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ABM of Labor Markets with informality and Vacancy information Flow through Social Networks

Proyecto de Investigación

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ABM of Labor Markets with informality and Vacancy information Flow through Social Networks

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DEDICATORY

To Lorena, my love.

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Resumen

Desarrollamos tres Modelos de Agentes de mercados laborales con informalidad. Dos modelos utilizan las redes sociales como medio por donde fluye la información sobre vacantes como mecanismo de emparejamiento entre empresas y trabajadores. El modelo restante utiliza emparejamiento aleatorio. El principal objetivo del artículo es observar y medir los efectos de la incorporación de redes en un modelo de mercado laboral. Los resultados muestran que las redes crean una proporción más significativa de informalidad. Además, los modelos pueden reproducir resultados obtenidos en otros artículos de emparejamiento en el mercado laboral.

Palabras clave: Modelo de Agentes, Emparejamiento, Redes Sociales, Función de Emparejamiento, Instituciones, Emergencia, Sistemas Adaptativos Complejos

Abstract

We develop three ABMs of labor markets with informality. Two models use social networks where information about vacancies flows as the matching mechanism between firms and workers. The remaining model uses random matching. The paper's main objective is to observe and measure the effects of incorporating networks in a labor market model. The results show that networks create a more significant share of informality. Moreover, the models can reproduce results obtained in other papers on Search and Match in the labor market.

Keywords: ABM, Search and Match, Networks, Matching Function, Institutions, Emergence. Complex Adaptive Systems

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1 Introduction

Labor markets are systems composed of workers and firms interacting numerous times with each other through time and making decisions based on multiple factors. It is difficult for mathematical models to capture every aspect of the labor market. The mechanism in which workers and firms meet is an essential labor market component that mathematical models obviate. Moreover, when two markets co-exist, formal and informal, the matching mechanism could factor in the search process, workers' decisions, and aggregate population outcome. Agent-based models are precisely designed to capture environments where agents repeatedly interact with each other. Social networks, a tool many people use to gather job information, could be implemented in an Agent-based Model as a matching mechanism. The focus of this research paper is dedicated to the exploration of labor markets with informality through the development of three Agent-Based Models. Our approach incorporates social networks as the essential facet of the matching mechanism between firms and workers in two distinct models. In contrast, the third model employs a random matching mechanism. Three constructed models enable us to compare by performing a sensitivity analysis of the results. The kernel of our paper revolves around meticulously observing and quantifying the multiple effects that originate from the integration of networks within a labor market model with informality.

Search and Match(SM) models have long been recognized as valuable tools for analyzing the labor market. They are an improvement from the traditional Walrasian Model, where equilibrium is supposed to be achieved only by the assumption of equalizing labor demand and supply. The Walrasian model could not explain unemployment and labor dynamics since it assumes perfect information and instantaneous matching between job seekers and job offers (Yashiv (2007)). Search and match models incorporate new features to represent the labor market better but still hold an equilibrium concept for solving the model. One of these new features is the theory of friction in the labor market. Frictions or obstacles in the labor market prevent instant and efficient matching between job seekers and job offers. These frictions can include incomplete information, geographic mismatch, wage discrepancy, and time required for job seekers and employers to evaluate potential matches. SM models capture friction by using the Matching Function(MF) concept. Only a fraction of the workers and vacancies get matched because of friction, and the MF quantifies that fraction. The MF quantifies the number of matches per unit of time based on the number of workers searching and vacancies available. The main characteristics of the MF are that it is homogeneous with degree one and has a constant return to scale. Other theoretical incorporations of SM models include the endogenous creation of labor demand(vacancies), labor supply (searching workers), and the notion of Nash Bargaining to determine wages. Together with the MF that quantifies matching probability, the model can build the expected value equations of firms posting vacancies and workers searching. For solving these equations and the model itself, assumptions like free entry of firms, workers maximizing value, and Nash equilibrium are needed. The model explains unemployment and represents the labor market in a detailed manner but still relies on theoretical concepts like the MF and has an equilibrium solution concept with the assumptions already mentioned. SM models became more sophisticated, incorporating search while working, job destruction, business cycles, and informal markets. As the sophistication grew higher, more assumptions were needed to reach equilibrium

Even if they were an improvement in the literature, these models still rely on several idealized assumptions, meaning entities that don't exist in reality (Runde (1997)). The MF, equilibrium, and Nash Bargaining for determining wages are clear examples. Idealized assumptions are made to simplify and model complex real-world phenomena. However, these assumptions sometimes overlook important aspects of the economic process, especially when analyzing complex systems like the labor market. For example, by assuming the MF, the model overlooks the real process of how actual workers search for jobs and obtain vacancy information. By assuming free entry of firms and generalizing value equations, the model fails to describe a credible theory of how firms post vacancies and workers decide to search.

Complex adaptive systems are dynamic systems composed of individual agents that interact with each other and adapt to a changing environment (Chan (2001)). Labor markets fit this description; firms and workers are the agents interacting to create labor contracts and adjust their decisions based on information. An essential characteristic of complex adaptive systems is that they produce emergent properties. Emergent patterns or properties arise from the interactions and behaviors of individual agents in a system, leading to collective outcomes that cannot be predicted based on the characteristics or actions of each agent in isolation (Miller and Page (2009)), making the system more complex than the sum of its parts. Agent Base Models (ABMs) are an excellent tool for understanding complex adaptive systems (Miller and Page (2009)). These Models comprise interactive, heterogeneous, autonomous agents that can adapt, decide, and exhibit emergent patterns when analyzed. They simulate the behavior of individual agents from the bottom-up, allowing researchers to understand how the actions and interactions of these agents contribute to the overall emergent patterns and behaviors of the system.

But how exactly are ABMs better than classic mathematical models? In a word, Emergence. ABMs do not need specific conditions to produce outputs since their results are the emergent properties given by the model. An emergent property or pattern arises in the model's development without being programmed; it emerges as a result of the interaction of the agents in the model. Mathematical models, on the other hand, need simplifications and equilibrium conditions to be solved analytically and produce an outcome. However, simplifications wash away information related to the process of interactions and require unrealistic conditions to be met. Besides the flexibilization of the conditions of the model to produce an output, Emergence gives researchers key information on the institutions that are part of the phenomenon. Institutions are rules of behavior that structure human interaction (Hodgson (2006)). In an ABM, the rules of behavior and interaction are embedded in the algorithm and programming, and they play a role in Emergence. ABMs give researchers information on which institutions and processes may contribute or give rise to different phenomena (Ghorbani (2022)). An example will be the Walrasian model itself. Information on how coordination between demand and supply emerges is lost by assuming the unrealistic equilibrium conditions between demand and supply. Hayek (2013) famous essay on how free pricing enables coordination is the perfect example of how an institution (free pricing) gives rise to the emergent property (coordination). Thinking about the process gives scientists deeper insights into how the economy behaves.

An important aspect that SM literature washes away and can be incorporated into an ABM is the social network where vacancy information flows. Networks, our main interest, play an important part in job finding (Putnam (2000)). Even from an intuition standpoint, asking a friend if he knows where they are hiring people seems the logical action to take when looking for a job. Including social networks in the model allows for examining how information flows through social connections and influences job search behavior and market outcome. The main purpose of this research is to construct various ABMs to understand better the importance of social networks in markets with informality.

To simulate the complexity of an informal labor market, we incorporate social networks, self-employment in informality, and endogenous mechanisms to create vacancies and for workers to decide on searching. Even though we differ from search and match literature, some of their ideas were integrated into our model in an ABM adaptation. For the construction of the network, we create an artificial Ecuador. To achieve this, we grouped the workers into households according to Ecuador's household size distribution. This was done to replicate a scale model of a country with high informality. After having an initial network of households, graph algorithms were used to create a social network to connect workers in different homes. The information was taken from Ecuador's official labor survey ENEMDU. Information about wages in both sectors was used to calibrate the model. Finally, three models are created to compare the degree of impact of implementing networks in a Model. One of the Models uses random matching between firms and workers as the pairing mechanism, while the other two rely on the networks; this will enable us to observe and quantify model differences and conduct a sensitivity analysis.

The paper is organized as follows. Section 2 reviews the literature. Section 3 describes the data used. In Section 4, we describe the models in detail. In section 5, we explain the simulation and calibration of the models. In Section 6, we present the main results. Section 7 provides a Discussion. Section 8 concludes.

2 Literature review

Many of the concepts implemented in our Models come from Search and Match literature since they were the first to describe the particularities of the labor market, and we adapted the concepts to an ABM environment. The ideas in search and match models can already be found in Friedman (1997) idea of the "natural rate of unemployment." He argues this natural rate is the percentage of unemployment produced by the frictions that can not be captured in the Walrasian model. Mortensen and Pissarides (1994) model is the literature's primary search and match model. The concept of a matching function is developed in the model to capture the friction in the market. The other important aspect of search and match literature is vacancy creation. In previous literature, the numbers of jobs were fixed (Pissarides (2011)), but Pissarides (1979) shows that the number of vacancies is a fraction of the current filled vacancies. The canonical model already stated in Mortensen and Pissarides (1994) incorporates an endogenous vacancy creation in a two-sided search space of firms and workers.

Other matching scenarios later included the search framework developed by Mortensen and Pissarides (1994). The RBC model by Andolfatto (1996) used the search theoretic framework and improved the model's empirical performance. One of the first papers that used search and match ideas in informality is Boeri et al. (2005), in which search and match ideas were used to explain shadow activity. From this paper onward, an increasing literature of search and match models with informality begins. Mariano Bosh and Julen Esteban-Pretel's papers are search-theoretical models in an economy with an informal market.Bosch and Esteban-Pretel (2006) describe flows between unemployment, formality, and informality over business cycles using Brazilian data, and their two papers Bosch, Esteban-Pretel, et al. (2009) and Bosch and Esteban-Pretel (2012) describe how policy intervention could affect the flows. Ulyssea (2010) also analyzes policy intervention, showing that reducing entry costs in the formal sector reduces the informal sector. Another approach is analyzing the relationship between sectors; Tümen (2016) shows that if the informal market creates human capital, the informal market is less sensitive to policy than if it is a dead end for workers. The search and match framework is regarded as an excellent tool for describing behavior in markets with informality like the ones in our Models. This is why many of their concepts were ABM adapted into our Models

Our agent-based approach follows the tradition of computational modeling labor markets. Bergmann (1990) is the first ABM computational model; it is elementary with random matching and exogenous labor demand since the paper's objective was to serve only as an introduction. Models like Neugart (2008) show more sophistication; workers acquire skills to enter different jobs in different sectors. With time, the complexity got to models like Boudreau (2010), where heterogeneous agents can develop skills to compete for higher wages and firms grow in relationship to the production of their workers.

Later literature on ABM of labor markets can be divided into two (Michael, M. G. Richiardi, et al. (2018)), partial and embedded. Partial models focus on labor markets to understand stylized facts and policy. In contrast, embedded models focus on the interaction of markets with themselves and other economic entities. Our model is part of the partial tradition. Partial models rely on the concept of emergent properties. Stylized facts are the emergent properties that partial models try to replicate (Heckbert, Baynes, and Reeson (2010)).

The stylized facts that have been targeted are Okun's law curves (OL), the wage curve(WC), the Beveridge Curve(BC), the matching function(MF), and the size of firms. Fagiolo, Dosi, and Gabriele (2004) successfully reproduces OL, BC, and WC by capturing the interactions of firms with the market. The relationship between firm size and unemployment theory was explored in Russo et al. (2007) by observing the interaction of the firms with the financial cycle. The ABM papers exploring the MF are M. Richiardi (2004) and M. Richiardi (2006); both are non-equilibrium models, and the MF characteristics were not duplicated. This is an essential result since the MF, a building block of the system in search and match models, was not replicated in an ABM. Our approach relates directly to this because we don't rely on MF or equilibrium.

Informality has also been explored in ABMs; Aguilar and Allet Acuña (2021) incorporates the ability of workers to become self-employed under certain conditions. This feature represents the propensity of choosing informality in less developed countries. A computational model that contains a social network that replaces the MF is Calvó-Armengol and Zenou (2005). The results show that, in the aggregate, the model can replicate the MF characteristics except for the homogeneity. These two studies are relevant to our model since we incorporated self-employment, informality, and a social network as the matching mechanism.

Partial Models focusing on networks have also been created. Lewkovicz, Thiriot, and Caillou (2011) creates a labor market with networks to explore the importance of constructing a detailed network structure to reproduce stylized facts. The results showed that the evolution of the network changed the initial structure, making it secondary to the evolution.

One of the main reasons to create computational models is to simulate real-world scenarios. Searching through a social network is essential to finding jobs in real life. Studies like the well-known Granovetter (1973) explore the relationship between social networks and job search. The study indicates that weak ties(neighbors of neighbors) increase the probability of finding a job. Recent papers like Putnam (2000) or Aldridge, Halpern, and Fitzpatrick (2002) suggest that social networks are essential in job finding and promotions. Surveys like Shuttleworth, Green, and Lloyd (2008) indicate that word-to-word communication is ranked second in finding a job .Afridi and Dhillon (2022) is a survey on the literature on networks and the labor market in developing countries that finds network effects on labor productivity. This literature suggests that incorporating a social network in a model will bring real-world aspects.

The networks in our models must be constructed appropriately. The information about vacancies will flow between agents in a social network, so we need them to resemble real social networks to capture this feature. For this task, we used graph theory, a strong foundation for network creation. The network algorithms used in our model are Erdős and Rényi (1959) and Barabási and Albert (1999), both recognized in graph literature for capturing the construction of social network environments. The Erdos Reyni(ER) algorithm is used to build random graphs by specifying the number of nodes and the probability for each pair of nodes to be connected by an edge. Its evolution resembles structures of real communications nets and the development of social relations (Erdős and Rényi (1960)). On the other hand, the Barabasi-Albert(BA) algorithm is a preferential attachment algorithm used for generating scale-free networks that mimic real-world phenomena such as the growth of social networks or the formation of the World Wide Web (Barabási and Albert (1999)).

Three traditions follow our research: partial ABM of labor markets, search and match theoretic framework with informal markets, and information flow through a social network constructed with graph algorithms. To the best of my knowledge, this is the only computational model that includes all of them.

3 Data description

We are interested in three main statistics:

1. The distribution of sizes of productive or potential productive workers in households. This distribution will serve us in constructing the country structure that will function as a central part of our Network.

2. The distribution of organizations between informal, formal, and unemployed in each household when conditioned on the household size. This information helps assign each worker an original status at the beginning of the models

3. Descriptive statistics on salaries in informal and formal markets. This information is helpful for the initial calibration of the models

The empirical data collected for our model is taken from Ecuador employment surveys ENEMDU. These surveys are realized by Ecuador's official statistical organization, INEC. The polls have been going on since 2003 in a trimester manner. For our model, we take the data of the second trimester yearly, starting in 2008 and finishing in 2017. The data are cross-sectional surveys, so we look for descriptive information in the aggregate. The data is structured by surveys of different employment aspects to all members of a specific household. This characteristic benefits our models since we can gather household information for our networks. To get precise data, we do some filtering. We focus our observations on people aged 18 to 65 since this is the working age in Ecuador. Also, we only observe people who belong to one of the following three categories: formal, informal, or unemployed. Each person is consistently classified under these three categories on the database, so we follow our model with their classification. Lastly, we filtrate our data based on the number of potential workers per household since we want workers to be part of a net. The number in a household can increase to 20 in some given year, so we cut the data to households of a maximum of 4 because the probability of belonging to a household bigger than 4 is very slim. Table 1 shows the frequency of household sizes; after 4, the frequency in all years is trivial, under five percent. Note also how the frequency tendency in all year is monotonically decreasing, so the bigger the household size, the less frequent to almost negligible.[1]

[1]Figure 24 is the distribution of houses for a trimester. It shows visually how insignificant households of size larger than four are

Having done the filtering, we construct the final data. First, we find the distributions of household sizes for each year. Note that this quantity only represents the number of workers or potential workers in each home since we already filter children and elderly. Table 2 shows the results for each year. The data is similar each year, with most concentration in the lowest numbers and then declining in bigger households.[2]

Then, we found the probability of household organization conditioned to household size. Tables 3 to 6 show the results .We found this feature since the data is gathered from household surveys, so we have all the information for different households. The numbers on the left of each table are tuples representing the household's organization. The first digit is the number of formal workers in the home, the second informal, and the third unemployed. Finally, after filtering outliers from the wage data, we construct Table 7 with information on wages in informal and formal markets for calibration. The table also contains information on the annual distribution of formal, informal, and unemployed workers.

