterized by four micro procedures – *Production, Wages, Buying, Consumption* –, and two meso procedures – *Selling, Migration*. The detailed model description is given in Appendix A.

The four micro procedures determine how individual-level decisions are made. *Production* and *Wages* determine output per worker and the average wages earned. *Buying* and *Consumption* rules follow the decision making logic described in the box above which ensures a minimum level of consumption is maintained even in the face low income levels.

Two meso procedures defined how locations interact with each other; *Selling* and *Migration*. The meso procedures are extended over the original model to make the decision making process considerably more dynamic. The extensions include a more advanced search-and-match algorithm for selling goods across a large set of markets and a migration procedure that allows agents to make a more informed decision about the choice of destination. The two meso procedures are central to model outcomes and are summarized below (see Appendix A for a formal description).

The *Selling* procedure is driven by locations having a preference for maximizing profits. In order to do so, locations evaluate all markets in the region. Profits are earned when the selling price is greater than the production cost plus distance-based transportation costs. The location offering the highest profit margin is selected first before moving onto the next location offering the second best profit margin. Subsequently, rest of the locations are iterated until either, all stock is sold, or all locations are exhausted. Relative changes in expected profits drive the decision on how much to sell in each location at each time period. If any stock is leftover after exhausting all the locations in the region, it is sold outside the region at cost price. The assumption here is that sellers prefer to be locally monopolistic with some power over price setting, allowing them to earn monopoly rents, as opposed to being globally price-takers selling goods at cost. The search-and-match algorithm, which follows a *tatonnement* process (Albin and Foley 1992; Foley 1994), is repeated until all locations achieve their equilibrium price trends. In such a system, a shock to one seller, or a number of sellers, results in the reconfiguration of the supply network. In case, there are few sellers available in a location, or there is insufficient supply due to production shock, prices will go up in the short-run to adjust to existing demand. The search-and-match algorithm developed for this model is unique in its formulation as it allows sellers to maintain their characteristic profit-seeking behavior while being to operate in a continuously evolving environment. This iterative process is better able to adjust to sudden shocks and changes in the spatial environment as opposed to standard modeling techniques where sellers solve a portfolio maximization problem with perfect information and perfect foresight in a deterministic environment.

The original *Migration* procedure presented in Naqvi and Rehm (2014) is extended to allow agents to make a more informed migration decision choice using migration probabilities across multiple draws. The location selection decision is operationalized as a two-step process. In the first step, an agent evaluates all locations in terms of real incomes and distances to come up with a migration probability vector. Once relative probabilities are determined, a probability distribution is generated where locations with a higher real income gain have a higher chance of being selected. Through this process, an agent has a chance of selecting the "right" location, but it does not guarantee it. In other words, an agent is allowed to make a mistake. This has multiple effects. Across different simulation runs, the same agent can choose different locations even if starting from the same point (referred to as "random seeding" in ABM terminology). Therefore, by changing the destination choice of one agent, the next agent's probability vector is modified, changing the subsequent structure of migration decisions. In a second step, an agent's destination choice is controlled by allowing for multiple draws for a location choice. If the same location is repeatedly selected, it becomes a sure destination choice. Multiple draws allow for minimizing complete randomness in the choice of destination where a sequence of bad decisions, an outcome that is probabilistically possible, can result in implausible model outcomes. In theory, some agents can make mistakes but not all of them. A higher number of draws ensures that on average the right, or at least the better, destination is almost always selected.

5. Simulations

The model is set up in Netlogo (Wilensky 1999), an open-source software for ABMs. Location data is extracted from the GIS map shown in Figure 1 as "nodes" and standardized to the Netlogo coordinate system called the "grid". The Netlogo grid takes on a value of $\{0,0\}$ in the center, therefore latitude and longitude information is transformed to coordinates relative to the origin. Road information is extracted as "links" connected between nodes to form a network in Netlogo.

The model runs for a period of 1200 "ticks", a Netlogo time unit, where two ticks are assumed to equal one day. Simulations are conducted multiple times with random seeds, to allow for variations in migration decisions to emerge which subsequently feed back on all other decisions. Data is collected for each agent and each location, for each tick across each simulation run. To make the information presentable, data points are averaged out across all simulations runs to generate mean trends. Data is further aggregated at the monthly level (60 ticks = 1 month) for temporal analysis and at the location (village or city) level for spatial analysis (see Section 6 below). Simulations run for a total of one year to allow stable post-shock patterns to emerge. The movement of workers across locations is also tracked in the model. The movement speed only determines the speed of convergence of the model to a new steady state and does not play a crucial role in determining outputs.

5.1. Calibration

The model requires two sets of information to initialize. A set of parameter values which drive the decision making rules described in Appendix A and a set of initial conditions which allow the model to reach the target set of indicators. Since poor data exists for the region on post-shock outcomes, the model is calibrated to replicate pre-shock levels of population distribution, and income and consumption levels as the starting point for the earthquake shock experiment.

Parameters

The model is defined by a benchmark parameter vector summarized in Table 1.

Table 1: Parameters

Parameter	Description	Benchmark	Source
w	Daily wage rate (\$)	0.25	ERRA-UN (2006); FBS (2010b)
c_{1F}	MPC food out of income	0.9	FBS (2006)
c_{1G}	MPC good out of income	0.05	FBS (2006)
δ	Food inventories (days)	10	ERRA-UN (2006); FBS (2010a)

The values of these parameters are derived from empirical literature using either region specific studies or using various national censuses. As shown in Table 1, four parameters drive the model. The unit wage rate w which defines the wage bill is set to a value of USD 0.25 per unit of output per day. The baseline marginal propensity to consume food out of income c_{1F} is set at the higher end of 0.9 out of current income, the marginal propensity to consume goods out of income c_{1G} is fixed at 0.05. The desired number of days, the food inventories are held, is assumed to be 10 days. The model is also tested for parameter sensitivity and loss function sensitivity. The results of sensitivity testing are discussed in Appendix C.

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Initial conditions

Two key initial conditions are used to achieve pre-crisis empirical trends in three key indicators; population distributions across villages and cities, income levels, and consumption levels.

The first key initial condition is the relative size of cities to villages. According to the national level databases (FBS 2006), villages are roughly equal in size with an average population of 9,000 individuals. The relative size of the three cities – Muzaffarabad, Mansehra, Abbottabad – to villages in terms of low-income work availability, is extracted from the labor force survey (FBS 2010b) using crude estimates and is summarized in Table 2. Since the production process in both villages and cities require the same type of homogenous labor, the relative output sizes are sufficient to determine pre-crisis population distributions of low-income. The level of output in villages is set exactly equal while the output in cities is set as a multiple of village output according to Table 2.

Table 2: Baseline distribution of City populations

Location	Low-income jobs	Urban-to-Rural job ratio
Muzaffarabad	72,300	8:1
Abbottabad	44,500	5:1
Mansehra	37,700	4:1

The second key initial condition is the ratio of output-to-workers which determines the relative average income per worker. In order to achieve an average annual income level that is close to the yearly average of USD 395[6], the model is populated with 1,000 workers. In the model, output is defined in kilos such that the level of output is set to achieve pre-crisis income levels based on the number of agents, and the average wage rate. For the the model this is set at 58 kilos of food production in villages while cities calculate their average output as a multiple defined in Table 2. For example, in Muzaffarabad, total output equal $58 \times 8 = 464$ kilos of food-equivalent tradeable goods.

The initial conditions are summarized in Table 3.

Table 3: Initial variables

Variable	Description	Value
X_j^{max}	Food output per village per day	58 kilos
$\sum n$	Total workers	1000 agents
C^{min}	Minimum food consumption per day	1 kilo = 1700 kcal
u_j	Autonomous production in villages	7 kilos

In addition to the first two variables in Table 3, described above, two other variables are defined. The third variable in Table 3 is the minimum consumption threshold, C^{min}, where consumption of 1 kilo of food is assumed to provide 1700 kilo calories (kcals) of nutritional value per adult per day. This is the absolute minimum consumption threshold, in caloric value, below which individuals are considered starving (FAO 2010).

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[6]Values are converted into US dollars (USD) based on 2005 exchange rate of USD 1 ≈ PKR 60.

