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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 et al., 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 (Troitzsch, 2017), ranging from individual to (possible) collective effects (Gutierrez-Garcia et al., 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 (Anzola et al., 2016; Gambetta, 1996). 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 et al. (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.
- 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.

[1] An emergency number.

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

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.

In this regard, INEGI (2018) has estimated an average dark figure of 98.22% for Mexico in 2017. At state level, estimates range from 93.77% for the state of Aguascalientes to estimates close to 100% for the states of San Luis Potosí and Tamaulipas, which indicates a generality of the phenomenon, i.e., victims do not denounce. Figure 1.1 show the dark figure estimated for each state of Mexico.

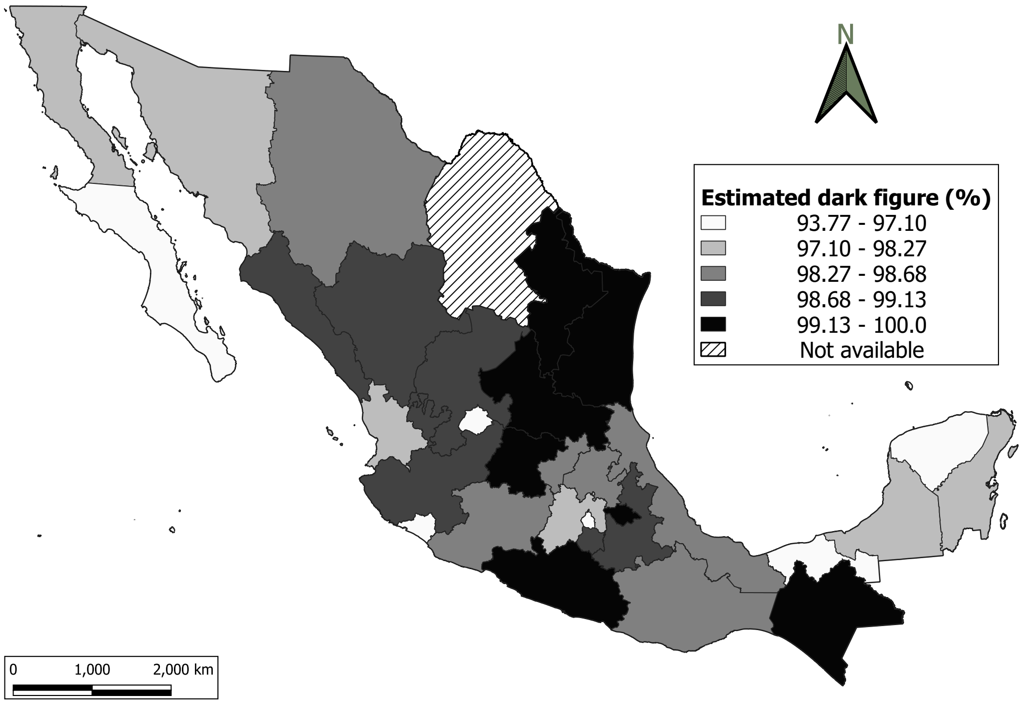

Figure 1.1: Dark figure of extortion estimated for each Mexican state in 2017. Source: Own elaboration based on estimations of INEGI (2018, Table 3.6).

Morales et al. (2015) also argue 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 normative and behavioral aspects of extortion racketeering has been extensively studied from the Agent-Based modeling and simulation perspective (Elsenbroich & Badham, 2016; Nardin et al., 2016; Nardin et al., 2017; Troitzsch, 2014), which is useful to realistically represent the phenomenon of extortion.

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. The test used to contrast our null will be explained in detail in Section 4.4.

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 et al. (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 provides a detailed description of the Agent-Based models implemented following the ODD protocol. Chapter 4 gives the experimental setup used to carry on the simulations, measuring the model robustness and the test used to identify changes in the distributions of macroeconomic variables. Chapter 5 describes the main results obtained through simulation, although before it presents the empirical validation of the models. And finally, chapter 6 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 describe 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 et al., 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 Agent-Based Approach

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 Assenza and Gatti (2013), Bianchi et al. (2007), Boero (2015), Delli Gatti et al. (2005), D'Orazio and Silvestri (2014), Dosi et al. (2013), Gallegati et al. (2017), Morini and Pellegrino (2015), Riccetti et al. (2015), Terna (2015), 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 (Delli Gatti et al., 2011; Gaffeo et al., 2015; Gintis, 2007; Tesfatsion, 2006) 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 Agent-Based Approach

Different Agent-Based models of extortion have been proposed in literature. Extortion can be carried out by individuals, but it is more often executed by organized groups configuring extortion racket systems. The outcomes of the European project GLODERS [1] (Global Dynamics of Extortion Racket Systems), resulting in a large corpus describing the behavior of extortion racket systems (Andrighetto, Brandts, et al., 2016; Nardin et al., 2017; Spina et al., 2014), are very useful to understand the microfoundations of extortion, as well as the normative, legal and social aspects that help to understand and fight against it (Andrighetto, Giardini, et al., 2016; Lotzmann et al., 2013; Nardin et al., 2016; Realpe-Gómez et al., 2018; Villatoro et al., 2015). Other efforts focused on the immediate effect of crime from the criminologist perspective can be found in the work by Gutierrez-Garcia et al. (2013).

Unfortunately, most of these works do not adopt a macroeconomic perspective. An exception is Troitzsch (2014), who analyzes extortionist groups by focusing on three aspects: the effect on wealth distributions of firms and criminals; the change in the propensity of firms to contribute to the fight depending on the attitude of the public towards extortionist groups; and the study of individual agent behaviors showing the greatest effect on society as a whole. On the first aspect, which is in fact related to the scope of this work, Troitzsch concludes that:

> The distribution of the overall economic success of the extortionists is extremely skewed to the left which shows that for a majority of input parameter combinations the success of extortionists is low, the main determinant for low success being the prosecution propensity.

Troitzsch's model is a good starting point to analyze the effects of extortion on other macroeconomic signals. In order to achieve this goal, our model does not

[1] https://cordis.europa.eu/project/id/315874

abstract the market of goods and labor to observe the emerging behavior on unemployment, inflation, and production. Table 2.1 summarizes a selection of extortion models that were taken into consideration while creating the model proposed in this work.

Reference	Extortion	Payment	Capture	Refund
Troitzsch (2014)	To the nearest reachable firm within its territory. Successful extortionist will then protect the shop against the rival extortionists.	If a firm cooperates, the pizzo is a proportion (low 25%, high 50%) of the period's income. If a firm refuses to pay the pizzo, the punishment may be a proportion (low 25%, high 50%) of all assets.	Police captures with a probability of success (30%). Captured extortionists are jailed for 6 periods (no time scale is given).	All assets are taken from the extortionist and firms are compensated following a first come first served principle.
Elsenbroich and Badham (2016)	Every period, extortionists choose a random firm within its territory, if it has not been extorted, they tries to extort it.	The pizzo is constant in 100 units.	Neither capture nor imprisonment is specified.	No refund specified.
Nardin et al. (2016)	Search details are not specified.	The pizzo is a proportion (low 3%, high 10%) of the firm resources. The punishment is a proportion (low 50%, high 75%), which is applied with a probability (low 50%, high 90%).	There is a probability of capture (low 20%, high 80%). Captured extortionists are jailed, the number of periods is not specified.	The victim support fund is made up of a percentage of the mafia's resources (0% or 50%).
Nardin et al. (2017)	Search repeatedly until a new firm is found. After each attempt there is a probability (10%) of abandoning the search.	The pizzo is a proportion (low 3%, high 10%) of the wage of firm. The punishment is a proportion (low 50%, high 75%, very high 90%) of the wage of firm.	There is a probability of being captured (low 20%, high 80%). Captured extortionists are jailed, the number of periods is random with a normal probability distribution function with mean low 100 (or high 500) and standard deviation low 5 (or high 100). Each period represents a day.	The victim support fund is made up of a percentage of the mafia's resources (0% or 50%). Firms who have denounced form in a queue, if the fund is sufficient a firm is refunded and returned to the queue.

Table 2.1: Summary of selected extortion models.

Chapter 3. Specification

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 Agent-Based Model and Simulation (ABMS) paradigm used (Section 3.1), then is described the protocol to document the models and ensure their applicability (Section 3.2). A formal description of the models implemented following such protocol is given in Sections 3.3 and 3.4. Finally, the platform chosen to code the agents of our economic system with extortionists and the implementation of BAM and BAMERS (Section 3.5) is presented.

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 ODD protocol

As mentioned earlier (Section 3.5), 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.

3.3 BAM: The Baseline Economic model

As Alves-Furtado and Eberhardt (2016) point out, one of the main problems faced in macroeconomic analysis is the choice of a base model, since some of them are too generic while others are specialized in particular markets, e.g., energy or labor. Dawid and Gatti (2018) make a classification of macroeconomic Agent-Based models according to their size and distinguish between large, medium and small. Small models are characterized by having only two types of agents, households and firms, interacting in two markets, consumer goods and labor. Large models present at least three types of agents and at least five markets.

The BAM model (Figure 3.1) is a generic, medium-sized, economic model that belongs to the Complex Adaptive Trivial Systems (CATS) family of models reviewed by Dawid and Gatti (2018); being one of the best documented, more extended, and widely used models among this family (Gatti & Desiderio, 2015; Gualdi et al., 2015; Klimek et al., 2015). The model is composed by three types of agents:

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

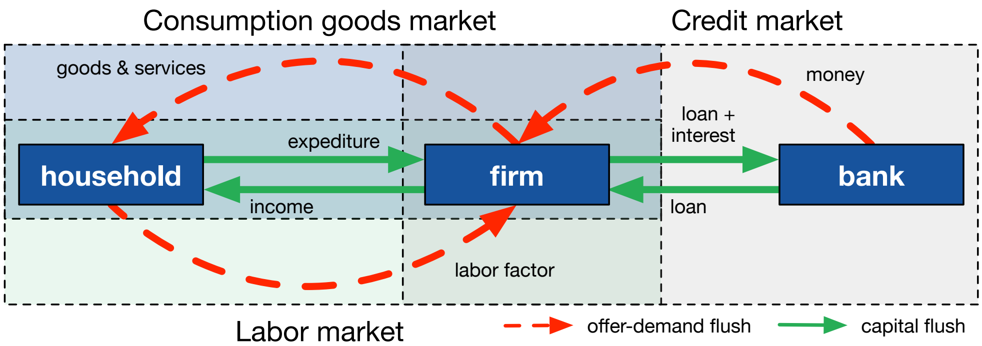

Figure 3.1: The Bottom-up Adaptive Macroeconomics (BAM) model.
Source: Own elaboration based on Delli Gatti et al. (2011).

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.

Table 3.1: State variables by agent in the BAM model.

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			

3.3.1 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) A decentralized credit market opens. B) Credit market closes. C) Labor market closes.

4. Firms produce.
5. A) Goods market opens. B) Goods market closes.
6. Firms pay loans and dividends.
7. Firms and banks survive or die.
8. Bankrupt firms and banks are replaced.

3.3.2 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 (ξ).
- Determination of contractual interest rate offered by banks to firms (ϕ).
- The strategy to set prices (η).
- The strategy to determine the quantity to produce (ρ).

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.

Table 3.2: Parameters initialization for the BAM model.

	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
σ_P	R&D investment of poorest firms	0
σ_R	R&D investment of richest firms	0.1
h_ξ	Maximum growth rate of wages	0.05
H_η	Maximum growth rate of prices	0.1
H_ρ	Maximum growth rate of quantities	0.1
H_ϕ	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
δ	Fixed fraction to share dividends	0.15

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.

3.3.3 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.
7. If $V_{it} > 0$, wage offered is $w^b_{it} = max(\hat{w}_t, w_{it-1}(1 + \xi_{it}))$, where ξ_{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^k_{it} and contract for 1 period.
12. If $A_{it+1} > 0$ the payment scheme is $B_{it}(1 + r^k_{it})$.
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., $R^k_{it} = \bar{r}(1 + \phi_{kt}\mu(\ell_{it}))$.
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 ϕ_{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^l_{it} to not be less than your average costs:

$$P^l_{it} = \frac{W_{it} + \sum_k r_{kit} B_{kit}}{Y_{it}}$$

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:

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

where: η_{it} is a randomized term uniformly distributed in the range $(0, h_\eta)$ and P^l_{it} 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:

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

where ρ_{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 π_{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. Θ 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.

3.4 BAMERS: The BAM under Extortion Racket Systems model

The model called Bottom-up Adaptive Macroeconomics under Extortion Racket Systems (BAMERS) [1] extends BAM by introducing extortionists in the system. In what follows, it is described following the ODD protocol (Grimm et al., 2006; Grimm et al., 2010).

3.4.1 Overview

Purpose

BAMERS is designed to explore the effect of individual extortion activities in macroeconomic signals like GDP, inflation, unemployment rate, and Gini index.

Entities, state variables, and scales

- **Environment.** Originally the grid environment where the agents are situated was used exclusively for debug purposes, displaying information useful for validating the behavior of the system, e.g., the number of workers laboring in a firm, their presence when working and buying goods, etc. Beyond this, the BAMERS model uses neighborhood in this space when computing some decisions, even when such relation has not geographical meaning, i.e., neighbors are not assumed to be geographically closed together.
- **State variables.** Firms and workers, as originally defined in the BAM model, are extended with the variables shown in Table 3.3 for registering the effect of extortion activities. Unemployed workers may become extortionists and keep a list of firms to extort and possibly punish. When captured, an extortionist will be in jail a given number of periods (time-in-jail). Firms register if they are being extorted and keep record of the amount of wealth they paid as pizzo or punishment.

[1] https://www.comses.net/codebases/e03074bc-714e-47b3-b01d-c0b6b2e61380/

- **Scales.** Time is represented in discrete periods, each step representing a month.

Table 3.3: State variables added to the firm and worker agents defined in the BAM model to reflect extortion activity in the BAMERS model.

Firm		Worker	
Attribute	**Type**	**Attribute**	**Type**
being-extorted?	Bool	extortionist?	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 in the BAMERS model occurs after closing the goods market and before firms pay loans and dividends, i.e., in between steps 5 and 6 of the BAM model schedule. The new steps added to the schedule are as follows:

5. A) Goods market opens. B) Good market closes.
   - E1. Unemployed poor workers decide whether to become extortionists or not.
   - E2. Extortionists look for firms to extort.
   - E3. Firms pay the pizzo or refuse to pay and denounce.
   - E4. Extortionists punish firms that refused to pay or, when captured, they go to jail and lose their wealth.
   - E5. Prisoners that have served their time in prison are released as regular unemployed workers.
6. Firms will pay loans and dividends.

3.4.2 Design concepts

Basic Principles

Economic pressure and socioeconomic status induce a process of decision making on how to respond to basic needs, even considering the idea of becoming criminals. Abrahamsen (1949, p.140) wrote about this:

> 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

Following the basic principle enunciated above, every time the goods market closes, unemployed workers belonging to the poorest quartile in the population decide as to whether they will become extortionists or not with a propensity ϵ. The propensity to become a criminal is orthogonal to any other variable, e.g., the probability of being imprisoned λ. This enables a controlled complete parameter exploration to evaluate the macroeconomic effect of extortion. When ϵ is equal to zero, our model corresponds to the baseline macroeconomic model without extortion, i.e., the BAM model.