4 Models

4.1 General Description of the Models

The models are based on the same spirit of Bosch, Esteban-Pretel, et al. (2009), adapting search theoretical concepts in an agent-based manner. Three important features were taken from the original model and brought into ours. The first is an idiosyncratic productivity match between the firm and the worker. The match represents the productivity relationship between the firm and the worker. The higher the number, the bigger the production of surplus. This match also determines the future actions of both parties at each turn. Lastly, the two other features are endogenous job creation and the timing of the interactions. The main innovations of the models are the ability of workers to become self-employed informally and an initial household distribution that mimics an actual household distribution of a country that serves as the basis for the structure of the social network. Finally, models two and three contain a social network of workers where the information on open vacancies flows.

The models are agent-based, discrete-time, search, and matching labor models. Workers and firms try to meet in the market to form contracts based on their interests. Workers can

[2]Figure 25 is the distribution of houses for a trimester on the filtered data.

search for jobs while hired, and a direct transition is allowed between formal and informal firms.

We constructed three different models. The first is without a social network and random matching; the other two are with networks and information flow. It follows a detailed description of the Models.[3]

4.2 First Model Description

4.2.1 Description of the Worker

Each worker has two intrinsic characteristics that have heterogeneity between them. The first characteristic is their ability to bargain for a salary. The higher his ability to bargain, the more significant the fraction from the surplus produced he receives as a wage. The second attribute is his ability to produce an income independently as a self-employed informal worker.

Workers' primary objective is to find a job with a wage according to their reservation wage. Workers can either be searching for a job or not. Workers who are unemployed or working in an informal firm always look for jobs—workers who are looking for a job search firstly the formal firms in the market. If the firm they meet in the current turn has vacancies available, it makes an offer. If the wage offer made by the firm is higher or equal to the reservation wage, the worker becomes hired by the firm with an income equal to the wage offer. Searching workers who did not find a job in the formal firms search in the informal ones, and if the firms fulfill the same conditions as formal ones (vacancies and a good wage offer), they become hired by the firm. If the worker does not find a job, he reduces his reservation wage to align his expectations with the market.

If a worker has not found a job in a formal or informal firm for a certain amount of turns, he considers becoming self-employed informally. If his ability to produce an income informally self-employed is higher than his reservation wage, the worker opts for this option. Workers under these working conditions evaluate each turn if they search for a job in firms the following turn. They decide to return searching using a Montecarlo process using the number **Probability_of_reinsertion** as the threshold; in that sense, based on probability,

[3] Uniform distribution is used to generate all random numbers in the model. Also, a computational description of the Models is given in the Appendix 10.1

a certain number of workers will return the search.

Workers currently working in a formal firm can also be searching. The idiosyncratic productivity match number between the firm and the worker determines the search decision. As stated, the match represents the relationship between the firm and the worker for the turn; the higher the number, the better the relationship for creating surplus. The idiosyncratic match changes each turn since working relationships change through time. Each turn, a random number is drawn for each worker in formal or informal firms. If the number exceeds the threshold number **Productivity_threshold**, the worker does not look for a job in other firms since their relationship is adequate in their current firm. On the contrary, if the number is below, workers search for better job opportunities in other firms. The idiosyncratic productivity match also determines layoffs. If the number for the turn is below the number **Destructio_Threshold**, then the relationship is insufficient for the firm, and the worker is laid off. Workers become unemployed, and their reservation wage is a portion of their former income since workers look for wages based on their experience and expectations.

4.2.2 Description of the Firm

A firm's main intrinsic attribute is its production capacity. The attribute only changes between formal and informal firms; all formal firms have the same production capacity, and informal firms have the same capacity between them. The parameters **Powerformal** and **Powerinformal** represent each of these capacities Firms primarily aim to incorporate workers in their payroll to produce surplus and earnings. To achieve this, firms hire and fire workers to have an appropriate payroll, create and post vacancies with an offered wage to recruit workers, and produce a surplus based on the capacity of their workers.

The surplus produced by each worker is the multiplication of the idiosyncratic match times the firm's production capacity. As already stated, each turn, a new idiosyncratic match is drawn for workers to determine how productive they are in the firm, and workers with idiosyncratic matches under a certain threshold are laid off. This process allows the model to have variations in worker-firm relationship through time. Once the surplus of each worker is calculated, the wage of each worker is calculated by multiplying their bargaining power by the surplus. Each worker's salary depends on their productivity and ability to bargain. Firms post vacancies based on their current payroll productivity. The logic of the model is that the bigger the profits, the more vacancies it posts since it speculates more workers will make the profits expand. And it has more savings to gamble on future returns. Firms decide how many vacancies they post for the following turn, considering the average productivity of the idiosyncratic match between them and each worker in payroll. The more productive they are, the more expectations they have for hiring new people. The equation that determines the number of vacancies per turn is the following.

$$\textbf{Vacancies} = \text{ceiling}(\text{mean}(\textbf{Prod}) + \textbf{Maxvacancies} - 10)$$

In the equation **Prod** represents the idiosyncratic productivity matches; for arbitrary purposes, the matches are on a 0 to 10 scale. Since the idiosyncratic matches are on a 0 to 10 scale, the maximum the average productivity can get is 10. Suppose we subtract ten from the average productivity. In that case, the maximum value that subtraction can produce is 0, and by adding the parameter **Maxvacancies**, the maximum value will be **Maxvacancies** itself. **Maxvacancies** is the number in the model that represents the maximum number of vacancies a firm can offer per turn. We have an equation that produces vacancies based on the current productivity of the employees since the greater the average idiosyncratic matches, the more vacancies are produced, and we can control the maximum number of vacancies produced by turn. The equation is only activated when the value is positive. Otherwise, the firm stays with the remaining vacancies from the last turn.

The parameter **Maxvacancies** represents two aspects: the maximum number of vacancies a firm can post and the vacancy cost. Once ten is subtracted from the parameter **Maxvacancies** in the equation, the result becomes a constant negative number[4]. This number represents the cost of posting vacancies. The bigger the resulting number, the higher the price for posting vacancies. So the more significant the parameter **Maxvacancies** is, the less cost is on the average productivity. The **Maxvacancies** parameter dictates the maximum number of vacancies a firm can post, and it functions as a cost posting parameter.

When a new worker is added to the firm, his productivity potential remains unknown. To mimic this feature, newly added workers have the average productivity of the current workers on the payroll as their idiosyncratic productivity match. Also, when a worker is offered a job, the offered wage is calculated based on this speculated average productivity and the worker's

[4]Since in all calibrations of the Models **Maxvacancies** is always less than 10

bargaining capacity. Their idiosyncratic match will begin changing as everybody else after their first turn in the firm and their actual capacity is revealed. Finally, when no workers exist, a random number between 0 and **Maxvacancies** is drawn to offer that number of positions. A random idiosyncratic match is also drawn to calculate the wage offer for all potential workers.

There are two differences between formal and informal firms. The first is their production capacity, with formal firms having a higher capacity than informal ones. The second is that informal firms have a maximum capacity of employed workers in their payroll since they want to avoid notoriety from the control agencies. The vacancy production of an informal firm is reduced according to this maximum capacity.

4.2.3 Descrition of the Market

The market has two functions. The first is to set up the initial conditions in which firms and workers will meet, and the second is to create the matching between firms and workers for them to decide if they form a relationship. The first step in setting up the conditions is determining the ratio of formal to informal firms with a Montecarlo process using the number **Probinformal** as a threshold. Then, the market distributes the workers in households using a Montecarlo process according to the desired distribution of household sizes, therefore creating the households with the workers. Then, in each household, using the conditional probability of house organization conditioned in household size, another Montecarlo process assigns each worker its original status of formal or informal workers or unemployed. This process is used in each of the created households. When workers are assigned a formal or informal status, they are matched with a random firm of their corresponding type to start working with them. Since the workers are unemployed, their reservation wage is zero, and they will accept any wage offered by the firm. To ensure that formal firms have vacancies at the beginning of the model, they have the same number of vacancies as workers in the model. On the other hand, informal firms have the maximum number of allowed vacancies. If a worker assigned the informal status gets matched with an informal firm without vacancies, he becomes informally self-employed. This process produces an artificial market with the household distribution and inner household distribution of a desired market. The market matches workers and firms randomly. The matching process is the following. First, each searching worker gets matched with a firm randomly, each with the same probability of matching. If the firm has vacancies, the firm calculates the speculated surplus the worker will produce based on the average productivity of their current workers and, together with the worker's bargaining power, produces a wage offer. If the offered wage exceeds the worker's reservation wage, the worker gets hired. The worker looks for an informal firm if there are no vacancies or the salary is insufficient. The matching process of workers with informal firms is the same as for formal firms.

4.2.4 Timing

The model has two phases: the **initial** when the setting is done and the **interaction** phase when firms and workers interrelate. Workers and firms are created in the **initial stage**. The firms are then divided by the market between formal and informal. At this point, the market prepares the initial conditions for workers and firms, setting the worker's reservation wages and firms' vacancies accordingly. Then, households are created by the market, with the workers in each home being assigned their initial work status to be incorporated into a firm or become independent in the informal market. In the **interaction phase**, the firms assign the idiosyncratic productivity match for all their workers for the turn; in this stage, the workers that belong to the firm decide to search for this turn based on their new idiosyncratic match. Then they fire the workers under the **Destruction_threshhold**. Firms then produce surplus, set the wages, and create the vacancies in that order.

The matching starts, and searching workers look for jobs in formal firms. If the worker doesn't find a job, he looks for informal firms. Then, the informally self-employed workers decide whether to search for jobs in firms the following turn. Then, workers who have been unemployed longer than the threshold number **Waitingtime** evaluate becoming self-employed informally. Finally, the workers that didn't find a job in the current turn discount their reservation wage. The interaction phase repeats for a determined amount of times.

4.2.5 Global Parameters

The following is a list and explanation of all the parameters that serve as input in the model with a brief description. Some of them were explicitly mentioned in this section, while others were implicit.

- **Maxwageinformal:** The maximum wage a worker can receive while working self-employed informally. Informal independent workers can not create a significant surplus since they have limited resources while working alone and trying to prevent notoriety at the same time. So, their production capacity is limited.

- **Productivity_threshhold:** A threshold number for the idiosyncratic match between a worker and a firm for an employed worker to stop looking for jobs in the current turn. If the relationship between both parties is appropriate the worker does not look for other jobs. This number represents the threshold for not looking.
- **Discountreswage:** Discount rate for the reservation wage of the workers. Workers discount their reservation wage under certain conditions. This number represents the rate of discount
- **Probability_of_reinsertion:** The probability for a self-employed worker in the informal sector to return to job searching.
- **Powerinformal:** An integer that quantifies the production capacity of an informal firm.
- **Maxvacancies:** The maximum number of vacancies a firm can offer each turn. It is also a vacancy cost parameter. The greater the number, the cheaper a firm can provide vacancies in the market.
- **Maxinformal:** The maximum number of informal workers an informal firm can hire. This feature was added since informal firms in developing countries are small-scale to prevent notoriety (Pratap and Quintin (2006)).
- **Destruction_threshhold:** A threshold number for the idiosyncratic match determining if the worker is laid off. If the relationship between the firm and the worker does not produce a sufficient surplus, the firm lets the worker go. This number represents the threshold for this to happen.
- **Powerformal:** An integer that quantifies the production capacity of a formal firm.
- **Probinformal:** a firm's probability of being informal.
- **Waitingtime:** An integer that quantifies the number of iterations a worker will wait before considering becoming self-employed informally.
- **Ite:** Number of iterations for the simulation.

- **NumbWorker:** Number of workers in the simulation.
- **NumbFirms:** Number of firms in the simulation.

4.3 Seccond and Third Model Description

Both models incorporate the same features as the first one, with some exceptions; since these two models include social networks, the main differences revolve around this feature. The second model creates an Erdős–Rényi network between the workers, while the third creates a Baraba-Albert network.

The following description emphasizes only the difference between the first and the other Models. There is no description of the Workers since, between models, workers are identical in their behavior. Note that the first model has a double stage in the matching where searching workers go to the formal market and then to the informal. This feature is based on the original model used as our base. However, in the network models, there is a new modification. We only have one stage where the worker looks at firms recommended by other workers in their network with no distinction between formal or informal.

4.3.1 Description of the firm

Establishes a network between the workers that are currently employed in the firm. This feature resembles how social networks constantly evolve by adding new individuals because of their proximity in everyday environments.

4.3.2 Description of the Market

The model simulates how a worker asks his acquaintances for information about vacancies since the worker is connected to a social and household network from which he can get it. The workers incorporate all the firms where their connections work into a list. Then, randomly choose one of the firms with equal probability; if the firm has vacancies and the wage offered is more than their reservation wage, the firm hires the worker. Note that in the previous model, through the matching method, the worker's pool of choice of firms was all the available firms in either formal or informal categories. In contrast, this method narrows the pool to firms where their acquaintances work without differentiating between formal and informal, simulating how people only have limited access to information.

4.3.3 Timing

The timing differs from the first model in three different stages. The first is in the initial phase; after the households and statuses are assigned, the social network is constructed between workers. The second model forms an Erdős–Rényi network, and the third a Barabási–Albert. In the interaction phase, the firms, after creating vacancies, create a small network among their workers. The final different aspect is the matching between workers and firms. In the first model, we have the double phase we already state about. In the new models, we have only one stage with a matching simulation of an actual interaction for job searching, where workers ask their acquaintances for information and search for a job in a firm from the data gathered.

4.3.4 Global Parameters

All the other parameters used in the previous models are also used in these ones. The only new parameters are the ones used in the social network construction. Each model has a different network between the workers. So, each one has a global parameter for constructing the network. In both cases, the bigger the parameters, the more connected the network.

- **ER**: The parameter for constructing an Erdős–Rényi network between the workers. This parameter determines the network's connectivity. It represents the probability of linking edges between pairs of nodes.

- **BA**: A vector parameter for creating a Barabási–Albert network between the workers. The first number represents the number of initially connected nodes. The second is the number of connections a new node must make with the existing network. It influences the growth of the network, where nodes are added over time, and their links are formed based on a preferential attachment mechanism.

5 Simulation

We simulated 21 different models with different input parameters to get a comprehensive global scope of the model. Each model is simulated 1000 times. The output of each model is the distribution of workers in formality, informality, and unemployment. Then, we constructed a time series for each model's output, taking the average for each period of the 1000 results we have in that instance. We ran each model over a 500-period interval. So we ended up with 63-time series of 500 periods each. This same method was used to build the series and data in Bosch, Esteban-Pretel, et al. (2009).

The objective of constructing time series of so many different models is to compare the effects of having information flow through a social network against not. We divided the models into three groups of 7 for comparison purposes. Each group of 7 had a different global parameter of vacancies rate, **Maxvacancies**, different from the other groups. Within a group, one of the models did not use social networks in the matching, while the remaining six did. Three had an Erdős–Rényi network algorithm and the remaining three had a Barabási–Albert. The six models with networks had different parameters for constructing the net according to their specific algorithms. In this manner, we could compare the effects of having social networks against no social networks within groups since the rest of the model is cetris paribus. Also, we could get a general view of how one parameter, **Maxvancancies**, affects the development of the environment in different situations. We did sensitive analyses of two parameters: vacancy rate and social networks.