The fourth variable is the autonomous production output u_j in villages which is set equal to 7 kilos per day, or approximately 12% of pre-crisis production levels. Autonomous production in cities is set as a multiple of this based on Table 2. In the earthquake-affected region, this assumption also mimics a shared tenancy scheme where owners of productive capital (land, in case of villages) can produce a certain level of output (for example through mechanization) while the rest is outsourced to workers (Ray 1998: Chap. 10). Similarly in cities, small firms can expand production by hiring more workers. Autonomous production implies that some minimum level of economic activity will always exist in each location even in the absence of workers. A minimum level of economic activity ensures that some minimum level of food and goods supply is always available, preventing prices from exploding, an unlikely scenario, even in a high intensity shock environment.

Replication of pre-crisis trends

The simulations are initialized using the benchmark parameter together with initial conditions and run until stable trends are achieved. The initial conditions are set to ensure several outcome variables – population distributions, income, and consumption levels – match pre-crisis trends. The simulations are conducted 50 times using random seeds to allow for variations in migration decisions. Outputs from the model are summarized in Table 4.

Table 4: Simulations vs Empirical estimates

Indicator	Simulations	Empirical	Source
Rural population (%)	84.4	84	World Bank 2010
	(0.17)		
Average annual income (USD)	389.05	395	ADB-WB 2005
	(3.31)		
Average daily consumption (kcal)	2,059.10	2,100	FAO 2009; FBS 2006
	(8.91)		

Note: Standard deviations given in brackets. Table generated from 50 simulation runs using random seeds.

The model achieves the rural population level of 84%, while average annual income in the simulations is USD 389, close to the empirical values of USD 395 per worker. Food consumption in the model approximately matches to average caloric intake of 2,100 kilo calories (kcal) per day.

The results above show a weak form of validation of the model for pre-crises trends. Lack of reliable post-shock data for this region, makes any kind of validation and micro analysis almost impossible to conduct.

6. Results

Once stable pre-crisis trends are achieved, the model is subjected to an earthquake-like shock using capital and labor loss functions described in Section 4.3. Key indicators are tracked for a period of one year. Three sets of results are presented. The first set discusses overall changes in key economic indicators, the second set shows temporal variations in key indicators, and the third set deals with location-wise changes.

Table 5 shows percentage changes in key region-wide macro indicators between a pre-shock period and a one year post-shock time period, two time periods that exhibit stable trends in outcomes.

Table 5: Macro indicators

Variable	Pre-shock	One year	% change
Total output (Index)	100	45.3	-54.7
	(0)	(0)	
Total workers (Agents)	1287	1123	-12.7
	(0)	(10.7)	
Percentage urban (%)	14.1	14.4	2.7
	(0.24)	(0.59)	
Real income (Index)	100	37.7	-62.3
	(0.944)	(0.958)	
Food price (Index)	100	111	11
	(0.32)	(0.65)	
Percentage starving (%)	7.9	46.9	492.9
	(0.5)	(1.8)	
Income (Gini)	0.12	0.19	53.4
	(0.0054)	(0.015)	
Consumption (Gini)	0.11	0.16	42.2
	(0.0042)	(0.012)	

Note: Standard deviations given in brackets. Table generated from 50 simulation runs using random seeds.

Table 5 shows that there is approximately a 55% decline in overall output and a 13% loss of human life. Displacement leads to a slightly higher share of urban population which increases by almost 3%. Income levels are 62% lower, and food prices 10% higher on average. These changes imply rising levels of starvation, which increase almost five fold, as both food availability and affordability falls. This is also reflected in a rise in income inequality (53.4% increase) and consumption inequality (42.2% increase). The last two indicators have two implications. First, a rise in income and consumption inequality implies that the impact of the shock is not homogeneously distributed across workers. Second, change in consumption inequality is lower than change in income inequality highlighting that workers on average are able to better smooth out consumption despite facing a large decline in income.

The indicators in Table 5 indicators show plausible trends at a regional level, but they do not highlight temporal and spatial impacts of the shock. Figure 6 shows the location-wise output and labor losses from an earthquake-like shock in the simulations. These are generated based on the loss functions described in Figure 3.

As shown in Figure 6, the ratio of output-to-labor lost varies based on the normalized Euclidean distance from the fault line. Furthermore, the spatial distribution of villages and cities, with various degrees of road connectivity, implies that location-specific characteristics will also have a non-homogenous impact on remaining capital and worker stocks. Therefore the temporal and spatial evolution of various indicators becomes relevant for understanding how vulnerabilities might be distributed across the region.