Sensing

Firms can observe a given number of firms to know if they are paying for pizzo or not.

Interaction

Interaction happens when an extortionist finds a firm and asks for the payment of pizzo. Firms can in turn accept, or refuse to pay and denounce.

Stochasticity

Processes exhibiting randomness include becoming an extortionist, being imprisoned, and trying to extort a firm. The search for potential firms to extort is also stochastic.

3.4.3 Details

Initialization

Table 3.4 shows the default parameter initialization for the BAMERS model. Parameter values are influenced by the work of Elsenbroich and Badham (2016), Nardin et al. (2016), Nardin et al. (2017), Troitzsch (2014). Their use is fully described below, in the submodels section.

Submodels

1. The number of extortionists in the system can change every time step. Each unemployed worker in the quartile with the lower savings become a criminal if the propensity to be an extortionist ϵ is greater than a randomly generated value with a uniform distribution between 0 and 100.
2. An extortionist has X attempts to find a new victim. If an extortionist selects a firm that is already being extorted, it is considered as a failed attempt.
3. Extortionists choose their victims by searching randomly over all firms.

Table 3.4: Default parameter initialization for the BAMERS model.

	Parameter	Value
ϵ	Propensity to become an extortionist	20%
λ	Probability of being imprisoned	30%
R_t	Rejection threshold	15%
X	Number of attempts to extort a new firm	1
CF	Number of observable closest firms	3
Pi	Proportion of net worth asked as pizzo	20%
Pu	Proportion of net worth taken as punish	30%
C_m	Proportion of wealth as confiscated money	50%
T_j	Number of time periods in jail	6

4. Firms can allow the extortion or refuse to pay. A firm refuses to pay the pizzo when the rejection threshold (R_t) is greater than the expected risk (ER) , which is calculated as follows:
$$ER = \frac{EF}{CF}$$
where, CF denotes number of observable firms (three by default), i.e., the closest ones; and EF denotes how many of them are being extorted. This cognitive mechanism is based on the work of Elsenbroich and Badham (2016). $R_t = 0$ makes firms to pay the pizzo at the slightest hint of extortion activity.
5. Firms that accept to pay the pizzo are asked for a proportion of their net worth, set by default to $Pi = 20\%$ as suggested by Nardin et al. (2016), Nardin et al. (2017), Troitzsch (2014).
6. Firms that refuse to pay the pizzo always denounce. The probability that a extortionist is imprisoned is set to $\lambda = 30\%$. Imprisoned extortionists stay $T_j = 6$ periods in jail. Additionally, a proportion $C_m = 50\%$ of their wealth is confiscated for supporting the victims of extortion that had denounced. All the previous default parameter values were adopted from the findings by Nardin et al. (2016), Nardin et al. (2017), Troitzsch (2014).
7. Extortionists that are not imprisoned punish the firm that denounced them, if any. The amount of money taken as punishment is a proportion of the net worth of the firm set by default to $Pu = 30\%$.
8. Firms who have denounced and being punished receive an equal proportion of the victim support fund raised from 50% of imprisoned extortionists wealth.
9. Extortionists who served their sentence become regular workers in the labor market, in the immediate following period.

3.5 Implementation

There are several platforms for the modeling of Multi-Agent Systems (Abar et al., 2017; Allan, 2010; Kravari & Bassiliades, 2015) 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 et al., 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 et al., 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.

BAM

Figure 3.2 shows the right side of the resulting GUI of the BAM model 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.

With the initial configuration of the parameters proposed by Delli Gatti et al. (2011) and presented in Table 3.2, the macroeconomic signals exemplified in Figure 3.3 are produced.

BAMERS

Figure 3.4 shows the resulting GUI interface of the BAMERS model that allows the configuration of parameters and provides a view of the agents in a grid environment. Individual and aggregate economic outputs by default configuration of the parameters adapted from GLODERS literature described in Chapter 2 are also showed.

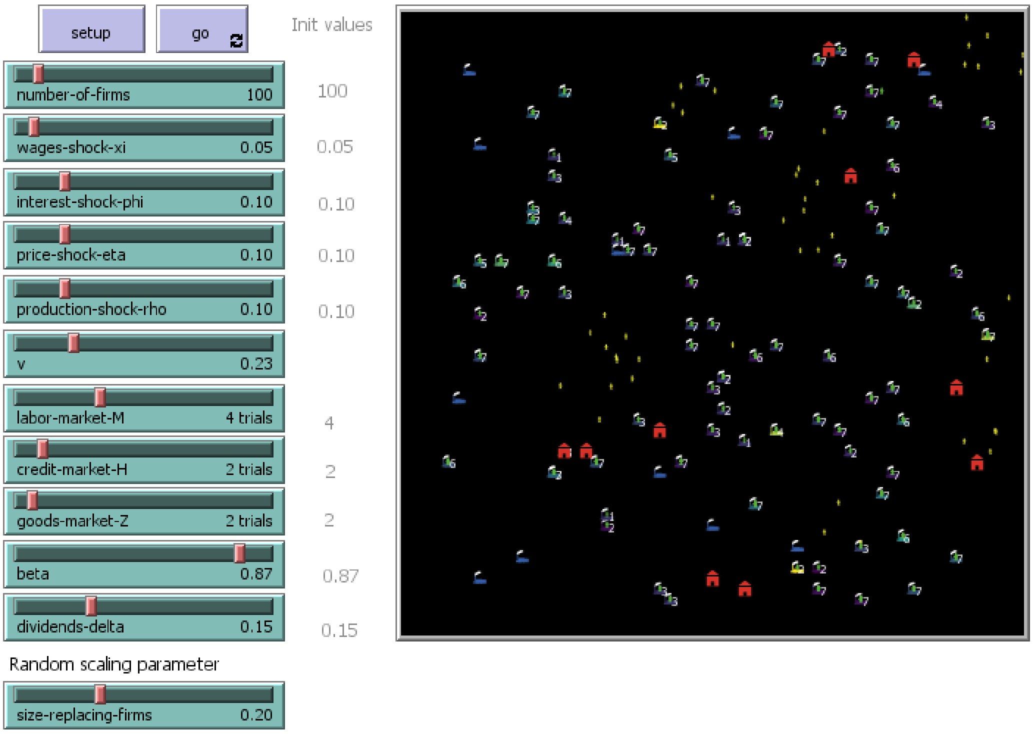

Figure 3.2: The BAM model GUI: Parameters and view of the world.

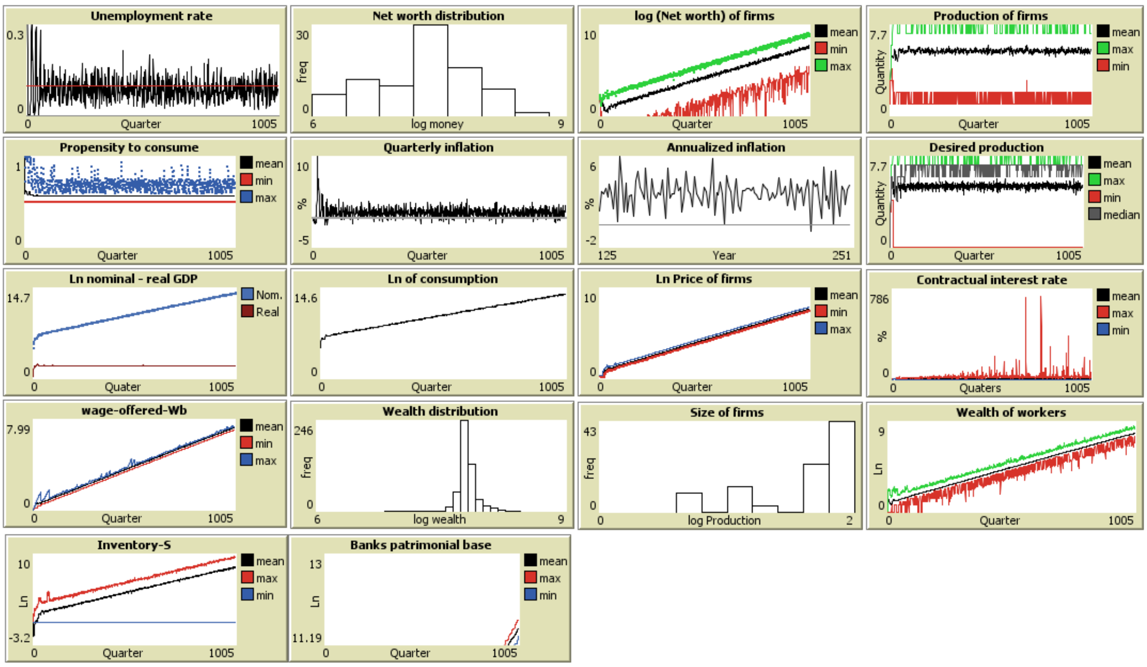

Figure 3.3: The BAM model GUI: Macroeconomic signals.

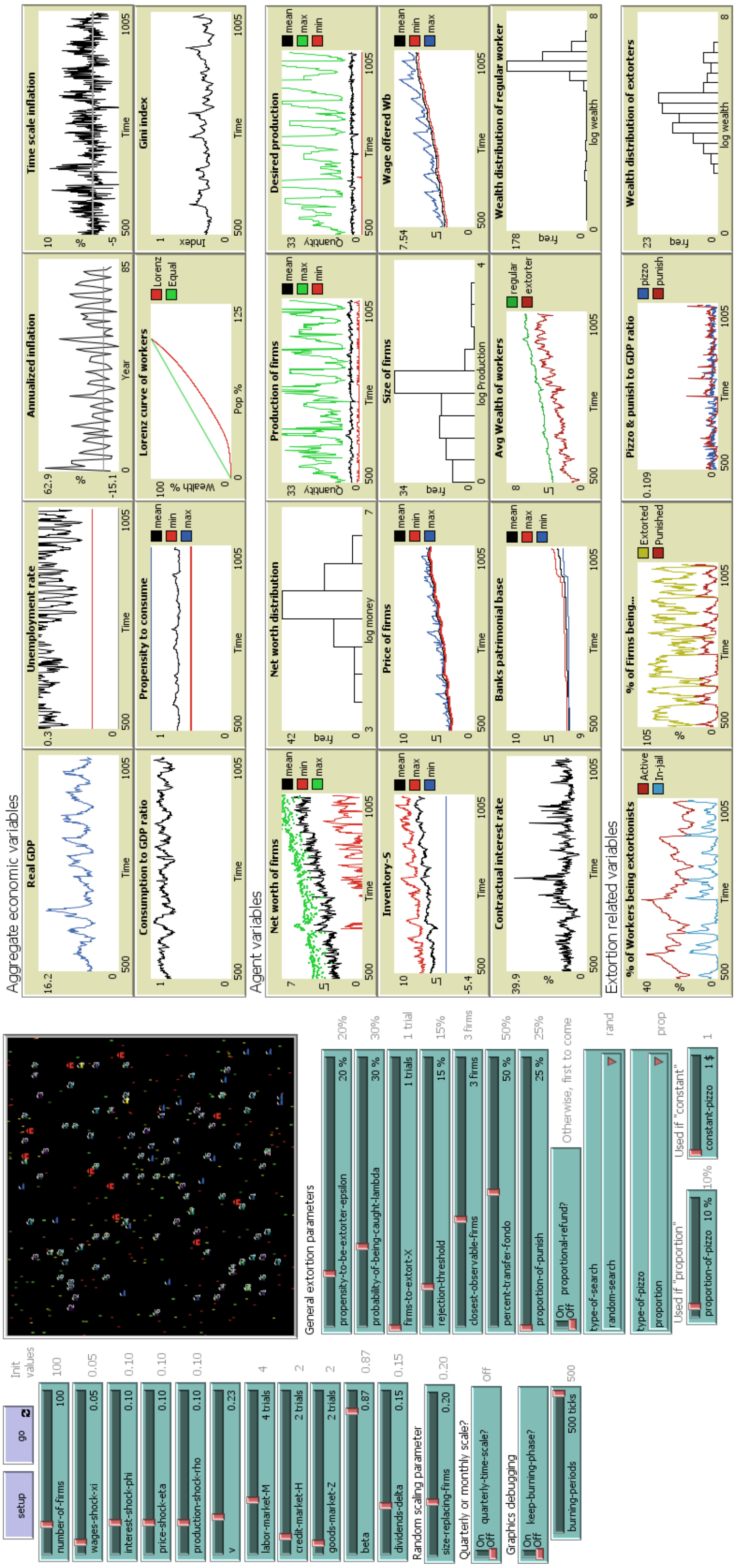

Figure 3.4: The BAMERS model GUI interface at the end of a simulation.

Chapter 4. Methodology

To compare the macroeconomic outcome of the simulated economies under different levels of extortion we define a set of scenarios through parametrization. First, we introduce the experimental setup producing these scenarios. Then, we justify the selection of macroeconomic variables used in our analyses. Finally, we describe the tests we performed on the selected variables, mainly: measuring the model robustness to understand what responses are emergent properties of the system and which ones are a direct consequence of the parametrization; and the Cucconi test to identify changes in the distributions of macroeconomic variables, i.e., to test hypothesis expressed in Chapter 1.

4.1 Experimental setup

We simulate a small baseline economy showing a stable growth and moderated unemployment rate consisting of 100 firms, 500 households and 10 banks, that were initialized as described by Delli Gatti et al. (2011) and implemented following Platas-López et al. (2019). Model is validated at micro and macro level as suggested by specialized literature.

Extortion is introduced in this economy as described in the previous section. A default scenario is defined initializing the parameters of the BAMERS model as shown in Table 3.4. Three of them are perturbed to induce different scenarios: The propensity to become an extortionist (ϵ) takes percentage values from 0 to 100 in increments of 5; The probability of being imprisoned (λ) is perturbed in the same way; The rejection threshold (R_t) differentiates the propensity to denounce of the firms, given the submodel for computing the expected risk (submodel 4) and the number of the observable closest firms ($CF = 3$). When $R_t = 0$ the firms never denounce extortion. For $0 < R_t \leq 33$, the firms denounce if none of the observable firms is under attack, i.e., extorted or punished. For $33 < R_t \leq 66$ the firms denounce if at most one of the observable firms is under attack. For $66 < R_t \leq 99$ the firms denounce if at most two of the observable firms is under attack. When $R_t = 100$ the firms always denounce. A low tendency to denounce ($R_t = 15$) and a moderate one ($R_t = 45$) are explored here, since higher or lower tendencies seem unrealistic.

All experimental settings and tests were performed over 20 independent runs. Each simulation run represents around 40 years, using a monthly time scale with 1000 periods and discarding the first 500 time steps as burning period.

Heat maps or contour plots are used as way to see and get information about parameters interactions in the parameter space, the objective is understand which processes dominate the system's dynamics under which conditions. According to Railsback and Grimm (2012, Section 23.2) "contour plots are a useful way to examine interactions of two parameters when all other parameters are kept constant. Because of its simplicity, this method is often very useful for understanding how two parameters, and the processes they represent". To see more than two parameters interactions on more than one variable, multi-panel heat maps are used.

4.2 Variables of interest

Different economic paradigms emphasize different macroeconomic variables, e.g., while classical Keynesianism focus on demand, neoclassical economy does on productivity. However, any macroeconomic analysis should consider at least the following three key variables: production, employment and price. We measure these variables using the real GDP, the unemployment rate and inflation, respectively. Since the distribution of wealth is an important component in economic development analysis, the Gini index will also be considered. Finally, the wealth of extortionists and household consumption are also included to be compared with the results by Troitzsch (2014) and Astarita et al. (2018).

