Innovation and employment: an agent-based approach for studying the effects of technological change on the labor market

by

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Short Bio

Fábio José da Rocha Neves was born on the 25th of September 1993 in Porto, Portugal.

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Abstract

While the effects of innovation on employment have been a controversial issue in economic literature for several years, this economic puzzle is particularly relevant nowadays, as we are witnessing tremendous technological developments which threaten to disrupt the labor market, due to their potential for significantly automating human labor. As such, this dissertation presents a study of the dynamics underlying the relationship between innovation and employment, using an agent-based model developed in Python. The model represents an economy populated by firms which are able to perform either Product Innovation (leading to the discovery of new tasks, which require human labor) or Process Innovation (leading to the automation of tasks previously performed by humans). The analysis performed throughout this dissertation has led to two major conclusions, valid in the context of the presented model. The first takeaway is that the Employment Rate in a given economy is dependent on the automation potential of the tasks in that economy and dependent on the type of innovation performed by firms in that economy (with Product Innovation having a positive effect on employment and Process Innovation having a negative effect). The second conclusion is that higher levels of Process Innovation, and lower levels of Product Innovation, lead to a more intense decline of wage shares and to a wider gap between employee productivity growth and wage growth.

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Chapter 1 – Introduction and Motivation

The effects of innovation on employment are still a controversial issue in economic thought (Vivarelli, 2014). In fact, while some authors defend that advancements in technology will ultimately have a positive impact in the general level of employment of a given economy, the problem of "technological unemployment" is still a concern for many economists (Vivarelli, 2014).

This issue has a distinct relevance nowadays, as we are seeing tremendous technological developments, particularly in the field of Artificial Intelligence (AI), which threaten to render obsolete the involvement of humans in numerous tasks (Ford, 2015). As a result, automation and its remarkable potential for the disruption, not only of the manufacturing sector (a trend known as "Industry 4.0"), but also of the services sector, has become an issue of major priority for business leaders around the globe (Manyika et al., 2017). Nonetheless, automation is not simply a concern for the corporate sphere, but rather a phenomenon with potentially massive economic and social implications. Indeed, as pointed out by DeCanio (2016) in a recent study which examines the potential effects of the spread of Artificial Intelligence technologies on wages, it has been estimated that 40%-50% of the workforce is vulnerable to being replaced by AI in the next couple of decades (Frey and Osborne, 2013; CEDA, 2015; Citi, 2016) (cfr. DeCanio, 2016). However, DeCanio (2016) begins his analysis by recognizing it is currently widely accepted that technological change can increase employment in some occupations or sectors, while decreasing it in others (Baumol, 1967; Katz and Murphy, 1992; Krusell et al., 2000; Acemoglu, 2002; Saint-Paul, 2008; Acemoglu and Autor 2011; Autor, 2014; Goos et al., 2014; Rodrik, 2016) (cfr. DeCanio, 2016), which means there remain questions to be answered regarding the overall effect of innovation on employment.

While economic theory, throughout the years, has proposed several compensation mechanisms which may counter-balance the labor-saving effect of innovation, it does not provide a clear answer to which mechanisms may indeed be effective, since every compensation mechanism has been highly questioned and met with some criticism, as stated by Vivarelli (2014). Furthermore, in its survey, the author analyzes several empirical studies on the relationship between innovation and employment, concluding that this approach does not allow for a definite conclusion on this matter either, since empirical studies have their own limitations and they do not seem to yield consensual results.

In this context, the questions remain as to (i) what is the overall effect of innovation on employment, (ii) which are the labor-saving and the compensation mechanisms at play, and (iii) which activity sectors will be more affected. Given the complexity of these issues, and the inability of both theoretical and empirical approaches to provide a clear answer to the questions at hand, an agent-based approach presents itself as a promising alternative for attempting to answer this puzzle.

When applied to studying economic phenomena, agent-based models enable "the study of coordination processes, self-organization, distributed processing, micro diversity and innovation through recombination, all in a way that is far beyond the capabilities of any representative agent model (Potts, 2000)" (Safarzynska & van den Bergh, 2010, p. 341). Agent-based models have been commonly used within the evolutionary economics perspective, which provides much more realistic settings than neoclassical economics by allowing the consideration of learning agents acting in a context of disequilibrium and bounded-rationality (Silva, 2009). Furthermore, the possibilities inherent to agent-based systems are particularly useful for understanding innovation processes, and these models have already been successfully used in explaining empirical stylized facts regarding innovation (Dawid, 2006).

Bearing this in mind, this dissertation intends to use an agent-based model, developed in Python, for studying the controversial relationship between innovation and employment.

This dissertation is structured as follows. After this overview, Chapter 2 presents a brief survey of the main theoretical and empirical approaches on the effects of innovation on employment. On Chapter 3, a literature review is once again presented, only this time it regards agent-based modelling, both from the perspective of economic applications and from a methodological perspective. Following, Chapter 4 presents the main features of the model developed, described according to the ODD (Overview, Design concepts and Details) Protocol. Chapter 5 contains the results of the simulations performed on the model as well as a series of analysis of those results. Towards the end, Chapter 6 presents the Concluding Remarks of this Dissertation, including mentions to limitations of this work and potential future research paths. Finally, the programming code for the described model can be found in the Appendix.

Chapter 2 – Main perspectives on innovation and employment: a literature review

2.1. Economic theory

While the direct effect of innovation may be a labor-saving effect, economic theory has proposed several mechanisms which may compensate this initial consequence (Vivarelli, 2014). In this sense, it is important to consider the distinction between process innovation, which may allow for the production of the same amount of output with a lower amount of labor, and product innovation, which allows for the introduction of new products into the market. As it is straightforward to conclude, process innovation has a direct labor-saving effect, thus having a direct negative influence on employment. The effects of product innovation will be addressed later in this literature review.

Besides the direct labor-saving effect of process innovation, economic theory has proposed an indirect way through which innovation may have a negative effect on employment: the creative destruction effect. Introduced by Schumpeter (1943), the concept of creative destruction was first used as a mechanism in a dynamic model of growth for studying unemployment by (Aghion & Howitt, 1994). In their model, firms are seen, essentially, as an "institutional embodiment of knowledge" (p. 478) where, after bearing a sunk cost for setting up the facilities, innovations are produced according to a Poison process. In order to implement the innovations, firms must pay a fixed cost for constructing a machine which embodies the new technology. The production of final goods then takes place in "production units", set up by the firms, each of them comprising a machine embodying technology, a worker appropriately matching the machine, and an amount of human capital which price increases at the average growth rate of the economy. As such, in a growing economy, all production units face increasing fixed costs, which is particularly damaging for production units from firms which are not innovating, since these production units may, eventually, not be able to cover their fixed costs, leading to the closure of the unit and the unemployment of the worker. Finally, we can conclude that the creative destruction effect exerts influence in two different ways. First, an increase in the growth rate of the economy will lead to an increase of the growth rate of the price of human capital, thus reducing the life-time of production units and increasing the job-destruction rate. Second, in an economy with a higher growth rate, the expected life-time of the production unit would be lower, resulting in lower expected returns for the production unit, and firms would therefore have a lower incentive to enter the market and create job openings. However, it should be noted that, in the model of Aghion & Howitt (1994), the creative-destruction effect is counterbalanced by the so-called capitalization effect, which is the negative correlation between growth and unemployment, first identified within a theoretical framework by Pissarides (1990) (cfr. Neto & Silva, 2013), combining a search and matching model with the possibility of economic growth.

Since its first introduction in a dynamic model for studying unemployment by Aghion & Howitt (1994), the creative destruction effect has become one of the mechanisms most widely used in economic literature for understanding the relationship between innovation, growth and unemployment (Neto & Silva, 2013). Of the subsequent studies referring to the creative destruction effect, one in particular deserves being analyzed in this literary review. The model developed by (Moreno-Galbis, 2012) identifies some possible limitations to the creative destruction effect. Using an endogenous job destruction framework in the style of (Mortensen & Pissarides, 1998) as a starting point, the author introduces in the model: heterogeneous skills, the possibility of unskilled workers to receive training, the risk of human capital depreciation during a period of unemployment and different matching processes for skilled and unskilled workers. Additionally, in the model of (Moreno-Galbis, 2012), firms have the possibility of updating their technology if they choose to do so, which may, but not necessarily will, limit the creative destruction effect. In fact, technological renovation causes two different effects: on the one hand, there is a wage increase, since wages rise at the same pace as the technological frontier (labor cost effect), and, on the other hand, technological renovation leads to a productivity increase (actualization effect). Therefore, if the actualization effect dominates the labor cost effect, the creative destruction effect is hindered, due to the possibility of updating technology.

Having identified the direct and indirect negative effects of innovation on employment, the present analysis will now focus on the compensating effects. In a recent survey, Vivarelli (2014) presents a comprehensive and systematic review of the economic literature on the relationship between innovation and employment, both from a theoretical and empirical perspective, which has guided, to some extent, the literary review in this dissertation. The author begins his analysis by enumerating a series of mechanisms, identified by economists, which can counterbalance the initial labor-saving effect of innovation, consisting of what Karl Marx named the "compensation theory" (Marx, 1977, 1989) (cfr. Vivarelli, 2014). Having enumerated the compensation mechanisms proposed by the economic theory, Vivarelli (2014) further identifies the criticisms and limitations identified for these mechanisms. The following table intends to provide a summary of the aforementioned mechanisms and the respective criticisms and limitations. It should be noted that the references included in this table were kept as found in the original survey by Vivarelli (2014).

Table 1 – Mechanisms that may compensate the labor-saving effect of innovation

Compensation Mechanism	Criticisms and Limitations
"via new machines": In order to implement the process innovations, new machines would need to be produced and, therefore, new jobs would be created in these capital sectors. Although the original mechanism referred to machines, a similar reasoning may be applied to other types of innovations.	The compensation mechanism "via new machines" has been practically disregarded as being enough to fully compensate the initial labor-saving effect of process innovation. In fact, as Karl Marx ([1905–1910] 1969, 552) put it, the introduction of a machine in the production process will only be profitable if it is the product of fewer labor than the amount of labor it will replace.
"via decrease in prices": the introduction of innovations in the production process would lead to a decrease in the production costs, due to an increase in efficiency. In a competitive market, this would naturally cause a decrease in prices, which could in turn have an increasing effect in demand and, consequently, in production and employment. This mechanism has been proposed several times by different economists throughout the years, such as Steuart ([1767] 1966, 256); Clark (1907, 270); Pigou ([1920] 1962, 672), Dobbs, Hill and Waterson (1987); Hall and Heffernan (1985); Heffernan (1981); Neary (1981); Nickell and Kong (1989); Stoneman (1983a, chs. 11 and 12).	The compensation mechanism "via decrease in prices" considers the positive effect that a decrease in prices may have on aggregate demand, however, it must also be noted that, due to the initial labor-saving effect, aggregate demand will decrease as a result of workers' unemployment, as noted by Thomas R. Malthus ([1836] 1964, 551-560) and Jean Charles Léonard Sismondi ([1819] 1971, 284). Therefore, it is unclear whether the net effect on demand, and consequently on employment, will be positive, as James S. Mill ([1848] 1976, 97) observed. Additionally, this mechanism does not take into account that demand constraints may occur, such as low demand elasticity or delays in expenditure decisions. Finally, this mechanism is based on the hypothesis of perfect competition, which is often not the case, and will be highly undermined if the cost savings do not lead to decreasing prices, as noted by Sylos-Labini ([1956] 1969, 160).
"via new investments": since the decrease in prices may not follow the decrease in costs immediately, innovative entrepreneurs may achieve increased profits which they can then reinvest, thus increasing production and employment. This mechanism was initially proposed by Ricardo ([1821] 1951), being later analyzed by the German school economists Lederer (1931), Lowe (1976) and Neisser (1942),	Regarding the compensation mechanism "via new investments", it must be noted that it relies on additional profits being reinvested, which may not always happen, as a result of several factors, such as Keynesian "animal spirits" and economic agents' expectations, which must be taken into account (Appelbaum and Schettkat 1995; Freeman and Soete 1987; Pasinetti 1981; Pianta 2005; Vivarelli 1995).

who considered this mechanisms to be critical to the compensation theory. Subsequently, this mechanism was reused in studies by marginalist economists such as Alfred Marshall ([1890] 1961, 542) and Paul H. Douglas (1930, 936), and in more recent dynamic models by John R. Hicks (1973), also Hagemann and Hamouda (1994) and Paul Stoneman (1983a, 177-81; and 1983b).	Additionally, even if the profits are reinvested, the nature of the new investments is relevant: if the new investments are capital intensive instead of labor intensive, the compensation of unemployment can only be partial.
"via decrease in wages": the unemployment resulting from the initial effect of process innovations may be compensated by the adjustment of the labor market through a decrease in wages. Indeed, in a neoclassical framework, a decrease in the price of labor would, ceteris paribus, increase the demand for this production factor. This mechanism as a compensation for technological unemployment was first proposed by Knut Wicksell ([1901–1906] 1961, 137), who was then followed by John R. Hicks (1932, 56), Arthur C. Pigou (1933, 256), and Lionel C. Robbins (1934, 186). In modern times, wage adjustment is a component of several partial equilibrium models.	In which regards the compensation mechanism "via decrease in wages", the main criticism is its inconsistency with the Keynesian theory of effective demand: while a decrease in wages could lead firms to hire more employees, this decrease in wages would weaken aggregate demand, which, by being expected by employers, would lead them to hire fewer employees. An additional criticism takes into account a long term perspective. Indeed, when taking into account the cumulative nature of technological change, if we consider it to be labor-saving in the long term, it is unlikely that temporary small reductions in the relative price of labor will be effective (Freeman and Soete 1987, 46).
"via increase in incomes": the cost savings for the companies, in an economy in which unions have a certain negotiating power, would be partially distributed to the workers, thus increasing their income and, consequently, consumption. In order to meet the increase in demand, companies would need to increase their production, which could lead to an increase in employment. This mechanism arose from the Keynisian and Kaldorian schools of thought, and has been proposed by Boyer (1988a, 1988b, and 1990) and Pasinetti (1981), among others.	When commenting on the compensation mechanism "via increase in incomes", Vivarelli (2014) notes that it assumes a Fordist mode of production, in which workers would capture a portion of the productivity gains resulting from technological progress, whereas, nowadays, the labor market has once again become competitive, with the distribution of income becoming very different, thus hindering this compensation mechanism.
"via new products": as mentioned before, technological innovation may consist of product innovations, that is, the development of new products and their introduction in the market. The production and commercialization of new types of products could lead to the creation of new jobs. This mechanism is regarded as a way in which technological progress can have a positive effect on employment, with various studies (Edquist, Hommen and McKelvey 2001; Freeman, Clark and Soete 1982; Freeman and Soete 1987, 1994; Vivarelli and Pianta 2000) agreeing with this conclusion.	The compensation mechanism "via new products" remains as the most effective one in compensating the labor saving effect of technological innovation. Nevertheless, Vivarelli (2014) mentions the different potential of generating new products that different technologies may have as a determining factor for the effectiveness of this compensation mechanism. Besides, attention should be payed to the "substitution effect", that is, the potential removal of mature products from the market, which could have a negative effect on employment (Katsoulacos 1984, 1986).

Source: Own elaboration based on Vivarelli (2014).

After considering the potential compensation mechanisms and the respective criticisms identified in economic theory, Vivarelli (2014) concludes that they do not provide a conclusive answer regarding the impact of innovation on employment.

In addition to the criticisms presented in Vivarelli's survey, two others deserve being mentioned. First, regarding the compensation mechanism via new machines, it seems logical to conclude it lost relevance nowadays, since many new products are digital, and even physical products are reproducible through less labor intensive processes.

Secondly, regarding the compensation mechanism via new products, it should be noted that the effectiveness of this mechanism is based on the assumption that new products will require additional labor in order to be produced, which may not be the case for highly automated production processes. Therefore, the fundamental question is not whether new products will be developed, but whether new tasks performed by human workers will be required. A different way through which the introduction of new products could be an effective compensation mechanism would be if, everything else being equal, it led to an overall increase in demand. This appears to be a plausible assumption at the micro-level, if we consider that a product innovation is likely to lead to an increase of the value perceived by consumers, and, therefore, to an increase of demand. However, at an aggregate level, and on the long run, it is not clear that product innovations may have a significant impact on the consumption propensity of a given economy.

2.2. Empirical studies

In his survey on economic literature regarding innovation and employment, Vivarelli (2014) identifies three problems associated with an empirical approach to these issues: the first one is that innovation is difficult to measure; the second problem is that the final impact of innovation on employment is dependent upon institutional mechanisms which can be very different at the micro, meso and macro levels and in different economic contexts; and the third problem is that it is difficult to isolate the final effect of innovation on employment, since the latter depends on many other factors.

Furthermore, Vivarelli (2014) states that macro-level empirical analysis, despite having the advantage of accounting for all the direct and indirect effects of innovation, are particularly subject to these limitations, while noting that sector-level empirical analysis also present these problems. On the other hand, firm-level analysis may, when compared to the two previous alternatives, allow for a more direct and precise measurement of innovation and its direct effect on employment, however, it brings with it two other issues. In the first place, firm-level analysis does not fully account for the indirect compensation effects, and secondly, it may suffer from a positive bias, since innovative firms tend to perform better, gain market share and, therefore, generate more employment, while some of these analysis may not take into account the "crowding-out" effect that innovation will cause on employment in non-innovate rival firms, which will see their business activity reduced. Regardless of these limitations, a review of several empirical studies on the puzzle of innovation and employment is presented below.

Regarding the macro-level empirical studies, Vivarelli mentions some studies attempting to assess the efficacy of compensation mechanisms within partial or general equilibrium frameworks (Sinclair, 1981; Layard & Nickell, 1985; Nickel & Kong, 1989; Vivarelli, 1995; Vivarelli & Pianta, 2000) (cfr. Vivarelli, 2014). However, these studies do not provide conclusive answers neither regarding the overall effect of innovation on employment, nor regarding which compensation mechanisms are more effective.

Sectoral level empirical studies are particularly interesting for comparing the effects of innovation on the manufacturing and services sectors. As such, it is curious that studies focused on the manufacturing sectors (Clark, 1983, 1987; Pianta et al, 1996; Vivarelli et al, 1996; Pianta, 2000; Antonucci & Pianta, 2002) (cfr. Vivarelli, 2014) seem to indicate the existence of a negative correlation between the introduction of innovations and employment, while studies focused on the services sectors (Evangelista, 2000; Evangelista & Savona 2002) (cfr. Vivarelli, 2014), despite also indicating a negative effect of innovation on employment in financial-related sectors and traditional sectors like trade and transport, point to a positive correlation between technological change and employment in the most innovative and knowledge-intensive service sectors. It is also interesting that sectoral level empirical studies which analyze both manufacturing and services sectors point to an overall positive effect of innovation on employment (Mastrostefano & Pianta, 2009; Bogliacino & Pianta, 2010; Bogliacino & Vivarelli, 2012) (cfr. Vivarelli, 2014).

