Ali Asjad Naqvi
Miriam Rehm

SHELscape: A Multi-agent Policy Toolkit

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SHELscape: A Multi-agent Policy Toolkit

Ali Asjad Naqvi*  Miriam Rehm†

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Abstract

This paper presents a computational model, emphasizing feedback effects and the heterogeneity of agents in situations of large economic shocks. It therefore complements the well-developed body of literature modeling economic shocks using input-output models or computational general equilibrium models, which are naturally suited to the assumptions of zero or perfect substitution, respectively. We show in the framework of a stock-flow consistent, spatio-temporal dynamic micro simulation that large economic shocks can have negative effects on distribution and that these furthermore can exhibit some hysteresis. In particular, we find that income inequality worsens in the medium run after a shock, while consumption inequality increases in the short run.

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*Center for Economic Research in Pakistan (CERP), asjad.naqvi@cerp.org.pk.
†Chamber of Labour Austria, miriam.rehm@akwien.at.
## Contents

1 Introduction .................................................. 4
  1.1 Literature Review ........................................ 4
  1.2 Methodology ............................................ 7

2 The Model ................................................... 8
  2.1 Framework ................................................ 8
  2.2 Labor Markets ......................................... 10
  2.3 Production ................................................ 14
  2.4 Goods Markets ......................................... 15
  2.5 Consumption ............................................ 19
  2.6 Modeling Shocks ........................................ 21

3 Economic Impact of Shocks .................................. 22
  3.1 Headline Results ........................................ 22
  3.2 Dynamic Processes ...................................... 23
  3.3 Distributional Effects .................................. 25
  3.4 Sensitivity Analysis ....................................... 28

4 Conclusions .................................................. 30

References ..................................................... 32

A List of Symbols ............................................. 36

B Model Setup .................................................. 37
  B.1 Environment Setup ...................................... 37
  B.2 Behavioral rules notation ................................ 38
  B.3 Economy description ..................................... 38
List of Figures

2.1 Circular flow economy ......................................................... 9
2.2 Micro-economic interactions .................................................. 9
2.3 Real income-based probability distribution of migration ............... 11
2.4 Distance-based probability distribution of migration .................... 12
2.5 Joint probability distribution of migration ................................ 13
2.6 Production ........................................................................... 14
2.7 Goods market interactions ...................................................... 16
2.8 Transfer, buy and consume procedures ...................................... 19
3.1 Percentage Loss in Regional GDP ................................................. 22
3.2 Percentage Population Displaced ............................................... 23
3.3 Consumption Good Price Dynamics ......................................... 24
3.4 Rural Population ...................................................................... 24
3.5 Population Transitions .............................................................. 25
3.6 Distributions - Income ............................................................. 26
3.7 Distributions - Consumption .................................................... 27
3.8 Inequality ........................................................................... 28
3.9 Sensitivity to Shocks ............................................................... 29
B.1 Stylized Economy ................................................................ 37
1 Introduction

Disaster-like negative income shocks can have severe effects on the population in low-income regions (Aufreitter 2003; Cavallo and Noy 2010; Amin and Goldstein 2008). There is an extensive literature estimating the impacts of natural disasters using Input-Output (IO) models and, more recently, Computational General Equilibrium (CGE). While these are useful tools to investigate the cases of zero and full adaptation by economic agents in response to a shock, little research has delved into the wide field of limited substitution between these two extremes.

Capturing feedback effects is crucial to an understanding of the impacts of natural disasters. First, shocks result in non-linear adaptation processes where uni-directional channels of causality are hard to determine. Agents facing highly non-linear environments make adaptive decisions based on their current settings, which leads to non-Pareto optimal choices (Epstein and Axtell 1996). Second, since shocks are localized, both the temporal and spatial dispersion of the effects of shocks can vary substantially. Third, there are important feedback loops between regional population movements, and income and consumption distributions, which is important for identifying vulnerable population groups.

In order to address these open questions, this paper develops a multi-agent modeling framework that we term ‘SHELscape’, Simulation Hub for Economic Landscapes. SHELscape is an agent-based model (ABM) of a low-income region that aims at capturing its adjustment processes following a disaster-like negative production shock. In the steady state, heterogeneous agents engage in production and consumption, and interact on labor and goods markets in a monetary circular flow economy that is spatially defined and stock-flow consistent. Migration and market supply equilibrate wages and prices across space and over time.

Following a disaster-like shock to productive capacity, agents accommodate through the same channels available to them, including migrating for work and adapting their supply networks. The model is solved computationally and yields probabilistic estimates for income and consumption distributions, goods prices, and trade and migration flows.

The rest of the paper is organized as follows: A literature review and the methodology of computational modeling for natural disasters form the rest of the first section. Section (2) describes the model in detail, and section (3) presents the effects of natural disasters in the model. Section (4) concludes.

1.1 Literature Review

The economics of natural disasters is a budding research field whose key questions have been approached through different modeling methods. Since the pioneering work by Dacy and Kunreuther (1969), the focus of the economic literature on natural disasters has mainly been on loss estimation. Input-output (IO) models had been used since World War II for estimating disaster effects (Rose 2004: 24). Their simple structure based on a representation of the productive sector meant that they are well equipped to capture regional as well as sectoral distributive effects.

Early economic work thus provided sectoral assessments of direct and indirect effects of natural disasters from input-output (IO) models (e.g. Cochrane 1974 incorporating linear programming,
Increasing refinement of the methods of IO modeling, such as ever more fine-grained sectoral disaggregation, focused the calculation on losses from business interruption, as performed for instance by Gordon, Moore II, Richardson, Shinzuka, An, and Cho (2004) and Rose and Benavides (1998).

The simplicity of IO models makes it possible to integrate them with other approaches, such as network models (Okuyama 2007: 17, see also the contributions to that special issue). The economic literature on natural disasters developed this approach especially for utility lifelines and transport interruptions. The former is treated, among others, in Boisvert (1992); Chang, Seligson, and Eguchi (1996); Rose, Benavides, Chang, Szezsmiak, and Lim (1997), while the latter is covered by the SCPM2 model of Cho, Gordon, and Richardson (2000), and developed in the subsequent literature (Cho, Gordon, Moore, Richardson, Shinzuka, and Chang 2001; Gordon, Moore II, Richardson, Shinzuka, An, and Cho 2004).

Another shortcoming of traditional IO models is the limited modeling of other sectors, such as households and the government. This is remedied by another extension of IO models, Social Accounting Matrices (SAMs). They represent national accounting data in a matrix form. By adding economic sectors to the production sectors typically encompassed in IO models, they are capable of capturing institutional structures. They thus make it possible to depict distributions both between and within different sectors.

Cole (1995) makes use of this greater flexibility of SAMs with respect to distributional outcomes, by analyzing the impact natural disasters on different socio-economic groups in the Caribbean island of Aruba. The disaggregation of the demand side allows (Cole 1995: 235f) to separate welfare effects on various groups and sectors of the economy, and thus to extend the reach of IO models to encompass distribution between socioeconomic groups.

IO models are therefore powerful tools for the calculation of losses from business interruption, as well as spatial and sectoral distribution of output losses and income losses of different groups. However, their rigid coefficients and static nature continue to complicate the incorporation of feedback effects and behavioral elements (Rose and Liao 2005: 76) despite the significant advances in relieving their constraints (Hallegatte 2012). Price and substitution effects, as well as behavioral feedback effects, do not lend themselves naturally to incorporation into IO models.

A relatively recent development in the modeling of disaster modeling is the introduction of Computable General Equilibrium (CGE) models. These are, on the one hand, macroeconomic models with the concurrent balancing constraints (Mitra-Kahn 2008: 54f), which are governed, on the other hand, by microeconomic optimization of economic actors.

CGE models are well suited for taking substitution effects into account, and thus remedy a major shortcoming of IO models. Their emphasis tends to be on the long run, optimal responses, and on equilibrium outcomes (Rose and Liao 2005: 79f). Rose and Guha (2004: 130f) and Rose and Liao (2005) thus modify the parameters of their production functions in order to dampen the strong substitution effects of CGE models in response to an earthquake, and Rose, Oladuso, and Liao (2007) reduce the substitution elasticity of a CGE model of a terrorist attack in the United States. CGE models have also been extended to include network effects. Ueda, Koike, and Iwakami (2001) and Tsuchiya, Tatano, and Oikawa (2007) incorporate transportation into spatial CGE models of earthquakes in Japan.
Dynamic Stochastic General Equilibrium (DSGE) modeling of disasters is even less established. An exception is Keen and Pakko (2007), who apply a two-state Markov state analysis and find that, in order to mimic the sharp output losses of a flexible wage and price after a disaster, monetary authorities following a Taylor rule should raise interest rates.

