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**Macroeconomic effect of extortion:
An Agent-Based approach**

TESIS

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# Abstract

This work proposes an agent-based approach to study the effect of extortion on macroeconomic aggregates, despite the scarce data about this criminal activity resulting from its hidden nature. The main idea is to simulate both a healthy economy without extortion and the same economy under the influence of extortion, comparing then the macroeconomic signals produced in both cases. For this, the Bottom-up Adaptive Macroeconomics (BAM) model was implemented and validated in order to simulate an economy with healthy macroeconomic signals, i.e., moderate inflation, as well as a reasonable unemployment rate. The BAM model defines the usual interactions among workers, firms, and banks in labor, goods and credit markets. Then, crime is introduced by defining the propensity of the poorest workers to become extortionists, as well the efficiency of the police in terms of the probability of capturing them. The definition of the BAM under Extortion Racket Systems (BAMERS) model is completed with a threshold for the firms rejecting the extortion. These parameters are explored exhaustively and independently. Results show that even low levels of propensity towards extortion are enough to notice considerable negative effects as a marked contraction of the Gross Domestic Product and an increase of the unemployment rate, consistent with the few data known about the macroeconomic effect of extortion. Effects on consume, Gini index, inflation, and wealth distribution are also reported. Interestingly, our results suggest that it is more convenient to prevent extortion, rather than combat it once deployed, i.e., there is no police efficiency level that achieves the healthy macroeconomic signals observed in the absence of extortion.

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# Chapter 1. Introduction

According to Uhrmacher and Weyns (2009) the application of the Multi-Agent Systems (MAS) approach has been recognized as a useful metaphor for modeling and simulation of complex systems in a large number of contexts, ranging from natural to social systems, which are characterized by the presence of autonomous entities whose action and interaction in their physical environments determines the evolution of the system. Despite being a relatively young approach, compared for example with the analytical approach based on equations, it is considered one of the most successful perspectives for modeling and simulation, for reasons that will be discussed in this document. In this thesis we propose the application of this approach to analyze the macroeconomic effects of extortion.

We can define extortion as a *tax*, normally paid in cash, imposed by organized crime (OC) on companies established in a region, and for which the OC offer protection to other OC (Astarita, Capuano, & Purificato, 2018). Extortion as a type of criminal activity is present in many economies (Konrad & Skaperdas, 1998), but given its dark/hidden nature it is difficult to determine both its presence and its diverse and complex effects within society (Klaus G. Troitzsch, 2017), ranging from individual to (possible) collective effects (J. O. Gutierrez-Garcia, Orozco-Aguirre, & Landassuri-Moreno, 2013). This work is mainly interested in the evaluation of macroeconomic effects and the microfundaments that generate them.

Although empirical studies have been carried out, there is no precise answer about the magnitude of the extortion racketeering. In New York, for example, according to interviews with Chinese business owners, they found that most of them had meetings with gang members who approached for money, goods or services, and that most owners pay (Venkatesh & Chin, 1997). Around the world, the numbers vary, but in some cases it is estimated that up to 80% of companies have paid some type of extortion (Gambetta, 1996; Anzola, Neumann, Möhring, & Troitzsch, 2016). One of the common causes for the propagation of extortion racketeering is the lack of reliability of the police.

In Mexico, according to the research developed by Morales, del Mar Vélez Salas, Rodríguez, and Salas (2015), official statistics show an annual growth of extortion complaints, however, these complaints only represent a small sample of what happens around this phenomenon, since according to the same entity that provides the criminal statistics (Secretariado Ejecutivo del Sistema Nacional de Seguridad Pública) mentions that the following events are **not represented** in the statistics:

- Cases in which Produraduría de Justicia (PJ) of some states do not record the event when it was not consummated.
- Complaints made to 066[1] and registered by the C4[2] of each State.

[1] An emergency number.

[2] Government administrative unit that provides mechanisms for coordination in matters of security, through technology and communications infrastructure.

- Complaints made directly to the police (local or federal), the Army or the Navy, and that were not then transferred to a PJ.
- Obviously, the cases in which the victim opted to avoid reporting.

In addition to this, the preliminary investigations do not tell us about the number of total victims, since a preliminary investigations can be promoted by more than one victim. According to the data collected by Morales et al., the crime of extortion in Mexico has come to present a dark figure of 97.8 %, this means that for every 22 reported extortion crimes, there are 978 others that were not reported.

Finally, she argues that another important limitation of the statistics in Mexico is that the type of extortion is not disaggregated, that is, whether they are by pizzo or telephone extortion. This does not allow analysis or specific recommendations to eradicate this phenomenon.

So the question here is:

*How can we correctly evaluate the effect of extortion on macroeconomic aggregates such as production, inflation and unemployment?*

It is important to mention that, as far as is known, there is no work that analyzes the effects of extortion on macroeconomic indicators from an Agent-Based perspective. Although extortion racketeering has been extensively studied from the Agent-Based modeling and simulation perspective (Elsenbroich & Badham, 2016; Klaus G. Troitzsch, 2015; Luis G. Nardin et al., 2016; Luis Gustavo Nardin, Székely, & Andrighetto, 2017).

## 1.1 Problem statement

As we can notice, extortion racketeering is a phenomenon, that match with characteristics of complex systems described by Boccara (2010), that is:

1. it consists of many agents that interact with each other,
2. it exhibits emerging global properties and,
3. it lacks a centralized control governing such properties.

In our case study, there are different types of agents that interact in a virtual space called economy, such as workers (legal or illegal) and firms. The interaction of agents generates different macroeconomic signals such as production, employment and/or inflation. And finally there is no central actuator that directs the decisions of the agents or the aggregate behavior. Analyzing these systems as a whole is an extremely complicated task, so models are used to describe them. A model is an abstract representation of reality, in which only the relevant characteristics of the system are considered for the analysis. In social sciences such as economics, two approaches are distinguished to model this phenomena, the classical Equation-Based Approach (top-down) and a new approach (bottom-up) based on agents.

### 1.1.1 Equation-Based models

Central statement of top-down economic models establishes that from the interaction between supply and demand derives a general equilibrium on all markets. An important characteristic of Equation-Based economic models is the market clearing condition (Walrasian auctioneer), which is given by central authority that proposes a set of prices, determines an excess of demand at these prices and adjusts them to their equilibrium values.

The roots of classical approach go back to the nineteenth century, when many economist tried to formulate a full general equilibrium model, but it was conceived until 1874 by Leon Walras, a French economist (Starr, 2011). The most recent versions of this model incorporate dynamism (the economic variables consider the expectations of the future), and randomness (as a source of uncertainty) and are called Dynamic Stochastic General Equilibrium (DGSE) models. The solution in this type of models is found when solving systems of equations, e.g., households optimize a utility function subject to a budget constraint, while companies maximize their profit subject to the restriction of technological resources (Cabezas-Gottschalk, 2016).

One of the main limitations of these models is the assumption of equilibrium, since it is too simplistic for collecting the complexity of economic processes over time. Although external shocks can be used to get out of the equilibrium, by its nature, DSGE picks up small fluctuations around a stationary state, analyzing and predicting the signals of the economy in this way. So, these models behave well when there are no disturbances, but predict poorly when risk and uncertainty come into play.

Another disadvantage of this approach is that by the very nature of this approach, modeled through equations, agents are assumed homogeneous, i.e., they have the same information and worse, they have complete information of the system with which they determine their optimal plans. Finally, the Walrasian trial and error mechanism has no counterpart in the real market economy, and goes against the spirit of complex systems, where there is no centralized control.

### 1.1.2 Agent-Based Models

On the other hand, the bottom-up models conceive complex systems as composed of autonomous interactive agents. Agents base their behavior on simple rules and interact with other agents, which in turn influences their behavior. Two important features of this type of models are that 1) each agent has its own attributes and behavior, i.e., heterogeneity, and 2) the effects of the diversity among agents can be observed in the behavior of the system as a whole, emergency (Macal & North, 2010). Despite their simplicity, these models are not devoid of rationality (De Grauwe, 2010), economic agents guide their behavior to achieve a utility, i.e., instead of coding a specific goal, a measure is defined, allowing the agent to decide what is better for them, e.g., higher salary offered by firms, lower interest rate of banks, better leverage of firms. Although always within the cognitive limitations of the agents.

Bottom-up models do not make assumptions about the efficiency of markets or the existence of an equilibrium, so they can absorb the tensions or disturbances generated in periods of crisis through the emerging behavior resulting from the interaction between agents, in such a way that the panic of agents eventually spreads to the whole system. Finally, these models are non-linear, which implies that the generated effects do not have to be proportional to their causes. This allows to identify the causes in areas that in principle are not related. In some models, the effects can be of a magnitude much greater than the causes that provoke them while in others the effects dissipate in a conventional manner.

Now, our work beyond the aspects of a healthy economy, incorporates the possibility that extortion agents appear in the system which interact with other agents and can generate new emergent behavior and changes in macroeconomic variables such as inflation, unemployment and the GDP. This approach is considered not only adequate but also required to correctly understand this social phenomenon that, due to its criminal nature, is difficult to trace, measure and diagnose.

## 1.2 Research question

*Is there an effect of extortion on macroeconomic aggregates such as production, inflation or unemployment?*

## 1.3 Justification

As previously discussed, extortion is a criminal economic activity that is extremely difficult to trace. Therefore, it is not possible to get real data to analyze the macroeconomic effects of extortion in order to give economic policy recommendations in an appropriate way. One approach to overcome the absence of information is by simulating the phenomenon of extortion **as real as possible**, that is, from the dynamics of human behavior (microfoundations) to aggregate behavior.

Putting in perspective the existing approaches to carry out the simulation exposed in section 1.1, it is easy to opt for the Agent-Based Approach, where it is natural to go from an individual description of the agents that make up the system to the aggregate manifestation of the phenomenon that is has under study.

## 1.4 Hypothesis

Our null hypothesis is:

*There is no significant effect of extortion on macroeconomic indicators such as production, inflation and unemployment.*

And the alternative is that null is not true. Formalization of this hypothesis, also the test used to contrast our null will be explained in detail in chapter 3.

## 1.5 Objectives

Our objectives are the following:

### 1.5.1 General

Implement an Agent-Based Model and Simulation to analyze the effects of extortion on a theoretically stable economy.

### 1.5.2 Specifics

- Replicate the economic system implemented in Delli Gatti, Desiderio, Gaffeo, Cirillo, and Gallegati (2011) as a generic stable economy.
- Evaluate the effects of extortion on macroeconomic aggregates such as inflation, unemployment rate, GDP and distribution of wealth.

## 1.6 Organization

Thesis is organized as follows, chapter 2 introduce two best-known approaches to model economic systems and how extortion has been modeled from both approaches. Chapter 3 gives the methodology used from the Agent-Based Model and Simulation perspective as well as the platform chosen to code the agents of our economic system with extortive agents. Chapter 4 describes the main results obtained through simulation, although before it presents the empirical validation of the model through the reproduction of stylized facts. And finally, chapter 5 concludes by giving a broad description of the advantages of the agent-based approach versus the dominant approach based on equations. As well as a public policy recommendation to combat the negative effects on the macroeconomic signals derived from extortion.

# Chapter 2. Related work

This chapter is organized as follows, at first the two best-known approaches are introduced to model economic systems. Secondly and following the same logic, we present how extortion has been modeled from both approaches.

## 2.1 Economic model

In this section we will approach the two existing approaches to model social systems, specifically economic ones. On the one hand we present the classical approach based on equations, which has largely predominated in the economic literature through the so-called Dynamic Stochastic General Equilibrium (DSGE) models. On the other hand, we present a relatively novel approach, based on agents.

### 2.1.1 Classical approach

Within the macroeconomic research, there exists in our days, a consolidated and celebrated (Delli Gatti et al., 2011) methodology known as Dynamic Stochastic General Equilibrium (DSGE) model. A research methodology defines the general strategy that should be applied to research questions in a field (in this case macroeconomics), defines how the research will be conducted and identifies a set of methods and restrictions on what is allowed (Korinek, 2017). To understand the DSGE approach, Korinek define the concepts that restrict this methodology.

**Dynamic** means that the model will take into account future expectations, in an infinite horizon, that is, decisions made by consumers and producers are intertemporal, since decisions of how many job vacancies to offer, how much to consume, or how much capital to accumulate, is considered in a future planning horizon. This brings benefits such as elegant economic descriptions where each period follows the same law of motion. As a disadvantage, we have first of all the complexity that introduces to compute the model, and secondly, models are only susceptible to be analyzed by standard methods when the infinite horizon model has a ergodic steady state. However, in the real world there are many processes that do not follow an ergodic distribution.

**Stochastic** not only represents the consideration that must be had about uncertainty, but in a standard methodology it also represents the introduction of shocks, of different types, but mainly to productivity. However, when macroeconomic fluctuations are controlled by productivity disturbances, the system remains Pareto efficient in the allocation of resources and there are no motivations to intervene in the economy, so it is debatable that the productivity disturbances are the best benchmark

**General Equilibrium** means that all markets are always in equilibrium, although exogenous and unpredictable disturbances may temporarily deviate economy from its equilibrium. "The economy is viewed as being in continuous equilibrium in the sense that, given the information available, people make decisions that appear to be optimal for them, and so do not knowingly make persistent mistakes" (Wickens, 2012, p.1). Within this approach a distinction is often made between short-run and long-run equilibrium, while in short-run it is always assumed that economy is in equilibrium, in the long-run there is a mathematical property that describes the path of the economic model through which past shocks have been completely absorbed.

According to Korinek (2017), reporting a macroeconomic model under this approach includes the following aspects:

- a set of stylized facts must be established to be reproduced through the interaction of macroeconomic variables. Stylized facts are moments of the data about phenomena that always happen and with the same properties,
- a set of shocks that capture the interactions described, and
- validation, this is, demonstrate that the model can replicate real data when it is fed with stochastic shocks by the assumed shock process.

Regarding the last aspect, there is no convention on the set of moments to carry out the validation. Once the moments to be compared have been chosen, there is no statistical test to analytically measure the goodness of fit of the model.

Integrating all these elements into the model increases the difficulty to solve them, the more ambitious the restrictions and the conjugation of variables to reproduce stylized facts, the greater difficulty in the optimization process. To this end, a large number of global resolution methods have been developed (Fernández-Villaverde, Ramírez, & Schorfheide, 2016), which are precise but computationally expensive. According to Goessling (2019), the main source of complexity comes from general equilibrium and stochastic processes, although this author recently developed a more efficient method for calculating DSGE.

### 2.1.2 ABMS

According to Gilbert (2008, p. 2), an Agent-Based model is a method that allows the researcher to create, analyze and experiment with models composed of agents that interact within an environment. Gintis (2007, pp. 1280-1281) describes these types of models as:

> "*...a computer simulation of the repeated play of a game in which a large number of agents are endowed with software-encoded strategies governing both how they play the game and how they gather information and update their behaviour. The disequilibrium behaviour of agents in our Agent-Based models is governed by a replicator dynamic in which, over time, successful agents tend in Darwinian fashion to increase in frequency at the expense of unsuccessful agents. We describe the process of shifting from lower to higher payoff strategies as imitation, although this is indistinguishable from saying that unsuccessful agents die and are replaced by copies of successful agents.*"

Agent-based simulation is increasingly being used in the social sciences as an approach in a way that allows the researcher to construct models where individual entities and their interactions are directly represented.

In comparison with variable-based approaches using structural equations or in the systems-based approach using differential equations, Agent-Based simulation offers the possibility of modeling individual heterogeneity, explicitly representing agents, decision rules and placing agents in any type of space. What allows to generate complex representations closer to reality, which would be difficult to achieve with other modeling approaches.

Given these advantages, at present, Agent-Based simulation (ABS) is a very active research area in economics, from which the term Agent-Based Computational Economics is given in the seminal work of Tesfatsion (2002). From then on and with the gradual improvement in personal computers (Hamill & Gilbert, 2016), more specialized researchers in the area have emerged Delli Gatti et al. (2005), Bianchi, Cirillo, and and Pietro A. Vagliasindi (2007), Dosi, Fagiolo, Napoletano, and Roventini (2013), Assenza and Gatti (2013), D'Orazio and Silvestri (2014), Riccetti, Russo, and Gallegati (2015), Boero (2015), Terna (2015), Morini and Pellegrino (2015), Gallegati, Palestrini, and Russo (2017), among others.

The vast majority of these works perform the simulation taking as an explicit or implicit framework of reference, some economic model, either neo-Schumpeterian (Pyka & Fagiolo, 2005), Walrasian (Tesfatsion, 2006; Gintis, 2007; Delli Gatti et al., 2011; Gaffeo, Gallegati, & Gostoli, 2015) or Keynesian (Dosi et al., 2013). Although it seems somewhat trivial, the selection of the underlying economic model is of great importance if you want to contrast the theory with the results of the simulation, however one of the advantages offered by Multi-Agent simulation is that these schemes can be extended to eliminate the generality that supposes the reduction to a system of equations.

## 2.2 Extortion models

In the following sections, we present the works that are found in the literature of the extortion modeling, or that consider it in their analysis, from a *macroeconomic perspective*. Therefore is important to emphasize that none of the works, as far as is known, has analyzed the macroeconomic effect of extortion. Since they have focused on the normative and behavioral aspects of criminal organizations such as the mafia.

### 2.2.1 Classical approach

From literature that emerges from traditional modeling (Equation-Based Modeling), Astarita et al. (2018) propose a post-Keynesian model to study the macro-economic impact of organized crime. In this type of models it is assumed that effective demand determines income levels and growth rates. Some activities characteristic of organized crime, such as extortion, illegal trade and corruption, reduce demand by extracting resources from the legal sector; while others, such as money laundering, increase demand. So, although the empirical evidence seems to detect an adverse effect of organized crime in the economy, a theoretical framework to explain all the forms of influence that organized crime exerts on an economy through its typical crimes has yet to be developed, example, the positive aspects of money laundering.