GDP is a measure of the value of the output of an economy. The real GDP captures the effect of changes in prices over time, its values being comparable at different times. The unemployment rate is a measure that relates the number of unemployed people to the total amount of available labor force, this excludes people in prison. Inflation is measured by the Consumer Price Index and it is defined as a change in the prices of a basket of goods and services that are typically acquired by a specific group of households. In the BAMERS model, inflation is summed up to the change in the price of the only good produced in monthly periods.

Wealth is composed of the income of workers as well as their savings, inequality in the distribution of wealth among individuals is measured through the Gini Index, which is based on the comparison of cumulative proportions of the population against cumulative proportions of wealth they have, and it ranges between 0 in the case of perfect equality and 1 in the case of perfect inequality. Like regular workers, the wealth of extortionists is made up of their income from extortion and punishment of firms as well as their savings. Finally, household consumption is an aggregate variable that represents the total purchases of goods made by individuals in the system. At micro level, the marginal propensity to consume c (defined in Submodel 27 of BAM) reflects the variation in consumption with respect to the variation in income/wealth, the complement representing the marginal propensity to save. The higher the income/wealth the lower the proportion spent on consumption. That is, rich people usually tend to have a lower marginal propensity to consume c than poor people.

It is important to mention that all the variables related to money (wealth, pizzo, consumption, etc.) will be analyzed with respect to the GDP, so that different scenarios (at different values of ϵ, λ and R_t) can be compared appropriately.

4.3 Robustness analysis

Robustness analysis examines the effect of varying input parameters on the output of the simulation. High sensitivity to these values suggests that such an effect would be due to parametrization, rather than being an emerging property of the model (Helton, 2008). The robustness of the BAMERS model is determined by modifying the probability of becoming an extortionist (ϵ) and the probability of being imprisoned (λ), as these are considered to be the most important parameters for this work.

We increase the value of ϵ and λ from 0 to 100 in steps of 5 units independently from all other parameters. The output of each setting is then compared with that of the model with all the parameters set to their default values using the A-Test (Vargha & Delaney, 2000). This is an effect-magnitude test used to determine if there is any statistically significant difference between simulation responses under different conditions, thus indicating how robust the model is to changes of its parameters and the points at which parameter perturbation results in significant changes in the simulation (Alden et al., 2013).

The A-Test can be applied both to discrete (at least ordinal) and continuous distributions, which makes it applicable to behavioral and social science domains where discrete scales are common. It makes no assumptions of normality or homogeneity of variance, and it is easier to compute than the CL-Test (Vargha & Delaney, 2000, p.102).

We can interpret the result of the A-Test as follows: We have stochastic equality between two populations when $A_{ij} = A_{ji} = 0.5$, where A_{ij} denotes the comparison of population i to j. Vargha and Delaney (2000) propose thresholds to interpret the effect size Δ, i.e., the standardized difference between populations, which are summarized in Table 4.1.

Table 4.1: Thresholds to interpret the A-test effect size.

Δ	A-Test	Difference
0.50	1.00	Total
0.21	0.71	Large
0.14	0.64	Medium
0.06	0.56	Small
0.00	0.50	None
0.06	0.44	Small
0.14	0.36	Medium
0.21	0.29	Large
0.50	0.00	Total

4.4 Comparison of macroeconomic signals

Different levels of extortion are expected to produce different macroeconomic signals in the simulation. Comparing these outputs poses the problem of comparing distributions of variables of interest in which normality or any other property cannot be guaranteed. Since both mean and variance may differ between distributions, separate tests for difference in location and scale parameters may not be appropriate in this situation. Therefore, a joint non-parametric test for the so called location-scale problem is preferable. For a brief review of the variety of tests available see Murakami (2016).

We use the non-parametric Multisample Cucconi test (MC) (Cucconi, 1968; Marozzi, 2014) to compare $K = 2$ independent sample distributions generated with the baseline macroeconomic model ($\epsilon = 0$) against those generated under different levels of extortion ($\epsilon \geq 0$) and efficiency of police ($\lambda \geq 0$) . This test is suited for the location-scale problem and, according to Marozzi (2009), it is slightly more powerful than the Lepage test (Lepage, 1971), especially in the presence of many ties. The value of the test statistic is expected to be zero if the null hypothesis is true, i.e., the macroeconomic signals have no differences in both 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, which is defined as follows:

$$MC = \frac{1}{K}\sum_{k=1}^{K}\frac{U_k^2 + V_k^2 - 2U_kV_k\rho}{2(1-\rho^2)}$$

where U is based on the standardized sum of squared ranks of the first sample elements in the pooled sample distributions, and V is based on the standardized sum of squared contrary-ranks of the first sample elements in the pooled sample distributions and ρ is the correlation coefficient between U and V.

As already mentioned, the sample distributions to be compared were obtained by performing 20 independent runs with different ϵ and λ values from 0 to 100 with increments of 5. Each of those combinations is compared against the base economy without extortion, represented with $\epsilon = 0$. As MC is performed as a permutation test, a random sample of $n = 10000$ permutations of the pooled sample distributions is adopted since, the larger the n, the more accurate the estimate of significance level of test results will be (Marozzi, 2009).

Chapter 5. Results

In this chapter we solve the specific objectives proposed in Section 1.5. First, a economic system implemented in Delli Gatti et al. (2011) as a generic stable economy called BAM is both replicated and validated. Second, effects of extortion on macroeconomic aggregates such as inflation, unemployment rate, GDP and distribution of wealth are evaluated through an implemented, calibrated and validated Agent-Based Model called BAMERS.

5.1 Economic model

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.

5.1.1 Validation

Output of BAM 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 (2019a, 2019b) 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 (Figure 5.1).

To prove that the distributions of wealth of 100 independent runs have a positive skew (Figure 5.2), level of skew was calculated with the method described by Joanes and Gill (1998):

$$b_1 = \frac{m_3}{s^3} = \left(\frac{n-1}{n}\right)^{3/2} \frac{m_3}{m_2^{3/2}} \,. \tag{5.1}$$

where,

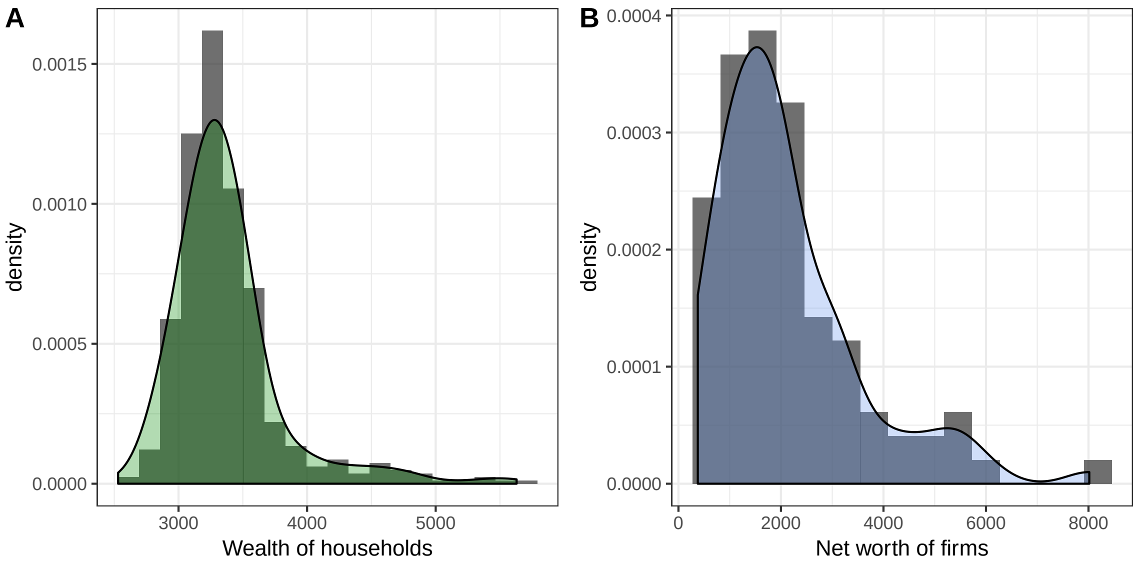

Figure 5.1: Examples of our distribution of wealth (A) and net value (B) of a selected run.

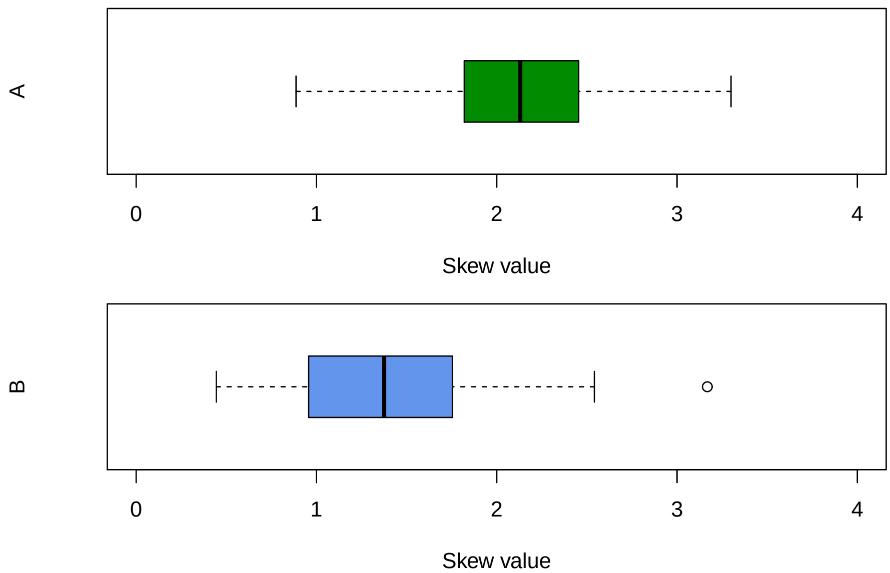

Figure 5.2: Skewness values obtained over 100 independent runs of wealth distribution (A) and net worth (B). It is considered that values greater than 1 correspond to highly positively skewed distributions

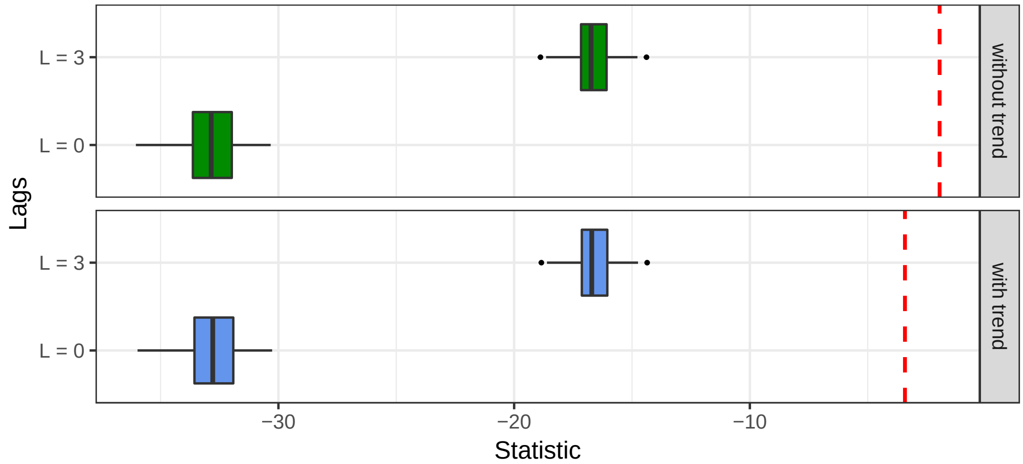

Figure 5.3: Distribution of Dickey-Fuller t-statistics for logarithmic first differences of last 500 GDP quarters over 100 independent runs. Dashed lines are critical values.

$$m_r = \frac{1}{n}\Sigma(x_i - \bar{x})^r \ . \tag{5.2}$$

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 et al., 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 Figure 5.3, for every independent run this stylized fact is fulfilled, GDP growth rate series are mean stationary.

5.1.2 Sensibility

The effect of shocks was tested varying wages (ξ), prices (η), and interest rates (ϕ) 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 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

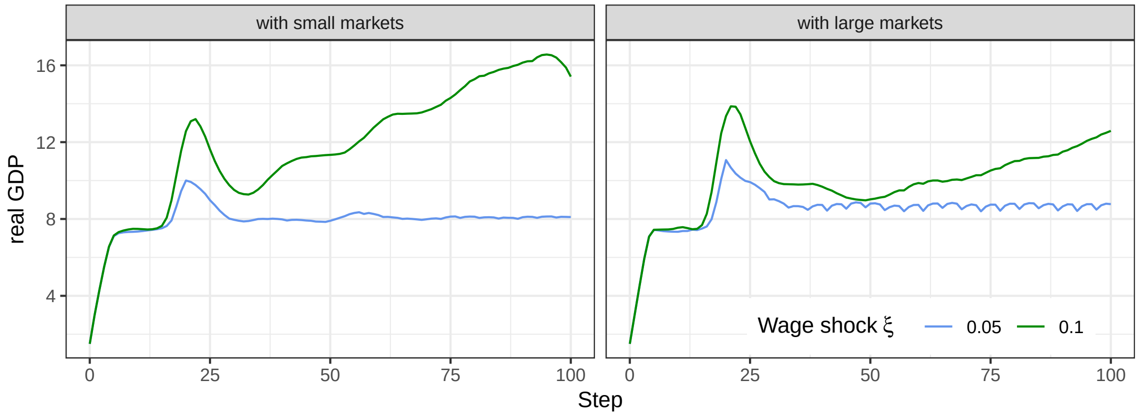

Figure 5.4: Dynamics of GDP under wage shocks of different size in small ($M = H = Z = 2$) and large ($M = H = Z = 4$) markets.

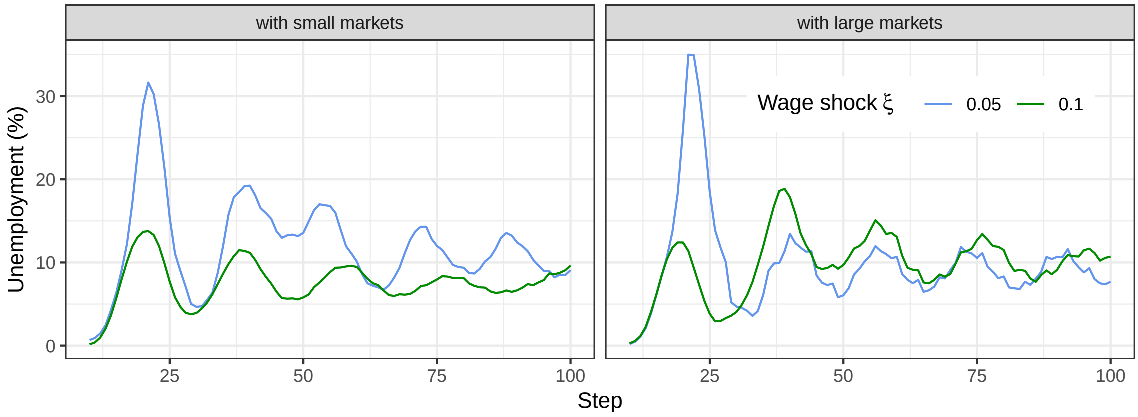

Figure 5.5: Dynamics of unemployment rate under wage shock in small and large markets.

values, although arbitrary, represent acceptable big increments with respect to the small values.

