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Complex network effects on price setting: an agent-based computational approach

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O presente trabalho em nível de mestrado foi avaliado e aprovado por banca examinadora composta pelos seguintes membros:

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Certificamos que esta é a **versão original e final** do trabalho de conclusão que foi julgado adequado para obtenção do título de Mestre em Economia.

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"Let everything happen to you: beauty and terror.
Just keep going. No feeling is final".
Rainer Maria Rilke

Resumo

A formação de preços é um tema com muitas questões ainda não resolvidas, que podem ser exploradas pelo uso da ciência das redes e da complexidade, uma agenda que vem ganhando destaque na pesquisa econômica. Esta abordagem possui ferramentas adequadas para incluir alguns padrões observados empiricamente na fixação de preços, como fricções informacionais, vieses cognitivos, heterogeneidade de expectativas. É possível representar um ambiente de formação de preços com interação social através de um modelo computacional baseado em agentes. Para tanto, adaptar-se-á um modelo novo keynesiano de concorrência monopolística com expectativas racionais e agentes representativos em um modelo em rede complexa com expectativas interativas e agentes heterogêneos. Tratamos a formação de preços como um processo de escolha discreta em que a cada rodada, estes agentes podem escolher uma estratégia deflacionária, neutra e inflacionária com o incentivo de escolher aquela que leve a maiores ganhos de utilidades ao longo do tempo. Com base no modelo, verificamos que no modelo em rede complexa os agentes convergem para a dominância da estratégia neutra sob condições em que, no modelo em rede regular, a estratégia inflacionária sobrevive no longo prazo. Ademais, é possível ordenar com maior confiança as estratégias da mais forte para a mais fraca, já que novos equilíbrios surgem quando os agentes começam com homogeneidade de estratégias, diferente do modelo em rede regular. Por último, flutuações monetárias causam aumentos do produto no curto prazo, mas seus efeitos não são persistentes. Os resultados das simulações demonstram que em geral, mesmo após o relaxamento de diversas hipóteses necessárias para a solução do modelo novo keynesiano de referência, nosso modelo é capaz de reproduzir suas conclusões.

Palavras-chave: Modelo baseado em agentes. Racionalidade limitada. Redes complexas. Formação de preços.
Classificação JEL: C63, D80, E30.

Resumo expandido

Introdução

Um dos grandes temas da economia é a busca de um maior entendimento sobre a formação de preços, central para o funcionamento de mercados em concorrência monopolística. Embora muito tenha sido discutido sobre o tema, a macroeconomia contemporânea ainda não conseguiu desenvolver um entendimento completo sobre a rigidez de preços e a sua relação com a política monetária. Com a ascensão dos modelos baseados em agentes e do estudo da ciência das redes e da complexidade, torna-se possível pesquisar sobre a formação de preços sob este prisma, levando em consideração os efeitos de externalidades de rede sobre este processo. Assim, o presente trabalho irá adaptar um modelo novo keynesiano de formação de preços resolvido analiticamente em um modelo computacional baseado em agentes com estrutura de rede endógena. Desta forma é possível relaxar hipóteses simplificadoras como a do agente representativo com racionalidade perfeita e preferências homogêneas, para observar como agentes heterogêneos com racionalidade limitada estabelecem seus preços em um ambiente caracterizados por externalidades de rede. Considerando isto, pode-se afirmar que a presente dissertação está inserida numa cada vez mais relevante agenda de pesquisa macroeconômica após a crise de 2008 e as dúvidas que ela gerou sobre o poder explicativo dos modelos ortodoxos.

Objetivos

O objetivo geral desta dissertação é avaliar a influência de externalidades de rede numa economia na qual formação de preços se dá por concorrência monopolística. Para tanto, serão apresentadas teorias sobre formação de preços, interação social e heterogeneidade em economia e como estes fatores podem ser levados em conta utilizando elementos de teoria das redes. Desta forma será possível observar propriedades emergentes do modelo para diferentes distribuições iniciais de estratégias entre os agentes e diferentes valores dos parâmetros.

Metodologia

Silva (2012) propõe uma abordagem computacional baseada em agentes com o intuito de adicionar racionalidade limitada a externalidades de rede a um modelo novo keynesiano de formação de preços, em que os produtores serão defrontados com a escolha entre três estratégias de previsão da tendência do nível geral de preços, a saber: deflacionária, neutra e inflacionária. As preferências de cada agente serão caracterizadas por uma função utilidade dividida em duas, uma parte determinística (com componentes social e privado) e outra estocástica. Estes 10,000 agentes possuem funções utilidade que representam diferentes preferências, trazendo heterogeneidade ao modelo. Depois eles serão dispostos em uma rede com possibilidade de dois agentes quaisquer trocarem informações sobre os preços, com a frequência dependendo de uma probabilidade de religação. O modelo será calibrado com uma série histórica de inflação de preços ao produtor com um algoritmo de otimização até encontrar um valor dentro da tolerância dos erros da série calibrada em relação à empírica.

Resultados e discussão

Primeiro, foi reproduzido o ABM em rede regular proposto por Silva (2012) que é o ponto de partida do ABM com rede complexa proposto na presente dissertação. Nesta rede são inseridos 10,000 agentes que escolhem entre as três expectativas citadas acima, definem seus preços com base nelas, comparam eles ao nível geral de preços e de acordo com as utilidades obtidas nesse processo, podem manter ou mudar de estratégia no próximo período. No ABM em rede regular, tomado como modelo de referência, não ocorreu a total convergência para a total dominância da estratégia neutra, com a estratégia inflacionária coexistindo no longo prazo. Depois o ABM foi calibrado incluindo a probabilidade de religação e desta vez convergiu para total dominância da estratégia neutra. Analisando as propiredades emergentes, podemos classificar as expectativas, da melhor para a pior por ordem de predominância na população de agentes, em neutra, inflacionária, deflacionária. Quando o modelo inclui flutuações monetárias, estas são absorvidas mais pelo produto do que pelo nível de preços, mas sem causar efeitos duradouros no nível de produto. Por fim, a variância dos preços aumenta quando há probabilidade de religação e ainda mais quando são adicionadas as variações monetárias.

Considerações finais

Esta dissertação buscou entender melhor a dinâmica de formação de preços utilizando um ABM de economia em concorrência monopolística com uma rede complexa. O modelo mostrou robustez ao aumento de complexidade, já que as conclusões encontradas na versão com rede endógena foram consistentes com a versão com rede regular, proposta originalmente por Silva (2012). De fato houve uma melhora, já que mesmo com uma amplitude de ajustes de preço mais realista a rede foi capaz de chegar à convergência completa para a estratégia neutra, que não havia sido possível na versão com rede regular com esta nova amplitude reduzida de ajustes de preços. Desta forma, o trabalho contribui para a cada vez mais relevante literatura de macroeconomia sob a perspectiva das redes complexas.

Abstract

Price formation is a theme with many still unsolved questions, that might be explored by usage of complexity and network science, an agenda that is gaining prominence in economic research. This approach possesses adequate tools for including empirically observed patterns in price setting, such as informational frictions, cognitive biases and heterogeneity of expectations. We can represent a price setting ambient with social interaction through an agent-based computational model. To do so we will adapt a new Keynesian monopolistic competition model with rational expectations and representative agents into a complex network model with interactive expectations and heterogeneous agents. We treat price formation as a discrete choice process where on each round, these agents might choose a deflationary, neutral or inflationary strategy with an incentive of choosing the one that leads to the largest utility gains over time. Based on the model, we verify that in the complex network model agents converge to neutral strategy dominance under conditions where, in the regular network model, the inflationary strategy survives in the long run. Furthermore, we are able to rank the strategies from strongest to weakest with more confidence, as new equilibria emerge after when agents start with homogeneous strategies, unlike the regular network model. Lastly, monetary fluctuations cause short-term raises in output, but their effect is not persistent. Simulation results demonstrate that in general, even after relaxing various hypotheses needed to solve the new Keynesian model of reference, our model is able to reproduce its conclusions.

Keywords: Agent-based model. Bounded rationality. Complex networks. Price setting.

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1 Introduction

Price setting is a theme that has been long debated throughout the story of economics, even before the emergence of macroeconomics mainly due to Keynes (1937), with many works dedicated to it, e.g. Hayek (1935), Wicksell (1936), and Myrdal (1939). After macroeconomics was well-established as a branch of economics, perhaps the premier one in terms of public recognition and curiosity, the effect of uncertainty and expectations on price setting came to be of most interest.

With the rational expectations revolution, two macroeconomic schools of thought arose, namely the new classical and the new Keynesian. Mankiw (1985) points out that the main difference between their stances on prices are that in new classical models, prices are perfectly flexible, whereas new Keynesian models feature rigidity. Thus, the existence of nominal rigidity ends up generating real rigidity, even with public knowledge that the shock is monetary.

Research on the diverse possibilities of rigidity is ample and well-documented in economics, mainly divided between price and salary rigidities. For the first, Mankiw (1985) proposes menu costs, that is, the cost of changing prices – referring to restaurants needing to print new menus in the classic example – as the main reason. Even though most businesses are long past the kind of issues described by the original example, the idea of menu costs has become a mainstay of economics, applied to many different scenarios even if it is not the driving force of price stickiness.

On the other hand, research on overlapping contracts by Taylor (1980) is pioneer in investigating salaries rigidity as the determinant to price stickiness. It is important to consider, however, that contemporary new Keynesian literature presents other sources of rigidity. Such can be imperfect information, sticky information or customer markets for price rigidity and efficiency wage models for salary rigidity.

Most new Keynesian models assume that individuals formulate expectations independently and employ a representative agent, in a way that individuals have similar preferences, access to the same information and the same reasoning prowess. Moreover, all of these agents are rational and make choices in a similar way, so studying this agent's behaviour is supposed to be enough to understand the economy as a whole. Of course, these assumptions are not to be taken literally, but they are the foundations on which the canonical new Keynesian models are built.

However, Flieth and Foster (2002) remark that representative agent models face hardships in reproducing patterns found empirically, meaning that there has been a pervasive need to discuss new ideas about the formation of expectations and how they affect price setting. Interest in such a thematic raised the number of studies about social interaction in an economic context and how they affect expectations and, therefore, prices.

To do so, an agent-based model (ABM) can be employed. According to Macal and North (2005), this is an important tool to evaluate social systems composed by different agents that interact amongst them. These agents learn with past experiences, influence each other and adapt their behaviour looking for the best answer to their environment.

Agent-based modelling, as Arthur (2006) points out, can be useful in assessing out-of-equilibrium economics, as it is known in real life that economic agents are continually adjusting their market moves to the situations created by the set of these decisions from all agents. Tesfatsion (2006) remarks that Agent-based Computational Economics (ACE), an approach of economic process as dynamic systems of interacting agents, is particularly good for managing market power, institutional arrangements, behavioural uncertainty and learning – which are all relevant topics to our work.

Caballero (2010) says that mainstream economics has become too interested by the models' technical progress and started mistaking their precision inside their own internal logic with precision in real-life insights extracted from them, neglecting the increasing complexity of markets and pushing it to the periphery of macroeconomics. Romer (2016) goes as far as saying that in the last three decades, economics has gone backwards by embarking on a quest to gain legitimacy as something closer to a hard science with an excessive focus on the mathematical theory inside the models.

To face these new issues, Gatti et al. (2010) argue for a necessity of replacing the reductionist approach of dynamic stochastic general equilibrium (DSGE) models in contemporary macroeconomics with a more open-ended approach rooted in complexity, network science and agent-based modelling. While ABMs can coexist with a mainstream approach, economists need to be sensible about what can be expertly understood with models from the mainstream tool kit and what needs to go through more novel approaches.

This study's proposed model takes as reference the model developed by Silva (2012), which builds an ABM to evaluate the existence of incomplete nominal adjustment in a monopolistic competition economy. More precisely, the agents must choose on each round a strategy between maintaining the price, raising it or lowering it.

Their choices depend on the agents' preferences. In turn, these are represented by utility functions that depends on observable attributes (features of each strategy themselves) and non-observable attributes (idiosyncratic features of the agent itself). The observable attributes are the deterministic term of the utility function and the non-observable attributes are the stochastic term.

The deterministic term is split between two components: private deterministic utility and social deterministic utility. The first is explained by prediction accuracy, that is, when a prediction deviates from the global price level its private utility lowers, and the inverse is true. Social utility represents network effects, introducing the possibility that an agent's choice is affected by the other agents.

Our main contribution is to reinforce the model, as the author works only with a regular network (where neighbourhoods have the same topology during the entire simulation). However, as Cassar (2007) and Topa (2001) remark, different network structures such as small-world (where nodes, mostly, are not neighbours, but it is possible to go from one to another in a few steps) or even a random network (where the neighbourhood follows a probabilistic distribution on each period) can generate distinct results.

In the famous Watts and Strogatz (1998) model, the network's topology is defined by the rewiring probability, p. Therefore, we will add a calibration function to the original model, without fixing the network structure *a priori* – that is, trying to find the best-fitting value of p.

Recent literature such as Fainmesser and Galeotti (2016) or Fainmesser and Galeotti (2020) highlight that network effects can be very important in price setting, with firms and consumers looking at their neighbourhood to gather information in order to make better decisions. This influence can depend on various factors like the strength of network effects, network size and behaviour of a few very influential vertices.

While a more standard approach to macroeconomic models sees only one rational equilibrium arise from its solving, Cabral (2011) remarks that a computational model with network effects can have multiple stable equilibria emerging from the process. Price setting is far from a solved question and applying a network methodology to it can improve our understanding about it, because pricing decisions by firms are very much of network affairs and it makes plenty of sense that there can be various equilibria instead of a single one.

The main objective of this master's thesis is to evaluate the influence of network effects, such as differing network topologies (regular, small-world or random setups) on price setting dynamics, considering a monopolistic competition economy of goods producers. To carry out this task, the main objective is broken down into smaller specific objectives.

Namely, these objectives are to present theory and empirical evidence on price setting, display the basics of network theory and how it can be employed to turn an analytically-solved new Keynesian pricing model under rational expectations into an agent-based computational model. It will be calibrated with a real-life data set and, instead of rational expectations, it will feature interactive expectations.

To do so, this thesis is organised as follows. Besides this introduction, there are four more chapters. Chapter 2 presents relevant research on this study's main themes that will be used to discuss and contextualise its results. Section 2.1 discusses past and present theories proposed and stylised facts found about price stickiness. Section 2.2 discusses the ever-growing importance of social interaction in economics and usage of heterogeneous agent models. Lastly, section 2.3 presents some essential concepts of network science that will be utilised later.

Chapter 3 presents the formal structure of the model employed. Section 3.1 presents a ternary choice framework with a deterministic and a random component, useful for modelling of bounded rationality. Section 3.2 shows the adaptation of Ball and Romer (1989) into a computational model using the framework laid out in the previous section. Section 3.3 explains the computational implementation of the model and 3.4 details the calibration process.

Chapter 4 presents the model's results and discusses its emergent properties. First off, section 4.1 rebuilds Silva (2012), only switching the price change magnitudes, for the sake of comparison. Afterwards, Section 4.2 presents results from calibration implementing a root-finding algorithm, updating the data set and adding the p variable. Then, Section 4.4 adds monetary fluctuations to the model.

Lastly, Chapter 5 presents the concluding remarks, where we will discuss how our results contribute to price setting literature and how could future researchers build upon these results to better our understanding of these questions, as it is one of the most important topics in economics, with unsolved macro and micro questions and real-life policy implications.

2 Price stickiness, social interaction and networks

To understand the following chapters, where the model and its results are presented, we need to go through some key concepts such as relevant findings about price stickiness, the ever-growing literature of social interaction in economics and the occurrence of small-world phenomena in network theory.

This chapter is organised as follows. Section 2.1 presents theories on price stickiness and empirical evidences, Section 2.2 presents social interaction in economics and how it is challenging important research paradigms in macroeconomics and lastly, Section 2.3 presents concepts of network theory essential to our model.

2.1 Some theoretical results and empirical evidences on price stickiness

If a complete nominal adjustment occurs, all the money stock variation will have, consequently, a variation of the same signal and amount in price level, thus there is no change in real economic variables. However, if part of a monetary shock is absorbed by an output variation, there is an incomplete nominal adjustment. Hence the market's inability to fully adjust to a monetary shock in real time is key to effectiveness of monetary policy (BILS; KLENOW, 2004).

In spite of the prevalence of the arguments from the new Keynesian school, which moved towards a reconcilement between short-run rigidities with long-run neutrality, the debate about real and nominal effects is ample and topical in economics (ROMER, 2018). Therefore, there is not a unified, comprehensive theory that explains in a completely satisfactory way the existence of price and wage stickiness.