Figure 6: Model loss estimates
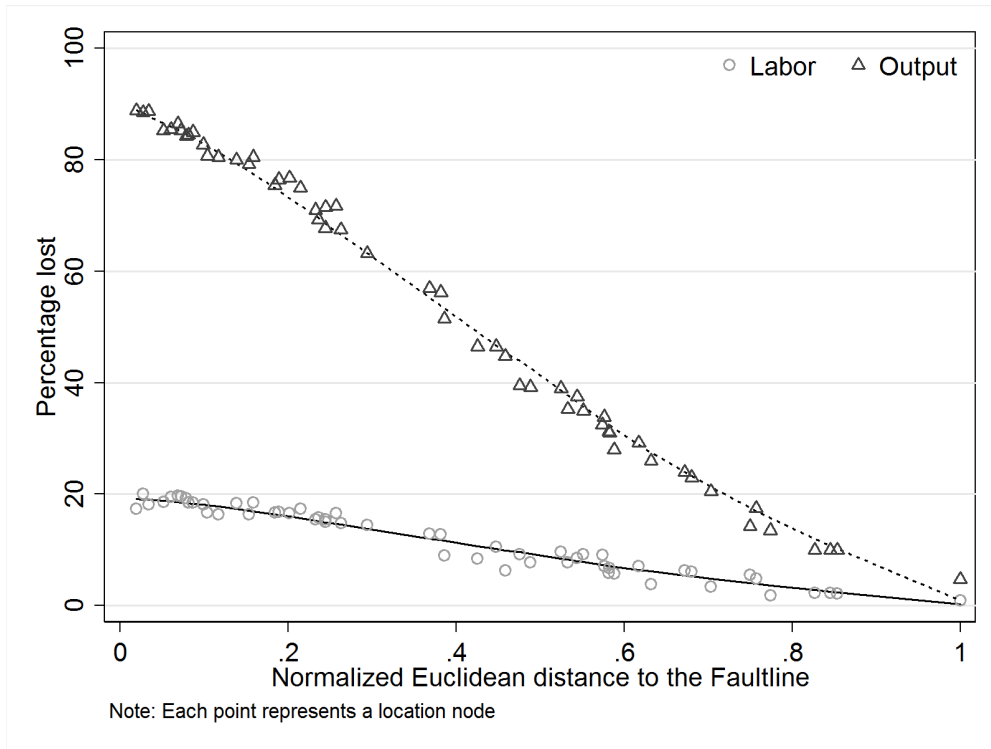

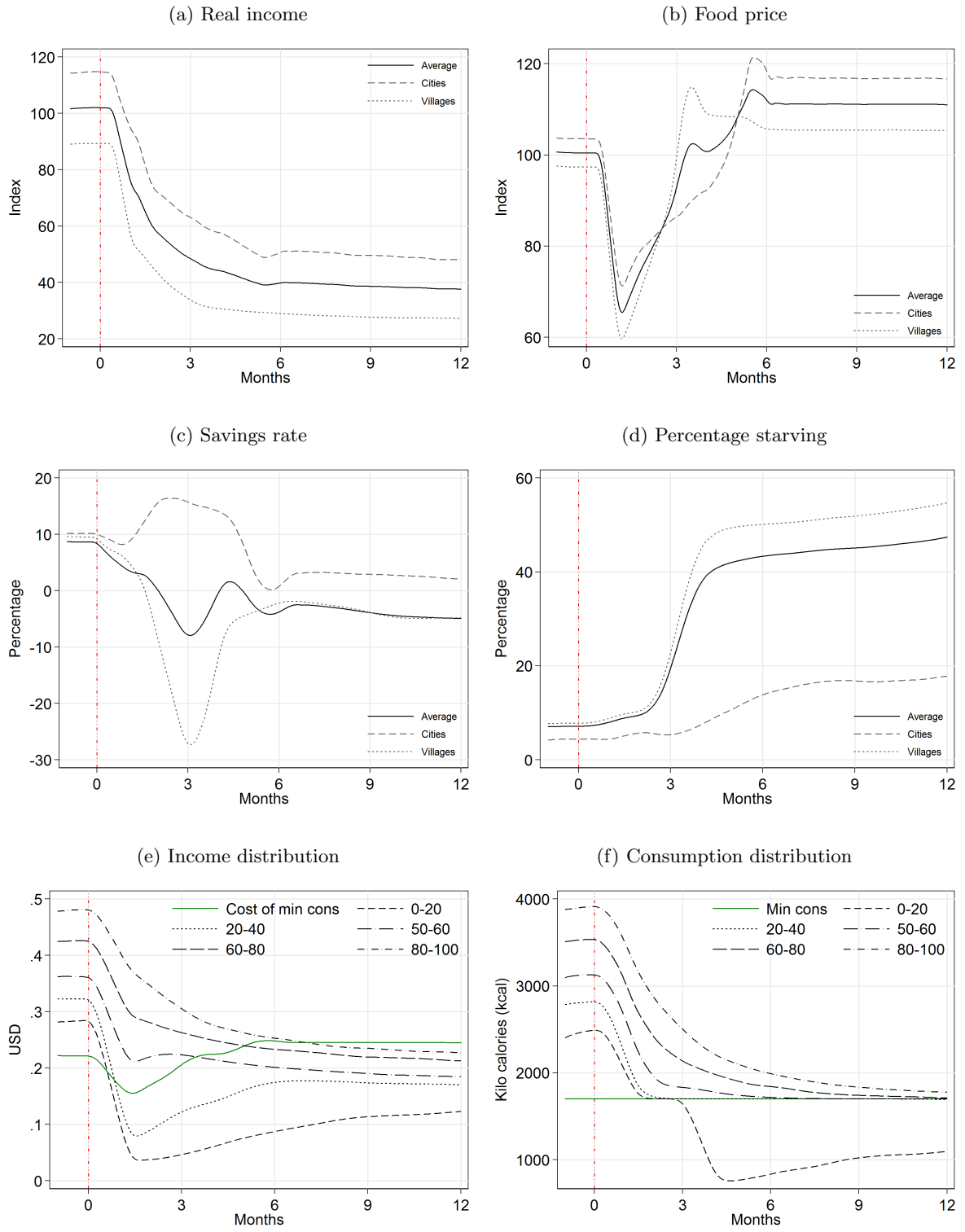Note: Each point represents a location node

Figure 7 shows the temporal evolution of aggregate indicators. Figure 7a highlights the changes in real incomes. As the loss in output after the shock is higher than the loss of workers, real incomes fall disproportionately across locations. As a result of real income disparities, workers migrate across the region to find better work opportunities. The consequence of this worker movement is a region-wide decline in overall real income levels as they stabilize at a lower level. Similarly, Figure 7b shows a rise in food prices as a result of output losses, which also exhibit different trends across villages and cities.

As real incomes fall and prices rise, workers are unable to afford their desired consumption levels. To purchase food, at least the minimum consumption bundle, workers start reducing their money savings. This is indicated by Figure 7c, where the pre-crisis savings rate of 10% quickly decline to zero eventually falling below resulting in negative savings as workers run down their money stocks. According to Figure 7c, at the disaggregated level, villages are worse off than cities with negative saving rates as high as -30% while workers in cities manage to stabilize savings rates to slightly above zero. Figure 7c also highlights that the changes in the savings rates are not homogenous across time. The time between zero and six months shows high volatility levels due to the population adjustment process. This transition phase shows the potential emergence of high levels of vulnerability and food insecurity, which one would not observe, for example, if data is collected six months after the shock. This is also reflected in Figure 7d, where around the three month mark, there is a sharp increase in the level of starvation in a very short time span before the rate-of-change slows down. Figure 7d also highlights rural-urban variation where cities are better able to prevent populations from starving as opposed to villages. This can be explained by an increase in rural population and a rise in food prices. These rural-urban disparities also highlights the major challenges faced by aid institutions after the shock. They tend to focus more on cities, due to better infrastructure and accessibility, usually assuming that populations are likely to move towards more developed urban cities in a post-shock scenario. A risk of this approach is that some of the most vulnerable populations left behind in remote areas are at the risk of missing out on much-needed aid.

Figures 7e and 7f show the evolution of income and consumption distributions broken down by quintiles. These two graphs highlight how some workers manage to completely hedge against the shock while others quickly fall below minimum income and consumption thresholds. Therefore, heterogeneity in outcomes can still persist despite homogeneity in skills across workers. This can potentially depends on several factors including the location of the worker at the time of the shock, proximity to the fault line, timing of migration, and the level of savings. Figure 7e shows that the income of all quintiles fall below the cost of minimum consumption line, implying that, no one can afford the minimum consumption based on their current income level. The graph also shows that the rate of decline of income is not homogenous. The bottom two quintiles fall very fast while the top three show a relatively slower decline allowing them to implement consumption smoothing strategies more easily. As a consequence, not all groups fall towards the minimum consumption line at the same rate as shown in Figure 7f. Once, the quintiles do approach this minimum consumption threshold, they manage to stay on it except for the bottom quintile. The bottom quintile runs out of savings immediately, falling to starvation levels at the three month mark. This insight, that income and consumption vulnerabilities vary, can help policy makers decide between different policy response schemes. This, for example, can include distinguishing populations requiring food versus cash transfers, two popular policy instruments used in low-income regions (see for example, Currie and Gahvari 2008).

Figure 7: Temporal transitions

(a) Real income

(b) Food price

(c) Savings rate

(d) Percentage starving

(e) Income distribution

(f) Consumption distribution

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While Figure 7 gives an interesting temporal breakdown of disaggregated trends, the geo-simulation framework presented here can also analyze the above indicators at the location level over time. Figure 8 analyzes these trends for six key indicators. In order to account for limitations of space, results are presented only for changes in indicators a year after the shock at the location node level. Changes from baseline indicators are shown as "O" for positive and "△" for negative. Relative sizes indicate the scale of the change and the extent of the change is indicated at the bottom of each sub-figure. The first four graphs show percentage changes while the last two show level differences. For the last two variables – Starvation and Consumption Gini – level differences have been used for convenience of representing changes in reasonable numbers since percentage changes are extremely high due to very small baseline values.

Figure 8a shows the percentage of output lost. The city on the fault line – Muzaffarabad – losses as much as 80% of its output. In contrast, farther away cities – Abottabad and Mansehra – are barely affected. Since the damage dissipates over distance, villages show progressively fewer losses in output as the distance from the fault line increases.

Population adjustments are shown in Figure 8b. A year after the shock, locations near the fault line see a decline in population as agents move farther away. The change in populations near the fault line is also not homogenous. One can attribute this to the level of clustering of locations, and density of road networks which might play a role in mitigating the extent of migration.
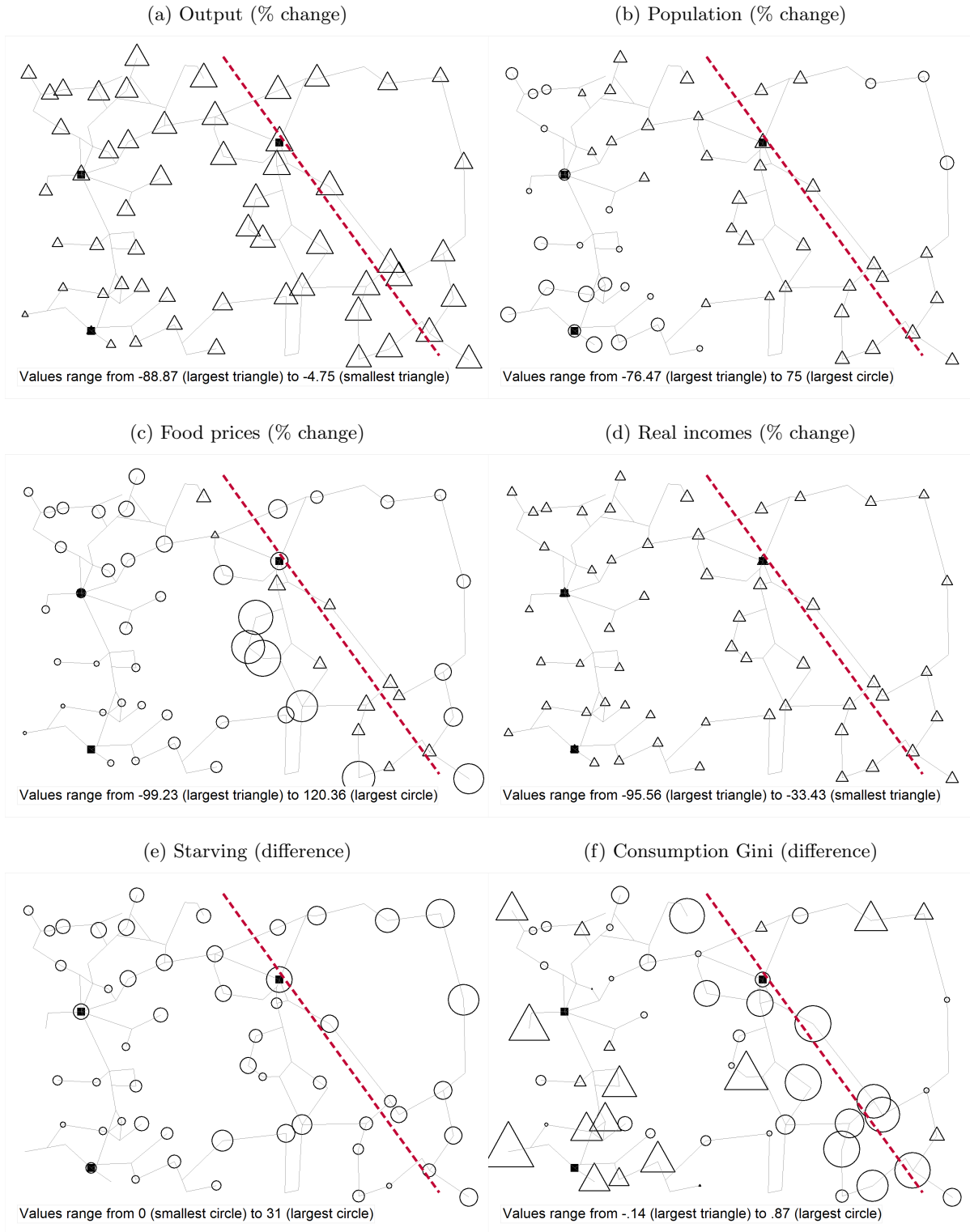
Figures 8c and 8d shows the economic impact of the shock in terms of food prices and real income levels respectively. Food prices in Figure 8c show two interesting trends. First, the villages near the fault line see the highest increase in prices as production levels fall drastically relative to further away locations. Second, locations on, or very close, to the fault line see an actual decline in prices. This is driven by a demand-side affect resulting from out-migration of local populations. Figure 8d shows an overall, relatively homogenous, decline in real income levels. This result is not surprising since migration allows for equalization of real income differences and is a main driver of migration in the model.