The main contribution of Astarita et al., is that its model explains how it is that organized crime has, predictably, an undetermined effect on levels of economic activity and growth processes; identifying at the same time, the analytical conditions for a positive or negative effect of these activities on the economy. To validate the forecast of the model, the Italian economy is used as a case study. Modeling and simulation in this context allow the authors to formulate various policy recommendations. The adoption of the post-Keynesian model is due to the fact that the study focuses on the impact of organized crime on the demand of an economy, instead of the offer.

According to this author, every criminal organization has the following characteristics:

- They tend to act in geographical areas characterized by an institutional vacuum, with the aim of filling the void left by legitimate authority and thus regulating relations between individuals.
- They are involved in various activities, economic and non-economic, legal and non-legal.
- They develop several structures to coordinate their affiliates.
- They use violence, or the threat of violence, to achieve their goals.

The negative effects of organized crime on the economy are given through three channels:

1. A reduction in productive capital, due to a decrease in domestic savings and foreign investment; in fact, less security in property rights, leads to a poor business environment, discouraging innovation and entrepreneurship.
2. The diversion of public resources destined for policies that improve growth, for example, education and infrastructure; towards policies that guarantee protection against crime.
3. A reduction in the labor supply, since people can choose to provide their service in the illegal sector, instead of the legal one.

Post-Keynesian literature states that organized crime can alter the balance of income level, thus affecting the effective demand and the Keynesian multiplier. It has been established that the demand for illegal goods is a linear function of legal income that focuses on three elements:

1. The propensity to consume illegal goods through legal disposable income.
2. The ability of organized crime to appropriate legal revenues through crimes such as extortion.
3. The propensity to consume illegal goods through illegal income.

Astarita et al., they implement the principle of effective demand through a standard neo-Kaleckian investment function, where the investment decision of a company depends on the level of economic activity. Four crimes are considered:

1. *Extortion.* A tax normally paid in cash by companies in the region to organized crime. It pursues several objectives: 1) Establish a constant flow of income; 2) establish a social and economic network that facilitates the infiltration of organized crime in the legal economy; 3) reach a monopolistic position in some productive sector.
2. *Corruption* of public officials, allows to appropriate part of the public resources destined to transfer income, services and infrastructures.
3. The *trade in illegal goods*, mainly drug trafficking, represents the main source of income for organized crime and a flight of income from the legal economic system.
4. The *money laundering*, allows to conceal the illegal origin of criminal profits and transform them into effective purchasing power, that is, in a potential demand for consumption and investment.

### 2.2.2 ABMS

In the literature on Agent-Based modeling, the efforts that have been made to extend the **macroeconomic models** towards the analysis of the effects produced by criminal activity are reduced, rather they have focused on understanding the behavior of criminal organizations (Luis Gustavo Nardin et al., 2017; Klaus G. Troitzsch, 2015), as well as the immediate effect of the crime from the criminological point of view rather than economic (J. Octavio Gutierrez-Garcia, Orozco-Aguirre, & Landassuri-Moreno, 2013).

Extortion can be executed by individuals, but it is more often by organized groups which have been cataloged as Extortion Racket Systems. Only in some cases such groups are mafia-like organizations. GLODERS has analyzed normativity aspects (Lotzmann, Möhring, & Troitzsch, 2013; Villatoro, Andrighetto, Conte, & Sabater-Mir, 2015; Andrighetto, Giardini, et al., 2016; Luis G. Nardin et al., 2016; Realpe-Gómez, Vilone, Andrighetto, Nardin, & Montoya, 2018) and behavior (Andrighetto, Brandts, et al., 2016; Luis Gustavo Nardin et al., 2017).

In 2015, Klaus G. Troitzsch, analyzes this type of groups and focused on three aspects:

1. The effect on the distribution of wealth, both of companies and criminals.
2. The change in the propensity of companies to contribute to the fight against the mafia depending on the attitude of the public toward these extortionist groups.
3. Which of the behaviors of the different agents of society has the greatest effect on society as a whole?

On the first aspect, which is in fact part of the objectives of this thesis, he concludes that “the distribution of the overall economic success of the extorters is extremely skewed to the left which shows that for a majority of input parameter combinations the success of extorters is low, the main determinant for low extorter success being the prosecution propensity". But their conclusions do not give a very clear idea about other macroeconomic aspects that are also relevant, in fact, in their model[1] the interaction of labor and goods markets is abstracted.

[1] http://ccl.northwestern.edu/netlogo/models/community/EONOERS

# Chapter 3. Methodology

To understand precisely how the actions of an extortionist agent affect the whole society, seen as a system, is an extremely complex task, hence the need to abstract reality in models, defined as a simplified but useful version of the world.

As we review in chapter 2, it is possible to distinguish two types of macroeconomic models. The first type of models is called top-down (or Equation-Based models) in which some or all economic agents are able to understand the "complete picture" and use this superior information (given through systems of equations and with assumptions of equilibrium) to determine their optimal plans.

The second type of models has been called bottom-up (or Agent-Based models) in which all agents experience cognitive limitations. As a consequence, these agents are only able to understand and use small pieces of information, and act using simple rules of behavior, from which emerges an aggregate behavior, in which the aggregate balance is compatible with the individual imbalances between the agents, reproducing the macroeconomic dynamics.

For the purposes of this research it is considered that a representation for the macroeconomic analysis that is more in line with reality (individual rules of conduct and interaction structures that are consistent with empirical observations) is the bottom-up approach, in which we can codify our agents with as much heterogeneity as necessary to guide decision makers and help us forecast.

So in the following sections we will introduce the methodology used from this perspective, the Agent-Based Model and Simulation as well as the platform chosen to code the agents of our economic system with extortive agents.

## 3.1 ABMS

In some way, the complexity of the scientific models remained linked to the ability to express the phenomena mathematically, and to solve them using the differential calculation approach, scientists tried to keep them as simple as possible. With computer simulation, the limitation of mathematical ability is eliminated and problems with more realistic and therefore less simple models begin to be treated. ABMs are less simplified in one specific and important way: they represent system's individual components and their behaviors. Instead of describing a system only with variables, representing the state of the whole system, we model its individual agents (Railsback & Grimm, 2012).

By agent we must understand a computer entity that represents an individual (worker, firm or bank) or group of individuals. According to Page et al. (2013) the kind of each agent can be characterized considering two aspects: *internal reasoning* that guides the decision-making process and *interactions* with other agents (coordination).

Decision-making process has different degrees of sophistication, the so-called *reactive* agents perform a direct mapping between the perception of the value of a key parameter (internal or external) and the action; whereas *cognitive* agents "implement more complex decision-making processes by explicitly deliberating about different possibilities of action and by referring to specific representations of their environment"(Page et al., 2013, p.506). For the purpose of our simulation, it is not necessary to provide our agents with an inference system to guide decision-making process, so the reactive level will be used.

As we have expressed previously, each agent makes decisions given the perception of internal parameters (a worker agent can perceive their own level of wealth) but also external (the price set by a company agent to a certain good). This perception of external variables is given through the interaction (with the environment or with other agents, although it is assumed that rest of agents are part of environment). According to Bousquet (2001), three types of interaction are distinguished (as cited in Page et al., 2013, pp.507-508), which are:

**Individual** Interaction through peer to peer communication. Agents control the information they can share with another agent through peer-to-peer communication protocols.

**Environment** Interactions between agents via the environment. It is assumed that the information can be obtained through browsing among other agents that make up the system, which can be limited to a spatial or social proximity.

**Collective** Interaction via the collective level. Here the information is controlled by belonging or not to a group or an institution, it is a level of organization in which the behavior is guided by rules, norms, goals and roles.

Our model implements an interaction through the environment, characterized by social encounters in virtual labor, goods and financial markets, as well as by some spatial encounters, specifically in the extortion model.

## 3.2 NetLogo

There are several platforms for the modeling of Multi-Agent Systems (Allan, 2010; Kravari & Bassiliades, 2015; Abar, Theodoropoulos, Lemarinier, & O'Hare, 2017) and it is even possible to implement an Agent-Based model in any language (Wilensky & Rand, 2015). Regarding the multiple platforms to develop models based on agents Railsback and Grimm (2012) conclude in the first place, that there is no single ideal platform; they are inevitably compromises that may not be the best for all applications. Second, however, they mention that NetLogo clearly stands out as the best platform for beginners and even for many serious scientific models.

Given the purpose of our simulation, as well as the architecture of reasoning and interaction between agents that we have chosen, NetLogo is the platform we choose for our analysis. NetLogo provides a simplified programming language and graphical interface that allows users to design, observe and use Multi-Agent Systems without the need to learn the complex details of a standard programming language (Railsback & Grimm, 2012).

NetLogo is a platform designed by Wilensky in 1999 and has been in continuous development since then in the Center for Connected Learning and Computer-Based Modeling, it is free and the source code is open, which allows for example to extend or modify the architecture of the agents, going from being reactive agents to BDI type (Sakellariou, Kefalas, & Stamatopoulou, 2008).

According to NetLogo manual (Wilensky, 2019), it is especially suitable for modeling complex systems that develop over time. Modelers can instruct hundreds or thousands of agents who operate independently. This allows us to explore the connection between the behavior at the micro level of individuals and the macro level patterns that **emerge** from their interaction. It allows students to open simulations and "play" with them, exploring their behavior under various conditions. It is also an authoring environment that allows students, teachers and study plan developers to create their own models. NetLogo is simple enough for students and teachers, but advanced enough to serve as a powerful tool for researchers in many fields.

It has an extensive documentation and tutorials. It also comes with a "Models Library", a large collection of pre-written simulations that can be used and modified. These simulations address content areas in the natural and social sciences, including biology and medicine, physics and chemistry, mathematics and computer science, economics and social psychology. Several study and research plans are based on models that use NetLogo, those that are available and, there are more that are in development.

It runs on the Java virtual machine, so it works on all major platforms (Mac, Windows, Linux, etc.). It runs as a desktop application. Command line operation is also supported, which is useful to perform experimentation in a practical way through scripts. Some other interesting features described in the recent manual (Wilensky, 2019) are the following:

- Language is **Logo dialect** extended to support agents.
- **Mobile agents** (turtles) move over a grid of **stationary agents** (patches).
- **Link agents** connect turtles to make networks, graphs, and aggregates.
- Large vocabulary of built-in language **primitives**.
- **First-class function** values (functional programming).
- **Interface builder** w/ buttons, sliders, switches, choosers, monitors, text boxes, notes, output area.
- Info tab for **annotating your model** with formatted text and images. We describe our model following ODD protocol (Grimm et al., 2006; Grimm et al., 2010; Grimm, Polhill, & Touza, 2013).
- **Export and import** functions (export data, save and restore state of model, make a movie).
- BehaviorSpace, an open source tool used to **collect data from multiple parallel runs** of a model.

- NetLogo 3D for modeling **3D worlds**.
- Headless mode allows doing batch **runs from the command line**.
- Line, bar, and scatter **plots**.
- Controlling API allows **embedding NetLogo** in a script or application.
- Extensions API allows **adding new commands and reporters** to the NetLogo language; open source example extensions are included.

## 3.3 ODD protocol

As mentioned earlier (Section 3.2), for the sake of reproducibility, the details of the model will be described following the ODD protocol, which was designed with the objective of standardizing published descriptions of Agent-Based models (ABMs) (Grimm et al., 2006). The main reason was to make the descriptions of the models more comprehensible and complete, and with it, to diminish the criticism for giving irreplicable results. Although the standard was designed for ABMs, it can help in the documentation of any complex or large-scale model. ODD is mainly organized in three parts:

1. **Overview**. A general description of the model, including its purpose and its basic components: agents, variables describing them and the environment, and scales used in the model, e.g., time and space; as well as a processes overview and their scheduling.
2. **Design concepts**. A brief description of the basic principles underlying the model's design, e.g., rationality, emergence, adaptation, learning, etc.
3. **Details**. Full definitions of the involved submodels.

The entire elements that are part of this protocol are listed below (Grimm et al., 2010).

1. Purpose.
2. Entities, state variables and scales.
3. Process overview and scheduling.
4. Design concepts.
   (a) Basic principles.
   (b) Emergence.
   (c) Adaptation.
   (d) Objectives.
   (e) Learning.
   (f) Prediction.
   (g) Sensing.
   (h) Interaction.
   (i) Stochasticity.
   (j) Collectives.
   (k) Observation.
5. Initialization.

6. Input data.
7. Submodels.

## 3.4 Economic model

Despite the criticism for its excessive abstraction, the Walrasian economic model has persisted as a fundamental paradigm (Tesfatsion, 2006). Indeed, because of its simplicity, it is a good starting point for exploring both perfect and imperfect economic models.

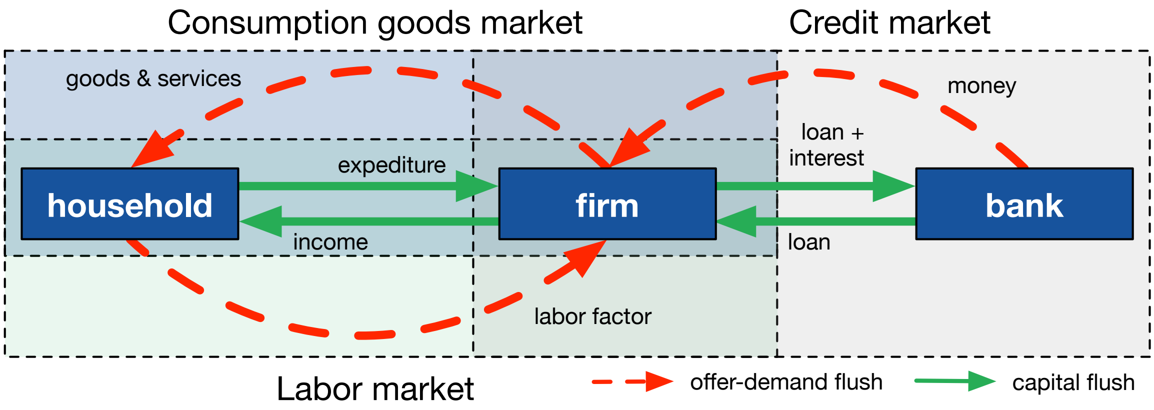


Figure 3.1: The Bottom-up Adaptive Macroeconomics Model (BAM).

The Bottom-up Adaptive Model (BAM) (Delli Gatti et al., 2011) adopted in this paper is Walrasian in nature. As shown in Fig. 3.1, it is composed by the following types of agents:

- **Houselholds** representing the point of consumption and labor force.
- **Firms** representing the transformation of work in goods and / or services.
- **Banks** providing liquidity to firms if necessary.

A large number of autonomous households, producers and banks operate adaptively in three totally decentralized and interconnected markets:

- A **labor market**, in which each household offers an inelastic unit of work per period, while firms demand depending on their production plans;
- A perishable consumer **goods market**, in which households spend all or part of their wealth and firms offer goods at different prices; and
- A **credit market** in which firms demand money if their resources are insufficient to cover their production expenses, and banks offer money at different interest rates.

Opportunities for exchange in these markets are discovered through a sequential process characterized by optimization, namely, maximizing wages, minimizing the price of goods consumed and minimizing the price of money (interest rate). Firms can modify prices and quantities adaptively given the signals of the inventory and the market price.

BAM was adopted because the agents that intervene in the model are those necessary to model disturbances that are similar to those observed in a real world economy; while generating macroeconomic signals of interest, e.g., inflation, unemployment, wealth, production among others are generated.

### 3.4.1 Overview

**Purpose.**

Exploring the use of the agent-based approach for the study of macroeconomic signals, particularly the effect of the agent's activities in such signals.

**Entities, state variables, and scales.**

- Agents: Firms, workers, and banks.
- Environment: Agents are situated in a grid environment which is meaningless with respect to the model. The environment is used exclusively as a visual aid for debugging.
- State variables: The attributes that characterize each agent are shown in Table 3.1.
- Scales: Time is discrete, e.g., each step represents a quarter. Quarters are adequate for long periods, months can be used for short ones.

**Process overview and scheduling.**

The main loop of the simulation is as follows:

1. Firms calculate production based on expected demand.
2. A decentralized labor market opens.
3. A decentralized credit market opens.
4. Firms produce.
5. Market for goods open.
6. Firms will pay loan and dividends.
7. Firms and banks will survive or die.
8. Replacing of bankrupt firms/banks.

Table 3.1: State variables by agent.

| Agent | Attribute | Type | Agent | Attribute | Type |
|---|---|---|---|---|---|
| Firm | production-Y | Int | Worker | employed? | Bool |
| | desired-production-Yd | Int | | my-potential-firms | AgSet |
| | expected-demand-De | Int | | my-firm | Ag |
| | desired-labor-force-Ld | Int | | contract | Int |
| | my-employees | AgSet | | income | Float |
| | current-numbers-employees-L0 | Int | | savings | Float |
| | number-of-vacancies-offered-V | Int | | wealth | Float |
| | minimum-wage-W-hat | Float | | propensity-to-consume-c | Float |
| | wage-offered-Wb | Float | | my-stores | AgSet |
| | net-worth-A | Float | | my-large-store | Ag |
| | total-payroll-W | Float | Bank | total-amount-of-credit-C | Float |
| | loan-B | Float | | patrimonial-base-E | Float |
| | my-potential-banks | AgSet | | operational-interest-rate | Float |
| | my-bank | AgSet | | interest-rate-r | Float |
| | inventory-S | Float | | my-borrowing-firms | AgSet |
| | individual-price-P | Float | | bankrupt? | Bool |
| | revenue-R | Float | | | |
| | retained-profits-pi | Float | | | |

### 3.4.2 Design concepts

#### Basic Principles.

The model follows fundamental principles of neoclassical economics (Woodford, 2009), since it gives great importance to money in economic processes and also the strategy for determining prices is given considering both supply and demand.