Another recent development in the modeling of natural disasters are long-run growth models that focus on the financial impact of extreme events, such as the CATSIM model that explicitly models the macro level coping mechanisms and resilience of government finances in natural disasters (Mechler, Hochrainer, Aaheim, Salen, and Wreford 2010: 750).

To conclude, the prevalent approaches to the economic modeling of natural disasters have improved substantially on standard versions of IO and CGE models. That is, researchers have successfully mitigated their rigidity and their over-flexibility respectively and introduced spatial elements. Yet, the underlying shortcomings of these methodological approaches to short-run fluctuations have not been entirely remedied. Heterogeneity, networks and feedback effects, and stock-flow consistency remain a challenge to models of natural disasters (Hallegatte 2012: 41).

This paper argues that multi-agent models extend the spectrum of tools for modeling natural disasters. They are particularly well suited for research questions pertaining to the processes taking place in the immediate aftermath of a disaster. Their computational nature leads to a flexibility that relieves many technical constraints (Bonabéau 2002; Tesfatsion 2006), even as it places greater demands on the theoretical and empirical micro-foundations to provide restrictions for the model event space. Another important advantage of multi-agent models is their disaggregated method, which makes them well suited for the study of distributional aspects of natural disasters. Finally, the inherent dynamics make them well suited to incorporating endogenous feedback effects that capture both behavioral and market-mediated substitution effects.

ABMs have evolved from simple representation of agents following basic rules (Gardner 1970, Schelling 1978, Holland 1992) to simple representation of societies, for example in the pioneering work of Epstein and Axtell (1996) to more advanced models that are constructed to replicate economies (Albin and Foley 1992; Cioppa, Lucas, and Sanchez 2004; Dean, Gumnerman, Epstein, Axtell, Swedlund, Parker, and McCarroll 2000; Lebaron 2002). Large scale models are Axtell and Farmer's1 current work on replicating the US economy, the EURACE model of the European economy (Deissenberg, van der Haag, and Dawid 2008), Epstein's (2009) model of global pandemics, and Torrens' (2007) models on residential mobility and panic scenarios.

In contrast to agent-based models of the economies and especially financial markets of Europe and the U.S., low-income economies and natural disaster economics have not yet received much attention in the literature. This paper thus draws inspiration from a number of papers on agent-based modeling that are not directly referring to natural disasters in low-income regions.

A seminal contribution to agent-based modeling that is a foundation for this work is Epstein and Axtell's (1996) Sugarscape model. Epstein and Axtell (1996) trace production, trade, and consumption through simple behavioral rules in a non-monetary model of an artificial economy. Limiting societal institutions to a bare minimum, their model describes a two-good nomadic hunter-gatherer society, and it shows a Pareto optimal distribution of wealth. However, if the

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economy faces constraints such as non-infinite life spans, limited and asymmetric information, then outcomes are sub-optimal resulting in unequal welfare distributions.

There are some other multi-agent models that are tangentially related to this paper. These include some of the mid-range models in Miller and Page (2004), and the labor migration model in Rehm (2012).

1.2 Methodology

This paper develops a meso-level model of the adjustment processes following a natural disaster. This leap beyond the existing literature is made possible by the use of a new and different method of analyzing natural disasters, agent-based modeling. Agent-based modeling is a computer-based simulation approach that uses individuals as the basic unit of analysis, and models their interactions with each other and with the environment.

This technique makes it possible to address a number of key issues in short-term disaster analysis that standard models have difficulty in handling adequately. For policy analysis of natural disasters, one of the most limiting aspects is the deficiency in information and data, especially in the immediate aftermath. Agent-based modeling is parsimonious in its data requirements, and flexible in incorporating non-standardized sources of data. The model uses as essential inputs only geographic data and baseline assumptions, while additional data can be updated according to availability.

Another key advantage of agent-based modeling is its ability to trace vulnerability in different population groups in the short to medium run. The lack of consistent data sets collected in emergency situations makes it hard for empirical work to identify and analyze distributional changes. This is particularly the case within a time frame that is close to the event, and with sufficiently large data sets. Agent-based modeling is a powerful tool for incorporating heterogeneity of agents, the environment and their interactions into disaster analysis. Far from a representative agent approach, agent-based modeling makes it possible to generate distributions of income and consumption and, hence, to investigate supply bottlenecks and vulnerable populations at a very disaggregated level. For the emergency relief after natural disasters, the differences in affected populations are pivotal to tailored policy responses.

Since the elements are modeled at the individual level, agent-based modeling satisfies the demands of standard macroeconomics by providing solid micro-foundations. Furthermore, the computer programming-based nature of agent-based modeling makes it possible to make these micro-foundations realistic, and to incorporate qualitative and quantitative insights into human behavioral patterns.

At the same time, the flexibility of agent-based models in incorporating complex feedback effects between the elements of the model creates the possibility of emergent properties on the macro level. Agent-based modeling thus does not restrict the total to a simple multiple of the parts. The technique directs the focus towards the meso-level, while permitting control of both model inputs and outputs against real-world data on the micro- and macro-level respectively.

Feedback effects link to the strength of agent-based modeling in analyzing processes rather than just states. For the aftermath of disasters, the path along which an economy tends towards
a long-run equilibrium outcome is the phenomenon of interest to researchers and especially to political decision-makers. Hence, gradual adaptation mechanisms and slow adjustment processes in the short run are key to the analysis of natural disasters in order to correctly estimate the resilience of economic systems.

This is related to a notion of equilibrium employed in this paper that departs from a standard understanding of immediate, costless adjustment. Here, equilibrium is seen more like a center of gravity towards which variables tend, but from which they can deviate substantially in the short run that is the focus of this paper.

Furthermore, agent-based modeling excels in tracking flows as well as stocks and ensuring that they are consistent. This is pivotal to an analysis that hinges on the movement of goods and the migration of those affected as much as on savings and the availability of buffer stocks. The flexibility of agent-based models with respect to agent and environment heterogeneity makes them well-suited for spatial and network analysis. Both geographical distances and linkages between people have to be taken into account in the investigation of the aftermath of disasters.

Finally, simulating policy outcomes with agent-based models makes it possible to provide counterfactual scenarios, run experiments and provide probability distributions at extremely low costs in terms of time, financial resources and data. It can therefore not only provide theoretical insights, but is suitable for policy analysis under resource and information constraints.

2 The Model

This section describes the model. Subsection 2.1 gives an overview of the circular flow of goods and money in the economy. The following subsections describe the micro-foundations of the model with respect to labor markets (2.2), production (2.3), goods markets (2.4), and consumption (2.5). Internal trade (2.4.1) and internal migration (2.2.2) are discussed in the respective subsections on which they have the most direct impact, goods markets and labor markets respectively. Finally, subsection 2.6 describes the shock scenarios under which the reactions of the system are tested. It details both the reduction in the productive capacity of capital stock, which is the standard first approximation to estimates of indirect losses from natural disasters in low income regions, and its recovery process.

2.1 Framework

The model is set up as a circular flow economy with spatially distributed village and cities. Figure 2.1 below shows a stylized version of the region’s economic interactions between the two groups of agents, owners and workers. Using land and labor, villages produce a consumption good while capital cities can produce a tradable good with capital stock and labor. Villages and cities are connected through a road network along which migration and transportation of goods take place. Owners and workers exchange money for goods and labor on decentralized goods and labor markets.

Whether agents belong to the group of owners or workers is determined by their ownership of capital goods. These endowments are pre-determined and uniform among the two groups as a
first approximation\(^2\). As shown in Figure 2.2, agents can own three basic stocks, *capital, goods, and money*, and they are capable of deploying their *labor*.

Figure 2.1: Circular flow economy

*Capital* comprises the capital stock required for producing goods, such as land and machinery, and is only held by owners. *Goods* owned by agents include the essential consumption good and the tradable good. *Money* is the most liquid form of stock held by agents. It performs both a function as a store of value in the form of savings, and it acts as a medium of exchange for transforming holdings between the other categories of stocks held by agents. Owners are indexed by \( h \), workers by \( i \), goods are indexed by \( j \), and locations in the region are indexed by \( k \).

Figure 2.2: Micro-economic interactions

\(^2\)Subsequent versions of the model can allow for the endogenous determination of capital stock (land or firms), and thus of the status of their respective owner as owner or worker.
The micro-foundations of these individual behavioral rules are described in detail in the subsequent sections on labor markets (2.2), production (2.3), goods markets (2.4), and consumption (2.5). Their titles represent the essence of the behavioral rules described in each subsection in the form Rule[Parameters] → Agentset : Asset\*\+, where parameters are the exogenously defined set of inputs required to operationalize the rule\(^3\). The resulting rule increases or decreases one of the two assets held by an agent set, money and goods. This novel notation captures the micro behavior-based nature of computational models as well as their macro stock-flow consistency.