Finally, microeconometric studies are also not conclusive about the possible employment impact of innovation (Entorf & Pohlmeier, 1990; Smolny, 1998; Machin & Wadhwani, 1991; Blanchflower et al, 1991; Brouwer et al, 1993; Zimmermann, 1991; Doms et al, 1997; Klette et al, 1998; Van Reenen, 1997; Blanchflower et al, 1998; Greenan & Guellec, 2000; Piva, 2003; Harrison et al, 2008; Hall et al, 2008; Lachenmaier & Rottmann, 2011) (cfr. Vivarelli, 2014). However, recent panel investigations tend to support a positive link between innovation and employment, in particular when the study focuses on high-tech sectors (Greenhalgh et al, 2001; Coad & Rao, 2011; Bogliacino et al, 2012) (cfr. Vivarelli, 2014). Nevertheless, the specific limitations of microeconomic empirical studies should still be taken into consideration, namely the omission of indirect effects and the aforementioned positive bias.

More recently, a study by Stare & Damijan (2015), using firm-level data, focused on the consequences, for employment and skills, of the innovation spillovers from vertically linked sectors, therefore taking into consideration the indirect effects of firm innovation. This study allows for the conclusions that spillovers of product innovations have a significant positive effect on employment and skill upgrading for the firms benefiting from those spillovers, whereas spillovers of process innovation in vertically linked sectors have a negative effect on employment growth and skill composition for firms subject to those spillovers. These findings are coherent with the economic theory previously reviewed.

Within the literature regarding innovation and employment, the topic of Artificial Intelligent has deserved growing attention lately. In a recent study, DeCanio (2016) investigates the effects of the spread of Artificial Intelligence on wages using a production function with human labor, robotic capital and ordinary capital as parameters. Furthermore, the paper focuses on the role of the elasticity of the substitution between human labor and robotic capital. By using cross-sectional data on U.S. productivity, DeCanio concludes that if the elasticity of substitution between human and robotic labor is greater than the 1.7–2.1 range, the spread of AI technologies will lead to a decrease in aggregate wages, ceteris paribus.

Chapter 3 – Main perspectives on agent based modelling: a literature review

3.1. Agent-based modeling of economic phenomena

As Axelrod & Tesfatsion (2005) put it, agent-based modeling (ABM) is a method for studying systems composed of interacting agents and exhibiting emergent properties, that is, exhibiting properties arising from the interactions of the agents that cannot be deduced from the properties of the agents themselves. Furthermore, multi-agent models are particularly appealing for their ability to study the interactions of heterogeneous agents, characterized by learning and bounded rationality (Safarzynska & van den Bergh, 2010).

The growing attention that ABM of economic phenomena has received in recent years is due, to a great extent, to the inadequacy demonstrated by the prevailing theoretical frameworks for economic analysis, during and after the global financial crisis of 2007-2008. Indeed, a growing number of leading economists identify the limitations of the dominant economic theory (such as assumptions of rational expectations, representative agents and perfect markets) as a significant aspect of the recent economic crisis (Kirman, 2010; Colander et al., 2009; Krugman, 2009, 2011; Caballero, 2010; Stiglitz, 2011; Kay, 2011; Dosi, 2011; Delong, 2011) (cfr. Fagiolo & Roventini, 2012). In this context, ABM of economic phenomena, also known as Agent-based Computational Economics (ACE), has been proposed as a relevant and promising alternative framework for economic analysis (Bouchaud, 2008; Fagiolo & Roventini, 2012; Farmer & Foley, 2009). Furthermore, ACE models have been extensively used as a "laboratory" for policy design, in addition to being widely successful in explaining micro and macro stylized facts (Fagiolo & Roventini, 2012). An illustrative example of the ambitious steps being taken in the field of ACE is the development of EURACE, an attempt to construct an agent-based model of the European economy (Deissenberg, van der Hoog, & Dawid, 2008).

Having introduced the topic of agent-based modeling of economic phenomena, a literary review of agent-based models, applied in the contexts of both innovation dynamics and labor market dynamics, is presented in the following subsections.

3.1.1. Agent-based models of innovation dynamics

The characteristics of agent-based systems make them especially suited for modelling innovation phenomena. Indeed, the process of technological change in an industry is a “highly decentralized dynamic search process under strong substantive and procedural uncertainty, where numerous heterogeneous agents search in parallel for new products/processes, but are interlinked through market and non-market interactions” (Dawid, 2006, p. 1240), whose main characteristics can be represented in an ABM.

In his survey on agent-based models of innovation and technological change, Dawid (2006) organizes previous studies on these phenomena according to their ability to address properties inherent to innovation dynamics, namely: knowledge accumulation, knowledge structure and spillovers; dealing with substantive uncertainty in the design of innovations, in the search across the technology landscape, and in the prediction of market response; and heterogeneity of innovation strategies. However, the author notes that his survey does not elaborate on the topic of networks emergence and information diffusion models.

Given the purpose of this dissertation, this literary review will intentionally not mention the models which the author highlights for addressing the properties of (i) substantive uncertainty in the prediction of market response and (ii) heterogeneity of innovation strategies. In the first place, since the product innovation dynamics to be modelled in this work are quite simple, the models addressing substantive uncertainty in the prediction of market response are of no particular interest to this dissertation, since they simulate more complex product innovation dynamics in which market acceptance is a key factor. In the second place, since almost every ABM regarding technological change features heterogeneous behavior, the models highlighted for addressing the “heterogeneity of innovation strategies” are simply models “explicitly focused on the effects of strategy heterogeneity from a firm and an industry perspective” (Dawid, 2006, p.1255), which are of no particular interest to this dissertation.

The first model highlighted by Dawid (2006) for addressing knowledge accumulation, knowledge structure and spillover dynamics is an oligopoly model developed by Cantner & Pyka (1998), in which firms compete by introducing new products and processes. The firms in this model may present different strategies regarding the allocation of their R&D expenditure, which can be directed towards increasing the

R&D capital stock or increasing the firms' "absorptive capacity", a concept referring to "the firm's ability to identify, assimilate, and exploit knowledge from the environment" (Cohen & Levinthal, 1989, p. 569). The inclusion of a bell-shaped spillover function and the dependency of the size of spillovers on the heterogeneity of technologies allow this model to consider a point often ignored in models of technological spillover: that, in order to increase a firm's knowledge, received information must be complementary to the firm's current knowledge (Dawid, 2006). As such, simulations using this model tend to show that investing in absorptive capacity leads to superior results in technologically heterogeneous environments (Cantner & Pyka, 1998).

Gérard Ballot & Taymaz (1997, 1999) perform simulations on models inspired by a micro-macro model of the Swedish economy, known as MOSES. In their models, firms can invest in training for harnessing stocks of specific skills, which enable them to increase productivity, or training for harnessing stocks of general knowledge, which increase the likelihood of success of the innovations. They conclude that there is an optimal sequence for resources allocation, beginning by an investment in general knowledge, which is reflected in the fact that, in their model, innovators perform better than imitators. For the purpose of this dissertation, it should be noted that the models used in these studies present a representation of the labor market, and therefore it could be argued that they bridge both the innovation and labor market dynamics. However, and in spite of the completeness of the models used, these studies focus on the effects of the firm's human capital policies on innovation and growth, without directly addressing the effects of innovation on employment.

Gilbert, Pyka, & Ahrweiler (2001) developed a model for simulating the evolution of innovation networks in real world industries. In their model, the knowledge base of an agent is a "kene", which contains a number of "units of knowledge", with each unit being represented as a triple of: a given technological capability, a corresponding specific ability and the agent's level of expertise in that specific ability. Agents may alter their kenes through their own R&D efforts, which comprise both incremental research and radical research, or by cooperating with a partner. Additionally, partners may extend their relationship to more members and establish a persistent connection, thus starting a network. Dawid (2006) considers this to be a very promising approach, since it allows for a very structured study of the accumulation of knowledge in an industry. It should be noted that this model has been further developed by Pyka et al. (2007) and new research has been published applying it in the study of the impact of different learning activities within the contexts of ‘‘organizational learning’’ (Gilbert, Ahrweiler, & Pyka, 2007) and in the study of the relative importance of agency-oriented patterns versus structure-oriented patterns in innovation networks (Ahrweiler, Gilbert, & Pyka, 2011).

Models dealing with substantive uncertainty in the design of innovations and in the search across the technology landscape focus on the fact that it is often impossible for a firm to predict the outcomes of an innovation project and, therefore, there is no obvious way for a firm to search the technology landscape and select an innovation strategy (Dawid, 2006). In order to address this issue, Cooper (2000) develops a model rooted in the perspective that firms engaging in R&D efforts for process and product innovations can be seen as trying to solve "design problems", meaning that these problems are often impossible to solve optimally through standard analytical techniques. Therefore, this model attempts to simulate the processes through which firms attempt to solve these problems, namely "individual experimental search" and "partial imitation", by resorting to the "simulated annealing" and "genetic algorithm" techniques, respectively.

Also mentioned in the survey by Dawid (2006) is an agent-based model of endogenous economic growth developed by Fagiolo & Dosi (2003), which represents the space of technological opportunities by associating technologies to points in a metric space, which can be explored and exploited by the firms, thus simulating dynamics of innovation and imitation.

Additionally, recent works by Dosi, Fagiolo, & Roventini (2006, 2008, 2010) study an agent-based model of endogenous growth and business cycles comprising firms, consumers/workers and the public sector. In this model, firms belong to one of two industries: one industry in which firms engage in R&D efforts and produce heterogeneous machine tools; and another in which firms invest in new machines and produce a homogenous consumption good. As such, in this model, innovation occurs at the level of the capital-good industry, in which firms try to increase their profits by improving their technology. In order to improve their technology, firms must invest a fraction of their past sales in R&D expenditures, which are used to hire researchers. Then, firms must split their R&D efforts between two processes: innovation and imitation, which are modelled through two-step stochastic processes.

3.1.2. Agent-based models of the labor market

Agent-based models of the labor market represent a significant part of agent-based macroeconomic models. In their survey on agent-based models of the labor market, Neugart & Richiardi (2012) trace the roots of these models back to the microsimulations performed by Bergmann (1974) and Eliasson (1976) (cfr. Neugart & Richiardi, 2012) and further classify ABMs of the labor market into two classes: partial models used with the goals of evaluating labor market policy and explaining stylized facts of labor markets, and more complex models which embed a labor market and aim at simulating the behavior of multiple interacting markets. For the purposes of this literary review, the models presented belong to the first class. Indeed, models belonging to the second class were developed with the goal of analyzing feedback processes between the goods or financial markets and the labor market, and, as such, are not in the scope of this dissertation.

Regarding partial models with the goal of evaluating labor market policy, the first example given by Neugart & Richiardi (2012) is that of a very simple model developed by Bergmann (1990) attempting to analyze the effects of an unemployment insurance program. In this model, workers were homogenous, labor demand was exogenous, matching was random and wages were not modelled, hence its simplicity and limitations. More recently, Neugart (2008) developed a model in which workers have different skills and firms in different sectors have distinct skill requirements in order to analyze the effects of a training policy. In a similar fashion, Boudreau (2008) developed a model with different wages in which workers have different skills and the possibility to invest in order to improve their productivity. Additionally, Martin & Neugart (2009) (cfr. Neugart & Richiardi, 2012) developed a model in which economic policy is endogenous.

Partial models have also been used with the goal of explaining stylized facts of labor markets, such as the wage curve, the Beveridge curve and Okun's law (Neugart & Richiardi, 2012). Authors developing such models include Fagiolo et al. (2004), focusing on the labor market and output dynamics; Richiardi (2003, 2006), including on-the-job search, entrepreneurial decisions and endogenous wage determination in his models; Ballot (2002), including an internal labor market and distinguishing between open-ended and temporary positions; and the already mentioned Dosi, Fagiolo, & Roventini (2006, 2008, 2010).

In addition, Neugart & Richiardi (2012) highlight two important characteristics of agent-based (AB) labor market models: behavioral rules and interaction structure. Regarding behavioral rules, and given the possibilities made available by the ABM method, the authors identify several alternatives used for modelling both firms' and workers' decisions, namely: random choice, local search algorithms, genetic algorithms, rule-based approaches, adaptive rules, and reinforcement learning. Since the role of social networks in the labor market is constantly acknowledged, and given the possibilities of ABM for simulating network interactions, it would be expectable that ABMs including such interacting structures would be the norm, but in fact is they are actually uncommon (Neugart & Richiardi, 2012). The few exceptions include Tassier & Menczer (2001, 2008) and Gemkow & Neugart (2011) (cfr. Neugart & Richiardi, 2012).

3.1.3. Agent-based models of innovation and labor market dynamics

As previously seen, ABMs considering either innovation or labor market dynamics separately are quite common in ACE literature. However, when it comes to combining both dynamics (innovation and labor market), the literature is surprisingly scarce, given that, as seen before, this topic has deserved plenty of attention in both theoretical and empirical economic studies.

Nonetheless, two studies combining both sides of the equation stand out. In their paper, Fagiolo et al. (2004) present an agent-based model of output and labor-market dynamics in which labor productivities change due to technical progress. However, the model portrays technical change is a simplistic way, without considering the firms' decisions regarding innovation (Dawid, 2006). In a more recent study, Silva, Valente, & Teixeira (2012) take a similar approach to Fagiolo et al. (2004), but considering two types of workers, routine and non-routine, as well as firms with heterogeneous institutional settings. Despite being more realistic and complex than Fagiolo's approach, this model still represents technological change in a rather simple way.

3.2. Agent-based modeling methodology

Despite recent methodological advances, agent-based modeling is still subject to methodological concerns, which can be divided in two categories: model presentation and empirical validation.

Regarding model presentation, the problem resides in defining an adequate and generally accepted protocol for describing an ABM in a transparent manner (Tesfatsion, 2016). It should be noted that some attempts have already been performed in this direction, such as: the "Overview, Design Concepts, Details" (ODD) Protocol for the description of ABMs (Grimm et al., 2010; Grimm, Polhill, & Touza, 2013; Grimm & Railsback, 2012); or the TRACE (TRAnsparent and Comprehensive Ecological modelling documentation) Protocol for documenting the steps to design, evaluate, and validate ABMs (Grimm et al., 2014); or even the Open Agent-Based Modelling Consortium, which attempted to create a community framework for agent-based modelling (Janssen et al., 2008).

In respect to empirical validation, Fagiolo et al. (2007) identify the heterogeneity of methods for validating ABMs as one of the reasons why this can be a problematic issue. The authors further identify the three major approaches for empirical validation of ABMs: the Indirect Calibration approach, the Werker-Brenner approach and the History Friendly approach.

Having presented, in this section, a literary review containing both ABM examples and methodological practices, the following section contains a description of the model developed for this dissertation.

Chapter 4 – The model

4.1. Introduction

In this chapter, the developed ABM is presented. In order to better describe the model, the "Overview, Design Concepts, Details" (ODD) protocol will be used. As previously mentioned, the ODD protocol (Grimm et al., 2006, 2010) aims at becoming a standardized format for the documentation of ABMs, and its main goal is to make model descriptions simultaneously more rigorous in their formulation and easier to understand.

Regarding the implementation methodology, it is important to mention that the present ABM was developed in Python, using the Mesa framework (Masad & Kazil, 2015). Mesa is an open-source Python package developed with the goal of becoming a Python-based alternative to popular ABM frameworks such as NetLogo, Repast, or MASON. The choice for this framework was largely due to its Python-based nature, and the resulting advantages, namely: easy to learn, quick to develop, highly flexible, and well documented. (Pérez et al., 2011)

The following sections match the elements of the updated ODD protocol (Grimm et al., 2010).

4.2. Purpose

The purpose of this model is to study the dynamics underlying the relationship between innovation and employment. It is not the ambition of this model to provide a set of quantitative outputs which accurately mimic past quantitative empirical data, nor to allow for a prediction of the future levels of employment in our societies. Rather, this model aims for three main goals.

First, the model intends to allow for a *Gedankenexperiment* (a thought experiment which is, generally, impossible to perform in the real world) on this issue, by providing the reader with a set of questions, hypothesis, and conclusions regarding the issue under analysis. Second, the model intends to present a representation of the reality in what concerns the relationship between innovation and employment, which is simultaneously: new in the economic literature, detailed enough to be more accurate than existing representations, and abstract enough to allow for valid general conclusions. Finally, the last goal of this ABM is to lay the groundwork for the development of more complex models revolving around its central concepts and dynamics.

4.3. Entities, state variables and scales

The model is composed by three main entities: tasks, firms (agents), and the economy (environment).

4.3.1. Tasks

The basic unit of the model is a task. In order to develop a certain amount of their product, firms need to complete a certain set of complementary tasks. Tasks are characterized by whether or not they are "automatable", their "added value", and the "activity" category they belong to:

1. **Automatable or not:** tasks than can be performed only by human labor are considered non-automatable, whereas tasks that can potentially be performed by either human labor or robotic labor are considered automatable. However, it should be noted that a firm can only perform a task using robotic labor if the firm has learnt how to automate that task.
2. **Added value:** the added value of a task reflects the contribution of that task to the overall value of an output unit. More specifically, the value of one unit of output, produced by a given firm, equals the average of the added value of the tasks performed by that same firm.
3. **Activity:** tasks can belong to different activity categories. Some activities have a higher automation potential than others, that is, they include a higher proportion of automatable tasks than others. Regarding added value, there is no differentiation between activities, that is, the mechanism that generates the tasks in the model uses the same probability distribution, for the added value of tasks, across the different activity categories.

4.3.2. Firms (Agents)

The agents in the model are firms. These agents produce output by performing tasks using human labor and robotic labor as inputs. Firms have, among others, the following attributes:

1. **Known tasks:** each firm has its own set of tasks which it knows how to perform, out of all the existing tasks in the model. It is possible for two firms to have the same task in their set of known tasks. This attribute also contains information on whether each of the tasks has been automated or not by the firm in question, that is, whether or not that firm can perform the task using robotic labor.
2. **Current tasks:** at each time step, a firm must decide on the 10 tasks it will perform during that period. "Current tasks" is the attribute containing the information on which those 10 tasks are.[1]
3. **Employees:** a numerical attribute representing the amount of human labor units the firm employs at a given time step.
4. **Robots:** a numerical attribute representing the amount of robotic labor units the firm owns at a given time step.
5. **Output quantity:** this attribute refers to the amount of output units the firm has produced at a given time step.
6. **Unitary value of output:** this attribute refers to the value of each output unit the firm has produced at a given time step. As previously mentioned, the value of one unit of output, produced by a given firm, equals the average of the added value of the tasks performed by that same firm.
7. **Revenues:** a firm's revenues at a given time step are the product of its Output quantity and its Unitary value of output value at that time step.
8. **Salary costs:** a firm's Salary costs at a given time step are the product of its number of Employees and the Salary in the economy at that same time step.

[1] It should be noted that the number of tasks to be performed was arbitrarily selected as 10, considering that it provides an adequate degree of consistency, and requires a reasonable amount of computational resources. In fact, this figure is largely irrelevant, only influencing the model's results when it is exceptionally low (since, in that case, the samples used are smaller, the results are more likely to be affected by random events in the model and, therefore, less likely to be consistent). On the other hand, higher values for this figure provide little improvements in the model's consistency while considerably increasing the number of computations required.