#### Emergence.

The model generates adaptive behavior of the agents, without the imposition of an equation that governs their actions. Macroeconomic signals are also emergent properties of the system.

#### Adaptation.

At each step, firms can adapt price or amount to supply (only one of the two strategies). Adaptation of each strategy depends on the condition of the firm (level of excessive supply / demand in the previous period) and/or the market environment (the difference between the individual price and the market price in the previous period).

#### Objectives.

Agents do not explicitly have an objective, but implicitly they try to maximize a utility or attribute.

### Learning.

None for the moment, however, see the future work section for possible uses of learning in this model.

### Prediction.

Firms predict the quantities to be produced or the price of the good produced based on the excess of supply/demand in the previous period and the differential of its price and the average price in the market.

### Sensing.

- Firms perceive their own produced quantity, good's price, labor force, net value, profits, offered wages; as well as the average market price and the interest rate of randomly chosen banks.
- Workers perceive the size of firms visited in the previous period, prices published by the firms in actual period and wages offered by the firms.
- Banks perceive net value of potential borrowers in order to calculate interest rate.

### Interaction.

Interactions among agents are determined by the markets:

- In the labor market, firms post their vacancies at a certain offered wage. Then, unemployed workers contact a given number of randomly chosen firms to get a job, starting from the one that offers the highest wage. Firms have to pay the wage bill in order to start production. A worker whose contract has just expired applies first to his/her last employer.
- Firm can access to a fully decentralized credit market if net worth are in short supply with respect to the wage bill. Borrowing firms contact a given number of randomly chosen banks to get a loan, starting from the one which charges the lowest interest rate. Each bank sorts the borrowers' applications for loans in descending order according to the financial soundness of firms, and satisfy them until all credit supply has been exhausted. The contractual interest rate is calculated applying a mark-up on an exogenously determined baseline interest rate. After the credit market is closed, if financial resources are not enough to pay for the wage bill of the population of workers, some workers remain unemployed or are fired.
- In goods market, firms post their offer price, and consumers contact a given number of randomly chosen firms to purchase goods, starting from the one which posts the lowest price.

### Stochasticity.

Elements that have random shocks are:

- Determination of wages when vacancies are offered ($\xi$).
- Determination of contractual interest rate offered by banks to firms ($\phi$).
- The strategy to set prices ($\eta$).
- The strategy to determine the quantity to produce ($\rho$).

**Collectives.**

Markets configure collectives of agents as described above. They include labor, goods, and credit markets. In addition, firms and consumers are categorized as rich and poor.

**Observation.**

Along simulation are observed:

- Real GDP.
- Unemployment rate.
- Annual inflation rate.
- Wealth distribution.
- Gini index.

At end of simulation are computed:

- Distribution of the size of firms.
- Distribution of wealth of households.
- Growth rate of real GDP.

### 3.4.3 Details

**Initialization.**

The initialization parameters described in Delli Gatti et al. (2011) was adopted. For the values not provided in the text, they were obtained through experimentation. Table 3.2 shows the initial values of the model.

**Input data.**

None, although data from real economies might be used for validation.

**Submodels.**

1. Production with constant returns to scale and technological multiplier: $Y_{it} = \alpha_{it} L_{it}$, s.t., $\alpha_{it} > 0$.
2. Desired production level $Y^d_{it}$ is equal to the expected demand $D^d_{it}$.
3. Desired labor force (employees) $L^d_{it} = Y^d_{it}/\alpha_{it}$.
4. Current number of employees $L^0_{it}$ is the sum of employees with and without a valid contract.
5. Number of vacancies offered by firms $V_{it} = max(L^d_{it} - L^0_{it}, 0)$.
6. If there are no vacancies ($V_{it} = 0$), wage offered is $w^b_{it} = max(\hat{w}_t, w_{it-1})$, where $\hat{w}_t$ is the minimum wage determined by law.

Table 3.2: Parameters initialization.

| | Parameter | Value |
|---|---|---|
| $I$ | Number of consumers | 500 |
| $J$ | Number of producers | 100 |
| $K$ | Number of banks | 10 |
| $T$ | Number of steps | 1000 |
| $C_P$ | Propensity to consume of poorest people | 1 |
| $C_R$ | Propensity to consume of richest people | 0.5 |
| $\sigma_P$ | R&D investment of poorest firms | 0 |
| $\sigma_R$ | R&D investment of richest firms | 0.1 |
| $h_\xi$ | Maximum growth rate of wages | 0.05 |
| $H_\eta$ | Maximum growth rate of prices | 0.1 |
| $H_\rho$ | Maximum growth rate of quantities | 0.1 |
| $H_\phi$ | Maximum amount of banks' costs | 0.1 |
| $Z$ | Number of trials in the goods market | 2 |
| $M$ | Number of trials in the labor market | 4 |
| $H$ | Number of trials in the credit market | 2 |
| $\hat{w}$ | Minimum wage (set by a mandatory law) | 1 |
| $P_t$ | Aggregate price | 1.5 |
| $\delta$ | Fixed fraction to share dividends | 0.15 |

7. If $V_{it} > 0$, wage offered is $w_{it}^b = max(\hat{w}_t, w_{it-1}(1 + \xi_{it}))$, where $\xi_{it}$ is a random term evenly distributed between $(0, h_\xi)$.
8. At the beginning of each period, a firm has a net value $A_{it}$. If total payroll to be paid $W_{it} > A_{it}$, firm asks for loan $B_{it} = max(W_{it} - A_{it}, 0)$.
9. For the loan search costs, it must be met that $H < K$
10. In each period the $k$-th bank can distribute a total amount of credit $C_k$ equivalent to a multiple of its patrimonial base $C_{kt} = E_{kt}/v$, where $0 < v < 1$ can be interpreted as the capital requirement coefficient. Therefore, the $v$ reciprocal represents the maximum allowed leverage by the bank.
11. Bank offers credit $C_k$, with its respective interest rate $r_{it}^k$ and contract for 1 period.
12. If $A_{it+1} > 0$ the payment scheme is $B_{it}(1 + r_{it}^k)$.
13. If $A_{it+1} \leq 0$, bank retrieves $R_{it+1}$.
14. Contractual interest rate offered by the bank $k$ to the firm $i$ is determined as a margin on a rate policy established by Central Monetary Authority $\bar{r}$, s.t., $R_{it}^k = \bar{r}(1 + \phi_{kt}\mu(\ell_{it}))$.
15. Margin is a function of the specificity of the bank as possible variations in its operating costs and captured by the uniform random variable $\phi_{kt}$ in the interval $(0, h_\phi)$.
16. Margin is also a function of the borrower's financial fragility, captured by the term $\mu(\ell_{it})$, $\mu' > 0$. Where $\ell_{it} = B_{it}/A_{it}$ is the leverage of borrower.
17. Demand for credit is divisible, i.e., if a single bank is not able to satisfy the

requested credit, it can request in the remaining $H-1$ randomly selected banks.

18. Each firm has an inventory of unsold goods $S_{it}$, where excess supply $S_{it} > 0$ or demand $S_{it} = 0$ is reflected.
19. Deviation of the individual price from the average market price during the previous period is represented as: $P_{it-1} - P_{t-1}$
20. If deviation is positive $P_{it-1} > P_{t-1}$, firm recognizes that its price is high compared to its competitors, and is induced to decrease the price or quantity to prevent a migration massive in favor of its rivals; and vice versa.
21. In case of adjusting price downward, this is bounded below $P_{it}^l$ to not be less than your average costs:

$$P_{it}^l = \frac{W_{it} + \sum_k r_{kit} B_{kit}}{Y_{it}}$$

22. Aggregate price $P_t$ is common knowledge, while inventory $S_{it}$ and individual price $P_{it}$ are private.
23. Only the price or quantity to be produced can be modified. In the case of price, we have the following rule:

$$P_{it}^s = \begin{cases} \max[P_{it}^l, P_{it-1}(1+\eta_{it})] & \text{if } S_{it-1} = 0 \text{ and } P_{it-1} < P \\ \max[P_{it}^l, P_{it-1}(1-\eta_{it})] & \text{if } S_{it-1} > 0 \text{ and } P_{it-1} \geq P \end{cases}$$

where: $\eta_{it}$ is a randomized term uniformly distributed in the range $(0, h_\eta)$ and $P_{it}^l$ is the minimum price at which firm $i$ can solve its minimal costs at time $t$ (previously defined).

24. In the case of quantities, these are adjusted adaptively according to the following rule:

$$D_{it}^e = \begin{cases} Y_{it-1}(1+\rho_{it}) & \text{if } S_{it-1} = 0 \text{ and } P_{it-1} \geq P \\ Y_{it-1}(1-\rho_{it}) & \text{if } S_{it-1} > 0 \text{ and } P_{it-1} < P \end{cases}$$

where $\rho_{it}$ is a random term uniform distributed and bounded between $(0, h_\rho)$.

25. Total income of households is the sum of the payroll paid to the workers in $t$ and the dividends distributed to the shareholders in $t-1$.
26. Wealth is defined as the sum of labor income plus the sum of all savings $SA$ of the past.
27. Marginal propensity to consume $c$ is a decreasing function of the worker's total wealth (higher the wealth lower the proportion spent on consumption) defined as:

$$c_{jt} = \frac{1}{1 + \left[\tanh\left(\frac{SA_{jt}}{SAt}\right)\right]^\beta}$$

where $SA_t$ is the average savings. $SA_{jt}$ is the real saving of the $j$ -th consumer.

28. The revenue $R_{it}$ of a firm after the goods market closes is $R_{it} = P_{it}Y_{it}$.
29. At the end of $t$ period, each firm computes benefits $\pi_{it-1}$.
30. If the benefits are positive, shareholders receive dividends $Div_{it-1} = \delta\pi_{it-1}$.
31. Residual, after discounting dividends, is added to net value from previous period $A_{it-1}$. Therefore, net worth of a profitable firm in $t$ is:

$$A_{it} = A_{it-1} + \pi_{it-1} - Div_{it-1} \equiv A_{it-1} + (1-\delta)\pi_{it-1}$$

32. If firm $i$ accumulates a net value $A_{it} < 0$, it goes bankrupt.
33. Firms that go bankrupt are replaced with another one of size smaller than the average of incumbent firms.
34. Non-incumbent firms are those whose size is above and below 5%, the concept is used to calculate a more robust estimator of the average.
35. Bank's capital:

$$E_{kt} = E_{kt-1} + \sum_{i\in\Theta} r_{kit-1}B_{kit-1} - BD_{kt-1}$$

36. $\Theta$ is the bank's loan portfolio, $BD_{kt-1}$ represents the portfolio of firms that go bankrupt.
37. Bankrupted banks are replaced with a copy of one of the surviving ones.

## 3.5 Extortion model

We have a macroeconomic baseline model that produces some signals such as inflation, production and unemployment. In order to achieve our objective we need to incorporate extortion to the model and analyze the effect on some macroeconomic indicators. So, being $K$ different levels of extortion beginning with level zero (baseline model). With $K \geq 2$ independent random macroeconomic signals $\mathbf{X}_k = (X_{k1}, \ldots, X_{kn_k})$ from populations with continuous distributions functions $F_k(x) = F(\sigma_k x + \mu_k)$, $n_k \geq 2$, $k = 1, \ldots, K$. The function $F$, location parameters $\mu_k$ and scale parameters $\sigma_k$ are unknown. Our hypothesis will be expressed as follows:

$H_0$**:** $(\mu_1, \sigma_1) = (\mu_2, \sigma_2) = \ldots = (\mu_K, \sigma_K)$
$H_1$**:** $H_0$ is not true.

We use nonparametric Multisample Cucconi test (Cucconi, 1968; Marozzi, 2014) to constrast our null hypothesis against alternative. This test is used because according to Marozzi (2009),

> "*... it is not a quadratic form combining a test for location and a test for scale differences, and it is based on squared ranks and squared contrary-ranks. Moreover, it is easier to compute the test of Cucconi than those of Lepage, Manly–Francis, Büning–Thadewald, Neuhäuser, Büning and Murakami. ... Simulations show that the test of Cucconi maintains a size very close to* $\alpha$

*and is more powerful than the Lepage test, and therefore should be taken into account as a better alternative when it is not possible to develop an efficiency robust procedure for the problem at hand. The simulation study considers also the case of different shapes for the parent distributions, and the case of tied observations which is generally not considered in power studies. The presence of ties does not lower the performance of the Cucconi test, the contrary happens for the Lepage test.*"

In conclusion, Multisample Cucconi test is a robust way to compare distributions, this is, our baseline (without extortion) macroeconomic indicator $\mathbf{X}_1$ against the same macroeconomic indicator $\mathbf{X}_{k>1}$ with different levels of extortion. According to Cucconi test, statistic value is expected to be zero if the null is true (macroeconomic indicator has no differences among treatments), but if at least two distributions differ in the mean and/or variance, the value of the statistic will be greater than zero, the greater the difference, the greater the value of the statistic.

After establishing the contrast test of our hypothesis, we will introduce the extortion model, again in terms of ODD protocol. However, a large part of the ODD elements listed in section 3.4 remain the same, as long as the comparison against the BAM model is desired. In such a way that when incorporating extortion, we will name our model BAMERS, and only the ODD elements that extend the BAM model will be added.

### 3.5.1 Overview

**Purpose.**

Exploring the effect of the agent's extortion activities in macroeconomic signals.

**Entities, state variables, and scales.**

- Environment: Agents are situated in a grid environment. In this case, adopting Klaus G. Troitzsch (2015) and Elsenbroich and Badham (2016), the geographical aspect is used both in the strategy of search by proximity and in the decision to accept/reject the pizzo.
- State variables: Attributes related to extortion that characterize each agent are shown in Table 3.3. They extend the attributes in Table 3.1.

Table 3.3: State variables related to extortion by agent.

| Agent | Attribute | Type | Agent | Attribute | Type |
|---|---|---|---|---|---|
| Firm | being-extorted? | Bool | Worker | extorter? | Bool |
| | amount-of-pizzo | Float | | firms-to-extort | AgSet |
| | amount-of-punish | Float | | firms-to-punish | AgSet |
| | | | | time-in-jail | Int |

#### Process overview and scheduling.

Extortion occurs after goods market finishes. The sequence of events inside the extortion step is as follows:

1. Unemployed workers can become extortionists.
2. Those who became extortionists look for firms to extort. Firms can refuse to pay.
3. Firms will pay pizzo.
4. The extortionists can go to jail and lose their wealth. Otherwise extortionists punish firm that refused to pay pizzo.
5. The prisoners serve their sentence in jail.

### 3.5.2 Design concepts

#### Basic Principles.

One of the main differences with the extortion models developed by GLODERS, is our adaptation process of formal workers in criminals and viceversa, explained in detail below. This behavior that we have incorporated is based on the idea that economic pressure and socioeconomic status induces a process of decision making on how to respond to basic needs. About this Abrahamsen (1949, p.140) says:

> *There are a few questions that are frequently asked in regard to our findings that family tension is the basic cause of criminal behavior. The first has to do with economics. It is reasonable to assume, intellectually speaking, that when one is without what is necessary for subsistence and cannot get it, he will simply take it for himself and his loved ones. This is instinctive, and it has to do with self-preservation.*

#### Adaptation.

At every step of the time, after the goods market has closed. Each worker with a wealth in the poorest 25% can become an extortionist with an $\epsilon$ propensity. Unlike the GLODERS project, where a predetermined initial amount of extortionists is assumed, we incorporate this microfoundation taking as reference the principles enunciated in 3.5.2.

#### Sensing.

- Firms can observe the nearest firms to know if they are paying for pizzo or not.

#### Interaction.

The interaction is generated when an extorter finds a firm to request the payment of pizzo, the firms can refuse to pay it.

Table 3.4: Parameters initialization.

| | Parameter | Value |
|---|---|---|
| $\epsilon$ | Propensity to be an extorter | 20% |
| $\lambda$ | Probability of being caught | 30% |
| $R_t$ | rejection threshold | 15% |
| $X$ | Number of trials to extort a new firm | 1 |
| $CF$ | Number of observable Closest Firms | 3 |
| $Pi$ | Proportion of Net Worth A as pizzo | 10% |
| $Pu$ | Proportion of Net Worth A as punish | 25% |
| $C_m$ | Proportion of wealth as confiscated money | 50% |
| $T_j$ | Amount of time periods in jail | 6 |

**Stochasticity.**

Elements that have random shocks are:
- The decision to become an extortionist $\epsilon$.
- The probability that the extortionist is caught by the police $\lambda$.

### 3.5.3 Details

**Initialization.**

Initialization parameters described in Elsenbroich and Badham (2016), Klaus G. Troitzsch (2015), Luis G. Nardin et al. (2016), Luis Gustavo Nardin et al. (2017) were adopted. Table 3.4 shows the initial values of the model.