There are many research programs with different approaches, each one focusing in a possible market imperfection that grants theoretical foundation to incomplete nominal adjustment, and this section intends to provide a primer on some that will be relevant to discuss after implementing the computational model.

Taylor (1999) argues that prices do not have the necessary flexibility for monetary policy to have instant effects on prices. based on empirical evidence for the United States, the author points out the following conclusions: i) wage rigidity is more popular in markets compared price rigidity, which does not necessarily mean it is more important; ii) there is heterogeneity in price and salary formation, particularly amongst sectors; iii) neither prices nor salaries move in a synchronised way, except when workers have stronger bargaining power – that is, strong unions; iv) interest rate is determinant to the frequency of price and salary changing.

Due to these facts, Taylor (1999) points out that in the long run, monetary shocks only affect inflation, but in the short run there are real effects. In the same research line, Klenow and Malin (2010), with databases from the Bureau of Labor Statistics (BLS), remark that prices take 4.4 months to change, taking sales into account. Controlling for sales, the time raises to 5.5 months, showing a certain degree of stickiness which grants monetary policy the power to influence real variables in the short run.

In that regard, Levy et al. (1998) have studied the price adjustment process at multiproduct retail stores and found out that it is a very complex work that at some moments is not rigorously planned. The authors remark that some of price stickiness is caused by item pricing law and fear of making mistakes while setting prices and making their firms vulnerable to lawsuits and damages to its reputation.

Still on the topic of firm-side microeconomic evidences, Nakamura (2008) presents findings relevant to us, due to its decomposition of price changes in big retailers. According to the author's data 16% of variation is common all across the market, 65% is common only within a same retail chain and 17% of the variation is completely idiosyncratic. If such a significant part of price changes is idiosyncratic, that adds to an argument for using bounded rationality in models.

Midrigan (2011) too, finds that it is more probable that a particular product has its price changed if a big fraction of the other prices within the same store are being changed, even more when the price changes are in similar goods. He also points out, based on weaker evidence than the previous finding, that there is some level of synchronization across stores in a given city.

Fischer (1977) and Taylor (1980) propose a salary-based explanation. Both authors point out microeconomic foundations for incomplete nominal adjustment through formal or implicit contracts, with the infrequent salary adjustment the main factor leading to short-run impacts on real output.

More recent microeconomic evidence on wages as a determinant for stickiness is provided by Druant et al. (2012), with survey data from 17 European countries featuring firms of various sectors. The authors find that wages are less frequently adjusted than prices, which are dependent on wages in a way that they are more flexible when labour costs are lower and markets are more competitive. On the other hand, price rigidities are higher when firms have more high-skilled workers.

In contrast to the European experience, in the United States prices tend to be more flexible, as the research of Dhyne et al. (2006) finds out. The authors discard the level and effect rates of inflation or differences in consumer preferences as determinants of higher flexibility. Suggested explanations are the heterogeneity in firms, as smaller retailers have a bigger market share in Europe and they change prices less frequently. Another point is that American consumers appear to be more sensitive to sales, so firms have more of an incentive to change prices for that reason. Lastly, a higher variability of wages due to less labour protection and less anti-competitive regulation too might help to explain the lesser stickiness in United States.

To expand on the point of the influence from sales on prices, Kehoe and Midrigan (2015) remark that on macro level, price changes induced by sales might have an influence, but not enough to hinder the effectiveness of monetary policy in a significant way. In that regard, the authors dispute the claim by Bils and Klenow (2004) that prices are quite flexible and are more in tune with Nakamura and Steinsson (2008) which study the same data set and come to the conclusion that by removing sales, price changes go from a frequency of 4.3 months to 7-11 months, which is fairly sticky.

Amongst more recent works, there is Anderson et al. (2017), which reinforces again that sales are a complex event to model around and to try to extract conclusions. Their results, with standard new Keynesian models using data from the BLS, found out that firms close to profit maximising, thus using sales rather efficiently. However, it has been shown that no matter how firms decide when to put on sales, they are quite influential on price adjustment even if not enough to dampen the impact of monetary policy (KEHOE; MIDRIGAN, 2015).

Another line of research is the effect of monopolistic competition market structures on price changes. In this context, Akerlof and Yellen (1985) affirm that money is not neutral in the short run because of suboptimal price and salary adjustments by firms. After a money stock change, firms would adjust slowly, with small and long-run losses, while the effect on real variables would be short-run. This is the reason why the authors define these firm as “almost rational” – take small losses, but allow real short-run expansions.

Still on the same theme, Ball and Romer (1987) and Ball and Romer (1989) remark that price stickiness may cause negative externalities. Both the private and the social costs of stickiness are not immediate, however social costs may be substantially higher. Thus, a sticky price equilibrium would cause a convergence towards inefficient fluctuations in output, that is, an incomplete nominal adjustment.

Another approach is the imperfect information one from Lucas (1972). According to the author, under rational expectations, for the money to not be neutral in the short run, there is a need for information to be incomplete. Woodford (2001) works within the same framework, concluding that agents have limited capacity to process information, avoiding a perfect price adjustment for this reason.

Another contribution on information is Mankiw and Reis (2002), which focuses not on completeness of information, but on their spreading. Therefore, agents are rational but work with lagged information. In sticky information, the information is perfect, but does not spread as it should, taking into account that acquiring and processing information can be hard tasks. The authors reach three conclusions: i) deflations are never expansionary; ii) inflation variations have a positive correlation with raises in economic activity; iii) monetary policy reaches maximum effect after a certain lag.

Another model from Woodford (2009) with substantial information costs (that means, it is hard for a firm to review pricing policies in the short run) is able to reconcile evidence on the frequency of price changes with the fact that nominal disturbances are able to bring about real consequences.

This is linked to a research agenda known as "rational inattention" proposed by Sims (2006), which means that agents have finite information-processing skills, so even though all their decisions are optimising behaviour, they are not fully optimising because they choose to focus on certain information. Agents react in discrete ways to a continuous flow of information.

Carrol (2006) highlights the importance of information for economic modelling. The author suggests that expectations are formed in an epidemic-like manner, supposing that some agents are rational indeed. These agents formulate expectations on their own and they spread through media, in a way that even though not all agents have access to information, it spreads like a disease.

Lastly, there is the evolutionary approach, very important to this research agenda. Bonomo et al. (2003) employ evolutionary games to evaluate the transaction costs between two equilibria to reach disinflation. Agents with traits of bounded rationality suffer worse losses than more rational agents; and strategies with below average performance have their use reduced with the passage of time. This way, there is an incomplete nominal adjustment while agents that adopted optimal strategies during the inflationary equilibrium do not change to optimal strategies for the transition period. However, in the long run they will eventually be able to learn which strategy leads to more gains.

Saint-Paul (2005) aims to find a motivation for price stickiness. The author aims to answer two main questions: (i) if the economy converges to a rational expectations equilibrium; (ii) in case this does not happen, whether is it possible to find a particular behaviour of sticky prices. The author builds a model where economic agents are imperfectly rational and interact in a local way with others. The author argues that, even though the rational expectations equilibrium is among the possible choices by agents, the economy does not converge to this equilibrium. On the contrary, the economy converges to an equilibrium where the global price level does not react completely to monetary shocks. Therefore, price stickiness is caused by two factors, namely a high local interaction and a low variance in monetary shocks.

Still on evolutionary dynamics, Silveira and Lima (2008) elaborate a model with emergence of monomorphic (where only one price-setting strategy between the perfectly and bounded rational survives) and polymorphic (both survive) equilibria. However, while on the monomorphic equilibria the money is neutral, on polymorphic equilibria the money might not be neutral.

Another model from Lima and Silveira (2015) allows firms to choose the Nash strategy (update their information and establish optimal prices) by paying a cost, else they can choose the bounded rationality strategy (which is free) with lagged information. Evolutionary dynamics take the process to a long-run equilibrium where, even though most or all firms employ the bounded rationality strategy, the price level is the same as the one from the symmetric Nash equilibrium. Monetary shocks in this situation possess persistent, but not permanent, effects on real output.

Online prices are another recent issue of price stickiness which was approached by Cavallo (2018), whose web scraping has shown that in comparison to the average, online prices tend to have a longer duration. His data set was quite robust, with 181 retailers from 31 countries, showing we cannot discard the hypothesis that online prices are stickier than most.

2.2 Social interaction in economics

With an interest in bringing theory closer to empirical data, research in economics has been more observing of the importance of social interaction between economic agents. Hommes (2006) reminds that, in a social interaction framework, the payoff received by a certain agent for his actions is directly related to the agents next (be it in a geographical, economic or social sense) to him. More precisely, his gains do not come only through market mechanisms, but also through imitation, learning, peer pressure and other externalities, where agents are affected by the behaviour of others.

In this scenario, financial economics was an early stage to many heterogeneous agent models, such as Hommes (1997), Lux (1998) and Boswijk et al. (2007) observing interaction between different investor styles. Finance had a head start in the usage of such models, because of its features that made the need for modelling complexity and heterogeneity easier to be seen. Traits such as a high degree of interconnectedness, enormous amounts of available data, focus on information and a proneness to behavioural biases.

Social interaction modelling allows the emergence of certain behaviour patterns between groups that fit well some real-life situations, such as herd behaviour in financial markets, as highlighted by Lux (1995). For instance, an investor might decide on selling an asset with good fundamentals due to the rest of the market having an emotional reaction faced with bad news about the company.

Still on the theme of company stocks, Hommes (1997) builds a rather simple evolutionary model for asset pricing and does not find a single rational choice equilibrium, but rather a multitude of chaotic equilibria, where prices fluctuate up and down moving around a strange attractor. The prices are indeed close to what they should be based on fundamentals, but there are constant changes and they do not converge to a stable value.

A variation on the same theme is Lux (1998), employing an ABM not to securities, but to exchange rate trading. The agents are separated between fundamental traders basing themselves on what the exchange rate "should be" due to macroeconomic analysis and technical analysts that seek patterns and trends in the charts, looking to win a short-term profit. The author also finds chaos with appreciation peaks and huge drops due to interaction between the traders, which do not happen without heterogeneity in agents. They can be optimistic or pessimistic according to their idiosyncratic feelings, and can change strategies by comparing their performances to their neighbours. While the author was more concerned about the explaining power of complexity in exchange rate variations, which is mentioned to be very hard to understand (much less accurately predict), an evolutionary approach could also check if a dominant strategy emerges from competition between both.

Boswijk et al. (2007) propose a model of heterogeneous agents with bounded rationality for dynamic asset pricing. While the fundamental value of a risky asset is known, agents disagree on the persistence of the decoupling between stock prices and fundamental benchmarks. Same as the Lux (1998) model, there are fundamentalists and chartists, and their model fit well a long data set of US stock prices, showing that regime changes between both sides could explain well asset price fluctuations during the past century. Such a work is even more relevant today considering the bull runs in many stock exchanges after quantitative easing was introduced to offset the negative impact from the 2008 global financial crisis. It might be that with the diffusion of information and the interdependence of contemporary economies, network effects will become ever more relevant in explaining macroeconomic phenomena, as Gatti et al. (2010) and Caballero (2010) remark.

In macroeconomics, with the prevalence of the new neoclassical synthesis and DSGE models, the start was rather timid, but more recently models with social interaction have been getting more attention. This is happening because current mainstream models are coming under fire since the 2008 crisis, facing hardships when trying to fit empirical findings well, as Romer (2016) staunchly points out. ABMs, however, can account for the features mentioned beforehand such as interaction and bounded rationality.

On interactive expectations, Flieth and Foster (2002) remark that the expectation formation process involves discussion amongst agents. An individual has his expectations influenced by opinions of friends, business partners and also competitors. Topa (2001) highlights that interactions are between social neighbours – which share certain socioeconomic proximity, but not necessarily geographic – that could be individuals that took the same classes at school, coworkers or any attendants of the same social activities, even if they do not live close to each other.

Gale and Kariv (2003) and Tichy (1992) highlight the possibility that, under bounded rationality and uncertainty, exists the chance that agents might improve their decisions observing their neighbourhoods. As neighbours might carry important information, there is reasoning to take social interaction into account in economic models.

On consumer habits, Goolsbee and Klenow (1999) find evidence that personal computer acquisition by American families in 1997 suffered influence from social interaction. Controlling for many individual traits, authors found a higher probability of individuals acquiring computers in case many families in the neighbourhood or close friends had acquired a computer previously. The authors remark that this phenomenon happened due to network effects, where computer owners convinced their social neighbours into also buying one.

E-commerce is also something that is deeply affected by social interaction, remark Wang and Yu (2017). They find out that observational learning and word of mouth are important to determine whether a consumer will buy a product or not, as consumers take into account opinions from their peers and observe their purchases to obtain information about the product.

A more pertinent example to this line of research is the price adjustment between firms in a given neighbourhood. If a firm decides to raise the price of a good it produces, it cannot raise the price much higher than the neighbouring firms that produce close substitute goods, as that raises the chance of losing clients, therefore not maximising profits. Bernhardt (1993) points out there is a cost in price adjustment in the sense that not coordinating with close firms means that an increase in price might in fact not be profit maximising even though it would only be following a nominal change in money supply.

In this context, Hohnisch et al. (2005) propose an interactive expectations model to study business environment amongst entrepreneurs. Each entrepreneur is faced with a ternary choice between negative, neutral or positive expectations and changes its evaluation of business climate based on the opinions of its neighbours, with the results emulating well some traits of the German business confidence index.

Another study on business cycles, Westerhoff (2005) points that consumer confidence is also influenced by the neighbourhood. In this model, there are optimistic agents (which spend most of their income) and pessimistic agents (which do not spend most of their income) and it is interaction that causes agents to change sentiment. If most of the agents are optimistic, there is a tendency towards consumer bubble formation, but if too many are pessimistic there is a recessionary effect.

Ballot et al. (2015) point out that after their rise in popularity, not only have ABMs contributed to our understanding of macroeconomic disequilibria, but also to studying equilibrium in more realistic settings. For instance, while Dosi et al. (2013) work inside an evolutionary framework based on Nelson and Winter (1977) or an old Keynesian framework that does not intend to reconcile with a neoclassical mainstream, Guerrero and Axtell (2011) propose an agenda of "agentization", which is turning mainstream models with simplifying hypotheses into computational models, to search for possible breaking points in them.

Recently, Jackson et al. (2017) discuss the effects of the social network structure of today's society on economics. The authors point out the importance of accounting for social relationships in economic models, as they have features such as cognitive biases and perverse incentives that might lead to suboptimal equilibria.

Fainmesser and Galeotti (2016) develop a model with a monopolistic firm that sells a network good and price discriminates by using information about consumers' influence and their susceptibility to influence from their peers. The monopoly's maximising behaviour is to offer a discount to influential consumers (that will popularise their good) and charge premia to susceptible clients (that are more likely to go along with influential consumers and make a purchase). Fainmesser and Galeotti (2020) make new progress by showing that this influence marketing leads to inefficient consumer-product matches, leading firms to invest in information. This competition for information brings firms' profits closer to zero but increases consumer surplus.

Dosi and Roventini (2019) remark that The Great Recession was a natural experiment in macroeconomics that showed issues with the DSGE approach and that price stickiness, for instance, can be better approached under the lens of agent-based modelling, which features empirically consistent microfoundations. As such, social interaction and complexity might be key factors in price stickiness.

Dosi et al. (2020) mention that price stickiness might arise from heterogeneity, imperfect information and coordination hurdles. In fact, their models do not fit empirical data well when parameters representing information and rationality are set higher, showing that we can improve our understanding of macroeconomics when taking these issues into account.

2.3 Elements of network theory

The previous section highlighted the important role of social interaction in economic decision making and the difficulty of including it on models, which is one of the reasons for its underrepresentation. However, mathematical and computational advances in the last decades brought network science to a new public, which includes the economists. Applying network theory and its analytical toolbox allows the insertion of social interaction into economic models to observe agents interacting and their effects, as Guerrero and Axtell (2011) remark.

Goyal (2012) explains that networks of a given system might be represented mathematically through graph theory, according to which a network might be represented by $G = (N, B)$ in which N is a set (non-empty and finite) of nodes and B is the set of edges, formed by unordered pairs of distinct nodes.

In the view of Ahuja et al. (1993), nodes might be interpreted as agents inside a system, which in economics might be consumers or firms, for instance. Edges might represent connections between different agents, such as a market formed by firms that are geographic neighbours. Still according to Goyal (2012), a network is undirected if the influence between nodes happens both ways. If a network is direct, the influence between nodes occurs happens only one way.

It can be said of two nodes i and j of a given network G that both are connected if there is a sequence of nodes connected amongst themselves that link the i node to the j node. The set formed by nodes connected by edges to a given node of interest composes the neighbourhood of the node.