5.1 Calibration for initialization

To create the households with the Montecarlo method, we used the averages from Table 2. As we already stated, the household distribution is identical every year in a stylized fact manner in Ecuador, so choosing the average is appropriate for our model to simulate an artificial one. To assign each member their initial type of job, we used the means of Tables 3 to 6. This method will produce a household organization similar to Ecuador.

5.2 Shared Global Parameters Calibration

Model Parameters

- **Maxwageinformal:** 600
- **Productivity_threshhold:** 7
- **Discountreswage:** 0.9

- **Probability_of_reinsertion:** 0.3
- **Powerinformal:** 80
- **Maxinformal:** 10
- **Destruction_threshhold:** 2
- **Powerformal:** 200
- **Probinformal:** 0.4
- **Waitingtime:** 3
- **Ite:** 500
- **NumbWorker:** 500
- **NumbFirms:** 50

We chose the values for these parameters based on intuition and common sense. The model was not trying to capture empirical data or reality. We compared models, particularly with and without social networks, everything else cetris paribus. The few parameters that had an empirical relation are related to wage equations. Since we took the household distribution of formal and informal from actual data, we based the wage difference in informal and formal markets on the same data. We will explain the calibration for parameters that have an empirical basis which are only three.

Powerformal and **Powerinformal** values were chosen based on the data. Table 7 shows the mean and median wages for formal and informal workers in Ecuador for ten years. Also, we can see the ratio between formal and informal in average and median for the same ten years. The average salary for formal workers is around 500, and for informal is about 200. Their ratio is about 2.5 between them. The production capacity of a formal firm is 2.5 times bigger than an informal one. Using our equations that determined salaries, we can work backward to find firms' production capacity. The equations are the following

Wage=Bargaining*Surplus
Surplu=Prod*Firmpower
Wage=Bargaining*Prod*Firmpower

To clarify, **Firmpower** is a number that represents the power capacity of a firm. It is equal to **Powerformal** if the firm is formal and **Powerinformal** if it is informal. As stated, **Prod** is a random number from one to ten, and **Bargaining**, which represents the intrinsic bargaining power of a specific worker, is a random number from zero to one. The average worker will have a **Prod** of five and a **Bargaining** of 0.5. With a **Firmpower** of 200, the average wage will be 500. So, a **Powerformal** of 200 is a good calibration for the model. Finally, the production capacity of a formal firm is 2.5 times bigger than that of an informal one; setting the parameter **Powerinformal** to 80 is appropriate and coherent since the average informal workers' salary will be 200, the Ecuadorian average.

The last parameter with an empirical basis is **Maxwageinformal**. In Table 7, the maximum infornal wage is around 600. Since the salary for an informal self-employed worker is:

Selfproductivity*Maxwageinformal

Where **Selfproductivity** represents a worker's intrinsic capacity to produce independently in the informal market, is a random number between 0 and 1. Setting the **Maxwageinformal** parameter to 600 will be appropriate since the more productivity, the more significant the fraction of the **Maxwageinformal** he will receive.

5.3 Calibration of the networks and vacancy rate parameter

The rates of the vacancy parameter for our models were **Maxvacancies**=4,5,6. These values gave us a spectrum to compare different models and analyze how sensitive a model is to slight changes in the vacancy rate, an essential element of markets.
The network parameters were decided in the same spirit of having an ascending spectrum. The bigger the parameters' values, the more connected the social net. The ER values are: 0.10,0.15,0.20 The BA values are:[60,20],[40,10],[20,5]

6 Results and Analysis

6.1 Sensitivity analysis of network implementation

Figures 1 to 21 from our models show a stabilization phase in the first periods. After the stabilization phase, all models converge in the distribution of the categories of workers. We took the last 100 periods of each series and constructed Tables 8 to 10 to do comparative statistics and analyze our graphs. Since the standard deviations of our data are minimal, and all of the graphs clearly show a convergence phase in their distributions, we used the mean to compare each model convergence stage. But first, let us start by analyzing the graphs produced by the models to get a general idea of the results. We begin by comparing Figure 1 with Figures 2-7, which all have the exact calibration except for the matching method. Figures 2-7 have a network matching; we can see that figures with networks are very similar, including the stabilization phase. They end up with a higher percentage of informal workers followed by a significant percentage of formality, and the percentage of unemployment is meager. Conversely, Figure 1 shows a more considerable percentage of formality followed closely by informality and a low percentage of unemployment.

In the second group of Models with the exact calibration except for the matching method, we see they are more uniform. Like in the last group, the models in Figures 9 to 14 with networks look exactly like each other, with a higher percentage of formality followed by informality and a low percentage of unemployment. In Figure 8, the Model with random matching, we also see that formality surpasses informality, and we have a low percentage of unemployment. Still, the gap between formal and informal is more extensive than in the other models.

We can see the most significant discrepancy between random matching and network models in the final group of models where the vacancy cost is higher. Figure 15 represents the Model without networks, and we see a more considerable percentage of informality followed by a significant percentage of formality. As in all graphs until now, unemployment is the lowest percentage. However, Figures 16 to 21, in the models with networks, all have the same structure of having almost all of the workers located in informality, while unemployment and formality are almost at zero. The informal markets embrace all of the workers.

Table 8 shows the means of formal workers of each Model from the time series constructed from the convergence phase of the models. The Model without networks and a **Maxvacancies** parameter of 5 has a mean of around 0.47, while all the network models with the same parameter produce means between 0.34 and 0.36. With M**axvacancies** equal to 6, the mean of the no-network Model is around 0.62, while the models with a network lie between 0.57 and 0.59. Finally, with a **Maxvacancies** Parameter of 4, the difference is very significant, with 0.34 percent in the Model without networks and a range of 0.029 to 0.034 in the others. When comparing the means of formal workers of each Model with a network with their respective without, we can see that the models without a network have a more considerable percentage of formality than all others.

The informality convergence results from our models are shown in Table 9. Informality has the opposite pattern of formality. Models with networks have a more significant mean than the respective Model without a network. Informality in models with networks and **Maxvacanncies** equal to 5 has an average that ranges between 0.50 and 0.53, while the Model without a network has an average of 0.42. The same fact happens with **Maxvacancies** equal to 4 since models with networks have an average of informal workers that range between 0.93 and 0.95, while the mean in the Model without a network is around 0.52. The exception lies when the **Maxvacancies** parameter is at its highest with 6. Here, the Model without networks has an average of 0.30 in informality. The models with networks have slightly bigger values, except for the Model in Figure 15, which has a mean of 0.29, slightly below. Even though there is this exception, networks decrease the percentage of formal workers and increase the informal share, and the overall ratio of informality to formality increases in a market.

When we compared the models with network implementation with the respective Model without it and everything else cetris paribus, we could see that the models with networks differ significantly from those without. However, the models with networks are almost identical. It is interesting since it shows how an actual space where information flows changes the Model's results. But, there are no significant fluctuations for different types of networks.

6.2 Results of sensitivity analysis of the vacancy parameter

Figures 1, 8, and 15, the Models without networks, show a trend once the stabilization phase happens. Figure 1 has a greater **Maxvacancies** parameter than Figure 15. The first graph shows that the formal percentage of workers is more significant than the informal by around 5 percent on average. On the other hand, Figure 15 has more informal workers than formal ones, and their average gap difference is about 18 percent. As the vacancy creation parameter decreases, i.e., as vacancy costs increase, the formal market decreases.

A different outcome is produced when comparing Figure 1 with Figure 8, a Figure representing a Model with a bigger parameter **Maxvacancies**. Both have more formal workers than informal workers, but the Model represented in Figure 8 shows a difference of around 30 percent between them. As the **Maxvacancies** parameter increases, there are more workers in the formal market compared to the informal. Also, we can see a monotonic tendency on our graphs; the bigger **Maxvacancies**, the more significant the percentage of formal workers. Meanwhile, informal and unemployed rates fall as the parameter increases. The sensitive analysis produces stylized facts results already found in our based model Bosch, Esteban-Pretel, et al. (2009) and in Ulyssea (2010). These results show the validity of our Model from the grounding standpoint, a validation technique that duplicates expected stylized facts (Carley (1996)).

As already stated, **Maxvacancies** represents the cost of posting a vacancy. The smaller the number, the more expensive it is to post a vacancy. As the cost of posting vacancies in the formal market increases, the share of formality decreases, and unemployment increases. In our experiments, we diminished and enlarged the cost of vacancies in both sectors. Nevertheless, our Model still replicated the stylized facts. It may even suggest stronger results; no matter if vacancy costs in the informal market are reduced, the share of formality will increase if the formal market also reduces its vacancy cost.

When doing the sensitivity analysis of network models, the results are almost identical. The Model can still reproduce one of the stylized facts. In each network model, formality decreases, and informality increases as the cost of posting vacancies increases. We can see this easily since when **Maxvacancies** is 6, there is a more considerable percentage of formal workers over informal in all network Models. Then, when the parameter is 5, formality and informality flip, having a more significant percentage of informality. Finally, in all Models with **Maxvacancies** 4, the informal market is around 93 percent of all workers. But the other stylized fact of unemployment falling when the cost of posting vacancies is reduced was not reproduced entirely, since unemployment falls when **Maxvacancies** goes from 4 to 5.

6.3 Statistical analysis

We conducted a statistical hypothesis test with our data to give our results more strength than comparing the means only. Since our data is not normally distributed and has different standard deviations but has 100 observations from the last 100 periods, we can use the Wilcoxon rank-sum test and Welch's t-test (Fagerland and Sandvik (2009)). When comparing the formality percentage of models with a network against the one without, we use the one-sided alternative hypothesis that the non-network Model is greater than the others. On the other hand, when comparing informality, we used an alternative hypothesis of less than in the non-network Model.

The results are recorded in Tables 11 to 13 for informality and 14 to 16 for informality. The results show p values smaller than 0.05 in all tests, except when comparing the exception model already reported in the last section, rejecting the null hypothesis and accepting the alternative. Even though we have this exception, when we consider that networks increase the informal market and decrease the formal, we can say that networks increase the ratio of informality to formality.

To prove this, we constructed a new time series. We created the first group of time series when dividing the percentage of informal workers over formal ones for each of the last 100 periods in each of the 21 models. We constructed the other group of series using the same idea of the series composition but with a difference: subtracting informal workers from formal ones. The new series captures the relationship between informal and formal workers in the 21 models. In the first group, the bigger the number, the more informal workers we have compared to formal ones. In the second group, the bigger the number, the more formal we have compared to informal workers. Then, we did the same statistical hypothesis tests comparing series with networks to their respective series without. Using as the alternative hypothesis that the Model without networks was less than the others in the first group of the series. The alternative hypothesis in the second series group was that the Model without networks was more significant than all the Models with networks. Tables 17 to 22 show the results; the p-values are smaller than 0.05 in all cases, so we accepted the alternative hypothesis. In this manner, we have evidence for assuring that network introduction in all of our models increases the ratio of informal to formal workers.

6.4 Results of the Initial Phase

The first result in our models is the exact initial distribution of workers in the first turn. In all graphs of our models from Figure 1 to Figure 21, we can see that the initial distribution of workers starts with more workers in the formal sector. Followed closely by the informal workers, but there are always in all 21 models more formal workers than informal. Finally, we have a small percentage of workers in unemployment. This initial distribution in the first period corresponds in a stylized facts manner precisely to the distribution of workers in Ecuador in the ten years of our data, as shown in Table 7. We created Figure 22 with the initial distribution of each Model. When comparing Figure 22 and Figure 23, which represent the Ecuadorian distribution, we can see their similarities in distribution. These results imply that our models can replicate Ecuador's aggregate distribution and construct an artificial country using household distributions, giving the initial phase of all our Models validation from a grounding standpoint.

7 Discussion

7.1 How did we get rid of Idealizations

As said in the Introduction, big idealizations were made to yield results in Search and Match models. So how exactly did we replace the value functions representing workers' and firms' interests, the MF, Nash Bargaining Theory for determining wages, and the equilibrium state for determining the number of vacancies, searching workers, and market behavior? The individual agents with limited information and heterogeneity for objective satisfaction replaced the value equations. Instead of using the MF, we incorporated random matching in the first model. Even though it seems rudimentary, the process still captures the friction since not all matches were successful because of reservation wage limitations or vacancy exhaustion. Also, the matches still depended on the vacancies available and the number of searching workers. The other two models incorporated networks as the matching method, still capturing the frictions already stated. Instead of the assumptions of equilibrium to solve the model, we endogenized;

- Vacancy creation based on speculation from current workers' productivity and a parameter representing the cost of posting vacancies.

- Searching status and Job destruction based on the value of the idiosyncratic match, a concept already found in traditional search and match models but adapted to ABM. The fact that the idiosyncratic match is actualized each turn represents how workers and firms evaluate their partnership.

Instead of using Nash's theory, wages were determined on the heterogeneity of each worker's capacity to bargain their salary from the surplus they bring to the firm.

7.2 Discussing Results

The first discussion will be on how network matching produces higher levels of informality. Firstly, the importance of networks in the Model's outcome is evident. Networks created a lower share of formal employment in all scenarios over random matching. Workers appear to choose informality because they don't receive information about vacancies in formal markets. There are vacancies available since firms post an arbitrary random number of vacancies each turn, even without workers on the payroll. However, the information seems not to be delivered to agents to choose formality. Workers in network models are not exposed at each turn to information in formal firms like in the random matching Model with the two stages in the interaction phase. This feature limits the amount of data that flows, limiting the knowledge of hiring firms, unlike in random matching, where all firms are potential matches and workers are constantly receiving this information. Workers in our Models can become self-employed informally when they have yet to find a job a certain number of turns. The lack of vacancies contributes to more workers choosing this option. Once the workers are under this status, they lack information about vacancies, and searching for other workers is hindered since they lack information from their network about firms with open vacancies. This feature is accentuated when the vacancy cost is at its highest since almost all workers enter the informal market. It seems to be that once a certain percent of the population ignores information about vacancies, it affects everybody because pairing with firms depends on the global flow of information, leading to a massive expansion of the informal market. We can see the importance of incorporating networks in models since they affect the results and processes in a significant manner. It may be the case that Search and Match Models ignore an essential aspect of the labor market that could explain the considerable percentage of informal markets in certain countries. Finally, we can infer the importance of the search method being used by a community since that institution alone produces far different results and may significantly impact the labor market outcome of a population.

Our random and network-matching approaches produced the same results in other papers relating vacancy cost to formality. What our Model has done to the result as vacancy cost reduces the formal market increases compared to the informal market is make it more robust.

This result appears in various models of informality under different structural assumptions; the assumptions made in our Model are far weaker than those made in those models. Our structural assumptions are more credible since they are not idealizations.

Both economist theorists Cartwright (2009) and Sugden (2000), even though they disagree on several points, agree that to make the inductive inference from the Model to the real world(Vacancy cost reduction causes an increase in the share of formality in the Model, so Vacancy cost reduction may cause an increase in the share of formality in the real world), less perilous; the structural assumptions in the Model need to be credible. Credible means that the features being analyzed in the Model behave according to principles dictated by structures existing in the real world that may exhibit those principles. In our Model, the structures in the real world are the agents, and the principles are all of the rules of behavior. As already stated, their rules are the institutions. On the other hand, the principles in the search and match model structures are idealized, or the structures themselves don't exist at all, like the Matching Function. ABMs trade idealizations for institutions, which is an excellent business for making inductive inferences.

Cartwright (2009) point out a second concern about the inductive leap, especially in economics. She argues that a feature in the Model with some capacity may not have that same capacity in the real world or may not be fixed. She points out that models can not reveal capacities; they only measure them. For example, in physics, the Model of the orbit. Masses always have the capacity to attract each other, i.e., gravity. Gravity, initial velocities, and laws of physics yield the results of the orbit formation. Note that the Model incorporated gravity from empirical observation, and the Model did not reveal that gravity was acting. It only measures results. The orbit phenomenon results from the fixed capacity of gravity and established laws of how forces behave. Physics's advantages over economics are that they found principles of behavior (i.e., Newton's laws) and fixed capacities like gravity. Capacities are not set in economics and the social sciences. An example is the subjugation of women. Women have the capacity for creativity and independence of thought. But that capacity is not fixed and depends on the institutions that will enable women to exploit them. How can economists construct models without them?