**Submodels.**

1. The model does not consider a fixed initial amount of extortionists as the literature does (Elsenbroich & Badham, 2016; Klaus G. Troitzsch, 2015; Luis G. Nardin et al., 2016; Luis Gustavo Nardin et al., 2017). Instead, take the first quartile of workers with the least amount of savings $SA$ and who are unemployed. And randomly set them to be extorted If the propensity to be an extortionist $\epsilon$ is greater than a randomly generated value with a uniform distribution between 0 and 100.
2. The worker (now extortionist) has $X$ trials to find a new (and not already extorted by someone else) firm.
3. The extortionists have two possible strategies to search for firms, random and by *geographic* proximity.
4. In any of the strategies, if in his attempt $X$ the extortionist selected a company that has already been extorted by someone else who provides "protection", the worker loses that chance to extort.
5. The firm can decide if it allows extortion or if it refuses to pay.

6. The firm decides not to pay the pizzo when its rejection threshold ($R_t$) is greater than the expected risk (ER).
7. A threshold of 0% represents that the firm at the slightest hint of extortion in the area will choose to pay the pizzo.
8. The expected risk is calculated as follows:

$$ER = \frac{EF}{CF}$$

   where, $CF$ represents a small observable number of Closest Firms (default 3) and the number of Firms Extorted in that small set are $EF$. This cognitive mechanism is based on Elsenbroich and Badham (2016).
9. Firms that accept to pay the pizzo are extorted. The required amount of extortion will be a proportion $Pi$ of the net worth A (default) as in Klaus G. Troitzsch (2015), Luis G. Nardin et al. (2016), Luis Gustavo Nardin et al. (2017) or a constant amount like Elsenbroich and Badham (2016).
10. Each time a company decides not to pay the pizzo, it generates the possibility that the extortionist is caught by the police with a probability $\lambda$.
11. If the extortionist is caught by the police, a certain amount of time periods $T_j$ is sent to jail. Additionally, wealth of the extortionist will be confiscated.
12. The confiscated money $C_m$ is sent to a fund to support victim firms.
13. If the extortionists were not captured by the police, they execute a punishment against the companies that refused to pay the pizzo. Again, the required amount of punishment $Pu$ will be a proportion of the net worth A.
14. Each company punished is eligible to receive a refund from the victim support fund.
15. Compensation can be given proportionally among all the firms punished, or with an amount equivalent to the punishment they received in the current period, following the principle "first to come, first to serve" until the funds are finished.
16. Extortionists who serve their sentence in prison, are again eligible in the labor market, in the following period.

# Chapter 4. Results

## 4.1 Economic model

The BAM model was implemented in Netlogo (Wilensky, 1999). Fig. 4.1 shows the right side of the resulting GUI that allows the initialization of parameters and provides a view of the agents in a grid environment. As mentioned, the spacial issues in this view are meaningless, but the output is useful for debugging the system: Blue factories are the firms, red houses are the banks, green humans are employed workers while yellow ones are unemployed. Workers group around the firms where they work and shop. Factories display the number of employees.

As we shown in following subsections, our implementation of the BAM model behaves correctly under stable conditions, i.e., those induced by its default configuration, as well as when introducing shocks, varying the propensity to consume, and the size of markets. These results contribute to validate the feasibility of the BAM model along with the fidelity and applicability of our implementation. This allows the use of the BAM model to investigate phenomena that are difficult to represent analytically, e.g., the dynamics of GDP as a function of shocks and size of markets, particularly when the scenario is composed by heterogeneous agents.

### 4.1.1 Validation

With the initial configuration of the parameters proposed by Delli Gatti et al. (2011), the macroeconomic signals exemplified in Fig. 4.2 are produced. This output reflects a stable fictitious economy, with unemployment rate close to 10% and moderate inflation in the range of 1 to 6%. According to data from the World Bank (2019b, 2019a) during the period 2014 - 2018, the average unemployment among the countries is 8.22%, while the average annual inflation is 4.43%. The model shows a good sensitivity to the parameters and is, generally, very responsive to them. In particular, we observe that short and medium term dynamics of standard macroeconomic indexes, e.g., GDP or unemployment rate, correspond to those that we would expect empirically. In the next subsection, some stylized facts that theoretically should show these signals will be tested.

At the micro level, validation consists of verifying the existence of stylized facts concerning statistical distributions of state variables at an individual level (Delli Gatti et al., 2011). Wealth and net worth in our case are characterized by a positive skew, which implies that there are few agents that become rich (Fig. 4.3).

To prove that the distributions of wealth of 100 independent runs have a positive skew (Fig. 4.4), level of skew was calculated with the method described by Joanes and Gill (1998):

$$b_1 = \frac{m_3}{s^3} = \left(\frac{n-1}{n}\right)^{3/2} \frac{m_3}{m_2^{3/2}} \; . \tag{4.1}$$

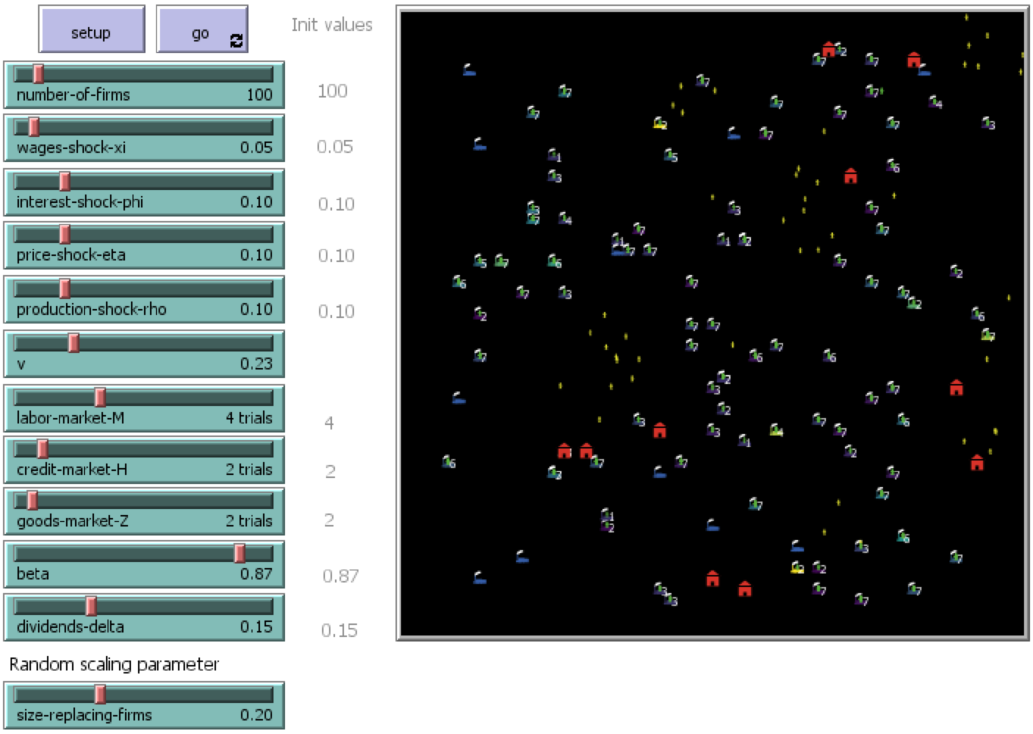


Figure 4.1: The BAM model GUI: Parameters and view of the world.

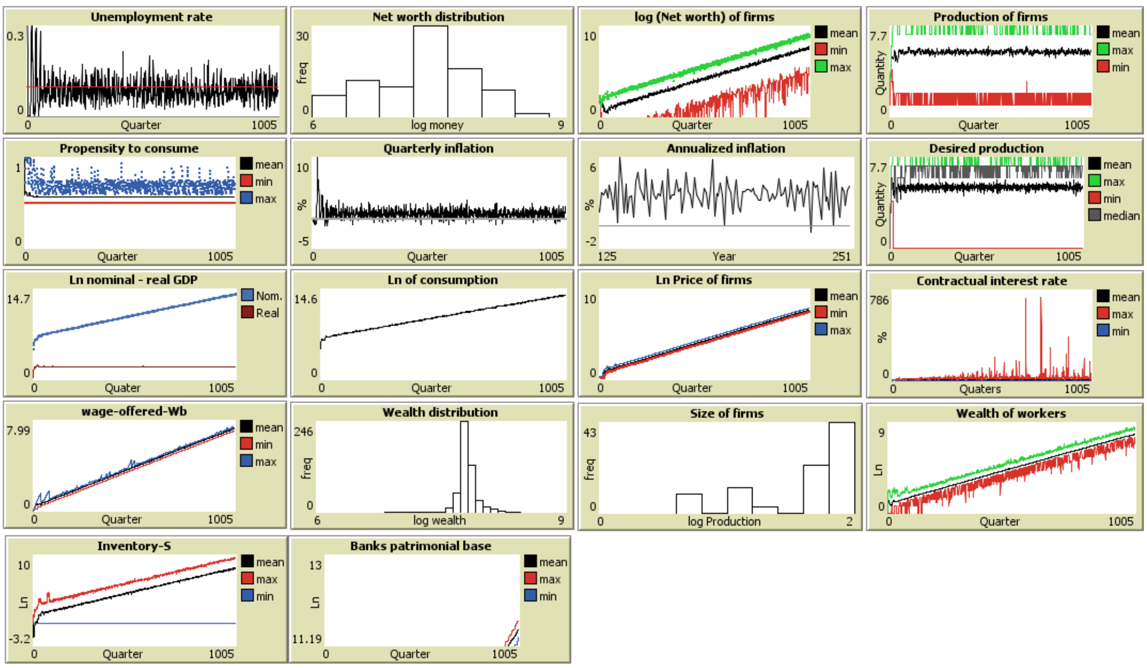


Figure 4.2: The BAM model GUI: Macroeconomic signals.

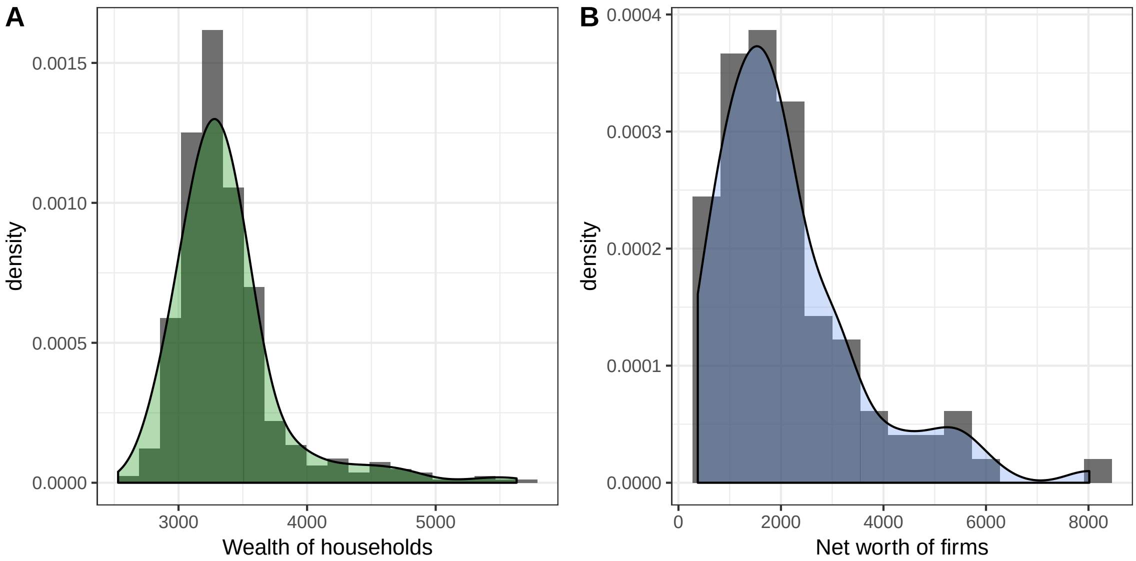


Figure 4.3: Examples of our distribution of wealth (A) and net value (B) of a selected run.

where,

$$m_r = \frac{1}{n}\Sigma(x_i - \bar{x})^r \ . \tag{4.2}$$

At the macro level it is assumed that a economy is characterized in the long run by balanced growth, so this assumption implies for example that growth rate of GDP is mean stationary (Evans, of Hong Kong. School of Economics, & Finance, 2000), in other words, series do not have time-dependent structure. There are a number of non-stationary tests and the Augmented Dickey-Fuller may be one of the more widely used. It uses an autoregressive model and optimizes an information criterion across multiple different lag values (Harris, 1992).

Applying the test without and with trend for zero and 3 lags on last 500 quarter series of GDP growth of 100 independent runs, with $\alpha = 0.05$, it is possible to reject the null hypothesis of non-stationarity if the t-statistic value is less (more negative) than the critical values (-1.95 for test without trend and -3.42 for test with trend). As we shown in Fig. 4.5, for every independent run this stylized fact is fulfilled, GDP growth rate series are mean stationary.

### 4.1.2 Sensibility

The effect of shocks was tested varying wages ($\xi$), prices ($\eta$), and interest rates ($\phi$) with values in $\{0.05, 0.1\}$. We also vary the propensity of consumption $\beta \in \{0.5, 0.85\}$. Replications of 20 runs for each combination of parameters were performed. A correlation between the presence of shocks and the dynamics of macroeconomic variables was observed, although it is less clear how the presence of shocks

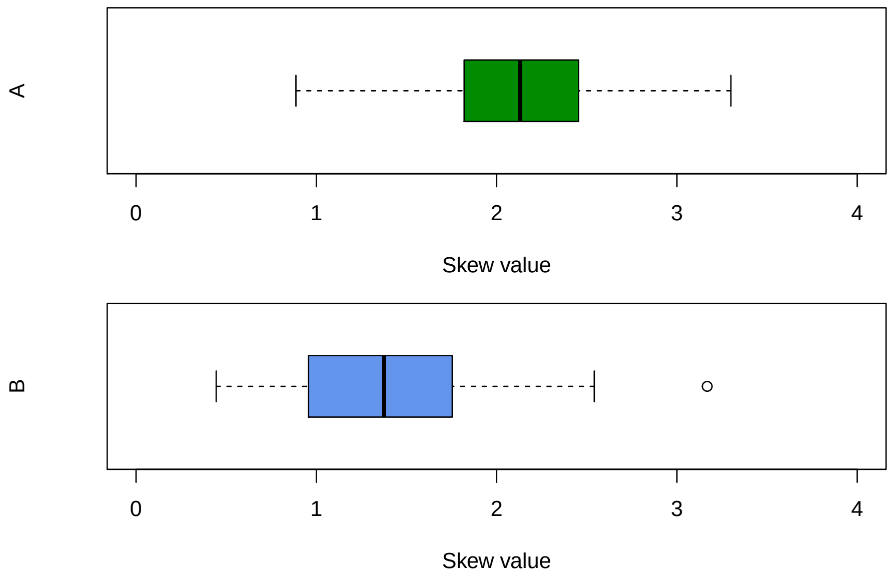


Figure 4.4: Skewness values obtained over 100 independent runs of wealth distribution (A) and net worth (B). It is considered that values greater than 1 correspond to highly positively skewed distributions

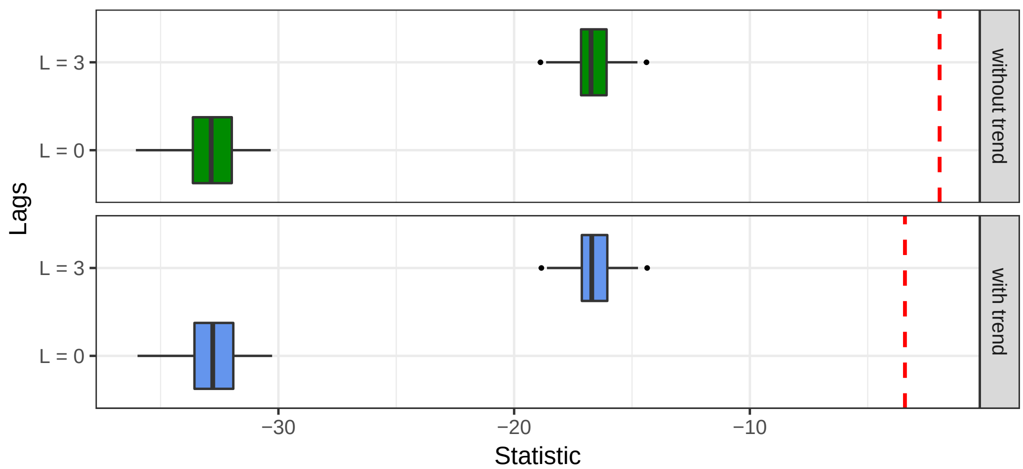


Figure 4.5: Distribution of Dickey-Fuller t-statistics for logarithmic first differences of last 500 GDP quarters over 100 independent runs. Dashed lines are critical values.

may be affected by the size of the markets, defined in terms of trials, i.e., the number of possible encounters among participant agents ($M, H, Z \in \{2, 4\}$). The small values for all these parameters were adopted from Delli Gatti et al. (2011) while large values, although arbitrary, represent acceptable big increments with respect to the small values.

Figure 4.6 shows the effect of varying the size of shocks when updating wages (Sub-model 7) on markets with two different sizes. As expected from theory, wage shocks lead to an increase in the GDP that is less evident in large markets (right) than in smaller ones (left). Similarly, as expected in macroeconomics, wage shocks produce a fluctuation in the unemployment rate that is less marked in large markets, as shown in Figure 4.7.