9. **Robot costs:** the costs a firm bears for owning robots are the opportunity cost of the investment (a function of the interest rate in the economy) and the depreciation costs (a function of the depreciation rate). No costs are incurred at the moment of acquisition or sale of robots because it is assumed that the firm is always able to recover the net value of the assets. Therefore, a firm's Robot costs at a given time step are the product of its number of Robots, by the unitary value of a Robot, and by the sum of the interest rate and the depreciation rate.
10. **R&D stock:** a firm's R&D stock determines the likelihood that its innovation attempts will be successful. The value of a firm's R&D stock is the result of accumulation of its previous R&D expenses.
11. **R&D expenses:** if, at a given time step, a firm has positive earnings, after considering salary costs and robot costs, it will invest a fraction of those earnings in R&D. The percentage of earnings that goes into R&D expenses is the same for all firms in the economy, so the relative amount of R&D expenses between firms depends only on their earnings.
12. **Operating net income:** a firm's Operating net income at a given time step is computed by subtracting a firm's Salary costs, Robot costs and R&D expenses from its Revenues at that same time step. This attribute can be positive, negative or zero.

4.3.3. Economy (Environment)

In this model, the environment in which the agents (firms) interact is an economy, which contains, among others, the following attributes:

Input attributes (exogenous):

1. **Number of firms:** the total number of firms in the economy. It should be noted that this parameter remains constant throughout the different time steps of the simulations. In fact, whenever a firm is considered to have gone bankrupt, and only in that event, a new firm is created. Moreover, it should be noted that the new firm will incorporate characteristics which match the average of the characteristics of the surviving firms.

2. **R&D Intensity:** this parameter defines the percentage of earning that each firm will invest in R&D at each time step. Since it is an attribute of the environment, and not of each specific firm, it is, as previously mentioned, equal for every firm. It should also be noted that this parameter remains constant throughout the different time steps of the simulations.
3. **Expected Growth:** refers to the expected growth rate of the total output units in the economy. The total expected output units in the economy influences the planned production of the firms. It should also be noted that this parameter remains constant throughout the different time steps of the simulations.
4. **Product Innovation Propensity:** firms in the model can perform two types of innovation: product innovation or process innovation. At each step, each firm chooses one of the two types of innovation to perform, so this parameter, ranging from 0 to 100, influences their propensity to choose product innovation over process innovation. The mechanism through which this influence is exerted will be detailed more thoroughly below.
5. **Interest rate:** the interest rate in the economy is used to compute a firm's opportunity cost of owning robots. It should also be noted that this parameter remains constant throughout the different time steps of the simulations.

Output attributes (endogenous):

1. **Product Innovation Rate and Process Innovation Rate:** as previously mentioned, firms can perform product innovation or process innovation. These two attributes measure the percentage of firms in the economy that successfully performed product innovation, or process innovation, at a given time step.
2. **Threshold Unitary Value of Output:** this value refers to a certain percentile of the observations of Unitary Value of Output for all firms in the economy, at a given time step. The percentile rank used to compute the Threshold Unitary Value of Output is the economy's Product Innovation Propensity. Simplistically speaking, firms will perform Product Innovation if their Unitary Value of Output is lower than the Threshold Unitary Value of Output, and will perform Process Innovation if it is equal or higher; this means that, in an economy with a Product Innovation Propensity of X, at any given time step, X% of the firms will be

performing Product Innovation, while the remaining ones will perform Process Innovation. To be accurate, the model considers other factors affecting the firms' decision, but this is the most relevant one.

3. **Firm Replacement Rate:** As previously mentioned, whenever a firm is considered to have gone bankrupt, a new firm is created in order to replace it. In that sense, the Firm Replacement Rate refers to the percentage of firms in the economy that were replaced by a new firm at a given time step.
4. **Active population:** this attribute refers to the standard definition of Active Population, that is, the fraction of a population that is either employed or actively seeking employment.
5. **Employed population:** the total number of employees in every firm in the model at a given time step.
6. **Employment Rate:** the fraction of the Active population which is Employed at a given time step.
7. **Human share of input:** the fraction of the total tasks performed, at a given time step, which are performed by humans.
8. **Salary:** since the model assumes that every employee has the same characteristics, it also assumes that they all receive the same salary - the Salary in the economy at a given time step.
9. **Wage Share:** this attribute measures the fraction of the total Output in the economy that has been distributed as Salaries, at a given time step.
10. **Weighted average profit margin:** this attribute measures the average profit margin of the firms in the economy at a given time step, weighted by the firms' revenues.

4.4. Process Overview and Schedule

During a time step in a simulation, the following procedures take place:

1. **Firms' actions:** each of the firm's in the model are activated in a random order and they perform their own schedule of procedures at the micro-level.
2. **Market dynamics:** this procedure takes place at the macro-level and consists of a set of computations regarding the goods and services market and the labor market in the simulated economy.

3. **Reporting of output data:** at this stage, the model stores data regarding the status of the economy and of its agents, namely innovation and labor market statistics.
4. **Replacement of bankrupt firms:** before the period ends, the model replaces bankrupt firms with new firms incorporating characteristics which match the average of the characteristics of the surviving firms.

Firms are activated in random order, and each of them performs the following actions:

1. **Choose the tasks to perform:** out of all the tasks a firm knows how to perform, it needs to choose 10 tasks to perform at a given time step.
2. **Hire employees and acquire robots:** having decided on which tasks to perform at a given time step, a firm must obtain the production inputs required to perform those tasks.
3. **Produce output:** the execution of a firm's chosen tasks by the obtained inputs results in a certain quantity of output with a certain unitary value.
4. **Budget:** towards the end of its schedule, the firm must compute its revenues, costs, earnings, R&D budget, and its next period's production expectations.
5. **Innovate:** before its action ends, a firm must decide whether it wants to attempt product or process innovation, and observe the resulting outcome.

4.5. Design concepts

4.5.1. Basic principles

The model is governed by a series of underlying principles and simplifying assumptions regarding:

1. **Innovation mechanisms:** As previously mentioned, in this model, firms can perform either product or process innovation. In this context, process innovation refers to the automation of a certain task by a firm, whereas product innovation means the discovery of a task which was previously unknown to that firm and which allows the firm to produce Output with a higher Unitary Value. Each of these types of innovation present in the model has its own set of basic principles:
   a. **Product Innovation**

i. **Motivation for product innovation** – The firms in the model perform product innovation with the goal of increasing their Unitary Output Value. There are two motivations behind this goal. The first is the fact that the Unitary Output Value of a firm directly affects its revenues and, therefore, its profits. The second is the firms' belief that, by providing their customers with a highly valuable product, they will be able to win, or not lose, market-share moving forward.

ii. **Newly discovered tasks are manual at first –** In the model, whenever a firm successfully performs product innovation and, as a result, a new task is added to its set of known tasks, that task is always initially manual. If the task in question is automatable, a firm can later learn how to perform it using robots (by means of process innovation), but, initially, it must always be performed by a human.

i. **Product innovation is only incremental –** the model considers that product innovation is merely the introduction of tasks in the productive process which allow for the creation of higher-value products. That is, the model doesn't consider the possibility of disruptive product innovations that introduce entirely new products.

b. Process Innovation

i. **Motivation for process innovation** – The firms in the model perform process innovation with the goal of decreasing their costs. In fact, by being able to replace humans with robots in the performance of a given task, a firm is able to replace salary costs with the costs of owning and operating the robots, which are assumed to be lower.

ii. **Automation potential –** As previously mentioned, some activity categories have a higher automation potential than others, that is, they include a higher proportion of automatable tasks than others. The automation potential of tasks belonging to each activity category was defined according to a McKinsey Global Institute report regarding the automation potential for activities in the US economy (Manyika et al., 2017). Similarly, the proportion of tasks belonging to each category was defined based on the proportion of time spent on each activity, according to the same report. It should be noted that the definition of "automation potential" used in the report considers only the potential for automation resulting from the adaptation of currently demonstrated technologies. Therefore, the utilization of this data in such a core feature of the model limits its applicability to the temporal horizon of "adaptation of current technology". In fact, the development of new technological breakthroughs could lead to an increase of the automation potential of the tasks in the economy, and this is not represented in the model.

iii. **Cloud robotics –** a firm's knowledge regarding the automation of tasks is automatically and immediately shared with all the robot units it owns. This mechanism attempts to simulate the concept of cloud robotics, according to which robots are able to share the same knowledge and computational power by accessing a central storage and processing unit (Ford, 2015).

2. **Production**

   a. **Full complementarity of the selected tasks –** as previously mentioned, at each time step, each firm must select the 10 tasks it will perform. All of these 10 tasks need to be performed once in order to produce 1 unit of output, that is, they are complementary. The natural implication of this is that the production function of a firm *i,* which is able to perform each task j for T_j times, is $Output\ Quantity_i = min(T_1, \ldots, T_{10})$.

   b. **Full substitutability of the known tasks –** Even though the 10 selected tasks are considered to be fully complementary once selected, a firm's known tasks are considered to be fully substitutable during the selection process. That is, firms are allowed to select whichever 10 tasks they want from their set of Known Tasks, without replacement, without any combination restriction, but following a certain selection criteria.

c. **Preference for value over profitability** – the criteria used by firms to select the 10 tasks to be performed is their added-value, that is, their ability to add value to the firm's output. This means that firms will choose the highest value tasks even if they are aware of tasks that would make the firm more profitable (tasks which don't have the highest added value, but which have been automated). The reasoning behind these criteria is rooted in the firms' belief that, by providing their customers with a highly valuable product, they will be able to win, or not lose, market-share moving forward. Since the agents in the model hold this belief, and their goal is to maximize their profitability not only in the current time step, but also in the following time steps, these criteria can be deemed adequate for the attainment of their goal.

d. **Unitary task-productivity of labor units** – each unit of labor in the model, be it human or robotic, can perform only one task at each time step, and it can perform that task only once during that time step.

e. **Preference for robots over humans in automated tasks** – it is assumed that, whenever a task becomes automated, firms will always prefer to perform that task by using robots instead of humans. This assumption is rooted in two other assumptions of the model. The first, is that whenever a task becomes automated, it is possible for a robot to perform that task with the exact same quality standards as a human (in such a way that a consumer would be unable to identify from the product whether it had been produced by a human or a robot), or with even higher quality standards. The second assumption is that, once a task has been automated, it is always more costly to perform it using human labor than robotic labor.

3. **Output market**

a. **One-period full market clearing** – it is assumed in this model that every unit being produced is consumed in the same time step, that is, aggregate production necessarily creates an equal quantity of aggregate demand in the same period. This exaggeration of Say's law is a simplification introduced in the model which effectively causes the model to be inappropriate for studying the economic effects of demand-side economic phenomena. However, since the focus of the model is essentially the study of supply-side economic phenomena, it is fair to conclude that this is not a crippling assumption. In any case, the conclusions drawn at the end of this dissertation take into account the possible consequences of considering this assumption.

b. **Intrinsic product value** – the value of products in the model is assumed to be intrinsic to the products themselves, being a direct result of the tasks which were performed in order to produce it. As such, the value of the products is not considered to be subjective and does not reflect each consumer's preferences. In a similar fashion, the price of a product is assumed to exactly match its value, meaning that there's no consideration for inflation and prices are not considered to be, in any degree, a monetary phenomenon.

c. **Constant and equal quantity market shares** – firms' market shares, measured in Output Quantities are considered to be equal for every firm at every time step. However, it should be noted that firms' market shares, measured in Revenues, are a function of both Output Quantity and Unitary Output Value, so these can change. Furthermore, it could be argued that quantity market shares should also be a function of Unitary Output Value, since a higher value perceived by consumers could lead to a higher market share, and vice-versa. However, for simplicity purposes, and in order to prevent the model's results from being influenced by such industry dynamics, the model assumes that quantity market shares are stable and equal at every time step. Nevertheless, it should be noted that firms are considered unable to perceive this model feature and, as previously mentioned, hold the belief that it is possible for them to win or lose customers. In fact, this belief ultimately determines firms' innovation decisions, in such a way that it can be seen as an automatic stabilizer of quantity market-shares. That is, firms which believe they are susceptible of losing customers will display innovation decisions which could ultimately lead them to gain market share, while firms which believe they are likely to gain customers will display innovation decisions which could ultimately lead them to lose market share. These dynamics are explained in more detail in the section destined to explaining firms' innovation decisions. Finally, it should be noted that firms' belief that they can win or lose customers is maintained even after their quantity market share remains stable despite their innovation efforts.

4. **Employees / Labor market**
   a. **Active population** – In this model, it is assumed that all the population is active. Additionally, the Active Population matches, at every time step, the total number of tasks that need to be performed in order to produce the Total Output Units in the economy, regardless of those tasks being performed by humans or robots. Therefore, the Active Population always grows at the same rate as the Total Output Units, which is a rate defined exogenously. Another consequence of this relationship between Active population and Total tasks performed is the fact that the Employment Rate in the economy will always match the Human Share of Input, that is, the percentage of the Active population which is employed, always matches the percentage of the Total tasks which are performed by humans.
   b. **Homogeneity of human skills** – workers are assumed to have the exact same skills, that is, they are assumed to be able to perform every task with the same quality standards.
   c. **No barriers to hiring or firing –** firms in the model are able to hire and fire employees with total freedom, that is, at every time step, they can hire or fire as many employees as they which, without incurring any costs, and with immediate effect.
   d. **Inelastic labor demand –** the demand for labor in the model does not depend on the Salary in the economy. In fact, the only factors affecting firms' demand for labor units are their technology, that is, how many of their current tasks are manual or automated, and their planned production.
   e. **Linear labor supply –** the supply of labor in the model is assumed to be linear, with 0 workers willing to be employed at a salary of 0, and all of

the active population willing to be employed at a salary rate which matches the *Average Expected Employee Productivity*. There are two main implication from this assumption and the assumption of inelastic labor demand:

i. Knowing the labor demand in the economy is enough to know the employed population in the economy at a given time step;
ii. Knowing the Employment Rate and the *Average Expected Employee Productivity* in the economy is enough to know the Salary in the economy at a given time step. In fact, the Salary in the economy will always match the product of the Employment Rate and the Average Expected Employee Productivity. An alternative way to interpret this relationship is by considering that Employment Rate determines the bargaining power of employees, which in turn determines the portion of the Average Expected Employee Productivity that employees are able to capture in the form of salaries.

4.5.2. Emergence

In this model, the individual decisions of firms, regarding which type of innovation to perform, lead to aggregate outcomes in the labor market.

4.5.3. Adaptation

In the model, firms adapt their decisions regarding which type of innovation to perform according to the Unitary Value of Output of other firms. This decision mechanism is explained in more detail in the Submodels section.

4.5.4. Objectives

Agents in the model act with the objective of maximizing their overall profits, that is, maximizing their profit not only in the current time step, but also in the following time steps. This objective informs firms' hiring, production and innovation decisions.

4.5.5. Learning

Agents in the model do not possess learning abilities, that is, they are unable to change their adaptive traits based on their past experiences.

4.5.6. Prediction

Firms perform predictions of their future Output Quantity, as well as the required number of Employees and their Expected Productivity. The way in which firms perform these predictions is described in detail in the Submodels subsection, namely in the paragraphs relative to the “Budget” procedure performed by firms.

4.5.7. Sensing

Firms are able to perceive all of their own internal state variables, as well as the Unitary Output Value of other firms, and macro-level state variables such as Salary and Interest Rate.

4.5.8. Interaction

The model assumes there is no direct interaction between individual agents. However, agents interact indirectly by competing for market share. In fact, as previously mentioned, even though the model assumes that quantity market shares are stable over time, firms hold the belief that that it is possible for them to win or lose customers. And, in any case, firms are still able to increase their market share in terms of revenues, by improving their Unitary Output Value. This way, the model represents the competitive behavior of firms in a realistic way, even though it represents one of the aggregate outcomes of that behavior in a rather simplistic way. Nevertheless, firms’ competitive behavior still leads to some complex interactions:

1. **Competition by product value** – as previously mentioned, firms believe that, by providing their customers with a highly valuable product, they will be able to win, or not lose, market-share. This is the basic motivation behind firm’s product innovation attempts, and their preference for high value tasks. It should be noted that, by improving their unitary output value, firms will be willing to pay their employees a higher salary (since their employees will have a higher productivity, measured in terms of output value, not output quantity). As such, this type of

competition, besides having a positive influence on a firm's revenues, also has a positive influence in the Salary in the economy and, therefore, a negative influence on other firm's profitability.

2. **Competition by process innovation –** firms perform process innovation with the goal of decreasing their costs. It should be noted that, by automating tasks, firms will be willing to pay their employees a higher salary (their employees will have a higher productivity, since the firm will be able to produce the same quantity of output while employing fewer workers). However, because process innovation will also have a negative influence on the economy's employment rate, the net effect of process innovation on the salary in the economy is completely neutral.

4.5.9. Stochasticity

Certain processes in the model include some degree of randomness, namely:

1. **Task generation –** as previously mentioned, tasks in the model are characterized by Added Value, Activity, and whether or not they are automated. The details of the task generation process are presented in the submodels section.
2. **Task allocation –** when firms are created in the model, their set of known tasks is randomly selected, with replacement, from the set of tasks in the economy. In a similar way, when a firm successfully performs product innovation, the new task to be added to their set of known tasks is randomly selected from the set of tasks in the economy which were previously unknown to this firm, and which added-value is higher than the firm's Unitary Output Value.
3. **Innovation success factor –** a firm's innovation attempt is considered successful when the observed value of a random variable called Success Factor is greater than 1. The Success Factor follows a Poisson distribution with the parameter λ matching the firm's relative R&D Stock. That is, the Success Factor represents the number of discrete independent occurrences of a certain phenomenon during a given time range, with the expected number of occurrences being $\lambda = \frac{R\&D\ Stock_{i,j}}{Average\ R\&D\ Stock_{j}}$, for firm i in period j. This way, firms with an R&D Stock below average have an expected Success Factor which is lower than 1, and firms with an R&D Stock above average have an expected Success Factor which is higher than 1.

4.5.10. Collectives

The model has no consideration for collectives of agents. In particular, it could be expected from such a model that it would include innovation networks. However, not having found evidence, in the economic literature, linking the existence or the structure of innovation networks with the impact of innovation on employment, this was not considered as an hypothesis to be tested, and, as such, innovation networks were not included in the model.

4.5.11. Observation

The model stores the data on the state variables at the end of each time step, immediately before the replacement of bankrupt firms with new firms

4.6. Initialization

When a simulation is initialized, the initial set of tasks is generated, and the initial set of firms populates the model. The number of tasks in the economy and the number of firms is determined exogenously and can therefore differ between simulations.

Finally, it should be noted that, in the initial state, it is assumed that none of the tasks has been automated, since the tasks were defined based on data referring to tasks currently performed by humans. The following subsection gives a more detailed explanation on the data used for defining the tasks.

4.7. Input data

As previously mentioned, the automation potential of tasks, as well as the proportion of tasks belonging to each category, was defined according to a McKinsey Global Institute report regarding the automation potential for activities in the US economy (Manyika et al., 2017). It should be noted, however, that the definition of "automation potential" used in the report, as mentioned above, considers only the potential for automation resulting from the adaptation of currently demonstrated technologies.

Moreover, the model considers as input data the initial value for some of its state variables, namely: number of firms, number of tasks in each generation, number of tasks known by each firm, expected output quantity in the economy at the first time step, interest rate, R&D intensity, expected growth and Product Innovation Propensity.

