Automation, Job Polarisation, and Structural Change[*]

Luca Eduardo Fierro [†‡§]

lucaeduardo.fierro@santannapisa.it

Alessandro Caiani[¶]

alessandro.caiani@iusspavia.it

Alberto Russo[‖§]

russo@uji.es

[*]**Declaration of interest: none**

[†]Corresponding Author

[‡]Scuola Superiore Sant'Anna, Institute of Economics, Pisa, Italy

[§]Università Politecnica delle Marche, Department of Management, Piazzale Martelli Raffaele, 8, Ancona, 60121, Italy

[¶]University School of Advanced Studies (IUSS), Department of Science, Technology and Society, Piazza delle Vittoria, 15, 27100, Pavia, Italy

[‖]Universitat Jaume I, Department of Economics, Avda Vicente Sos Baynat s/n E-12071 Castello de la Plana, Spain

Abstract

The increasing automation of tasks traditionally performed by labour is reshaping the relationship between skills and tasks of workers, unevenly affecting labour demand for low, middle, and high-skill occupations. To investigate the economy-wide response to automation, we designed a multisector Agent-Based Macroeconomic model accounting for workers' heterogeneity in skills and tasks. The model features endogenous *skill-biased* technical change, and heterogeneous consumption preferences for goods and *personal* services across workers of different skill types. Following available empirical evidence, we model automation as a manufacturing-specific, productivity-enhancing, and skill-biased technological process. We show how automation can trigger a structural change process from manufactory to personal services, which eventually increases the share of high and low-skilled occupations, while reducing the share of middle-skilled ones. Following the literature, we label this dynamics as *job polarisation* throughout the paper. Finally, we study how labour market policies can feedback in the model dynamics. In our framework, a minimum wage policy (i) slows down the structural change process, (ii) boosts aggregate productivity, and (iii) accelerates the automation process, strengthening productivity growth within the manufacturing sector.

Keywords: Agent-Based Model, Automation, Structural Change, Wage Polarisation, Minimum Wage

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1 Introduction

Automation can be referred to as a specific type of technological change which enables capital to be used in tasks that were previously performed by labour or increases the productivity of capital in those tasks (see Acemoglu and Restrepo, 2020b). As such, automation can hardly be considered a novelty. In fact, it has been the distinctive trait of development since the early industrial revolution. A large and growing literature, that we will partly discuss below, points to tasks usually performed by low-skilled workers as the most exposed to the displacement risk of automation. Though possibly to a lesser extent, this was also true for "old" types of innovations. The distinctive trait of modern automation seems to be that new automated machines do not only replace workers previous performing certain tasks but also require, in order to be operated, the execution of high-skilled tasks, thereby increasing the demand for that type of workers. Indeed, the major advances in robotics, machine learning, and artificial intelligence experienced over the last two decades have exacerbated this process, replacing humans in an ever growing share of tasks traditionally performed by unskilled or low-skilled workers and, in prospect, being likely to replace them also in more complex occupations. An increasing consensus, as expressed in Brynjolfsson and McAfee (2014) or Ford (2015), points now to automation as a major force that will radically transform work and labour markets in the next decades, and anxieties for its impact on employment conditions and living standards of a wide share of workers are contextually growing.

Automation, till now, has posited two main questions: Will new machines reduce labour demand and therefore generate technological unemployment? And, what are the distributional implications of automation?

So far, most of the research has been focusing on the former aspect, motivated by the anxiety for job-stealing machines which has been a recurrent fear throughout modern history[1]. Recent influential researches have warned about the potential disruptive effects of automation in terms of jobs destruction. For example, Frey and Osborne (2017) gained exceptional media

[1]For a historical appraisal of machine anxiety see Mokyr et al. (2015)

coverage and sparked an intense academic debate after having estimated that about 47% of total US employment is at high risk of automation, possibly within the next two decades[2]. This threatening estimate, however, only focuses on one side of the story. Arguably, technological revolutions destroy some jobs as they also generate new ones.