Taylor and Higham (2009) show that a network G might be represented by an adjacency matrix defined by $A = [a_{ij}]$ square of order L, such that A will have L agents – each node is represented by a row and column. In the matrix, if $a_{ij} = a_{ji} = 1$, that means nodes i and j are connected. If $a_{ij} = a_{ji} = 0$, nodes are not connected. As A is a symmetric matrix, if two agents are connected, both can observe the strategy adopted by the neighbouring agent.

It is common to analyse three structural properties of a network, namely: the degree of a node, the distance between nodes and the clustering coefficient. The degree of the i node, denoted by k_i, is the number of agents from the network which i is connected to and defines the number of its neighbours, thus being the sum of the agents contained in the i-th line of the A matrix:

$$k_i = \sum_{j=1}^{L} a_{ij}. \tag{2.1}$$

The distance between nodes is the minimum number of edges to be crossed to go from the i node to the j node in a given network G. In complex networks, the distance measure commonly employed is the average distance between pairs of nodes, represented by ℓ, which is the simple mean of the distances amongst all nodes.

Lastly, the clustering coefficient of the neighbourhood of the i node, which will be represented by E_i, is defined by the proportion of nodes neighbours to i that are also neighbours amongst themselves. It can be calculated by dividing the number of neighbours that are connected amongst themselves by the highest feasible number of connections. The global clustering coefficient, E, is given by the simple mean of the clustering coefficients E_i of the network's nodes:

$$E = \frac{1}{L}\sum_{i=1}^{L} E_i = \frac{1}{L}\sum_{i=1}^{L} \frac{L_p}{\frac{1}{2}k_i(k_i - 1)}, \tag{2.2}$$

where L_p is the number of connected neighbouring pairs.

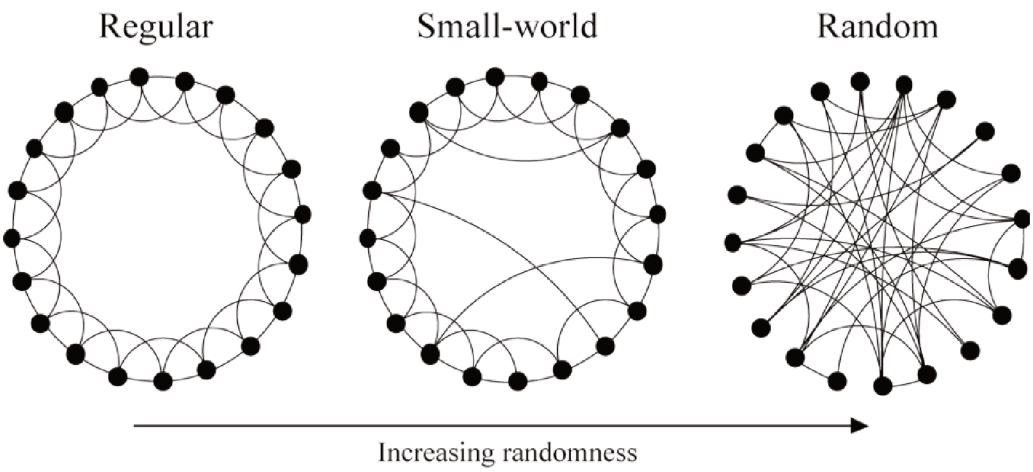
In complex networks, a node can connect with another node very far from its geographical location, and the same might happen to this second one. This means nodes can be linked even though their positions in the network are far from each other, and nodes that are all far from each other might be linked in a sequence with few steps. Small-world phenomena is how Milgram (1967) has described these kinds of events.

In order to represent complex networks, Watts and Strogatz (1998) suggest the usage of ring networks (see Figure 1), where nodes are in a circumference and uniformly distributed throughout the circumference. In this network, each of the nodes is linked to K neighbours in clockwise sense and K neighbours in counterclockwise sense. Having defined a ring network it is possible to eliminate the edge between the i-th node and one of its neighbours and afterwards create a new link between i and any other node chosen randomly with a probability $p \in [0, 1] \subset \mathbb{R}$, in an operation called *rewiring*.

A network is called regular when $p = 0$, and its main feature is having the same number of edges for all nodes. For any i node, in a regular network the connected edges are always the same. Moreover, the authors remark that they possess a high E and a ℓ that increases linearly with the network size.

If $p = 1$ the network is called random. Such networks present a low E and an ℓ that increases in logarithmic scale with the network size. Watts and Strogatz (1998) remark that, empirically, social networks tend to present a high clustering coefficient, E, but a low average distance between nodes, ℓ.

Figure 1 – Complex network types



Source: Watts and Strogatz (1998).

As it has been pointed out by Watts and Strogatz (1998), these traits put the networks found empirically halfway between the regular and random networks, and in case $p \approx 0,1$ the network can be called small-world. In this topology, the average distance between nodes is comparable to the distance of a random network, but the clustering coefficient is strictly superior to the one from a random network.

3 A price-setting game on a complex network

This chapter will show the adaptation of a new Keynesian price-setting model, proposed by Ball and Romer (1989), into an ABM with bounded rationality and network effects. To do so, as suggested by Flieth and Foster (2002), rational expectations are substituted by interactive expectations and the price-setting dynamic will be analysed by computational simulations. This model was primarily adapted by Silva (2012), however the only network topology used by the author was a regular one. Differently from this author, this thesis will calibrate the rewiring probability and employ a complex network.

To do so, the price-setting game described by Ball and Romer (1989) needs to be transformed into a network game. Goyal (2012) points that a network game presents the following traits: i) a population of players; ii) a set of actions that can be chosen on each round of the game; iii) an established relationship amongst players; iv) defined payoffs for each player, on each round, due to the interaction amongst players.

The chapter is organised as follows. Section 3.1 is based on the heterogeneous strategy switching protocol proposed by Hommes (1997). Section 3.2 is based on the price setting game from Ball and Romer (1989), incorporating the framework mentioned in the previous section. Section 3.3 shows the model's implementation through computer programming. Lastly, section 3.4 details model calibration.

3.1 A discrete choice model

Consider an agent i that must choose between three mutually exclusive alternatives, denoted by $-1, 0$ e 1. Let $\sigma_i \in \{-1, 0, 1\}$ be the i-th agent's choice in period $t \in \mathbb{N}$. At any period t, each agent can choose between lowering one's price ($\sigma_i = -1$), maintain the same ($\sigma_i = 0$) or raise it ($\sigma_i = 1$).

Train (2009) remarks that preferences (and, consequently, the utility function that represents them too) depend on observable motivations and non-observable motivations, the last depending on idiosyncratic traits of an agent. Due to non-observable motivations, decision-making phenomena is stochastic, not deterministic, to someone that is able to watch from the outside.

To account for that, the utility function will feature a deterministic component referring to observable traits and a stochastic one associated to non-observable traits:

$$\mathcal{U}(\sigma_i) = \mathcal{U}^d(\sigma_i) + \varepsilon(\sigma_i), \tag{3.1}$$

where $\mathcal{U}^d(\sigma_i)$ is the function's deterministic component, associated to observable motivations, and $\varepsilon(\sigma_i)$ the stochastic component, associated to non-observable motivations.

After defining the utility function, next step is evaluating the agent's optimal choice. Choosing a certain value $\sigma_i \in \{-1, 0, 1\}$ is the agent's optimal choice in case it fulfills the following condition:

$$\mathcal{U}(\sigma_i) \geq \mathcal{U}(\sigma_i'), \forall \sigma_i' \in \{-1, 0, 1\}. \tag{3.2}$$

It is possible to rewrite (3.2) using (3.1) as follows:

$$\mathcal{U}^d(\sigma_i) - \mathcal{U}^d(\sigma_i') \geq \varepsilon(\sigma_i') - \varepsilon(\sigma_i), \forall \sigma_i' \in \{-1, 0, 1\}, \tag{3.3}$$

in a way to highlight that choosing a certain σ_i will be an optimal choice for the i-th agent if the net gain from the observable component (left-hand side) is bigger than the net gain from the stochastic component (right-hand side), associated to any σ_i' alternative.

However, even if the observable utility of a given strategy σ_i is bigger than the others, that does not guarantee that σ_i will be chosen by the i-th agent. Non-observable incentives from one of the other strategies might be bigger than the ones from the σ_i strategy. Thus, it is only possible to define the probability of the i-th agent choosing $\sigma_i \in \{-1, 0, 1\}$ from (3.2) e (3.3):

$$\begin{aligned} Prob(\sigma_i) &= Prob\Big(\mathcal{U}(\sigma_i) \geq \mathcal{U}(\sigma_i')\ \forall \sigma_i'\Big), \\ &= \textstyle\int_{-\infty}^{\infty} I\Big[\varepsilon(\sigma_i') - \varepsilon(\sigma_i) \leq \mathcal{U}^d(\sigma_i) - \mathcal{U}^d(\sigma_i')\ \forall \sigma_i'\Big] f(\vec{\varepsilon}_i) d\vec{\varepsilon}_i, \end{aligned} \tag{3.4}$$

where $f(\vec{\varepsilon}_i)$ is the joint probability density function (PDF) of the random variables vector $\vec{\varepsilon}_i = \Big(\varepsilon(\sigma_i = -1), \varepsilon(\sigma_i = 0), \varepsilon(\sigma_i = 1)\Big)$ and $I[\cdot]$ an indicator function, equal to 1 if the inequality between brackets is true and zero in case it is false. What follows is that function (3.4) is a cumulative density function (CDF) of the utility function's random component given by equation (3.1). This CDF indicates the i-th agent's propensity towards choosing a certain strategy $\sigma_i \in \{-1, 0, 1\}$. The propensity towards choosing σ_i raises together with the difference between observable incentives, meaning idiosyncratic motivations have their importance diminished with this differential's raise.

Train (2009) highlights that diverse discrete choice models might be derived from distinct specifications of the PDF given by $f(\vec{\varepsilon}_i)$, with the most common being the one whose final result is the logit model. To do so, suppose the random components of (3.1) are random variables independent amongst themselves, with the same probability distribution for extreme values. That means for each $\varepsilon(\sigma_i)$, the PDF is a Type-1 Gumbel formally given by:

$$f(\varepsilon(\sigma_i)) = \beta e^{-\beta\varepsilon(\sigma_i)} e^{-e^{-\beta\varepsilon(\sigma_i)}}, \tag{3.5}$$

with $\beta > 0$ being a real constant.

The CDF corresponding to the PDF given by (3.5) is in turn given by:

$$F(\varepsilon(\sigma_i)) = e^{-e^{-\beta\varepsilon(\sigma_i)}}., \tag{3.6}$$

and inserting (3.5) and (3.6) in (3.4) it is possible to obtain the logistic CDF, defined by the following equation:

$$\begin{aligned} Prob(\sigma_i) &= \frac{e^{\beta U^d(\sigma_i)}}{e^{\beta U^d(\sigma_i)} + e^{\beta U^d(\sigma_i')} + e^{\beta U^d(\sigma_i'')}}, \\ &= \frac{1}{1 + e^{-\beta[U^d(\sigma_i) - U^d(\sigma_i')]} + e^{-\beta[U^d(\sigma_i) - U^d(\sigma_i'')]}}, \end{aligned} \tag{3.7}$$

where σ_i, σ_i' e σ_i'' are three distinct choices.

An interpretation of β that will be relevant in analysing the results is offered by Brock and Hommes (1997), remarking that *ceteris paribus*, the smaller the β, the bigger is the impact of non-observable incentives on the probability of choosing a certain strategy. Therefore, choices little depend on deterministic utility. But if β has a bigger value, by analogy, it is easy to see that the strategy chosen will probably be the one which offers the biggest deterministic utility.

Durlauf (1996) and Brock and Durlauf (2001) propose including a third term on the function (3.1) to represent network effects, that is, the i-th agent makes his/her decisions influenced by the social neighbourhood, henceforth called n_i. Formally, n_i is the set of agents whose decisions are observed by the i-th agent and influence his/her decisions.

Including network effects as an observable incentive causes the deterministic component of the utility function to be represented as follows:

$$\mathcal{U}^d(\sigma_i) = \alpha\, \mathcal{U}^p(\sigma_i) + \mathcal{U}^s(\sigma_i, \vec{\sigma}_i^e), \tag{3.8}$$

with α being a parametric constant that measures the relative weight of deterministic private utility, $\mathcal{U}^p(\cdot)$, that represents all observable incentives except network effects, and $\mathcal{U}^s(\cdot)$, the social deterministic utility that suffers network effects. It is worth highlighting that $\mathcal{U}^s(\cdot)$ depends not only on the choice from the i-th agent, but also on the choices from the n_i neighbourhood, represented by the vector $\vec{\sigma}_i^e \equiv \{\sigma_j^e\}_{j \in n_i}$.

Inserting (3.8) in (3.1), we are able to obtain a new equation for the utility of the i-th agent when he/she chooses σ_i:

$$\mathcal{U}(\sigma_i) = \alpha \mathcal{U}^p(\sigma_i) + \mathcal{U}^s(\vec{\sigma}_i) + \varepsilon(\sigma_i), \tag{3.9}$$

and after this adaptation, employing the same reasoning used in deriving equation (3.7), it is possible to obtain the probability of choosing the σ_i alternative, but with $\mathcal{U}^d(\sigma_i)$ now defined by (3.8).

Lastly, the social deterministic utility $\mathcal{U}^s(\cdot)$ will be derived. It depends on the network topology, but for demonstration ends, a regular network with quadratic form (square lattice) and N agents will be assumed. Therefore, the n_i social neighbourhood of the i-th agent located in the coordinates $(\ell, c) \in \{1, ..., N\}^2$ of order N will be defined by:

$$n_i = \{(m, n) \in \{1, 2, ..., N\}^2 : |k - m| + |\ell - n| = 1\}. \tag{3.10}$$

After defining n_i, it is possible to define the social utility of the i-th agent located in the coordinates $(\ell, c) \in \{1, ..., N\}^2$ as:

$$\mathcal{U}_i^s(\vec{\sigma}_i) = \frac{J}{4} \sum_{j \in n_i} \delta_{\sigma_i \sigma_j}, \tag{3.11}$$

where $J > 0$ is a parametric constant that measures the degree of influence in the neighbourhood and $\delta_{\sigma_i \sigma_j}$ is the Kronecker delta. If $\sigma_i = \sigma_j$, então $\delta_{\sigma_i \sigma_j} = 1$. Otherwise, $\delta_{\sigma_i \sigma_j} = 0$, so that the Kronecker delta can be rewritten as:

$$\delta_{\sigma_i \sigma_j} = \sum_{j \in n_i} \frac{1}{2} \left[\sigma_i \sigma_j + 3\sigma_i^2 \sigma_j^2 - 2\left(\sigma_i^2 + \sigma_j^2\right) + 2 \right]. \tag{3.12}$$

Substituting (3.12) in (3.11), it is possible to redefine social utility as:

$$\mathcal{U}_i^s(\sigma_i) = \frac{J}{8} \sum_{j \in n_i} \left[\sigma_i \sigma_j + 3\sigma_i^2 \sigma_j^2 - 2\left(\sigma_i^2 + \sigma_j^2\right) + 2 \right]. \tag{3.13}$$

In short, if $\alpha / J > 1$, then agents will put more weight on private utility, else they will be more affected by network incentives. As for β, the lower it is, the more random it will be, including bounded rationality in the model, as an agent might make bad choices from a deterministic utility viewpoint, going with a worse strategy if he/she puts a low intensity on choosing based on observable incentives.

3.2 Adaptation of a new Keynesian price-setting model

The model proposed by Ball and Romer (1989) is a simplified version of a model first outlined by Blanchard and Kiyotaki (1987), where N producers fabricate distinct goods, that are produced by their own labour (thus suppressing labour markets), sold and profits are used by purchase products from other producer-consumers. The goods, however, are close substitutes amongst themselves.

Indeed, it is a price-setting model with monopolistic competition that, by ignoring labour markets, is able to focus on price stickiness and its effects on output. As is custom, the authors employ the rational expectations hypothesis to be able to analyse the model's price-setting equilibrium. By doing so, the authors are able to elegantly solve the model analytically. Under rational expectations, the model's conclusion is that of a symmetric Nash equilibrium where the representative agents eventually settle on a price and there is no long-run effect of a money shock on aggregate output, but with some caveats.

To expand on that, authors point out that private and social costs of stickiness are second order, but social costs still can be quite large relative to private costs and an equilibrium rigidity in fact can produce very inefficient output fluctuations. However, they do point out that externalities caused by price stickiness are large only for implausible parameter values, thus casting a doubt on the possibility of stickiness causing big welfare losses. The authors comment that for a given distribution of shocks, the first order gains and losses from output fluctuation average to zero. The average welfare effect of rigidity is negative though, but it is second order and might not exceed the average private menu cost, so it might be better to suffer this negative effect than adjust prices.