4.8. Submodels

4.8.1. Agents' actions

As previously mentioned, at each time step, firms must perform the following procedures:

1. Choose the tasks to perform;
2. Hire employees and acquire robots;
3. Produce output;
4. Budget;
5. Innovate.

Choose the tasks to perform

Out of all the tasks a firm knows how to perform, it needs to choose 10 tasks to perform at a given time step. As mentioned before, the firm attempts to maximize the unitary value of its output at every step, so the tasks selected must be the ones with the highest added-value. In order to achieve this result, each firm follows these steps:

1. Sort the set of known tasks by added-value;
2. Select the top 10 tasks as current tasks.

Hire employees and acquire robots

Having decided on which tasks to perform at a given time step, a firm must obtain the production inputs required to perform those tasks, by following these steps:

1. From the set of current tasks, identify the tasks that the firm has learned how to automate and the tasks that are manual;
2. Count the number of automated and manual tasks, that is, the number of tasks that will be performed by robots and the number of tasks that will be performed by humans;
3. Compute the number of employees and robots required by firm *i* during the time step *j*:

$$Employees_{i,j} = Round\ (Expected\ Output_{\ i,j} * Number\ of\ current\ manual\ tasks_{i,j})$$

$$Robots_{i,j} = Round\ (Expected\ Output_{i,j} * Number\ of\ current\ automated\ tasks_{i,j})$$

4. Hire the required production inputs (as mentioned before, the salary is defined at the macro-level, and it is assumed that the firm is able to obtain all the employees and robots it requires immediately).

Produce output

The execution of a firm's chosen tasks by the obtained inputs results in a certain quantity of output with a certain unitary value. In order to compute these values, a firm must perform the following computations:

1. The Obtainable Output from Manual Tasks is computed through the integer division of the number of employees by the number of current manual tasks. If there are no manual tasks in the current tasks set, then the obtainable output from manual tasks is considered to be infinite, since it does not constitute a production bottleneck (that is, the Quantity of Output is not at all limited by the need to perform manual tasks).
2. Similarly, the Obtainable Output from Automated Tasks is computed through the integer division of the number of robots by the number of current automated tasks. If there are no automated tasks in the current tasks set, then the obtainable output from automated tasks is considered to be infinite, since it does not constitute a production bottleneck (that is, the Quantity of Output is not at all limited by the need to perform automated tasks).
3. The quantity of output units produced by a firm *i* at the time step *j* is given by:

$$Quantity\ of\ Output_{i,j} = min\ (Obtainable\ Output\ from\ Manual\ Tasks_{i,j},\ Obtainable\ Output\ from\ Automated\ Tasks_{i,j})$$

4. The value of an output unit of firm *i* at the time step *j* is given by:

$$Unitary\ Value\ of\ Output_{i,j} = Average\ (Current\ Task\ Set_{i,j\ [Added-value]})$$

Budget:

Towards the end of its schedule in step *j*, a firm *i* computes its revenues, costs, earnings, R&D budget, and its production expectations for step *j+1*:

a. $Revenues_{i,j} = Quantity\ of\ Output_{i,j} * Unitary\ Value\ of\ Output_{i,j}$

b. $Salary\ Costs_{i,j} = Employees_{i,j} * Salary\ in\ the\ Economy_j$

c. $Robot\ Costs_{i,j} = Robots_{i,j} * (Interest\ Rate + Depreciation\ Rate)$

d. $R\&D\ Expenses_{i,j} =$

$$\begin{cases} 0, if\ (Rev\ i,j - Sal\ C\ i,j - RobC\ i,j) \leq 0 \\ (Revenues_{i,j} - Salary\ Costs_{i,j} - Robot\ Costs_{i,j}) * R\&D\ Intensity,\ otherwise \end{cases}$$

e. $R\&D\ Stock_{i,j} = R\&D\ Stock_{i,j-1} + R\&D\ Expenses_{i,j}$

f. $Operating\ Net\ Income_{i,j} =$

$Revenues_{i,j} - Salary\ Costs_{i,j} - Robot\ Costs_{i,j} - R\&D\ Expenses_{i,j}$

g. $Expected\ Output_{i,j+1} = Output\ Quantity_{i,j} * (1 + Expected\ Growth)$

h. $Expected\ Employees_{i,j+1} = Round(Number\ of\ current\ manual\ tasks_{i,j} *$

$Expected\ Output_{i,j+1})$

i. $Expected\ Employee\ Productivity_{i,j+1} =$

$$\frac{Unitary\ Value\ of\ Output_{i,j} - Number\ of\ current\ automated\ tasks_{i,j} * (Interest\ Rate + Depreciation\ Rate)}{Number\ of\ current\ manual\ tasks_{i,j}}$$

Regarding these computations, the following comments should me made:

1. Whenever a firm's operating net income has been negative for three consecutive time steps, the firm is considered to have gone bankrupt, and must therefore leave the market at the end of the third time step.
2. In the model, the robot unitary value is defined as 1 and the depreciation rate is defined as 20%, meaning that each robot is assumed to have a useful life of 5 years.
3. It should be noted that the expected number of employees for period *j+1* takes into account the expected output for *j+1*, but the number of manual tasks in period *j*. In fact, at this point, the firm has no clarity on which tasks will or not be automated or even selected in the next period. As such, the actual number of employees at the next period could be different from the expected.
4. Similarly to the previous comment, the Expected Employee Productivity, which will define a firm's reserve salary, only takes into account data regarding the period *j*. This results from the fact that, once again, the firm has no visibility on which tasks will be performed during the next period. It should also be noted that this concept of productivity doesn't exactly match the standard definition. However, computing the productivity in this way serves the intended purpose,

considering that, even though the selected tasks are fully complementary, the production inputs can be hired and acquired with total freedom.

Innovate

Before its action ends, a firm must decide whether it wants to attempt product or process innovation, and observe the resulting outcome. As such, firms perform the following steps:

1. A firm *i* decides whether to attempt product innovation or process innovation in period *j* in the following way:
    a. If none of a firm's Current Tasks in period *j* is automatable - that is, the 10 tasks it has decided to perform in period *j* (its 10 known tasks with the highest added-value) have either already been automated or are impossible to automate - then the firm decides to attempt Product Innovation. In fact, in this scenario, the firm would have nothing to gain in attempting to automate one of the lower added-value tasks which were not included in the Current Tasks, since it would never be performing it.
    b. If a firm's Unitary Value of Output *i,j* is inferior to the Threshold Unitary Value of Output in the economy at time step *j*, then the firm decides to attempt Product Innovation. The rationale behind this decision is that, having a Unitary Value of Output lower than the Threshold, a firm considers its position in the market to be threatened, and so its strategic focus becomes improving its products or services, rather than optimizing its processes.
    c. If none of these conditions are met, that is, if a firm still has Current Tasks which are automatable, and its Unitary Value of Output *i,j* is equal or superior to the Threshold Unitary Value of Output in the economy, then the firm attempts Process Innovation. The rationale behind this decision is that, having a Unitary Value of Output at the same level or above the Threshold, a firm considers its position in the market to be secure, and so its strategic focus becomes optimizing its processes, rather than improving its products or services.

2. A firm i checks whether it's innovation attempt in period j was successful in the following way:
    a. $\text{Success factor}_{i,j} = \text{Poisson}(\frac{\text{R\&D Stock}_{i,j}}{\text{Average R\&D Stock}_{j}})$, that is, a one element sample of a Poisson distribution with the parameter $\lambda = \frac{\text{R\&D Stock}_{i,j}}{\text{Average R\&D Stock}_{j}}$, in which $Average\ R\&D\ Stock_{\ j}$ is the Average R&D Stock in the economy at time step j.
    b. If $\text{Success factor}_{i,j} > 1$, then the firm's innovation attempt is successful.
3. If a firm's innovation attempt has been successful:
    a. If the firm has succeeded in process innovation, the firm's automatable task with the highest added-value becomes automated. This way, that particular task can be performed by this firm, in the following time steps, using a robot.
    b. If the firm has succeeded in Product Innovation, one of the existing tasks in the economy, which was previously unknown to this firm, and which added-value is higher than the firm's Unitary Output Value, is randomly selected to be added to the firm's set of known tasks. This way, the firm will be able to perform the new task in the following time steps, and, as a consequence, its Unitary Output Value will be higher than in the current time step.

With regards to a successful product innovation, it should be noted that, in the event that there are no existing tasks in the economy which are unknown to the firm and which added-value is higher than the firm's Unitary Output Value, the model triggers the generation of a new set of tasks with higher added-values, and one of those tasks is then randomly selected. This new set of tasks is said to belong to the "next generation". The details of the task generation mechanism are explained below, in the subsection dedicated to this procedure.

4.8.2. Environment-level procedures

The model contains some procedures which run at the macro-level, namely:

1. Market dynamics;

2. Reporting of output data;
3. Replacement of bankrupt firms;
4. Generation of new tasks.

Market dynamics:

This procedure takes place at the macro-level and consists of a set of computations regarding the goods and services market and the labor market in the simulated economy.

1. At the level of the goods and services market, there aren't many procedures, since the price of output is determined entirely by its Unitary Value, which is determined by the added-value of the tasks performed to produce it, and the quantity of goods and services sold is determined by the amount produced, given that the model assumes that the demand will match supply at every time step. As such, the only procedures taking place are computations of aggregate metrics, such as the Total Output Quantiy and the Total Output Value.
2. At the level of the labor market, the model must compute the Salary in the economy for the time step j+1, by performing the following computations:
   a. $Employed\ population_j = \sum_i Employees_{i,j}$
   b. $Active\ population_j = Total\ Output\ Quantity * 10$, in which 10 refers to the number of tasks performed by each firm to produce one unit of output, thus enforcing the matching relationship between active population and the total number of tasks performed.
   c. $Employment\ rate_j = \frac{Employed\ population_j}{Active\ population_j}$
   d. $Total\ expected\ employees_{j+1} = \sum_i Expected\ employees_{i,j+1}$
   e. $Total\ expected\ employee\ productivity_{j+1} = \sum_i Expected\ employee\ productivity_{i,j+1} * Expected\ employees_{i,j+1}$
   f. $Average\ expected\ employee\ productivity_{j+1} = \frac{Total\ expected\ employee\ productivity_{j+1}}{Total\ expected\ employees_{j+1}}$
   g. $Employee\ bargaining\ power_{j+1} = Employment\ rate_j$
   h. $Salary_{j+1} = Average\ expected\ employee\ productivity_{j+1} * Employee\ bargaining\ power_{j+1}$

Reporting of output data:

The model stores data regarding the status of the economy and of its agents, namely innovation and labor market statistics. Among the reported data, the following statistics are included: Product Innovation Rate and Process Innovation Rate; Threshold Unitary Value of Output; Firm Replacement Rate; Active population; Employed population; Employment Rate; Human share of input; Salary; Wage Share; Weighted average profit margin. The computations for these parameters have already been explicitly expressed above in this dissertation, either via their definition, or via formula.

Replacement of bankrupt firms:

Before the period ends, the model replaces bankrupt firms with new firms incorporating characteristics which match the average of the characteristics of the surviving firms, by following these procedures:

1. Let A_j be the set of all firms in the simulation at the step j, and B_j the set of bankrupt firms at the end of time step j, so that $A_j \supseteq B_j$.
2. A_{j+1} is initialized as being equal to A_j.
3. Each bankrupt firm, belonging to the set B_j is removed from the set of all firms for step j+1, A_{j+1}.
4. For each element in B_j, a new firm k is added to A_{j+1}, containing the following attributes:

   i. $Number\ of\ known\ tasks_{k,j+1} = \frac{\sum_i^{|A_j - B_j|} Number\ of\ known\ tasks_{i,j}}{|A_j - B_j|}$

   j. The set of Known Tasks is randomly selected from the set of existing tasks in the economy.

   k. $Probability\ that\ each\ known\ task\ is\ automated_{k,j+1} = \frac{\frac{\sum_i^{|A_j - B_j|} Number\ of\ automated\ tasks_{i,j}}{|A_j - B_j|}}{Number\ of\ known\ tasks_k}$

   l. For each of firm k's Known Tasks in time step j, the property of it having or not already been automated follows a Bernoulli distribution with $p = Probability\ that\ each\ known\ task\ is\ automated_{k,j+1}$

   m. $Expected\ Output_{k,j+1} = \frac{\sum_i^{|A_j - B_j|} Output\ Quantity_{i,j}}{|A_j - B_j|} * (1 + Expected\ Growth)$

   n. $R\&D\ stock_{k,j+1} = \frac{\sum_i^{|A_j - B_j|} R\&D\ Stock_{i,j}}{|A_j - B_j|}$

Generation of new tasks

As previously mentioned, the task generation mechanism is triggered at the beginning of the simulation, and when a firm which has successfully performed Product Innovation finds no Unknown Tasks in the economy which have a higher added-value than it's Output Unitary Value. Tasks are characterized by Activity, Added Value and by whether or not they are automatable, with these attributes being defined in the following way:

1. **Activity** – the category to which each task belongs is randomly selected from a set of 7 activity categories, and the probability that it belongs to each category is determined by the proportion of time currently spent on each activity, according to a McKinsey Global Institute report regarding the automation potential for activities in the US economy (Manyika et al., 2017).
2. **Added Value** – each task has an Added Value which is randomly selected from a range of 10 possible integer values, with the probability of each value being selected being uniformly distributed. The range of possible values depends on the task generation in the following way:
    a. When the simulation starts, the range of possible Added Values is [1, 10]. These initial tasks are said to belong to the Generation 0.
    b. When the task generation mechanism is triggered again, the range of possible values is [1 + Generation * 10, 10 + Generation * 10]. Thus, the tasks belonging to the Generation 1 have Added Values ranging from 11 to 20, and so on.
3. **Automatable or not** - for each new task, the property of it being or not automatable follows a Bernoulli distribution, with the probability p of each Bernoulli distribution being different across each of the different activity categories. Indeed, for each category, the probability p equals the automation potential for that activity in the US economy, as defined in the already mentioned McKinsey Global Institute report (Manyika et al., 2017).

Chapter 5 – Simulation and Data Analysis

Having presented, in detail, the model developed in this dissertation, it is now adequate to analyze the results obtained from performing simulations on the model.

Indeed, by performing simulations, and analyzing the results of those simulations, we are able to obtain a deeper understanding of (i) the relationships between variables in the model and (ii) the evolution of those variables. As such, this section is divided into two subsections: "Analysis of the final state of the economy" and "Analysis of the dynamics in the economy".

5.1. Analysis of the final state of the economy

This subsection presents an analysis of statistics obtained at the last time step of each simulation, with the goal of understanding the relationships among them and between them and the initial parameters.

The variables which will be analyzed are the following:

1. **Product Innovation and Process Innovation Rates Over Time:** as previously mentioned, Product and Process Innovation Rates measure the percentage of firms in the economy that successfully performed product innovation, or process innovation, at a given time step. The suffix "Over Time" in these variables refers to the fact that they represent the average of the respective rates over every time step of the simulation. In addition to the effective innovation rates, some of the analysis in this section contain Innovation Attempts Rates and Innovation Success Rates, which measure, respectively, the percentage of firms that attempted a given type of innovation, and the percentage of the attempts which were successful.
2. **Employment Rate:** the fraction of the Active population which is Employed at the last time step of the simulation, that is, the total number of Employees in all the firms in the economy divided by the Active population.
3. **Human share of input:** the fraction of the total tasks performed, at the last time step of the simulation, which are performed by humans.
4. **Wage Share:** the fraction of the total Output in the economy that has been distributed as Salaries, at the last time step of the simulation.

5. **Firm Replacement Rate Over Time:** the average, over every time step of the simulation, of the percentage of firms in the economy that were replaced by a new firm at a given time step.
6. **Weighted average profit margin:** the average profit margin of the firms in the economy at the last time step of the simulation, weighted by the firms' revenues.

The reason why some of the statistics collected contain information only regarding the last time step is because these attributes, like the employment rate or the profit margins, are not independent from the results of previous time steps. That is, the value of these statistics at the last time step is the result of mechanisms which, to a great extent, build on top of the historical values for these statistics in the previous time steps. As such, the value for this statistics at the last time step represents the final value of an evolution over time.

On the other hand, the Innovation Rates and Firm Replacement Rates statistics contain information on the average over every time step because the mechanisms which determine their values at every time step do not rely on the historical values of these statistics in the previous time steps. That is, the value of these statistics at the last time step does not represent the final value of an evolution over time and is, indeed, unlikely to provide valuable information regarding the simulation. However, the average of the values of these statistics over every time step provides us with important information for characterizing the results in the simulation.

5.1.1. Simulation

In order to obtain statistically relevant data from the simulations performed on the model, different values for some of the initial parameters of the model were set, and, for each possible combination of the initial parameters, a series of 10 iterations of the model were run.

From the initial parameters of the model, the following have been arbitrarily set to a single value, since it is logically clear, from the way the model was built, that they would have no influence on the results of the simulations:

i. Number of firms: 100;
ii. Number of tasks in each generation: 1000;

iii. Number of tasks known by each firm: 10;
iv. Expected output quantity in the economy at the first time step: 100000;
v. Interest rate: 5%.

On the other hand, the following parameters have been assigned a set of different possible values:

vi. R&D Intensity: {0.25; 0.5; 0.75};
vii. Expected Growth: {0; 0.02; 0.1};
viii. Product Innovation Propensity: {0; 25; 50; 75; 100};

The following is a reiteration of the definition of these parameters:

R&D Intensity: this parameter defines the percentage of earning that each firm will invest in R&D at each time step. Since it is an attribute of the environment, and not of each specific firm, it is, as previously mentioned, equal for every firm. It should also be noted that this parameter remains constant throughout the different time steps of the simulations.

Expected Growth: refers to the expected growth rate of the total output units in the economy. The total expected output units in the economy influences the planned production of the firms. It should also be noted that this parameter remains constant throughout the different time steps of the simulations.

Product Innovation Propensity: at each step, each firm chooses one of the two types of innovation to perform, so this parameter, ranging from 0 to 100, influences their propensity to choose product innovation over process innovation. Since it is an attribute of the environment, and not of each specific firm, it is equal for every firm. It should also be noted that this parameter remains constant throughout the different time steps of the simulations.

As a result of running 10 iteration for each possible combination of initial parameters, a total of 450 simulations of the model were run.