For instance, Klenert et al. (2020), using sector-level data, find no effect whatsoever on labour demand composition within manufacturing. Similarly, using a panel of manufacturing firms in Spain to study the impact of industrial robots adoption, Koch et al. (2021) find no significant negative effect on either aggregate employment or low-skilled workers' employment.[3] Domini et al. (2021) find no evidence of any impact of automation on employment at firm level, not even in the shares of employment of different occupational categories. This, however, does not necessarily preclude the possibility of a displacement effect at sectoral level if the beneficial effects for the workers of the firm that automates, possibly emerging from its better performance and enhanced sales, are outweighed by the loss of jobs in competing firms. Dauth et al. (2021), for example, find evidence for a displacement effect in manufacture but at the same time show that complementarity and expansion of economic activity in other industries, is an important adjustment mechanism that offsets the displacement effect on employment at the aggregate level[4], thereby contradicting the popular interpretation of robots as jobs killers. In addition, looking at earnings, they find that automation widens the earnings gap between managerial and skilled technical occupations and routine-intensive ones. With regards to the effects of automation by education levels, they find that automation affects positively earnings of high skilled workers, while it affects negatively medium and low-skilled with approximately equal negative point estimates.[5] This take, which points to a skill biased-character of automation, is confirmed by Graetz and Michaels (2018) and

[2]A similar exercise has been performed by Arntz et al. (2016) for OECD countries, who remarkably downsize the effect estimated by Frey and Osborne, and Pajarinen and Rouvinen (2014) who instead confirm the magnitude suggested by Frey and Osborne for the Finnish economy.

[3]At the same time, they find a positive effect in employment levels of automation-adopters, due to improved performances and higher scales-of-production, and a negative one for their competitors that do not automate.

[4]Acemoglu et al. (2020) arrives to a similar conclusion, showing that the adoption of robots within manufacturing is correlated with increasing employment in the business service sector.

[5]A result this latter that, as they explicitly state in the VoxEu column that precedes the published version Dauth et al. (2021), `https://voxeu.org/article/rise-robots-german-labour-market`, should "provide evidence at the micro level that robots are a form of skill-biased technological change".

Borjas and Freeman (2019) who use sector-level data finding that automation tends to favour high-skilled employment at the detriment of low-skilled one. Similarly, though focusing on the broader category of digital technologies rather than just on automation, Balsmeier and Woerter (2019) find that investment in digital technologies is positively associated with employment of high-skilled workers and negatively associated with employment of low-skilled workers within the firm, with an overall positive net effect on employment. Using German plant-level data to assess the determinants of robotisation, Deng et al. (2021) show that low-skilled labour positively impacts robot adoption suggesting that, other things equal, low-skilled labour performing simple and easily automatable tasks is more likely to be replaced by robots. They also find that manufacturing plants impacted by the introduction of a minimum wage in 2015 were more prone to adopt robots. Similar results, though based on industry-level data, are obtained by de Vries et al. (2020). Finally, like Barbieri et al. (2019) and Pellegrino et al. (2019), find a positive effect of firms' innovative efforts on their employment dynamics to be present only for large firms operating in high-tech sectors, while they suggest the existence of a significant labour-saving effect of embodied technological change (i.e. investment in capital and new machineries) for small and medium enterprises and non-high tech sectors.[6]

As this review of the ever growing empirical literature on the impacts of automation reveals, estimating the micro and macro net effects of automation on employment and isolating it from other possible contributing factors is extremely difficult. Besides the methodological differences, these controversial results are likely to be partly attributed to high heterogeneity in the database employed, concerning the type of data, their time, sectoral and geographical coverage, as well as the measure of automation employed. However, though the debate is far from being settled, the majority of contributions reviewed seems to converge on the possible overestimation of the actual risks of displacement connected automation, at least on the aggregate level, and on the opposite impacts that automation exerts on high and low-skilled

[6] Other contributions studying employment effects of automation, that we do not discuss for space reasons, are Acemoglu and Restrepo (2018), Acemoglu and Restrepo (2019), Benzell et al. (2015), Berg et al. (2018), Caselli and Manning (2019), Chiacchio et al. (2018), DeCanio (2016), Gregory et al. (2022), and Korinek and Stiglitz (2018).

workers.