Figures 8e and 8f provide two indicators of vulnerability; starvation levels and consumption inequality, respectively. Starvation is defined as the percentage of population that has fallen below the minimum consumption line. As shown in Figure 8e, starvation levels rise across the whole region but are not uniformly distributed. The remote villages, especially to the east of the fault line, are affected the most. This result can be explained by poor road connectivity to cities or proximity to nearby village clusters resulting in insufficient food supply for local populations. Figure 8f shows consumption inequality captured by the Gini index. While consumption inequality worsens, especially near the fault line, the rate of change is not homogenous across locations. Several factors play a role in this outcome. First, consumption levels for all workers might be falling resulting in a reduction in the inequality index. Second, spatial clustering of locations and road connectivity can allow some locations to have better access to food supplies at lower prices.

Detailed spatial transition graphs are shown in Appendix B using heat maps at three month intervals to highlight how some of the patterns evolve in the simulations. The contours of the heat maps are generated using Shepard interpolation where inverse distance-weights are used to fill in the missing data points to generate a continuous surface (Jacobs et al. 1986; Press et al. 2007). These graphs show the percentage change from baseline indicators, and highlight how network density, proximity, and clustering plays a role in determining the spatial and temporal non-linear emergence of outcomes.

The analysis presented above shows that the impact of a natural disaster is non-uniformly

Figure 8: Spatial indicators one year post-shock (Change from baseline value)

(a) Output (% change)

Values range from -88.87 (largest triangle) to -4.75 (smallest triangle)

(b) Population (% change)

Values range from -76.47 (largest triangle) to 75 (largest circle)

(c) Food prices (% change)

Values range from -99.23 (largest triangle) to 120.36 (largest circle)

(d) Real incomes (% change)

Values range from -95.56 (largest triangle) to -33.43 (smallest triangle)

(e) Starving (difference)

Values range from 0 (smallest circle) to 31 (largest circle)

(f) Consumption Gini (difference)

Values range from -.14 (largest triangle) to .87 (largest circle)

distributed even with homogeneous agents and a homogenous work environment. Results highlight how a geo-simulation framework can help identify patterns of internal migration and clusters of consumption vulnerability and can help formulate more effective and timely policies to help limit second-round negative effects of natural disasters.

7. Conclusions

This paper applies a spatially-explicit ABM, or a geo-simulation, to a specific natural disaster and geographical region; the 2005 earthquake in northern Pakistan. The aim of this exercise is to show the applicability and usefulness of geo-simulations for near real-time policy responses especially when reliable data post natural disasters is not available. Geo-simulations are preferred over other modeling techniques in their ability to handle short-term non-linear spatial-adjustment processes using bottom-up rules. The paper uses a simulation framework developed for low-income workers where the decision making is governed by six behavioral modules – Production, Wages, Buying, Consumption, Selling, and Migration – the combination of which, produces a complete artificial economy with location-specific independent by inter-connected labor and goods markets. The behavioral modules are developed to specifically focus on the decision making process of low-income workers in order to identify extent of migration and consumption vulnerability in a post natural disaster-like scenario.

The model is calibrated to replicate pre-crisis outcomes in population distributions, income, and consumption levels. To this end, this paper extends the model of the artificial economy developed in Naqvi and Rehm (2014) by incorporating the spatial setup of the earthquake affected region in northern Pakistan, and extends two meso level procedures – *Selling* and *Migration* – to allow for more dynamic decision making processes. This includes a more efficient search-and-match selling algorithm across a large set of markets, and a more informed migration decision making process using multiple draws to select destinations. A GIS map of the region is used as the physical environment in which the model of the artificial economy is situated. This includes salient features key to the functioning of the model such as the precise locations of villages, cities, and roads. This artificial region is subsequently shocked to simulate an earthquake using the actual location of the fault line along with calibrated output and labor loss functions.

The model outputs shows plausible patterns; there is a large decline in the level of output and income that is heterogeneously distributed across the region. This triggers low-income worker populations to smooth out consumption using three strategies; increasing consumption out of income, consuming out of savings and food inventories, and migration to find better income opportunities. The result of this is a demographic transition where populations from affected locations move to unaffected areas, cascading the shock and exacerbating inequalities in the process. Disruptions to the flow of goods result in market imbalances and food price spikes. The combination of low income levels and rising food prices imply that consumption levels fall, leading to an increase in starvation levels. Due to heterogeneity in the spatial layout of the region, and variations in the decision making processes, not all workers are equally affected. Some show high level of resilience against the shock while others quickly fall below the minimum consumption line resulting in starvation and food insecurity. The model is equipped to highlight both spatial and temporal patterns as they evolve over time and can pin-point reasonably where clusters of vulnerability are likely to emerge. This goes beyond what existing modeling tools which usually focus on long-term loss estimations of natural disaster affected regions.

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While these results are exploratory in nature and validation remains a challenge due to limited data availability, they help provide insights about distributional changes as regional economies respond to shocks. If the model is able to provide an adequate description of outcomes of pre- and post-shock in real-world scenarios, then the insights drawn from the model can be used to identify pockets of vulnerable populations so that a more timely and effective policy response following natural disasters can be implemented. In particular, since food insecurity can be traced in the model, it can point to required policy measures to minimize starvation with limited aid resources. Furthermore, timely action can alleviate bottlenecks through targeted policy response and help limit secondary spillover effects, namely mass internal migration and the disruption of functioning markets in other parts of the region, that might hamper regional growth and well-being in the long-run.

Much remains to be done in helping low-income regions prepare for natural disaster relief and bolster communities' resilience. The framework presented here can be extended in several ways before any real policy implications can be drawn. First, a larger, more detailed geographical component can be added to the model that can help more accurately predict population and goods flows. This, for example, can include altitude and slope information, variations in road types, and weather conditions. Second, a more detailed behavioral component can be added where more complex household decisions are simulated. This, for example, can include households with multiple members, community based network decisions, heterogeneity in skill endowments, heterogeneity in access to information, and incorporating learning behavior in a limited information environment. In addition to this, geo-simulations are well suited to incorporate cultural and sociological aspects of decision making as well. For example, different behavioral rules for men, women, and children, role of asset ownership and extent of property rights in decision making processes, and community-based versus family-based migration decisions. Third, given modern technologies, real-time data can be integrated within such a model. This can include incorporating satellite data that is currently available at frequent intervals and can quickly give damage estimates especially on infrastructure losses. Additionally, crowd-sourced information can help calibrate the model based on some real time information. This, for example, can include identifying food shortages, transport bottlenecks, and location preferences for migration.