5.1.2. Exploratory Analysis

Univariate Analysis

The following table contains a set of statistics intended to provide information on the location and dispersion of the output variables considered:

Table 2 – Location and dispersion statistics for output variables

Variables	Minimum	Maximum	Mean	Std. Deviation
Process Innovation Rate Over Time	1%	17%	11%	5%
Process Innovation Attempt Rate Over Time	2%	57%	30%	17%
Process Innovation Success Rate Over Time	27%	70%	43%	10%
Product Innovation Rate Over Time	14%	31%	20%	5%
Product Innovation Attempt Rate Over Time	43%	98%	70%	17%
Product Innovation Success Rate Over Time	24%	37%	29%	2%
Employment Rate	53%	98%	71%	14%
Human Share of Input	53%	98%	71%	14%
Wage Share	48%	97%	67%	15%
Firm Replacement Rate Over Time	2%	11%	4%	3%
Weighted Average Profit Margin	-1%	33%	14%	9%

From these statistics, one can draw the following conclusions:

1. The minimum, maximum and mean of the Product Innovation Rate Over Time are higher than those of the Process Innovation Rate Over Time. The explanation for this fact cannot lie in the Success Factor, since Process Innovation Success Rates are even higher than Product Innovation Success Rates. Indeed, the explanation lies in the fact that, on average, a higher proportion of firms attempt Product Innovation instead of Process Innovation. The reason why more firms attempt Product Innovation could be the Product Innovation Propensity, however, that is not the case, since the average Product Innovation Propensity across simulations is 50 (the possible values considered for this parameter were 0, 25, 50, 75 and 100). Indeed, the reason why more firms perform Product Innovation is the fact that some firms are performing Product Innovation because they've already automated all of their current tasks, even if their Unitary Output Value is above the Threshold Value. Finally, one possible explanation for why, on average, Process Innovation Attempts have a higher Success Rate than Product Innovation Attempts, is the fact that Process Innovations will usually be attempted by the firms with the highest Unitary Output Values, which, *ceteris paribus*, means they

have higher profits and, therefore, higher R&D expenses and stocks, which in turn increases their likelihood of innovation success.

2. The Employment Rate and the Human Share of Input present the same values for these statistics. In fact, as previously mentioned, these attributes always match, as a result of the imposed relationship between Active Population and the Total number of tasks performed at a given time step. Therefore, from this point on, we will only present data on the Employment Rate and not on the Human Share of Input.
3. The Wage Share presents a range of values close to the range of values of the Employment Rate, which one can hypothesize to be a consequence of the significance of the Employees Bargaining Power in determining the Salary in the economy.

Bivariate Analysis

In order to identify whether or not the output variables are correlated, and if so, how, the Spearman's Rank-Order Correlation Coefficient for each pair of variables was computed and the Spearman's Rank-Order Correlation Test was performed. The reasons for choosing Spearman's coefficient and test over Pearson's coefficient and test are as follows:

1. Spearman's coefficient does not consider the correlation between the original value of the variables but rather the correlation between the respective ranks. Therefore, Spearman's coefficient, unlike Pearson's, measures correlation even if it is not linear, and is not sensitive to distribution asymmetries and outliers.
2. Spearman's test does not require that the variables being analyzed follow a normal distribution, unlike Pearson's.

The following table contains the values of the Spearman's coefficient and the p-value of Spearman's test (2-tailed) for each pair of variables:

Table 3 – Spearman's Rank-Order Correlaction Coefficients and Tests for pairs of output variables

		Process Innovation Rate Over Time	Product Innovation Rate Over Time	Employment Rate	Wage Share	Firm Replacement Rate Over Time	Weighted Average Profit Margin
Process Innovation Rate Over Time	Correlation Coefficient	1,00	-0,89	-0,96	-0,96	-0,83	0,68
	Sig. (2-tailed)		0,00	0,00	0,00	0,00	0,00
Product Innovation Rate Over Time	Correlation Coefficient	-0,89	1,00	0,93	0,93	0,85	-0,67
	Sig. (2-tailed)	0,00		0,00	0,00	0,00	0,00
Employment Rate	Correlation Coefficient	-0,96	0,93	1,00	1,00	0,85	-0,69
	Sig. (2-tailed)	0,00	0,00		0,00	0,00	0,00
Wage Share	Correlation Coefficient	-0,96	0,93	1,00	1,00	0,86	-0,69
	Sig. (2-tailed)	0,00	0,00	0,00		0,00	0,00
Firm Replacement Rate Over Time	Correlation Coefficient	-0,83	0,85	0,85	0,86	1,00	-0,62
	Sig. (2-tailed)	0,00	0,00	0,00	0,00		0,00
Weighted Average Profit Margin	Correlation Coefficient	0,68	-0,67	-0,69	-0,69	-0,62	1,00
	Sig. (2-tailed)	0,00	0,00	0,00	0,00	0,00	

From these results, one can conclude, with a 1% significance level, that all the variables present a significant ordinal correlation. In fact, the null hypothesis that the variables do not present ordinal correlation is rejected, with a 1% significance level, for every pair of variables.

Additionally, one can conclude that the following pairs of variables present positive, or negative, ordinal correlation:

1. **Positive ordinal correlation**
    a. Process Innovation Rate Over Time and Weighted Average Profit Margin;
    b. Product Innovation Rate Over Time and Employment Rate;
    c. Product Innovation Rate Over Time and Wage Share;
    d. Product Innovation Rate Over Time and Firm Replacement Rate;
    e. Employment Rate and Wage Share;
    f. Employment Rate and Firm Replacement Rate Over Time;
    g. Wage Share and Firm Replacement Rate Over Time.
2. **Negative ordinal correlation**
    a. Process Innovation Rate and Product Innovation Rate;
    b. Process Innovation Rate and Employment Rate;
    c. Process Innovation Rate and Wage Share;

d. Process Innovation Rate and Firm Replacement Rate Over Time;
e. Product Innovation Rate and Weighted Average Profit Margin;
f. Employment Rate and Weighted Average Profit Margin;
g. Wage Share and Weighted Average Profit Margin;
h. Firm Replacement Rate Over Time and Weighted Average Profit Margin.

Being aware of the dependency mechanisms embedded in the model, one can consider the following points to be the main conclusions to be drawn from the previous results:

1. Product Innovation has a positive correlation with the Employment Rate in the economy, whereas Process Innovation has a negative correlation with the Employment Rate in the economy;
2. The Employment Rate has a positive correlation with the Wage Share in the economy;
3. The Wage Share has a negative correlation with firms' Profit Margins;
4. Profit Margins are negatively correlated with the Firm Replacement Rate;

It should be noted that all of these results were expected and seem to be intuitive based on the way the mechanisms were represented in the model. However, when interpreting these results, one should bear in mind that correlation does not necessarily mean causality.

In order to assess whether or not the values for the initial parameters have a significant effect on the values of the output statistics, a series of Kruskal-Wallis tests were performed. The Kruskal-Wallis test verifies the hypothesis that the distribution of a variable is the same across different independent samples. Being a non-parametric test, it does not rely on the assumption that the variable must be normally distributed, unlike the ANOVA method.

The goal was therefore to test whether the distribution of each output variable was the same across the different possible values of each initial parameter (Expected Growth, R&D Intensity, and Product Innovation Propensity).

The following is the SPSS output from the Kruskal-Wallis tests across values of Expected Growth:

Table 4 – SPSS output from the Kruskal-Wallis tests across values of Expected Growth

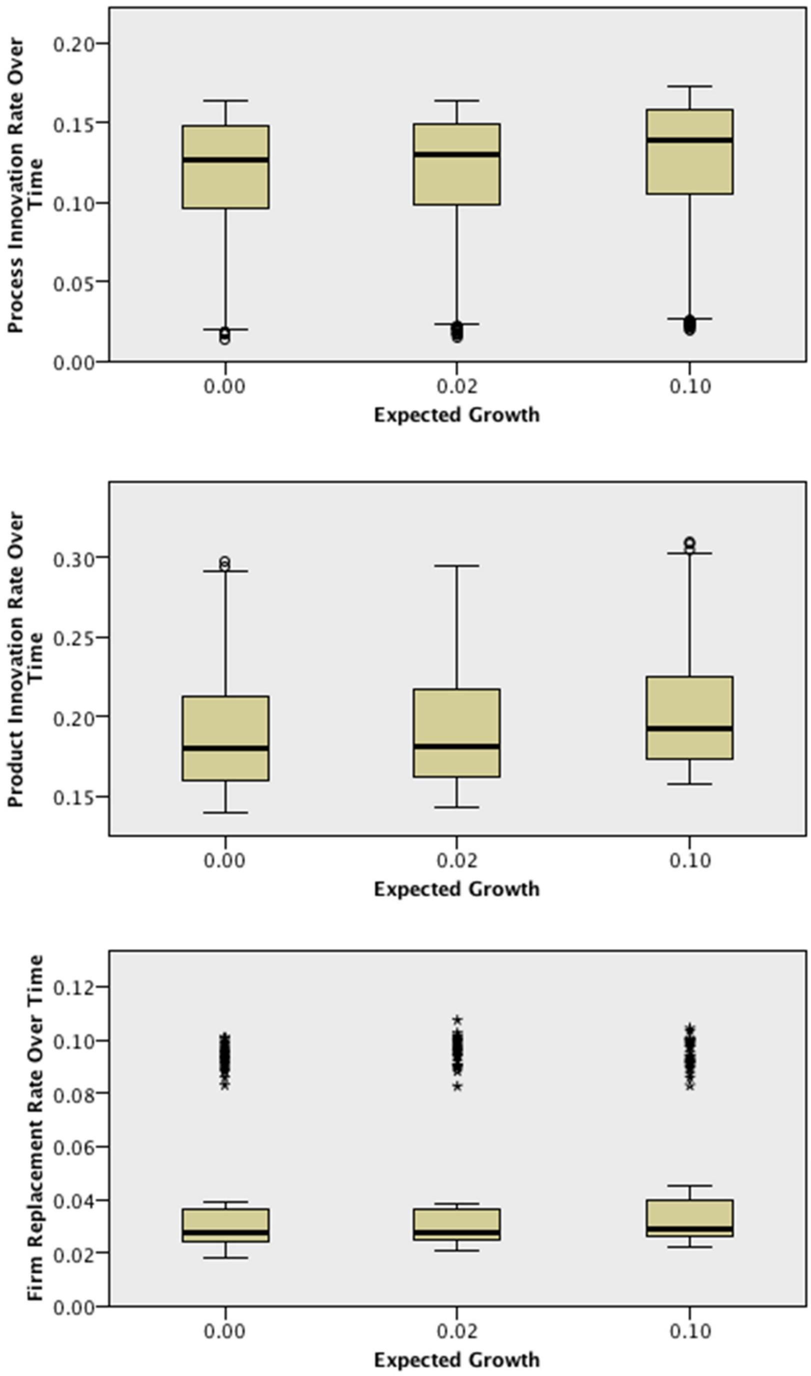
Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of Process Innovation Rate Over Time is the same across categories of Expected Growth.	Independent-Samples Kruskal-Wallis Test	.001	Reject the null hypothesis.
2	The distribution of Product Innovation Rate Over Time is the same across categories of Expected Growth.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
3	The distribution of Employment Rate is the same across categories of Expected Growth.	Independent-Samples Kruskal-Wallis Test	.894	Retain the null hypothesis.
4	The distribution of Wage Share is the same across categories of Expected Growth.	Independent-Samples Kruskal-Wallis Test	.937	Retain the null hypothesis.
5	The distribution of Firm Replacement Rate Over Time is the same across categories of Expected Growth.	Independent-Samples Kruskal-Wallis Test	.025	Reject the null hypothesis.
6	The distribution of Weighted Average Profit Margin is the same across categories of Expected Growth.	Independent-Samples Kruskal-Wallis Test	.907	Retain the null hypothesis.

Asymptotic significances are displayed. The significance level is .05.

From this output, we can conclude with a significance level of 5% that Innovation Rates and Firm Replacement Rate Over Time present different distributions across the different values of Expected Growth. The following outputs are the boxplots of these variables across the different categories of Expected Growth:

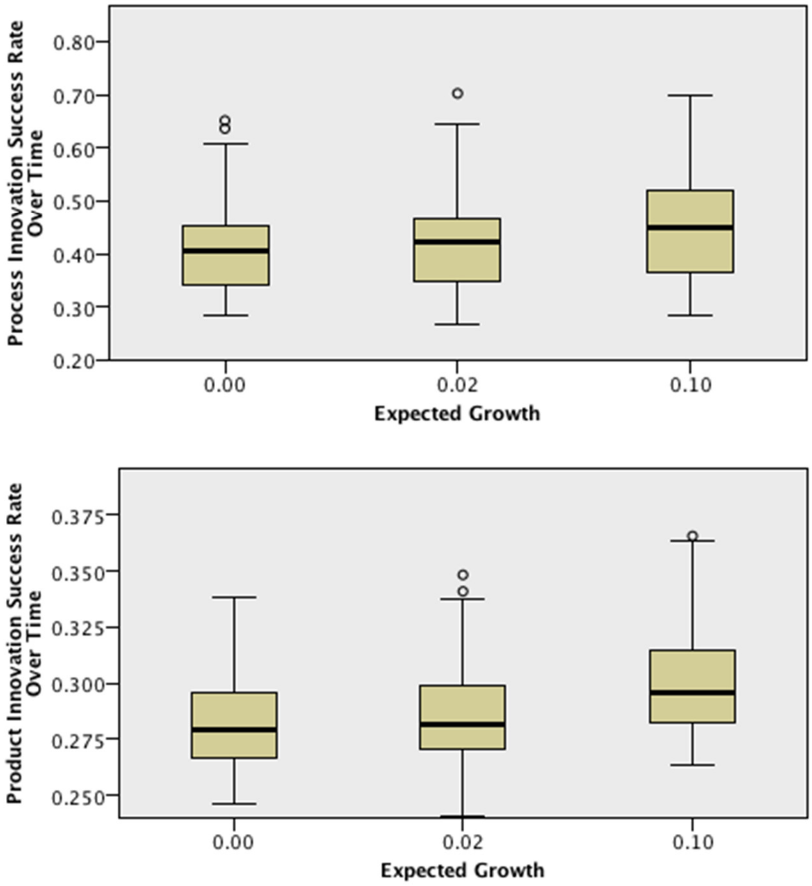
Figure 1 – Boxplots of output variables across the different categories of Expected Growth



From these outputs, it is possible to see that both the Product and Process Innovation Rates present distributions with higher values when the Expected Growth presents its highest value. Regarding the Firm Replacement Rate Over Time, it also appears to present a distribution with higher values for the last category.

The fact that the distributions for both Innovation Rates present higher values can only be explained by higher Innovation Success Rates when the Expected Growth is higher. In fact, the sum of the two Innovation Attempt Rates is always 100%, so it would be impossible to see an increase in both Attempt Rates at the same time. In order to confirm the previous affirmation, the boxplots for both Innovation Success Rates are presented below:

Figure 2 – Boxplots of Innovation Success Rates across the different categories of Expected Growth



As expected, both Innovation Success Rates present a distribution with higher values when the Expected Growth is the highest. Nevertheless, this result raises the question of why would Success Rates be higher under these circumstances. Indeed, this appears to be the result of the fact that relative R&D Stocks, which are the only determinant of the Innovation Success Factors, are computed by taking into consideration the average R&D Stock in the previous time step and, therefore, a higher growth of a firm's revenues from one period to another may lead to a higher relative R&D Stock, since it may lead to a higher increase of profits and, therefore, to a higher increase of R&D Stocks. As such, this appears to be the result of the model configuration, rather than a result from which one can draw valid economic conclusions.

The following is the SPSS output from the Kruskal-Walis tests across values of R&D Intensity:

Table 5 – SPSS output from the Kruskal-Wallis tests across values of R&D Intensity

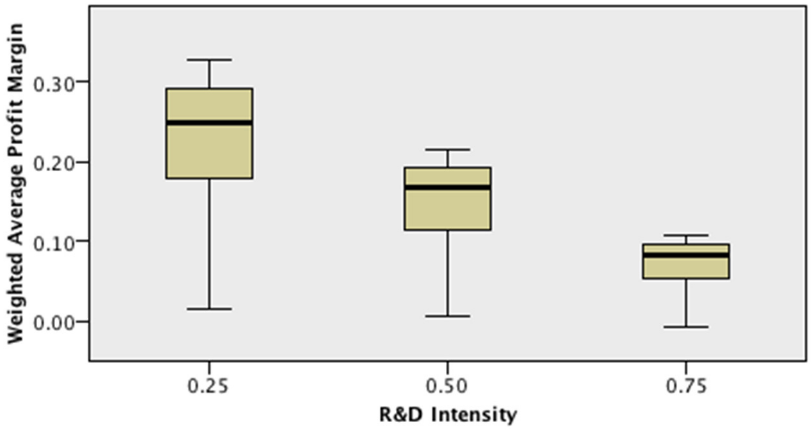
Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of Process Innovation Rate Over Time is the same across categories of R&D Intensity.	Independent-Samples Kruskal-Wallis Test	.989	Retain the null hypothesis.
2	The distribution of Product Innovation Rate Over Time is the same across categories of R&D Intensity.	Independent-Samples Kruskal-Wallis Test	.950	Retain the null hypothesis.
3	The distribution of Employment Rate is the same across categories of R&D Intensity.	Independent-Samples Kruskal-Wallis Test	.997	Retain the null hypothesis.
4	The distribution of Wage Share is the same across categories of R&D Intensity.	Independent-Samples Kruskal-Wallis Test	.989	Retain the null hypothesis.
5	The distribution of Firm Replacement Rate Over Time is the same across categories of R&D Intensity.	Independent-Samples Kruskal-Wallis Test	.762	Retain the null hypothesis.
6	The distribution of Weighted Average Profit Margin is the same across categories of R&D Intensity.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.

Asymptotic significances are displayed. The significance level is .05.

From this output, we can conclude with a significance level of 5% that the Weighted Average Profit Margin presents different distributions across the different values of R&D Intensity. The following output is the boxplot of this variable across the different categories of R&D Intensity:

Figure 3 – Boxplots of Weighted Average Profit Margin across the different categories of R&D Intensity



As it is clear to see, for higher values of R&D Intensity, the distributions of the Weighted Average Profit Margin present lower values. This result is expected and intuitive, considering that the R&D Intensity determines a firm's R&D Expenses, which affects its Profit Margin.

It is also not surprising that we cannot reject the hypothesis that the Firm Replacement Rate Over Time is not different across different values of R&D Intensity, since firms only incur in R&D Expenses if their Revenues net of Production Costs are positive. That is, R&D Intensity may affect how high a firm's net profitability is, but it doesn't affect whether it is positive or negative.