The answer relies on emergence and credibility (Gangotena (2016)). Complex adaptive systems produce emergent results. Results that the properties of individual agents of the system cannot predict. In this sense, the orbit result is not a complex adaptive system since the individual agents and their principles can predict the orbit. On the contrary, the result from our models is an emergent capacity. It was not programmed for agents to choose formality as the vacancy cost was reduced. We agree that the capacity of cost reduction to expand formality may not be fixed since it was not originally programmed. It was sustained by the principles of the structures, i.e., institutions of the agents in the Model. We observed how agents' capacities(capacity to produce firms, capacity to search for work, etc.) interact to produce emergent capacities. Of course, the agents have fixed capacities, but as already stated, the agent's capacities and principles should be credible. Credible capacities can be obtained from empirical investigation of political institutions or cognitive sciences and be used at an agent level for the Model. Plausible ABMs can reveal emergent capacities and give us an insight into the institutions that allow them to rise.

ABMs help the inductive inference leap and shed light on the institutions and processes that sustain the result. Thanks to the inductive claim, we suspect that cost reduction causes the expansion in informality. Now, we have a theory of the institutions necessary for this capacity to emerge since all the structures, capacities, and principles in our models are credible or at least more plausible than the ones in Search and Match Models. It may be the case that workers search based on a constantly changing relationship with their firms, and firms post vacancies based on current speculation. All of the substitutions we made clear at the beginning of the section contribute to our theory of how a market is composed.

Our Model shows that the capacity for vacancy reduction to decrease unemployment emerged when the matching was random. But, when networks did the matching, the result did not hold, showing how ABM models and Cartwright's second concern coexist. Capacities are not fixed. Let us construct a theory of this result using the whole context of the Model. Network Models with **Maxvacancies** equal to 4 have an informal market of around 93 percent, resulting in an insufficient vacancy information flow about jobs, so the workers choose self-employment in the informal sector. Workers are no longer constantly fired by firms and rotate between jobs while searching since most work independently. Hence, the unemployment rate is almost negligible in a big informal market. This theory was only possible because we knew the institution choosing independent informality was available for workers after a certain number of turns. Two institutions, network searching and informality combined, contributed to an interesting emergent phenomenon like having the lowest unemployment when vacancy cost is the highest. We can see from our results how institutions of behavior matter in the outcome and, more importantly, how they matter in complex adaptive systems in general.

There is an interesting fact about our models. Under some calibration, all of them can reproduce Ecuador's original distribution in a stylized fact manner. The network models produced the distribution with a lower vacancy cost. This validation technique is called calibrating (Carley (1996)) when a model can reproduce the empirical data under some calibration. However, a calibration may always exist that will reproduce the data without any insight into relationships between variables. ABM models have far more power in processes than just in producing results.

Finally, since all of our network models have identical patterns between them when they share the same calibration except the network, we can rely on the findings of Lewkovicz, Thiriot, and Caillou (2011). They found that the initial network changes as the model progresses and becomes secondary to the evolution. It may be the case that our initial network changed with the new ties formed in the firms, and these new ties determined the outcome. Since all our Models have the same network evolution based on new relations in the firms, they all have the same result.

8 Conclusions

We wanted to observe the importance of networks in searching for jobs. We constructed different ABMs to compare them. The results show that incorporating networks in the Model expands the informal market. Also, using the information from our Model, we can speculate on the mechanisms of how networks promote informality. Finally, our Model produced stylized facts seen in other models, but in ours, they were Emergent results that arose from far weaker and more credible assumptions.

We explored the relationship between networks and the informal market because we suspected that narrow information is a sustaining factor of informality. Ecuador has significant social class divisions (Cajas Guijarro et al. (2015)). These divisions may contribute to sustaining the informal market since information about vacancies is not shared outside the class division. Our Model shows how limiting information can affect the aggregate population. Our networks are not clustered based on social division. Nevertheless, their incorporation produced more significant informal markets. More clustered networks may deliver more significant shares of informality, making class division a vital factor in maintaining informal markets. However, implementing this will be difficult since finding how people are connected socially in any community is complicated.

For future research, three adaptations could be made to the Model:

- At the beginning of the turn, the type of worker, formal, informal, or unemployed, determines the probability of connection between workers. The likelihood of forming a network connection between the same kind of workers would be higher. This will mimic how a country is divided by social classes and allow the researchers to compare results with other networks. Even though it is not the same as basing the networks on an actual social environment, the findings could give us insight into how networks based on a social condition affect the labor market as a whole. To whitewash the degree of importance of the initial network, we would make it the only information delivery mechanism and not alter it. Based on our findings, it seems that the original distribution will play an essential role in the development of the Model since the information won't be able to spread past the clusters.

- Workers in our Model ask their neighbors for information; the adaptation could incorporate Granovetter's theory. Granovetter's result was not implemented in our Model. If workers find information about vacancies from the neighbors of their neighbors, it may be the case that information spreads wider through the networks. Our results show that if a certain percentage of the population does not have information, everyone is hindered significantly. Granovetter's matching mechanism could prevent the lack of flow from happening.

- Incorporate more credible capacities at an agent level, like the cost of searching, taxation, wage determination, and the vanishing of firms. A lot of these capacities can be found in Search and Match Models. Even though Search and Match Models have limitations, many of their ideas are credible and can be implemented in an ABM to create credible environments. A more credible environment may give more insights into the mechanisms of the labor market. For example, if the firms are not productive after certain turns, then they disappear, which may be a capacity that provides insights into how big firms emerge while others disappear.

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10 Appendix

10.1 Models

It includes the same global parameters already described in Section 4.

10.1.1 First Model Description

Description of the class Worker Attributes of the Worker

- **Id:** A unique identifier integer for each worker.
- **Market:** A reference to the market in which the worker operates.
- **Memory:** An integer that counts the number of turns the worker has been in the same firm.
- **Memoryselfinformal:** An integer that counts the number of turns a worker has been informally self-employed.
- **Memoryunemployed:** An integer that counts the number of turns a worker has been unemployed.
- **Formal:** A boolean variable that represents whether the worker is employed formally or informally.
- **Income:** The worker's current income.
- **Firm:** A reference to the firm that the worker is employed in.
- **Firmid:** Refers to the unique identifier of the firm the worker is employed in.
- **Em:** A boolean variable that represents whether the worker is employed or unemployed.
- **Search:** A boolean variable representing whether the worker is searching for a job in the current turn.
- **Bargaining:** A random value from 0 to 1 determines each worker's bargaining power over their wage. This variable varies between workers to have heterogeneity between them.

- **Selfproductivity:** A random value from 0 to 1 determines each worker's capacity to generate income by being self-employed informally. This variable varies between workers to have heterogeneity between them.
- **Reswage:** The worker's reservation wage for the current turn.
- **Selfin:** A boolean variable that represents whether the worker is self-employed informally.
- **HhId:** The household ID that the worker belongs to.
- **HhSize:** The household size that the worker belongs to.

Functions of the Worker

- **Hiring:** This function sets the worker attributes when hired by a firm. This function assigns the worker to the hiring firm. Since the worker is employed in the firm, it makes the attributes **Em** equal to **True**. The attribute **Firm** is equal to the hiring firm, and the attribute **Firmid** is equal to the hiring firm's id. That way, the worker is linked to the firm they are working for. It makes the **Income** attribute of the worker equal to the wage the firm offers him. It sets the **Selfin** and **Search** boolean attributes to **False** since a firm hires the worker and won't be looking for a job in the first turn he is employed. If the firm is formal, the attribute **Formal** is set to **True**; otherwise, if the firm is informal, the attribute is set to **False**. Finally, it returns the attributes **Memoryunemployed** and **Memoryselfinformal** to zero.
- **Selfinformal:** This function activates when the worker's reservation wage is less than what he can win informally self-employed:

  $$\textbf{Selfproductivity} \times \textbf{Maxwageinformal} > \textbf{Reswage}$$

  Sets the worker income **Income** equals the global parameter **Maxwageinformal** times the worker's attribute **Selfproductivity**. That way, depending on the worker's productivity, he will receive a proportion of the highest income being informally self-employed. The worker's reservation wage **Reswage** becomes his newly assigned income. It sets the Booleans **Em** and **Selfin** equal to **True** since the worker is self-employed in the informal market. The Boolean attributes **Search** and **Formal** are set to **False** since the worker won't be looking for a job as soon as he becomes self-employed and the worker is not in the formal market.

- **Firing:** This function activates when a worker is laid off. The booleans **Formal** and **Em** become **false** since the worker has returned to unemployment. The attribute **Firm** and **Firmid** are reset to **None** since the worker no longer has a relationship with the firm. The worker returns to search for a job, so the attribute **Search** is set to **True**. The attributes **Income** and **Memory** go back to zero since the firm is no longer paying the worker and working for it. Finally, the reservation wage of the worker **Reswage** is the income he was receiving from the firm times the global parameter **Discountreswage** since the worker will be willing to work in a future firm based on what he used to win but will be able to lower his reservation wage since he is unemployed.

- **Analyze:** This function determines if a worker is searching for a job while working in a formal firm. It depends on the idiosyncratic productivity shock that the worker draws each turn in the formal firm. If the shock exceeds the global parameter **Productivity_threshhold**, the worker will not search for a job, and the attribute **Search** will become **False**. Otherwise, he will be looking, and the attribute will be set to **True**. On the other hand, workers in informal firms always search for a job.

- **Analyzeunemplyed:** The function activates when a worker is unemployed after the searching phase of the model. It adds one to the **Memoryunemployed**, and it multiplies the **Reswage** of the worker times the global parameter **Discountreswage**. That way, each turn the worker is unemployed, his reservation wage will decrease.

- **Selfinformalanalyzed:** The function updates informal self-employed workers. It adds one to the **Memoryselfinformal** attribute since the worker is one more turn in this status. It also draws a random number. If the number is less than the global parameter **Probability_of_reinsertion**, the worker searches for work in a firm, so his **Search** attribute is set to **True**. Otherwise, the worker decides not to search and stays in its current status, and the attribute remains **False**.

- **SetHouseHold:** This function sets the worker's **HhId** and **HhSize** attributes. It assigns an integer **HhId** to the households each worker belongs to, and it sets **HhSize** to the number of workers who belong to that house.

Description of the class Firm Attributes of the firm

- **Id:** A unique identifier integer for each firm.

- **Market:** A reference to the market in which the firm operates.
- **Formality:** A Boolean variable indicating whether the firm is a formal or informal employer.
- **Vacancies:** An integer representing the number of job vacancies the firm has to offer in the current turn.
- **Workers:** A list of workers currently employed by the firm.
- **Workersid:** A list of unique identifiers corresponding to each worker's attribute **Id** employed by the firm.
- **Surplus:** A list of surplus values produced by each worker the firm employs.
- **Prod:** A list of idiosyncratic match productivity levels corresponding to each worker the firm employs.
- **Wage:** A list of salaries paid to each firm-employed worker.
- **Potentialproductivity:** A number representing the idiosyncratic productivity level of the match between the firm and potential future employees.
- **Firmpower:** An integer representing the production power of the firm in the market.

Functions of the Firm

- **Createvacancies:** Creates job vacancies based on the productivity levels of the workers currently employed by the firm. Since the value generated by the firm depends directly on the production of their workers. The more productive workers, the more profit the firm has. Based on this rationale, we make the number of vacancies rely on the idiosyncratic matches, **Prod**. The equation for producing vacancies is the following.

  $$\mathbf{Vacancies} = \text{ceiling}(\text{mean}(\mathbf{Prod}) + \mathbf{Maxvacancies} - 10)$$

  The equation shows that the bigger the parameter **Maxvacancies** is, the c¡heaper it is to produce vacancies. Also, since the mean(**Prod**) maximum number can be 10. The maximum number of vacancies a firm can create in one turn is **Maxvacancies**. Finally, the function sets **Potentialproductivity** equal to mean(**Prod**) since potential workers will start working with the average productivity of the other workers until their new productivity is revealed in future turns.

The equation is only activated when the value is positive. Otherwise, the firm stays with the remaining vacancies from the last turn and maintains the **Potentialproductivity** value. If the firm has no workers, it sets the number of vacancies to a random value between 0 and the global parameter **Maxvacancies**. Also, The **Potentialproductivity** attribute is set to a random number between 0 and 10. If the firm is informal and the number of vacancies plus current workers exceeds the global parameter **Maxinformal**, it reduces the number of vacancies accordingly.

- **Hiring:** Hires a worker by adding him and his **Id** to the **Workers** and **Workersid** lists, sets their productivity level by adding the value of **Potentialproductivity** to the **Prod** list and updates the **Vacancies** attribute by subtracting one since there is one less vacancy to offer.

- **Firingfirm:** Removes a specific worker by removing him from the list of **Workers** and his information from **Prods** and **Workersid** lists. Lastly, it calls the **Firing** function for the fired worker to update his status. It mimics a laid-off.

- **Destruction:** Fires workers whose productivity levels fall below the global parameter **Destruction_threshhold**. Calls the **Firingfirm** function for each of these workers.

- **Idio:** calculates the idiosyncratic productivity level **Prod** of each worker in the list of **Workers** who have worked for the firm for more than one turn. Their new **Prod** is a random number between 1 and 10. Each worker has a different **Prod** to have heterogeneity. Newly added workers stayed with a productivity level **Prod** of **Potentialproductivity** for their first turn in the firm. Calls the **Analyze** function for each worker whose productivity level changes. This function mimics how the productivity level of the match between a worker and a firm changes over time.

- **Production:** Calculates the **Surplus** each worker produces based on their productivity level **Prod** and the firm's production power **Firmpower**. The list **Surplus** equals **Firmpower** times each member of the list **Prod**; it is a vector times scalar multiplication. It adds one to the **Memory** of each worker in the list of **Workers** since they have completed a turn working for the firm.

- **Setwages:** Calculates the **Wage** paid to each worker based on their value produced, **Surplus**, and each worker's bargaining power **Bargaining**. Each **Wage** = **Bargaining** × **Surplus** for each worker in the list of **Workers** and their corresponding bargaining capacity and value they have produced. It sets each worker's **Income** and **Reswage** equal to their new **Wage**.

- **SetFormality:** Changes the formal/informal **Formality** attribute of the firm and updates the **Firmpower** variable accordingly. Formal firms have the **Firmpower** attribute equal to the global parameter **Powerformal**, while informal firms have **Powerinformal**.

Descrition of the class Market Attributes of the Market

- **Worker:** Represents the list of workers that operate in the market.
- **Firm:** Represents a list of firms that operate in the market.
- **Numbersemployedformally:** Number of workers employed formally.
- **Numbersemployedinformally:** Number of workers employed informally.
- **Unemployed:** Number of unemployed workers.
- **Firm-formal:** List of formal firms.
- **Firm-informal:** List of informal firms.
- **Households:** List of households in the market.

Functions of the Market

- **Identifier:** Identifies formal and informal firms and adds them to their corresponding list.

- **Match:** Randomly matches a worker with a formal firm. If the firm has vacancies and the wage offered based on the **Potentialproductivity** attribute creates a salary more significant than the worker's reservation wage, the firm hires the worker. If the worker is working for another firm, he is fired and employed by the new one. If the worker matches with his current firm and offers him a more significant wage, then this function mimics a promotion.