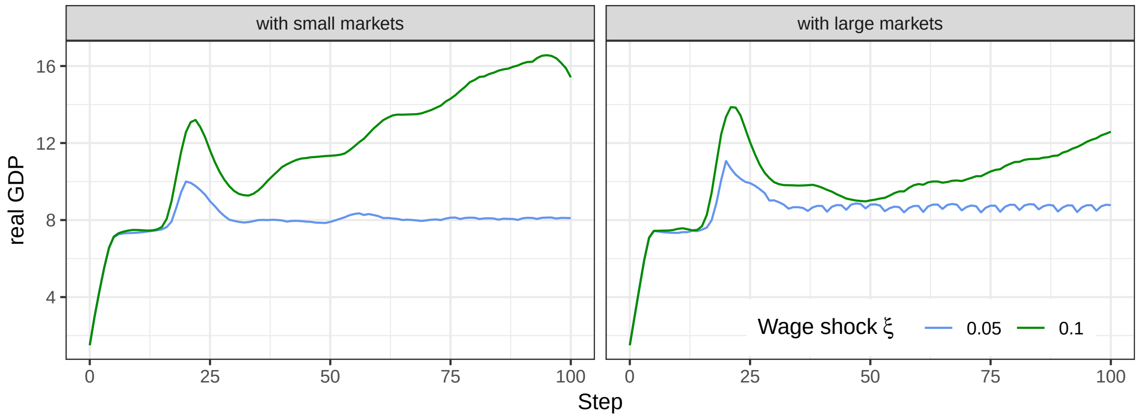


Figure 4.6: Dynamics of GDP under wage shocks of different size in small ($M = H = Z = 2$) and large ($M = H = Z = 4$) markets.

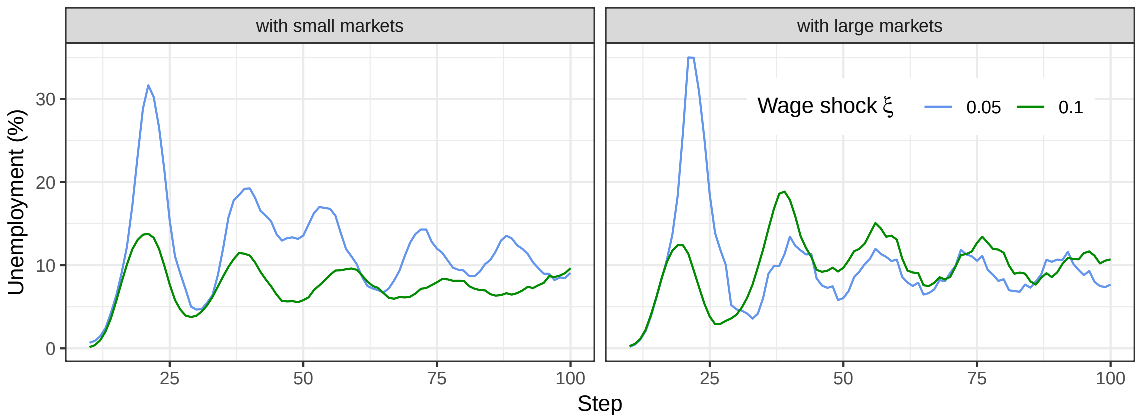


Figure 4.7: Dynamics of unemployment rate under wage shock in small and large markets.

Figure 4.8 shows the effect of price shocks (Sub-model 23). It is appreciated that the shock of the salary produces higher inflation in small markets than in large markets, which is even more evident with large-sized wage shocks. This result was expected, since the fact that agents have more market trials reduces the pressure on prices.

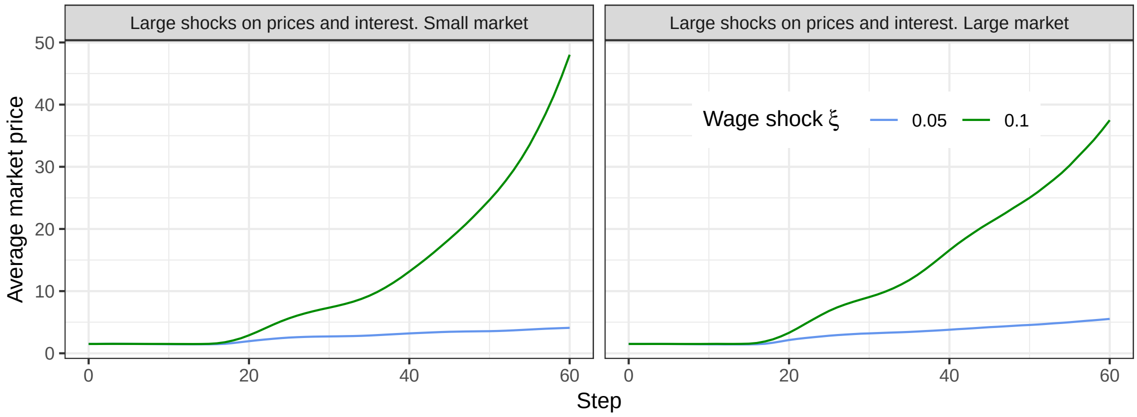


Figure 4.8: Dynamics average market price on small and large markets.

Figure 4.9 shows how propensity to consume (Sub-model 27) interacts with the dynamics of prices. Changes in the $\beta$ parameter do not have evident effects, which is consistent with the observed wealth distribution, since having a positive skew indicates the existence of few rich people, i.e., homogeneity in the propensity to consume that therefore do not induce rising prices.

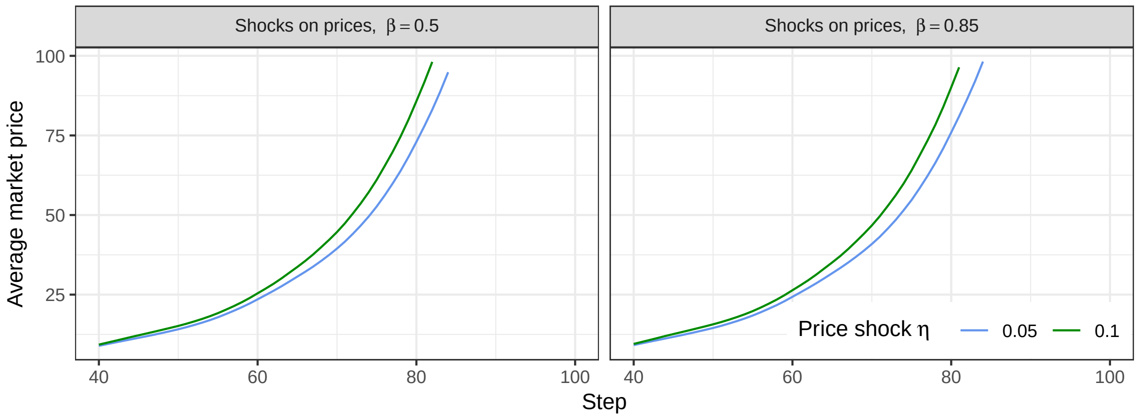


Figure 4.9: Dynamics of average market price when varying propensity to consume $\beta$.

## 4.2 Extortion model

In the following part we present the main results of our research, that is, the analysis of the effects of extortion on macroeconomic indicators. First, an analysis of robustness of the main parameters of BAMERS, propensity to be an extorter $\epsilon$ and probability to be caught $\lambda$. Second, we present the evaluation of our hypothesis. Finally, we evaluate the distributive effects of extortion, to contrast with the some results from Klaus G. Troitzsch (2015).

### 4.2.1 Parameter robustness

In this section we will examine the implication of any uncertainty or calibration of parameters in the simulation result. This reveals how sensitive the simulation is to disturbances of the parameter values, in some cases it may suggest that the changes observed in the simulation are a direct result of the parameterization and not an emergent property of the system.

The parameters robustness is determined by disturbing each parameter independently of others which remain at their baseline value. The response of the simulation under perturbation conditions is compared with the response of the baseline values using the A-Test of Vargha-Delaney (Vargha & Delaney, 2000), which is an effect-magnitude test used to determine if there is a significant statistical difference between the simulation responses under different conditions.

Some of the characteristics of this test is that 1) it can be applied both discrete (at least ordinal) or continuous distributions, which makes it applicable in behavioral and social science domains, where discrete scales are more common 2) makes no assumptions of normality or homogeneity of variance, 3) is easier to compute compared to the CL-Test(Vargha & Delaney, 2000, p.102).

Test is interpreted as follows, if $A_{12} = A_{21} = 0.5$, where indexes of A refer to the two populations to be compared, we say that the two populations are stochastically equal to each other. We can say that the standardized difference between populations $\Delta$ is small if $\Delta = 0.2$ or large if $\Delta = 0.8$. In our experiments, we considerate as critical values $A = 0.29$ and $A = 0.71$, upper and lower bound respectively.

With the initialization of parameters shown in table 3.4, and disturbing the propensity to be an extortionist $\epsilon$ and probability to be caught $\lambda$, simulating 500 time steps periods with the monthly scale (around 40 years), we observe that most of our responses in simulator are robust to parameter perturbation. Regarding the propensity to be criminal (Figure 4.10), there are significantly different responses to more or less 5% of the base value epsilon in Gini index and propensity to consume $c$. But no changes are induced in a set of macroeconomic indicators of our interest, such as unemployment rate, real GDP, net worth of firms and aggregate market prices.

In a similar way Figure 4.11 shows how the perturbation on the probability of being caught $\lambda$ has a statistically significant effect on the Gini index and propensity to consume, it also influences real GDP and aggregate market price for medium/high levels of police efficiency in comparison with baseline value.

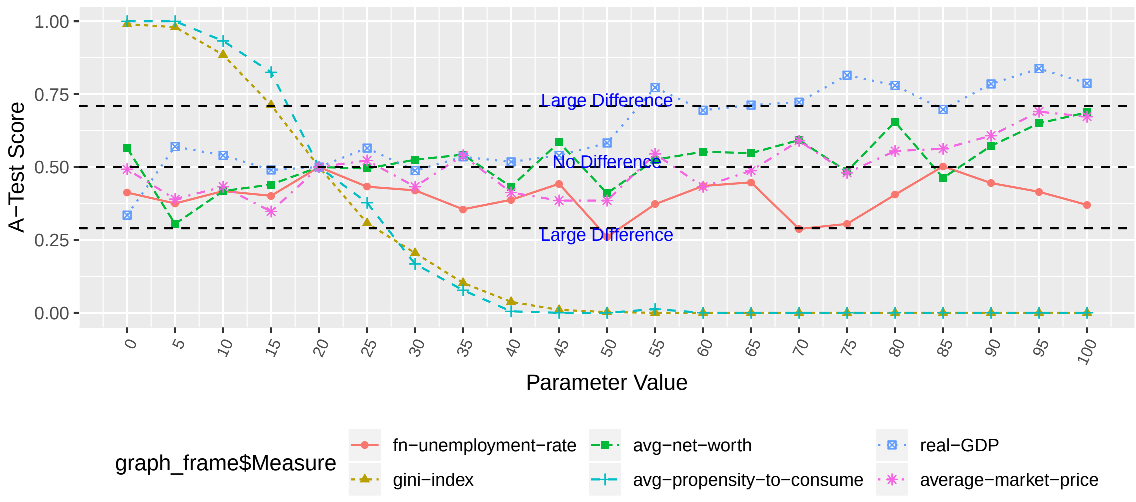


Figure 4.10: A-Test scores when adjusting parameter propensity to be extorter $\epsilon$.

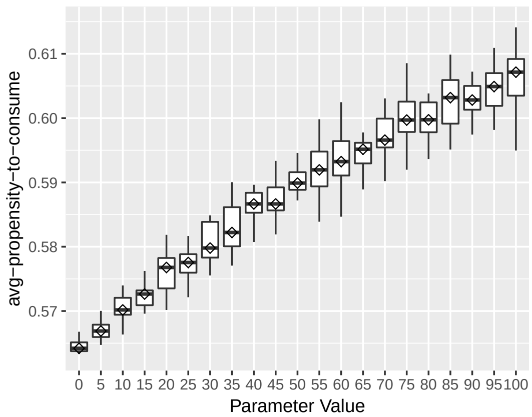


Figure 4.12: Distribution of propensity to consume $c$ response when altering parameter $\epsilon$

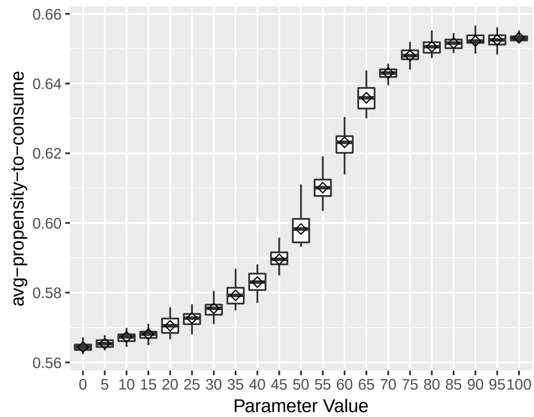


Figure 4.13: Distribution of propensity to consume $c$ response when altering parameter $\lambda$

### 4.2.2 Macroeconomic effect of extortion

There are some interesting dynamics, in particular the effect on propensity to consume $c$ when the parameter propensity to be a extorter $\epsilon$ is perturbed shows a clear positive linear relationship, that is, when the motivation to be an extortionist increases in the system, it translates into a propensity to spend (Figure 4.12). This means that at an aggregate level, everyone has become poorer, and they need to spend a higher proportion of their wealth to meet their needs. Although, of course, among more criminals in the economy, both the rivalry and the probability of being detected generate a greater variability in the effect on the propensity to consume and therefore in the effect on poverty, clearly visible through the length of the boxplot.

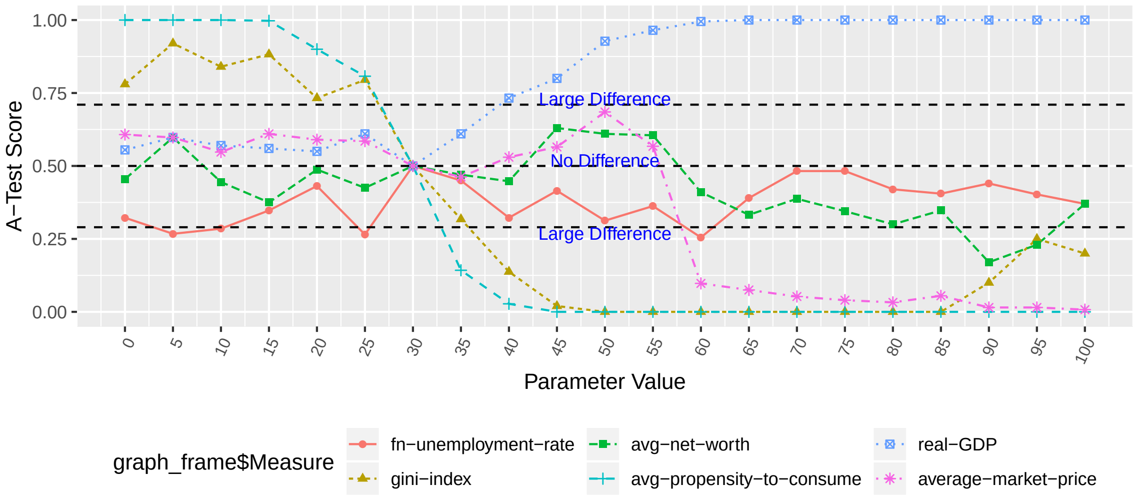


Figure 4.11: A-Test scores when adjusting parameter probability of being caught $\lambda$.

Figure 4.13 shows the dynamcic with the parameter related to the effectiveness of the police to capture extortionists $\lambda$ and the propensity to consume $c$. This seems a sigmoidal relationship between the variables. The effect of confiscating the goods to the extortionists seems to induce greater poverty, so the propensity to consume increases, and as has been mentioned before, this means that workers require a higher proportion of their income to meet their needs, they are less able to generate savings/wealth. This does not mean that confiscating property to criminals is bad, but that it is an emerging phenomenon on the economic system of a legal action to avoid the proliferation of extortionists. With low efficiency of the police, the effect on the propensity to consume is limited, but as increases $\lambda$ the effect becomes greater and decreases again until it stabilizes, given that the rest of parameters remain constant, including $\epsilon$, the propensity to be an extorter.

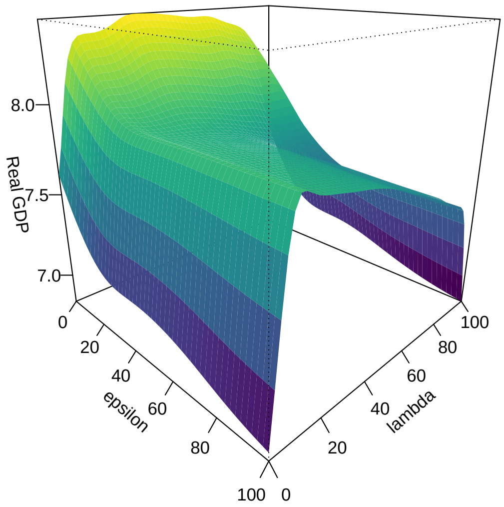


Figure 4.14: Real GDP response when altering parameter $\epsilon$ and $\lambda$

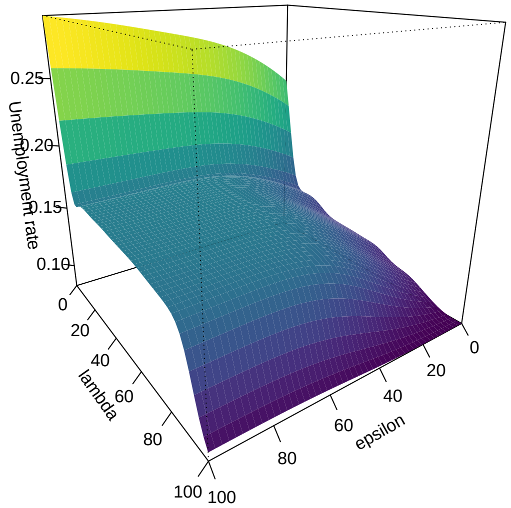


Figure 4.15: Unemployment rate response when altering parameter $\epsilon$ and $\lambda$

Figure 4.14 shows contraction in real GDP as a response to increments in number of criminal in the system.