The following is the SPSS output from the Kruskal-Walis tests across values of Product Innovation Propensity:

Table 6 – SPSS output from the Kruskal-Wallis tests across values of Product Innovation Propensity

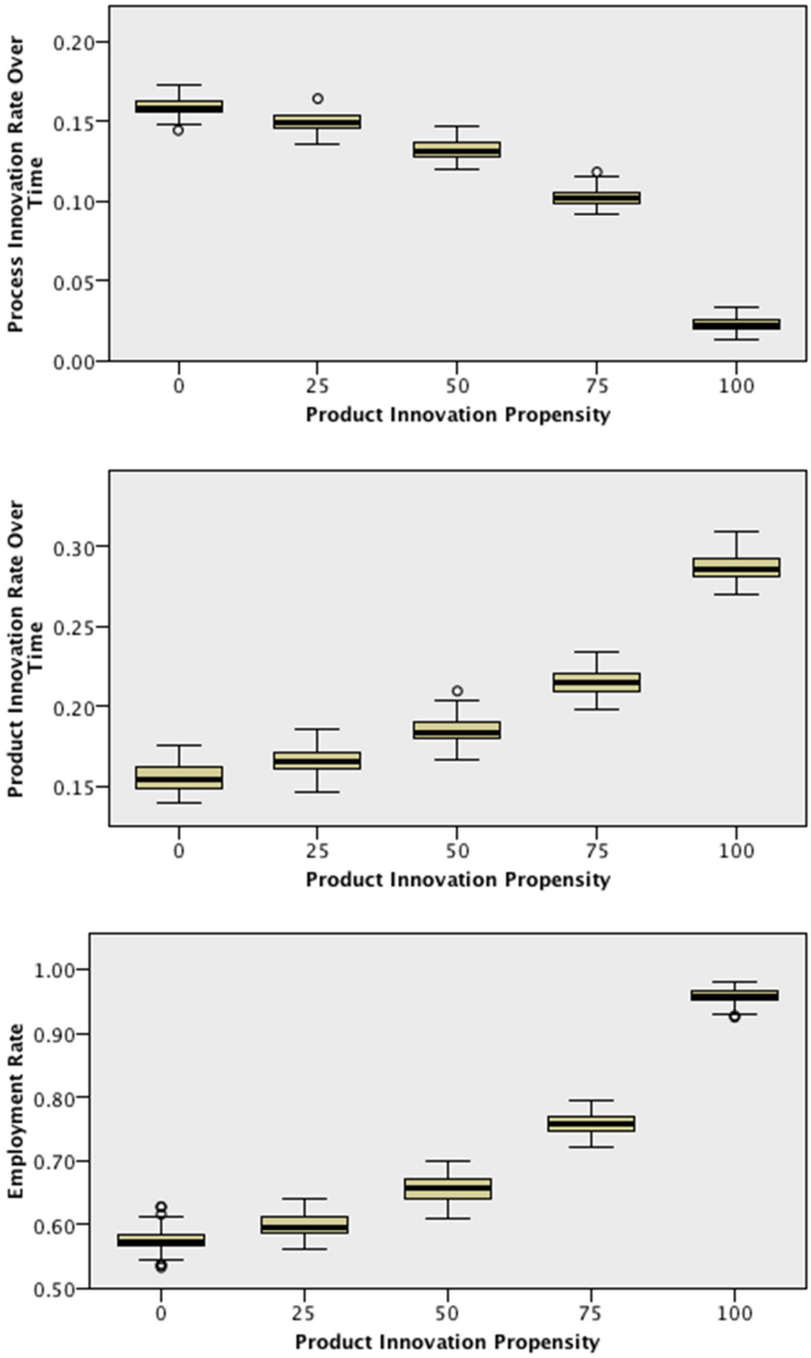
Hypothesis Test Summary

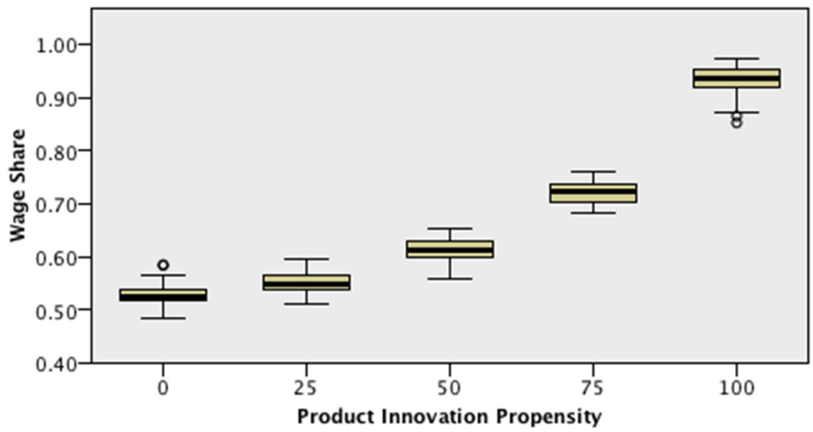
	Null Hypothesis	Test	Sig.	Decision
1	The distribution of Process Innovation Rate Over Time is the same across categories of Product Innovation Propensity.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
2	The distribution of Product Innovation Rate Over Time is the same across categories of Product Innovation Propensity.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
3	The distribution of Employment Rate is the same across categories of Product Innovation Propensity.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
4	The distribution of Wage Share is the same across categories of Product Innovation Propensity.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
5	The distribution of Firm Replacement Rate Over Time is the same across categories of Product Innovation Propensity.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
6	The distribution of Weighted Average Profit Margin is the same across categories of Product Innovation Propensity.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.

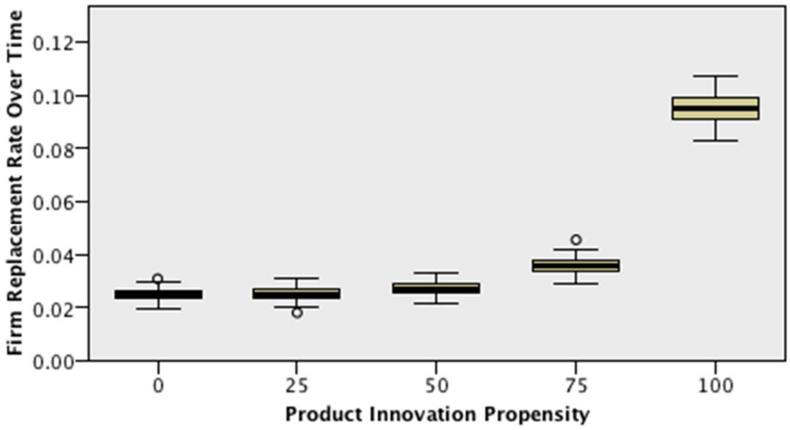
Asymptotic significances are displayed. The significance level is .05.

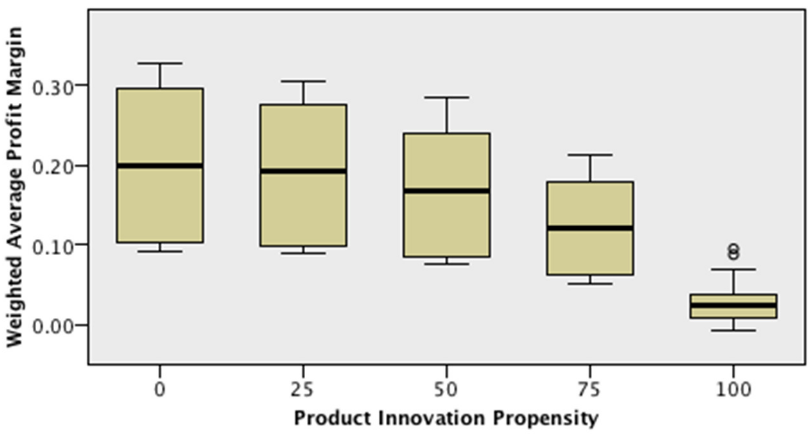
From this output, we can conclude with a significance level of 5% that all the output variables present different distributions across the different values of Product Innovation Propensity. The following outputs are the boxplots of each variable across the different categories of Product Innovation Propensity:

Figure 4 – Boxplots of output variables across the different categories of Product Innovation Propensity









Once again, these results are not surprising. Product Innovation Propensity is highly determinant of both Product and Process Innovation Rates, and, as a result, of the other output variables. In fact, these results are coherent with the previously seen results on the correlations between Innovation Rates and the remaining output variables.

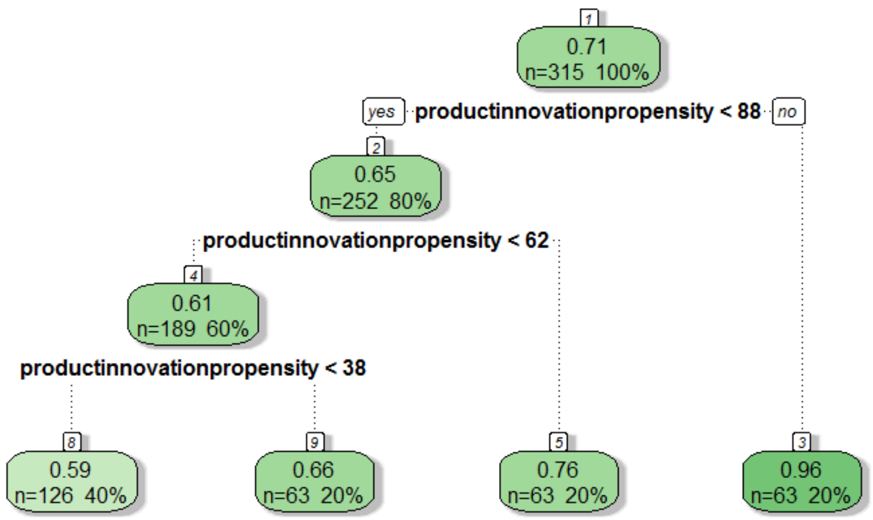
Considering the main goal of this dissertation, it is particularly relevant to understand to which extent the Product Innovation Propensity is determinant of the

Employment Rate in the economy. With this goal in mind, a regression model is developed, which attempts to predict the Employment Rate in the economy based only on the Product Innovation Propensity. The model chosen was a Regression Tree.

The output data from the 450 simulations was separated into training and test data, with the training data consisting of the first 7 iterations out of the 10 iterations performed for each combination of initial parameter values. This way, both the training and test datasets are balanced in terms of the weight of the different combinations of initial parameter values. The training data is then composed by 315 observations, and the test data is composed by 135 observations.

The regression tree obtained, using the R package "rpart", was the following:

Figure 5 – Regression Tree for predicting Employment Rate based on Product Innovation Propensity



Different levels of post-pruning were tried, based on the Mean Squared Error (MSE) obtained when applying this Regression Tree to the training set, but the full tree was the one with the lowest MSE. The MSE obtained was 0,00031, which is considerably low. As such, it is possible to conclude that the Product Innovation Propensity is highly effective for predicting the Employment Rate in the last time step of the economy.

5.2. Analysis of the dynamics of the economy

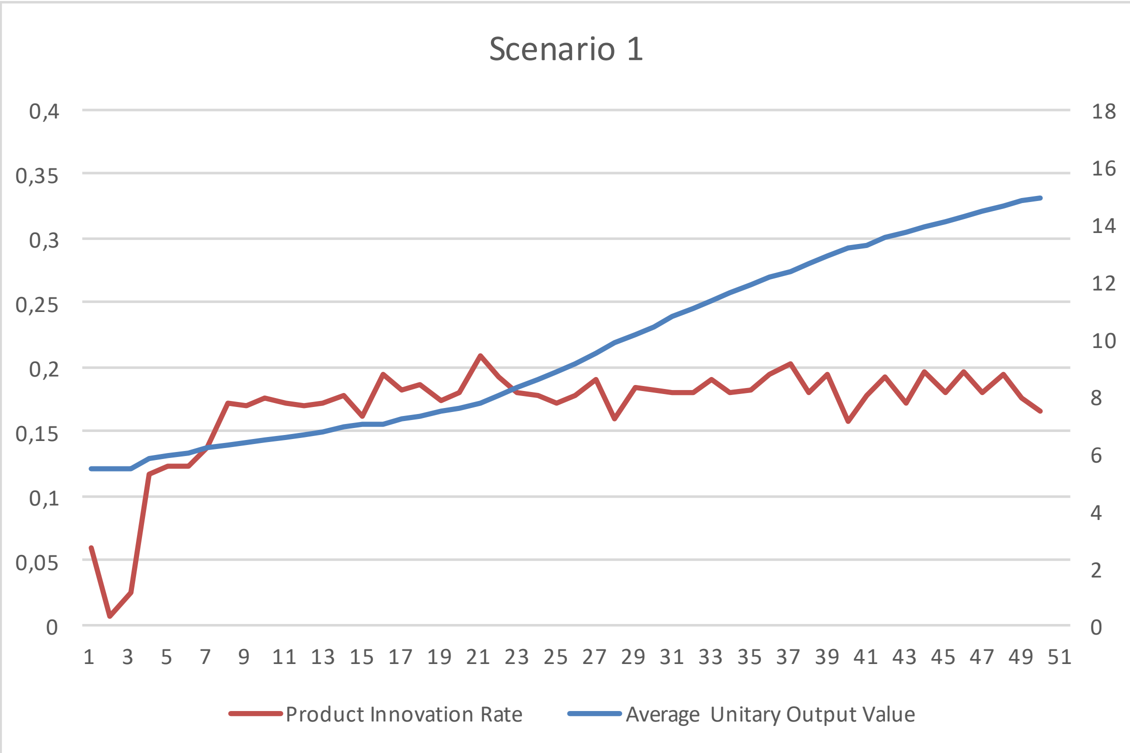
In order to obtain a better understanding of the results seen in the previous section, regarding the last time step of each simulation, it is important to consider the evolution of the output variables throughout the time steps of simulations.

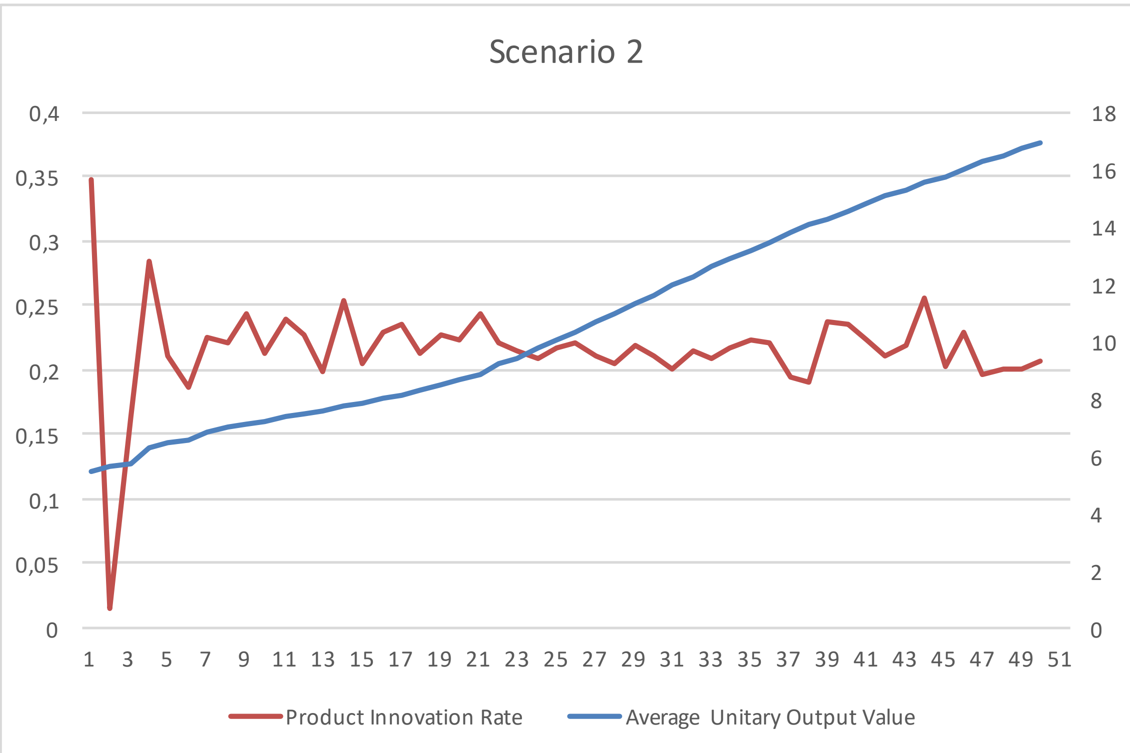
With this goal in mind, the present section contains a series of charts depicting the evolution of the values of each output variable throughout simulations. In order to achieve a compromise between comprehensiveness and simplicity of the results, only one initial parameter was considered as having more than one initial value: the Product Innovation Propensity. Indeed, as previously seen, this is the initial parameter with the most influence on the outcomes of the model. As such, two scenarios will be considered, one in which the Product Innovation Propensity is 25 and one in which it is 75, that is: one can expect more firms to be attempting Product Innovation in Scenario 2 than in Scenario 1 and more firms to be attempting Process Innovation in Scenario 1 than in Scenario 2. The Expected Growth was set to 2% and the R&D Intensity was set to 50%.

In order to prevent the obtained values from being merely a result of the degree of randomness of the model, 10 iterations of each scenario were run, and the values presented are the average of the results of those 10 iterations, in each scenario, at each time step. On every other aspect which was not mentioned, these simulations followed the same characteristics as the ones presented in the previous section.

The first two charts represent the evolution of the Average Unitary Output Value and Product Innovation Rate in both Scenarios:

Figure 6 – Evolution of the Average Unitary Output Value and Product Innovation Rate in Scenarios 1 and 2

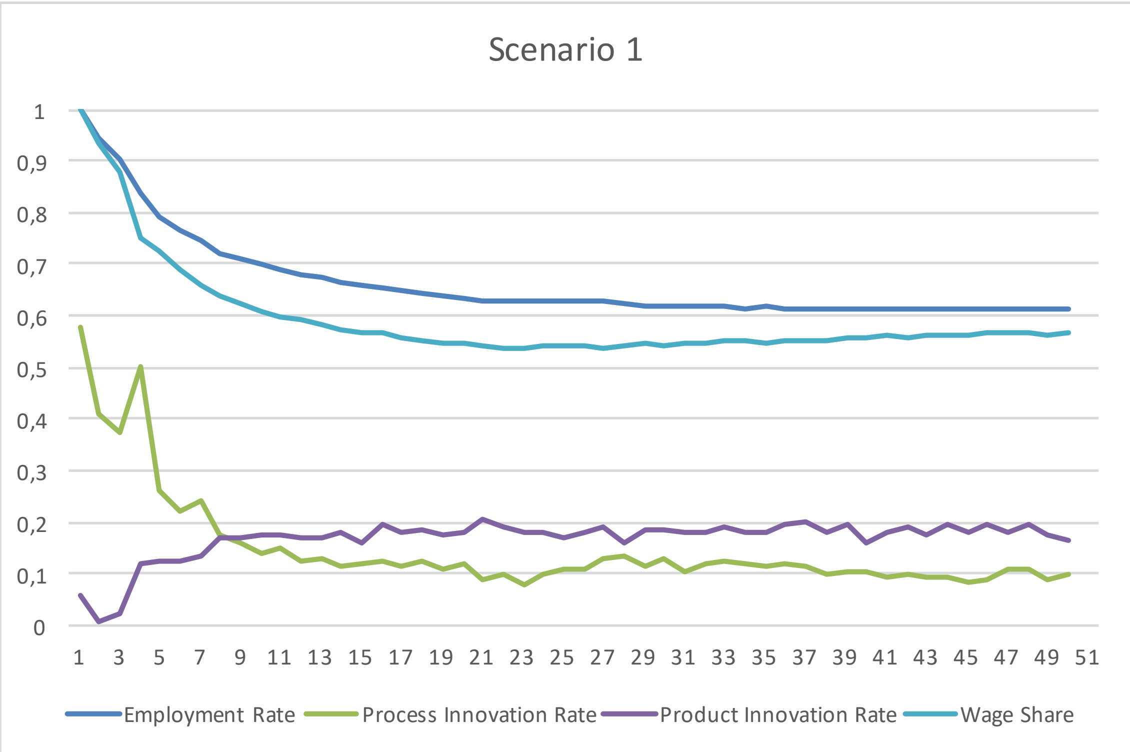


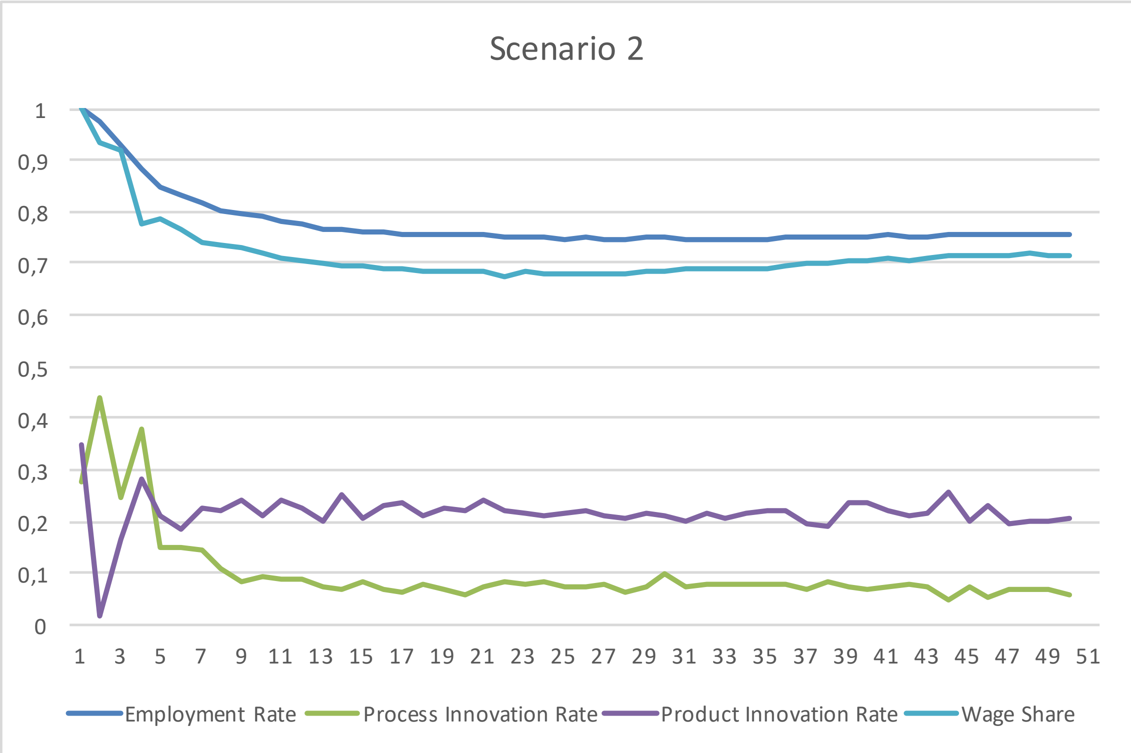


In both scenarios, the Average Unitary Output Value (plotted on the right axis) keeps increasing over time. However, while in Scenario 1 the Average Unitary Output Value only reaches a level of about 15, in Scenario 2 it reaches a level of about 17. On the other hand, Product Innovation Rates (plotted on the left axis) seem to be generally higher in Scenario 2 than in Scenario 1. This result is expected, since Product Innovation is the mechanism responsible for the increase in Unitary Output Value.