### 2.2 Labor Markets

Agents that do not possess capital (land or businesses) to produce goods search for work on labor markets. Their labor provides owners of the capital stock with higher output and the opportunity to generate profits, while the workers receive wages that allow them to purchase the consumption good.

#### 2.2.1 Pay wages[\(\rho, \lambda\)] → Workers: \(m^+_h\), Owners: \(m^-_h\)

There is full employment in the model both because of workers’ and employers’ incentive structure. Workers search for work in order to sustain their consumption, so the implicit reservation wage is zero. This simplifying assumption may be more appropriate, the more limited societal insurance mechanisms against income shortfalls are. Owners maximize output in a first step\(^4\), and do not impose hiring limits. This conforms to Post-Keynesian theories of firm behavior (Galbraith 1967; Eichner 1976).

Each agent is endowed with a productivity capacity \(\rho_k\), distributed uniformly across agents as a first approximation. However, as the cost of labor is determined by the wage rate \(\lambda\) paid per actual unit of output produced by workers\(^5\) \(\rho_{it}\), the falling productivity associated with a larger number of workers on the same plot of land or in the same business drives workers’ incomes down. Wages are thus defined as

\[
w_{it} = \lambda \rho_{it}
\]

(2.1)

Since productivity is uniform across workers, this amounts to uniform wages\(^6\). The total wage bill \(W\) of owners is thus given as

\[
W_{ht} = \lambda \sum_i \rho^h_{it}
\]

(2.2)

This results in a reduction in the money stock of owners at time \(t\)

\[
m_{h,t+1} = m_{ht} - W_{ht}
\]

(2.3)

\(^3\)For a detailed description of this notation, see Appendix B.

\(^4\)For the second step of profit maximization, see subsection 2.4.1

\(^5\)It is straightforward to incorporate empirically observed large-employer wage premia by adding a term \(\epsilon \Pi_{ht}\) to equation 2.1, where \(\Pi\) are revenues of owners and \(\epsilon\) is a parameter.

\(^6\)Higher skills would lead to higher levels of output and therefore wages, implying constant returns to skills.
and an increase in workers’ money stock

\[ m_{i,t+1} = m_{it} + w_{it}. \]  \hfill (2.4)

### 2.2.2 Migration

Wages are driven towards their equilibrium value in the model through worker mobility. The decision to migrate of each worker depends on the joint probability distribution of income differentials and distances, where the probability to migrate correlates positively with income, and negatively with distance. Income maximization as a motivation to migrate is well developed in the literature (Borjas 2001). The gravity model of migration, incorporating a penalty for distance, is another well-established approach (Greenwood 1975). A third theory, network migration, can easily be incorporated into agent-based models (Rehm 2012), and is a fruitful avenue for future research.

In determining income-based migration, real income, i.e. normalized by local consumption prices, is used to incorporate the effects of differential costs of living in different locations. Real income is given as

\[ \bar{w}_{ik,t-1} = \frac{w_{ik,t-1}}{\sum_k p_{jk,t-1}} \]  \hfill (2.5)

or the weighted average of workers’ income in location \( k \) by local market prices \( p_{j} \) of good \( j \). Since agents do not have perfect foresight in this model, the comparison is with last period’s income. That is, in making the migration decision a worker compares the real income earned at the current location with the average real income in another market that is observable to them. The probability of migrating is then calculated using a logistic function

\[ P_w = \frac{1}{1 + 1500e^{-3.6(\bar{w}_k/w_0)}} \]  \hfill (2.6)

Figure 2.3: Real income-based probability distribution of migration
Here, \( (\hat{w}_k / \hat{w}_0) \) is the ratio of real income in market \( k \) over real income in the local market, indexed as 0. The calibration of the log function to realistic values results in the curve shown in Figure 2.3. If the ratio of real incomes is less than or equal to 1, the probability of migrating is almost negligible. As the ratio increases, the probability of migrating rises and reaches almost 100% if another market is offering upwards of three times the income in the local market.

The distance-based probability of migration incorporates the observation that workers face a cost of moving that increases with distance. Distances are not calculated as the linear distance, but rather as the actual length of the road network connecting two locations. This may make a substantial difference in the complex or relief terrain of remote areas.

Furthermore, relative distances form the basis of the migration probability. That is, analogous to income-based migration, the distance between markets is normalized by the maximum distance in the road network \( \hat{x} \)

\[
\hat{x}_k = \frac{x_k}{\hat{x}} \quad (2.7)
\]

where \( \hat{x}_k \) is the normalized distance to market \( k \) from the current location. Thus nearer places are given a higher weight than farther ones\(^7\).

The probability of migrating based on distance is then calculated using an inverse logistic function:

\[
P_x = 1 - \frac{1}{1.05 + 30e^{-8.5\hat{x}_k}} \quad (2.8)
\]

Again, the calibration yields realistic values of the probability of migration, as shown in Figure 2.4. There is an inverse relationship between the probability to migrate and distance, and the furthest location is assigned a negligible probability of migration.

**Figure 2.4:** Distance-based probability distribution of migration

Finally, for the decision to migrate the above two distributions are combined and yield the joint probability distribution of migration.

\(^7\)If the road network is complex with multiple nodes (junctions), shortest paths are calculated using Dijkstra’s algorithm (Dijkstra 1959). See Appendix B for normalized distance matrices.
Figure 2.5: Joint probability distribution of migration

\[ P_{migration} = P_w \times P_X \]

Figure 2.5 depicts the probability of migrating based on the joint probability distribution of income differentials and distance. It is clear from Figure 2.5a that, while proximity and high income lead to a high migration probability and the combination of the inverse leads to low migration probability, there is a trade-off between income and distance in the middle ranges. Migrants move to a far place in order to earn substantially higher income, while for a somewhat higher income they are willing to move to a nearby location. The contour plot in Figure 2.5b illustrates this point through 0.1 probability intervals of the probability for migration.

This procedure thus yields a joint probability of migration for each location, where the choice among locations is based on a probabilistic procedure that includes a stochastic element. That is, the probabilities to migrate to each location are sorted into a cumulative probability distribution list. Several draws are made from the list and the location with the highest occurrence is selected. This iterative process yields more precise results than a single random draw due to the finite number of agents through two channels; first, agents that choose a low probability place for migration in a single step have an opportunity to revisit their decision, and second, if two places’ probability of being selected are very similar, then several draws allow agents to choose more carefully between the two options. Locations with a higher probability from the joint probability function are thus more likely to be selected as the number of draws goes up. That is, a single draw results in more noise in the data (more random outcomes), which implies that less information is contained in the actual decisions taken. Since a more volatile system can “till” in one direction, fewer draws increase the probability of multiple equilibria outcomes.

To conclude, there is full employment in the model with flexible wages; wages are paid out of the realized revenues from the goods that labor produced; and the mobility of migrants ensures the fluctuation of wages around equilibrium, though not their perfect or immediate convergence.
2.3 Production

Land, the form capital stock takes in villages, and businesses, capital stock in cities, have an exogenously determined output capacity of a good $\bar{x}_j$, where $j$ is either an essential consumable crop in the former case or a tradable good in the latter case. Owners of capital stock then produce up to their maximum production capacity $\bar{p}_h$ and hire workers for the remaining possible output of their plot of land. As described above in subsection 2.2.1, workers are also endowed with production capacity $\bar{p}_i$, allowing them to produce goods in exchange for wages by utilizing owners’ capital stock, where the actual productivity $\bar{p}_i$ depends on the number of workers employed at the current location. This production dynamics amounts to output maximization as a first step on the part of owners\(^8\) that is reminiscent of the theory of market share maximization as developed by Post Keynesian analysis (Lavoie 1992: 104). Figure 2.6 gives an overview of the processes involved in production.