At a first glance, the skill-biased character of automation in favour of high-skill workers and to the detriment of low-skilled workers may seem partly at odds with the mounting evidence on job-polarisation in advanced economies[7], that is the growth of jobs located at the two poles of the skill distribution relative to jobs located at the middle of the skill distribution.

While one may be prone to explain this as a consequence of the still limited diffusion of robots, a growing literature (Manning, 2004; Lee and Clarke, 2019; Mazzolari and Ragusa, 2013) points to the existence of sizeable spillover effects from the consumption of high-skilled to the employment of low-skilled and, more specifically, to the growth of caring jobs, jobs in bars, shops and restaurant, home-cleaning services, etc. that are typically taken by low-skill workers. In our model, we label this type of non-tradable, low-skilled, low-productivity market services serving functions such as consumption of food at restaurants, catering, delivery services, accommodation, personal caring, cleaning, cleaning, etc. as *personal services* and we formally characterise them in section 3.

Our work aims to formalise the link between automation diffusion, the evolution of employment conditions of different skill groups, structural change, and the emergence of job polarisation within a Agent Based-Stock Flow Consistent (from now on AB-SFC) framework. We study: (i) which types of jobs/occupations are generated and which ones are suppressed because of automation; (ii) how the changing working condition of different skill groups may concur to determine a structural change from manufacture to personal services; (iii) how automation and the rise of services/decline of manufacture affect the labor demand for each skill group; (iv) how relative wages may feed back on the diffusion of automation. After having investigated within our framework the links between these aspects, we then aim to study how a policy impacting on the relative wages of high and low-skilled workers, namely a minimum wage policy, may affect the adoption of automation and the structural change process of the economy.

[7] See Autor et al. (2006), Autor and Dorn (2013), Ciarli et al. (2018), Goos and Manning (2007), Goos et al. (2009), Goos et al. (2014), and Naticchioni et al. (2014).

Our work contributes to the growing macroeconomic modelling literature on automation and job polarisation. Within the general equilibrium literature one of the most notable contribution in this field is probably Acemoglu and Restrepo (2020a) who design and estimate a spatial-general equilibrium model in which machines substitute workers for an increasing number of tasks in production finding that, for the US economy, one additional robot per thousand workers reduces the employment rate by 0.18-0.34 percentage points and wages by 0.25-0.5 percent, therefore maintaining a pessimistic view about the aggregate effect of automation. A similar general equilibrium framework also characterise Autor and Dorn (2013) and Bárány and Siegel (2018) whose models aim to grasp the link between structural change and job polarisation. Autor and Dorn (2013) model a two sectors economy, where goods are produced by combining capital, low-skilled labour and high-skilled labour, whereas services are produced by employing low-skilled labour alone. There is only one capital vintage available to consumption firms, which substitutes for low-skilled workers and complements for high-skilled ones. Technological innovation is simply modelled as an exogenous capital price decline, thus no effect on productivity or labour substitutability/complementarity is directly exerted. Autor and Dorn show that if the elasticity of substitution between capital and low-skilled labour in the good sector is larger than the elasticity of substitution in consumption between goods and services, then the falling capital price brings about a fall in low-skilled wages in the consumption sector relative to high-skilled wages and low-skilled wages in the service sector (wage polarisation). Eventually, the fall in low-skilled wages in the good sector pushes low-skilled workers into the service sector, effectively polarising the labour market through a structural change dynamics. Conversely, Bárány and Siegel (2018) assume a three sectors economy composed by a good sector and two types of services, low and high-skill. Workers are heterogenous in the sector-specific skill dimension, but can be employed in any type of occupation. Similarly to Autor and Dorn (2013), relative wages govern the sorting mechanism of workers across the three sectors. The findings of Bárány and Siegel (2018) are very close to Baumol's intuition, indeed the model predicts that when productivity in manufacture grows faster relative to the other sectors (and services and goods are complements), then workers migrate from manufacturing to both low and high-skilled service sectors, therefore generating job polarisation through structural change.