Figure 4.15 shows that unemployment rate depends mainly on police efficiency ($\lambda$), with low level efficiency, the highest unemployment rates are shown, which are even higher when combined with high levels of crime. There is a sudden recovery in the unemployment rate, when justice improves marginally but unemployment remains inelastic until high levels of police efficiency are reached. In this space, the optimum is found when there is no crime and when the police have maximum efficiency.

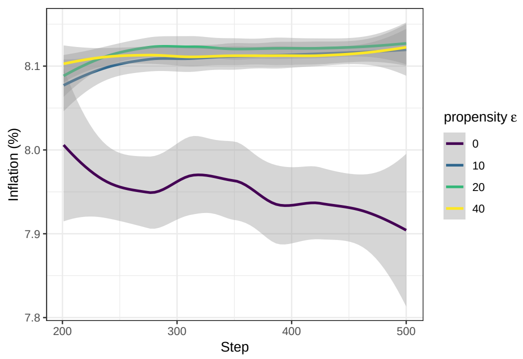


Figure 4.16: Dynamic of inflation when altering parameter $\epsilon$. Gray bands are confidence intervals at 95%.

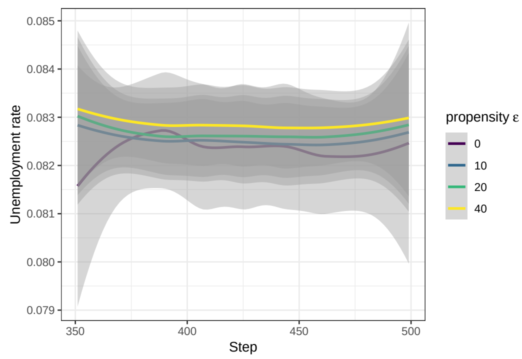


Figure 4.17: Dynamic of unemployment rate when altering parameter $\epsilon$. Gray bands are confidence intervals at 95%.

Other important macroeconomic indicator are inflation and unemployment. Next set of experiments are simulated with a monthly scale around 40 years and instantiates the values of parameters as suggested by Klaus G. Troitzsch (2015), Elsenbroich and Badham (2016), Luis G. Nardin et al. (2016), Luis Gustavo Nardin et al. (2017). We obtain the results shown in Figures 4.16 and 4.17. Regarding inflation, a high sensitivity is observed with respect to the base model, however once crime is incorporated, level of propensity to be an extorter controled $\epsilon$ seems not to be relevant, since inflation remains at similar levels, around 8%. Meanwhile, the unemployment rate seems not to be sensitive to changes in the propensity to be an extortionist $\epsilon$.

Discarding the first 200 time steps, considered as a burning period to reach the convergence of the model, we will use the described test in 3.5 to confirm if the difference in macroeconomic signals is statistically significant, beyond the visual evidence provided by the figures shown, we considered a random sample of 10000 permutations of the pooled sample and we computed the p-values. As Table 4.1 show, tests find enough evidence in data for rejecting at the 0.05 nominal significance level the null hypothesis that locations and scales of inflation percent are not the same at different levels of propensity to be extorter $\epsilon$, both in the comparison by pairs as the aggregate against all levels of extortion.

Table 4.1: Multisample Cucconi test for inflation indicator to different individual and pooled epsilon treatments, p-values are in parentheses. Base economy is equivalent to $\epsilon = 0$.

| vs | $\epsilon$ | | | |
|---|---|---|---|---|
| | $\{10\}$ | $\{20\}$ | $\{40\}$ | $\{10, 20, 40\}$ |
| **Base economy** | 114.5521 (0.0000) | 125.0616 (0.0000) | 129.3128 (0.0000) | 97.21859 (0.0000) |

According to the Cucconi statistic, in the case of the unemployment rate there is also sufficient evidence in the data to reject the null hypothesis, which mentions that there is no significant effect of extortion on macroeconomic indicators, although the statistic values are relatively small compared to those obtained for the effect of inflation (See Table 4.2). Although considered a test with less power (Conover, 1999), the Kolmogorov-Smirnov test of two samples is used to compare the signals at different levels of extortion, with D statistic values of $\{0, 10\} = 0.19$, $\{0, 20\} = 0.203$ and $\{0, 40\} = 0.23$ again it is possible to reject the null hypothesis that the distribution of the indicators is the same. In conclusion, if there is a statistically significant difference in the aggregate behavior of unemployment and it is possible to say that, as the propensity to extort decreases, the unemployment rate also decreases, as shown in Figure 4.17.

Table 4.2: Multisample Cucconi test for unemployment rate indicator to different individual and pooled epsilon treatments, p-values are in parentheses. Base economy is equivalent to $\epsilon = 0$.

| vs | $\epsilon$ | | | |
|---|---|---|---|---|
| | $\{10\}$ | $\{20\}$ | $\{40\}$ | $\{10, 20, 40\}$ |
| **Base economy** | 12.50489 (0.0000) | 15.34982 (0.0000) | 19.17498 (0.0000) | 9.094435 (0.0000) |

The effect on production is evident (Figure 4.18), although we can highlight the sensitivity of the system to a slight change from 0 to 10% in the propensity to be an extortionist. Applying the Cucconi test it is not surprising that it is possible to reject the null hypothesis (Table 4.3). One point we should pay attention to is that both authors with Equation-Based and Agent-Based models have considered a fixed number of extortionists in the model. If this is so, we can wrongly assume that there is no effect on the economy, since the money flows back into the economy as Astarita et al. (2018) suggest, and seems to be true as we can see in Figure 4.18, GDP is constant and with little variation to throughout simulation for any $\epsilon$ level. But with small perturbation in propensity $\epsilon$ we get different amount of production value (GDP), in general, a 10% increase in the propensity to extort produces a 1% decrease in real GDP.

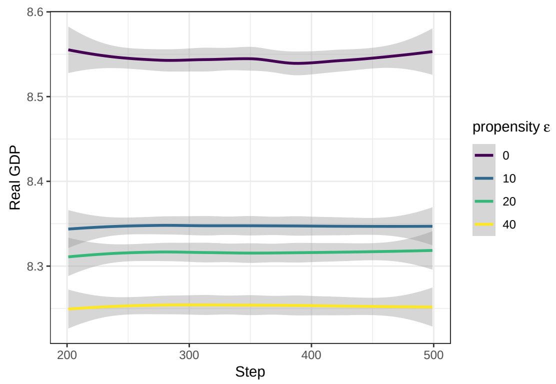


Figure 4.18: Dynamic of real GDP when altering parameter $\epsilon$. Gray bands are confidence intervals at 95%.

Table 4.3: Multisample Cucconi test for real GDP indicator to different individual and pooled epsilon treatments, p-values are in parentheses. Base economy is equivalent to $\epsilon = 0$.

| vs | $\epsilon$ | | | |
|---|---|---|---|---|
| | $\{10\}$ | $\{20\}$ | $\{40\}$ | $\{10, 20, 40\}$ |
| **Base economy** | 201.0189 (0.0000) | 219.7847 (0.0000) | 224.6256 (0.0000) | 245.5533 (0.0000) |

### 4.2.3 Distribution effects

Klaus G. Troitzsch (2015) showed the non-linear dependency between the assets of the extortionists (wealth of workers) and the propensities to denounce (rejection threshold) and to prosecute (probability of being caught $\lambda$). Specifically, it showed that the variability in assets of the extortionists decreases when the propensity to prosecute increases. He also showed that the assets of the extortionists are insensitive to the propensity to denounce. With the equivalent parameters in our model we show that these relationships are met.

Figure 4.19 shows how the low efficiency of the police to capture the extortionists generates greater variability in their assets, denoted by the greater breadth of confidence intervals. This same figure shows that there is no relationship between the amount of wealth and the rejection threshold to pay the pizzo. Figure 4.20 shows more clearly the non-linear dependence between the wealth and efficiency of the police, as well as the null relationship with the rejection threshold.

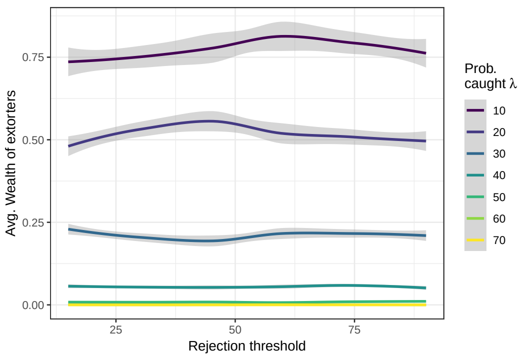


Figure 4.19: Wealth of the extortionists when $\lambda$ is disturbed. Gray bands are confidence intervals at 95%.

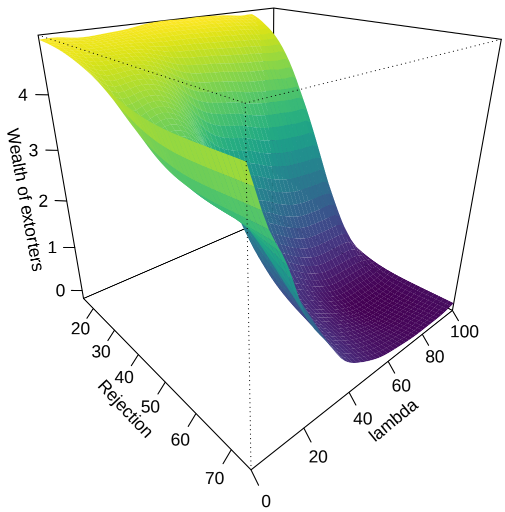


Figure 4.20: Fitted non-linear dependence between wealth of extortionists and probability of being caught $\lambda$.

# Chapter 5. Conclusion

Contrary to the current predominant economic analysis based on equations, the theory of complexity (Boccara, 2010) conceives the economy as a complex system of heterogeneous interacting agents (Delli Gatti et al., 2005; Delli Gatti et al., 2011), which are characterized by having limited information of the system and bounded rationality, as in real life. Agent-Based models are an analytical and computational tool developed for researchers who prefer this emerging methodological approach, and which has been applied successfully in a wide variety of domains (Uhrmacher & Weyns, 2009), including the economic one, where new models are continuously being developed (See 2.1.2).

This thesis applied this new approach based on agents, to a case study on the macroeconomic effects of extortion, a model that is discussed in detail in chapters 2 and 3 and that turns out to be a complex phenomenon, it is an architecture with reactive agents, that was modeled in the NetLogo language, which facilitated the implementation, understanding of the model, extension, as well as distribution, even for those with a background not related to programming.

It should be noted that despite following the NetLogo programming style guidelines, which facilitates the understanding and transmission of the model, it was also chosen to document the model following the ODD protocol (Grimm et al., 2006; Grimm et al., 2010; Grimm et al., 2013), with the aim of facilitating understanding not only in the model if not in the report itself, likewise facilitates the replicability in other languages with which the researcher feels comfortable programming, not only those agents oriented languages (Allan, 2010; Kravari & Bassiliades, 2015; Abar et al., 2017) but of different purpose (Wilensky & Rand, 2015).

The application of our proposal can be broken down into two stages, the first following Delli Gatti et al. (2011) where a healthy generic economy is modeled, that is, with indicators of unemployment and inflation similar to those observed in real economies, which constitutes a contribution in itself of this work, it is a tool open to the community of researchers interested in this approach, and that as mentioned above, being programmed in NetLogo and the available code, it can be easily modified to analyze different scenarios, external disturbances, incorporation of new classes of agents such as government, new markets for interaction between the bank and households, incorporation of productivity, learning, etc.

In our case, in a second stage, the extortion layer is included based on the extension and detailed investigation of the GLODERS European project, which, despite its extensive and detailed work, has remained pending in the analysis of macroeconomic effects. In this sense, our work is inserted as a novel analysis in the sense that it had not been explored as far as we know.

At the end of both stages of project development, baseline economy and extortion, we can highlight some advantages and disadvantages of the Agent-Based approach. From our perspective, there is a key factor from which many advantages derived from the Agent-Based approach, which in turn can be considered disadvantages of the classical paradigm based on equations. This is, being able to be encoded *ascending*, with small pieces of the whole system, *model is not limited by the mathematical capacity* of the researcher, which in the case of the Equation-Based approach involved imposition of many assumptions to keep the model as simple as the developer's mathematical manipulation capacity.

As we discussed before, in ABMs the limitation of mathematical ability is eliminated and problems with more realistic and therefore less simple models begin to be treated. *ABMs are less simplified* in one specific and important way: they represent system's individual components and their behaviors. Instead of describing a system only with variables, representing the state of the whole system, we model its individual agents (Railsback & Grimm, 2012).

In our case of application, from the origins of the classical approach based on equations, it was not easy to reach the first approximation elaborated by Walras (Starr, 2011). And although it has been improved to what we know today as a Dynamic Stochastic General Equilibrium model, widely accepted but increasingly questioned (See section 1.2 in Delli Gatti et al., 2011; Chen, 2016, section 3.4.1), it still suffers from the assumption of equilibrium and from the fact that the agents participating in the model have complete cognition of the system thus optimizing their plans.

From this modeling advantage, others emerge, such as *heterogeneity*. While the Equation-Based models benefit analytically from the reduction of the characteristics in which the agents differ, in the Agent-Based models there is no negative effect if different values are assigned to the relevant characteristics of the agents. In our case, the agents that participate in the model have state variables (Tables 3.1 and 3.3) whose value can differ among the agents. In such a way that it is possible at each moment of the simulation to visualize the differences that exist between them, as in the case of wealth and its distribution among workers.

Again, derived from the previous characteristic, it is possible to *represent the space and the location of the agents explicitly* through coordinates ($X, Y$ and even $X, Y, Z$). What allows to define different interaction structures between agents. NetLogo is prepared to work the spatial layer, but they can be extended to any language assuming the coordinates as an attribute that differentiates the agents. In our baseline economic model, the spatial part was considered for debugging purposes, taking advantage of NetLogo's graphical interface that represents the "world". Meanwhile, for the extortion model, extortionists can use a search strategy based on proximity, and firms can evaluate the risk of not paying for the pizzo considering the presence of extortionists in the neighborhood.

Another interesting feature of this approach is the *bounded rationality* of the agents, that is, the information of the agents is private, and therefore access to that information can be restricted by providing the agents with a finite computing capacity. So even though they are aimed at improving their utility (not a specific goal), they make their decisions using simple heuristics with limited information learned by interacting with other agents. In the economic model, for example, agents (firms and workers) have a limited number of attempts to enter the markets of which they are part, looking for better interest rates, wages or prices, but not having all the information of the system, so their decisions may not be optimal.

After the aforementioned characteristics, we obtain an aggregate behavior of the agents that, for the case study, has generated macroeconomic signals such as unemployment and inflation, which on average adjust to those observed in reality. This is the *emergence property*, and implies that the agents have organized themselves in the different markets, without a precoded central control for this to happen. In fact, probably the most interesting emerging behavior is derived from the economic model, wealth distribution, which as we have tested has a positive bias that tends to occur in reality 4.1.1.

Throughout the whole process that involved the use of the Agent-Based approach to the analysis of the effect of extortion on macroeconomic aggregates, to say, modeling, calibration and experimentation. Some possible disadvantages are presented. As with the advantages, we present them in order of dominance, that is, the disadvantage from which other can derive.

In this sense, experimentation takes time depending on the number of agents, convergence is not fast. If we add that we must do a sensible amount of repetitions for statistical comparison purposes, *computationally it becomes expensive*. With the growth of computing capacity even in personal computers, is that Agent-Based modeling has gained ground against the predominant classical paradigm.

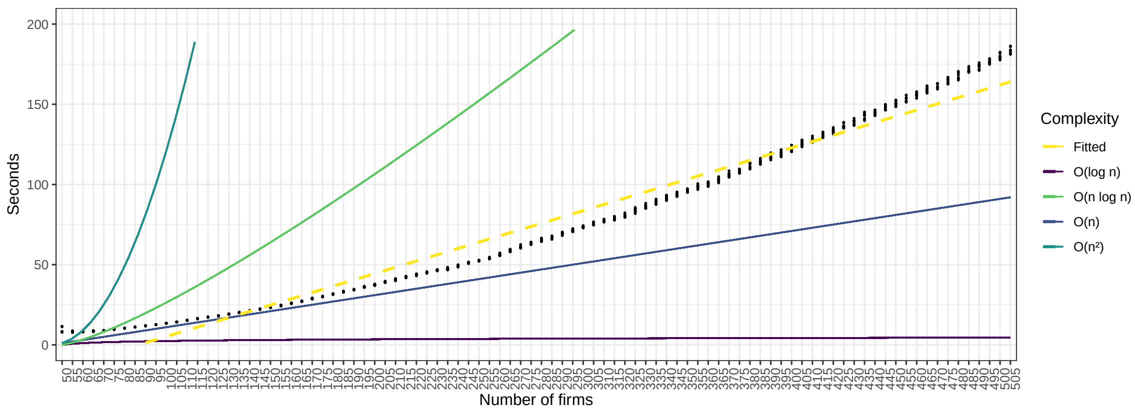


Figure 5.1: Time complexity of BAMERS.