- **Matchinformal:** Exactly like the **Match** function, but with informal firms.
- **Getrates:** Calculates the employment status distribution between formal, informal, and unemployed and assigns the number to the corresponding lists to keep track of the distribution.
- **HouseholdNet:** Creates households by connecting groups of workers in a network. The household size is determined by doing a Montecarlo process with the cumulative probability function of a given distribution. The procedure continues until all workers are incorporated into a household. Then, all households are added to the list **Households**.
- **Initializer:** Initializes the market by assigning workers to different firms using a Montecarlo process based on the probability distribution of the organization of workers in a household conditional on the household size. The function goes through all households in the list **Households**. Based on the household size, a different probability distribution is used in the Montecarlo process for assigning the types of work. The worker types are informal, formal, or unemployed. Formally designated workers are matched with random formal firms and hired since their reservation wage at the beginning of the model is 0. Informally appointed workers are matched with informal firms; if the firm has reached the maximum number of workers, the worker becomes self-employed informally.

  This function gives all workers an initial status. Instead of using the aggregate probability in all workers, we used this method to construct a more accurate artificial Ecuador in household organization.

Timing The model has two phases: the **initial** and **interaction** phase. Workers and firms are created in the **initial stage**. The firms are then divided between formal and informal using a Montecarlo process with the **Probinformal** global parameter. At this point, for the **Initializer** function to be executed, we set the number of vacancies in formal firms equal to the number of workers. In informal firms, it equals the maximum number of workers an informal firm can have, **Maxinformal**. There will always be vacancies in the firms, and the assigned workers will be hired since their initial reservation wage, **Reswage**, is zero. Then **Households** are created with the workers and assigned their initial work status with the **Households** and **Initializer** function.

In the **interaction phase**, the firms start drawing the idiosyncratic productivity match for all their workers with the **Idio** function; in this stage, the workers that belong to the firm decide to search for this turn based on their new idiosyncratic match by calling the function **Analyze**. Then they fire the workers under the **Destruction_threshhold** with the **Destruction** function. The firms then produce, set the wages, and create the vacancies in that order, invoking the functions **Production**, **Setwages**, and **Createvacancies**. Then, the matching starts, and workers look for a job in the formal market. The function **Match** is called for all the searching workers. Then, if the worker doesn't find a job, the **Match-informal** function is invoked for the remaining workers. Then, the informally self-employed workers decide whether to search for jobs the following turn by calling the **Selfinformal-analyzed** function. Then, workers who have been unemployed longer than the parameter **Waitingtime** evaluate becoming self-employed informally with their function **Selfinformal**. Finally, the workers that didn't find a job in the current turn discount their reservation wage by calling the **Analyzeunemplyed** function. The interaction phase repeats **Ite** number of times. In each iteration, the distribution of workers is stored.

10.1.2 Seccond and Third Model Description

Description of the class firm Functions of the firm

- **Firmnet**: Establishes a network between the workers that are currently employed in the firm

Description of the class Market The functions **Match** and **Matchinfoma**l are not used in these models since the matching occurs based on network information flow. So, the matching process changes for the new models. Also, note that in the first model, there is a double stage in the matching where searching workers go to the formal market and then to the informal. This feature is based on the original model used as our base. However, in the network models, there is a new modification. We only have one stage where the worker looks at firms recommended by other workers in their network with no distinction between formal or informal.
Functions of the class Market

- **Matchnet**: This function simulates how a worker asks his acquaintances for information about vacancies since the worker is connected to social and household networks where he can get information. The workers incorporate all of the firms of their connections in a list. Then, randomly choose one of the firms; if the firm has vacancies and the wage offered is more than their reservation wage, then the worker is hired by the firm. Note that in the previous model, through the matching method, the worker's pool of choice of firms was all the available firms in either category of formal or informal. In contrast, this method narrows the pool to firms where their acquaintances work without differentiating between formal and informal, simulating how people only have limited information access.

Timing The sequencing phase differs from the first model in three different stages. The first is in the initial phase; after the households and statuses are assigned, the social network is constructed between workers. The second model forms an Erdős–Rényi network, and the third a Barabási–Albert. In the interaction phase, the firms, after creating vacancies, call the **Firmnet** function to make a small network between their workers. In this sense, the model imitates how people meet in new jobs. The final different aspect is the matching between workers and firms. In the first model, we have the double phase we already state about. In the new models, we have only one stage with the **Matchnet** function simulating an actual interaction for job searching.

10.2 Figures

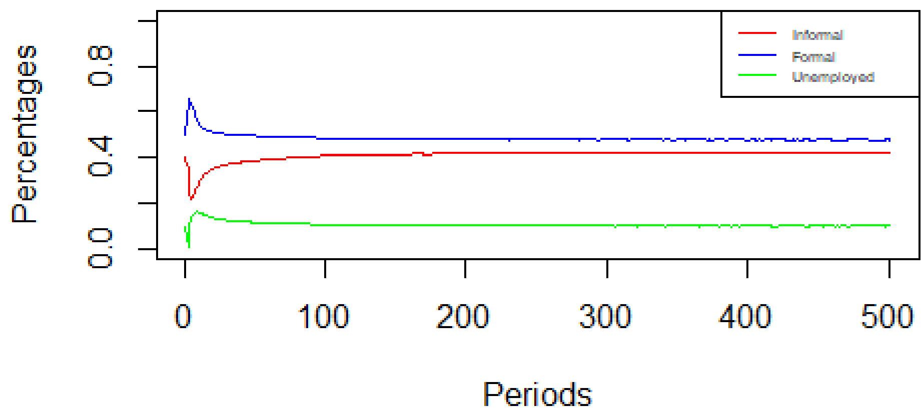

Figure 1: Distributions of workers with calibration: Maxvacancies=5,No Net

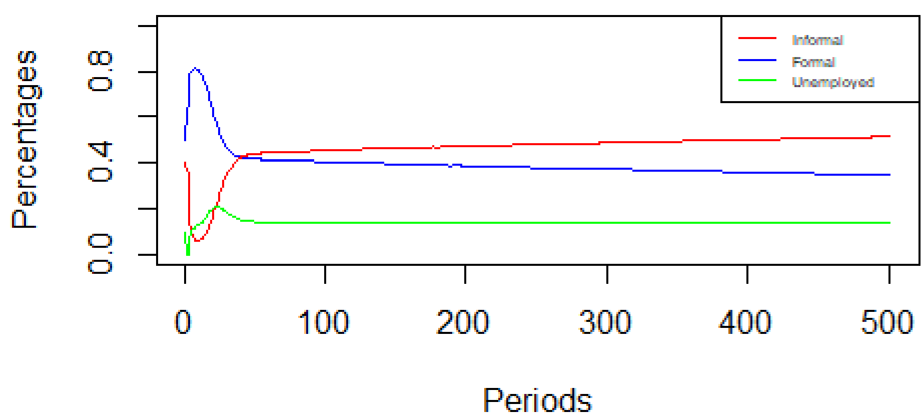

Figure 2: Distributions of workers with calibration: Maxvacancies=5,ER Net=0.20

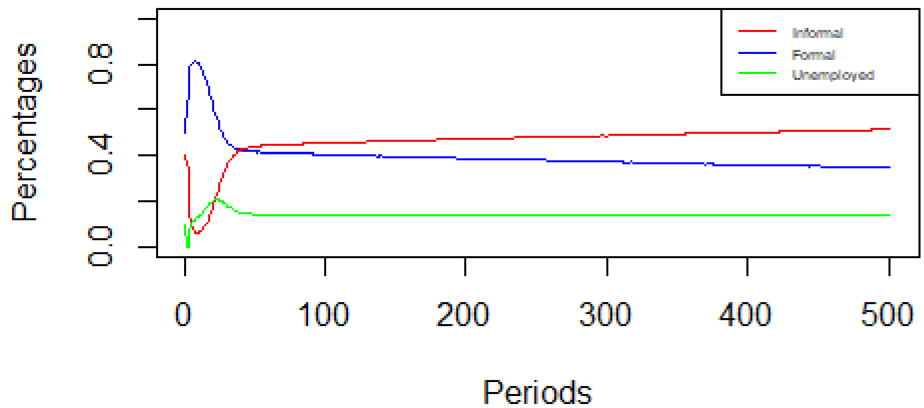

Figure 3: Distributions of workers with calibration: Maxvacancies=5,ER Net=0.15

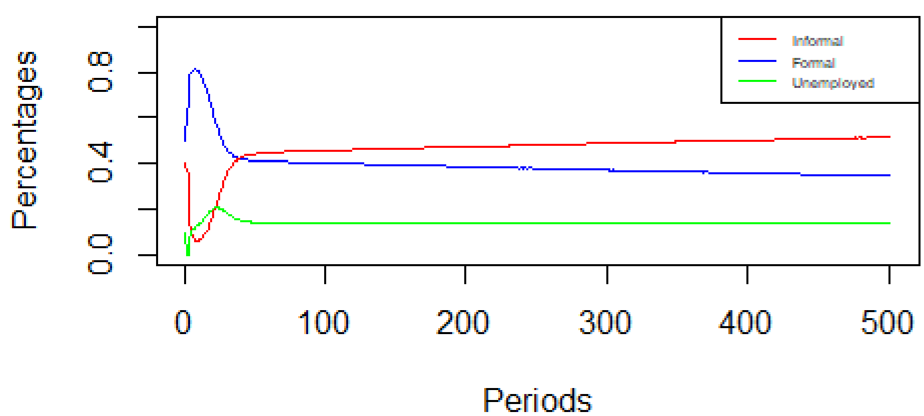

Figure 4: Distributions of workers with calibration: Maxvacancies=5,ER Net=0.10

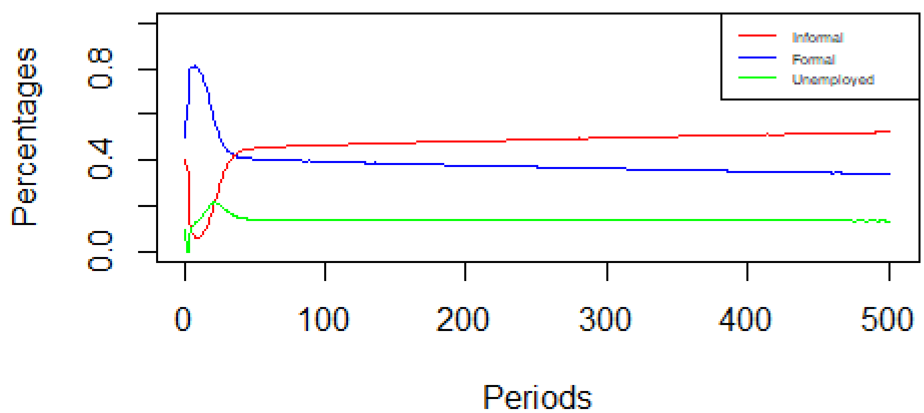

Figure 5: Distributions of workers with calibration: Maxvacancies=5,BA Net=[60,20]

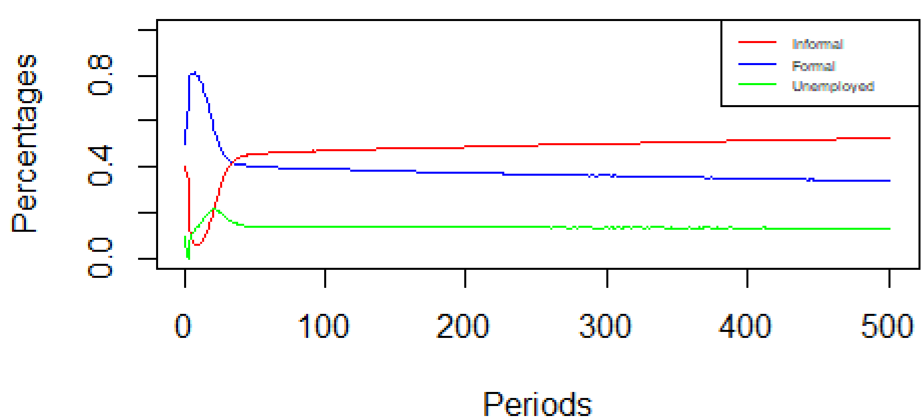

Figure 6: Distributions of workers with calibration: Maxvacancies=5,BA Net=[40,10]

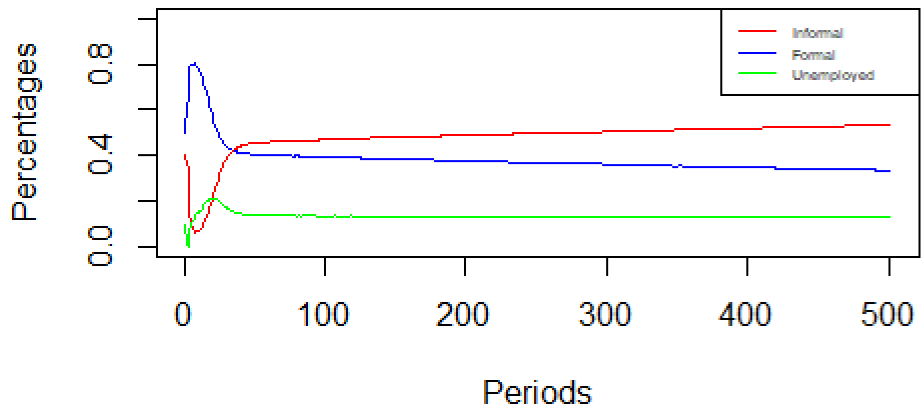

Figure 7: Distributions of workers with calibration: Maxvacancies=5,BA Net=[20,5]