Our contribution differs with the aforementioned ones in several respects. First of all, we model an endogenous process of technological change. Secondly, we employ a Leontief fixed-coefficients production function, where factors of production cannot be substituted at will, as in the CES production function. However, the model features endogenous technical change and since new technologies require different proportions of productive factors, there is *dynamic* factor substitution. Finally, a crucial role in our model is played by demand composition dynamics and demand spillovers.

In the last years also the Agent Based macro modelling literature aiming at studying job polarisation and automation has blossomed. Mellacher and Scheuer (2020), for example, augments the famous *K+S* model of Dosi et al. (2010) to show how technological innovation can alone polarise the labour market. The main difference with the present paper lies in the assumption shaping the innovation process and specifically the type of skill-biased involved: Mellacher and Scheuer assume *technical skill-bias against administrators* (i.e., middle-skilled workers), whereas we model automation as a skill-biased technology against low-skilled labour and neutral with respect to middle skilled workers. A prominent contribution in the modelling of automation is provided by Bordot and Lorentz (2021) who put forward a remarkable effort in modelling tasks needed in production, workers' skills and the matching between the two, with a level of detail probably unmatched in the current literaure. As in Mellacher and Scheuer (2020), they find that automation is the only polarising force, although the skill bias type of automation is not assumed, but it emerges endogenously in the model. A similar task-based approach is also employed in Dawid and Neugart (2021) who study how different types of automation affects industry output, the wage distribution, the labor share, and industry dynamics. Using an evolutionary framework based on the *K+S* model, Dosi et al. (2021) focus on the role played by process and product innovation in determining the long-run employment trajectory, showing that there exists a sort of equilibrium in which job creation and destruction tendencies cancel out, generating a stable employment path. Finally, a new and interesting strand of literature addressing the interplay among technological innovations, market competition and income inequality can be found in Dawid and Hepp (2022) and Terranova and Turco (2022).

Our proposed framework aims to capture the reciprocal influence between automation, the evolving composition of employment and of wage distribution, and the process of structural change of the economy. One main novelty of the paper is providing an explanation that connects into a unified framework pieces of theoretical and empirical literature that were largely separated, such as the analysis of the consumption habits of high-skilled workers, the literature on automation as a form of skill-biased technological change, and the literature on the structural change road to job polarisation that largely relied on a standard general equilibrium framework. Our intention is to formalize and shed light on a precise mechanism that relies on the spillover effect from high-skilled improved employment conditions to low-skilled workers job opportunities. In our model, the improved conditions of high skill workers arise from automation requiring more skilled workforce to be operated. The spillover operates through their enhanced consumption, which favours, through a Mazzolari and Ragusa (2013) inspired-effect, the growth of the personal service sector, and the consequent creation of low-skilled jobs, along the lines of Manning (2004) and Lee and Clarke (2019).

Furthermore, being our model calibrated using the available stylised facts and data on the phenomena relevant at the core of our analysis, we hope to provide an attractive laboratory to assess the pervasive impacts of different policies. In particular, we focus on a policy directly affecting the distribution of wages across occupations, that is a minimum wage policy indexed to the wage of high-skilled. We find that minimum wage policies dampen the structural change process from manufacturing to personal services. A more equal distribution of wages in fact implies a lower shift of aggregate demand from manufacture to personal services. Preventing the rise of the low-productivity personal service sector, in turn, allows the economy to attain a higher aggregate productivity. From an empirical point of view, this result is consistent with the literature on productivity slow-down, in particular with studies showing structural change from high to low productivity sectors as one, among many, determining factor (see Nordhaus, 2008 and Duernecker et al., 2017). Consistently with the empirical evidence provided by Deng et al. (2021), we also find that the minimum wage policy can exert an additional positive impact on productivity within manufacturing: this is the consequence of the enhanced incentives to automate production processes induced by the relative rise in the wages for low-skilled occupations which make high-skilled workers relatively cheaper, fostering a higher adoption of automated technologies.