In conclusion, a geo-simulation framework can provide a rich tool for estimating a host of policy questions in a lab-like setting, allowing for a more accurate and nuanced policy response that can minimize second-round impacts of natural disasters and help reduce risk in the long-run. Such a tool can play an essential role in low-income regions where knowledge of local markets and community-specific behavioral responses can be simulated to estimate post-shock outcomes for an effective, and timely response, with limited resource availability.

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Appendix A. The Model

In order to present the model, some notations are introduced for the sake of clarity. Agents are indexed as $i = 1...n$ and locations are indexed as $j = 0...m$ where 0 is an agent's current location. The time subscript t represents a "tick" or half a day in the simulations. Symbols without the time subscript are parameters for calibration or initial conditions. Model procedures are discussed below.

Appendix A.1. Micro procedures

- *Production:* Each location j has a pre-defined maximum production capacity X_j^{max} given in standard output units. Production is defined as either agriculture output referred to as "food" in villages and a tradeable "good" output in cities. The production process is split into two part. Owners of productive capital can produce an amount $u_j \leq X_{jt} \leq X_j^{max}$ of the total output themselves using existing technologies. Autonomous production is added in the model as a stabilizing mechanism to avoid the doomsday scenario where all production activity will die out in the absence of workers causing prices to spike out of control. This assumption is not unrealistic. Even in the face of very high shocks, some minimal level economic activity persists. Therefore prices can rise if demand outweighs supply but not indefinitely.

    Since owners of productive capital are not explicitly modeled, total output is determined at the location level where output per worker for each location j is defined as:

$$\lambda_{ijt} = \frac{X_{jt} - u_j}{n_{jt}} \tag{A.1}$$

    where n_{jt} is the number of workers employed at location j at time t. Equation A.1 implies that if X_{jt} is shocked, such that $X_{jt} < X_j^{max}$, less will be available for workers to produce resulting in less output per worker.

- *Wages:* Total wage bill is determined by a fixed rate w per unit of output times the total output produced by workers:

$$WB_{jt} = w(X_{jt} - u_{jt}) \tag{A.2}$$

    Wage earned per worker i in location j at time t can be derived as:

$$W_{ijt} = \frac{WB_{jt}}{n_{jt}} = w\lambda_{ijt} \tag{A.3}$$

    or wage rate times worker productivity. Equation A.3 implies that a higher workforce, n_{jt}, will reduce average income per worker earned.

- *Buying:* The amount of goods purchased are defined by two parameters. A preference to consume at least a minimum level of subsistence bundle C^{min} evaluated at current market prices p_{jt} and a preference to hold inventories of food for a certain time period δ days to allow for minor consumption smoothing. The amount of goods purchased B_{ijt}, in monetary terms, by a worker i is defined as:

$$B_{ijt} = Max[p_{jt}C^{min}, \ c_{1it}W_{ijt} + c_{2it}m_{ij,t-1}] \qquad (A.4)$$

where $c_1 \leq c_{1it} \leq 1$ is the marginal propensity to consume out of income and c_{2it} is the marginal propensity to consume out of money savings m_{ijt}. Marginal propensity to consume out of income in normal times, where income is sufficient to afford more than the minimum consumption level, equals c_1. $c_1 = c_{1F} + c_{1G}$ is a calibration parameter based on empirically defined value usually in the range of 0.7-1 for low-income populations, of which a large fraction is spent on food (c_{1F}) while a very small amount is allocated to purchasing tradeable goods (c_{1G}). c_1 can endogenously increase to 1 depending on the food price and income relationship such that, all the income can be used up to purchase food ($c_{1F} = 1$) (see Figure 5). In this scenario the tradeable good is not purchased ($c_{1G} = 0$).

The second parameter c_{2it}, the propensity to consume out of wealth, is also endogenously determined. If income is insufficient to sustain a minimum level of food consumption then $c_{2t} > 0$, implying a negative savings rate. In this scenario, the value of c_{2t} keeps increasing to allow purchasing the minimum food consumption bundle provided workers still have money savings left.

Changes in money savings are derived as:

$$\Delta m_{ijt} = (1 - c_{1it})W_{ijt} - c_{2it}m_{ij,t-1} \qquad (A.5)$$

Equation A.5 implies that in normal times, savings accumulate at a rate of $(1 - c_{1it})$. In a shock like scenario, saving rates become zero when $c_{1it} = 1$ or negative if $c_{1it} = 1$ and $c_{2it} > 0$.

- *Consumption:* Agents hold food inventories F_{ijt} out of which they consume a fraction δ every time period. From this consumption is defined as:

$$C_{ijt} = Max[C^{min}, \delta F_{ij,t-1}] \qquad (A.6)$$

The proportion of food stock consumed adjusts endogenously to income levels. Since consumption levels are bounded below at C^{min}, If workers have sufficient income, they will buy more food than they can consume and add it to their stockpile such that they hold food inventories for a duration of δ days. If consumption levels are low, then workers will prefer to consume the minimum amount C^{min}, either through shifting more of the income to consumption, or running down food stocks. They will continue this trend until their income-consumption choice allow them to do so. If for several reasons they cannot afford the minimum food bundle, they will reduce their consumption below the minimum consumption threshold to starvation levels.

The change in the food stock, F_{ijt}, of agent i can be derived as:

$$\Delta F_{ijt} = F_{ij,t-1}(1 - \delta) + \frac{B_{ijt}}{p_{jt}} \qquad (A.7)$$

where B_{ijt} is the value of food in money terms (equation A.4) and p_{jt} is the current price level of the food bundle at location j. For the sake of simplicity the tradeable goods (education, health, other services) are consumed as they are purchased with no stock-piling.

Appendix A.2. Meso procedures

To ensure consistency of calibrating the decision making processes, network distances are normalized between 0 and 1. The normalized network distance χ_j, to a location j, takes a value of 0 if it is the distance to self otherwise $\chi_j > 0$. A value of 1 is the largest distance in the network. Normalized network distances are used for two reasons. First, they allow for easier calibration of distance-based probabilities. If actually distances are used (for example in kilometers or miles), parameters would need to be calibrated if the network size changes. Second, distances bounded between 0 and 1 give a neat mapping to probabilities which are also bounded between 0 and 1.

- *Selling:* Locations sell the goods they produce either in different locations in the region or export them outside the region. The condition for selling in local markets is determined by profits earned over minimum costs. Unit costs are determined as:

$$r_{jt} = \frac{WB_{jt}}{X_{jt}} + \chi_j \tag{A.8}$$

where WB_{jt} is the total wage bill and the only production cost in the model, X_{jt} is the total output at the current location, and χ_j is the normalized network distance to market j which proxies for distance costs to location j.

Locations have a preference to maximize their own profits and thus evaluate all markets. Profits are earned where the selling price is greater than the cost price or $p_{jt} \geq r_{jt}$. Markets offering the highest profit margin are selected first before moving on to the next market providing the next best profit margin. Subsequently, rest of the markets are iterated until either, all stock is sold, or all markets are exhausted. If a market continuously offers profits, supply is incrementally increased in that market until supply is exhausted or the market no longer offers high profit margins. Any leftover stock is sold outside the region at cost price. The search-and-match algorithm, which follows a *tatonnement* process (Albin and Foley 1992; Foley 1994), is repeated until markets achieve their equilibrium trend prices.

Total supply S_{jt} in location j at time t can be defined as:

$$S_{jt} = \sum_{j=0}^{m} \theta_{jt} X_{jt} \tag{A.9}$$

where θ_{jt} is the fraction of output X_{jt} sold in market j from all other locations $j = 0...m$. Based on price signals, each location adjusts its supply to other locations by varying $0 \leq \theta_{jt} \leq 1$. If profits in location j are expected to rise or decline, θ_{jt} increases or deceases accordingly.

- *Migration* The probability of migrating to a location j is based on a joint probability distribution, Π_{jt}, defined as:

$$\Pi_{jt} = \Pi_t^{\chi_j} \times \Pi_t^{\hat{w}_{jt}} \tag{A.10}$$

where $\Pi_t^{\chi_j}$ is the probability of migration based on network distances and $\Pi_t^{\hat{w}_{jt}}$ is the probability of migrating based on the real income ratio of target location to the current location. Real income ratio, $\hat{w}_{jt}$, is defined as:

$$\hat{w}_{jt} = \frac{w_{jt}/p_{jt}}{w_{0t}/p_{0t}} \tag{A.11}$$

or the real income in location j over real income in current location indexed as 0.