![Production Diagram]

2.3.1 Produce $[j, \alpha, \rho] \rightarrow$ Owners: $x_j^+$

Each owner $h$ is endowed with an initial level of capital stock, which is capable of producing a maximum output of $\bar{x}_{hj}$. Since the key element of a natural disaster in the model developed here is a shock to output, total output has to be time variant, so current output is $x_{jt}$. The total production capacity of each good $j$ in the regional economy is therefore $\sum_h x_{hjt}$, that is, the total output of a good $j$ summed over the current production of all owners $h$ producing that good. Owners self produce a part of total production, $\bar{p}_h$, and the remaining amount ($\bar{x}_{hj} - \bar{p}_h$) is contracted out to workers in exchange for wages such that:

$$\text{Worker production} = \sum_i \bar{p}_{it} \leq (\bar{x}_{hj} - \bar{p}_h)$$ (2.9)

Equation 2.9 implies that the total work production, which can vary over time, is equivalent to the sum of the productive capacity $\bar{p}_{it}$ of the current stock of workers employed by owner

\(^8\)Owners maximize profit in a second step, as described in subsection 2.4.1.
h. Workers’ production cannot exceed the total non-owner produced production capacity, but it may fall short of the maximum production. In other words, workers might be under-utilizing their labor if there is crowding in the labor markets, and as a consequence might be underpaid.

From the above two equations, the stock of good $x_j$ accumulated by owner $h$ over time can be derived as follows:

$$x_{hj,t+1} = x_{hjt} + \rho_h x_{hjt} + \sum_i \rho_{jt}^i$$

(2.10)

### 2.3.2 Pay wages[$\beta, \lambda$]→Owners: $m^-$, Workers: $m^+$

Wages are not just a remuneration and thus an income to workers, but also a cost of production. In their former capacity, they lead to a flow of money from owners to workers as described in subsection 2.2.1. From the perspective of owners, the financing of production is a key question, as observed by Kalecki (1971). Since we abstract from intermediate inputs here, only wages have to be paid before there are sales revenues from the goods the workers produced. In the model, this sequencing problem is solved by wages being paid ex post, that is, after production has taken place and the resulting output has been sold.

### 2.4 Goods Markets

Goods markets are modeled as an applied adaptive *tâtonnement* process in the spirit of Albin and Foley (1992). The goods markets in the model enable agents to purchase, and producers to sell, the consumption and tradable goods produced in the economy. These markets can be thought of as middlemen in the distribution of goods, not unlike retail traders. They hold buffer stocks, which allow them to smooth out supply shocks. It is well established that buffer stocks can play an important role in enhancing the resilience of economic systems to a shock.

The mark-up or full cost pricing approach (Lavoie 1996: 60) is a theory of price setting by firms that is widely corroborated by firm-level evidence. This paper models firm supply as profit maximization under constraints in a locally monopolistic environment and with limited information as, for instance, described by Shapiro and Sawyer (2003). That is, on the supply side firms first set desired prices based on costs. They then aim at maximizing profits given their output of goods by selling in the market that offers the highest price.

On the demand side, individual agents’ desired consumption (see subsection 2.5) interacts with their savings and market prices to generate local demand. If there is a shortage of demand leading to prices in local markets falling below costs, then owners can use exports as a back-stop, where they are assumed to just recuperate costs. External trade thus balances aggregate supply

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9 Another possibility for dealing with this sequencing problem would be to model production loans.

10 This does not shift the risk of the realization of output to workers, since this risk is ruled out in the model through external demand (see subsection 2.4.1).

11 However, it should be noted that markets are not explicitly modeled as agents.

12 See Lim and Townsend (1998); Kazianga and Udny (2006); Fafchamps, Udny, and Crakas (1998); Chaudhuri and Paxson (2002) on a discussion of buffer stocks as informal consumption smoothing mechanisms in economies with imperfect credit markets.
and demand in the economy. These interactions of producers and consumers in goods (including export) markets are shown in Figure 2.7.

Figure 2.7: Goods market interactions

2.4.1 Sell\[j\]→Owners: \(x_{j}^{-}, m^{+}\), Markets: \(x_{j}^{+}\)

Owners sell their entire stock, apart from the goods destined for their own consumption, in the goods market\(^{13}\). Lacking perfect information on concurrent prices, they base the decision how much to supply to which market on last period’s price (and thus last period’s demand) in local markets and a distance-based cost element. In the model, the cost per unit of output is defined by the labor input cost \(\lambda\). Furthermore, the variable costs of the goods consumed by owners are included in the price calculation so that the production cost of the goods consumed is shifted to consumers. This can be interpreted as an implicit employers’ salary. The producers’ sell price \(\gamma_{jt}\) over time is thus

\[
\gamma_{jt} = \lambda \left( \frac{x_{jt}}{x_{jt} - d_{jt}} \right)
\]

(2.11)

The expression in brackets gives the price multiplier as the ratio of total goods produced (see section 2.3) to the net stock after consumption. For example, if the wage rate is 1 and the total production is 100 units, then if 50 units are consumed by the owner, the seller’s reservation price that allows the owner to cover their production cost will be 2.

Producers sell the output stock in the markets offering them the price that most exceeds their cost price. They do so by incrementally increasing their supply in those markets that offered the highest price net of distance costs in the previous period. The decision to sell in market \(k\) is based on their current unit cost \(\gamma_{h,jt}\), last period’s market price \(p_{jk,t-1}\) and the distance cost \(\vartheta_{k}\) to market \(k\). This gives the selling condition as

\[
\gamma_{h,jt} + \vartheta_{k} \leq p_{jk,t-1}
\]

(2.12)

\(^{13}\)The sequencing of selling decisions among producers is randomized.
As long as the condition in equation 2.12 holds, owners will be earning profits and will incrementally increase their supply $s_{jkt}$ in market $k$. Producers iterate this procedure over all regional markets. This drives prices in all local markets towards production costs. Since neither demand elasticity nor other producers’ supply decisions are known to producers, this process is somewhat turbulent. It can produce both local price undershooting that leads to losses for some producers in the short-run and temporary overshooting of prices with extraordinary profits. The mechanism by which producers choose between regional markets can thus be thought of as an applied adaptive tâtonnement process along the lines of Albin and Foley (1992) with a range of possible outcomes.

Competition between producers thus drives market prices towards their equilibrium value. Since both production and market locations are modeled in a spatially explicit way, markets are locally monopolistically competitive as transportation costs put producers located at a greater distance at a disadvantage. Nevertheless, intra-regional trade, that is producers selling in markets other than their closest one, takes place. Intra-regional trade thus ensures competition between producers and makes prices gravitate around their equilibrium value, similar to the way migration roughly equilibrates wages. In the event of a shock to local supply, this results in nearby producers providing supply as soon as local prices rise above prices in other markets.

It should be emphasized that this formulation ensures two elements crucial to a consistent and realistic formulation of goods markets. First, at no point do individual producers have information on current or future demand that they are facing. Producers also do not observe the elasticity of demand, but they do have information on past prices. Second, as a result of the competitive behavior of producers, prices tend towards an equilibrium value and sustained monopolies are not observed. However, given the limited information and adaptation speed of producers, this process takes time and leads to over- and undershooting of local prices for sustained stretches of time.

The stock available to suppliers equals the total good produced $x_{jt}$ less the amount consumed from own stock $d_{jt}$ (see section 2.5) such that the total amount sold satisfies the following condition:

$$\sum_k s_{jkt} \leq (x_{jt} - d_{jt})$$  \hspace{1cm} (2.13)

If producers miscalculate or local market prices are too low, and they therefore hold stock after the applied adaptive tâtonnement process is over, then they export the surplus amount $(x_{jt} - d_{jt}) - \sum_k s_{jkt}$ to foreign markets at cost price $\gamma_{jt}$.

Thus the profit $\Pi_{jt}$ earned by each owner $j$ can be derived as

$$\Pi_{jt} = \sum_k p_{jkt} s_{jkt} + \gamma_{jt} \left( (x_{jt} - d_{jt}) - \sum_k s_{jkt} \right) - \lambda x_{jt}$$  \hspace{1cm} (2.14)

or the revenue earned from selling in local markets plus the revenue from export, less production costs. In the model, the profits then feed back into wages (Section 2.2.1), purchase of the consumption good and money saving (section 2.5.1).
2.4.2 Supply \([j, r_j]\): Markets \(\rightarrow x_j^\sim\)

Markets hold buffer stocks to insure against minor supply shocks and to smooth transactions. They release a constant fraction \(0 \leq r_j \leq 1\) of their current good stock \(x_{jkt}\). This yields the time variant market supply \(\sigma_{jkt}\) in local markets

\[
\sigma_{jkt+1} = \sigma_{jkt} + r_j x_{jkt} - D_{jkt}
\]

which is equal to the current supply from producers plus the amount released from buffer stocks minus the amount bought based on local demand \(D_{jkt}\). Since current aggregate demand is not observable, markets calculate demand by observing the net change in supply stocks between two time periods such that:

\[
D_{jkt} = r_j x_{jkt} + (\sigma_{jkt} - \sigma_{jkt-1})
\]

Thus demand is given as the inflows through transfers less the net change in outflows from the previous two periods. The demand causes the current market stock levels to go down, the depleted market stock \(x_{jkt}\) is replenished through the sell procedure (from section 2.4.1 above) of owners. These flows give the change in market stocks as:

\[
x_{jkt+1} = (1 - r_j) x_{jkt} + S_{jkt}
\]

where \(S_{jkt}\) is the aggregate stock of good \(j\) added by owners in market \(k\) at time \(t\).