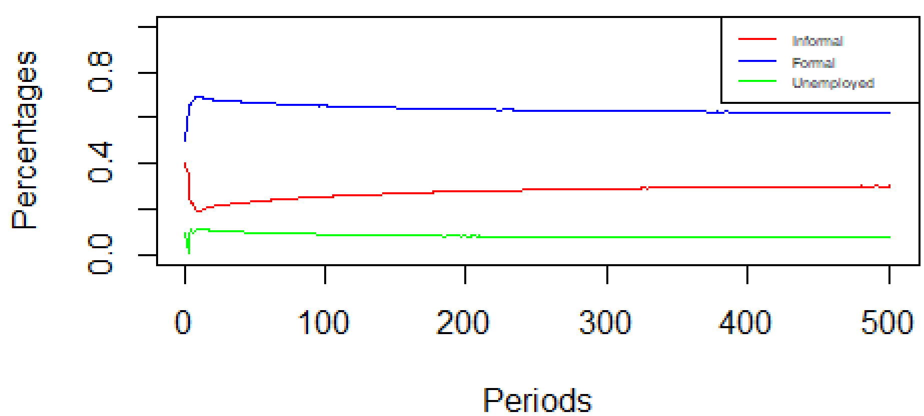

Figure 8: Distributions of workers with calibration: Maxvacancies=6,No Net

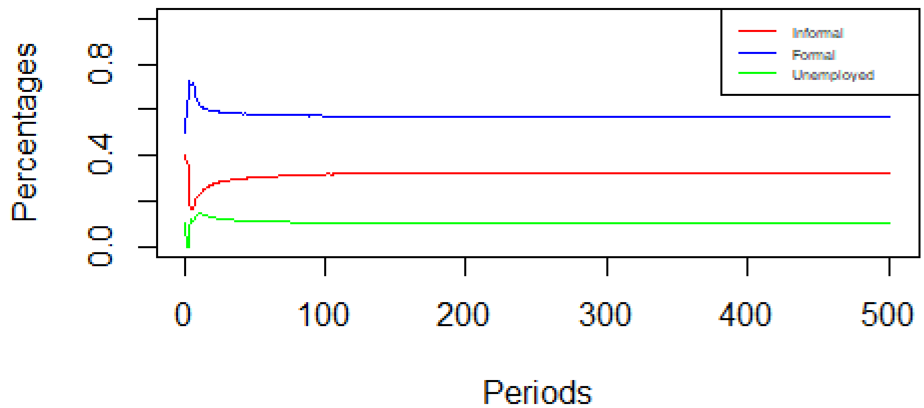

Figure 9: Distributions of workers with calibration: Maxvacancies=6,ER Net=0.20

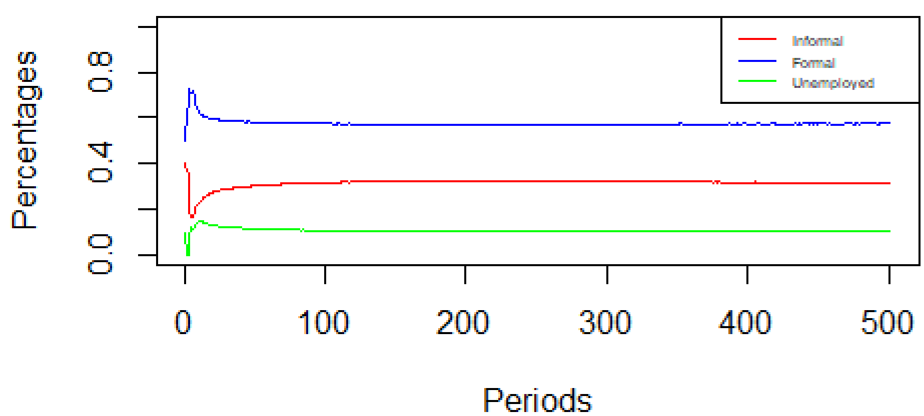

Figure 10: Distributions of workers with calibration: Maxvacancies=6,ER Net=0.15

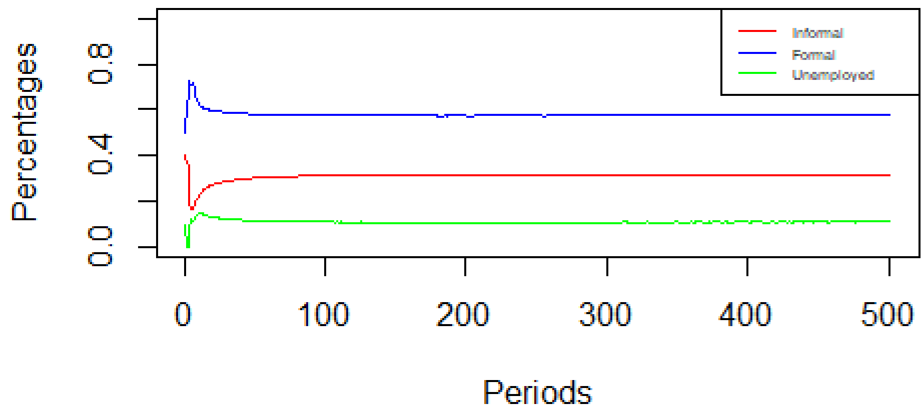

Figure 11: Distributions of workers with calibration: Maxvacancies=6,ER Net=0.10

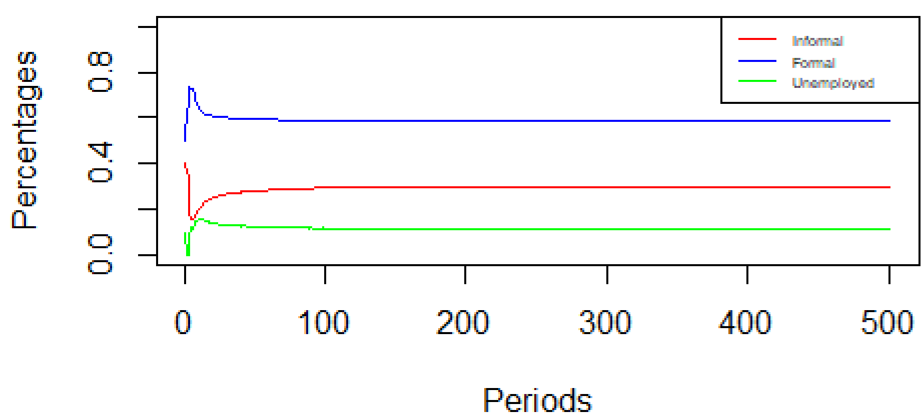

Figure 12: Distributions of workers with calibration: Maxvacancies=6,BA Net=[60,20]

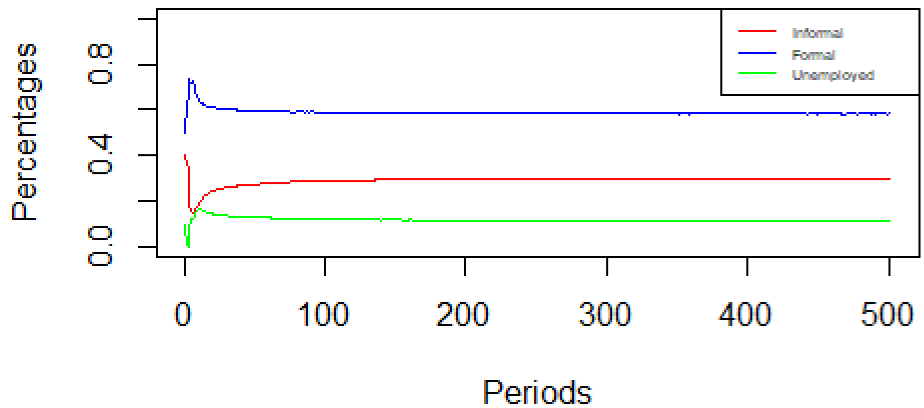

Figure 13: Distributions of workers with calibration: Maxvacancies=6,BA Net=[40,10]

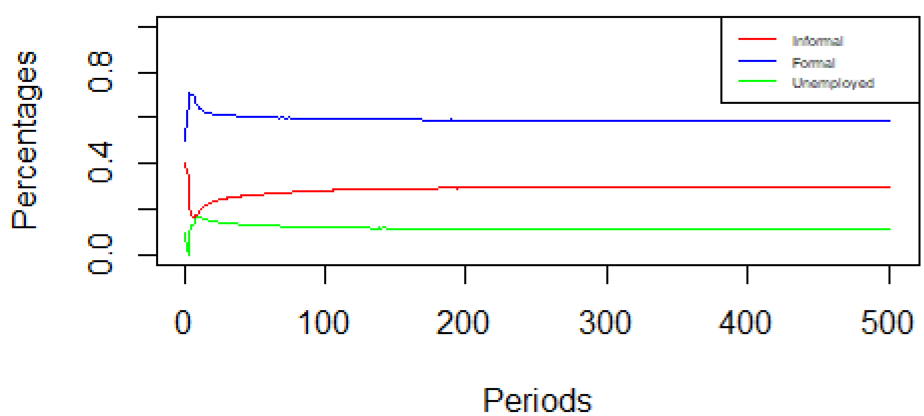

Figure 14: Distributions of workers with calibration: Maxvacancies=6,BA Net=[20,5]

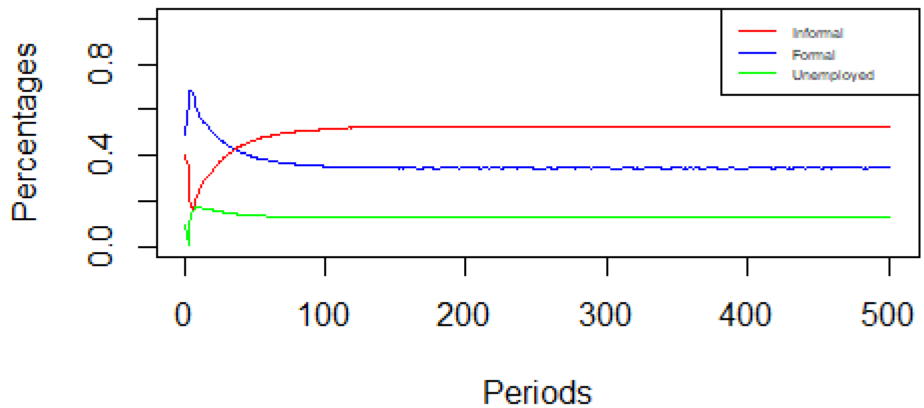

Figure 15: Distributions of workers with calibration: Maxvacancies=4,No Net

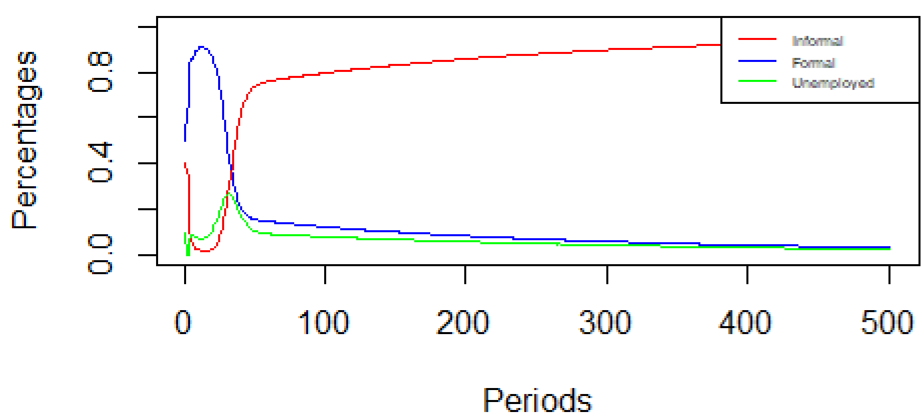

Figure 16: Distributions of workers with calibration: Maxvacancies=4,ER Net=0.20

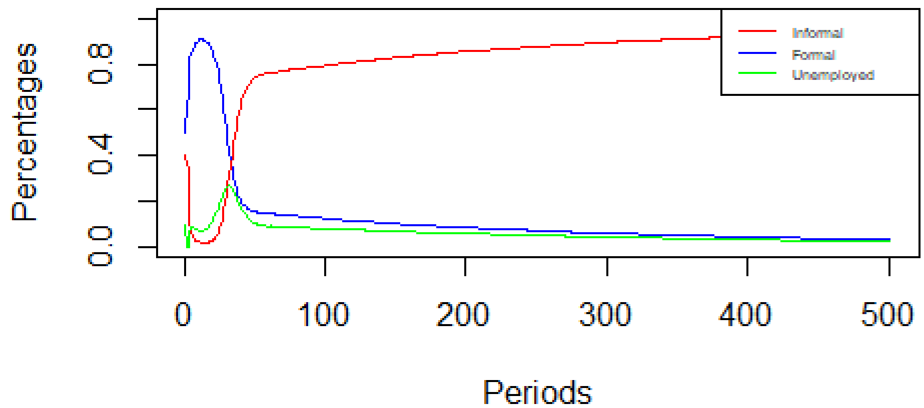

Figure 17: Distributions of workers with calibration: Maxvacancies=4,ER Net=0.15

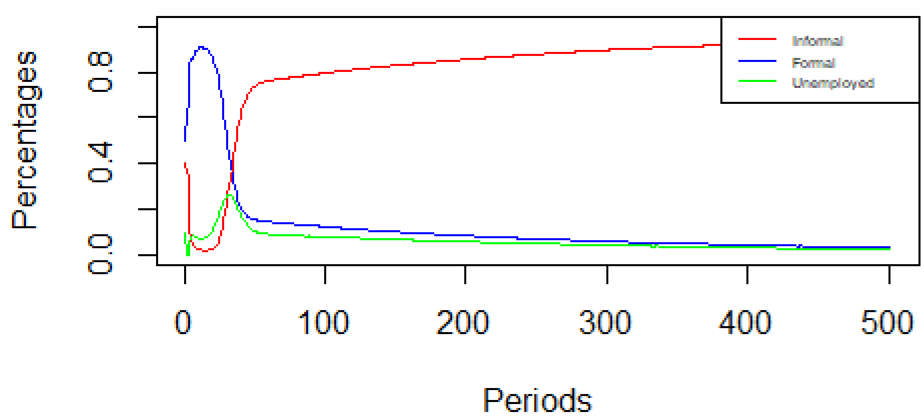

Figure 18: Distributions of workers with calibration: Maxvacancies=4,ER Net=0.10

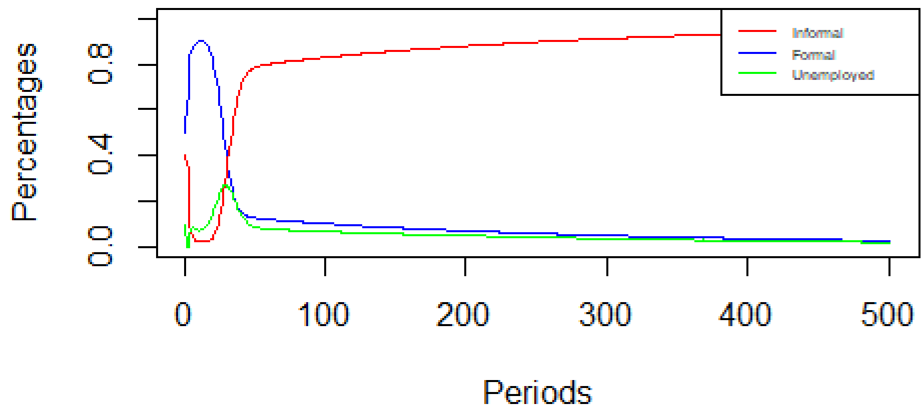

Figure 19: Distributions of workers with calibration: Maxvacancies=4,BA Net=[60,20]

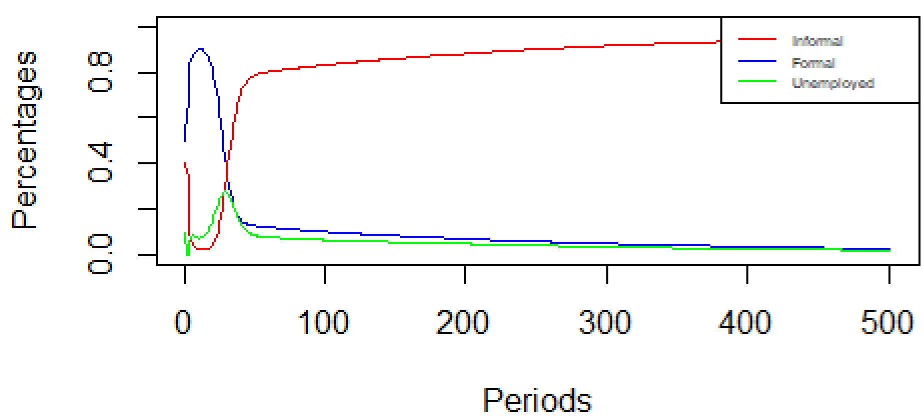

Figure 20: Distributions of workers with calibration: Maxvacancies=4,BA Net=[40,10]

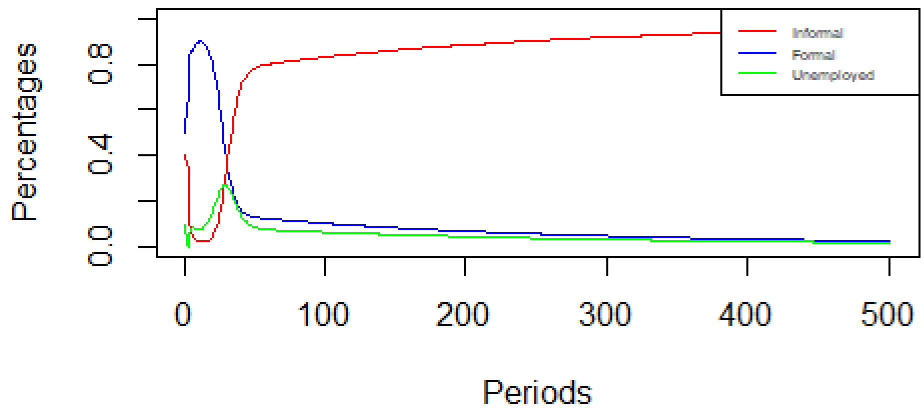

Figure 21: Distributions of workers with calibration: Maxvacancies=4,BA Net=[20,5]