Taking this model as basis, we can swap rational expectations for interactive expectations as suggested by Flieth and Foster (2002), considering the relevance of social interaction in price setting, as previously outlined on Chapter 2. Afterwards, the model can be computationally implemented by sorting heterogeneous agents in a network, as it will be explained in the next section, in order to tackle the issues raised by Ball and Romer (1989) under a different light.

For a start, the producers employ only their own labour endowments, in such a way that there is no job market. Initially, Ball and Romer (1989, p. 509) suppose that the utility function of the i-th producer is:

$$U_i = C_i - \left(\frac{\epsilon - 1}{\gamma\epsilon}\right) L_i^{\gamma} - zD_i, \tag{3.14}$$

where C_i is the producer's consumption index; $\epsilon > 1$ is the elasticity of substitution between any two goods; $\gamma > 1$ is marginal disutility of labour; L_i is the producer's amount of labour; D_i is a dummy variable that captures changes in the nominal price of the i good (taking on the value of 1 if it changes, 0 if it does not); lastly, z is menu cost. As menu costs are not the focus of this thesis, henceforth we take $z = 0$.

The consumption index of the i-th producer depends on the consumption of goods other than i, such that:

$$C_i = N\left[\frac{1}{N}\sum_{j=1}^{N} C_{ij}^{\frac{\epsilon-1}{\epsilon}}\right]^{\frac{\epsilon}{\epsilon-1}}, \tag{3.15}$$

with C_{ij} being the amount of the j good consumed by the i-th producer. Moreover, the i-th producer is subject to the following production function:

$$Y_i = L_i, \tag{3.16}$$

with Y_i being the amount produced of the i good.

By taking prices as exogenous, it is possible to find the quantities consumed that maximise the consumption index of the i-th producer, given by (3.15), subject to the budget constraint that follows:

$$\sum_{j=1}^{N} P_j C_{ij} = I_i, \tag{3.17}$$

where I_i is the income, here exogenously determined, of the i-th producer. Solving the maximization problem of (3.15) through Lagrange multiplier, conditioned to the constraint given by (3.17) and differentiating with respect to C_{ij}, for $j = 1, 2, ..., N$, the result is a system of equations given by:

$$\left(\frac{C_{ij}}{C_{ik}}\right)^{-\frac{1}{\epsilon}} = \frac{P_j}{P_k}; \ \ i, j, k = 1, 2, ..., N, \ \ j \neq k. \tag{3.18}$$

Equation (3.18), where for any given goods j and k, is the known equality between the marginal rate of substituion of both goods and the ratio between their prices.

By substituting (3.18) in equation (3.17), it is possible to find the optimal quantities of the N goods demanded by the i-th producer, that is, the Marshallian demands:

$$C_{ik} = \frac{1}{N}\left(\frac{P}{P_k}\right)^{\epsilon}\frac{I_i}{P}; \ \ i, j, k = 1, 2, ..., N, \tag{3.19}$$

with P representing the general price level, which is formally:

$$P = \left(\frac{1}{N}\sum_{j=1}^{N} P_j^{1-\epsilon}\right)^{\frac{1}{1-\epsilon}}. \tag{3.20}$$

Inserting (3.19) in (3.17), after some algebraic manipulation and use of definitions (3.15) and (3.20), which is detailed in Silva (2012), it is possible to define expenditure with the optimal bundle as:

$$C_i P = I_i. \tag{3.21}$$

As the i-th producer's income is determined by the price of i, and by its demand Y_i^D, income is therefore $I_i = P_i Y_i^D$. Assuming $Y_i = Y_i^D$, then:

$$I_i = P_i Y_i. \tag{3.22}$$

From the equality between (3.21) and (3.22), consumption is:

$$C_i = \frac{P_i Y_i}{P}, \tag{3.23}$$

which means the i-th producer's consumption is given by the his/her firm's real revenue.

The i good's demand is by definition the sum of its consumption by all producers, which is formally:

$$Y_i^D = \sum_{j=1}^{N} C_{ji}, \tag{3.24}$$

and inserting Marshallian demands (3.19) in (3.24), the good's demand might be written as follows:

$$Y_i^D = \sum_{j=1}^{N} \frac{1}{N} \left(\frac{P}{P_i}\right)^{\epsilon} \frac{I_j}{P}, \tag{3.25}$$

and inserting (3.22) in (3.25), it is obtained:

$$Y_i^D = C \left(\frac{P_i}{P}\right)^{-\epsilon}. \tag{3.26}$$

From (3.26), it it seen that demand for the i good is negatively inclined in relation to its own relative price, and positively inclined in relation to the economy's level of average consumption. Average consumption, C, might be written this way:

$$C = \frac{1}{N} \sum_{j=1}^{N} C_j. \tag{3.27}$$

With the defining of optimal decisions relative to quantities finalised, now there are the optimal decisions relative to prices. Substituting (3.23) in equation (3.14), it is possible to rewrite U_i as:

$$U_i = \frac{P_i Y_i}{P} - \left(\frac{\epsilon - 1}{\gamma\epsilon}\right) L_i^{\gamma}. \tag{3.28}$$

Furthermore, with $L_i = Y_i = Y_i^D$, which might be concluded from (3.26), it is possible to rewrite U_i again as:

$$U_i = C \left(\frac{P_i}{P}\right)^{1-\epsilon} - \left(\frac{\epsilon - 1}{\gamma\epsilon}\right) C^{\gamma} \left(\frac{P_i}{P}\right)^{-\gamma\epsilon}. \tag{3.29}$$

In the model built by Ball and Romer (1989), money is just a medium of exchange to realise transactions, so it is possible to employ money supply, M, as a proxy of aggregate nominal demand. Using the $M = PC$ equality, ergo, it is possible to rewrite (3.29) as:

$$U_i = \frac{M}{P} \left(\frac{P_i}{P}\right)^{1-\epsilon} - \left(\frac{\epsilon - 1}{\gamma\epsilon}\right) \left(\frac{M}{P}\right)^{\gamma} \left(\frac{P_i}{P}\right)^{-\gamma\epsilon}. \tag{3.30}$$

Equation (3.30) means that the i-th producer's utility depends on the price set for his/her own good, P_i, the general price level, P, which results from N price setting decisions taken simultaneously and on the money stock M, chosen by the monetary authority.

Therefore, the i-th producer's optimal price is that which maximises his/her utility. Optimal price, P_i^* is given by:

$$P_i^* = P^\phi M^{1-\phi}, \tag{3.31}$$

where $\phi = \frac{1+(1-\epsilon)(1-\gamma)}{1-\epsilon(1-\gamma)} \in (0,1) \subset \mathbb{R}$. This parameter is elasticity of the i-th producer's optimal price with respect to the general price level.

In the price-setting game described by Ball and Romer (1989), a symmetric Nash equilibrium occurs when $P_i^* = P$ for all $i = 1, 2, ..., N$. If that happens, then $P_i^* = P = M$, $C_i = C = 1$ and $Y_i = 1$ for all $i = 1, 2, ..., N$.

Relaxing the hypothesis that producers immediately identify the game's symmetric Nash equilibrium, it is possible to adapt the model here described to a network game. That means in period t, the i-th producer, in choosing the price $P_{i,t}$, must form an expectation of the general price level P_t to apply the optimal rule, which is given by:

$$P_{i,t} = \left(P_{i,t}^e\right)^\phi (M_t)^{1-\phi}, \tag{3.32}$$

where $P_{i,t}^e$ is the general price level expected on period t by the i-th producer.

As mentioned beforehand, one of the main changes is abandoning the rational expectations paradigm, where $P_{i,t}^e = P_t$. It is taken out in favour of interactive expectations (FLIETH; FOSTER, 2002), the model will take into account individual psychological factors, such as bounded rationality when faced with uncertainty. Under bounded rationality, interpersonal interactions between agents have effects on decision-making, assuming that individuals identify themselves with each other, even if they do not come to agreements. This is reflected by the fact that when an agent's neighbours choose a given strategy, the probability of him also choosing it raises, but he/she might still choose another one.

This way, agents need to choose, according to the theoretical framework outlined in section 3.1, their stance on each round. A producer might lower the price ($\sigma_{i,t} = -1$), keep it still ($\sigma_{i,t} = 0$) or raise it ($\sigma_{i,t} = 1$). To make a choice, an agent will choose the strategy which grants the most overall utility. From here onwards, the functioning of the utility function's three components in the context of the model proposed will be detailed.

Deterministic private utility is given by:

$$\mathcal{U}^p(\sigma_{i,t}) = \left(\frac{P_t - P_{t-1}}{P_{t-1}}\right)\sigma_{i,t}. \tag{3.33}$$

Notice that for $\mathcal{U}^p(\sigma_{i,t}) > 0$, both terms multiplying amongst themselves must have the same signal. Meaning that if the agent reduces his/her price ($\sigma_{i,t} = -1$) and the general price level falls ($P_t < P_{t-1}$), it follows that $\mathcal{U}^p(\sigma_{i,t}) > 0$. Analogously, the same happens in case the agent raises his/her price and the general price level goes up. If the agent is neutral ($\sigma_{i,t} = 0$), deterministic private utility follows the price variation's signal.

As for the deterministic social utility, assuming the network structure outlined in section 3.1, for the i-th producer, on period t, depends on the strategies of the producer himself and also of the n_i neighbourhood, being given by:

$$\mathcal{U}^s(\sigma_{i,t}) = \frac{J}{8} \sum_{j \in n_i} \left[\sigma_{i,t}\sigma_{j,t} + 3\sigma_{i,t}^2\sigma_{j,t}^2 - 2\left(\sigma_{i,t}^2 + \sigma_{j,t}^2\right) + 2 \right]. \tag{3.34}$$

As outlined in section 3.1, the stochastic component of the utility function will be given by random variables independent amongst themselves that follow the Type-1 Gumbel distribution, formally defined in equation (3.5). Based on these assumptions, it is possible to express the propensity to choose a certain strategy $\sigma_{i,t}$ in the following way:

$$Prob(\sigma_{i,t+1}) = \frac{1}{1 + e^{-\beta[U^d(\sigma_{i,t}) - U^d(\sigma'_{i,t})]} + e^{-\beta[U^d(\sigma_{i,t}) - U^d(\sigma''_{i,t})]}}. \tag{3.35}$$

Put that, the last step for model closure is defining how producers, given their states on period t, form their expectations for the general price level, $P^e_{i,t}$. If the agent is neutral, $P^e_{i,t} = P_{t-1}$. If the agent is inflationary, $P^e_{i,t}$ will be chosen randomly between $[P_{t-1}, 1.2P_{t-1}]$ and if the agent is deflationary, $P^e_{i,t}$ will be chosen randomly between $[0.8P_{t-1}, P_{t-1}]$.

In short, the above options can be described intuitively. Let $P^e_{i,t}$ be a uniformly distributed random variable, with its valued conditioned to the choice of $\sigma_{i,t}$, then the value of each agent's expected $P^e_{i,t}$ will be chosen amongst:

$$P^e_{i,t} = \begin{cases} \tilde{P}_{i,t} \in [0.8P_{t-1}, P_{t-1}], \text{ if } \sigma_{i,t} = -1, \\ P_{t-1}, \text{ if } \sigma_{i,t} = 0, \\ \tilde{P}_{i,t} \in [P_{t-1}, 1.2P_{t-1}], \text{ if } \sigma_{i,t} = 1. \end{cases} \tag{3.36}$$

Based on their expectations of the general price level, each agent will define an individual price on t by using the optimal rule given by equation (3.32), whereas the general price level is calculated by equation (3.20).

An outcome that could not happen in the original model by Ball and Romer (1989) can and will happen all the time in this one: at any given moment, there can be heterogeneity amongst producer prices and a general price level that is not the symmetric Nash equilibrium price level that would be reached assuming rational expectations.

Some variables of interest in Chapter 4 will be the output level and price variance. The authors define the money supply $M = PC$, and as the model does not mention investment or government expenditure we can, for each period, isolate the mean consumption index and treat it as the aggregate output:

$$Y_t = \frac{M_t}{P_t}, \tag{3.37}$$

and lastly, the price variance on each step can be described by the standard formula:

$$Var_t = \frac{1}{N} \sum_{i=1}^{N} \left[P_{i,t} - P_t \right]^2. \tag{3.38}$$

3.3 Computational implementation

The economic system described in sections 3.1 and 3.2 will be implemented through programming to build a network of the agents. To implement different network structures, we can do a rewiring procedure as described by Watts and Strogatz (1998), however instead of a ring network, it is in matrix form, as it is easier to program. For this procedure to be formally implemented to a matrix structure, there is the shortcuts routine as described by Taylor and Higham (2009).

By inputting the number of agents and how many nodes they connect to in a regular network (nearest neighbours), their script generates an adjacency matrix A of order L which means there are L agents. If $a_{ij} = a_{ji} = 1$, that means that nodes are connected and can see each other's strategy and a shortcut is generated to link them.

After having this information, we can add these edges between the agents that should be linked with each other. To solve the contour issue, agents in the last row and column will be linked with agents from the first row and column so that their neighbourhoods are complete. The last input is $p \in [0, 1] \subset \mathbb{R}$, the rewiring probability, that will be included in calibration – the bigger p is, the more random a network will be.

Each producer will have a choice set defined by $\sigma_{i,t} = \{-1, 0, 1\}$, which corresponds respectively to the deflationary, neutral and inflationary strategies, only being able to change strategy on the start of each round. It is known that the strategies distribution has a certain weight in producer decisions, thus in the $t = 0$ period initial conditions are set such that each one of the strategies starts with 33.33% of adherence by the agents, distributed randomly.

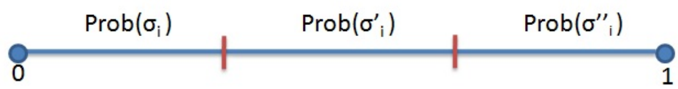
The same randomness principle is used by agents to form prices in the $t = 0$ period. Using an uniform probability distribution, these are spread randomly inside the interval $[0.8P_{t-1}, 1.2P_{t-1}] \subset \mathbb{R}$ in the network. After defining individual prices, the general price level is calculated in the $t = 0$ period, using the equation (3.20) presented in section 3.2. Moreover, the initial monetary supply is defined as 1 – this hypothesis will be relaxed later.

Having established the initial conditions, the period $t = 1$ is started. With the propensities toward strategies already defined, producers form their expected prices ($P^e_{i,t}$), as shown in equation (3.36) from section 3.2. After the expected prices are established, each agent's individual price is obtained based on equation (3.31).

After a round ends, the model feeds back to the firms the general price level, the output level and variance between prices set by the firms compared to the general price level. By using this information and also observing their neighbourhood and the strategies used by each agent linked to them, we are able to calculate each agent's utility function, according to equation (3.8) from section 3.1.

After calculating the utilities, the logistic CDF in (3.7) is taken to measure the propensity of choosing a given strategy in the choice set $\vec{\sigma}_{i,t} \in \{1, 0, -1\}$ and not only for the strategy adopted by the producer in the t period. A way to explain the expectations formation for the $t + 1$ period is Figure 2: after calculating the propensities towards choosing each alternative, these will be displayed in a line segment inside the $[0, 1] \subset \mathbb{R}$ with uniform distribution.

Figure 2 – Probability line



Source: adapted from Silva (2012).

Afterwards, a number $r_{i,t}$ contained inside the interval shown on Figure 2 will be chosen randomly. Thus, if $r_(i,t) < \sigma_{i,t}$ the producer will adopt the $t + 1$, else if $r_(i,t) > \sigma_{i,t}$ and $r_(i,t) < \sigma''_{i,t}$, the producer will adopt the inflationary strategy, else the producer will adopt the deflationary strategy. This is the how a new strategy distribution is formed and a new round can begin.

3.4 Model calibration

To make the simulations more realistic, we should find a set of parameters that offer a good fit for the model's central variable, the general price level. Silva (2012) picked from a set of 15,000 combinations of ϕ, α. β and J and we go further by adding a calibration routine – also, the addition of p would make manually finding the best fitting parameters much harder.

Therefore we will calibrate the model to find the set of parameters that holds up the best when compared to the actual time series. It is important to remember that the original new Keynesian model adapted is formed by goods producers and not consumers, so it would be rather inappropriate to simply use a consumer price index. Luckily there are many supply-side price indices to choose from, in order for the model to be more insightful and closer to what Ball and Romer (1989) intended to explain.

Because of its large sample and high quality of data, the series chosen for calibration was the Producer Price Index from the United States, more precisely the finished goods consumption index, as the model deals with pricing of finished goods and not inputs or raw materials. Monthly data was obtained from the Federal Reserve of St. Louis for the period from 04/1947 (the first entry of the series) until 12/2020, totalling 884 observations.