2.4.3 Prices \([\Delta_p]\) \(\rightarrow\) Markets: \(x^\Delta\), Owners: \(x^\pi\)

Since current aggregate demand is not observable for markets any more than for firms, local markets calculate expected demand in a backward-looking fashion using the effective total demand \(D_{jkt}\) derived in equation 2.16 above. Local current prices are then calculated as the ratio of expected demand and supply. In the model, prices are determined through a moving average to limit erratic price spikes. Transaction costs, but also formal and informal institutions can provide a rationale for non-instantaneous price reactions. The price in market \(k\) at time \(t\) is thus

\[
p_{jkt+1} = p_{jkt} + \psi \left( \frac{D_{jkt}}{\sigma_{jkt}} - p_{jkt} \right)
\]

where \(0 < \psi \leq 1\) is the smoothing factor, with full price adjustment if \(\psi = 1\).

As described in subsections 2.3 and 2.5, producers and consumers observe past market prices at each point in time, and adapt their supply and demand decisions accordingly. There are thus direct feedback loops between supply and demand, and prices.

To sum up the discussion of market mechanisms in the model, producers aim to maximize profits given their output, by exploiting the locally monopolistic market structure that results from

---

14 The use of buffer stocks in high-volatility environments is well-documented in the literature on natural disasters (see for example Chaudhuri and Paxson 2002).
transportation costs. Since producers cannot observe aggregate demand, however, they offer their goods in markets located further from their production location in an applied adaptive tâtonnement process. Prices in local markets are determined adaptively by supply and demand, and competition leads to a turbulent yet ultimately inexorable equalization of prices across all markets in the region.

### 2.5 Consumption

The following subsections 2.5.1 and 2.5 describe the individual elements of Figure 2.8, which outlines the behavioral rules leading to consumption.

Figure 2.8: Transfer, buy and consume procedures

To illustrate, under normal economic circumstances workers in villages will demand the consumption good and the tradable good from local markets. Landowners, on the other hand, will only purchase the tradable good since they are able to produce sufficient amounts of the consumption good for their sustenance.

#### 2.5.1 Buy[$i$, $c_j$, $δ_j$] → Owners, Workers: $x_j^+$, $m^-$

Agents demand the goods produced in the economy for consumption, while smoothing consumption over minor shocks to income by holding buffer stocks. Consumption smoothing in volatile environments through, among others, buffer stocks is well-documented in the literature (Townsend (1994); Deaton (1992); Lim and Townsend (1998); Morduch (1995)). In the model, the target level of buffer stock is agents’ consumption stock target $c_j$ times buffer days $δ_j$. Both
of these are exogenous parameters, where the former can be thought of for instance as influenced by preferences for conspicuous consumption and the latter as determined by the perception of risk or risk aversion of agents. An ample body of literature discusses the effect of the latter on risk mitigation behavior, see for instance Kazianga and Udry (2006); Fafchamps, Udry, and Czukas (1998); Chaudhuri and Paxson (2002).

If an agent’s stock of goods \( x_{jt} \) is sufficiently large to cover both the buffer stock and consumption target, then the agent does not purchase the good on markets, but rather consumes out of the goods stock. In contrast, if the agent’s stock of goods \( x_{jt} \) falls short, then this translates into desired demand \( d \) for the good \( j \) on markets. That is, for desired demand the following conditions hold:

\[
\text{desired demand} \begin{cases} \text{if} & x_{jt} < \bar{e}_j \delta_j \Rightarrow \quad \tilde{d}_j = \bar{e}_j \delta_j - x_{jt} \\ \text{else} & \tilde{d} = 0 \end{cases} \quad (2.19)
\]

If \( x_{jt} < \bar{e}_j \delta_j \), i.e., the stock of goods held by the agent does not reach the required level, then the agent purchases the remaining balance from markets using their income \( y_t \) and then money savings \( m_t \).

Desired demand, the shortfall of the good stock held from the buffer stock and consumption targets \( \bar{e}_j \delta_j \), is thus translated into realized demand \( d_{jt} \) through agents’ income \( y_t \) and current market prices:

\[
\text{realized demand} \begin{cases} \text{if} & y_{jt} < \tilde{d}_{jt} p_{jt} \Rightarrow \quad d_{jt} = \frac{y_{jt}}{p_{jt}} \\ \text{else} & d_{jt} = (\bar{e}_j \delta_j - x_{jt}) \Rightarrow \tilde{d} = 0 \end{cases} \quad (2.20)
\]

From the point of view of the individual consumer, given the monetary budget constraint of savings plus current income, the local market price determines the amount of goods that can be bought. If income is not sufficient, then agents will resort to consuming out of savings using an equivalent process.

Following Keynes (1936), saving or dis-saving by agents is a residual resulting from the difference between current income \( y_t \) and consumption expenditures \( \sum_j d_{jt} \). If income is sufficient to cover desired demand, then savings are defined as

\[
\varsigma_t = y_t - \sum_j d_{jt} \quad (2.21)
\]

Savings are then added to the money stock

\[
m_{t+1} = \varsigma_t + m_t - \sum_j \tilde{d}_{jt} \quad (2.22)
\]

where the variable \( \varsigma_t \) is the time variant growth factor of wealth in monetary terms. Thus if income falls below the current market price of desired goods stocks, then \( y_t - d_t = 0 \Rightarrow \varsigma_t = 0 \)

---

15 Note that for workers \( y_t = w t \) from equation 2.1 and for owners \( y_t = \Pi t \) from equation 2.14
\[ \sum_j \tilde{d}_{jt} > 0. \] This not only results in a zero growth of wealth, but also in agents draining their wealth to ensure target stock levels of the consumption good are met.

### 2.5.2 \textbf{Consume}[j, \hat{c}_j] \rightarrow \textbf{Agents}: x_j^{-}

Agents consume a fraction \( c_{jt} \) of their stock \( x_{jt} \) at any point in time. The consumption of good \( j \) per time unit is determined as

\[
\text{consumption: } 0 \leq c_{jt} \leq \hat{c}_j, \text{ such that } \begin{cases} 
    i f & x_{jt} < \hat{c}_j \Rightarrow c_{jt} = \frac{x_{jt}}{\delta} \\
    e l s e & c_{jt} = \hat{c}_j 
\end{cases}
\] (2.23)

That is, agents with a limited goods stock reduce their consumption in order to retain sufficient stocks for the buffer stock period at the new, reduced, consumption rate. This in effect makes the number of days for which agents wish to hold buffer stocks, \( \delta \), exogenous while keeping actual consumption \( c_{jt} \) endogenous. This choice allows \( \delta \) to be interpreted as an exogenous parameter of risk aversion. More importantly, however, this formulation is equivalent to consumption out of income and thus consistent with the formulation in subsection 2.5.1, because good stocks, the money stock and buffer stocks vary positively with income. Finally, it should be noted that in this two-good model, agents' preference structure is such that the consumption good is strictly preferred over the tradable good.

### 2.6 Modeling Shocks

This subsection describes the simulation of economic shocks to the system. These are modeled as a one-time decrease in the production capacity of capital assets, land and capital stock for \( n \geq 0 \) time periods. This is equivalent to a destruction of capital stock to the extent of the shock, even though it may also capture an inability to produce at former levels of production for other reasons, e.g. supply bottlenecks. The total production capacity of the economy after the shock therefore decreases by the level of shock \( \alpha \), such that at the time of the shock, indexed to 0, the current production capacity is given as a share of maximum production capacity \( \bar{x} \) of good \( j \):

\[
x_{j0} = \bar{x}_j (1 - \alpha) \] (2.24)

Here, \( 0 \leq \alpha \leq 1 \), where 1 implies a complete destruction of production capacity.