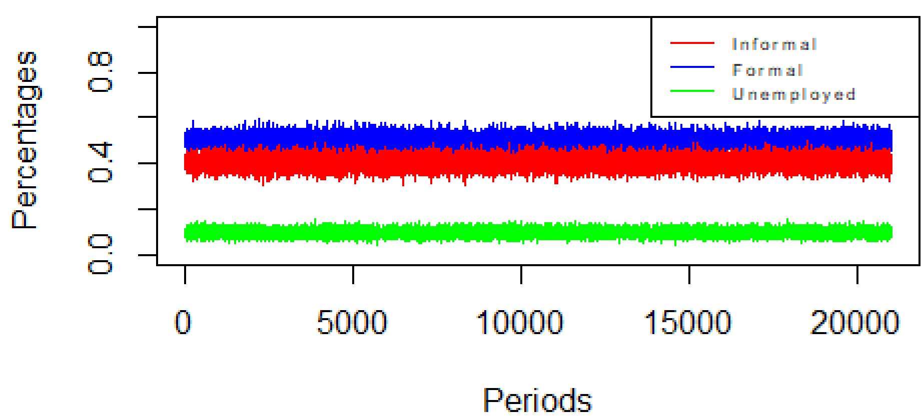

Figure 22: Distribution of initial point for each model

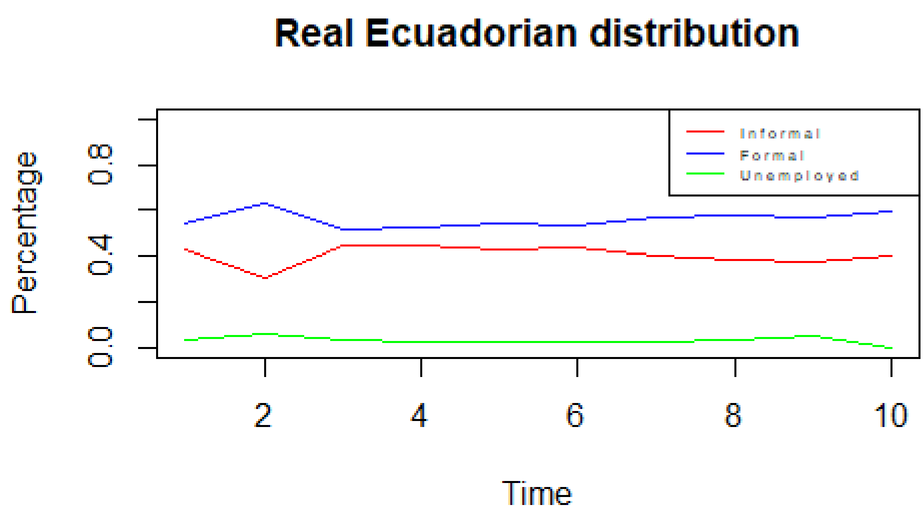

Figure 23: Real Ecuadorian Distribution

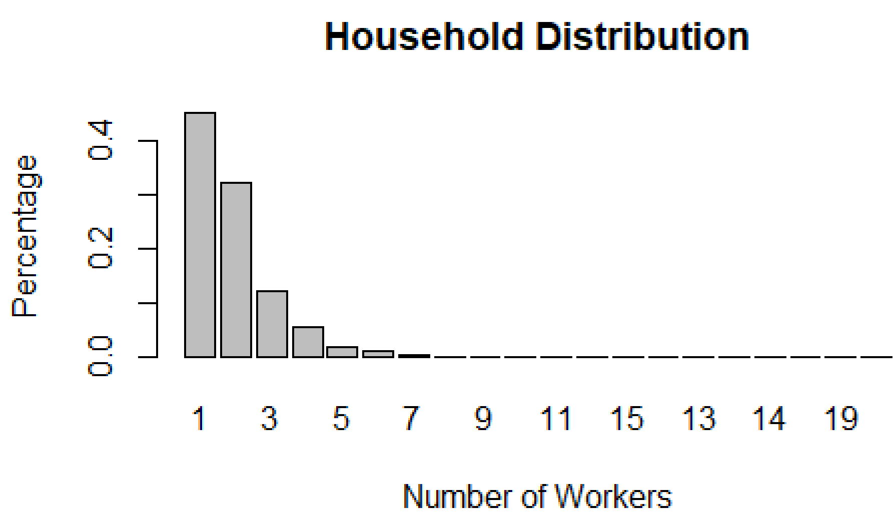

Figure 24: Ecuadorian Household distribution example for raw data

Figure 25: Ecuadorian Household distribution example for clean data

10.3 Tables

Table 1: Raw data of the Ecuadorian Household distribution for ten years.

HH Number/Years	1	2	3	4	5	6	7	8	9	10	Averages
1	0.401532278	0.357924878	0.447600096	0.447816256	0.436173729	0.443871123	0.512339056	0.471879445	0.441522439	0.451828993	0.441248829
2	0.310977141	0.325585312	0.269958997	0.256991551	0.268394262	0.264594708	0.282303801	0.307269442	0.329662096	0.322896282	0.293863359
3	0.137025873	0.148896749	0.145923782	0.156313221	0.157532888	0.157136857	0.110668302	0.11878676	0.121675283	0.122986602	0.137694632
4	0.075985933	0.086912582	0.070851423	0.072831132	0.076684075	0.07451851	0.050659105	0.054818744	0.058889638	0.058256812	0.068040795
5	0.038306958	0.040592892	0.034068982	0.034928002	0.031599127	0.032339353	0.024103311	0.025141276	0.02502435	0.021526419	0.030763067
6	0.018211505	0.018527876	0.015617463	0.014816137	0.014345211	0.015719686	0.010269773	0.011648022	0.012437252	0.012343821	0.014393674
7	0.009168551	0.010442985	0.008984563	0.008687374	0.008660012	0.006359873	0.004560086	0.005651021	0.005694163	0.005569773	0.00737784
8	0.003516704	0.005895233	0.003376749	0.003570154	0.003503669	0.002699946	0.002644083	0.002191212	0.002772159	0.002107482	0.003227739
9	0.002888721	0.002358093	0.001748673	0.0023206	0.001586567	0.001199976	0.001379522	0.001345481	0.001198771	0.000978474	0.001700488
10	0.001004773	0.001010611	0.000723589	0.000833036	0.000991604	0.000839983	0.000651441	0.000730404	0.000599386	0.000752672	0.00081375
11	0.00075358	0.000842176	0.000723589	0.000297513	0.000198321	0.000239995	0.00026824	0.000192212	0.000149846	0.00052687	0.000419234
12	0.00037679	0.000505306	0.000361795	0.000297513	0.000132214	0.000299994	7.66401E-05	7.68846E-05	0.00022477	0.000150534	0.000250244
13	0.000125597	0	0	0	0	0	0	7.68846E-05	0	7.52672E-05	2.77748E-05
14	0.000125597	0	0	0	0	0	0	0	0	0	1.25597E-05
15	0	0.00033687	6.02991E-05	0.000178508	0.000132214	0.000119998	0	7.68846E-05	7.49232E-05	0	9.79697E-05
16	0	0.000168435	0	5.95026E-05	0	0	0	3.84423E-05	0	0	2.6638E-05
17	0	0	0	5.95026E-05	6.6107E-05	0	0	7.68846E-05	7.49232E-05	0	2.77417E-05
18	0	0	0	0	0	5.99988E-05	0	0	0	0	5.99988E-06
19	0	0	0	0	0	0	3.832E-05	0	0	0	3.832E-06
20	0	0	0	0	0	0	3.832E-05	0	0	0	3.832E-06

Table 2: Clean data of the Ecuadorian Household distribution for ten years

HH Number/Years	1	2	3	4	5	6	7	8	9	10	Averages
1	0.561883738	0.518975149	0.624152759	0.625241054	0.615825868	0.622659825	0.646163323	0.613967568	0.590192499	0.612062547	0.603112433
2	0.356585725	0.373723753	0.306318781	0.301478466	0.31164545	0.303702676	0.302270327	0.325794595	0.3452539	0.328121122	0.32548948
3	0.066666667	0.091697168	0.059398003	0.064281123	0.063334905	0.064484815	0.044482577	0.052843243	0.054596747	0.051708447	0.061349369
4	0.01486387	0.01560393	0.010130457	0.008999357	0.009193777	0.009152683	0.007083773	0.007394595	0.009956854	0.008107885	0.010048718

Table 3: Distribution of Houses with one Worker for ten years

Type of home/Years	1	2	3	4	5	6	7	8	9	10	Averages
"001"	0.022786799	0.045657016	0.028141056	0.020219328	0.024243971	0.021046771	0.024104589	0.028736442	0.036131028	0	0.0251067
"010"	0.508905186	0.35783222	0.525922466	0.527644505	0.504784994	0.519265033	0.47984475	0.449992957	0.449177562	0.459854015	0.478322369
"100"	0.468308015	0.596510765	0.445936478	0.452136166	0.470971035	0.459688196	0.49605066	0.521270601	0.51469141	0.540145985	0.496570931

Table 4: Distribution of Houses with two Workers for ten years

Type of home/Years	1	2	3	4	5	6	7	8	9	10	Averages
"002"	0.001650846	0.008247423	0.00404473	0.004027482	0.002773575	0.003881279	0.004803493	0.004778338	0.006008171	0	0.004021534
"011"	0.026000825	0.037113402	0.031881989	0.019426676	0.018658598	0.020091324	0.015720524	0.02136979	0.029079548	0	0.021934268
"020"	0.23978539	0.144845361	0.252200809	0.262733949	0.228189612	0.24109589	0.206113537	0.196177329	0.190819515	0.209531014	0.217149241
"101"	0.043334709	0.07628866	0.0404473	0.039564084	0.038325769	0.031506849	0.041921397	0.048048845	0.073059361	0	0.043249697
"110"	0.266198927	0.245876289	0.257673091	0.242833452	0.271810388	0.269178082	0.234352256	0.257233873	0.254506128	0.295259708	0.259492219
"200"	0.423029303	0.487628866	0.413752082	0.431414357	0.440242057	0.434246575	0.497088792	0.472391824	0.446527277	0.495209279	0.454153041

Table 5: Distribution of Houses with three Workers for ten years

Type of home/Years	1	2	3	4	5	6	7	8	9	10	Averages
"003"	0.004415011	0.00210084	0	0.002222222	0.001240695	0	0.001978239	0.001636661	0	0	0.001359367
"012"	0.004415011	0.004201681	0.006134969	0.007777778	0.003722084	0.005376344	0.008902077	0.009001637	0.010638298	0	0.006016988
"021"	0.030905077	0.027310924	0.018404908	0.028888889	0.012406948	0.025806452	0.013847676	0.022094926	0.022796353	0	0.020246215
"030"	0.156732892	0.077731092	0.157055215	0.158888889	0.17369727	0.15483871	0.15727003	0.131751227	0.12006079	0.1632	0.145122612
"102"	0.013245033	0.012605042	0.014723926	0.008888889	0.007444169	0.010752688	0.002967359	0.008183306	0.016717325	0	0.009552774
"111"	0.041942605	0.079831933	0.023312883	0.031111111	0.021091811	0.033333333	0.027695351	0.031914894	0.045592705	0	0.033582663
"120"	0.141280353	0.117647059	0.17791411	0.153333333	0.155086849	0.155913978	0.137487636	0.127659574	0.133738602	0.1648	0.14648615
"201"	0.033112583	0.100840336	0.056441718	0.056666667	0.069478908	0.039784946	0.043521266	0.059738134	0.08662614	0	0.05462107
"210"	0.203090508	0.201680672	0.213496933	0.216666667	0.217121588	0.250537634	0.207715134	0.225859247	0.205167173	0.2976	0.223893556
"300"	0.370860927	0.37605042	0.332515337	0.335555556	0.338709677	0.323655914	0.398615232	0.382160393	0.358662614	0.3744	0.359118607

Table 6: Distribution of Houses with four Workers for ten years

Type of home/Years	1	2	3	4	5	6	7	8	9	10	Averages
"031"	0.02970297	0.012345679	0	0.007936508	0.008547009	0	0.01863354	0.005847953	0.016666667	0	0.009968033
"040"	0.108910891	0.074074074	0.136690647	0.158730159	0.094017094	0.083333333	0.086956522	0.128654971	0.1	0.102040816	0.107340851
"103"	0.00990099	0	0	0	0.017094017	0	0	0	0	0	0.002699501
"112"	0.00990099	0.037037037	0.014388489	0	0	0	0.01242236	0.005847953	0.016666667	0	0.00962635
"121"	0.02970297	0.024691358	0.028776978	0.031746032	0.025641026	0.03030303	0.00621118	0.01754386	0.008333333	0	0.020294977
"130"	0.069306931	0.061728395	0.057553957	0.063492063	0.102564103	0.075757576	0.136645963	0.081871345	0.075	0.142857143	0.086677748
"202"	0.01980198	0.037037037	0	0.023809524	0	0.015151515	0.02484472	0.005847953	0.025	0	0.015149273
"211"	0.059405941	0.086419753	0.007194245	0.031746032	0.017094017	0.037878788	0.00621118	0.023391813	0.033333333	0	0.03026751
"220"	0.148514851	0.086419753	0.115107914	0.103174603	0.205128205	0.143939394	0.074534161	0.128654971	0.133333333	0.204081633	0.134288882
"301"	0.079207921	0.098765432	0.050359712	0.071428571	0.042735043	0.075757576	0.043478261	0.046783626	0.108333333	0	0.061684947
"310"	0.207920792	0.172839506	0.201438849	0.206349206	0.162393162	0.25	0.198757764	0.169590643	0.15	0.275510204	0.199480013
"400"	0.227722772	0.308641975	0.381294964	0.301587302	0.316239316	0.28030303	0.378881988	0.356725146	0.283333333	0.275510204	0.311024003
"022"	0	0	0.007194245	0	0.008547009	0	0.00621118	0.023391813	0.033333333	0	0.007867758
"004"	0	0	0	0	0	0.007575758	0	0	0.008333333	0	0.001590909
"013"	0	0	0	0	0	0	0.00621118	0.005847953	0.008333333	0	0.002039247

Table 7: Descriptive Data of Ecuador

Data/Years	1	2	3	4	5	6	7	8	9	10	Averages
Maximum wageoin Informal Market	492	580	495	542	600	645	645	700	692	690	608.1
Average Formal(Wages)	387.5998473	408.8789678	394.1051643	435.1095089	471.4073528	495.5168421	556.4829381	570.3697234	566.3014575	581.8150713	486.7586873
Average informal(Wages)	156.1710401	182.0866886	157.0738279	178.2733871	198.4573897	208.7080605	225.1090939	220.553118	214.2997687	213.434045	195.4166419
Median Formal(Wages)	322.5	339	322	355	400	420	477	497	500	500	413.25
Median Informal(Wages)	140	160	140	160	180	192	200	200	190	190	175.2
Average formal/Average informal(Wages)	2.481893231	2.245518171	2.50904412	2.440686835	2.375358023	2.374210373	2.472058896	2.586087781	2.642566816	2.725971253	2.48533955
Median Formal/Median Informal(Wages)	2.303571429	2.11875	2.3	2.21875	2.222222222	2.1875	2.385	2.485	2.631578947	2.631578947	2.348395155
Unemployed(Percentage)	0.03471756	0.062815277	0.035601622	0.030637255	0.030072367	0.028397759	0.029934897	0.03632199	0.051148751	0	0.033964748
Formal(Percentage)	0.540136185	0.63163584	0.517951029	0.523186275	0.543071563	0.53286162	0.570663178	0.581568301	0.572866007	0.597545036	0.561148503
Informal(Percentage)	0.425146255	0.305548883	0.446447349	0.446176471	0.426856071	0.438740621	0.399401925	0.38210971	0.375985242	0.402454964	0.404886749