In Figure 5.1, the time in seconds required by BAMERS to reach 500 time periods is shown[1], as the number of firms agents varies and with an $\epsilon$ value of 20%. The complexity seems to follow a linear order, at least for that amount of companies in

[1] 10 repetitions by configuration were run on all cores of a server with Intel(R) Core(TM) i7-3930K CPU(3th generation) at 3.20GHz with 64GB of RAM running openSUSE Leap 15.1 (64 Bit)

which it was evaluated. However, it is known that the greater the number of agents, the longer the time to reach the convergence of the model (Gilbert & Troitzsch, 2005), so the order of complexity may be greater.

After the previous disadvantage, we now face the problem of *parameterization and calibration*, because given the problem of computational complexity, perform an exploration of the parameters that allow us to establish those values that give us a desired output, it is not a simple task. It should be clear, in the fact that the first phase of development of our model is a free re-implementation of the macroeconomic model developed by Delli Gatti et al. (2011), so only a part of the parameters were obtained through experimentation and some others taking as reference the literature both economic and extortion. If these data are not available, the calibration can be difficult, especially when the model has high sensitivity to disturbances, it is recommended to perform a parameter robustness analysis and to know previously which parameters should be handled with care.

Finally and responding directly to the question that has guided this work:

*there is an extortion effect, statistically significant, on macroeconomic aggregates such as production, unemployment and inflation.*

# Policy recommendation

Extortion can be seen as a tax that increases the cost of companies, which generates fear among entrepreneurs and decreases investment, spreads throughout the economic system, decreasing growth. So low levels of propensity to become extortionists are enough to notice considerable negative effects on macroeconomic indicators such as real GDP or the unemployment rate, which reproduces the results of the Astarita simulation, which show a decrease in economic activity with Italian data.

The simulation data shown suggests that, in the case of extortion, it is more convenient to prevent its occurrence than to combat it, since with no instance of the justice system efficiency parameter a recovery of economic activity is achieved, at levels shown in an economy without crime. In fact, high levels of efficiency are counterproductive. In this sense, what can be done to reduce the effect of extortion on the economy? How to discourage the proliferation of criminals?

One way is to make the extortion business less profitable. According to the results shown, the weakening of the wealth of criminals is strongly related to the threshold of rejection of firms for the payment of pizzo. Increases in the rejection threshold, and therefore in the number of complaints, can weaken the wealth of criminals, although it also depends on the probability that they will be captured, which is the most important factor for Klaus G. Troitzsch (2015).

As empirical studies have been shown, the common cause for the spread of extortion is the lack of credibility in the justice systems, which decreases citizen complaints. In this sense, the government's task to combat crime is to improve the reputation of the entire justice system, that is, to increase its efficiency in capture and convictions. To the extent that this message is propagated to citizens, complaints will eventually increase.

However, there are other causes for the proliferation of extortion rackets systems, according to Anzola et al. (2016), in Latin America it is strongly linked to a context of exclusion and deprivation, which involves poverty, indigents and bad income distribution. These crime proliferation factors were included in the model presented, incorporating as a basic principle the possible adaptation to the crime of unemployed and poor workforce, based on Abrahamsen (1949). One of the lessons derived from this is that it is necessary to generate policies aimed at the inclusion of vulnerable groups, including unemployed and low-income people.

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# Appendix A. Accepted paper

# Towards an Agent-based Model for the Analysis of Macroeconomic Signals

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**Abstract.** This work introduces an agent-based model for the analysis of macroeconomic signals. The Bottom-up Adaptive Model (BAM) deploys a closed Walrasian economy where three types of agents (households, firms and banks) interact in three markets (goods, labor and credit) producing some signals of interest, e.g., unemployment rate, GDP, inflation, wealth distribution, etc. Agents are bounded rational, i.e., their behavior is defined in terms of simple rules finitely searching for the best salary, the best price, and the lowest interest rate in the corresponding markets, under incomplete information. The markets define fixed protocols of interaction adopted by the agents. The observed signals are emergent properties of the whole system. All this contrasts with the traditional macroeconomic approach based on the general equilibrium model, where perfect rationality and/or full information availability are assumed. The model is defined following the Overview, Design concepts, and Details Protocol and implemented in NetLogo. BAM is promoted as a toolbox for studying the macroeconomic effects of the agent activities at the service of the elaboration of public policies.

**Keywords:** Agent-Based Model, Macroeconomic, ODD protocol

## 1 Introduction

Both in the natural and social sciences, there are complex processes that 1) consist of many agents which interact with each other 2) exhibit emergent global properties, and 3) lack a centralized control governing such properties [1]. Analyzing these systems as a whole is an extremely complicated task, so models are used to describe them. A model is an abstract representation of reality, in which only the relevant characteristics of the system are considered for the analysis.

In economics, the continuous relationship between various agents such as households, companies, banks and the government, generates a large number of macroeconomic signals, such as production, unemployment, inflation, interest rates, among others. In macroeconomics, two approaches are distinguished to model this phenomena, the classical approach (top-down) based on the theory of general equilibrium and a new approach (bottom-up) based on agents [2].

The top-down models rest on the theory of general equilibrium, whose central statement establishes that from the interaction between supply and demand derives a general equilibrium on all markets. An important characteristic of these models is the market clearing condition (Walrasian auctioneer), which is given by a central authority that proposes a set of prices, determines an excess of demand at these prices and adjusts them to their equilibrium values. The roots of this approach go back to the nineteenth century, when many economists tried to formulate a full general equilibrium model, but it was conceived until 1874 by Leon Walras, a French economist [3]. The most recent versions of this model incorporate dynamism (the economic variables consider the expectations of the future), and randomness (as a source of uncertainty) and are called Dynamic Stochastic General Equilibrium (DSGE) models. The solution in this type of models is found when solving systems of equations, e.g., households optimize a utility function subject to a budget constraint, while companies maximize their profit subject to the restriction of technological resources [4].

One of the main limitations of these models is the assumption of equilibrium, since it is too simplistic for collecting the complexity of economic processes over time. Although external shocks can be used to get out of the equilibrium, by its nature, DSGE picks up small fluctuations around a stationary state, analyzing and predicting the signals of the economy in this way. So, these models behave well when there are no disturbances, but predict poorly when risk and uncertainty come into play.

Another disadvantage of this approach is that by the very nature of this approach, modeled through equations, agents are assumed homogeneous, i.e., they have the same information and worse, they have complete information of the system with which they determine their optimal plans. Finally, the Walrasian trial and error mechanism has no counterpart in the real market economy, and goes against the spirit of complex systems, where there is no centralized control.

On the other hand, the bottom-up models conceive complex systems as composed of autonomous interactive agents. Agents base their behavior on simple rules and interact with other agents, which in turn influences their behavior. Two important features of this type of models are that 1) each agent has its own attributes and behavior, i.e., heterogeneity 2) the effects of the diversity among agents can be observed in the behavior of the system as a whole, emergency [5]. Despite their simplicity, these models are not devoid of rationality [2], economic agents guide their behavior to achieve a utility, i.e., instead of coding a specific goal, a measure is defined, allowing the agent to decide what is better for them, e.g., higher salary offered by firms, lower interest rate of banks, better leverage of firms. Although always within the cognitive limitations of the agents.

Bottom-up models do not make assumptions about the efficiency of markets or the existence of an equilibrium, so they can absorb the tensions or disturbances generated in periods of crisis through the emerging behavior resulting from the interaction between agents, in such a way that the panic of agents eventually spreads to the whole system. Finally, these models are non-linear, which implies that the generated effects do not have to be proportional to their causes. This allows to identify the causes in areas that in principle are not related. In some models, the effects can be of a magnitude much greater than the causes that provoke them while in others the effects dissipate in a conventional manner.

The main contribution of the paper is offering a complete and concise, basic Bottom-up Adaptive Model (BAM) based on the work of Delli Gatti et al. [9]. The model is described adopting the Overview, Design concepts, and Details (ODD) protocol [6,7], for the sake of reproducibility. The resulting system is available at Github [4]. The paper is organized as follows: Section 2 introduces the BAM model conceptually, for then offering details accordingly to the ODD Protocol. Section 3 presents the implementation of the model in NetLogo. Section 4 presents results, as well as the empirical validation of the model by fulfilling some stylized facts used in economic theory. Finally, Section 5 presents our conclusions and future work.

## 2 The BAM model

Despite the criticism for its excessive abstraction, the Walrasian economic model has persisted as a fundamental paradigm [8]. Indeed, because of its simplicity, it is a good starting point for exploring both perfect and imperfect economic models.

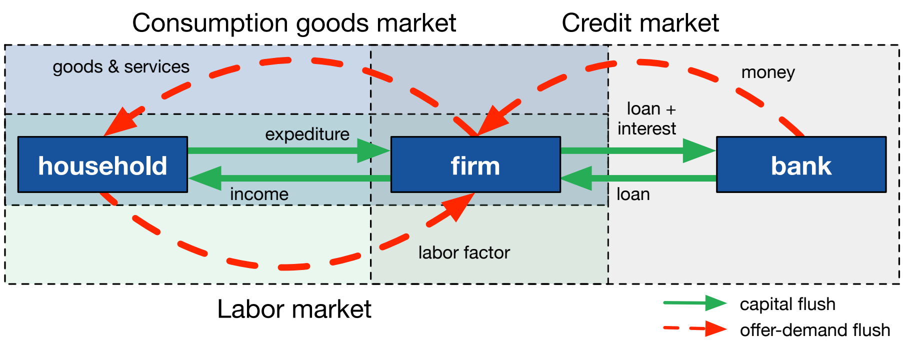


**Fig. 1.** The Bottom-up Adaptive Macroeconomics Model (BAM).

[4] https://github.com/alexplatasl/BAMmodel/

The Bottom-up Adaptive Model (BAM) [9] adopted in this paper is Walrasian in nature. As shown in Fig. 1, it is composed by the following types of agents:

- **Houselholds** representing the point of consumption and labor force.
- **Firms** representing the transformation of work in goods and / or services.
- **Banks** providing liquidity to firms if necessary.

A large number of autonomous households, producers and banks operate adaptively in three totally decentralized and interconnected markets:

- A **labor market**, in which each household offers an inelastic unit of work per period, while firms demand depending on their production plans;
- A perishable consumer **goods market**, in which households spend all or part of their wealth and firms offer goods at different prices; and
- A **credit market** in which firms demand money if their resources are insufficient to cover their production expenses, and banks offer money at different interest rates.

Opportunities for exchange in these markets are discovered through a sequential process characterized by optimization, namely, maximizing wages, minimizing the price of goods consumed and minimizing the price of money (interest rate). Firms can modify prices and quantities adaptively given the signals of the inventory and the market price.

BAM was adopted because the agents that intervene in the model are those necessary to model disturbances that are similar to those observed in a real world economy; while generating macroeconomic signals of interest, e.g., inflation, unemployment, wealth, production among others are generated.

As mentioned in the introduction, for the sake of reproducibility, the details of the model will be described following the ODD protocol, which is organized in three parts:

1. **Overview**. A general description of the model, including its purpose and its basic components: agents, variables describing them and the environment, and scales used in the model, e.g., time and space; as well as a processes overview and their scheduling.
2. **Design concepts**. A brief description of the basic principles underlying the model's design, e.g., rationality, emergence, adaptation, learning, etc.
3. **Details**. Full definitions of the involved submodels.

### 2.1 Overview

**Purpose.** Exploring the use of the bottom-up approach for the study of macroeconomic signals, particularly the effect of the agent's activities in such signals.

**Entities, state variables, and scales.**

- Agents: Firms, workers, and banks.
- Environment: Agents are situated in a grid environment which is meaningless with respect to the model. The environment is used exclusively as a visual aid for debugging.
- State variables: The attributes that characterize each agent are shown in Table 1.
- Scales: Time is discrete, e.g., each step represents a quarter. Quarters are adequate for long periods, months can be used for short ones.

**Table 1.** State variables by agent.

| Agent | Attribute | Type | Agent | Attribute | Type |
|---|---|---|---|---|---|
| Firm | production-Y | Int | Worker | employed? | Bool |
| | desired-production-Yd | Int | | my-potential-firms | AgSet |
| | expected-demand-De | Int | | my-firm | Ag |
| | desired-labor-force-Ld | Int | | contract | Int |
| | my-employees | AgSet | | income | Float |
| | current-numbers-employees-L0 | Int | | savings | Float |
| | number-of-vacancies-offered-V | Int | | wealth | Float |
| | minimum-wage-W-hat | Float | | propensity-to-consume-c | Float |
| | wage-offered-Wb | Float | | my-stores | AgSet |
| | net-worth-A | Float | | my-large-store | Ag |
| | total-payroll-W | Float | Bank | total-amount-of-credit-C | Float |
| | loan-B | Float | | patrimonial-base-E | Float |
| | my-potential-banks | AgSet | | operational-interest-rate | Float |
| | my-bank | AgSet | | interest-rate-r | Float |
| | inventory-S | Float | | my-borrowing-firms | AgSet |
| | individual-price-P | Float | | bankrupt? | Bool |
| | revenue-R | Float | | | |
| | retained-profits-pi | Float | | | |

**Process overview and scheduling.** The main loop of the simulation is as follows:

1. Firms calculate production based on expected demand.
2. A decentralized labor market opens.
3. A decentralized credit market opens.
4. Firms produce.
5. Market for goods open.
6. Firms will pay loan and dividends.
7. Firms and banks will survive or die.
8. Replacing of bankrupt firms/banks.

### 2.2 Design concepts

**Basic Principles.** The model follows fundamental principles of neoclassical economics [16], since it gives great importance to money in economic processes and also the strategy for determining prices is given considering both supply and demand.

**Emergence.** The model generates adaptive behavior of the agents, without the imposition of an equation that governs their actions. Macroeconomic signals are also emergent properties of the system.

**Adaptation.** At each step, firms can adapt price or amount to supply (only one of the two strategies). Adaptation of each strategy depends on the condition of the firm (level of excessive supply / demand in the previous period) and/or the market environment (the difference between the individual price and the market price in the previous period).

**Objectives.** Agents do not explicitly have an objective, but implicitly they try to maximize a utility or attribute.

**Learning.** None for the moment, however, see the future work section for possible uses of learning in this model.

**Prediction.** Firms predict the quantities to be produced or the price of the good produced based on the excess of supply/demand in the previous period and the differential of its price and the average price in the market.

**Sensing.**

- Firms perceive their own produced quantity, good's price, labor force, net value, profits, offered wages; as well as the average market price and the interest rate of randomly chosen banks.
- Workers perceive the size of firms visited in the previous period, prices published by the firms in actual period and wages offered by the firms.
- Banks perceive net value of potential borrowers in order to calculate interest rate.

**Interaction.** Interactions among agents are determined by the markets:

- In the labor market, firms post their vacancies at a certain offered wage. Then, unemployed workers contact a given number of randomly chosen firms to get a job, starting from the one that offers the highest wage. Firms have to pay the wage bill in order to start production. A worker whose contract has just expired applies first to his/her last employer.

- Firm can access to a fully decentralized credit market if net worth are in short supply with respect to the wage bill. Borrowing firms contact a given number of randomly chosen banks to get a loan, starting from the one which charges the lowest interest rate. Each bank sorts the borrowers applications for loans in descending order according to the financial soundness of firms, and satisfy them until all credit supply has been exhausted. The contractual interest rate is calculated applying a mark-up on an exogenously determined baseline interest rate. After the credit market is closed, if financial resources are not enough to pay for the wage bill of the population of workers, some workers remain unemployed or are fired.
- In goods market, firms post their offer price, and consumers contact a given number of randomly chosen firms to purchase goods, starting from the one which posts the lowest price.

**Stochasticity.** Elements that have random shocks are:

- Determination of wages when vacancies are offered ($\xi$).
- Determination of contractual interest rate offered by banks to firms ($\phi$).
- The strategy to set prices ($\eta$).
- The strategy to determine the quantity to produce ($\rho$).

**Collectives.** Markets configure collectives of agents as described above. They include labor, goods, and credit markets. In addition, firms and consumers are categorized as rich and poor.

**Observation.** Along simulation are observed:

- Logarithm of real GDP.
- Unemployment rate.
- Annual inflation rate.
- Interest rate.

At end of simulation are computed:

- Philips curve (inflation / unemployment).
- Distribution of the size of firms.
- Distribution of wealth of households.
- Growth rate of real GDP.

### 2.3 Details

**Initialization.** The initialization parameters described in Delli Gatti [9] was adopted. For the values not provided in the text, they were obtained through experimentation. Table 2 shows the initial values of the model.