The system is modeled to recover after a certain time period \( n \geq 0 \). The recovery process is determined by the parameter \( 0 < \beta \leq 1 \) such that

\[
x_{j,t+1} = x_{jt} + \beta (\bar{x}_j - x_{jt}) \] (2.25)

This allows productive capacity to recover from its initial post-shock state \( x_{j0} \) to its maximum of \( \bar{x}_j \).
3 Economic Impact of Shocks

This section presents the findings from the model developed in Section 2. Subsection 3.1 describes the headline results, which are a standard first approximation to the impacts of a natural disaster. It details both the reduction in output, which estimates indirect losses from natural disasters in low-income regions, and internal migration, or the share of the affected population that is displaced. Subsection 3.2 extends the analysis along the time axis, looking into the development of the indicators for transmission mechanisms within the economy, prices and population movements. The next subsection 3.3 makes use of the strengths of agent-based modeling by analyzing the impacts of the economic shock on income and consumption distributions. Subsection 3.4 concludes by testing the sensitivity of the model to different shock levels.

The model calibration is described in detail in B. The setup of the economy is a $(9 \times 3)$ village-city matrix, with the vector of initial exogenous parameters set to $E[10, 1000, 1000, 200, 1, 5, 20, 0.75, 1]$. The economic shock is modeled as a decline in the rural productive capacity of capital in rural areas (land) of 70%, i.e. $\alpha = 0.7$ at time $t = 0$. After one year, the recovery process starts with $\beta = 0.2$, restoring productive capacity after 2 years.

3.1 Headline Results

One of the foremost concerns of economic research into natural disasters is the projection of output losses. The agent-based model can readily be used to generate counter-factual scenarios. Figure 3.1 shows the output lost from a 70% output shock. In the first year, the regional economy faces a 35% reduction in GDP. The economy then recovers gradually, and output remains below its pre-shock peak in the second year following the crisis. Cumulatively, the economy loses 58% of output during the three years after the shock.

![Figure 3.1: Percentage Loss in Regional GDP](image)

Note: Generated from 25 simulations.

Similarly, the model can be used to estimate the number of internally displaced persons\(^{16}\) in

\(^{16}\)It should be noted here that the model focuses on the labor market effects of migration, and thus does not
the event of an economic shock. At a shock level of 70%, the model predicts that 76% of
the population in the affected areas is displaced in the first year. Migration rates remain high
throughout the adjustment process of the economy, as return migration set in in the second year
as economic opportunities improve.

Figure 3.2: Percentage Population Displaced

The next sections investigate the dynamics and the distributions underlying these headline num-
bers.

3.2 Dynamic Processes

The results presented in this subsection describe the outcomes for the various shock levels over
time; these were generated as the average of 50 simulation runs. The focus is here on the paths
along which the final outcomes are reached, and on the processes that are underlying these
This subsection therefore investigates the transmission mechanisms, i.e. migration (population
displacement) and price changes, that impact the outcome variables, output (production), income
and consumption.

A shock to production capacity leads to price increases that are transitive across shock levels,
as Figure 3.3 shows. Price spikes reflecting the increased scarcity of goods increase with the
magnitude of the shock. Prices remain at up to 145% of their pre-shock value for the period of
scarcity, but they swiftly return to their original levels as productive capacity approaches the
levels before the shock typically within one year after the start of the recovery process.

The relatively smooth path of the share of the rural population stock, however, covers the more
volatile migration flows underlying it. Figure 3.5 shows the transition matrices between the
two possible states (rural, urban) over time. It indicates that the inter-regional flows are not
necessarily uni-directional, even though there are two clearly dominating trends in population
movements.

distinguish between migrants for economic and for humanitarian reasons.
First, the immediate reaction of population flows to the negative shock is a peak of rural to urban migration, which leads to 6% of the total population migrating at a given point in time as the inhabitants flee the affected areas. With minimal flows in other directions, this results in a net decline in rural population of approximately 30% as can be seen in Figure 3.4. The other peak is urban-rural migration as the economy recovers in the shock-affected areas. However, there is a difference in the size of the two peaks, which is what lies behind the persistence in out-migration from the affected areas.

In addition to these dominant patterns, there is non-negligible village-village migration during the first year after the shock, and city-city migration in the second. These are the second-round effects generated as the large migration waves impact local labor markets of the receiving regions.
and lead to falling wages in some regions, and rising wages in others, and the concomitant labor migration.

Figure 3.5: Population Transitions

![Population Transitions Graph]

Note: Generated from 100 simulations.

To sum up, the share of population living in rural areas decreases abruptly after a shock as workers migrate to earn a living elsewhere. Out-migration continues until recovery sets in. However, there is hysteresis in migration, since the return of productive capacity to the original levels does not lead to a full recovery of rural population shares as a result of the frictions in the migration decision making process.

3.3 Distributional Effects

This subsection looks in more detail at the distributional dynamics set in motion by an economic shock. As above, the shock is a 70% reduction in potential output. The model allows tracking the distributions of income and consumption.

It should be emphasized here that any distributions generated in the model are the result of interactions between identically endowed agents. This phenomenon of *horizontal inequality* was developed in a statistical equilibrium framework by Feeny (1994, :342), and explored in detail in Epstein and Axtell (1996, :113). Horizontal inequality cannot exist in a Walrasian equilibrium by construction, that is, inequality cannot result from outcomes that are Pareto optimal.\footnote{see Mas-Colell, Whinston, and Green (1995) for a detailed exposition of the First Welfare Theorem.} Near Pareto optimality, however, such as the local interactions leading to limited monopoly power and profits in this model, is capable of generating horizontal inequality.

3.3.1 Income

Economic shocks have a substantial effect on income in the model. Figure 3.6a shows incomes for the 20th, 40th, 60th, 80th and 100th deciles, indexed to their levels relative to the highest income.
group at $t = 0$. All groups take substantial hits to their income as a result of the shock, and the downturn has a compressing effect on incomes. The income of the fifth quintile, for instance, falls to the pre-shock level of the third quintile. The drop in incomes is reversed during the recovery phase after the shock as all groups benefit from the employment opportunities offered by an increasing productive capacity. However, the spread between income groups is larger after the recovery than it was before the shock. Economic shocks, and especially the subsequent recovery, thus do not only reduce overall income, they also increase income inequality in the model.

Figure 3.6: Distributions - Income

![Graph showing income distributions](image)

Note: Generated from 100 simulations.

This point is emphasized by Figure 3.6b, which depicts the shares of the same percentiles in total income\(^\text{18}\). While overall income levels fall for all workers, as described above, they do not decrease equally. In particular, the top quintile sees its income share increase steeply, albeit with a lag, from 27% of total income to just under 35%. While its share decreases after the recovery sets in after one year, this takes place more gradually and the income share remains at about 30% after two years, higher than the initial level.

The share of the fourth income quintile remains relatively flat across the economic shock and the recovery process. The bulk of the counterpart to the increased share of the top quintile is thus in the bottom three quintiles. These lose around 2% of their share in total income. While the recovery process is somewhat similar for the top quintiles, the bottom quintile is the slowest to recover and ends up with a lower income share.

The figure also shows two bumps in the adjustment process, one immediately after the shock and a second during the recovery process. Since populations take time to adjust to changing economic environments, frictions in employment caused by non-instantaneous migration increase inequality levels, allowing some workers to make short-term gains before they settle down in stable trends.

This finding qualifies the headline result regarding output from subsection 3.1 in important ways. While total production and thus average income return to their original level within two years of recovery, not all income groups participate in the changes in income equally. Incomes are compressed during the downturn following the economic shock, but they spread beyond the

\(^{\text{18}}\)Note that these are not cumulative.
initial levels of inequality during the recovery process as high incomes rise disproportionately while low incomes recover more slowly. As a result, inequality is higher after recovery than at the outset. This hysteresis is a typical feature of complex systems with feedback effects.

3.3.2 Consumption

Figure 3.7 shows consumption levels by quintiles. The initial differences show a substantial shortfall in consumption, as the upper quintile consumes the desired consumption levels (indexed at 100) while the bottom quintile consumes almost 30% less. The result below shows that, unlike the income distribution, the consumption distribution is only marginally affected by the shock, as workers consume out of savings to smooth consumption. Low saving levels for the lower income group and rising prices force them to reduce consumption by the highest margin. This result shows that the capacity to hedge against income shocks varies across groups, even though agents face the same endowments and environmental constraints.

![Figure 3.7: Distributions - Consumption](image)

Note: Generated from 100 simulations.

These results highlight that natural disasters can exacerbate consumption vulnerability especially for the bottom quintile, which is the least able to hedge against the calamitous income and price changes after a shock. In contrast to income, however, the effect of the shock on consumption is transient in the model. Consumption patterns return to pre-shock levels with no long-term redistributive effects after recovery gets under way.