The rest of the paper is organised as follows: section 2 discusses the scope of our analysis and presents the model; section 3 describes the model calibration and discusses the empirical evidence employed to calibrate some key parameters. Section 4 is dedicated to the model validation and presents our main results; in section 5 we perform a sensitivity analysis on key parameters in order to clarify and strengthen our main results; in section 6 we perform a minimum wage policy experiment; section 7 concludes the paper.

2 The Model

In this section we sketch out the main features of our model and the purpose of our analysis. The core framework of the model is provided by the AB-SFC benchmark model proposed by Caiani et al. (2016) and, more precisely, its refinement featuring endogenous growth presented in Caiani et al. (2019, 2020). However, this core is complemented by three major features.

First and foremost, we introduce automation in the model, that we characterise as a form of skill-biased technical change. In particular, while non-automated capital goods were mainly directed to the replacement of routine tasks typically performed by low-skilled workers, automation has the additional distinctive feature of creating new job opportunities for high-skilled workers required to operate and mange them. We believe this to provide a fair approximation of the micro effects of automated machines on the labour demand for different skill-groups. While the empirical debate on the global effect of automation on employment is far from being settled, as discussed in our introduction, there seems to be indeed a growing, though still tentative, consensus on the fact that workers in routine, low-skilled occupations are more exposed to the risk of being replaced by automation, whereas high-skilled workers tend to benefit from it. Using German data on robotization at plant-level, for example, Deng et al. (2021) show that low-skill labour positively impacts robots adoption suggesting that, other things being equal, low-skill labour performing simple and easily automatable tasks is more likely to be replaced by robots. Similar results, though based on industry-level data, are found in de Vries et al. (2020). Dauth et al. (2021), find evidence for a displacement effect in manufacture but at the same time show that complementarity and expansion of economic activity in other industries is an important adjustment mechanism that offsets the displacement effect on employment at the aggregate level. In addition, with regards to the effects of automation by education levels, they find that automation affects positively earnings of high-skilled workers, while it affects negatively medium and low-skilled, interpreting this results as an evidence at the micro level that robots are a form of skill-biased technological change. Balsmeier and Woerter (2019) find that investment in digital technologies is positively associated with employment of high-skilled workers and negatively associated with employment of low-skilled workers within the firm. Within the modelling literature, Cords and Prettner (2022) also characterise automation as a skill-biased type of technical change and, focusing on employment in manufacture, show that the adoption of robots results in rising unemployment and falling wages for low skilled workers, and falling unemployment and rising wages for high skilled workers, with an overall positive effect on employment. A description of contemporary technological change assuming as a distinctive trait some type of skill-bias is also at the core of the AB model presented in Mellacher and Scheuer (2020) or General Equilibrium models *à la* Autor et al. (2003) and subsequent publications[8].

Based on on this tentative evidence, our model posits that automation, besides enhancing productivity levels, changes the composition of the labour demand by requiring a higher share

[8] Partly in contrast with these findings, a striking result is presented in Domini et al. (2021) who find no significant effect of automation on the shares of employment by different occupational categories and, in particular, for unskilled industrial workers. Though there is no perfect matching between occupational and skill-groups, this result might indeed question the skill-biased character of automation showing the need for more empirical analyses on the affects of automation based on micro data. Similarly, also Klenert et al. (2020) has challenged this dominant idea maintaining that low-skilled workers may not be harmed by industrial robots and showing that results in this field are still sensitive to the dataset, time frame, and empirical specification employed

of high-skilled workers and a lower share of low-skilled ones, while keeping, for simplicity reasons, the share of middle-skilled unaffected. Admittedly, in the blossoming literature on automation, there have been attempts to model the very micro interaction between workers' skills evolution on the one hand, and tasks generation and replacement trough automation within the firm on the other. Prominent examples are Bordot and Lorentz (2021) and Dawid and Neugart (2021). Differently from these contributions, however, we do not go into such a level of detail, nor we attempt to model the process that *generates* the effects of automation on firms' labour demand for different skill-groups. Rather, we *assume* them based on the available empirical evidence and we then focus our attention on the systemic effects generated by the diffusion of these technologies within manufacture.