Figure 5.4 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 5.5.

Figure 5.6 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 5.7 shows how propensity to consume (Sub-model 27) interacts with the

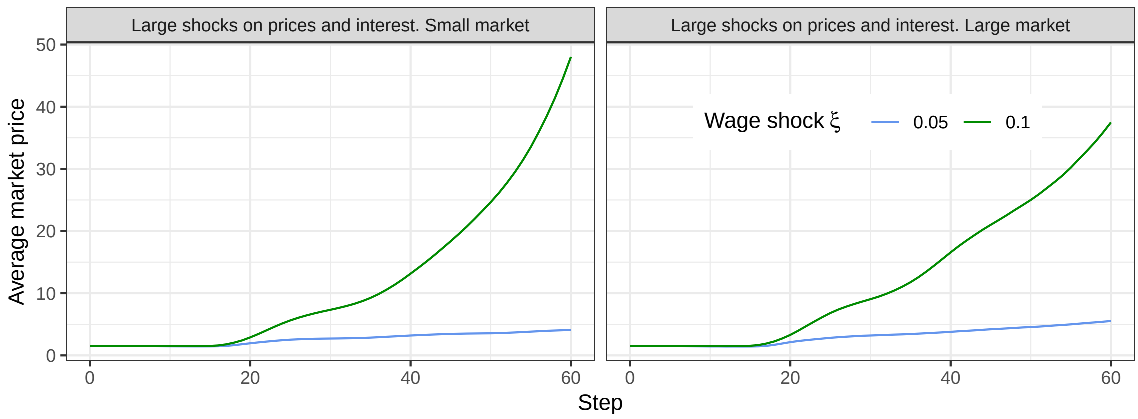

Figure 5.6: Dynamics average market price on small and large markets.

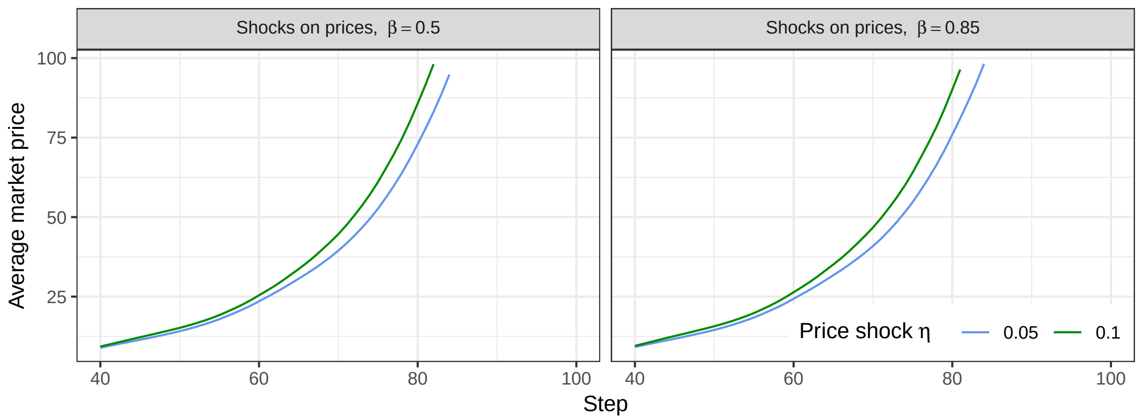

Figure 5.7: Dynamics of average market price when varying propensity to consume β.

dynamics of prices. Changes in the β 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.

5.2 Extortion model

This section analyzes the effect of extortion on macroeconomic aggregates. First, BAMERS is analyzed in terms of the proportion of workers acting as extortionists, jailed extortionists and extorted/punished firms. Then, a robustness analysis of the main parameters of the BAMERS model, i.e., the probability of becoming an extortionist and the probability of being imprisoned, is introduced. Finally, the effect of extortion on the macroeconomic variables of interest is evaluated, including a comparison of distributional effects of wealth with respect to previous findings by Troitzsch (2014).

5.2.1 Validation

The dynamics of extortion produced by the BAMERS model is shown in Figure 5.8, where we display the proportions of extorted firms, punished firms, workers acting as extortionists, and extortionists in jail for different values of ϵ, λ, and R_t. High values of λ decrease the percentage of firms being extorted, this effect is accelerated when the number of denounces increase, i.e., higher R_t. The highest percentage of extorted firms is generated in a region where the value of ϵ is between 5 and 30 and the values of λ remain low. This suggests that extortion performs optimally for these parameter values, whereas higher values of ϵ lead to a saturation of the criminal market. Raising the rejection threshold to $R_t = 45$ in turn increases the number of denounces and, as a result, it also increases the number of firms being punished, especially with $\lambda \leq 70$. Recall that a firm is punished when the extortionist is denounced but the police fails to imprison him or her.

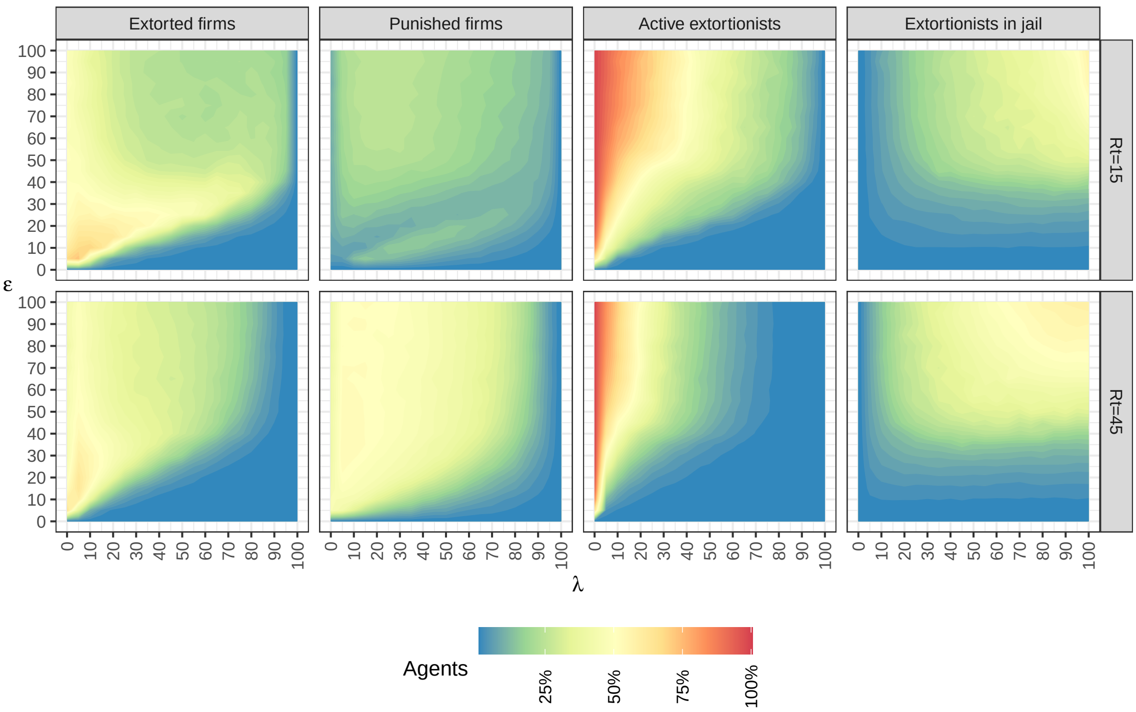

Figure 5.8: Percentage of extorted firms, punished firms, active extortionists and extortionists in jail for different values of ϵ, λ and R_t. Bluish regions denote a smaller proportion of agents.

The percentage of active extortionists (not in jail) is inversely related to λ, i. e., if the value of λ increases, the percentage of active extortionists decreases and vice versa. This process is catalyzed by R_t, which accelerates the efficiency of the police. Accordingly, the percentage of extortionists in jail is directly related with ϵ and λ, since higher percentages of incarcerated are obtained when increasing both the propensity to become an extortionist and the probability of being imprisoned.

Again, increasing R_t accelerates the effect of λ, as it can be seen by comparing the size of the yellow regions.

5.2.2 Parameter-robustness analysis

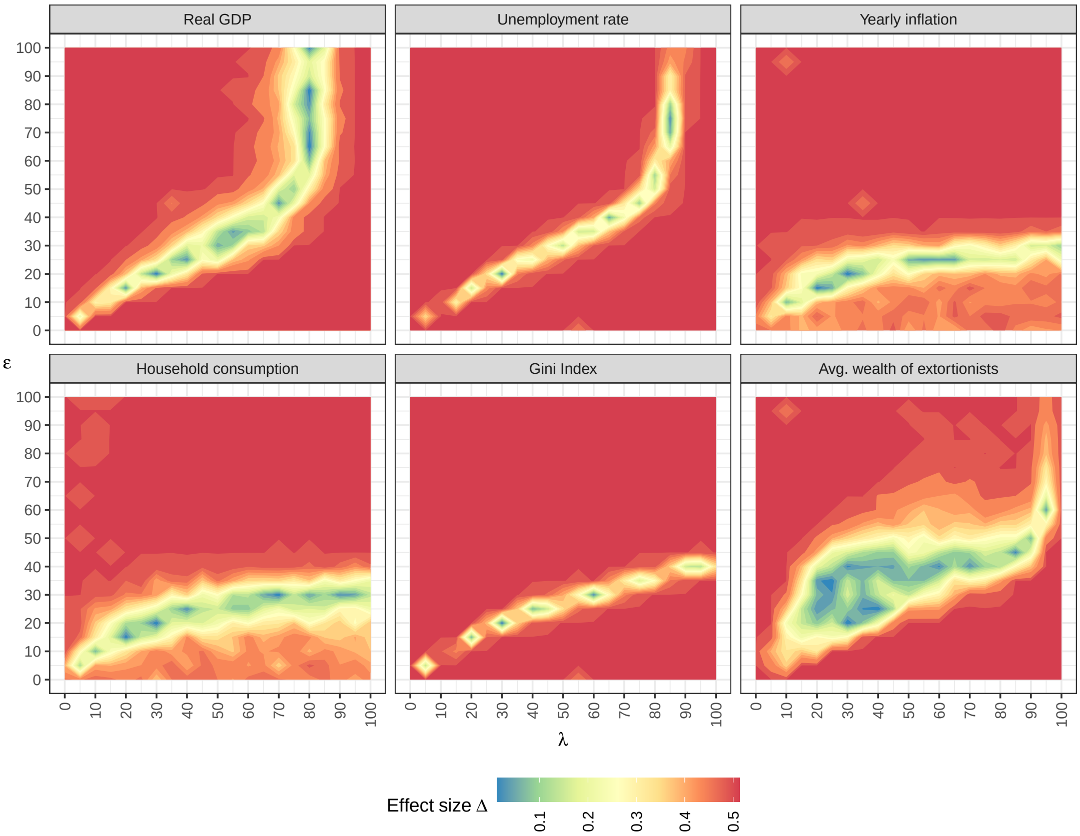

Figure 5.9: A-Test Δ effect-size scores when varying the propensity to become an extortionist (ϵ) and the probability of being imprisoned (λ) with respect to their default values ($\lambda = 30$ and $\epsilon = 20$). Bluish regions denote variable values with small to medium differences with respect to the values observed in the default parameter setting.

Figure 5.9 displays the Δ effect size for the variables of interest as computed by the Test-A of Vargha and Delaney (2000). Based on the thresholds defined for this test (see Table 4.1), reddish regions denote large differences with respect to the default setting (see Table 3.4), while bluish regions denote small to medium differences. A variable is considered to be robust if it shows small to medium differences in the surroundings of the default parameter values, i.e., when $\lambda = 30$ and $\epsilon = 20$.

The following four variables are robust to changes in λ (keeping ϵ constant at its default value): Production, inflation, consumption and average wealth of the extortionists. The average wealth of extortionists is also robust to changes in ϵ (keeping λ constant at its default value). Though, unemployment and the Gini index are sensitive to parametrization and their behavior may not be considered as an emergent property of the model.

Color patterns in these heat maps show variables that have a similar behavior when changing the parameters λ and ϵ. For instance, see the shape for the real GDP and the unemployment rate or that of inflation and household consumption. The nature of these relationships is further explored along the paper.

The plots also reveal alternative combinations of the parameters that behave similarly to the default values. For instance, when $\lambda = 80$ and $\epsilon = 70$, the real GDP shows a small difference with the one obtained from the default values. Note that there is no combination of parameters globally equivalent to the default values, i.e., producing bluish regions in the same coordinates for all variables. Therefore, a single public policy can not influence all these economic variables simultaneously, e.g., if there is a desire to maintain production at a similar level to that emerging from the default setting, a new chosen policy will likely vary inflation, household consumption and the distribution of wealth.

This robustness analysis gives a first insight into the patterns and emerging properties of the BAMERS model. In the following section, the origin of such patterns is analyzed in more detail, as well as the interrelationships between the variables under study.

5.2.3 Macroeconomic effect of extortion

This section evaluates the effect of extortion on the economic variables of interest to this work. We analyze each of the variables in isolation as well as the interrelation of some variables that explain the economy as a whole. Heat maps are used to represent the values obtained when changing the parameters, where bluish regions refer to low values while reddish regions denote high values of the simulated variable.

Production, unemployment and inflation

Figure 5.10 shows the effect of extortion on the three main macroeconomic variables: production, unemployment and inflation. Regarding the real GDP, a contraction is observed when increasing the propensity to become an extortionist, which is accentuated in the presence of low probabilities of being imprisoned. As expected, the probability of being imprisoned works as a stabilizer of the economy by suppressing the detrimental effect of crime propensity on society.

The rejection threshold R_t acts as a parameter that increases the number of denounces by firms and it is a catalyst that accelerates the effect of λ. For higher values of ϵ, getting the real GDP back to a value that is nearer to the base economy with no crime ($\epsilon = 0$) needs increasing the probability of imprisoning criminals but, while $R_t = 15$ requires an efficiency of $\lambda \geq 80$, $R_t = 45$ asks for a lower efficiency of $\lambda \geq 40$.