Since distances reduce probability of migration and incomes increase the probability of migration, locations have convex trade-offs as depicted by the joint-probability function in Figure A.9.

Figure A.9: Migration probability
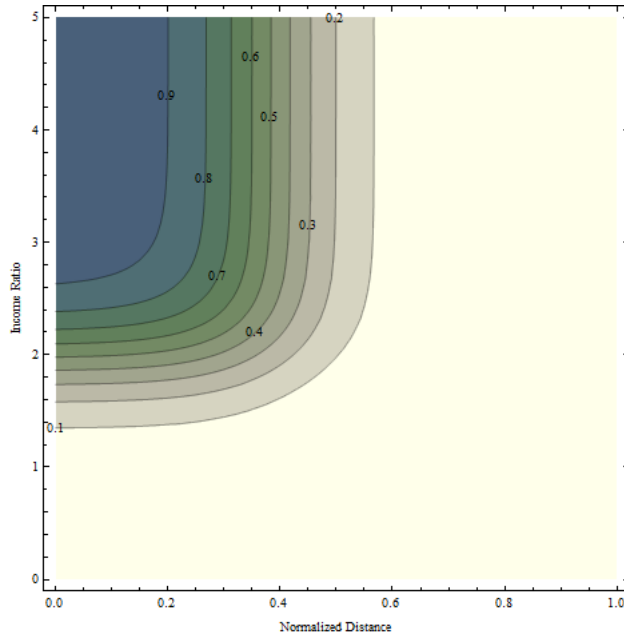
Note: Adapted from Naqvi and Rehm (2014)

Figure A.9 implies that, if other locations have the same income as a worker's current location, the probability of migration will be low since no incentives exist to switch locations. The probability increases exponentially as real income in a target location increases as a multiple of real income in current location. Additionally, the income-distance combination can give different locations the same probability assignment. For example, a father away location offering a higher real income gain can have the same probability of migration as a nearby location offering a lower real income gain.

Agents operationalize a two-step process to select a location which are explained through two hypothetical scenarios presented in Table A.6 where an agent needs to make a migration decision across three locations. In the first step, all locations are evaluated using equation A.10 to come up with a migration probability vector. If several locations are offering high real income gains, they can be assigned very high probabilities for migration. Therefore, the probability vector can sum up to more than one. In Scenario 1 in Table A.6, the probability vector for three locations adds up to 1.39. A value higher than 1 implies that several locations are offering a higher real income gain controlling for distances over the current location.

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Table A.6: Hypothetical probability scenarios

		Loc 1	Loc 2	Loc 3	No mig	Sum
Scenario 1	Probability of migration	0.56	0.65	0.18		1.39
	Normalized probability	0.40	0.47	0.13		1
	Cumulative probability	0.40	0.87	1		
Scenario 2	Probability of migration	0.18	0.05	0.2		0.43
	Normalized probability	0.18	0.05	0.2	0.57	1
	Cumulative probability	0.18	0.23	0.43	1	

These probabilities are normalized by the sum such that the second row in Scenario 1 adds up to 1. The second step simply normalizes the probability vector without losing the relative weights of locations. In the third row, these probabilities are cumulatively added such that the last location in the vector is always given a value of 1. The normalized probability distribution, which is bounded between 0 and 1, gives locations with a higher chance of migration a larger interval. To select a location, an agent randomly draws from a uniform distribution between 0 and 1. Using this draw, the agent hits a target interval on the cumulative probability distribution. A larger interval will have a larger chance of being selected, or two equally sized intervals will have an equal chance of being selected. For Scenario 1, the highest interval exists for Location 2 while Location 1 is a close second. In Scenario 2, all three locations provide small gains thus the "no migration" column has the higher interval with a 0.57 probability of being selected.

In the second step, multiple draws are used to come up a location destination to minimize complete randomness in outcomes. As an example, if three draws are used for Scenario 1 in Table A.6, an agent can end up with a destination vector $\{Loc2, Loc1, Loc2\}$ where the modal value is $Loc2$, the destination with the highest probability of migration. Thus by manipulating the number of draws, the randomness in the model can be controlled. In the simulation runs, three draws are used to avoid completely arbitrary choices while allowing some room for random outcomes.

Prices

Prices are taken as a residual in the model and are central to *Buying*, *Selling* and *Migration* decisions. Each location determines its own price level based on the local demand and supply mechanisms. In its simplest form the price is given as a moving average of past prices plus recent supply and demand conditions. Changes in price levels for each location j can be tracked as:

$$\Delta p_{jt} = (1 - \theta)p_{j,t-1} + (\theta)\frac{D_{j,t-1}}{S_{j,t-1}} \tag{A.12}$$

where $D_{j,t-1}$ is last period's realized demand at location j, $S_{j,t-1}$ is last period's supply to location j. The parameter $0 \leq \theta \leq 1$ gives the level of adjustment to the changes in prices where $\theta = 1$ implies no price smoothing. The parameter θ allows price spikes, for example through sudden food shortages, to be smoothed out, sustaining minor fluctuations in the short-run. Large sustained market shocks will eventually force prices to adjust to a new level.

In the model, prices play a key role in determining population and good distributions. Price changes across locations forces labor and goods to readjust while high price spikes might make food expensive or reduce real income levels causing pockets of vulnerability to emerge in the short-run.
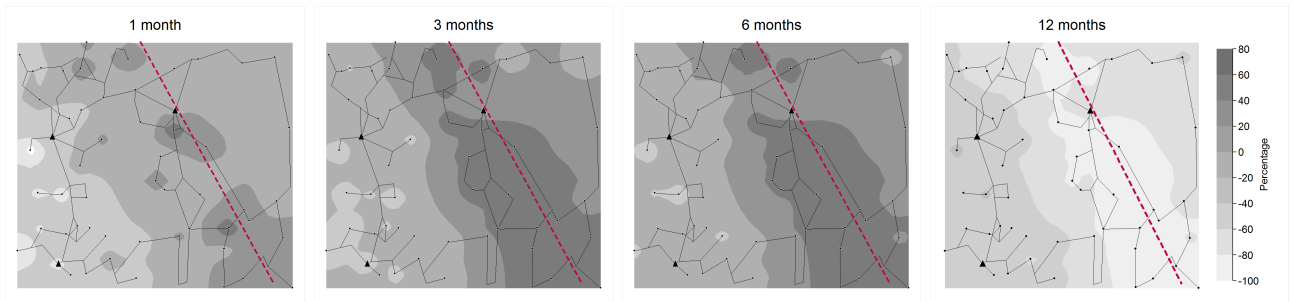
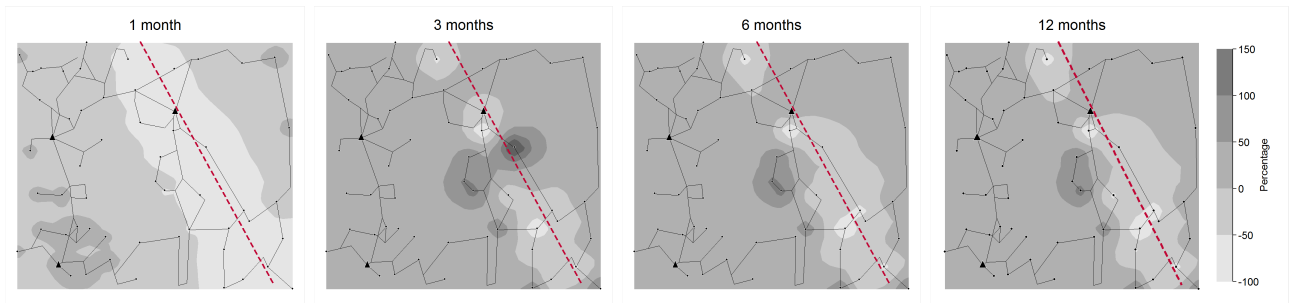# Appendix B. Transition graphs