In order to study these effects, however, we make a second fundamental integration by including an additional sector in the economy, namely the personal service sector. Section 3.2 provides a detailed definition of this industry in terms of NAICS codes. For now, let us define them as a type of non-tradable, low-skilled, low-productivity market services supplying recreational needs (e.g. foods at restaurants, catering, delivery services, accommodation, etc.) or addressed to replace tasks typically performed at home (e.g. caring, cleaning, laundry, house-keeping, etc.). While the literature dealing with the tertiarisation of the economy has been for long mainly focusing on the business service sector serving firms, a growing literature is now pointing to the non-negligible role played by these consumer services. Montresor and Marzetti (2007), for example, show that the process of tertiarisation/de-industrialization cannot be reduced to outsourcing of internal functions to business services and to vertical foreign direct investments. While in fact the weight of market services in the manufacturing subsystem increases, providing a counter balance to manufacturing decline, the manufacturing subsystem shares as a whole, including also outsourced services, still significantly decrease. This suggests that other factors, besides the rise of the business service sector, may have played an important role in the process of tertiarisation. The recent empirical literature has stressed the role played by low-skill intensive services in this respect. Autor and Dorn (2013) have argued that the strong rise in low-skill services occupations, such as restaurant meals, house-cleaning, security services, and home health assistance, accounts for most of the growth observed in low-skilled occupations that led to job polarisation in US and look to consumer preferences to explain this result. Mazzolari and Ragusa (2013) highlight how the consumption of high-skilled workers dedicated to market services replacing home production, creates significant spillovers on the employment of low-skilled. Manning (2004) argues that a growing demand for low-skill labour comes from the consumption of non-tradeables of high-skilled people and that this will bring "lots of caring jobs, jobs in bars, shops and restaurants" (Manning, 2004, p. 605).

Our model tries to connect the literature on the effects of automation to the literature on job polarisation by focusing on the role played by personal services. By this, we do not want to deny the role played by business services in the tertiarisation process, nor its possible role in the process of job polarisation. However, the business service sector has very different features from personal services, being characterised by greater shares of employment of high-skill labour, greater value added, greater complexity of tasks and greater technological dynamism, being also an adopter of digital and automated technologies. Under many respects, business services are then more similar to manufacturing than to traditional, low-skill-intensive, low-productivity, and low-innovation personal services considered in our model. Our choice to focus on this latter category mainly relates to the scope of our analysis: rather than attempting to provide a general explanation of all the channels by which automation may possibly impact the economy, our work tries to disentangle the link between the skill-biased character of modern productive technologies, the rise of high-skill labour, the growing importance of the personal service sector, and the creation of new job opportunities within this latter, and how these processes concur to create job and wage polarisation in the economy.[9]

In order to connect automation to the rise of personal services, however, we need a further ingredient. The third fundamental assumption we make is that different types of workers allocate their consumption budget in different proportions to manufactured consumption

[9]Admittedly, including the business service sector is one of the possible refinements of the model we are considering for future applications. Given the high-skill intensity of the business services, our educated guess is that this might possibly increase further the growth of demand for high-skilled workers and favour a non-damaging effect of automation on employment, along the lines suggested by Dauth et al. (2021), Acemoglu and Restrepo (2018), and Klenert et al. (2020).

goods and to personal services. More precisely, following the empirical evidence provided in Mazzolari and Ragusa (2013), we assume that high-skilled workers allocate a higher share of their consumption to personal services. Since these services require more low-skilled workers, this assumption opens the possibility of having spillovers from the rising consumption of high-skilled, emerging from their improved working conditions due to automation, to the employment of low-skilled, as posited by Mazzolari and Ragusa (2013), Manning (2004), and Lee and Clarke (2019).