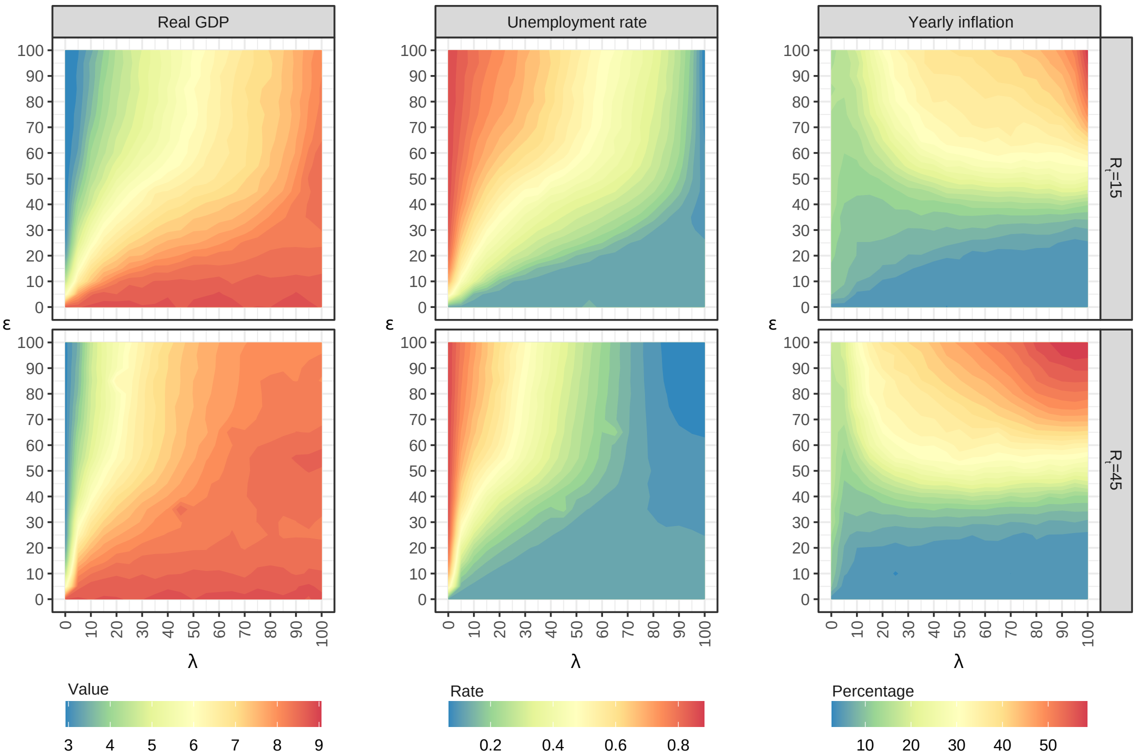

Figure 5.10: Real GDP, unemployment rate and yearly inflation for each combination of the model parameters λ, ϵ and R_t. In economic terms, it can be accepted that: for real GDP, a high value is desirable. For the unemployment rate and inflation, a high value is undesirable.

A clear effect of the propensity to become an extortionist on the value of production is also observed. The real GDP is sensitive to extortion, decreasing when ϵ goes from from 0 to 10 and remarkably going down when ϵ reaches 20. Increasing ϵ any further has only a marginal decreasing effect on production because the system gets saturated of extortionists with a limited number of firms to extort.

Unemployment rate increases when raising the propensity to become an extortionist and it decreases when the probability of being imprisoned is higher. Note how this is the reverse situation of that observed for the real GDP, which suggests that unemployment and production follow the Okun's Law (Furceri et al., 2019) in our simulation. By relying on the BAM model that maintains the productivity constant, the BAMERS model thus provides a policy tool to assess unemployment cost on aggregate supply.

The rejection threshold R_t, makes the effect of λ more elastic. When $R_t = 45$, more efficient labor allocations emerge in a rather unrealistic region where the propensity to become an extortionist is greater than 30 and the probability of being imprisoned is also high. This is due to the fact that a high percentage of extortionists is in jail for that combination of ϵ and λ parameters, what decreases the number of agents that can be unemployed (see also Figure 5.8).

Inflation follows a different pattern when compared to the effect of ϵ, λ and R_t on production and unemployment in Figure 5.10. Inflation is in fact related to household consumption, measured as a proportion of goods produced in the economy, as it can be observed from the similar pattern shown in Figure 5.11.

The macroeconomic theory of inflation (Bronfenbrenner & Holzman, 1963; Johnson, 1963) establishes that one of its possible determinants in the short term is related to the contraction of aggregate supply or the increase in aggregate demand (or a combination of both). In our case, given that the region with the highest inflation occurs with a high propensity to become an extortionist combined with a high probability of being imprisoned, the trigger appears to be a small amount of labor in the formal sector, which reduces the aggregate supply with a constant aggregate demand.

Consumption

Two different indicators have been used to analyze consumption. First, household consumption measures aggregate consumption as a proportion of the goods produced in the economy. As it was previously discussed, aggregate consumption follows a similar pattern to that observed in yearly inflation (see Figure 5.11, left). It can be noticed that the highest consumption ratio is generated when there is both a high propensity to become an extortionist and a high probability of being imprisoned. In this situation, the scarcity of productive labor, which generates goods, leads to a contraction of the aggregate supply. Therefore, although the economy seems to be more efficient, an inflationary process is induced. The BAMERS model exhibits a negative effect of extortion on the supply side, which is in line with the negative effects of crime found by Astarita et al. (2018).

Second, the propensity to consume measures individual consumption as the proportion of wealth workers require to meet their needs. This variable behaves the same as the unemployment rate (see Figure 5.11, right). In the presence of crime ($\epsilon > 0$), λ manages to recover the economy with the help of R_t. Note that the purchasing power of people is reduced in conditions of high unemployment rate, i.e., low probability of being imprisoned and presence of crime in society. In these situations, although some workers migrate to the criminal sector, they find a limited number of companies to extort and their success is not at all guaranteed. Saturating the economy with extortionists and keeping $\lambda = 0$ leads to the highest propensity to consume, that is, a situation in which workers need to allocate the largest proportion of their wealth to survive.

Wealth distribution

In what follows, we analyze the Gini index as a commonly used measure of wealth distribution (Lerman & Yitzhaki, 1984) and we also look at the skewness of wealth distributions as reported in related work by Delli Gatti et al. (2011) and Troitzsch (2014).

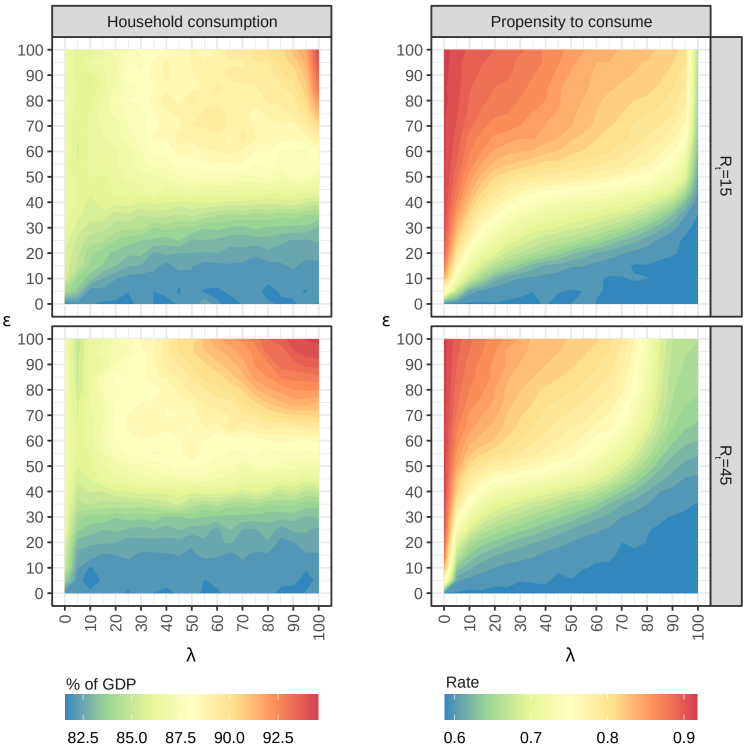

Figure 5.11: Household consumption and propensity to consume for each combination of the model parameters λ, ϵ and R_t. In economic terms, it can be accepted that: for aggregate household consumption, a high value will be worse in the short term; for the propensity to consume, a lower value is desirable.

Figure 5.12 shows the inequality in the distribution of wealth among workers, measured as the Gini index resulting from the simulations for each combination of the parameters λ, ϵ and R_t. Again, a pattern emerges in which λ mitigates the negative effect of crime. Inequality is harder to fight for higher values of ϵ, but the effect of λ can be accelerated when R_t is higher. Situations in which a high proportion of wealth is concentrated in a small proportion of workers are accentuated when the probability of being imprisoned is low.

Figure 5.13 shows the bias observed in the distribution of wealth for regular workers, firms, and extortionists. Skewness remains positive for most of the combinations of λ and ϵ, thus confirming the stylized fact found in the literature about the positive bias of wealth distributions.

For regular workers, an increase in bias is only observed for moderate extortion levels ($10 \leq \epsilon \leq 30$) and an unrealistic low probability of being imprisoned ($\lambda \approx 0$). λ maintains its regulatory function with R_t as a catalyst of such stabilization. There is a region showing less inequality for regular workers, where skewness tends to zero. In this region, high values of ϵ reduce the number of regular workers while high values of λ raise the number of imprisoned extortionists. As a result, the confiscated money from prisoners makes their wealth to more balanced once they are released.

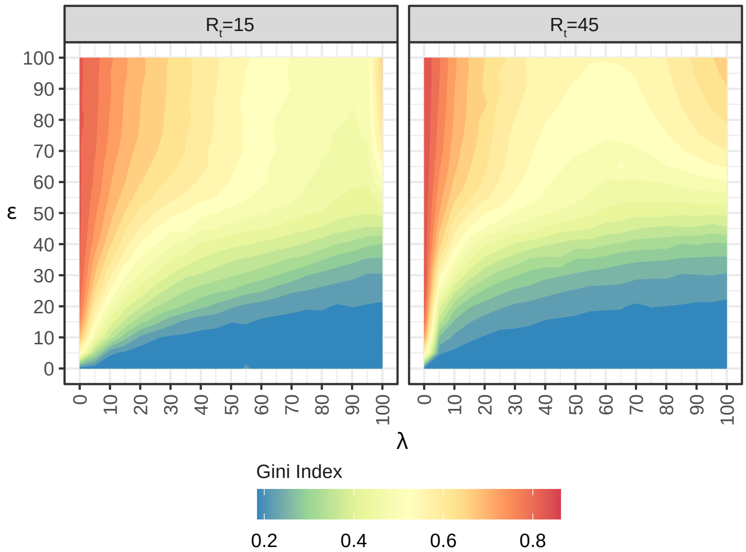

Figure 5.12: Gini index for each combination of the model parameters λ, ϵ, and R_t. In economic terms, higher values for the Gini index are usually accepted to be worse.

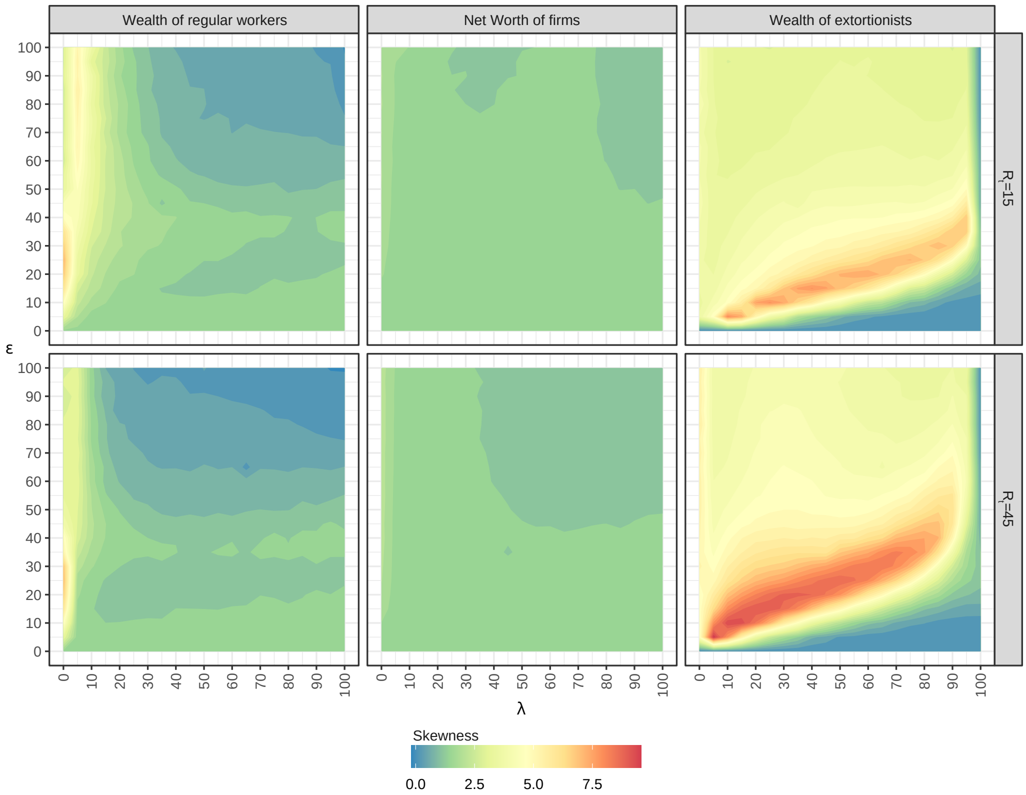

Figure 5.13: Skewness of wealth distribution and net worth for each combination of the model parameters λ and ϵ at different R_t values. In economic terms, higher bias are accepted to be worse.

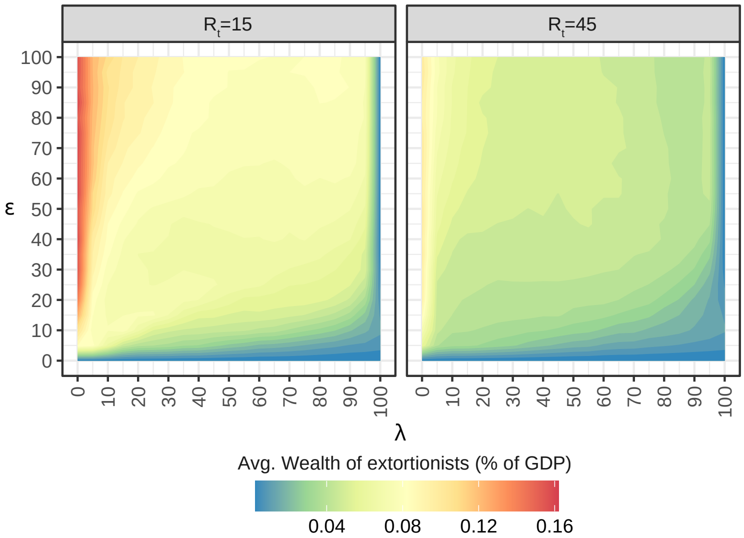

Figure 5.14: Average wealth of extortionists measured as the percentage of the GDP for each combination of the model parameters λ, ϵ and R_t. In economic terms, a higher average wealth of extortionists is accepted to be worse.

Skewness in the distribution of the net worth of firms does not show any significant change when varying the parameters. We recall that punished firms receive an equal proportion of the victim support fund raised from the wealth of the extortionists in jail.

The higher skewness obtained for the wealth of extortionists tells about the risk or volatility of this type of criminal activity. As Troitzsch (2014) pointed out, few extortionists become successful, the main determinant for low success being the "prosecution propensity". In our model, this is accentuated in the scenario with a greater tendency to denounce. The reddish regions show a phase where the probability of being imprisoned is enough to imprison a high proportion of extortionists in the system. This area is wider when the tendency to denounce is greater, since more attempts are generated to imprison extortionists.

The positive biases found in all wealth distributions comply with the stylized fact reported in the literature, regardless the change in its magnitude when varying the model parameters ϵ and λ.

Figure 5.14 shows the average wealth of extortionists as a proportion of the GDP. Increasing ϵ makes the average wealth of extortionists grow. Raising the rejection threshold makes extortionists less wealthy, even when λ is zero and there are no extortionists in jail. Still, λ has a stronger effect in this scenario, where the higher number of denounces helps the police to decrease the average wealth of extortionists.