The calibration criterion used was minimising the sum of squared errors. This method consists in finding the set of parameters that minimises the difference between empirical and simulated prices. Formally, the set found is the combination of parameters that minimises the following function:

$$\frac{1}{T}\sum_{t=1}^{T}(P_{e,t} - P_{s,t})^2, \tag{3.39}$$

with T being the number of periods, P_e the price index from empirical data and P_s the general price index from simulated data.

Based on this criterion, an optimisation algorithm will be employed to find the best-fitting combination of parameters $\{\phi,\ \alpha.\ \beta,\ J,\ p\}$ that minimises equation (3.39). Our algorithm utilises a variety of Newton's methods in order to find the answers to the optimisation problem inside a finite set of possible solutions.

Given the initial guesses plus the inferior and superior bounds of the parameters to be calibrated, the package chooses randomly a set of parameters, generates the simulated values and compares them to real ones. If the set generates a smaller distance than before, the function stores the new parameters and discards the previous, repeating the process until finding parameters that minimise the error with a certain tolerance.

The parameters will be calibrated, with each one of them being important in a different way to the model's functioning. Table 1 recapitulates briefly what each one means in the model's context.

Table 1 – Interpreting parameters

Parameter	Meaning
α	Private utility weight
β	Deterministic utility weight
ϕ	Elasticity of general price level
J	Network effects weight
p	Rewiring probability

Source: own elaboration.

4 Results and emergent properties of the model

This chapter intends to present first the basic results from our calibrated ABM and then its emergent properties, that is, different results that appear in an organic manner, out of agents interacting, after we change various starting conditions.

Considering that the ABM proposed by Silva (2012) is our starting place, since her model can be seen as a particular case of our ABM excluding p, on Section 4.1 we reconstruct her original model. However, we reduce the interval of price changes from 100% to 20% because such values are more empirically plausible.

Then, on Section 4.2 we present the results of our implemented calibration including now the aforementioned p. It already shows modest improvements over the regular network version even before testing for the emergent properties, as agents are able to converge to a neutral strategy dominance, which we couldn't replicate after lowering the prices adjustments on Silva (2012)'s ABM.

On Section 4.3 many tests are ran to better understand the impact of different starting conditions, more precisely by checking what happens when starting with homogeneity of strategies and after that, by checking the effects of different parameter values on the proportion of agents.

Section 4.4, the last one, shows what happens to prices, output and the strategy distribution when random monetary fluctuations are added to the economy with a maximum of 20% up or down (to mirror the magnitude of price changes). These random disturbances show to have more impact on prices than output and in the long run both output and product average to 1, showing that money supply changes have no lasting effect on output.

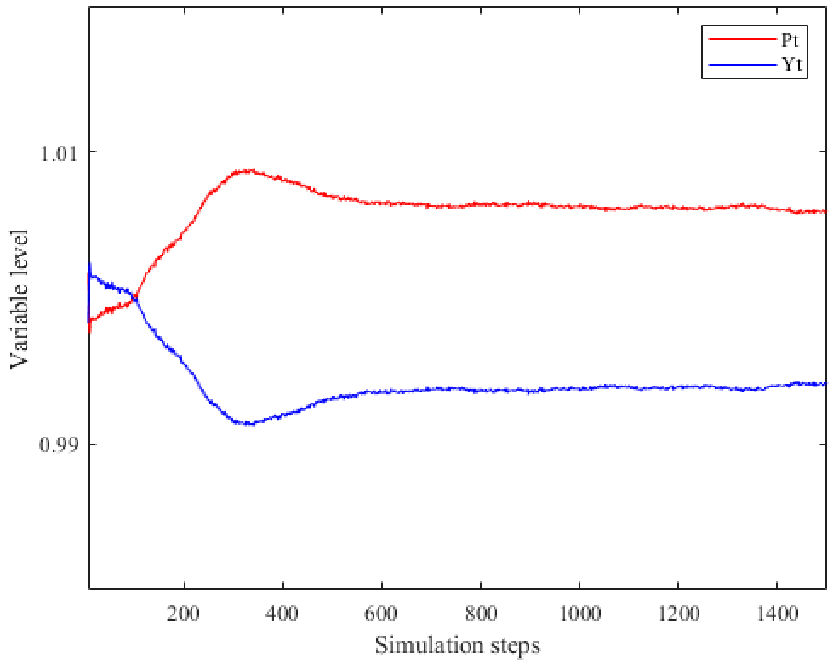
4.1 The benchmark case: a price-setting game on a regular network

For comparison, we have rebuilt the original model from Silva (2012) with the intent of comparing its results to our model with an endogenous network setting. We calibrated once again with the updated data set and found values of $\alpha = 0.01245$, $\beta = 2.0954$, $J = 6.9351$ and $\phi = 0.7653$, nearly identical to the ones found by the author in her work (see Table 2, except for $p = 0$ as it is a regular network).

From now on, all results are averaged from 30 simulations, except for the parameter tests from section 4.3, that are comprised by 100 simulations. The only change done was on the bounds of the interval price changes, from $[0, 2P_{t-1}] \subset \mathbb{R}$ to $[0.8P_{t-1}, 1.2P_{t-1}] \subset \mathbb{R}$.

This was done because prices changing by almost 100% in a somewhat regular manner is quite an unrealistic setting and changing by 20% is empirically, as seen in Section 2.1.

Figure 3 – Price and output level evolution, regular network



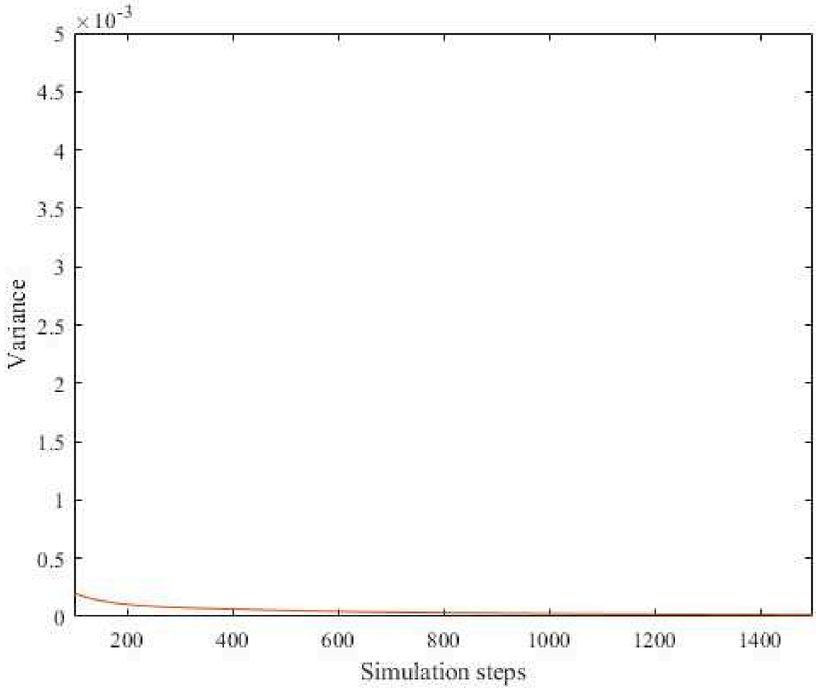
Source: own elaboration.

As demonstrated by Figure 3, price level and output evolution are rather similar to the benchmark ABM in absence of monetary shocks, except that instead of a perfectly elegant convergence to $P = Y = 1$, price level fluctuates between 1 and 1.01, as for the output level, it fluctuates between 0.99 and 1. However, probably because of the smaller interval of price setting, it does converge faster to this stable state compared to Silva (2012), where the convergence towards the symmetric Nash equilibrium happens between period 2,000 and 2,500. Our version of the model, however, sees the economy settle into this setup around period 500.

As shown in Figure 4, price level variance is very low and converges to zero between periods 500 and 1,000, correlated with the dying out of the deflationary strategy (see Figure 5). This is unlike Silva (2012) where price variance starts out much higher (due to the larger interval of price setting), although it only reaches zero when product and output stabilise, which is the same as the author's results. For variance plots we have excluded the first 100 observations due to an initial overshooting that does not really represent the simulation's trend, as agents are still learning.

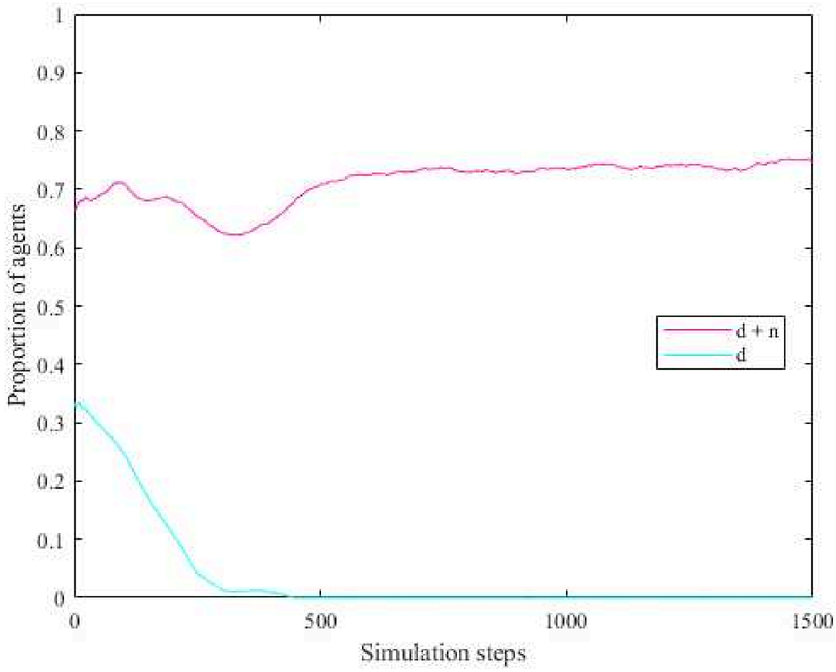
Next is the strategy distribution evolution (Figure 5), which should be read as follows. Below the d line is the proportion of deflationary agents at the present period. Below the $d + n$ line is the proportion of deflationary and neutral agents, therefore the gap between

Figure 4 – Price level variance, regular network



Source: own elaboration.

Figure 5 – Strategy distribution evolution, regular network



Source: own elaboration.

the d and $d+n$ lines is the proportion of neutral agents. Everything above $d+n$ is the proportion of inflationary agents. The strategy distribution evolution chart intends to show how agents are influenced by their neighbours and which conditions can produce an equilibrium of some sort. Here is the first interesting finding and a definite departure from Silva (2012): there is no convergence towards the neutral strategy, even as price level and output stabilise, with the inflationary strategy surviving in the long run.

This is an interesting result because it shows us that in a regular network, a smaller magnitude of price changes has a significant impact on strategy choices, going as far as making the inflationary strategy survive. In this case, the deflationary strategy dies out as the simulation nears 500 periods, afterwards the neutral strategy keeps fluctuating around 0.66 and 0.73, with the rest being composed by the inflationary strategy. For comparison, in Silva (2012) the neutral strategy emerges as dominant around period 2,150 with the inflationary strategy being the first one to go extinct around periods 2,000 and 2,050 followed by the deflationary. From this point onwards, the symmetric Nash equilibrium from Ball and Romer (1989) was reached.

4.2 Calibration of the proposed ABM: a price-setting game on a complex network

Running the optimisation algorithm, our initial approximation (see Table 2 for details) were the final results used by Silva (2012) in the regular network version, also updating the database by adding 13 years of data (from $t = 729$ to $t = 884$). For the new parameter, we used $p \approx 0.1$, which is the standard rewiring probability for small-world networks, believing that the price-setting network has good reasons to not have a regular topology (Section 2.2). The results can be found in Table 3, as after roughly 176,000 periods, that is, 200 runs of the 884 period data set, the optimisation algorithm found a combination of parameters. The chosen set was able to reach a point of minimum for the error function, meaning the algorithm stopped iterating.

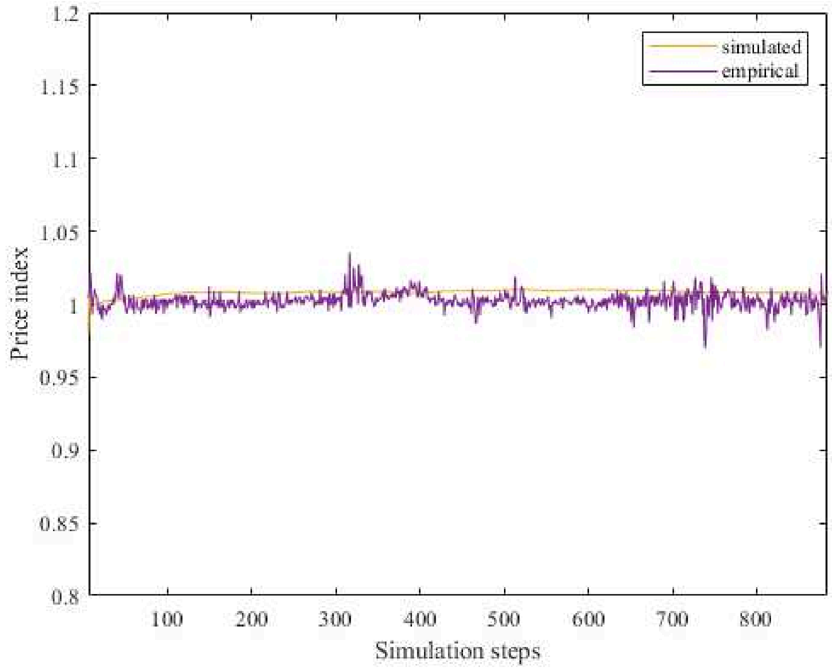
Table 2 – Initial values for calibration

Parameter	Initial value	Range of possible values
α	0.01228	$[0,5] \subset \mathbb{R}$
β	2.0954	$[0,5] \subset \mathbb{R}$
ϕ	0.75995	$[0,1] \subset \mathbb{R}$
J	6.9351	$[0,10] \subset \mathbb{R}$
p	0.1	$[0,1] \subset \mathbb{R}$

Source: own elaboration featuring data from Silva (2012).

Figure 6 compares the empirical price index with the simulated price index that stayed inside the tolerance bounds. In fact, we can see the empirical series is the more volatile

Figure 6 – Comparison between empirical and simulated price indices



Source: own elaboration.

one. We have excluded the first 4 observations due to the very high degree of randomness (which caused an initial overshooting) before agents start settling into a distribution.

Instead of following the empirical data set perfectly, the price index that minimised the error was one that smoothed the path between the highs and lows. It is important to remember that this is comparing the period's inflation (calculated by dividing P_t by P_{t-1}) to the PPI mentioned in Section 3.4, so naturally it will look quite different from the price level featured in the other plots.

Table 3 – Calibrated values for the main model

Parameter	Value
α	2.0288
β	2.0279
ϕ	0.7986
J	2.3246
p	0.5267

Source: own elaboration.

Following, some brief remarks about the found values. The closest result to the initial guess is ϕ whose value, much closer to one than to zero, shows that in choosing their optimal price agents strongly value their expected price rather than changes in money supply. This one shows that elasticity towards the money supply and price level do not seem to be dependent on the type of network structure.

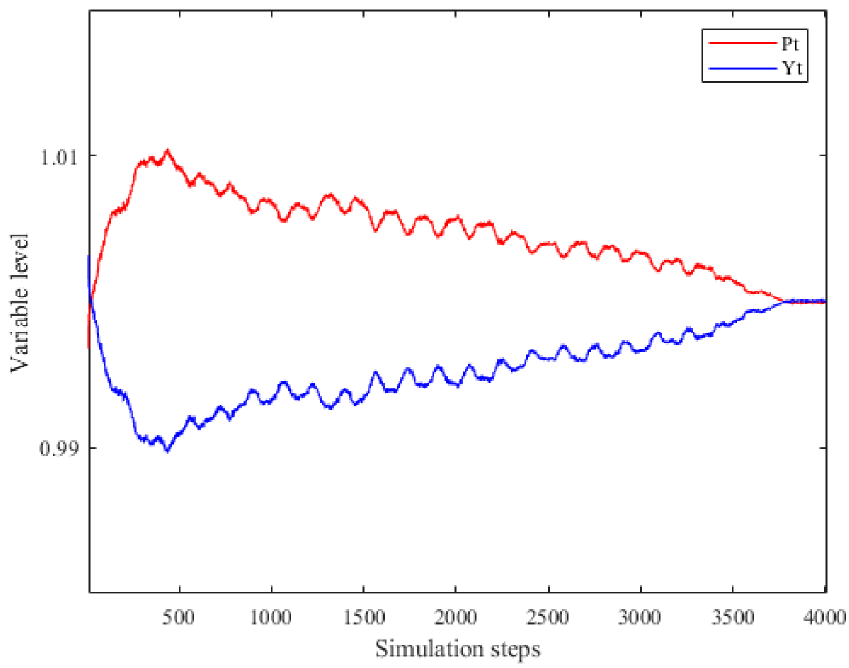
The β value, very close to the initial guess, shows that there is a relatively high weight from deterministic incentives on agents' choices, so each agent's individual decision will not be taken with a high degree of randomness – due to other factors, the model will present a large amount of randomness, but it is not coming from non-observable motivations from agents at all.