Table 8: Descriptive information of Formality

Model	Min.	X1st.Qu.	Median	Mean	X3rd.Qu.	Max.	Var.	Std.
NoNET,MAXV=5	0.476032	0.476769	0.477278	0.4772972	0.477845	0.47842	3.9078E-07	0.000625124
ErNet(0.20),MAXV=5	0.34865	0.350979	0.354	0.35415934	0.3570075	0.360546	1.2856E-05	0.003585533
ErNet(0.15),MAXV=5	0.3477	0.3516675	0.354488	0.3543505	0.357157	0.360662	1.4537E-05	0.00381274
ErNet(0.10),MAXV=5	0.34695	0.3501985	0.353554	0.35339286	0.355993	0.360356	1.27676E-05	0.003573184
BaNet(60,20),MAXV=5	0.342222	0.3448555	0.34738	0.34742062	0.350705	0.352316	1.05461E-05	0.003247473
BaNet(40,10),MAXV=5	0.33964	0.343103	0.344773	0.34543278	0.348787	0.35109	1.0386E-05	0.003222731
BaNet(20,5),MAXV=5	0.335936	0.3386615	0.341345	0.34164178	0.344927	0.348958	1.34103E-05	0.003662005
NoNET,MAXV=6	0.621372	0.6225105	0.623777	0.62361234	0.6244075	0.626044	1.41782E-06	0.001190723
ErNet(0.20),MAXV=6	0.570614	0.5711845	0.571554	0.57157846	0.5719085	0.573316	2.63618E-07	0.000513438
ErNet(0.15),MAXV=6	0.572628	0.57322	0.573565	0.57360404	0.5739325	0.575174	3.12303E-07	0.000558841
ErNet(0.10),MAXV=6	0.575338	0.576137	0.576571	0.57654194	0.576961	0.577874	3.36275E-07	0.000579892
BaNet(60,20),MAXV=6	0.583506	0.584047	0.584527	0.58451568	0.584965	0.585586	2.78833E-07	0.000528047
BaNet(40,10),MAXV=6	0.58175	0.582584	0.582826	0.5829675	0.5834335	0.584242	3.1596E-07	0.000562103
BaNet(20,5),MAXV=6	0.584188	0.5851315	0.585468	0.58553198	0.5858415	0.587124	3.24252E-07	0.000569431
NoNET,MAXV=4	0.3454	0.3461455	0.346706	0.34678918	0.347422	0.348372	6.0572E-07	0.00077828
ErNet(0.20),MAXV=4	0.031966	0.034061	0.037205	0.03727882	0.040033	0.04278	1.12823E-05	0.003358913
ErNet(0.15),MAXV=4	0.03298	0.035014	0.037827	0.03793208	0.0405665	0.044292	1.0578E-05	0.003252391
ErNet(0.10),MAXV=4	0.032438	0.0349635	0.037599	0.03775554	0.040288	0.043622	1.09004E-05	0.003301581
BaNet(60,20),MAXV=4	0.02832	0.0296715	0.031986	0.03239264	0.035091	0.036838	8.27944E-06	0.002877401
BaNet(40,10),MAXV=4	0.026262	0.028388	0.030842	0.03093772	0.033328	0.03602	8.6365E-06	0.002938793
BaNet(20,5),MAXV=4	0.025264	0.0271305	0.029728	0.0296599	0.031592	0.034532	7.11771E-06	0.002667903

Table 9: Descriptive information of Informality

Model	Min.	X1st.Qu.	Median	Mean	X3rd.Qu.	Max.	Var.	Std.
NoNET,MAXV=5	0.420234	0.421141	0.421614	0.42152812	0.421945	0.42245	2.93906E-07	0.000542131
ErNet(0.20),MAXV=5	0.500716	0.504588	0.50773	0.50774682	0.510828	0.51389	1.50154E-05	0.003874973
ErNet(0.15),MAXV=5	0.501222	0.5043355	0.507253	0.5074526	0.5104215	0.514092	1.51324E-05	0.003890038
ErNet(0.10),MAXV=5	0.501496	0.505831	0.508514	0.50855026	0.512082	0.515476	1.50896E-05	0.003884528
BaNet(60,20),MAXV=5	0.510358	0.51232	0.515918	0.51610782	0.5191565	0.522226	1.24519E-05	0.00352872
BaNet(40,10),MAXV=5	0.513848	0.516556	0.520384	0.51984646	0.522586	0.526516	1.24999E-05	0.003535519
BaNet(20,5),MAXV=5	0.51926	0.523776	0.527246	0.5269098	0.530525	0.533642	1.62761E-05	0.004034363
NoNET,MAXV=6	0.297334	0.298976	0.299995	0.300042	0.3014035	0.30243	2.00456E-06	0.001415824
ErNet(0.20),MAXV=6	0.32126	0.3215535	0.32193	0.32197674	0.322385	0.323164	2.29356E-07	0.000478911
ErNet(0.15),MAXV=6	0.317362	0.3179815	0.31855	0.31854274	0.319001	0.319736	3.13566E-07	0.000559969
ErNet(0.10),MAXV=6	0.312144	0.31279	0.313404	0.31335512	0.3138985	0.314708	4.74072E-07	0.000688529
BaNet(60,20),MAXV=6	0.299886	0.3003955	0.300609	0.3006372	0.3008425	0.301438	1.29798E-07	0.000360275
BaNet(40,10),MAXV=6	0.300014	0.300589	0.300914	0.3008907	0.301242	0.30179	1.71397E-07	0.000414001
BaNet(20,5),MAXV=6	0.29887	0.299639	0.299906	0.2998367	0.3001245	0.30074	1.62682E-07	0.000403338
NoNET,MAXV=4	0.522786	0.524218	0.524811	0.52465098	0.5252	0.525936	4.94641E-07	0.000703307
ErNet(0.20),MAXV=4	0.924792	0.9294225	0.934016	0.93428348	0.9398995	0.943254	3.20796E-05	0.005663885
ErNet(0.15),MAXV=4	0.922852	0.9288675	0.933646	0.93329004	0.93807	0.942046	3.17643E-05	0.005635983
ErNet(0.10),MAXV=4	0.92371	0.929308	0.934219	0.93384288	0.9385505	0.943018	3.13701E-05	0.005600906
BaNet(60,20),MAXV=4	0.935154	0.9387415	0.943545	0.94330832	0.947952	0.950566	2.44872E-05	0.004948452
BaNet(40,10),MAXV=4	0.938158	0.942017	0.946507	0.94606158	0.95044	0.954066	2.40384E-05	0.004902901
BaNet(20,5),MAXV=4	0.940788	0.9453485	0.948999	0.948842	0.952994	0.95657	2.02198E-05	0.004496646

Table 10: Descriptive information of Unemployment

Model	Min.	X1st.Qu.	Median	Mean	X3rd.Qu.	Max.	Var.	Std.
NoNET,MAXV=5	0.099834	0.1009385	0.101218	0.10117468	0.101436	0.102332	1.9534E-07	0.000441972
ErNet(0.20),MAXV=5	0.136828	0.1377455	0.138031	0.13809384	0.1384515	0.139314	2.62241E-07	0.000512094
ErNet(0.15),MAXV=5	0.136908	0.1378785	0.138217	0.1381969	0.13857	0.139316	2.61919E-07	0.00051178
ErNet(0.10),MAXV=5	0.136726	0.137757	0.13803	0.13805688	0.138384	0.139594	3.42753E-07	0.000585451
BaNet(60,20),MAXV=5	0.135034	0.1360745	0.136396	0.13647156	0.1369505	0.13752	3.23451E-07	0.000568728
BaNet(40,10),MAXV=5	0.13349	0.134419	0.134756	0.13472076	0.135044	0.136034	2.51167E-07	0.000501165
BaNet(20,5),MAXV=5	0.129872	0.130981	0.131426	0.13144842	0.131902	0.132694	4.22703E-07	0.000650156
NoNET,MAXV=6	0.075136	0.076006	0.076347	0.07634566	0.076607	0.077466	2.25495E-07	0.000474863
ErNet(0.20),MAXV=6	0.105208	0.1062135	0.10645	0.1064448	0.106692	0.107238	1.70421E-07	0.000412821
ErNet(0.15),MAXV=6	0.107064	0.107547	0.107808	0.10785322	0.108188	0.10925	1.92345E-07	0.000438571
ErNet(0.10),MAXV=6	0.10871	0.109698	0.110052	0.11010294	0.110439	0.111694	3.32231E-07	0.000576394
BaNet(60,20),MAXV=6	0.113656	0.1146185	0.114888	0.11484712	0.1151365	0.115816	2.08348E-07	0.000456451
BaNet(40,10),MAXV=6	0.115276	0.115897	0.116116	0.1161418	0.116402	0.117466	1.79678E-07	0.000423885
BaNet(20,5),MAXV=6	0.113394	0.1143135	0.114631	0.11463132	0.114906	0.115794	2.20691E-07	0.000469778
NoNET,MAXV=4	0.12738	0.128157	0.128577	0.12855984	0.1289825	0.129858	3.18691E-07	0.000564527
ErNet(0.20),MAXV=4	0.02471	0.026055	0.028704	0.0284377	0.0305445	0.032428	5.36517E-06	0.002316283
ErNet(0.15),MAXV=4	0.024964	0.026921	0.028566	0.02877788	0.030566	0.033038	5.72153E-06	0.002391972
ErNet(0.10),MAXV=4	0.024544	0.026486	0.028182	0.02840158	0.0303885	0.032668	5.32278E-06	0.002307116
BaNet(60,20),MAXV=4	0.02101	0.022406	0.024491	0.02429904	0.026134	0.028008	4.35491E-06	0.002086841
BaNet(40,10),MAXV=4	0.019582	0.0211785	0.022661	0.0230007	0.0246885	0.026224	3.90455E-06	0.001975992
BaNet(20,5),MAXV=4	0.018166	0.0199015	0.021158	0.0214981	0.023045	0.024798	3.39589E-06	0.001842794

Table 11: Informality T-tests between No net model and each Net model with Maxvancancies=5

Modeled Compared	Welch's t-test	Wilcoxon.rank.sum.test
ErNet(0.20)	1.0168E-139	1.28057E-34
ErNet(0.15)	2.3059E-139	1.28064E-34
ErNet(0.10)	5.2822E-140	1.28064E-34
BaNet(60,20)	6.8414E-149	1.28057E-34
BaNet(40,10)	1.5795E-150	1.28057E-34
BaNet(20,5)	1.5089E-146	1.28057E-34

Table 12: Informality T-tests between No net model and each Net model with Maxvancancies=6

Modeled Compared	Welch's t-test	Wilcoxon.rank.sum.test
ErNet(0.20)	8.5632E-139	1.28021E-34
ErNet(0.15)	2.1367E-135	1.28064E-34
ErNet(0.10)	1.6228E-124	1.28064E-34
BaNet(60,20)	4.33276E-05	0.000312235
BaNet(40,10)	3.6329E-08	1.22948E-05
BaNet(20,5)	0.917080393	0.830304889

Table 13: Informality T-tests between No net model and each Net model with Maxvancancies=4

Modeled Compared	Welch's t-test	Wilcoxon.rank.sum.test
ErNet(0.20)	4.3312E-191	1.28057E-34
ErNet(0.15)	3.0139E-191	1.28057E-34
ErNet(0.10)	1.2112E-191	1.28049E-34
BaNet(60,20)	1.5169E-199	1.28057E-34
BaNet(40,10)	2.2649E-200	1.28057E-34
BaNet(20,5)	8.5545E-206	1.28057E-34

Table 14: Formality T-tests between No net model and each Net model with Maxvancancies=5

Modeled Compared	Welch's t-test	Wilcoxon.rank.sum.test
ErNet(0.20)	1.213E-161	1.28078E-34
ErNet(0.15)	5.8014E-158	1.28078E-34
ErNet(0.10)	3.9281E-162	1.28064E-34
BaNet(60,20)	3.1147E-170	1.28078E-34
BaNet(40,10)	1.983E-171	1.28071E-34
BaNet(20,5)	8.667E-165	1.28078E-34

Table 15: Formality T-tests between No net model and each Net model with Maxvancancies=6

Modeled Compared	Welch's t-test	Wilcoxon.rank.sum.test
ErNet(0.20)	2.4719E-209	1.28071E-34
ErNet(0.15)	5.7248E-214	1.28057E-34
ErNet(0.10)	1.8301E-213	1.28064E-34
BaNet(60,20)	1.1648E-194	1.28057E-34
BaNet(40,10)	8.6316E-202	1.28042E-34
BaNet(20,5)	8.0122E-199	1.28057E-34

Table 16: Formality T-tests between No net model and each Net model with Maxvancancies=4

Modeled Compared	Welch's t-test	Wilcoxon.rank.sum.test
ErNet(0.20)	4.9784E-214	1.281E-34
ErNet(0.15)	1.3538E-216	1.28086E-34
ErNet(0.10)	2.2762E-215	1.28078E-34
BaNet(60,20)	1.6864E-228	1.28071E-34
BaNet(40,10)	1.0384E-226	1.281E-34
BaNet(20,5)	1.3953E-236	1.28086E-34

Table 17: Difference Formality minus Informality T-tests between No net model and each Net model with Maxvancancies=5

Modeled Compared	Welch's t-test	Wilcoxon.rank.sum.test
ErNet(0.20)	1.7196E-150	1.28107E-34
ErNet(0.15)	1.0576E-148	1.28107E-34
ErNet(0.10)	7.0446E-151	1.28107E-34
BaNet(60,20)	5.0278E-159	1.28093E-34
BaNet(40,10)	2.9392E-160	1.28107E-34
BaNet(20,5)	3.7271E-155	1.28107E-34

Table 18: Difference Formality minus Informality T-tests between No net model and each Net model with Maxvancancies=6

Modeled Compared	Welch's t-test	Wilcoxon.rank.sum.test
ErNet(0.20)	4.9562E-173	1.28093E-34
ErNet(0.15)	7.9584E-176	1.281E-34
ErNet(0.10)	1.7745E-174	1.281E-34
BaNet(60,20)	3.7013E-135	1.28107E-34
BaNet(40,10)	9.0574E-142	1.28078E-34
BaNet(20,5)	5.0148E-136	1.28107E-34

Table 19: Difference Formality minus Informality T-tests between No net model and each Net model with Maxvancancies=4

Modeled Compared	Welch's t-test	Wilcoxon.rank.sum.test
ErNet(0.20)	8.4838E-198	1.28093E-34
ErNet(0.15)	1.3872E-198	1.28107E-34
ErNet(0.10)	1.5589E-198	1.28107E-34
BaNet(60,20)	1.5793E-207	1.28107E-34
BaNet(40,10)	1.2012E-207	1.28107E-34
BaNet(20,5)	5.0636E-214	1.28107E-34

Table 20: Ratio Informality over Formality T-tests between No net model and each Net model with Maxvancancies=5

Modeled Compared	Welch's t-test	Wilcoxon.rank.sum.test
ErNet(0.20)	4.3038E-136	1.28107E-34
ErNet(0.15)	2.8756E-134	1.28107E-34
ErNet(0.10)	2.1453E-136	1.28107E-34
BaNet(60,20)	1.2341E-142	1.28107E-34
BaNet(40,10)	1.4367E-143	1.28107E-34
BaNet(20,5)	4.3051E-139	1.28107E-34

Table 21: Ratio Informality over Formality T-tests between No net model and each Net model with Maxvancancies=6

Modeled Compared	Welch's t-test	Wilcoxon.rank.sum.test
ErNet(0.20)	3.8724E-173	1.28107E-34
ErNet(0.15)	3.1532E-175	1.28107E-34
ErNet(0.10)	2.32E-172	1.28107E-34
BaNet(60,20)	1.2505E-115	1.28107E-34
BaNet(40,10)	2.6556E-122	1.28107E-34
BaNet(20,5)	1.1332E-114	1.28107E-34

Table 22: Ratio Informality over Formality T-tests between No net model and each Net model with Maxvancancies=4

Modeled Compared	Welch's t-test	Wilcoxon.rank.sum.test
ErNet(0.20)	2.1396E-100	1.28107E-34
ErNet(0.15)	1.2355E-102	1.28107E-34
ErNet(0.10)	8.3437E-102	1.28107E-34
BaNet(60,20)	6.0635E-102	1.28107E-34
BaNet(40,10)	1.9055E-99	1.28107E-34
BaNet(20,5)	1.6337E-101	1.28107E-34