The amount of money that flows into crime is increased through punishment, i.e., extortionists collectively obtain a greater amount of income through punishment than from pizzo (see Figure 5.15). R_t is a catalyst that further increases crime income, since it raises the number of denounces and, consequently, it also increases the level

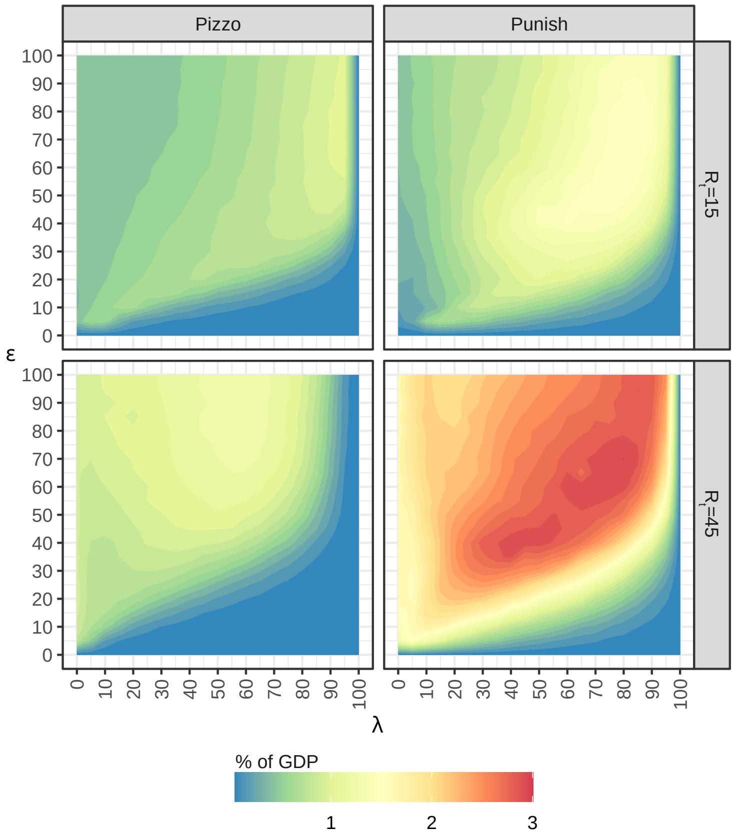

Figure 5.15: Sum of pizzo paid when varying the propensity to become an extortionist (ϵ), probability of being imprisoned (λ), and R_t. In economic terms it can be accepted that higher values for pizzo and punishment are worse.

of punishment. λ continues to have a stabilizing effect on the economy. Though, the highest revenue is not collected for low probabilities of being imprisoned but it is obtained in specific regions where both the propensity to become an extortionist and the probability of being imprisoned are higher. In this sense, the frontal fight against crime seems to be beneficial for a selected group of extortionists. Competition and risk is higher in these scenarios but so it is the reward they can obtain.

A counter intuitive trade-off emerges from the previous results. If the objective is to reduce criminal profits, the efficiency of the police should better be either limited or extremely high (the latter being rather unrealistic). On the other hand, if the objective is to improve macroeconomic indicators (regardless of the profit of criminal organizations), the police must be as efficient as possible.

Comparing distributions of macroeconomic signals

So far we have analyzed the response of the macroeconomic variables to changes in the model parameters. We now use the non-parametric Cucconi Test to check whether

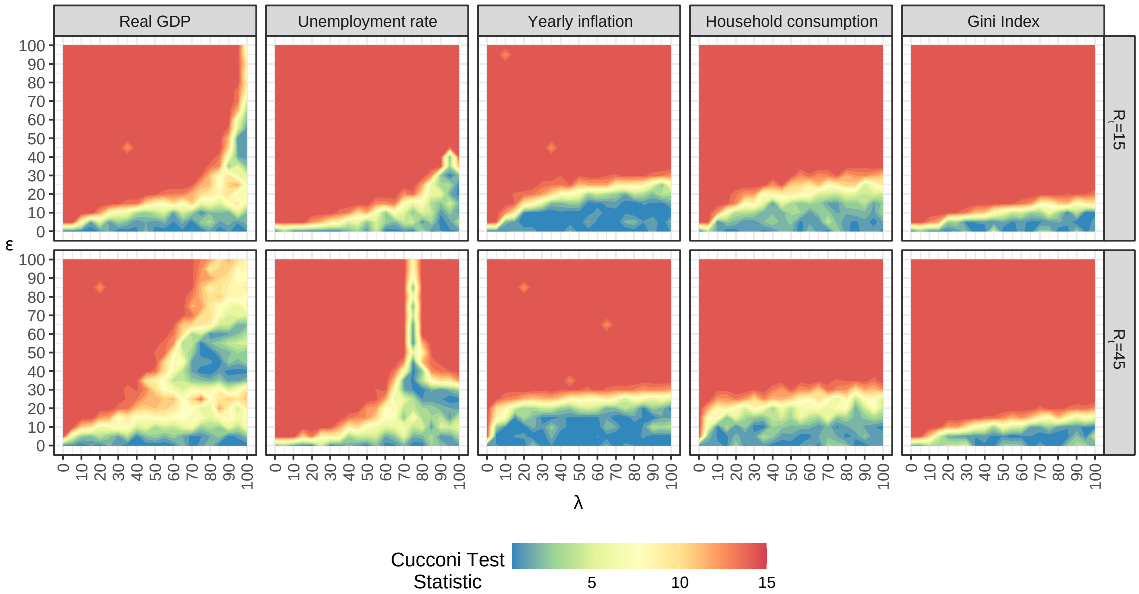

Figure 5.16: Cucconi test statistic for two sample distributions comparing base economy ($\epsilon = 0$) against all combinations of parameters ϵ, λ and R_t. Bluish regions indicate variable values with none or small differences with respect to the values observed in the base economy.

the distribution of the signals is different also in terms of their dispersion, i.e., the location-scale problem (Marozzi, 2009; Murakami, 2016).

The sample distribution generated with the baseline macroeconomic model without extortion ($\epsilon = 0$) is compared against all combinations of extortion ($\epsilon \geq 0$) and efficiency of the police ($\lambda \geq 0$). The value of the test statistic is expected to be zero if the macroeconomic signals have no differences in both treatments; but if 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. In the experimentation carried out, the value of the Cucconi Test statistic varies between 0 and 15 (see Figure 5.16).

A global view of these plots suggests an effect of extortion on economic variables. Bluish regions represent scenarios in which the behavior of the variables is statistically similar to that observed without crime. In turn, yellow regions can be seen as boundaries where small changes of parameters can lead to notable changes. Reddish regions represent scenarios in which the behavior of the variables is statistically different to that observed without crime. These phase transitions emerge from the BAMERS model as a function of ϵ, λ, and R_t for all the variables of interest, excepting unemployment at $R_t = 45$, that exhibits three phases, the third one showing unrealistic low levels of unemployment.

Policies can be designed that are oriented towards the desired directions. However, it must be observed that not all variables exhibit this effect exactly in the same way, e.g., the real GDP shows a broader margin of recovery when compared to the Gini index, which can not be recovered when $\epsilon \geq 20$. The same goes for inflation and consumption, although with a higher span of control. Designing a general policy that brings the economy under extortion closer to a ideal state (such as that observed in the absence of crime) means trying to keep all variables in the blue region, which is not always possible. Therefore, the decision maker needs to be aware of trade-offs and, sometimes, put a lower priority on some of the indicators to mitigate the effect of crime on other variables.

Chapter 6. Conclusion

This chapter is divided into two parts, the first one discusses the approach used in this research, which although relatively young compared to the Equation-Based approach, offers a large number of advantages that will be detailed. The second one focuses on the case study, that is, on the effects of extortion on macroeconomic indicators, and provides a set of public policy recommendations to try to combat the negative effects of extortion.

6.1 Discussion

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., 2011; Delli Gatti et al., 2005), 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 following its programming style guidelines, which facilitated the implementation, understanding of the model, extension, as well as distribution, even for those with a background not related to programming.

ODD protocol (Grimm et al., 2006; Grimm et al., 2010; Grimm et al., 2013) was also chosen to document the models, with the aim of facilitating understanding not only the model but the report itself, likewise facilitates the replicability in other languages with which the researcher feels comfortable programming, not only those agents oriented languages (Abar et al., 2017; Allan, 2010; Kravari & Bassiliades, 2015) 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.

The first advantage of Agent-Based models is that they can 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, so another advantage is that 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, is widely accepted but increasingly questioned[1] because 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.

Next advantage is *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.

Other advantage, derived from the previous one, consists of the possibility 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.

[1] See Section 1.2 in Delli Gatti et al. (2011) and Section 2.4.1 in Chen (2016)

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 advantage of this Agent-Based 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 advantages, 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*, the last advantage, and implies that the agents have organized themselves in the different markets, without a pre-coded 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 5.1.1.

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.

In Figure 6.1, the time in seconds required by BAMERS to reach 500 time periods is shown[2], as the number of firms agents varies and with an ϵ value of 20%. The complexity seems to follow a linear order, at least for that amount of companies in 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

[2]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)

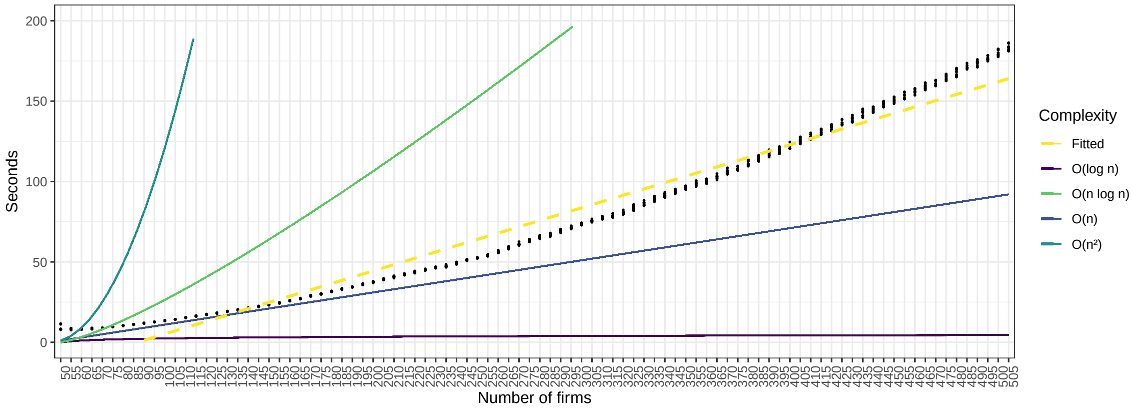

Figure 6.1: Time complexity of BAMERS.

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 (Section 1.2) was found that:

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

6.2 Policy recommendation

Beyond being a kind of tax that increases the cost of firms, extortion is also a source of fear that spreads throughout the economic system, decreasing investment and growth (Elsenbroich et al., 2016). Our simulation shows that even low levels of propensity towards becoming an extortionist are enough to notice considerable negative effects on macroeconomic indicators such as the real GDP and the unemployment rate. Such an impact corroborates the observations of Astarita et al. (2018) on Italian data that show a decrease in economic activity when facing criminal activities.

The BAMERS model can help to analyze what could be done to reduce the effect of extortion on the economy. Our simulation results suggest that preventing extortion may be more effective than combating it, i.e., there is no value of the probability of being imprisoned that achieves the levels of the baseline economy of the overall macro variables observed when extortion propensity is more than 15%. Even though, both policies should be evaluated in terms of monetary cost to determine their feasibility.

The results also suggest that macroeconomic variables have a less elastic reaction to changes in the probability of being captured than to changes in the propensity to become an extortionist, with the exception of the real GDP, where high λ values can still reproduce values close to those observed in the setting without crime.

One way of preventing extortion and discourage the proliferation of criminals is to make this activity less profitable. According to the output of our simulation, the average wealth of criminals is strongly related to the rejection threshold applied by firms when deciding whether to accept paying the pizzo. By increasing the number of denounces, firms can help decrease the average wealth of criminals, although this also depends on the probability of being captured as previously suggested by Troitzsch (2014). An effective and reputed justice system could be a way to raise this rejection threshold.

The propensity to become an extortionist (ϵ), the probability of being imprisoned (λ) and the rejection threshold (R_t) are orthogonal by design in the BAMERS model, i.e., we can explore any combination of these parameters exhaustively but independently. To overcome this limitation, the inclusion of adaptive learning agents is proposed as future work, e.g., studying how ϵ self-regulates as a result of extortionists learning in response to the effectiveness of the criminal justice system expressed by λ.

The lack of credibility in the justice system has been pointed out as an empirical cause for the spread of extortion (Spina et al., 2014). Improving the reputation of the entire justice system, e.g., by increasing the efficiency of criminal conviction, would prevent extortion to the extent that the population becomes aware of such efficiency. However, issues such as trust, credibility, or reputation were out of the scope of this research and remain as future work. The results of the GLODERS project about the normative patterns that promote and maintain extortion racket systems will be very useful for this purpose.

Other causes for the proliferation of extortion rackets systems may also be considered. For instance, in Latin America, extortion is strongly linked to a context of exclusion and deprivation, which involves poverty, indigents and bad income distribution (Anzola et al., 2016). The BAMERS model follows Abrahamsen (1949) and considers this source of proliferation by applying the propensity to become an extortionist to the poorest workers in the system. As future work, we aim to evaluate the effect of public policies for the attention to the economic deprivation of workers in reducing social discontent and, therefore, decreasing the propensity to become extortionists.

From a macroeconomic point of view, the BAMERS model allowed us to understand the behavior of the fundamental variables describing an economy under a specific type of crime such as extortion. By altering parameters such as the probability of capturing extortionists as well as the threshold of rejection to pay the pizzo, we were able to establish conditions that generate desirable and undesirable scenarios, which will shed light on the design of macroeconomic policies that are beneficial for society as a whole.

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Appendix A. Accepted papers

Micro-foundations of macroeconomic dynamics: the agent-based BAM model

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Abstract. This paper presents an open-source agent-based implementation of the BAM model, a micro-founded simulation of macroeconomic basic dynamics defined in the reference book *Macroeconomics from the Bottom-up*. By exploring the parameter space of our simulation we show that: i) BAM reproduces numerous stylized facts and its parameters influence the outputs plausibly; and ii) the effects of changing the size of markets and introducing shocks of different sizes are as expected. The outcomes are measured in terms of gross domestic product, inflation and unemployment rate, using monthly payments as time scale. These results confirm the fidelity and usability of our implementation, as well as the feasibility of the BAM model.

Keywords. Agent-Based Modelling, Simulation, Macroeconomics

1. Introduction

The complexity that emanates from economic processes requires appropriate conceptual and analytical tools. Refusing the Walrasian auctioneer, present in the classical approaches of macroeconomic analysis [1], implies that the results of the market must be derived from the interaction of a set of heterogeneous and adaptive individuals, instead of being deduced as equilibrium solutions from a system of differential equations. The process of removing externally imposed coordination devices induces a shift from the reductionist top-down perspective to a bottom-up approach. Approaches from Artificial Intelligence, such as Multi-Agent Systems, have proposed agent-based computational models [4,10,5,2,8,6] as a promising tool for analyzing macroeconomic dynamics with micro-foundations based on decentralized, heterogeneous and adaptive processes of individual decision-making.