In turn, α is much higher than the initial guess and shows there is a significant incentive from private behaviour in setting prices, much more than in the benchmark model, in which $p = 0$. That means in a complex network, the utility associated to setting the price in the same direction as the general price level is more important than in the original model.

J presents a moderate value, lower than the model with a regular network. This one is interesting considering that agents are more connected, but consistent with a higher value of α, and might actually be an effect of the endogenous network, which is the most important change in the model.

In turn, p goes beyond the expectation of a small-world network ($p \approx 0.1$) with a quite high value. Perhaps the high value of J in the regular network was actually higher because of the absence of small-world phenomena in the model. Now, with a high value of p, agents might take shortcuts, connect with another agent with a worse strategy and not be influenced by them.

Figure 7 – Price and output level evolution, complex network



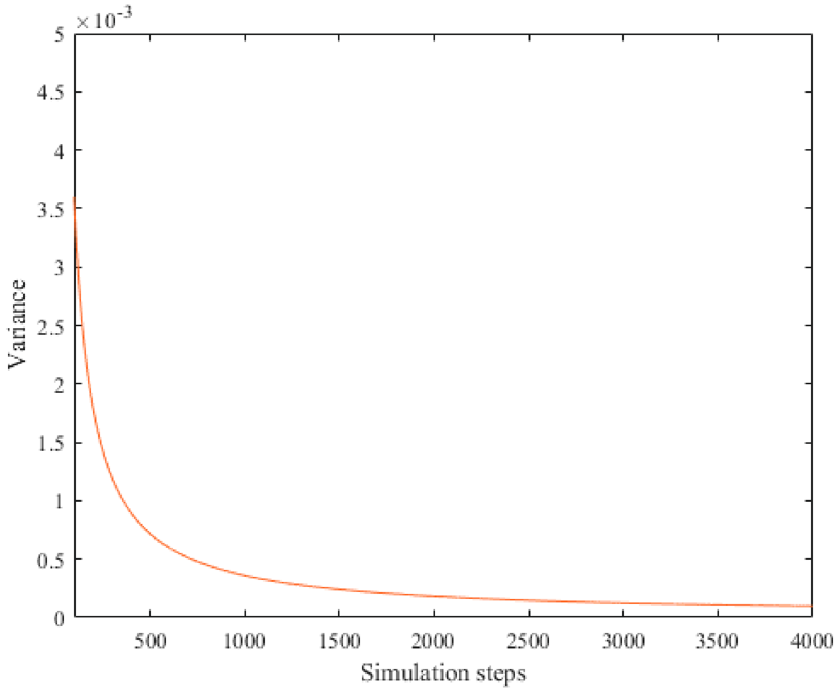
Source: own elaboration.

Our first analysis (Figure 7) was on the topic of convergence towards the equilibrium of

$P = Y = 1$ found in Ball and Romer (1989), which was reproduced perfectly by Silva (2012) in her original version and very closely in our ABM with a complex network featuring lower price adjustments. On that matter, we intend to check if the model reaches a convergence as elegant as that one by adding the rewiring probability. As mentioned beforehand, the lower price changes speed up the process of levelling it to the equilibrium price level, as instead of starting at more than 30% higher, it only reaches heights of around 1% higher. They also seem to cause a faster convergence to an eventual stable state, be it one of coexistence between strategies or dominance. Same as the original model, in the absence of monetary disturbances there is a perfect, inverse correlation between P and Y and between periods 3,500 and 4,000 the economy stabilises on $P = Y = 1$, with a higher precision than the regular network model from Figure 3.

As such, we can affirm that there is already a modest improvement over the regular network model, because even after relaxing the hypothesis of a regular network, the agents reach the symmetric Nash equilibrium in the absence of changes in money stock. This means we need not to forcefully constrict the network to a regular topology in order to reach the equilibrium found by Ball and Romer (1989), in fact, the fit is better than benchmark results from Section 4.1.

Figure 8 – Price level variance, complex network



Source: own elaboration.

On the other hand, variance is larger compared to the benchmark (Figure 4), as it takes as long as period 2,500 to become equal to the variance from the benchmark and does not get as close to zero. This was a predictable result, considering there is now a greater degree of randomness compared to that model.

4.3 Emergent properties

The previous section highlighted some differences between our reassembled regular network model and our main complex network model, such as small differences in the convergence to the symmetric Nash equilibrium of Ball and Romer (1989) and most interestingly, the long-run survival of inflationary expectations. Now we are faced with the most striking difference so far.

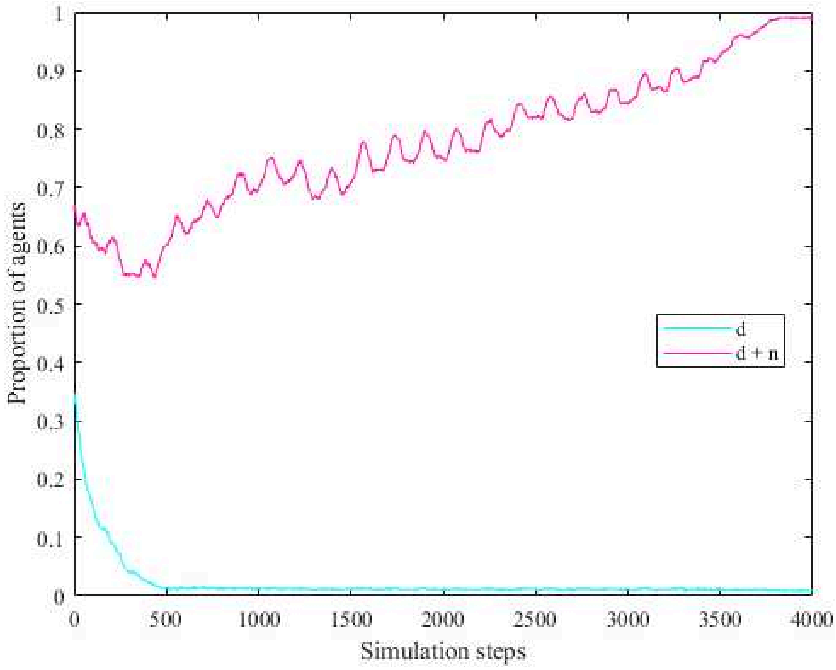
While Silva (2012) found the emergence of the neutral strategy as the only one in the regular network model, until now we could not replicate it by lowering the maximum price changes to 20%. While it held a majority, the inflationary strategy was able to coexist with it. However, by adding the p parameter to the model and the shortcuts provided by them, we are able to find the emergence of the neutral strategy as the dominant one to almost the same degree as the author in her work, as we can see in Figure 9. Due to the high level of randomness, none of the three strategies truly die out, but the deflationary and inflationary together end up fluctuating around 1% as we reach $P = Y = 1$, which might as well be going extinct. The emergence of the neutral strategy as a choice of 99% of the agents happens between periods 3,500 and 4,000, which is around 1,000 periods later than the results of Silva (2012). Another difference is that here the deflationary strategy seems to be weaker, as it gets closer to extinction around period 500, instead of dying out very close to the inflationary strategy.

The neutral strategy emerging as dominant is a most interesting result, because by relaxing our assumption of a regular network and adding the rewiring probability, we have shown once again that the model by Silva (2012) was not tailor-made to return such elegant results. The emergence of the symmetric Nash equilibrium and the neutral strategy dominating arose in a organic way, both in the author's original model and in our complex network model.

Some questions posited by these initial results, coupled with our regular network model from Section 4.1 are about the strength of the deflationary and inflationary strategies. Both our regular and complex network have shown a particular weakness of the deflationary strategy, but in Silva (2012) they seem to be equally weaker. Furthermore, we wonder if there is any situation where the neutral strategy would not dominate in the long run. We will now run several tests to analyse if such a dominance could not emerge under certain situations.. That can be done by stressing different parts of the model and check out what happens to agents when faced with these different conditions, be it on the starting distribution or coefficient changes.

To better understand how starting conditions can create very different emergent properties, we will run three tests. They will assess the effect of all agents starting with

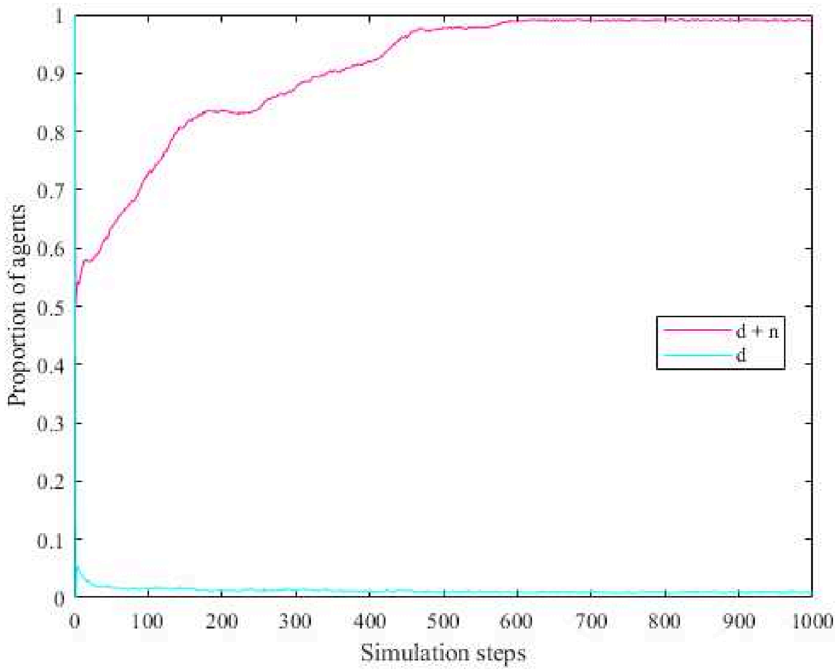
Figure 9 – Strategy distribution evolution, complex network



Source: own elaboration.

the same strategy, meaning all 10,000 of them will start being either deflationary, neutral or inflationary.

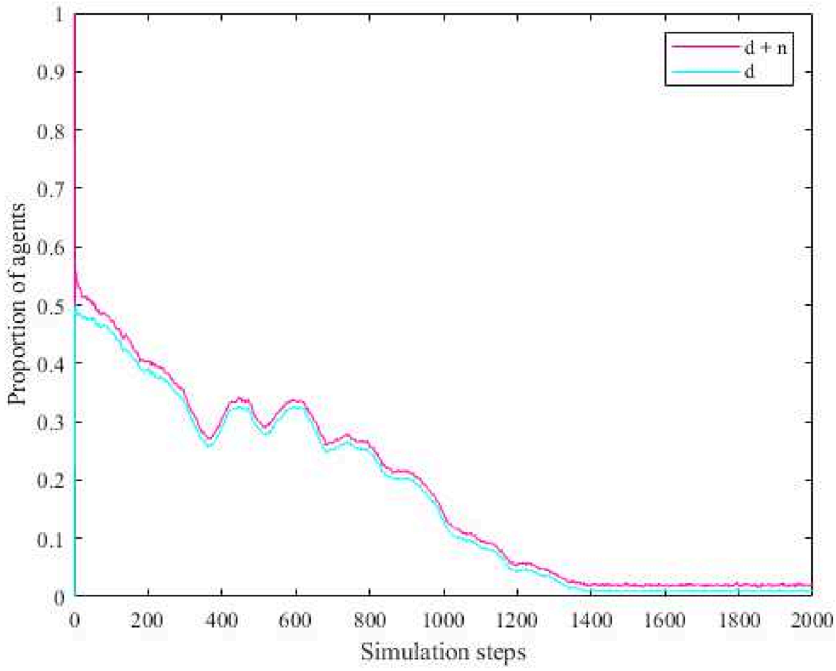
Figure 10 – Strategy distribution evolution, all agents starting as deflationary



Source: own elaboration.

The first test (Figure 10) shows what happens when all agents are deflationary in the first period, that is, $\sigma_{i,1} = -1$ for any $i = 1, 2, \ldots, 10^4$. We have already understood this from previous results, but this is one more evidence that the deflationary strategy is indeed the weakest. In period 2 almost all agents already move away from it, splitting between neutral and inflationary. Afterwards, we see the neutral strategy's climb towards the same spot as the simulation with balanced starting conditions (Figure 9). It does crush the inflationary strategy much faster, amassing a 98% fraction around period 600, which is around 3,000 periods earlier than the model with balanced starting strategies.

Figure 11 – Strategy distribution evolution, all agents starting as neutral

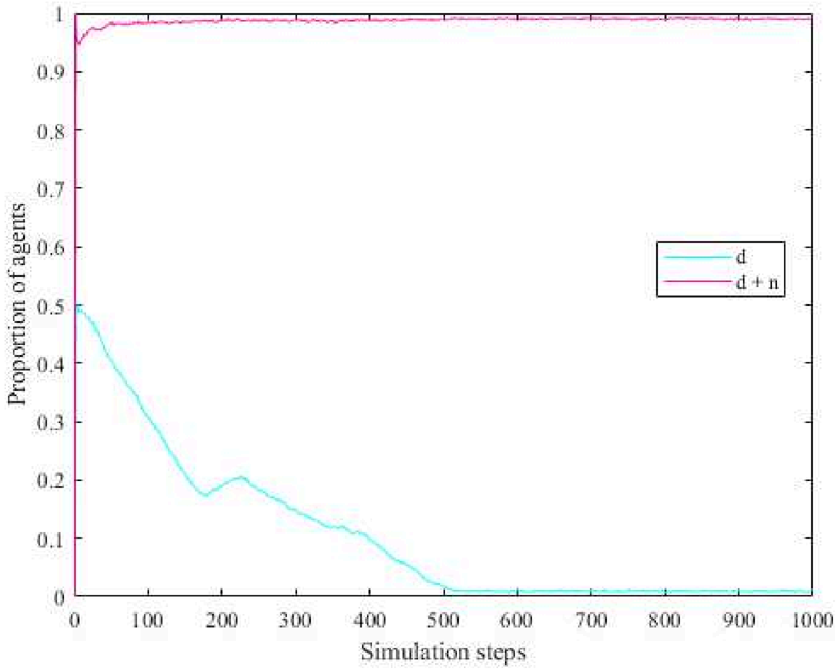


Source: own elaboration.

The second test (Figure 11) has all agents starting as neutral, that is, $\sigma_{i,1} = 0$ for any $i = 1, 2, \ldots, 10^4$. This one shows a very surprising result, as in period 2 the neutral strategy – dominant in all simulations so far – is switched out by a majority of agents. Between period 200 and 400 it is already very close to extinction. Then the deflationary strategy slowly dies out and by period 1,400 the inflationary strategy is already the choice of 99% of the agents. With this result, the deflationary strategy is cemented as the weakest one, as there does not seem to be any case where it ends as the dominant strategy.

Ultimately, the third test (Figure 12) features all agents starting with the inflationary strategy, that is, $\sigma_{i,1} = 1$ for any $i = 1, 2, \ldots, 10^4$. Now it is the inflationary strategy that is switched out by almost all agents in the second period, followed by the fastest of the near-extinctions in all of the results, with the neutral strategy establishing its firm dominance by period 500. Looking at Figures 10 and 12, they look like imperfect mirrors of each other, with the universal starting strategy getting close to extinction already at the start and the opposite strategy being dominated by the neutral one and being asymptotically extinct around period 600.

Figure 12 – Strategy distribution evolution, all agents starting as inflationary



Source: own elaboration.

Something common between all three tests is that by period 2, almost all agents discard the starting strategy – similar tests on the regular network model show that when all agents start on a single strategy, they never change. This reinforces the strength of the neutral strategy, as the only test where it is not the winning strategy is the one where it starts as the only one, and we have seen that it means the strategy is doomed to die out when that happens. We believe that this is caused by a bigger value of α, giving more weight to whether agents get the price change right compared to the global price level or not, and until settling near $P = 1$ it is quite volatile (check Figures 3 and 7), so they will certainly choose the wrong strategy at one of the early periods.