These findings are further reinforced by the Gini coefficient, which measures inequality on a scale from 0 to 1, where 0 is perfect equality and 1 is perfect inequality. Gini coefficients over time for income and consumption are shown in Figures 3.8a and 3.8b, respectively. The income Gini rises from low levels to 0.39 for a 75% productivity shock. As workers relocate through migration, the Gini drops back towards its original level, only to rise again, more persistently this time, with the return migration induced by the economic recovery. The Gini coefficient confirms the hysteresis in income inequality following the shock and recovery phase.
In contrast, consumption inequality remains higher than at the outset until well after recovery sets in at the beginning of the second year. Only roughly half of the immediate increase in the Gini coefficient of consumption after the shock is reversed. Inequality in consumption is thus more persistent through the shock phase, albeit at lower levels than income inequality. However, in the recovery phase the Gini coefficient of consumption returns to its original low level of about 0.05.

Figure 3.8: Inequality

Note: Generated from 100 simulations.

3.4 Sensitivity Analysis

This subsection looks into the sensitivity of model outcomes to different shock levels. The outcomes investigated here are the average changes in the population share living in affected areas, income levels, the price and the consumption of the goods produced in the affected area. Figure 3.9a shows the cross-sectional sensitivity of the model to shocks. Its box-and-whisker graphs plot the change of the outcome variables from their quasi-equilibrium values against shock levels to show the sensitivity of the artificial economy. The graphs are generated from 300 simulations.

It can be seen that the average loss of rural income ranges from 28% to 70% for shocks between 30% and 75%, and that it shows a linear trend. Accordingly, the loss in rural income results in out-migration from the affected areas which reduces the rural population, on average, from 5% to 75%. Internal displacement increases in a quadratic form as the shock severity increases. Consumption shortfalls are much smaller than changes in income, lying between 1% and 9% for the range of shocks investigated here. This very limited through-put of income losses is a result of agents’ attempts to maintain a minimum consumption level despite falling incomes by drawing on all the coping mechanisms available to them, including running down savings and migrating.

One finding from the sensitivity analysis conducted here is thus that there is a non-linear relationship between some variables and the shock level. For instance, the fall in population is convex to the origin across shock levels, as should be expected if agents increasingly resort to migration as shocks become more severe. Changes in consumption resulting from economic shocks are also clearly convex to the origin. This reflects the increasing inadequacy of endogenous stabilization through agents’ coping strategies as shocks become more severe.
Figure 3.9: Sensitivity to Shocks

(a) Income  
(b) Displaced Rural Population

(c) Consumption  
(d) Price (Consumption Good)

Note: Graphs generated from 300 simulations. Boxes are the 25-75th percentile range, whiskers are the 95% confidence interval, dots represent outliers.

The price of the consumption good, which is produced in the affected areas, shows a much more volatile response to varying shock levels than the other variables. Buffeted by lower production levels, increasingly mobile populations and suppliers switching markets, its range is around 5% and it tends to increase exponentially with higher variance levels as the intensity of shock increases. The price as a key signal in the economic system thus reflects the increasing turbulence as shock levels rise. If its fluctuations are violent, it can set off overshooting in agents’ behavioral responses. A higher variance in prices thus correlates with a higher variance in income and rural population levels.

To conclude, the variables investigated here are related to the shock level of the natural disaster in a broadly stable manner. Income decreases in a linear fashion at an elasticity of about 1. The population displaced by the natural disaster, on the other hand, reacts elastically to the level of the shock. As a result of the aggressive use of coping strategies, the shock elasticity of consumption is low. Finally, the price of the consumption good becomes substantially more volatile as the shock level increases and the coordination of production and consumption oscillations becomes more strenuous.

29
## 4 Conclusions

This paper developed a multi-agent model of the effects of natural disasters in a low-income region. There is an ample body of literature on modeling natural disasters through input-output and computational general equilibrium models under the assumptions, in the extreme cases, of zero substitution effects and perfect adaptation, respectively. This paper aims at exploring the interior ground between these corner solutions. Furthermore, models of natural disasters typically treat high-income economies of the United States or Japan, so this paper expands the scope of the literature by explicitly focusing on a small, rural, low-income region.

Computational models are well suited for disasters research for a number of reasons. First, large shocks to economic activity place the economy far from the equilibrium, which leads to non-linear adjustment processes that agent-based models are well equipped to deal with through feedback effects and emergent processes. Second, agent-based models address the deficiency in timely information and data in natural disaster situations, since they are parsimonious in their data requirements, yet flexible in incorporating non-standardized sources of data including micro-surveys and qualitative research. Third, and perhaps most importantly to this paper, agent-based models have thorough micro-foundations that make it possible to investigate distributions, and thus the effects of natural disasters on different groups.

The simulated economy, which is labeled SHELscape, is a stock-flow consistent, spatial-temporal model with heterogeneous agents and limited information. Two agent groups (workers and owners) produce two goods (a consumption and a tradable good) in two regions (urban and rural) using two inputs (land/capital and labor). Selling their labor, workers acquire money to purchase the essential consumption good, while owners receive labor for the production of the goods. These goods are sold on locally monopolized markets, generating revenue for the owners. A shock to the rural production of the consumption good, used for self-sustenance and trade, has a two-fold effect. First, the supply of the good decreases, which reduces wages and, secondly, forces workers to migrate to cities in search of work. This transmits the shock to cities through increased food demand, which, combined with reduced supply, raises food prices.

Sensitivity analysis shows that the variables investigated in this paper, the population share in the affected areas, income, consumption and the price of goods produced in the affected area, react in a broadly stable manner to changes in the shock level. The transmission mechanisms of migration and prices increase exponentially with the level of shock, whereby prices show a markedly increasing variance indicative of high levels of volatility in the regional economy. The flow variables of income and consumption, on the other hand, show varying degrees of resilience to the shock. Income levels drop more significantly as compared to consumption levels, because agents will smooth consumption through their savings and coping strategies in order to avoid starvation.

In the calibration of the model through the vector of exogenous parameters, the level of the economic shock is set to 70%, modeled as a fall in output capacity of land. This drop is all but reversed within the second year through a recovery process. We estimate that a shock of this magnitude, which can be interpreted as a 70% crop destruction, leads to a fall in output of 35% in the first year. Cumulatively, the economy loses almost 60% of potential output over the three years that it requires to fully restore productive capacity. The model furthermore projects a 30%
fall in population in the affected rural areas.

The dynamic processes underlying these results show that prices spike over the entire first year, but return to pre-disaster levels in the course of the second year. Both price levels and migration escalate as the shock level increases. Substantial out-migration takes place at the time of the shock, and there is somewhat lower return migration once the recovery is under way. This leads to hysteresis in the fall in rural population levels after the economic shock.

The income distribution also shows persistent effects of the natural disaster. While income falls across the board as a result of the natural disaster, the share of high-income groups, and in particular the top 20%, in total income increases after the shock. The income share remains high throughout the time of recovery, while, as a flip side, the income share of the bottom 60% falls lastingy. The Gini coefficient corroborates the hysteresis in income inequality following the disaster-like economic shock. Another important insight is that the recovery process can be almost as disruptive, in a sense, as the original shock. It is the differential effects of recovery that have the most long-lasting impact on the Gini coefficient of income.

Consumption inequality also increases, albeit to a more moderate degree, as a result of the shock, whereby the top 40% see their share rise and especially the bottom 20% are not able to sustain their already low consumption through the downturn. In contrast to income, these effects are transient, since agents resort to any coping mechanism available to them in order to achieve the minimum consumption levels.

These findings naturally lend themselves to policy conclusions. Since feedback effects and failing coping strategies have such a strong impact on the results for inequality and poverty, a timely policy response is crucial for mitigating the effects of large economic shocks. Furthermore, policies targeted at vulnerable population groups can go a long way towards reducing the harshest effects of natural disasters. This may include income or consumption support measures, even though improving the self-stabilizing properties of the economic system by strengthening the coping strategies available to agents, for instance through a well-designed public works program, can also prove viable. An important ancillary policy can be capping price spikes either through price agreements or food stock provision. This dampens the feedback effects between population movements and real incomes. The modeling framework presented in this paper can improve both on the reaction time and the targeting of economic first responders after a large shock. It makes it possible to probabilistically predict population flows, and identify vulnerable groups, supply shortages and price spikes close to real time, updating at little time and resource cost as information becomes available.