Following the work by Delli Gatti et al. [7] on the Bottom-up Adaptive Macroeconomics (BAM) model, we have implemented a complete version [1] of this micro-founded model of macroeconomic dynamics in NetLogo [13]. To the authors' knowledge, this is the first open-source available implementation of this model. In this paper, we present an exploration of the parameter space of the BAM model showing how different stylized facts are reproduced and how some parameters influence the aggregate variables in a very plausible way. We also show that the effects of changing the size of markets and of introducing shocks of different sizes on wages, prices and interest rates produce also expected results. The outcomes are measured in terms of gross domestic product (GDP), inflation and the unemployment rate. Results confirm the fidelity and usability of our implementation, as well as the general feasibility of the BAM model.

The paper is organized as follows: Section 2 introduces the full definition of our implementation of the BAM model. Section 3 discusses experimental results regarding the effect of parameter variations on some macroeconomic variables of interest. Finally, Section 4 draws conclusions and future work.

2. The Bottom-up Adaptive Macroeconomics Model

The BAM model [7] adopted in this paper is of Walrasian nature. Despite the criticism for its excessive abstraction, the Walrasian economic model has persisted as a fundamental paradigm [11]. Indeed, because of its simplicity, it is a good starting point for exploring both perfect and imperfect economic models. As Figure 1 shows, it is composed of the following types of agents: **households** representing the point of consumption and labor force; **firms** transforming work in goods and/or services; and **banks** providing liquidity to firms if necessary.

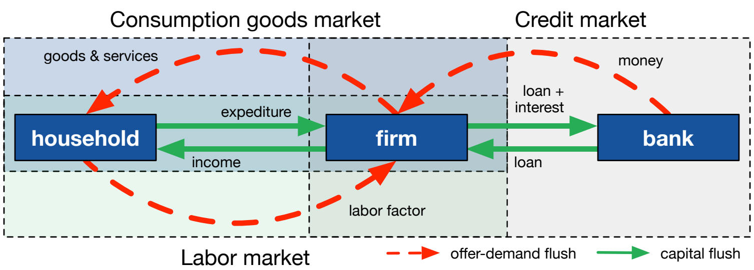

Figure 1. Overview of the Bottom-up Adaptive Macroeconomics (BAM) Model.

A large number of autonomous households (workers hereinafter), firms and banks operate in three totally decentralized and interconnected markets: a **labor market** where each worker offers a constant unit of work per period, while firms demand workers depending on their production plan; a **goods market** where workers spend all or part of their wealth and firms offer perishable goods at different prices; and a **credit market** where firms demand money if their resources are insufficient to cover their production expenses, and banks offer money at different interest rates.

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

Exchange trials are discovered in these markets through a sequential process characterized by optimization, i.e., maximizing wages, minimizing the price of goods consumed, and minimizing the price of money (interest rate). Firms can in turn adjust prices and goods on offer given their stock and the market price. In this way, the BAM model is able to reproduce disturbances that are similar to those observed in a real world economy while generating macroeconomic signals of interest such as inflation, unemployment, wealth or production, among others.

In what follows, for the benefit of replication, we describe the BAM model adhering to the Overview, Design concepts and Details (ODD) Protocol [9], a *de facto* standard for the description of agent-based models and simulations.

2.1. Overview

Purpose: Exploring the use of an agent-based approach for the study of macroeconomic signals. Particularly, we are interested in applying the BAM model to study the effect of agent behavior on such signals.

Entities, state variables and scales:

- Agents: Firms, workers and banks.
- Environment: A 2D grid is used as visual aid for debugging, but it is meaningless with respect to the model.
- State variables: The attributes that characterize each agent are shown in Table 1.
- Scales: Time is represented in discrete periods, each one represents a quarter.

Table 1. State variables for each agent, named as in code.

Agent	Variable	Type	Agent	Variable	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-num-employees-L0	Int		savings	Float
	num-of-vacancies-offered-V	Int		wealth	Float
	minimum-wage-W-hat	Float		prop-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. Unemployed workers look for a job.
3. A decentralized credit market opens. Banks will lend money to firms.
4. Firms produce.
5. A market for goods opens and workers buy.
6. Firms pay loans and dividends.
7. Firms and banks survive or go bankrupt.
8. Firms and banks that go bankrupt are replaced.

2.2. Design concepts

Basic Principles: The model follows fundamental principles of neoclassical economics [14], since it gives great importance to money in economic processes and also because the strategy for determining prices is given, considering both supply and demand.

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

Adaptation: Based on the evidence of survey data (See [7], p. 55), BAM assumes that the firms can adapt either the price or the amount of goods supplied, i.e., only one of them, at each step. Adaptation depends on the situation of the firm (supply-demand balance in the previous period) and the market (difference between the own and the market price).

Objectives: Agents do not have an explicit objective value but, implicitly, they try to improve a utility or attribute, e.g., workers always opt for the best known wage and price.

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

Prediction: Firms predict the quantity of goods to be produced based on the excess of supply-demand in the previous period and the difference between their own price and the average market price.

Sensing. Different for each kind of agent:

- Firms perceive their own quantity of goods produced, individual price, labor force, net worth, profits and 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, the prices published by firms in the actual period and the wages offered by firms.
- Banks perceive the net worth of potential borrowers to calculate interest rates.

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.

- Firms can access to a decentralized credit market if their net worth is in short supply for the wage bill. Borrowing firms contact a given number of randomly chosen banks and apply for a loan starting from the one charging the lowest interest rate. Banks sort applications 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 exogenous 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 the goods market, firms post their offer price, and workers contact a given number of randomly chosen firms to purchase goods, starting from the one which posts the lowest price.

Stochasticity: Random shocks are introduced in the setting of wages (ξ) and contractual interest rates (ϕ). Also in the strategies to set prices (η) and quantities to produce (ρ).

Collectives: Markets configure collectives of agents, they include labor, goods, and credit markets. In addition, firms and workers are categorized as rich and poor.

Observation: Gross Domestic Product (GDP), unemployment, inflation and interest rate are observed along the simulation. Distribution of firm sizes, workers' wealth and GDP growth rate are computed by the end of the simulation.

2.3. Details

Initialization: Table 2 shows the initialization parameters of the model, which are mainly taken from [7] or experimentally determined when not provided in the previous text.

Table 2. Initialization parameters.

	Parameter	Value		Parameter	Value
I	Number of consumers	500	H_η	Maximum growth rate of prices	0.1
J	Number of producers	100	H_ρ	Maximum growth rate of quantities	0.1
K	Number of banks	10	H_ϕ	Maximum amount of bank's costs	0.1
T	Number of steps	1000	Z	Number of trials in the goods market	2
C_P	Propensity to consume (poor)	1	M	Number of trials in the labor market	4
C_R	Propensity to consume (rich)	0.5	H	Number of trials in the credit market	2
σ_P	R&D investment of poorest firms	0	$\hat{w}$	Minimum wage (by law)	1
σ_R	R&D investment of richest firms	0.1	P_t	Aggregate price	1.5
h_ξ	Maximum growth rate of wages	0.05	δ	Fixed fraction to share dividends	0.15

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

Submodels: Agent behavior is defined as follows:

1. Production Y and technological productivity α: $Y_{it} = \alpha_{it} L_{it}$, s.t., $\alpha_{it} > 0$, where L is the labor factor of firm i at time t.
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. Number of vacancies offered by firms $V_{it} = max(L_{it}^d - L_{it}^0, 0)$.
5. Current number of employees L_{it}^0 is the sum of employees with a valid contract.

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 ξ_{it} is a random term evenly distributed between $(0, h_\xi)$.
8. At the beginning of each period, a firm has a net worth 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. Firms look for a limited number banks in the credit market $H < K$ since applying for a loan is considered an expensive task.
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 an 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 Bank $\bar{r}$, s.t., $R_{it}^k = \bar{r}(1 + \phi_{kt}\mu(\ell_{it}))$.
15. Margin is a function linked to each bank as possible variations in its operating costs and captured by the uniform random variable ϕ_{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 a stock 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:

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

22. Aggregate price P_t is common knowledge, while stock 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: η_{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.

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

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

where ρ_{it} is a random term uniform distributed and bounded between $(0, h_\rho)$.
25. Total income of workers 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 wage 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 (the higher the wealth the lower the proportion spent on consumption):

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

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 π_{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 worth 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 worth $A_{it} < 0$, it goes bankrupt.
33. Firms that go bankrupt are replaced with another one of size smaller than the average of incumbent firms. Non-incumbent firms' size is above and below 5%.
34. Bank's capital:

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

35. Θ is the bank's loan portfolio, BD_{kt-1}, i.e, firms that go bankrupt.
36. Bankrupted banks are replaced with a copy of one of the surviving ones.

3. Results

Parameters proposed in Table 2 generate a fictitious stable economy with unemployment rate around 10% and moderate inflation in the range of 1% to 6%. According to data from the World Bank [15,16] during the period 2014 - 2018, average unemployment among 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.

Stylized facts are an indirect calibration approach to show the capability of the model to reproduce empirical evidence. At micro level, validation consists in verifying the presence of stylized facts in the distribution of agent's state variables. For instance, we follow the method described by Joanes and Gill [3] to calculate skewness of wealth distribution and net worth in our simulations. Both of them are characterized by a positive skew > 1, as shown in Figure 2, which implies, as expected, there are few agents becoming rich.

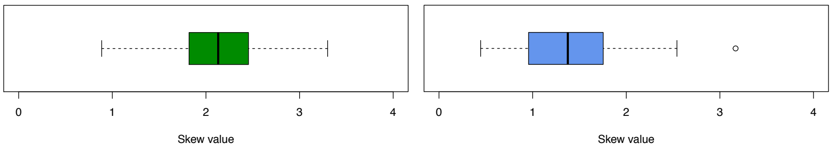

Figure 2. Skewness of wealth (left) and net worth (right) distribution over $n = 100$ independent runs. Values greater than 1 correspond to highly positively skewed distributions

The effect of shocks was tested varying wages (ξ), prices (η), and interest rates (ϕ) 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 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. [7] while large values, although arbitrary, represent acceptable big increments with respect to the small values.

Figure 3 shows the effect of varying the size of shocks when updating wages (Submodel 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.

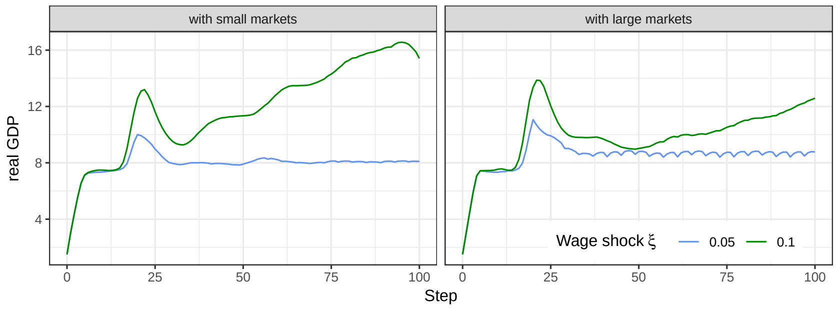

Figure 3. Dynamics of GDP under wage shocks of different size in small ($M = H = Z = 2$) and large ($M = H = Z = 4$) markets.

Figure 5 shows the effect of price shocks (Submodel 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 6 shows how propensity to consume (Sub-model 27) interacts with the dynamics of prices. Changes in the β 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.

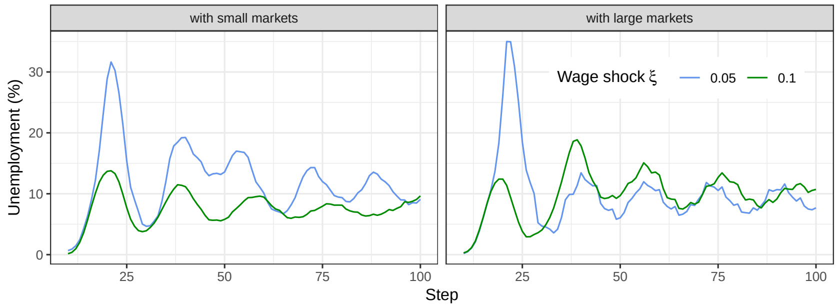

Figure 4. Dynamics of unemployment rate under wage shock in small and large markets.

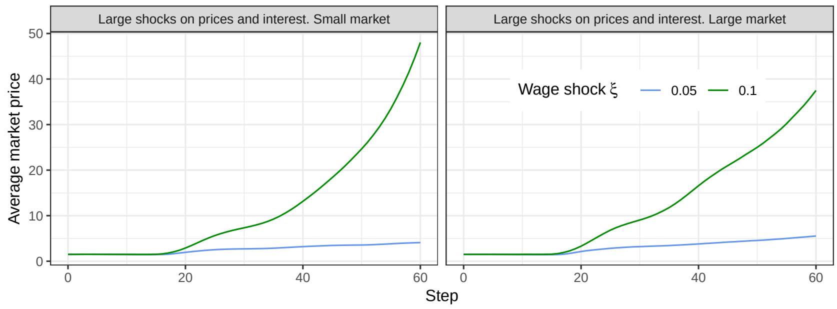

Figure 5. Dynamics average market price on small and large markets.

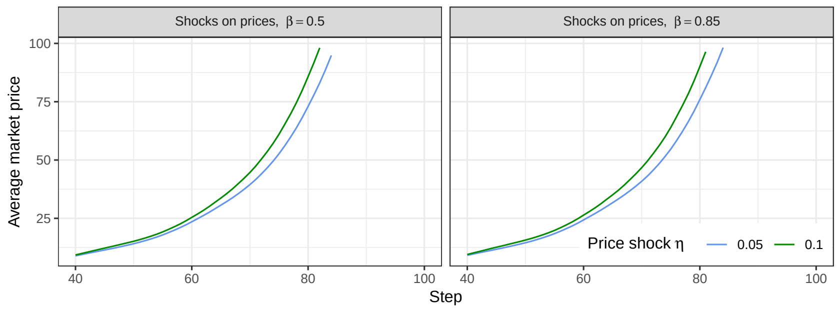

Figure 6. Dynamics of average market price when varying propensity to consume β.

4. Conclusions and Future Work

We provide a concise and complete description of the BAM model that adheres to the ODD protocol, which is argued to be relevant for reproducing results. 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.

As part of our future work, we are currently using the presented BAM implementation to test the effects of extortion in macroeconomic signals [12]. Agent behaviours can be modified so that some unemployed workers become extorters and affect the activity of the firms. The output of these simulations can then be compared with the one produced by the original BAM model, in order to study the changes on the macroeconomic signals produced by such an activity. Of course, such a method of comparison would only work if the BAM model behaves correctly, as evidenced here.

Acknowledgements

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Towards an Agent-Based Model for the Analysis of Macroeconomic Signals

Alejandro Platas-López, Alejandro Guerra-Hernández, Nicandro Cruz-Ramírez, Marcela Quiroz-Castellanos, Francisco Grimaldo, Mario Paolucci and Federico Cecconi

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

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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. [6]. The model is described adopting the Overview, Design concepts, and Details (ODD) protocol [7, 8], for the sake of reproducibility. The resulting system is available at Github.[1] The paper is organized as follows: Sect. 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, Sect. 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 [9]. Indeed, because of its simplicity, it is a good starting point for exploring both perfect and imperfect economic models.