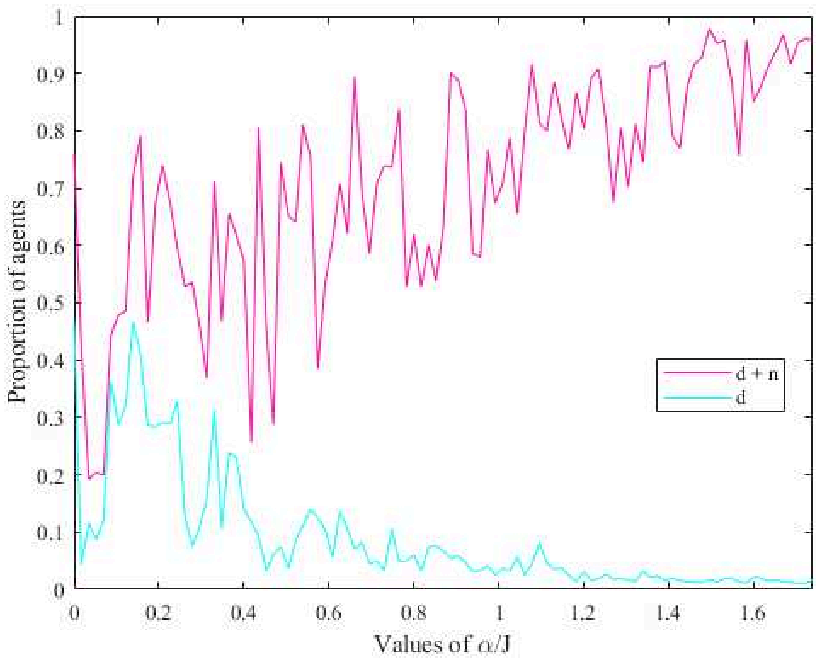
After all of them change to another strategy, there are big incentives in continuing with it, as the calibrated value of intensity of choice ($\beta = 2.0288$) being strictly positive prevents them from doing many random changes and the calibrated value of parameter $J = 2.3246$ from intensely deviating from their neighbours. Therefore, it makes sense that the starting strategy is brought to the brink of extinction very quickly.

Furthermore, we can also test how the model's parameters affect the strategy distributions. To do so, we create vectors with 101 values of three parameters of interest, α/J (J is fixed as the calibrated value from the model), β and p. For each parameter, we take the calibrated value as the central value and generate 50 equidistant values to the left and the right of the central value, with the lower bound being zero and the upper bound being double the central value.

We run simulations with $t = 1,000$ and discard the first 100 observations to avoid biases due to the very high degree of randomness before agents start settling into a distribution pattern that will be more representative of the overall trend for that specific parameter value. After doing that, we calculate the mean of the remaining 900 ones and discuss the effects of each variable's differing values on the proportion of agents.

Of these three tests, the first one we will run intends to evaluate how changing the α/J ratio impacts the frequency distribution of prediction strategies across producers, as this ratio captures the relative weight of private incentives with respect to social incentives. This means that agents will give more importance to guessing the prices right in lieu of following along with their neighbourhood. The simplest way to do so is keeping $J = 2.3246$ as it was calibrated and manipulating the value of α. Therefore, the interval starts at zero and is incremented by 0.0174 each time, thus closing at the value $\alpha/J = 1.74$.

Figure 13 – Average strategy distribution evolution as a function of α/J

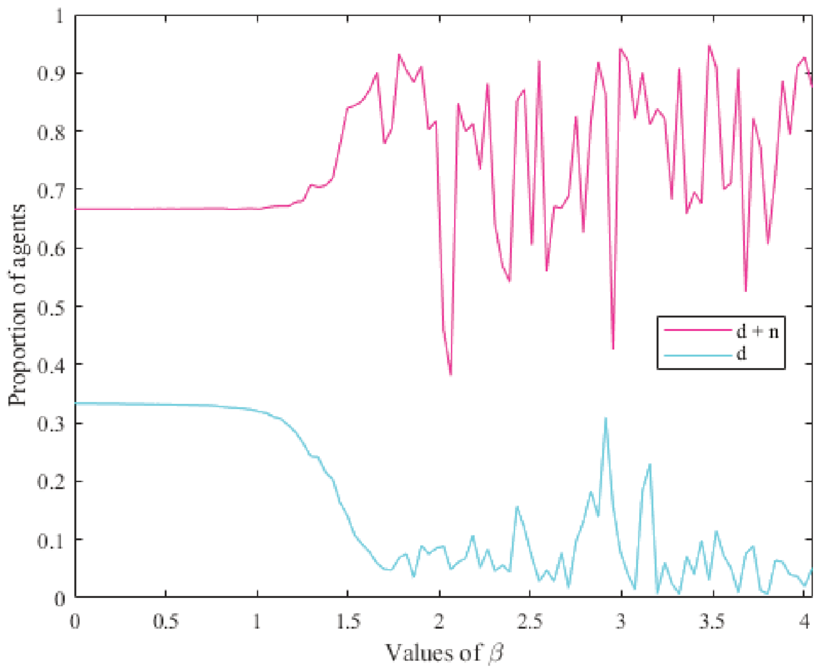


Source: own elaboration.

Figure 13 shows the results found, where we observe less agents choosing deflationary and inflationary expectations as the α/J ratio gets larger. Therefore, as the deterministic private utility's relative weight rises, a larger fraction of agents go with the neutral strategy, with the average proportion of agents choosing it getting as large as 95%. That means when network effects are relatively weak (i.e. when the ratio α/J is relatively high), the neutral strategy is the one that provides agents with the largest utility gains. However, for low values of α/J, giving a small relative weight to private incentives, the neutral strategy is more vulnerable indeed. For several values of $\alpha/J < 1$, the inflationary strategy is able to hold a majority, and for some values around 0.1, the neutral strategy in fact is going extinct.

Next, we test for values of β, the parameter that determines the intensity of choice, accounting for bounded rationality in the model. If values of β are low, we expect the proportions to remain near 33% *ad infinitum*, because choices are random, while larger values mean that agents will gravitate towards the strategy with the largest utility gains. That means we expect that as agents become more rational – that is, β raising – they will go with the strategy that has been showing the best performance so far which is the neutral one. Again, the interval starts at zero and ends at $\beta = 4.045$, which is double the calibrated value, with increments of 0.04005 each time.

Figure 14 – Average strategy distribution evolution as a function of β

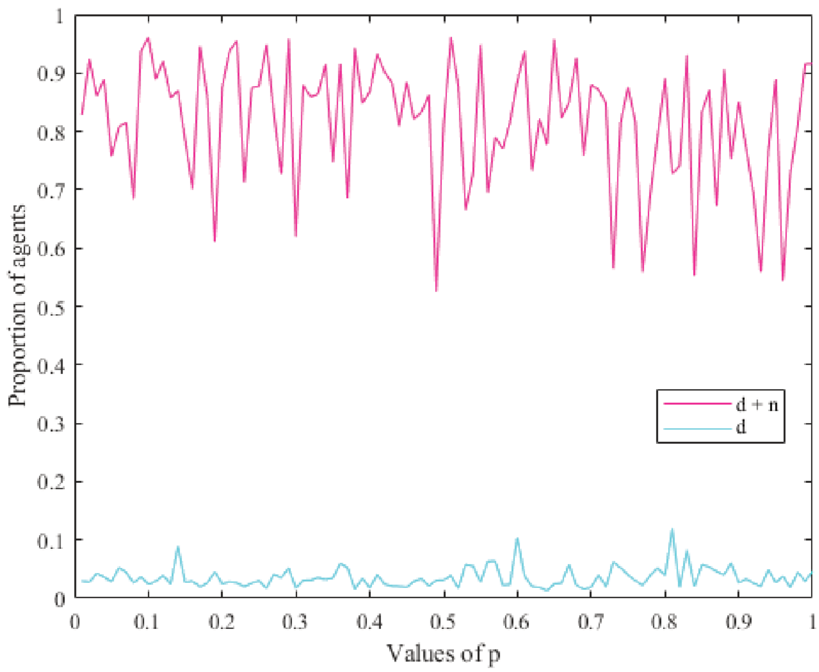


Source: own elaboration.

Figure 14 presents our results, and for low values of β our test reflects what was mentioned before, with values of $\beta < 1$ leading to the three strategies coexisting equally in the long run, even though there is a clear distinction in utility gains from picking between them. However, as predicted by Hommes (1997), as β rises agents pick with higher probability the strategy with relatively better performance in gaining utility, which is the neutral strategy, as the furthest value from the origin shows the largest proportion of neutral agents. The path is not the smoothest, but it does show a trend of agents moving towards the neutral strategy as decisions become more deterministic.

The last of the three parametric tests is for values of the rewiring probability, p, with results shown on Figure 15. If $p = 0$ then we have a regular network with no shortcuts, and if $p = 1$, a totally random network where all 10,000 agents will have shortcuts to other agents on any place in the network. We account for all values between 0 and 1 with a 0.01 increment.

Figure 15 – Average strategy distribution evolution as a function of p



Source: own elaboration.

Unlike the previous results, there is not a clear trend associated with raises in the rewiring probability, however the neutral strategy is established as a clear favourite for most values of p. It does remind us again that the neutral strategy is, on average, much more likely to emerge as the clearly dominant one, although for some values of p it faces a decent challenge from the inflationary strategy.

There are several conclusions to be taken from this section. A most important one is that by adding a rewiring probability and calibrating the model enables us to replicate the emergence of the neutral strategy even after lowering the bounds of price changes, unlike the regular network. Moreover, this convergence is slower than the one found by Silva (2012) with her model featuring larger price changes.

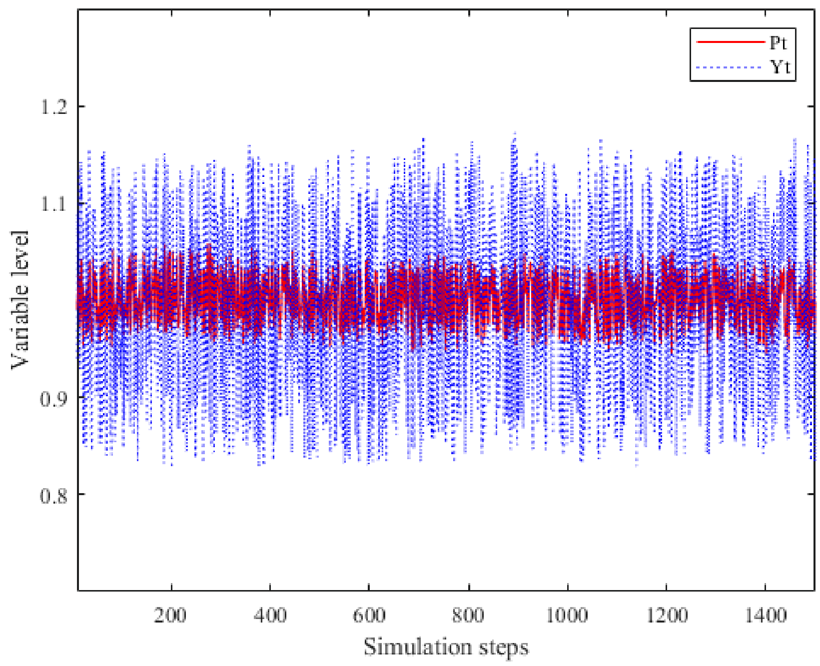
If instead of equally dividing agents between the three strategies, we set that all of them start with the same one, they converge faster towards a dominant strategy. The dominant one should always be the neutral, unless the network starts with all neutral agents. In that case, when they get the price change wrong, almost all of them abandon the neutral strategy and eventually the inflationary strategy crowds out the deflationary one. Thus, there seems to be a clear pecking order between neutral, inflationary and deflationary strategies, from best to worst.

The more private incentives are higher compared to network effects, and the more deterministic agents' choices are, the more we can see that the neutral strategy is indeed the one that generates the largest utility on average, as raising α and β strengthen its grip on agents' choices. On the other hand, raises in p do not follow any particular trend, unlike the two other tests. We assume that happens because the neutral strategy is so clearly superior that is does not need much interconnectedness to take over the network.

4.4 Adding monetary fluctuations to the model

In the previous sections we have ignored changes in the money stock, but obviously we know from empirical data that the nominal money supply is not fixed. In Silva (2012), the author's way of incorporating changes was a single shock from a given period, such as raising M by 5% or 10% in from period 3,000 onwards.

Figure 16 – Price and output level evolution in presence of monetary fluctuations



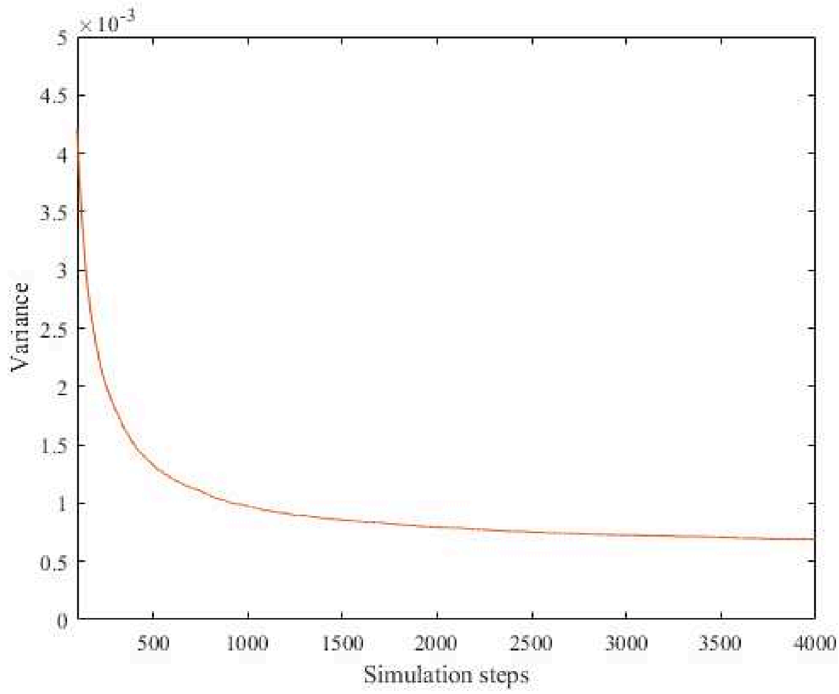
Source: own elaboration.

Differently from Silva (2012), we have decided on adding random monetary fluctuations on all periods, with a maximum of 20%, to mirror the allowed magnitude in price changes. Results for price level and output are shown on Figure 16.

While in the long run it does not converge to the symmetric Nash equilibrium with $P = Y = 1$, it does gravitate around it, with the price level averaging 1.0008 and output averaging 0.9949. Thus, there are no long-lasting effects on output and money is neutral in the long run. It is interesting to notice that a larger part of the disturbances does get absorbed by the output. Perhaps the reason for that is the high value of ϕ, which shows that when setting their prices, agents do not take into account the money supply as much as they do value their expected price. Thus, price changes are less intense than the money supply changes and the output level absorbs the rest, but it does not last for the long run.

As expected from looking at Figure 16, price variance is much higher than the one presented by the version without fluctuations in the money stock (see Figure 8). Results with money fluctuations are shown in Figure 17, starting quite higher than the version without monetary changes, and even though the variance does subside significantly, it is still higher in the long run.

Figure 17 – Price level variance in presence of monetary fluctuations

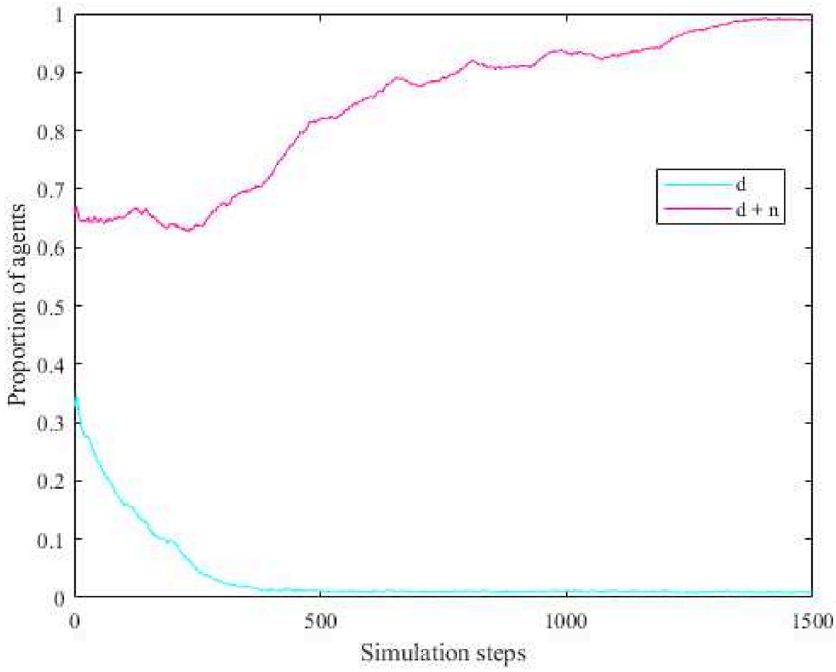


Source: own elaboration.