The following charts represent the evolution of the Employment Rate, Innovation Rates, and Wage Share in both Scenarios:

Figure 7 – Evolution of the Employment Rate, Innovation Rates and Wage Share in Scenarios 1 and 2





In both scenarios, Employment Rates and Wage Shares start decreasing until they stabilize around certain values. However, in Scenario 2, Employment Rate and Wage Share stabilize around 75% and 70% respectively, whereas in Scenario 1 they stabilize around 60% and 57% respectively. Additionally, Scenario 2 presents a larger gap between Product Innovation Rate and Process Innovation Rate than Scenario 1. Once again, these results are expected and are in line with the previously observed relationship between Product Innovation Rate, Process Innovation Rate, Employment Rate and Wage Shares.

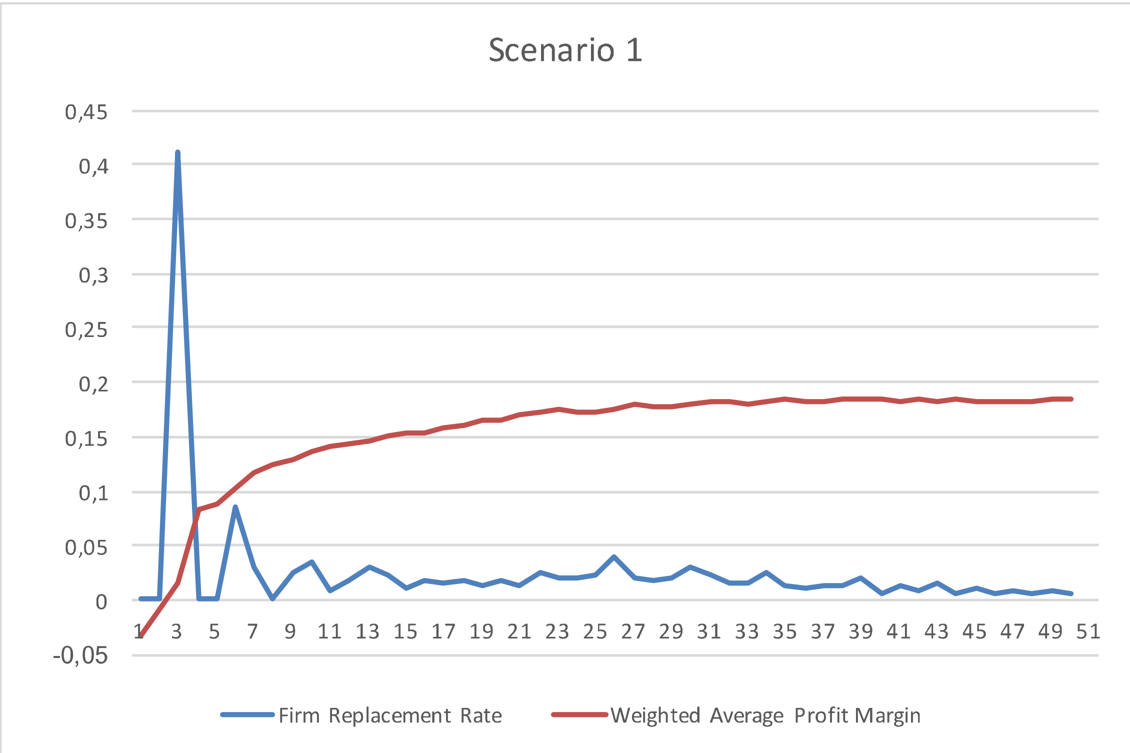
Regarding the evolution of Employment Rates, there appear to be two determining factors: the automation potential of tasks in the economy, and the gap between Product Innovation and Process Innovation Rates. The next two paragraphs attempt to explain the extent of influence of these factors.

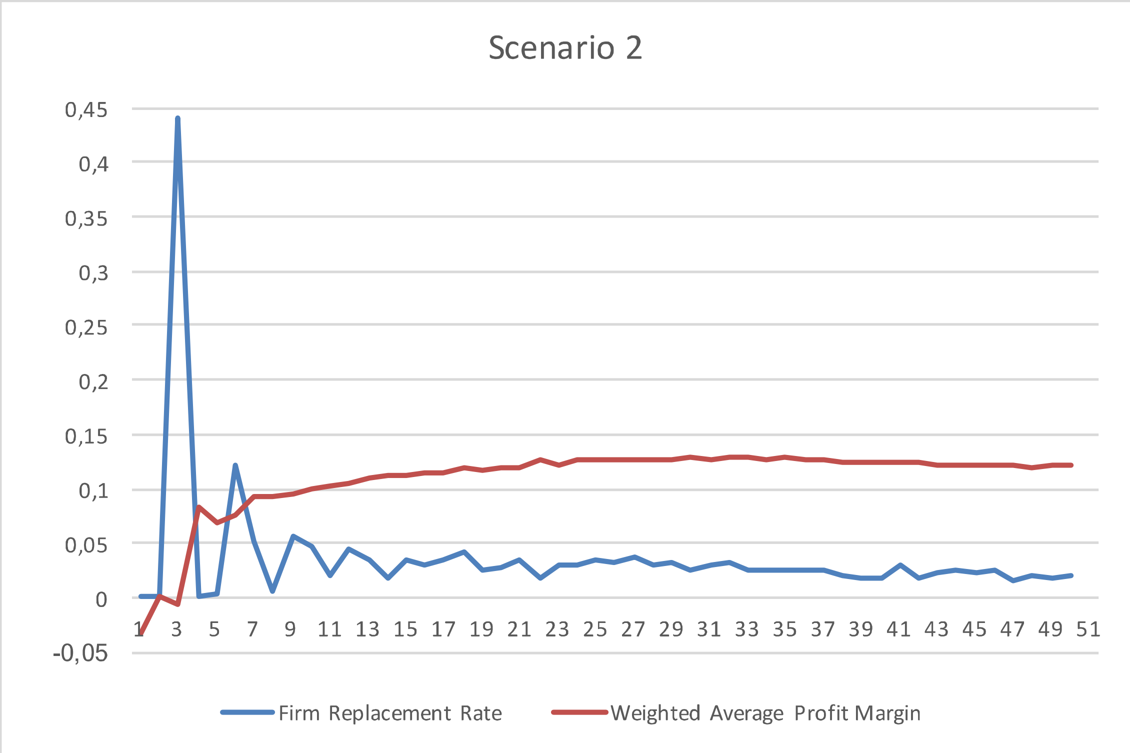
Even considering a hypothetical modelling scenario in which firms performed absolutely no Product Innovation, but were able to perform Process Innovation to the point that every automatable tasks would be automated, some tasks would still be performed manually, because they were considered to be non-automatable. In this scenario, the percentage of manually performed tasks, and therefore the Employment Rate, would tend to match the percentage of non-automatable tasks in the economy, which is determined by the automation potential considered for the tasks in the economy.

In the presented model, the average automation potential of tasks in the economy is around 46%, meaning that 54% of tasks are considered to be non-automatable. However, both Scenario 1 and Scenario 2 present Employment Rates constantly above 54%. The reason for this is the fact that, unlike the hypothetical modelling scenario considered in the previous paragraph, firms in the presented model are able to perform Product Innovation instead of Process Innovation. Effectively, the charts appear to indicate that the gap between Product Innovation Rates and Process Innovation Rates influences the extent to which Employment Rates are higher than the proportion of non-automatable tasks in the economy.

The following charts represent the evolution of the Weighted Average Profit Margins and Firm Replacement Rates in both Scenarios:

Figure 8 – Evolution of the Weighted Average Profit Margins and Firm Replacement Rates in Scenarios 1 and 2

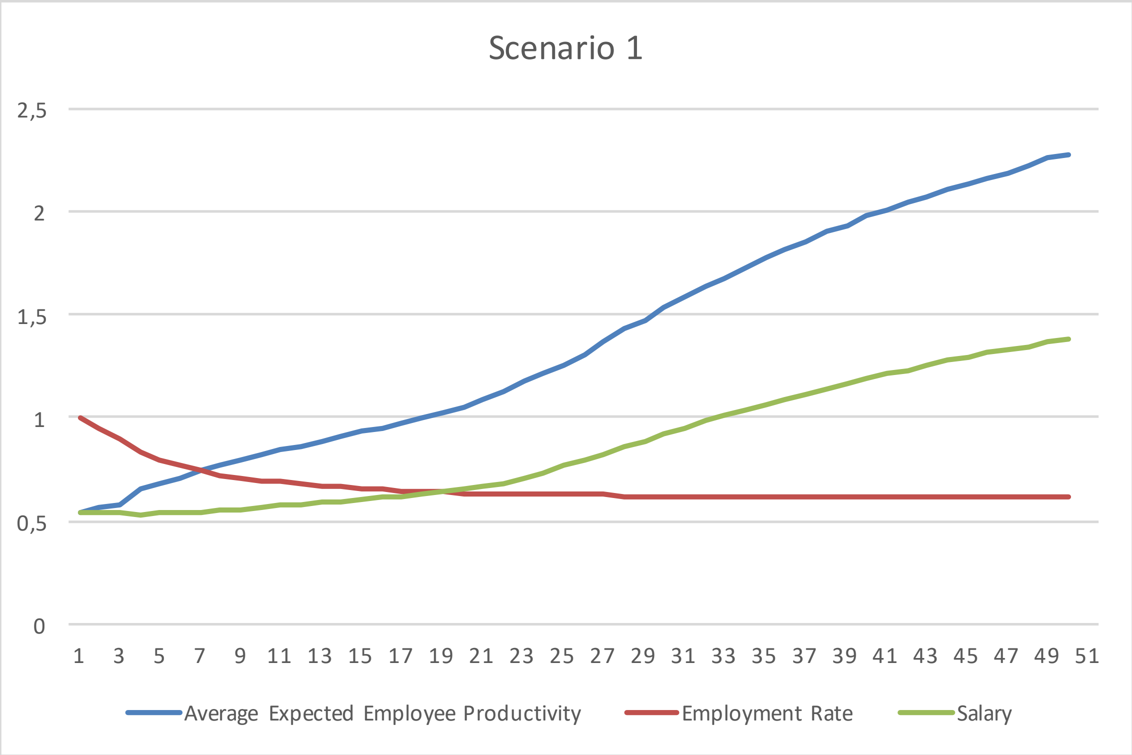


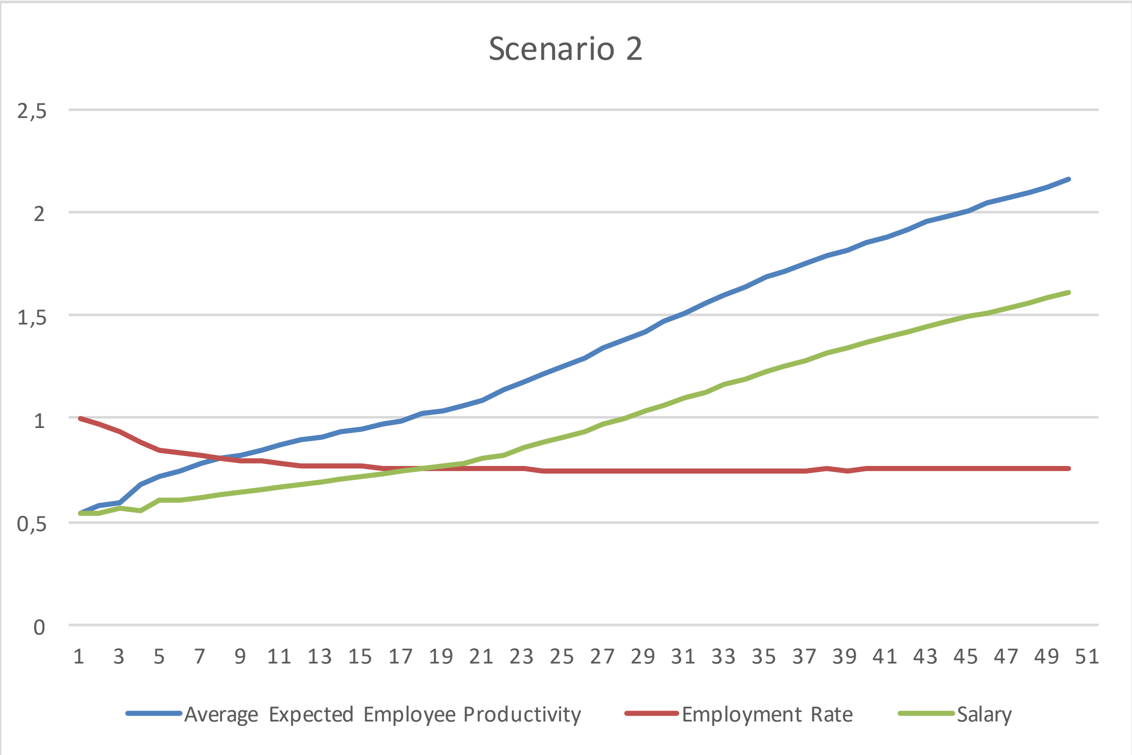


In both Scenarios, after a brief initialization period, Firm Replacement Rates and Profit Margins are rather stable. However, in Scenario 1, Profit Margins are consistently higher and Firm Replacement Rates are slightly lower than in Scenario 2. These results are expected and coherent with the previous results seen so far. As previously mentioned, the causal mechanism from Product Innovation Propensity to Profit Margins and consequently Firm Replacement Rates appears to be the Wage Share.

The following charts represent the evolution of the Employment Rate, Expected Employee Productivity, and Salary in both Scenarios:

Figure 9 – Evolution of the Employment Rate, Expected Employee Productivity, and Salary in Scenarios 1 and 2





In both scenarios, the Average Expected Employee Productivity and the Salary keeps increasing over time, while the Employment Rate decreases until it stabilizes. However, the Employment Rate stabilizes over a higher value in Scenario 2 than in Scenario 1 and, as a result, the gap between Average Expected Employee Productivity and Salary is larger in the first Scenario. In fact, a lower Employment Rate causes an inferior Employee Bargaining Power in Scenario 1, which in turn means Employees are able to capture a smaller share of the value they provide. It should also be noted that the Average Expected Employee Productivity is roughly equivalent over time in both Scenarios, even if slightly higher in Scenario 1.

These results provide an additional explanation for the pattern of lower Wage Shares in Scenario 1 than in Scenario 2, as presented in Figure 7. Indeed, Wage Shares are lower in Scenario 1 not only because there's a lower share of the population earning wages (since Employment Rates are lower), but also because the Employed Population earns as Salary a lower share of their productivity (since their Bargaining Power is lower).

In this regard, it is important to mention that related phenomena have been observed in economies around the world in recent years. In fact, since the early 1980s, wage shares have significantly declined in the majority of countries and industries. (Karabarbounis & Neiman, 2014). Additionally, according to a OECD working paper, "over the past two decades, aggregate labor productivity growth in most OECD countries has decoupled from real median compensation growth" (Schwellnus et al., 2017). Not surprisingly, these phenomena appear to be related, with the work from Schwellnus et al. (2017) indicating that the decoupling of both growth rates is associated with both a decrease of wage shares and an increase of wage inequality. In its turn, the work from Karabarbounis & Neiman (2014) indicates that about half of the decline in the global labor share can be explained by the decrease in the relative price of investment goods, such as information technology, which led firms to "shift away from labor and toward capital". As such, empirical data appears to support the conclusion that process innovation, driven by advancements in information technology, has led to a decline of wage shares and to the creation of a gap between productivity and wage growth, similarly to what one can observe in the performed simulations.

Chapter 6 – Concluding Remarks

Employment serves many functions in modern societies. It can be a means of survival, a vehicle of social mobility, a symbol of social validation, a tool for psychological well-being, or even a source of purpose. Indeed, employment is a fundamental socio-economical phenomenon, and attaining a better comprehension of how it can be affected is, therefore, of critical importance.

Bearing in mind the relevance of understanding the mechanisms influencing employment, the goal of this dissertation has been to study the relationship between innovation and employment by using an ABM methodology. The analysis performed throughout this dissertation have led to two major conclusions, valid in the context of the model presented:

i. The Employment Rate in a given economy is dependent on:
   a. the automation potential of the tasks in that economy, with a higher automation potential having a negative effect on employment;
   b. the type of innovation performed by firms in that economy, with Product Innovation having a positive effect on employment and Process Innovation having a negative effect.

ii. Higher levels of Process Innovation, and lower levels of Product Innovation, lead to a more intense decline of wage shares and to a wider gap between employee productivity growth and wage growth.