**Table 2.** Parameters initialization.

| | Parameter | Value |
|---|---|---|
| $I$ | Number of consumers | 500 |
| $J$ | Number of producers | 100 |
| $K$ | Number of banks | 10 |
| $T$ | Number of steps | 1000 |
| $C_P$ | Propensity to consume of poorest people | 1 |
| $C_R$ | Propensity to consume of richest people | 0.5 |
| $\sigma_P$ | R&D investment of poorest firms | 0 |
| $\sigma_R$ | R&D investment of richest firms | 0.1 |
| $h_\xi$ | Maximum growth rate of wages | 0.05 |
| $H_\eta$ | Maximum growth rate of prices | 0.1 |
| $H_\rho$ | Maximum growth rate of quantities | 0.1 |
| $H_\phi$ | Maximum amount of banks costs | 0.1 |
| $Z$ | Number of trials in the goods market | 2 |
| $M$ | Number of trials in the labor market | 4 |
| $H$ | Number of trials in the credit market | 2 |
| $\hat{w}$ | Minimum wage (set by a mandatory law) | 1 |
| $P_t$ | Aggregate price | 1.5 |
| $\delta$ | Fixed fraction to share dividends | 0.15 |

**Input data.** None, although data from real economies might be used for validation.

**Submodels.**

1. Production with constant returns to scale and technological multiplier: $Y_{it} = \alpha_{it} L_{it}$, s.t., $\alpha_{it} > 0$.
2. Desired production level $Y_{it}^d$ is equal to the expected demand $D_{it}^d$.
3. Desired labor force (employees) $L_{it}^d = Y_{it}^d / \alpha_{it}$.
4. Current number of employees $L_{it}^0$ is the sum of employees with and without a valid contract.
5. Number of vacancies offered by firms $V_{it} = max(L_{it}^d - L_{it}^0, 0)$.
6. If there are no vacancies ($V_{it} = 0$), wage offered is $w_{it}^b = max(\hat{w}_t, w_{it-1})$, where $\hat{w}_t$ is the minimum wage determined by law.
7. If $V_{it} > 0$, wage offered is $w_{it}^b = max(\hat{w}_t, w_{it-1}(1 + \xi_{it}))$, where $\xi_{it}$ is a random term evenly distributed between $(0, h_\xi)$.
8. At the beginning of each period, a firm has a net value $A_{it}$. If total payroll to be paid $W_{it} > A_{it}$, firm asks for loan $B_{it} = max(W_{it} - A_{it}, 0)$.
9. For the loan search costs, it must be met that $H < K$
10. In each period the $k$-th bank can distribute a total amount of credit $C_k$ equivalent to a multiple of its patrimonial base $C_{kt} = E_{kt}/v$, where $0 < v < 1$ can be interpreted as the capital requirement coefficient. Therefore, the $v$ reciprocal represents the maximum allowed leverage by the bank.
11. Bank offers credit $C_k$, with its respective interest rate $r_{it}^k$ and contract for 1 period.

12. If $A_{it+1} > 0$ the payment scheme is $B_{it}(1 + r_{it}^k)$.
13. If $A_{it+1} \leq 0$, bank retrieves $R_{it+1}$.
14. Contractual interest rate offered by the bank $k$ to the firm $i$ is determined as a margin on a rate policy established by Central Monetary Authority $\bar{r}$, s.t., $R_{it}^k = \bar{r}(1 + \phi_{kt}\mu(\ell_{it}))$.
15. Margin is a function of the specificity of the bank as possible variations in its operating costs and captured by the uniform random variable $\phi_{kt}$ in the interval $(0, h_\phi)$.
16. Margin is also a function of the borrower's financial fragility, captured by the term $\mu(\ell_{it})$, $\mu' > 0$. Where $\ell_{it} = B_{it}/A_{it}$ is the leverage of borrower.
17. Demand for credit is divisible, i.e., if a single bank is not able to satisfy the requested credit, it can request in the remaining $H - 1$ randomly selected banks.
18. Each firm has an inventory of unsold goods $S_{it}$, where excess supply $S_{it} > 0$ or demand $S_{it} = 0$ is reflected.
19. Deviation of the individual price from the average market price during the previous period is represented as: $P_{it-1} - P_{t-1}$
20. If deviation is positive $P_{it-1} > P_{t-1}$, firm recognizes that its price is high compared to its competitors, and is induced to decrease the price or quantity to prevent a migration massive in favor of its rivals; and vice versa.
21. In case of adjusting price downward, this is bounded below $P_{it}^l$ to not be less than your average costs:

$$P_{it}^l = \frac{W_{it} + \sum_k r_{kit}B_{kit}}{Y_{it}}$$

22. Aggregate price $P_t$ is common knowledge, while inventory $S_{it}$ and individual price $P_{it}$ are private.
23. Only the price or quantity to be produced can be modified. In the case of price, we have the following rule:

$$P_{it}^s = \begin{cases} \max[P_{it}^l, P_{it-1}(1 + \eta_{it})] & \text{if } S_{it-1} = 0 \text{ and } P_{it-1} < P \\ \max[P_{it}^l, P_{it-1}(1 - \eta_{it})] & \text{if } S_{it-1} > 0 \text{ and } P_{it-1} \geq P \end{cases}$$

where: $\eta_{it}$ is a randomized term uniformly distributed in the range $(0, h_\eta)$ and $P_{it}^l$ is the minimum price at which firm $i$ can solve its minimal costs at time $t$ (previously defined).
24. In the case of quantities, these are adjusted adaptively according to the following rule:

$$D_{it}^e = \begin{cases} Y_{it-1}(1 + \rho_{it}) & \text{if } S_{it-1} = 0 \text{ and } P_{it-1} \geq P \\ Y_{it-1}(1 - \rho_{it}) & \text{if } S_{it-1} > 0 \text{ and } P_{it-1} < P \end{cases}$$

where $\rho_{it}$ is a random term uniform distributed and bounded between $(0, h_\rho)$.
25. Total income of households is the sum of the payroll paid to the workers in $t$ and the dividends distributed to the shareholders in $t - 1$.

26. Wealth is defined as the sum of labor income plus the sum of all savings $SA$ of the past.
27. Marginal propensity to consume $c$ is a decreasing function of the worker's total wealth (higher the wealth lower the proportion spent on consumption) defined as:
$$c_{jt} = \frac{1}{1 + \left[\tanh\left(\frac{SA_{jt}}{SAt}\right)\right]^{\beta}}$$
where $SA_t$ is the average savings. $SA_{jt}$ is the real saving of the $j$ -th consumer.
28. The revenue $R_{it}$ of a firm after the goods market closes is $R_{it} = P_{it}Y_{it}$.
29. At the end of $t$ period, each firm computes benefits $\pi_{it-1}$.
30. If the benefits are positive, shareholders receive dividends $Div_{it-1} = \delta\pi_{it-1}$.
31. Residual, after discounting dividends, is added to net value from previous period $A_{it-1}$. Therefore, net worth of a profitable firm in $t$ is:
$$A_{it} = A_{it-1} + \pi_{it-1} - Div_{it-1} \equiv A_{it-1} + (1-\delta)\pi_{it-1}$$
32. If firm $i$ accumulates a net value $A_{it} < 0$, it goes bankrupt.
33. Firms that go bankrupt are replaced with another one of size smaller than the average of incumbent firms.
34. Non-incumbent firms are those whose size is above and below 5%, the concept is used to calculate a more robust estimator of the average.
35. Bank's capital:
$$E_{kt} = E_{kt-1} + \sum_{i \in \Theta} r_{kit-1}B_{kit-1} - BD_{kt-1}$$
36. $\Theta$ is the bank's loan portfolio, $BD_{kt-1}$ represents the portfolio of firms that go bankrupt.
37. Bankrupted banks are replaced with a copy of one of the surviving ones.

## 3 Implementation

The BAM model was implemented in Netlogo [10]. Fig. 2 shows the right side of the resulting GUI that allows the initialization of parameters and provides a view of the agents in a grid environment. As mentioned, the spacial issues in this view are meaningless, but the output is useful for debugging the system: Blue factories are the firms, red houses are the banks, green humans are employed workers while yellow ones are unemployed. Workers group around the firms where they work and shop. Factories display the number of employees.

## 4 Results

With the initial configuration of the parameters proposed by Delli Gatti et al. [9], the macroeconomic signals exemplified in Fig. 3 are produced. This output

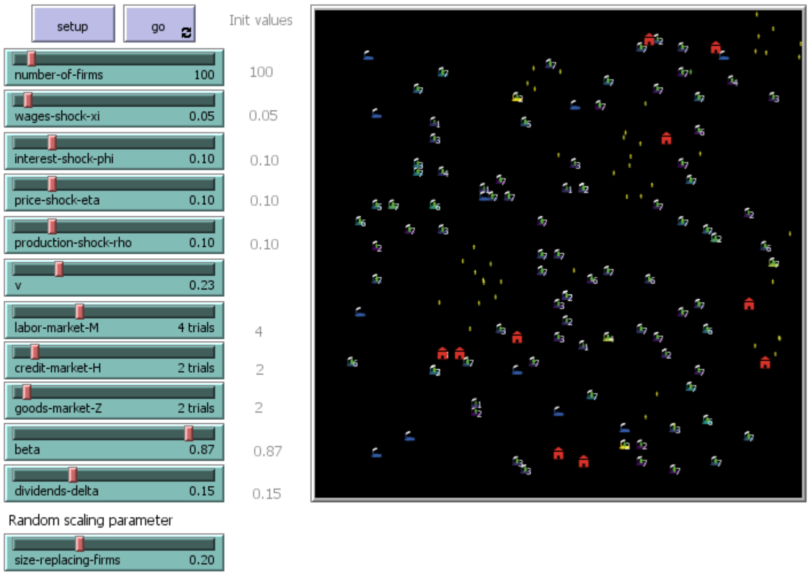


**Fig. 2.** The BAM model GUI: Parameters and view of the world.

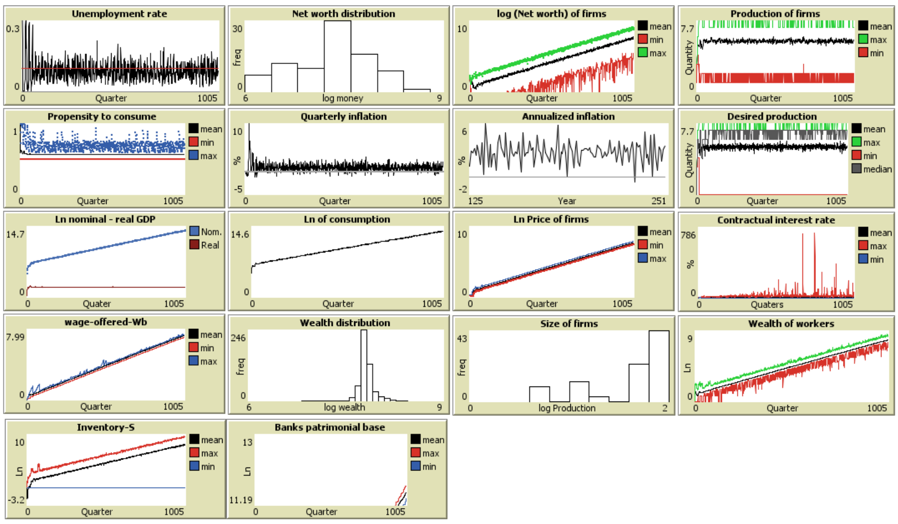


**Fig. 3.** The BAM model GUI: Macroeconomic signals.

reflects a stable fictitious economy, with unemployment rate close to 10% and moderate inflation in the range of 1 to 6%. In the next subsection, some stylized facts that theoretically should show these signals will be tested.

At the micro level, validation consists of verifying the existence of stylized facts concerning statistical distributions of state variables at an individual level [9]. Wealth and net worth in our case are characterized by a positive skew, which implies that there are few agents that become rich (Fig. 4).

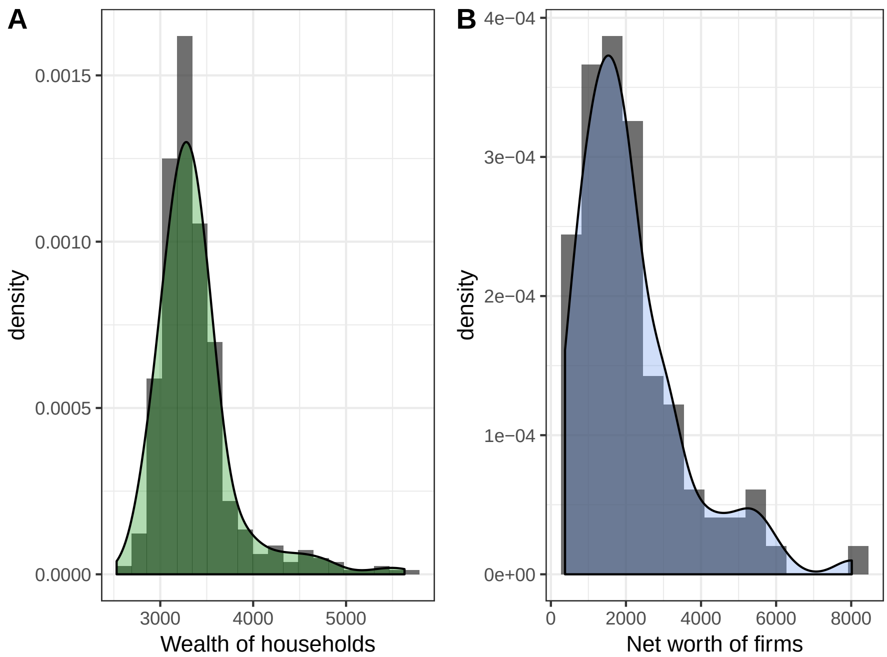


**Fig. 4.** Examples of our distribution of wealth (A) and net value (B) of a selected run.

To prove that the distributions of wealth of 100 independent runs have a positive skew (Fig. 5), level of skew was calculated with the method described by Joanes and Gill [11]:

$$b_1 = \frac{m_3}{s^3} = \left(\frac{n-1}{n}\right)^{3/2} \frac{m_3}{m_2^{3/2}} \ . \tag{1}$$

where,

$$m_r = \frac{1}{n} \Sigma (x_i - \bar{x})^r \ . \tag{2}$$

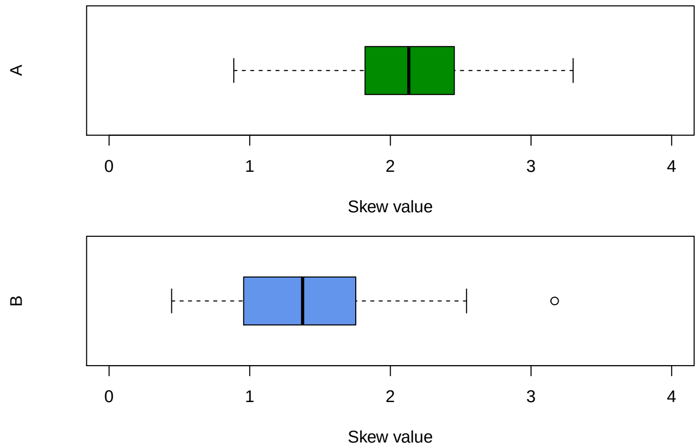


**Fig. 5.** Skewness values obtained over 100 independent runs of wealth distribution (A) and net worth (B). It is considered that values greater than 1 correspond to highly positively skewed distributions

At the macro level it is assumed that a economy is characterized in the long run by balanced growth, so this assumption implies for example that growth rate of GDP is mean stationary [12], in other words, series do not have time-dependent structure. There are a number of non-stationary tests and the Augmented Dickey-Fuller may be one of the more widely used. It uses an autoregressive model and optimizes an information criterion across multiple different lag values [13].

Applying the test without and with trend for zero and 3 lags on last 500 quarter series of GDP growth of 100 independent runs, with $\alpha = 0.05$, it is possible to reject the null hypothesis of non-stationarity if the t-statistic value is less (more negative) than the critical values (-1.95 for test without trend and -3.42 for test with trend). As we shown in Fig. 6, for every independent run this stylized fact is fulfilled, GDP growth rate series are mean stationary.

## 5 Conclusion and future work

The main contribution of this work is the complete definition of the BAM model and an open-source, full implementation of the model in NetLogo. The tests performed in this papers suggest that BAM is well suited for studying macroeconomic signals resulting from agent's activities and affected by external shocks, e.g., variation in the reference interest rate of the central bank.

Future work includes exploring the parameter space of BAM in order to get a better understanding of the behavior of the model, particularly for answering what-if questions, e.g., What happens to GDP if the reference interest rate change? Such exploration is also useful for validating other stylized facts.

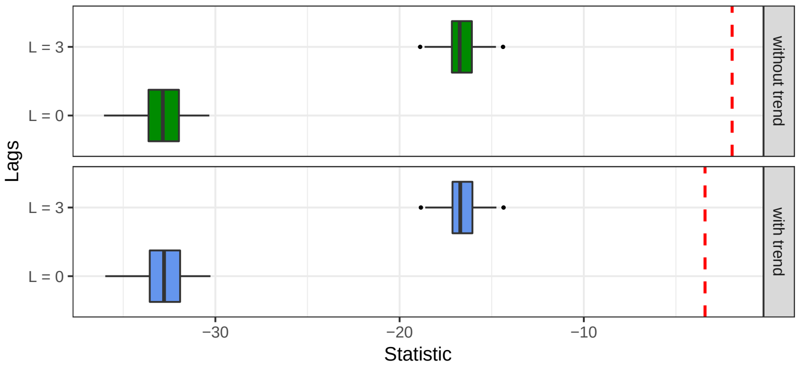


**Fig. 6.** Distribution of Dickey-Fuller t-statistics for logarithmic first differences of last 500 GDP quarters over 100 independent runs. Dashed lines are critical values.

BAM will be used to study the macroeconomic effects of extortion racket systems [14], e.g., with a certain probability, unemployed workers become extorters. They search for victims among their known companies that have not been already being extorted by another criminal. An extorted firm must take a decision about refusing to pay the extortion or paying; while extorters must decide to punish or not when the firms refused to pay. Such decisions depends on the probability of being punished, the probability of being captured by law, etc. What is the impact of extortion in the observed macroeconomic signals? Well, BAM can be used to compare such signals in the presence and absence of extortion.

Computational intelligence might be very useful for calibrating BAM for adjusting it to the behavior of a real particular economy. Data can be used to train models implementing the decisions of some of the agents in the model, e.g, the firms. Data can also be used to initialize the states variables of some agents, e.g., the workers. An study of modeling unemployment in Veracruz, Mexico based on Bayesian Networks [15], has followed this approach. Evolutionary computation might also be explored as a tool for parameter calibration, e.g., finding the parameter values that minimize unemployment.

The current state of BAM is very encouraging for continuing with these lines of research. Open-sourcing it is also important for the validation of the model and to observe its applicability in other projects.

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