Figure B.10: Spatial transitions
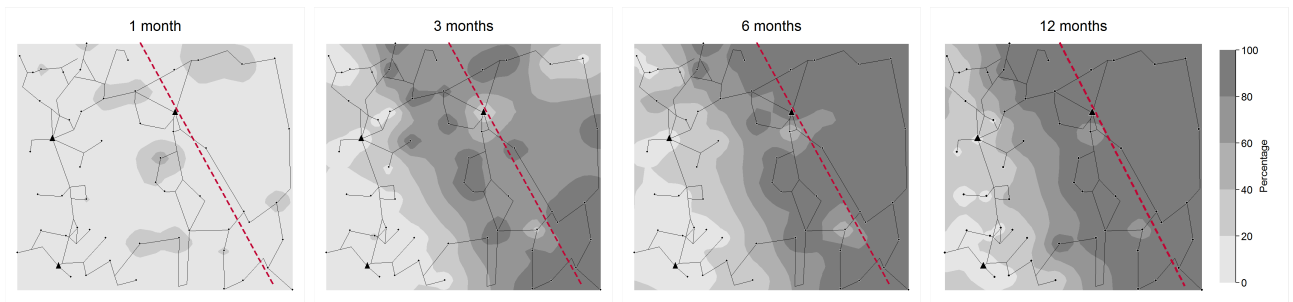
(a) Percentage change in population
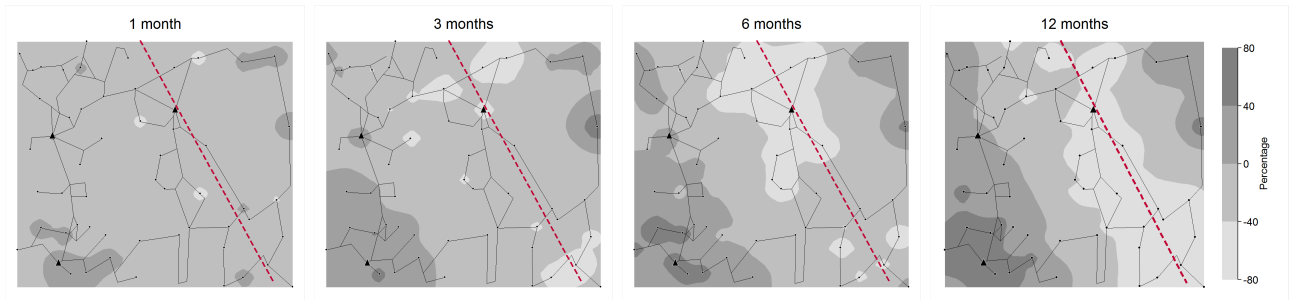
(b) Percentage change in real income

(c) Percentage change in food price

(d) Percentage starving

Appendix C. Sensitivity analysis

Two sets of sensitivity analyses are conducted on the model. The first set varies the initial parameter conditions to test for deviations from the benchmark parameter vector given in Table 1. The second set uses the benchmark parameter vector but varies the decay rates of the loss functions described in Figure 3b to test for senstivity of model outcomes.

Appendix C.1. Baseline parameters

The parameters are varied within a reasonable range of calibrated values given in Table 1. The aim of this exercise is to show deviations from the benchmark vector of parameters defined in Table 1 and test for sensitivity of the model to variations in parameter values.

Table C.7 show the combinations of parameters values. Each parameter is given a minimum value, maximum value, and the step between these values which gives the total number of combinations. For example, for the first parameter, the wage rate w, takes on the values of $\{0.2, 0.25, 0.3\}$, a total of three parameter values.
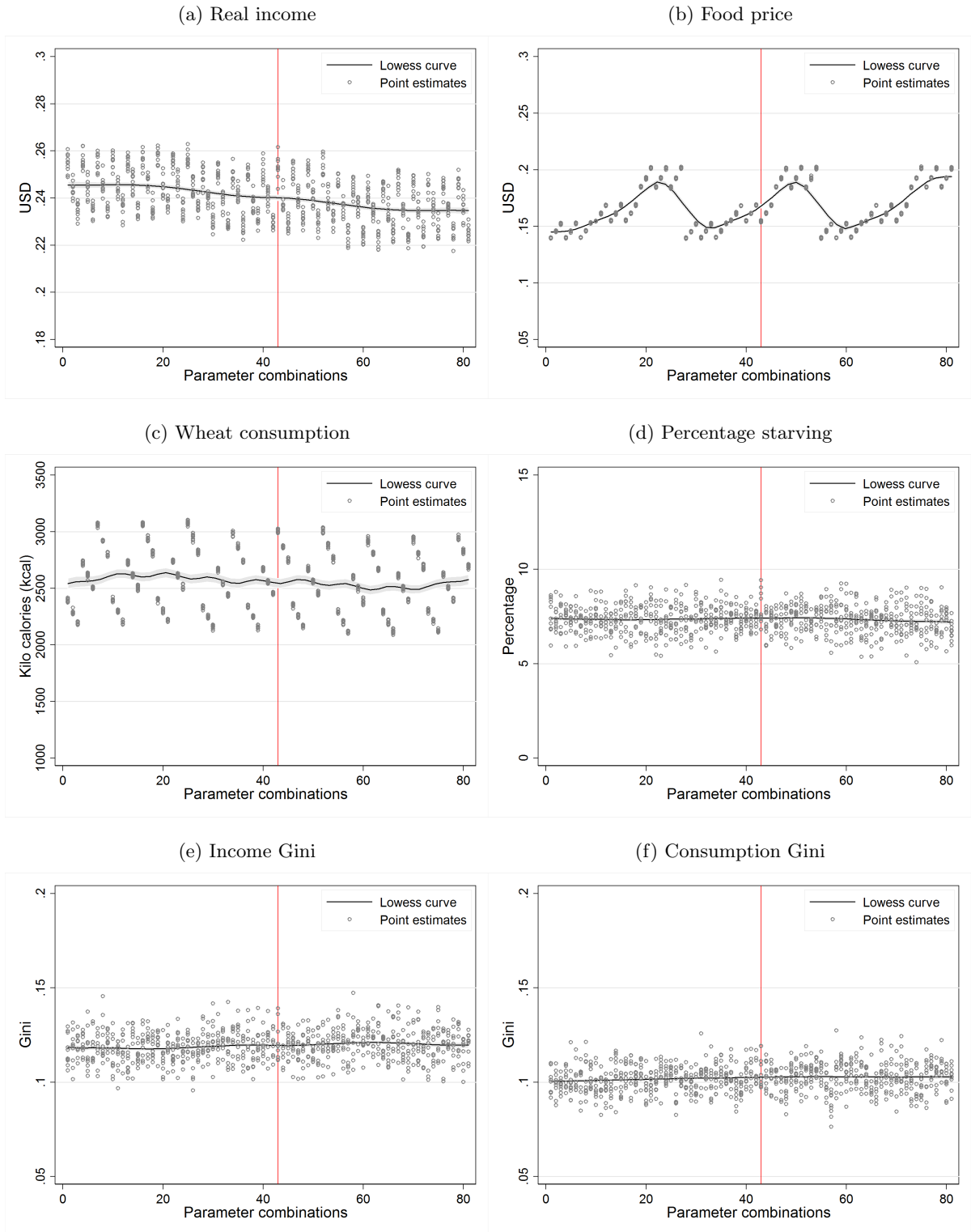
Table C.7: Sensitivity 1

Parameter	Description	Min	Step	Max	Combinations
w	wage rate (USD)	0.2	0.05	0.3	3
c_{1F}	mpc income (proportion)	0.7	0.1	0.9	3
δ	food stocks (days)	8	2	12	3
u_j	Autonomous production	5.7	1.4	8.6	3

The model runs for each parameter permutation ($3 \times 3 \times 3 \times 3 = 81$ in total) for a total of 10 times per permutation with random seeds. In total 810 simulations are conducted. The model runs till stable pre-crisis trends are achieved which are compared with the values of benchmark parameters.

Figure C.11 shows simulations of all parameter combinations. The values on the x-axis represent different parameter combinations and their results from ten runs are shown on the y-axis. The benchmark parameter vector is identified by the red vertical line and a fitted Lowess curve shows the smoothed-out average trends across all simulation runs. The figures highlight the robustness of the model in not being very sensitive to parameter values.