Taking into account these conclusions, it is particularly interesting to consider their implications regarding economic policy. Indeed, while policy-makers may have no control over the automation potential of the tasks in their economy, they can still influence the decisions of firms regarding the type of innovations they perform. As such, one could argue that, by putting into place a set of economic policies (such as, but not limited to, financial and tax incentives) aiming at encouraging Product Innovations instead of Process Innovations, policy-makers could have a positive effect on their economy's employment levels.

Nevertheless, when in the context of the real world, these conclusions must be considered with some caution, due to certain limitations of the developed model, namely:

1. The assumption concerning the nature of product innovation, which considers that new tasks must be initially performed by humans;
2. The assumption of homogeneous employee skill sets and of simple labor market dynamics;
3. The assumption concerning the nature of the aggregate demand for goods and services, which is considered to always match the aggregate supply;

Despite the recognizable limitations of this model, this dissertation still fulfills its purpose, which was that of developing and analyzing an agent-based model which represents an effective way of studying the dynamics of innovation and employment. In fact, this model presents a detailed yet general representation of reality, in what concerns the relationship between innovation and employment, which is, in itself, innovative in economic literature. Additionally, the analysis of the model and of the data resulting from simulations did provide interesting and coherent insights regarding this economic puzzle. As such, the basic components of this model may reveal themselves to be useful for further investigations on these dynamics.

Some examples of potential future research paths, built on top of the presented model, include:

1. Representing the possibility of fundamental technological breakthroughs, which would allow for the consideration of an increasing automation potential for the tasks in the economy, and its impact on the employment level.
2. Representing employees with heterogeneous skill sets and tasks with different skill requirements. Such representation would in turn require a more complex and realistic representation of the labor market, accounting for different demands and different compensations for the labor of employees with different skill sets. This model would allow the study of the impact of innovation on the employment and compensation levels across groups of workers with different skill sets.
3. Representing consumption in a more complex and realistic way, taking into account the disposable income and preferences of each consumer. This way, the model would be able to propagate the effects of variations in wage share and

income inequality back to the aggregate demand and, therefore, to the aggregate output. In such a model, it would be particularly interesting to study the overall implications of income inequality and of the introduction of a Universal Basic Income.

Appendix – Model Programming Code

```
from mesa import Agent, Model
from mesa.time import RandomActivation
from mesa.datacollection import DataCollector
from mesa.batchrunner import BatchRunner
import numpy as np
import pandas as pd

class Firm(Agent):
    def __init__(self, unique_id, model,numberknowntasks,probautomated,expectedoutputq,rdstock):
        super().__init__(unique_id, model)
        self.knowntasks = 
self.model.taskset.loc[np.random.choice(range(len(self.model.taskset.index)),numberknowntasks,replace
=False)]
        self.knowntasks['KNOWLEDGE'] = np.random.choice((0.90,0),numberknowntasks, 
p=[probautomated,1-probautomated])
        self.expectedoutputq= expectedoutputq
        self.rdstock = rdstock
        self.opnetincomehist = []
        self.outputq=0
        self.robots=0
        self.employees=0
        self.outputaddedval=0
        self.revenues=0
        self.opnetincome=0
        self.productinnovation = 0
        self.processinnovation = 0
        self.everythingautomated = 0
        self.belowthresholdaddedval = 0
        self.attemptprocessinn = 0
    def settasks(self):
        self.knowntasks = self.knowntasks.sort_values('ADDEDVAL',ascending=False)
        self.currenttasks = self.knowntasks.iloc[:self.model.nperformedtasks]
        self.allautomatedtasks = 
self.knowntasks[self.knowntasks['KNOWLEDGE']>=self.knowntasks['SKILLREQ']]
        self.allmanualtasks = 
self.knowntasks[self.knowntasks['KNOWLEDGE']<self.knowntasks['SKILLREQ']]
        self.allautomatabletasks = self.allmanualtasks[self.allmanualtasks['SKILLREQ']<=0.90]
        self.currentautomatedtasks = 
self.currenttasks.loc[self.allautomatedtasks.index.intersection(self.currenttasks.index)]
        self.currentmanualtasks  = 
self.currenttasks.loc[self.allmanualtasks.index.intersection(self.currenttasks.index)]
        self.currentautomatabletasks  = 
self.currenttasks.loc[self.allautomatabletasks.index.intersection(self.currenttasks.index)]
        self.numcurrautomatedtasks = len(self.currentautomatedtasks.index)
        self.numcurrmanualtasks = len(self.currentmanualtasks.index)
    def hire(self):
        goalemployees = round(self.numcurrmanualtasks * self.expectedoutputq)
        goalrobots = round(self.numcurrautomatedtasks * self.expectedoutputq)
        self.employees = goalemployees
        self.robots = goalrobots
    def produce(self):
        if self.numcurrautomatedtasks == 0:
            self.minautomated = -1
        else:
            self.minautomated = self.robots // self.numcurrautomatedtasks
        if self.numcurrmanualtasks == 0:
```

```
            self.minmanual = -1
        else:
            self.minmanual = self.employees // self.numcurrmanualtasks
        if self.minautomated == -1:
            self.outputq = self.minmanual
        elif self.minmanual == -1:
            self.outputq = self.minautomated
        else:
            self.outputq = min([self.minautomated,self.minmanual])
        self.outputaddedval = np.mean(self.currenttasks['ADDEDVAL'])
    def budget(self):
        self.revenues = self.outputq * self.outputaddedval * self.model.pricefactor
        self.salarycosts = self.employees * self.model.salary
        self.robotcosts = self.robots * self.model.robotunitvalue * (self.model.intrate + self.model.deprate)
        ebrd = self.revenues - self.salarycosts - self.robotcosts
        if ebrd > 0:
            self.rdexpenses = ebrd * self.model.rdintensity
        else:
            self.rdexpenses = 0
        self.rdstock += self.rdexpenses
        self.opnetincome = self.revenues - self.salarycosts - self.robotcosts - self.rdexpenses
        self.expectedoutputq = self.outputq * (1 + self.model.expectedgrowth)
        self.opnetincomehist.append(self.opnetincome)
        if self.model.stepcounter >= 3 and self.opnetincomehist[self.model.stepcounter] < 0:
            if self.opnetincomehist[self.model.stepcounter -1] < 0 and
self.opnetincomehist[self.model.stepcounter -2] < 0:
                self.model.toremove.append(self)
    def negotiatesalaries(self):
        if self.numcurrmanualtasks > 0:
            self.expectedemployeeproductivity = ((self.outputaddedval * self.model.pricefactor) -
(self.numcurrautomatedtasks * self.model.robotunitvalue * (self.model.intrate + self.model.deprate))) /
self.numcurrmanualtasks
        else:
            self.expectedemployeeproductivity = 0
        self.expectedemployees = round(self.numcurrmanualtasks * self.expectedoutputq)
    def innovate(self):
        chance = np.random.poisson(self.rdstock / self.model.averagerdstock,1)
        self.productinnovation = 0
        self.processinnovation = 0
        self.everythingautomated = 0
        self.belowthresholdaddedval = 0
        self.attemptprocessinn = 0
        if len(self.currentautomatabletasks.index) == 0:
            self.everythingautomated = 1
        if self.outputaddedval < self.model.thresholdoutputaddedval:
            self.belowthresholdaddedval = 1
        if len(self.currentautomatabletasks.index) > 0 and self.outputaddedval >=
self.model.thresholdoutputaddedval:
            self.attemptprocessinn = 1
        if chance > 1:
            if len(self.currentautomatabletasks.index) > 0 and self.outputaddedval >=
self.model.thresholdoutputaddedval:
                tasktoinnovate = self.allautomatabletasks['KNOWLEDGE'].idxmax()
                self.knowntasks.set_value(tasktoinnovate,'KNOWLEDGE',
self.knowntasks.loc[tasktoinnovate,'KNOWLEDGE'] + 0.9)
                if self.knowntasks.loc[tasktoinnovate,'KNOWLEDGE'] > 0.90:
                    self.knowntasks.set_value(tasktoinnovate,'KNOWLEDGE', 0.90)
                self.processinnovation = 1
```

```
        else:
            higheraddedvaltasks = self.model.taskset[self.model.taskset['ADDEDVAL'] >
self.outputaddedval]
            unknownhigheraddedvaltasks =
higheraddedvaltasks[higheraddedvaltasks.index.isin(self.knowntasks.index)==False]
            if len(unknownhigheraddedvaltasks.index)==0:
                self.model.generatetasks()
                higheraddedvaltasks = self.model.taskset[self.model.taskset['ADDEDVAL'] >
self.outputaddedval]
                unknownhigheraddedvaltasks =
higheraddedvaltasks[higheraddedvaltasks.index.isin(self.knowntasks.index)==False]
            tasktodiscover = np.random.choice(unknownhigheraddedvaltasks.index,1)
            self.knowntasks = self.knowntasks.append(unknownhigheraddedvaltasks.loc[tasktodiscover])
            self.knowntasks.set_value(tasktodiscover,'KNOWLEDGE',0)
            self.productinnovation = 1
    def step(self):
        self.settasks()
        self.hire()
        self.produce()
        self.budget()
        self.negotiatesalaries()
        if self.model.stepcounter >=1:
          self.innovate()
class InnEmpModel(Model):
    def __init__(self, nfirms, ntasks, nperformedtasks, numberknowntasks, probautomated,
expectedoutputq, rdintensity, productinnovationpropensity, expectedgrowth):
        self.running = True
        self.nfirms=nfirms
        self.ntasks=ntasks
        self.nperformedtasks=nperformedtasks
        self.rdintensity=rdintensity
        self.expectedgrowth=expectedgrowth
        self.productinnovationpropensity=productinnovationpropensity
        rdstock = 1
        self.activepopulation = self.nfirms * expectedoutputq * self.nperformedtasks
        self.schedule = RandomActivation(self)
        self.firmlist=[]
        self.emplist=[]
        self.intrate = 0.05
        self.deprate = 0.2
        self.salary = 1
        self.robotunitvalue = 1
        self.pricefactor = 1
        self.averagerev = 0
        self.averageoutputaddedval = 0
        self.averageproductivity = 0
        self.averagerdstock = 0
        self.stepcounter = 0
        self.taskgeneration = 0
        self.productinnovationratehist=[]
        self.processinnovationratehist=[]
        self.everythingautomatedratehist = []
        self.belowthresholdaddedvalratehist = []
        self.attemptprocessinnratehist = []
        self.firmreplacementratehist=[]
        self.taskset= pd.DataFrame()
        self.toremove = []
        self.generatetasks()
```

```
        for i in range(nfirms):
            afirm = Firm(i, self,numberknowntasks,probautomated,expectedoutputq,rdstock)
            self.schedule.add(afirm)
            self.firmlist.append(afirm)
        self.datacollector = DataCollector(model_reporters={"averageoutputaddedval": lambda m:
m.averageoutputaddedval, "salary": lambda m : m.salary, "averagerdstock": lambda m :
m.averagerdstock, "productinnovationrate": lambda m : m.productinnovationrate,
"processinnovationrate": lambda m : m.processinnovationrate, "employmentrate": lambda m :
m.employmentrate, "wageshare": lambda m : m.wageshare, "averageproductivity": lambda m :
m.averageproductivity, "firmreplacementrate": lambda m : m.firmreplacementrate,
"weightedaverageprofitmargin": lambda m : m.weightedaverageprofitmargin}, agent_reporters={})
    def step(self):
        self.schedule.step()
        self.outputmarketdynamics()
        self.labormarketdynamics()
        self.reportoutputmarketstats()
        self.reportinnovationstats()
        self.reportlabormarketstats()
        self.datacollector.collect(self)
        self.recycle()
        self.pricefactor = self.nextsteppricefactor
        self.salary = self.nextstepsalary
        self.stepcounter += 1
    def generatetasks(self):
        activitiessample = np.random.choice(7,self.ntasks,p=[0.07,0.14,0.16,0.12,0.17,0.16,0.18])
        addedvalssample =
np.random.choice(range(1+(self.taskgeneration*10),11+(self.taskgeneration*10)),self.ntasks)
        skillreqprobs = [0.09,0.18,0.2,0.25,0.64,0.69,0.78]
        skillreqsample = []
        for k in activitiessample:
            skillreq = np.random.choice((0.90,1),1,p=[skillreqprobs[k],1-skillreqprobs[k]])[0]
            skillreqsample.append(skillreq)
        self.taskset = pd.concat([self.taskset,pd.DataFrame({'ACTIVITY':activitiessample ,
'ADDEDVAL':addedvalssample, 'SKILLREQ':skillreqsample})],ignore_index=True)
        self.taskgeneration += 1
    def recycle(self):
        lastid = self.firmlist[-1].unique_id
        for afirm in self.toremove:
            afirm.active = False
            self.schedule.remove(afirm)
            self.firmlist.remove(afirm)
        if len(self.toremove)>0:
            totalnumberknowntasks=0
            totalnumberautomatedtasks=0
            totaloutputq = 0
            totalrdstock = 0
            for afirm in self.firmlist:
                totalnumberknowntasks += len(afirm.knowntasks)
                totalnumberautomatedtasks += len(afirm.allautomatedtasks)
                totaloutputq += afirm.outputq
                totalrdstock += afirm.rdstock
            averagenumberknowntasks = round(totalnumberknowntasks / len(self.firmlist))
            averagenumberautomatedtasks = totalnumberautomatedtasks / len(self.firmlist)
            averageprobautomated = averagenumberautomatedtasks / averagenumberknowntasks
            averageoutputq = round(totaloutputq / len(self.firmlist))
            averagerdstock = totalrdstock / len(self.firmlist)
        for afirm in self.toremove:
```

```
        newfirm = Firm(lastid + 1, self,averagenumberknowntasks,averageprobautomated,averageoutputq
* (1 + self.expectedgrowth),averagerdstock)
        for step in range(self.stepcounter + 1):
          newfirm.opnetincomehist.append(0)
        self.schedule.add(newfirm)
        self.firmlist.append(newfirm)
        lastid += 1
      self.toremove=[]
  def reportoutputmarketstats(self):
      self.averagerev = self.totalrev / self.nfirms
      previousaverageoutputaddedval = self.averageoutputaddedval
      self.averageoutputaddedval = self.totaloutputaddedval / self.totaloutputq
      self.outputaddedvalpercapita = self.totaloutputaddedval / self.activepopulation
      self.outputaddedvalperemployee = self.totaloutputaddedval / self.totalemployed
      self.weightedaverageprofitmargin = self.totalopnetincome / self.totalrev
      self.firmreplacementrate = len(self.toremove) / self.nfirms
      self.firmreplacementratehist.append(self.firmreplacementrate)
      self.firmreplacementrateovertime =  np.mean(self.firmreplacementratehist)
      if previousaverageoutputaddedval != 0:
        self.outputaddedvalincreaserate = self.averageoutputaddedval / previousaverageoutputaddedval -
1
      else:
        self.outputaddedvalincreaserate = 0
  def outputmarketdynamics(self):
      self.totaloutputq = 0
      self.totaloutputaddedval = 0
      self.totalrev = 0
      self.totalopnetincome = 0
      for afirm in self.firmlist:
        self.totaloutputq += afirm.outputq
        self.totaloutputaddedval += afirm.outputq * afirm.outputaddedval
        self.totalrev += afirm.revenues
        self.totalopnetincome += afirm.opnetincome
      self.nextsteppricefactor = self.totalrev / self.totaloutputaddedval
  def reportinnovationstats(self):
      self.totalrdstock = 0
      self.productinnovations = 0
      self.processinnovations = 0
      self.totaleverythingautomated = 0
      self.totalbelowthresholdaddedval = 0
      self.totalattemptprocessinn = 0
      self.totalnumcurrmanualtasks = 0
      self.totalnumcurrautomatedtasks = 0
      outputvallist = []
      for afirm in self.firmlist:
        self.totalrdstock += afirm.rdstock
        self.productinnovations += afirm.productinnovation
        self.processinnovations += afirm.processinnovation
        self.totaleverythingautomated += afirm.everythingautomated
        self.totalbelowthresholdaddedval += afirm.belowthresholdaddedval
        self.totalattemptprocessinn += afirm.attemptprocessinn
        self.totalnumcurrmanualtasks += afirm.numcurrmanualtasks
        self.totalnumcurrautomatedtasks += afirm.numcurrautomatedtasks
        outputvallist.append(afirm.outputaddedval)
      self.everythingautomatedrate = self.totaleverythingautomated / self.nfirms
      self.belowthresholdaddedvalrate = self.totalbelowthresholdaddedval / self.nfirms
      self.attemptprocessinnrate = self.totalattemptprocessinn / self.nfirms
      self.averagerdstock = self.totalrdstock / self.nfirms
```

```
        self.productinnovationrate = self.productinnovations / self.nfirms
        self.productinnovationratehist.append(self.productinnovationrate)
        self.processinnovationrate = self.processinnovations / self.nfirms
        self.processinnovationratehist.append(self.processinnovationrate)
        self.processinnovationrateovertime = np.mean(self.processinnovationratehist)
        self.productinnovationrateovertime = np.mean(self.productinnovationratehist)
        self.everythingautomatedratehist.append(self.everythingautomatedrate)
        self.belowthresholdaddedvalratehist.append(self.belowthresholdaddedvalrate)
        self.attemptprocessinnratehist.append(self.attemptprocessinnrate)
        self.everythingautomatedrateovertime = np.mean(self.everythingautomatedratehist)
        self.belowthresholdaddedvalrateovertime = np.mean(self.belowthresholdaddedvalratehist)
        self.attemptprocessinnrateovertime = np.mean(self.attemptprocessinnratehist)
        self.currmanualtasksrate = self.totalnumcurrmanualtasks / (self.totalnumcurrmanualtasks + self.totalnumcurrautomatedtasks)
        self.currautomatedtasksrate = self.totalnumcurrautomatedtasks / (self.totalnumcurrmanualtasks + self.totalnumcurrautomatedtasks)
        self.thresholdoutputaddedval = np.percentile(outputvallist,self.productinnovationpropensity)
    def reportlabormarketstats(self):
        self.wageshare = self.totalsalaries / self.totalrev
        self.unemploymentrate = 1 - self.employmentrate
        self.humanshareofinput = self.totalemployed / (self.totaloutputq * self.nperformedtasks)
        self.outputaddedvalperemployee = self.totaloutputaddedval / self.totalemployed
        self.salarygrowthrate = self.nextstepsalary /self.salary - 1
    def labormarketdynamics(self):
        totalexpectedproductivity = 0
        totalexpectedemployees = 0
        previousaverageproductivity = self.averageproductivity
        self.totalemployed = 0
        self.activepopulation = self.totaloutputq * self.nperformedtasks
        for afirm in self.firmlist:
            totalexpectedproductivity += afirm.expectedemployeeproductivity * afirm.expectedemployees
            totalexpectedemployees += afirm.expectedemployees
            self.totalemployed += afirm.employees
        self.totalsalaries = self.salary * self.totalemployed
        self.employmentrate = (self.totalemployed / self.activepopulation)
        employeebargainingpower = self.employmentrate
        self.averageproductivity = totalexpectedproductivity / totalexpectedemployees
        if previousaverageproductivity != 0:
            self.productivitygrowthrate = self.averageproductivity / previousaverageproductivity - 1
        else:
            self.productivitygrowthrate = 0
        self.nextstepsalary = self.averageproductivity * employeebargainingpower
```

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