Figure 18 shows the average proportion of strategies followed by agents when faced with these monetary shocks. Again, the deflationary strategy is the first to be crowded out and the neutral one dominates once again, achieving 99% of preference between agents faster than in the model without money changes (Figure 9).

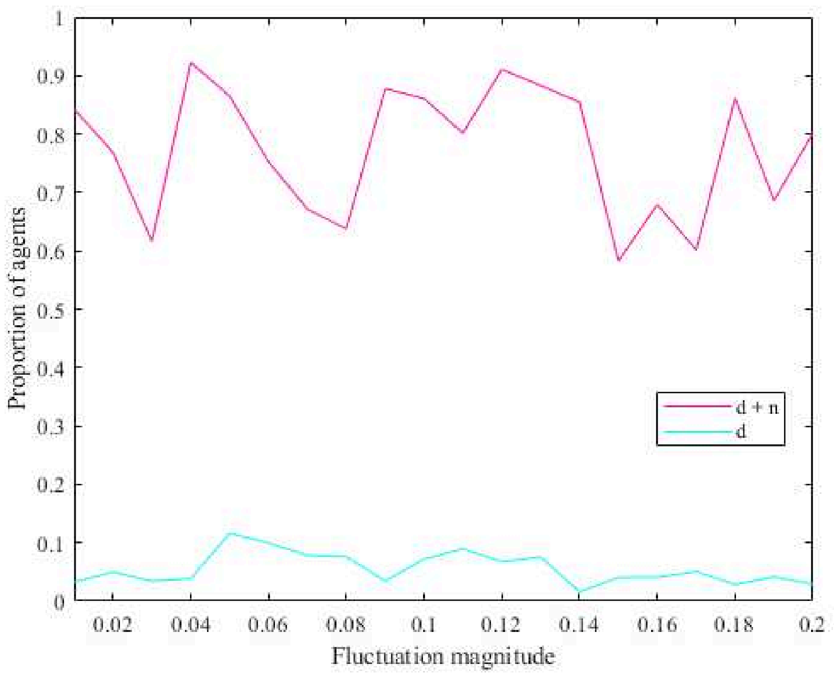
Figure 19 presents a new test, which employs the same methodology from the last three tests on Section 4.3 to these monetary fluctuations. We run the gamut from no shocks to the maximum of 20% with 1% increments, meaning 20 different scenarios were assessed. However, we do not notice any particular trend with a raise in fluctuation sizes, with the proportion of inflationary agents going up and down again as money shocks

Figure 18 – Strategy distribution evolution in presence of monetary fluctuations



Source: own elaboration.

Figure 19 – Average strategy distribution evolution with monetary fluctuation as a function of its magnitudes

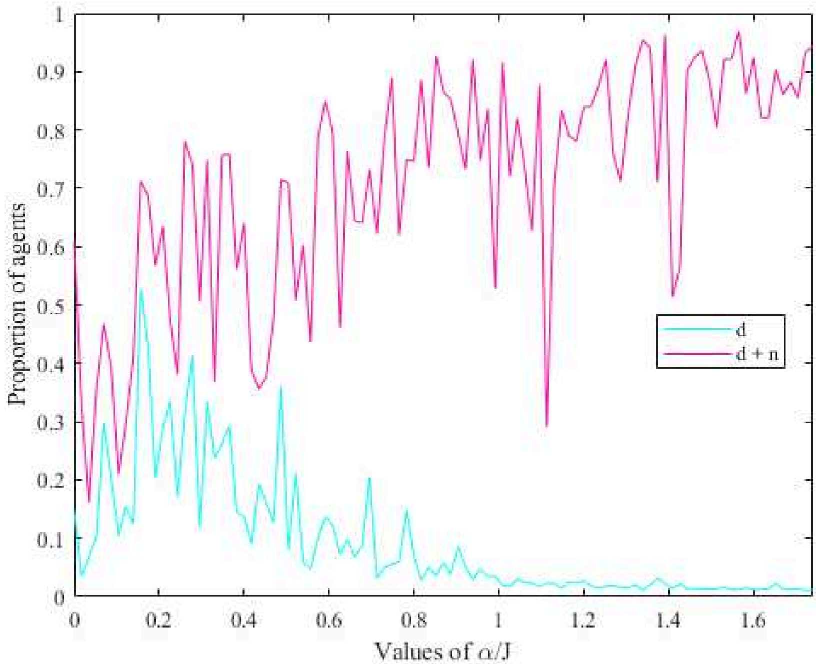


Source: own elaboration.

get bigger. The only takeaway is showing, again, that in no conditions the deflationary strategy performs strongly.

It might also be interesting to check if the emergent properties found in Section 4.3 hold true in presence of the monetary fluctuations. Thus, we have rerun the aforementioned section's parameter tests (see Figures 13, 14 and 15) employing the exact same methodology but featuring the 20% monetary disturbances.

Figure 20 – Average strategy distribution evolution as a function of α/J in presence of monetary fluctuations

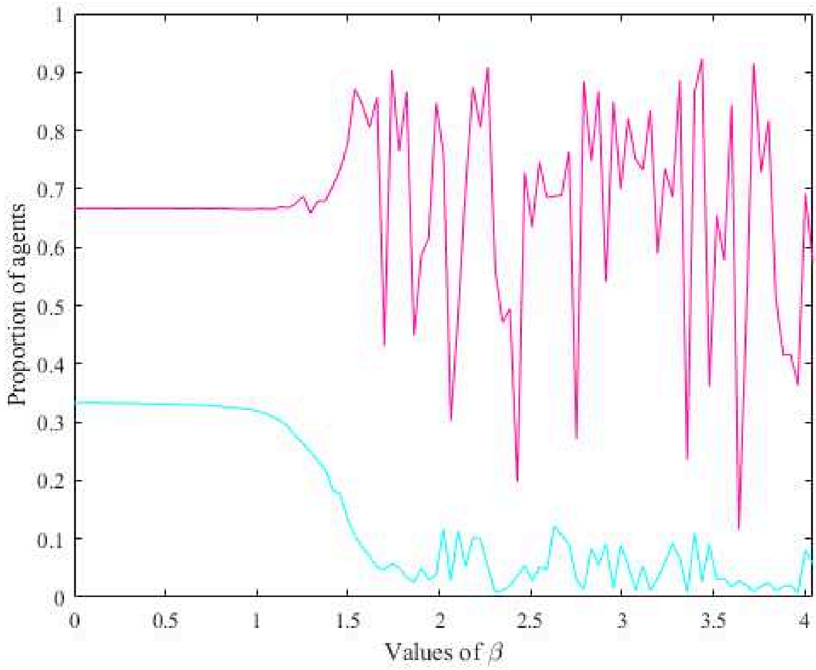


Source: own elaboration.

Figure 20 shows the results for the α/J ratio test. Differences are modest, but there are some interesting takeaways. There are more values of α/J for which the neutral strategy is fragile and for most values below 0.2 it is crushed between the inflationary and deflationary strategies. There are also some higher values where the inflationary strategy is again very strong in comparison to Figure 13, while the deflationary strategy presents a similar trend. But the conclusions are mostly the same with the neutral strategy gaining strength as the α/J ratio rises, even in face of money disturbances.

Figure 21 presents the results for the β test, which are most interesting compared to the previous one. While $\beta < 1.5$ the results are near-identical and as expected, if the value is smaller than one the choices might as well be considered random. But as β rises agents behave in different ways compared to Figure 14. In the version without monetary fluctuations, the neutral strategy presents a decent showing for some values around 3, keeping close to 33% after 1,000 periods. These showings are not replicated by the test featuring changes in money stock, with no points where the neutral strategy at least holds a percentage similar to the starting one. In fact, the inflationary and neutral strategies seem similarly strong in presence of monetary fluctuations, whereas in Figure 14 the neutral strategy presented a rising trend. For many more values of $\beta > 1.5$ the inflationary strategy performs very strongly, even holding more than two-thirds in some of them.

Figure 21 – Average strategy distribution evolution as a function of β in presence of monetary fluctuations

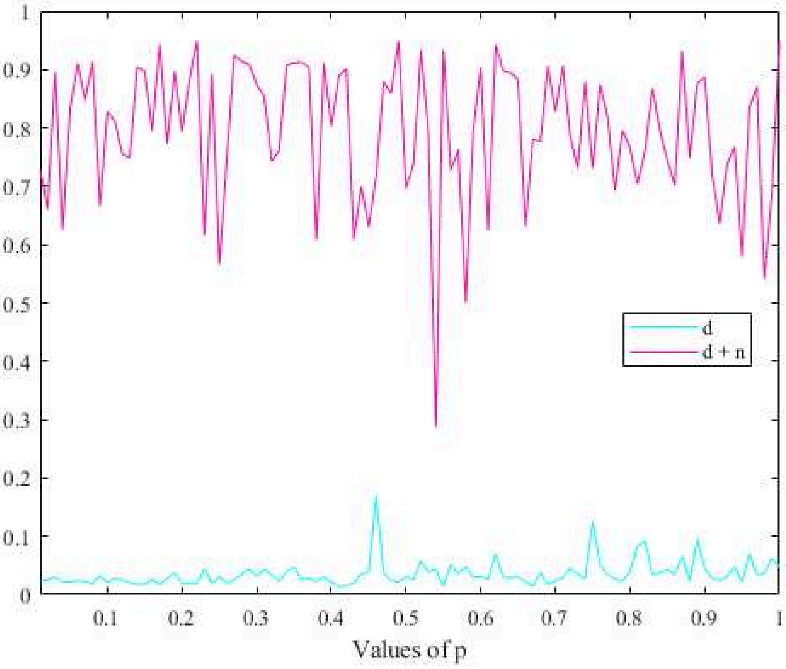


Source: own elaboration.

In sum, the results from Figures 20 and 21 are by and large similar to Figures 13 and 14, but with a difference: for some values the monetary fluctuations cause agents to prefer the inflationary strategy to a greater extent than before. It does make sense that they behave like this considering that the inflationary strategy has shown to have more upsides than the deflationary before monetary changes were involved.

The chapter's last test is presented on Figure 22, to check if monetary fluctuations cause the emergence of a clearer pattern when the rewiring probability is raised. Except for a stronger showing from the deflationary strategy around $p = 0.45$ and a stronger showing from the inflationary strategy around $p = 0.55$, when compared to Figure 15, results are mostly similar. Hence our conclusion is still the same: there is no clear relationship between the rewiring probability and strategy distributions with or without changes in money supply. What it actually does for the model is allowing agents to have access to information that they would otherwise not have and make better decisions, as some equilibria are only reachable with shortcuts between agents.

Figure 22 – Average strategy distribution evolution as a function of p in presence of monetary fluctuations



Source: own elaboration.

5 Concluding remarks

Concerns about how prices are formed and how do they interact with monetary policy have been central issues since the inception of macroeconomics. For the last decades, the study of these questions has been centred on new Keynesian models, in particular DSGE models. However, with their perceived failures in helping economists to explain events such as the subprime crisis, we have seen the appearance of alternative approaches to macroeconomics.

It has been said that many of the marquee new Keynesian economists have become too dazzled by the process of building DSGE models and have forgotten that they actually need to be employed as tools to help understanding or predicting the economic phenomena, technical progress notwithstanding. In this context, ABMs have presented themselves as a versatile, bottom-up approach aided by the advances in complexity and network sciences that can account for the increasing complexity of markets in general. As such, they are able to tackle issues that can be hard to include in mainstream models, e.g. network effects and heterogeneous expectations.

Empirical evidence shows that price setting is a very complex phenomenon depending on many issues such as geographical location, market power, rule of law, contracts, sales, interest rates, labour market and information inefficiencies. Many of these issues can fit under a growing umbrella of economic literature about the effects of social interaction in economics, as agents do not exist in a vacuum and might gather information through exchanges with other agents.

Social interaction needs not to be with close neighbours as there are many small-world phenomena in society – that is, when people in a social network that are very far from each are interconnected with a low average path length. With the rise of computational economics, we are able to account for these phenomena by building complex networks with a rewiring probability that allows agents to take shortcuts to places far from their neighbourhood.

The main objective of this thesis was to assess the influence of network effects on the price-setting problem. To do so, we have adapted an analytically-solved new Keynesian model with homogeneous, representative agents, rational expectations and sensible parameters assumed into an agent-based computational model featuring heterogeneous agents with interactive expectations and parameters calibrated by numerical methods. Using a regular network version as benchmark, we have added the rewiring probability to check whether it improves the model's explaining power or not. Each agent can, on each period, go with deflationary, neutral or inflationary expectations. If an agent adjusts the price of his/her product in the same direction as the aggregate price level, their deterministic social utility raises. Besides, if this agent sees one strategy prevailing in the neighbourhood, choosing the same one raises their social utility. The utility function also presents a stochastic term to consider non-observable motivations, thus accounting for bounded rationality – sometimes, agents do not choose the best strategy for a given moment.

As the model is composed by producers, we calibrated it using a Producer Price Index. The parameter values presented a higher emphasis on the relative weight of private utility with respect to network effects compared to the regular network model, a large weight on deterministic utility and a higher elasticity towards one's expected price level compared to the money supply. Our latest addition, the rewiring probability, presented a rather high value, showing that price setting indeed can present a high amount of influence from distant nodes in the network.

While the regular network, with a smaller interval of price setting (from 100% to 20%) was unable to show the emergence of the neutral strategy as the dominant one, with the complex network model we were able once again to see the neutral strategy achieving complete dominance again. However, the higher degree of randomness prevents true extinction of strategies, and what we call dying out is actually having less than 1% of agents using it, while the completely dominant one boasts a fraction of 99% of agents using it.

Afterwards, some tests were done to observe the emergent properties of the system. The first one was changing the starting conditions, as we know complex adaptive systems are very sensitive to these variations. By making all agents start with each of the three strategies, we have seen that by step two of the simulation all of them change strategies, with the starting one going extinct and the remaining two vying for dominance. These tests regarding the sensitivity to initial conditions show the neutral strategy is the strongest, and inflationary can be said to be in the second place, as it was able to crowd out the deflationary strategy when all agents started as neutral (which guaranteed it would die out soon). This is a most impressive result, as the regular network version showed a path dependence – agents never changed from the ubiquitous starting strategy.

Furthermore, we can stress different parameters to see which trends emerge from changing them. When the relative weight of private utility with respect to network effects gets higher, the neutral strategy becomes more dominant, showing it is the strongest when agents look only at their accuracy when comparing their price adjustments with the global price level. The same happens when the weight of deterministic utility is raised, showing that the more rational agents are, the more they gravitate towards the neutral strategy. The rewiring probability, however, does not show any particular trend by running the gamut from zero to one.

Then we add random monetary fluctuations to the model, and what happens is that there is indeed an incomplete nominal adjustment in the short run, with output absorbing more of the money supply changes compared to the global price level. This is to be expected because the money supply elasticity of price is lower than the expected price elasticity, thus it makes sense that short-run output variation is higher.

But like in the original new Keynesian model, the shocks don't have lasting effects with money and prices averaging around the same equilibria of 1, ergo money is again shown to be neutral in the long run. With the monetary fluctuations, the price variance is very high compared to the model's standard version.

Lastly, we ran parameter tests to check if emergent properties would change in presence of monetary disturbances, comparing its results to the results of the tests ran on the standard version. Changing the rewiring probability and the size of these money fluctuations did not show any particular pattern emerging.

While on the standard version the neutral strategy became more dominant when the weights of private utility with respect to network effects and deterministic utility were raised, in the version with money supply changes it caused the inflationary strategy to become stronger. This is a rather unsurprising finding, as constant monetary changes can make agents gain more utility from adopting the inflationary or deflationary strategy in lieu of the neutral one. And as the inflationary strategy has shown to perform better in general, these results are consistent with the model's big picture.

In sum, we show that by adding shortcuts to a previously regular network, we are able to reproduce the emergence of one strategy as dominant in the long run under a more difficult premise of lower price changes. Besides, it allows new equilibria to emerge from homogeneous starting conditions, something that did not happen in the regular network version. It also allows us to show in a more comprehensive way that there is a clear order in strength between strategies and lastly, to conciliate short-term fluctuations in output with long-run neutrality of money.

Essentially, we are able to find similar results to the new Keynesian model of reference, as the best strategy that emerges is to keep prices unchanged and money has no long-term effects on output. We are able to reach these results even after relaxing several staple hypotheses employed by the new neoclassical synthesis, e.g. perfect rationality and homogeneity of expectations. By doing this, we are able to criticise dubious mainstream models from a stronger standing place but also be more appreciative of the models whose conclusions still hold up when assuming more flexible hypotheses, showing they are not tailor-made to return certain specific outcomes.

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