Further development of the model could extend the research into the adaptive risk mitigation strategies and coping mechanisms at the agent level, and at a structural level could give further insight into the inner workings of the meso-level processes described in this paper. In addition, incorporating another level of decision making at the household level could provide a natural connection point to the bodies of literature on work diversification, and migration and crop choices. Finally, calibrating the model to macroeconomic, GIS or survey data would be the natural next step in making it applicable to real-world policy processes.
References


A List of Symbols

Table A.1: List of Symbols

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
<th>Limits</th>
<th>Indices</th>
</tr>
</thead>
<tbody>
<tr>
<td>c</td>
<td>consumption</td>
<td>[0, c]</td>
<td>h, i, j, t</td>
</tr>
<tr>
<td>c̄</td>
<td>consumption target</td>
<td>≥ 0</td>
<td>j</td>
</tr>
<tr>
<td>δ</td>
<td>buffer stocks in time units</td>
<td>≥ 0</td>
<td>j</td>
</tr>
<tr>
<td>d</td>
<td>realized demand</td>
<td>[0, d]</td>
<td>h, i, j, t</td>
</tr>
<tr>
<td>d̄</td>
<td>desired demand</td>
<td>≥ 0</td>
<td>h, i, j, t</td>
</tr>
<tr>
<td>D</td>
<td>aggregate demand</td>
<td>≥ 0</td>
<td>j, k, t</td>
</tr>
<tr>
<td>m</td>
<td>money stock</td>
<td>≥ 0</td>
<td>t</td>
</tr>
<tr>
<td>p</td>
<td>price</td>
<td>≥ 0</td>
<td>j, k, t</td>
</tr>
<tr>
<td>P_{mig}</td>
<td>joint probability of migration</td>
<td>[0, 1]</td>
<td></td>
</tr>
<tr>
<td>P_w</td>
<td>income-based probability of migration</td>
<td>[0, 1]</td>
<td></td>
</tr>
<tr>
<td>P_x</td>
<td>distance-based probability of migration</td>
<td>[0, 1]</td>
<td></td>
</tr>
<tr>
<td>r</td>
<td>market release of goods</td>
<td>[0, 1]</td>
<td>j</td>
</tr>
<tr>
<td>s</td>
<td>supply by producers</td>
<td>≥ 0</td>
<td>h, j, k, t</td>
</tr>
<tr>
<td>S</td>
<td>aggregate supply by producers</td>
<td>≥ 0</td>
<td>j, k, t</td>
</tr>
<tr>
<td>Π</td>
<td>profit of owners</td>
<td>≥ 0</td>
<td>h, t</td>
</tr>
<tr>
<td>w</td>
<td>wage rate per unit of output</td>
<td>≥ 0</td>
<td></td>
</tr>
<tr>
<td>̄w</td>
<td>average wages</td>
<td>≥ 0</td>
<td>k, t</td>
</tr>
<tr>
<td>W</td>
<td>wage bill</td>
<td>≥ 0</td>
<td>h, t</td>
</tr>
<tr>
<td>x</td>
<td>output</td>
<td>[0, x]</td>
<td>h, j, t</td>
</tr>
<tr>
<td>̄x</td>
<td>output limit</td>
<td>≥ 0</td>
<td>h, j</td>
</tr>
<tr>
<td>y</td>
<td>income: y = w for workers and Π for owners</td>
<td>≥ 0</td>
<td>h, i, t</td>
</tr>
<tr>
<td>α</td>
<td>shock level</td>
<td>[0, 1]</td>
<td></td>
</tr>
<tr>
<td>β</td>
<td>recovery rate</td>
<td>[0, 1]</td>
<td></td>
</tr>
<tr>
<td>γ</td>
<td>cost price per unit / reservation price</td>
<td>≥ 0</td>
<td>h, j, t</td>
</tr>
<tr>
<td>ϑ</td>
<td>distance cost</td>
<td>≥ 0</td>
<td>k</td>
</tr>
<tr>
<td>λ</td>
<td>wage rate / labor cost</td>
<td>≥ 0</td>
<td></td>
</tr>
<tr>
<td>ρ</td>
<td>current work production</td>
<td>[0, ρ̄]</td>
<td>h, i, t</td>
</tr>
<tr>
<td>ρ̄</td>
<td>productive capacity</td>
<td>≥ 0</td>
<td>h, i</td>
</tr>
<tr>
<td>σ</td>
<td>supply level in market</td>
<td>≥ 0</td>
<td>j, k, t</td>
</tr>
<tr>
<td>ɔ</td>
<td>savings</td>
<td>≥ 0</td>
<td>h, i, t</td>
</tr>
<tr>
<td>ψ</td>
<td>price smoothing factor</td>
<td>[0, 1]</td>
<td></td>
</tr>
<tr>
<td>χ</td>
<td>distance</td>
<td>[0, χ̄]</td>
<td>k</td>
</tr>
<tr>
<td>χ̄</td>
<td>maximum distance</td>
<td>≥ 0</td>
<td></td>
</tr>
<tr>
<td>Φ</td>
<td>initial population levels</td>
<td>≥ 0</td>
<td></td>
</tr>
<tr>
<td>D</td>
<td>effective aggregate demand</td>
<td>≥ 0</td>
<td>h, t</td>
</tr>
</tbody>
</table>

Note: Parameters and variables referring to individuals are lower case, aggregates capitals. All parameters without a time index are exogenous. See Appendix B for parameter rules.
B Model Setup

B.1 Environment Setup

The environment of the region is defined by three inputs, the total number of villages $V$ and cities $C$, and the road network $R$. The locations in the $V \times C$ economy are indexed spatially through the location index $h$. The road network $R$ joins these locations through a sparse network, such that all villages are linked to the nearest city and all cities are connected to each other. The model uses a stylized $9 \times 3$ economy with relatively evenly distributed villages around cities located in the center, as shown in Figure B.1.

Figure B.1: Stylized Economy

The maximum distance in the economy is given as $\tilde{\chi} = 144.49$ between Village 5 and Village 7, which is calculated using Dijkstra (1959)’s shortest network distance algorithm. The normalized distance matrix discussed in section 2.2.2 is therefore calculated as printed in Table B.1.
The normalized distance matrix is used in two behavioral rules, migration (section 2.2.2), and distance-based selling costs (section 2.4.1).

### B.2 Behavioral rules notation

The following notation is adapted and developed for behavioral rules from Naqvi (2012):

\[
\text{Rule}[\text{Parameters}] \rightarrow \text{Agentset} : \text{Asset stock}^\pm
\]

For example,

\[
\text{Pay wages}[\rho] \rightarrow \text{Owners} : m^-, \text{Workers} : m^+
\]

means that the rule “Pay wages” requires one exogenously defined input \( \rho \), the wage rate. When the rule is applied, the agent category “Owners” see a decrease in their money stock \( m \), while the money stock of the agent category “Workers” increases. It should be noted that the relationship is not necessarily linear; the complete exposition is detailed in section 2.3.

Since the model encompasses agent-agent and agent-environment interactions that are hierarchical, one agent category can supersede another. This top-down relationship is represented by a superscript. For example, several workers can be working for an owner or several owners can be selling in a single market. In the former case, worker production as described in section 2.3 is represented as

\[
\sum_i \rho_{it}^b
\]

This implies that the sum of productivity \( \rho_i \) of all workers \( i \) at a time \( t \) is aggregated at the owner \( b \) level. Without the superscript, this would imply the total production level of all the worker in the economy.

### B.3 Economy description

The model is initialized using the following two rules for the environment and the agents:

- Environment setup \([V,C,R]\), and
Agent interactions are defined by the following rules described in detail in the body of the paper:

- Produce \( [j, \alpha, \rho] \rightarrow \text{Owners: } x_j^+ \)
- Pay wages \( [\bar{\rho}, \lambda] \rightarrow \text{Owners: } m^-, \text{Workers: } m^+ \)
- Sell \( [\bar{j}] \rightarrow \text{Owners: } x_j^-, m^+, \text{Markets: } x_j^+ \)
- Supply \( [r_j] \): Markets \( \rightarrow x_j^- \)
- Prices \( [\Delta_p] \rightarrow \text{Markets: } x^\pm, \text{Owners: } x^\mp \)
- Buy \( [\bar{c}_j, \delta_j] \rightarrow \text{Owners, Workers: } x_j^+, m^- \)
- Consume \( [j, \bar{c}_j] \rightarrow \text{Agents: } x_j^- \)

The following set of parameters thus describes the complete set-up of the SHELscape model:

\[
E[V, C, R, \Phi_k, \Phi_i, j, \bar{x}, \bar{\rho}, \lambda, \bar{c}_j, \delta_j, r_j, \Delta_p]
\]

These exogenous parameters cover the complete economy, so they can be viewed as the calibration parameters that would need to be estimated for a region in order to replicate its economy. For the simulations in this paper, the following parameter values are used for initialization:

\[
= E[9, 3, \{\text{sparse}\}, 10, 1000, \{\text{wheat, tradeable good}\}, 1000, 200, 1, \{5, 5\}, \{20, 20\}, \{0.5, 0.5\}, 1]
\]