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

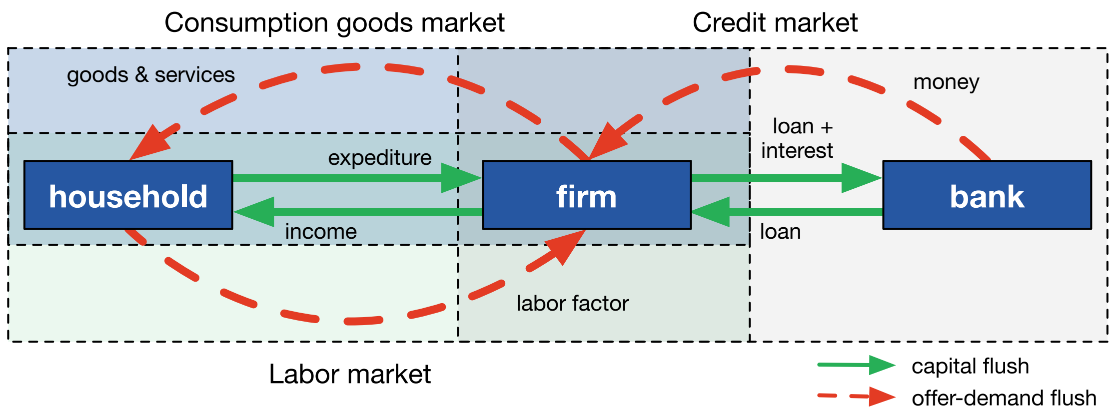

Fig. 1 The bottom-up adaptive macroeconomics model (BAM)

The Bottom-up Adaptive Model (BAM) [6] adopted in this paper is Walrasian in nature. As shown in Fig. 1, it is composed by the following types of agents:

- **Households** 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.

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			

– 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.

2.2 Design Concepts

Basic Principles. The model follows fundamental principles of neoclassical economics [10], 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 (ξ).
– Determination of contractual interest rate offered by banks to firms (ϕ).
– The strategy to set prices (η).
– The strategy to determine the quantity to produce (ρ).

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 [6] was adopted. For the values not provided in the text, they were obtained through experimentation. Table 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.
7. If $V_{it} > 0$, wage offered is $w^b_{it} = max(\hat{w}_t, w_{it-1}(1 + \xi_{it}))$, where ξ_{it} is a random term evenly distributed between $(0, h_\xi)$.

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
σ_P	R&D investment of poorest firms	0
σ_R	R&D investment of richest firms	0.1
h_ξ	Maximum growth rate of wages	0.05
H_η	Maximum growth rate of prices	0.1
H_ρ	Maximum growth rate of quantities	0.1
H_ϕ	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
δ	Fixed fraction to share dividends	0.15

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 ϕ_{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: η_{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:

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

where ρ_{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 π_{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. Θ 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.

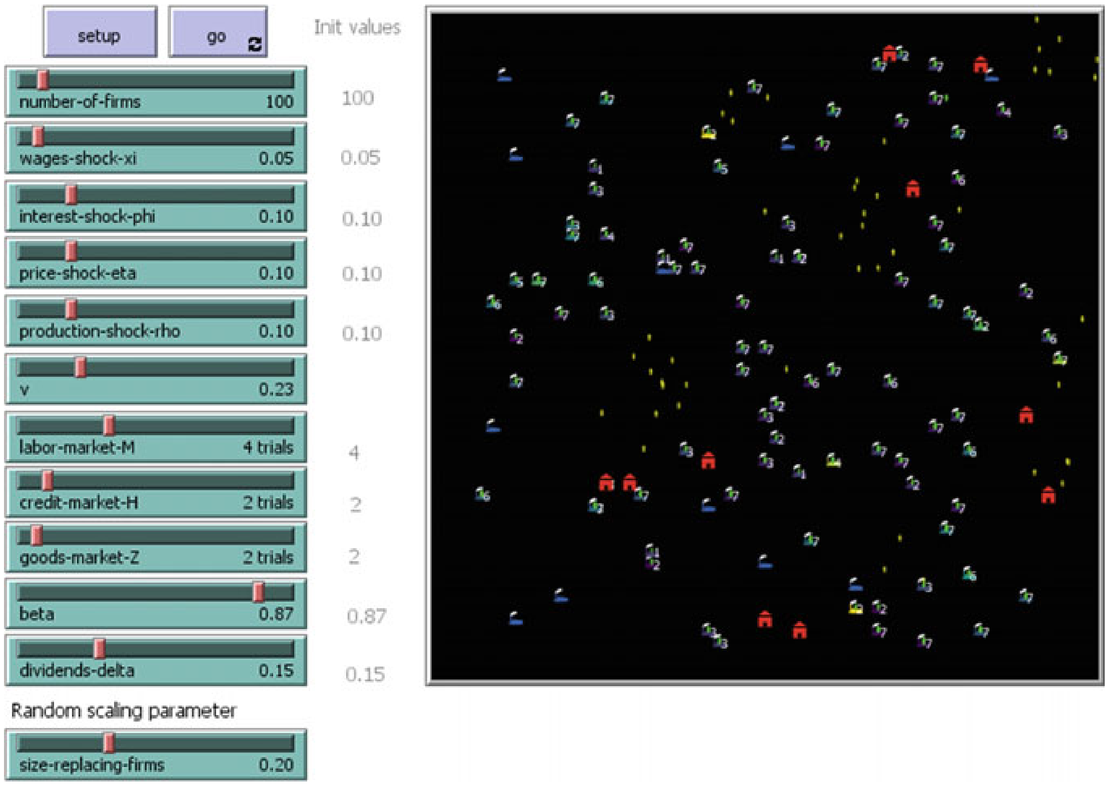

Fig. 2 The BAM model GUI: parameters and view of the world

3 Implementation

The BAM model was implemented in Netlogo [11]. Figure 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. [6], the macroeconomic signals exemplified in Fig. 3 are produced. This output reflects a stable fictitious economy, with unemployment rate close to 10% and moderate inflation in the range of 1–6%. In the next section, 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 [6]. Wealth

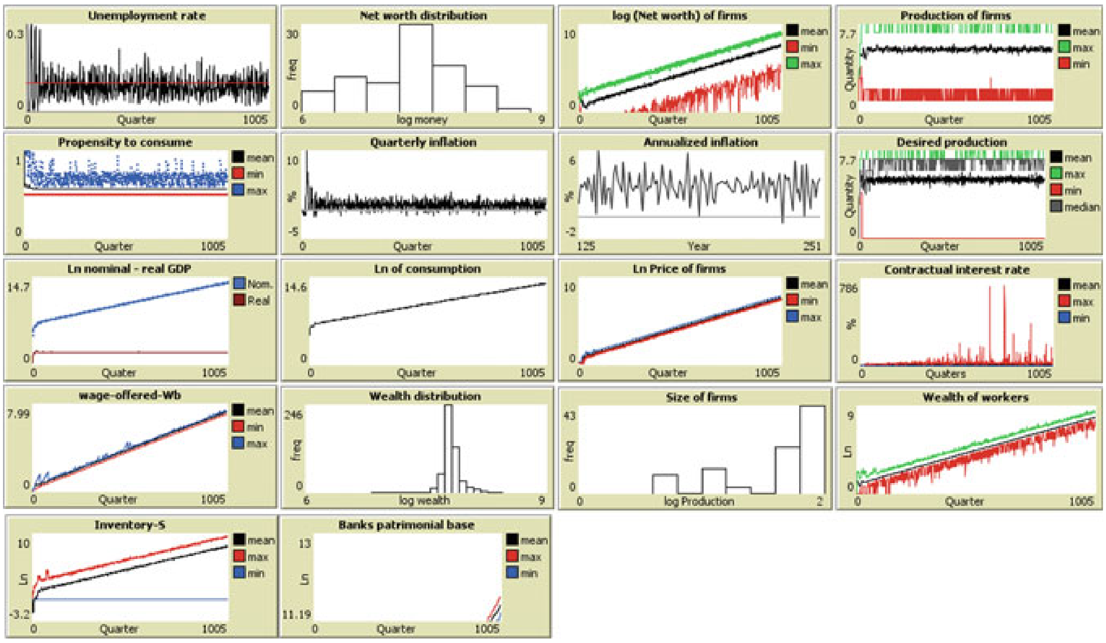

Fig. 3 The BAM model GUI: macroeconomic signals

and net worth in our case are characterized by a positive skew, which implies that there are few agents that become rich (Fig. 4).

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 [12]:

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

where,

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

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 [13], 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 [14].

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.

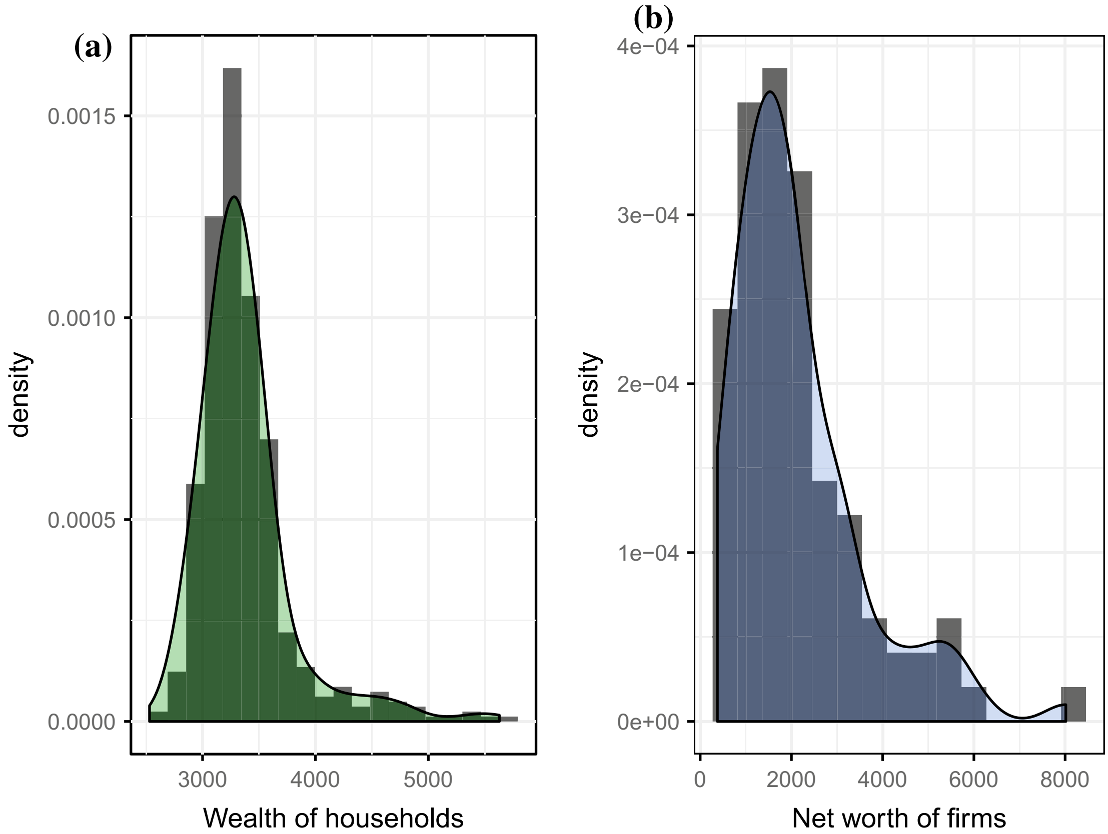

Fig. 4 Examples of our distribution of wealth (**a**) and net value (**b**) of a selected run

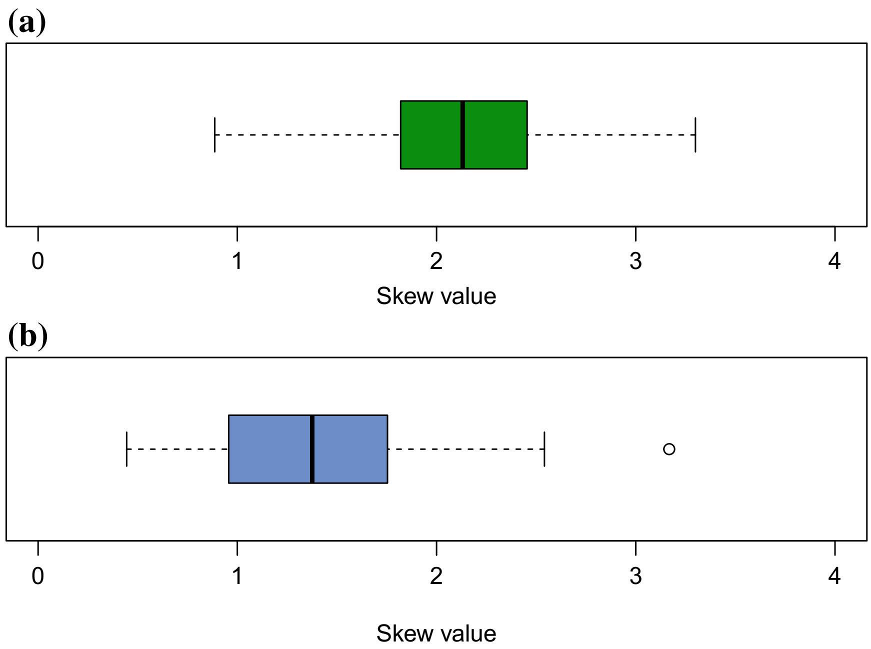

Fig. 5 Skewness values obtained over 100 independent runs of wealth distribution (**a**) and net worth (**b**). It is considered that values greater than 1 correspond to highly positively skewed distributions

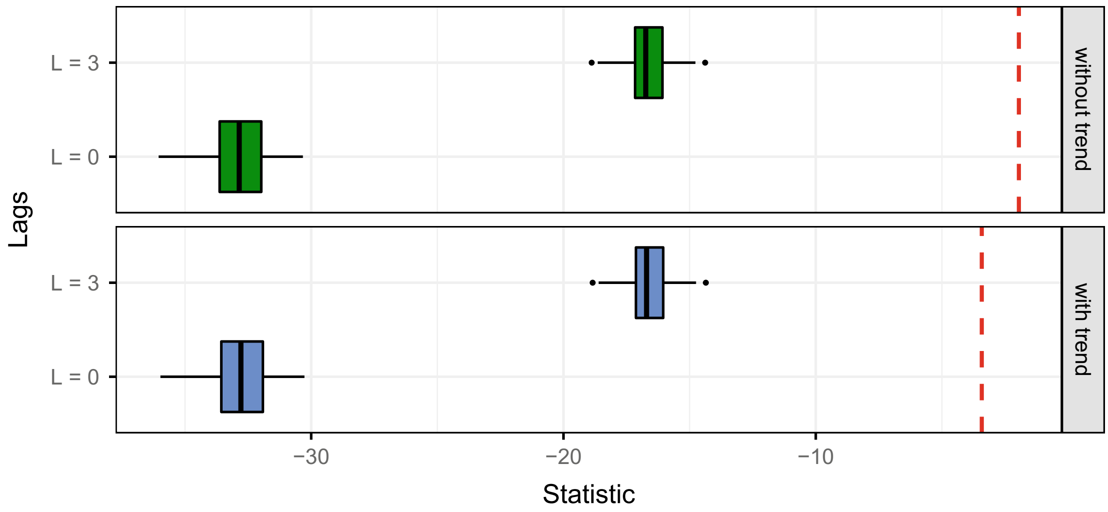

Fig. 6 Distribution of Dickey-Fuller t-statistics for logarithmic first differences of last 500 GDP quarters over 100 independent runs. Dashed lines are critical values

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.

BAM will be used to study the macroeconomic effects of extortion racket systems [15], 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 [16], 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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