Figure C.11: Sensitivity analysis

(a) Real income

(b) Food price

(c) Wheat consumption

(d) Percentage starving

(e) Income Gini

(f) Consumption Gini

Appendix C.2. Loss functions

In this subsection, the parameters for the loss estimation using the equation 1 where by using a $\pm 20\%$ variation in the decay function. This is set by modifying the β's in the loss function ($\beta^{output} = 5 \pm 20\%$ and $\beta^{life} = 4 \pm 20\%$) such that the following ranges are used:

Table C.8: Sensitivity 2

Parameter	Description	Min	Step	Max	Combinations
β^{output}	Slope the output loss function	4	0.5	6	5
β^{life}	Slope of the life loss function	3.2	0.4	4.8	5

A total of 5 values of for each parameter are used which gives a total of $5 \times 5 = 25$ parameter combinations. Each combination is run for a total of 10 times giving a total of 250 simulation runs. The $\pm 20\%$ bands around the loss function are shown in Figure C.12.
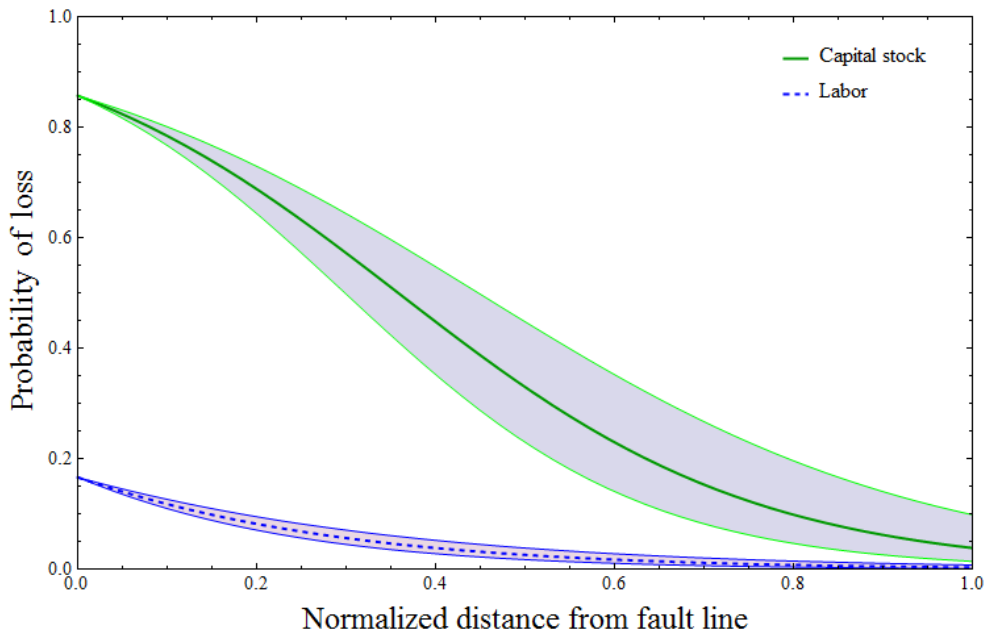
Figure C.12: Loss estimate bands

Table C.9 shows the sensitivity of the results pre-shock and one-year post-shock similar to Table 5. Pre and one year post-shock results are shown in the first two columns while column three shows the percentage changes. The last column shows the 10-90th percentile bands which compares the value ranges generated by the benchmark β's versus the value ranges generated by the full range of β's used for sensitivity analysis at the one year cut-off.

Figure C.13 shows the average temporal trends for six key indicators. The 10th–90th percentile bands are compared for the benchmark βs with the band generated from using the sensitivity βs. Graphs show reasonable trends around the mean values of the simulations given the variation in the decay rates of the loss functions.
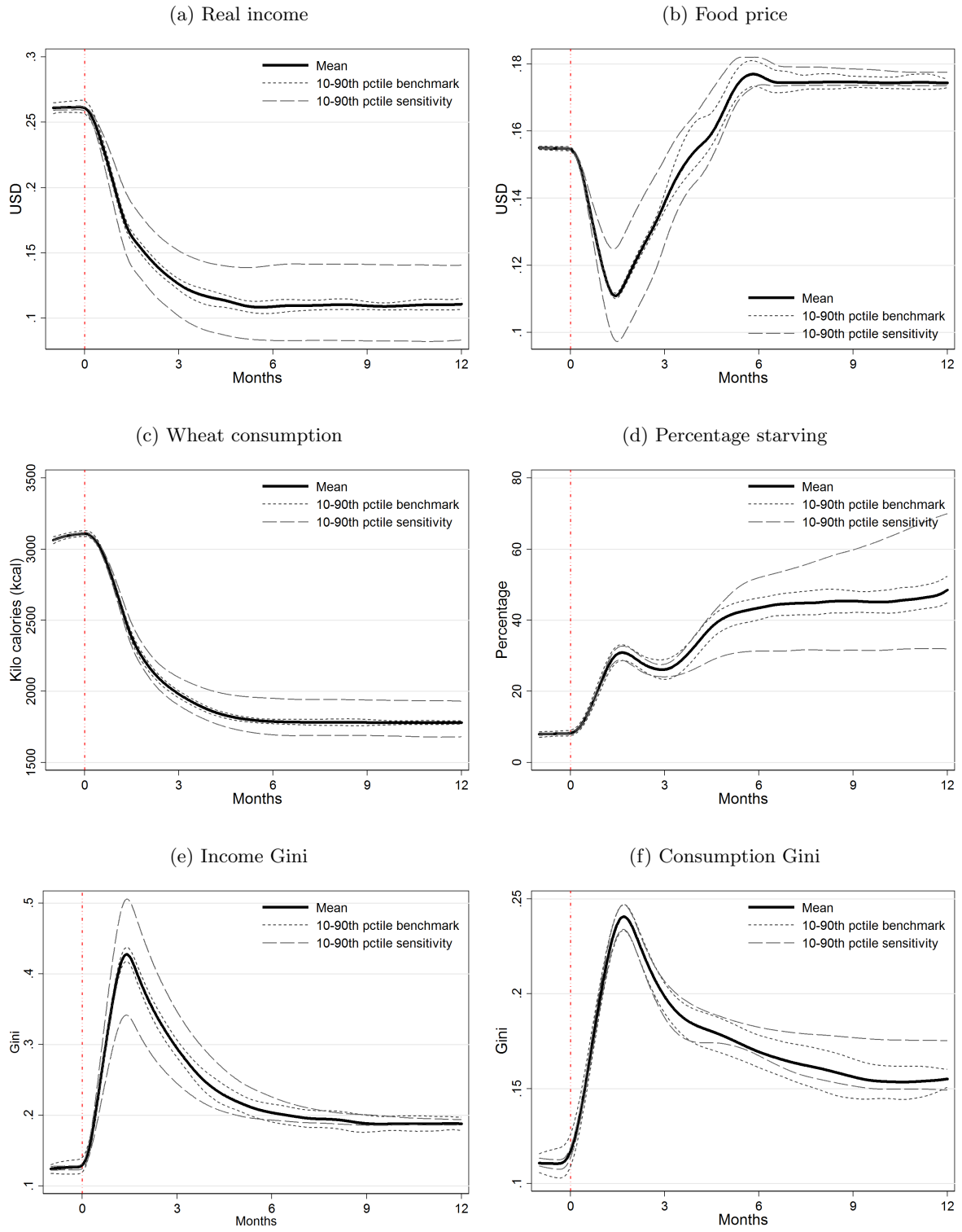
Figure C.13: Sensitivity analysis

(a) Real income

(b) Food price

(c) Wheat consumption

(d) Percentage starving

(e) Income Gini

(f) Consumption Gini

Table C.9: Sensitivity 2 – Summary Statistics

Variable	Pre-shock	One year	% change	10-90th percentile Benchmark (first row) Sensitivity (second row)
Output (Index)	100.00	53.41	-46.59	52.18 - 54.38
	(0)	(4.60)		47.29 - 60.25
Workers (number)	1287	1130.74	-12.14	1119.00 - 1143.50
	(0)	(16.77)		1109.50 - 1153.00
Percentage urban (%)	15.40	13.42	-12.86	12.71 - 15.099
	(0.37)	(0.68)		12.54 - 14.23
Real income (Index)	100.00	43.80	-56.20	40.94 - 45.89
	(1.23)	(8.29)		32.84 - 55.59
Food price (Index)	100.00	114.35	14.35	111.71 - 114.69
	(0.28)	(1.67)		112.58 - 116.09
Percentage starving (%)	8.12	47.17	480.91	44.48 - 49.96
	(0.59)	(14.32)		32.27 - 70.83
Income (Gini)	.122	.191	56.56	0.182 - 0.195
	(0.007)	(0.008)		0.180 - 0.201
Consumption (Gini)	0.110	0.159	44.55	0.148 - 0.161
	(0.005)	(0.0116)		0.147 - 0.177

Note: Standard deviations given in brackets. Table generated from 250 simulation runs.