2.1 Model structure and sequence of events

Our stylised economy is hence composed of capital good firms, consumption good firms, personal service firms, banks, households, a government, and a central bank. Capital firms, indexed by k, produce heterogeneous automated machines out of labour only and perform R&D in order to produce new, more productive machines. As already explained, new machines are characterised by a higher requirement of high-skilled workers and a lower of low-skilled. Consumption firms, indexed by c, combine machines purchased from capital firms through investment and workers in order to produce and sell a homogenous product. Service firms, indexed by s, employ labour only and provide homogenous services with a constant productivity. Initial proportions between different skill occupations are calibrated empirically. Capital and consumption firms have the same initial shares but for capital firms they remain constant, whereas the labour demand for each skill groups of consumption firms depends on the technical requirements of the vintages they invest upon, and thus evolves as new vintages are adopted. Service firms have a higher share of low-skill occupations compared to other sectors, and the proportions remain fixed throughout the simulation.

Households are indexed by z and grouped in three different skill categories: high, middle, and low-skilled workers. Households sell labour to firms and consume goods and services. High-skilled households, as anticipated, allocate a higher fraction of their consumption to services. Low and middle-skilled follow instead the same allocation.

The government hires a constant number of public workers, the proportions between different skill occupations being also empirically calibrated. In addition, it levies taxes on profits and income, it provides unemployment benefits for households, and it issues bonds. Banks, indexed by b, provide credit to firms, buy government bonds and collect deposits. Finally, the central bank provides cash advances to banks upon request and absorbs unsold government bonds.

The markets for manufactured goods (capital and consumption), personal services, credit and deposits, all operate through a decentralised matching mechanism common to previous versions of the model, where demanders may switch from a supplier to another one selected within a randomly sampled limited subset with a probability depending on the differences between their prices (or, in the case of capital goods, a combination of the prices and the technical features of the proposed vintages).[10] The functioning of the labour market follow a similar logic but requires some additional sophistication, as described in section 2.3.

While the following sections discuss the most relevant features of the model for the type of analysis performed, the complete description is provided in appendix A.

In each period of a simulation, events take place in the following order:

1. *Production planning*: consumption, service, and capital firms set their desired production level in order to match expected demand and attain the desired stock of inventories.

2. *labour demand*: given available technology and desired output levels, firms calculate their labour demand.

3. *Prices and interests settings:* firms set their prices and banks set interest rates on deposits and loans.

4. *Expanding productive capacity*: consumption firms determine desired investment based on their production capacity desired growth.

5. *Credit demand*: based on available internal funds, expected revenues and costs, firms decide whether to apply for loans to banks.

[10] See the appendix, in section A.1, for the details on the market-matching procedure.

6. *Credit supply*: banks gather and evaluate loans applications and possibly grant credit to firms.

7. *labour markets*: unemployed workers look for an occupation on the labour market, inelastically supply one unit of labour at their endogenous evolving reservation wage

8. *Production*: capital, consumption and service firms produce.

9. *Consumption markets*: Households buy goods and services from their preferred suppliers.

10. *Capital goods market*: consumption firms buy machines of their preferred vintage in order to match their desired capacity growth.

11. *Capital firms R&D*: capital firms perform R&D and, when successful, possibly update the capital vintage they produce thereafter.

12. *Interests payment*: Banks pay interest on deposits, firms pay interests on loans, and the government pays interests on bonds.

13. *Wages and dole*: firms pay wages and government pays wages and unemployment benefits.

14. *Taxes*: the government collects profit taxes from firms and banks and income taxes from households.

15. *Dividends*: banks and firms distribute dividends to households when profits are positive.

16. *Deposit market*: firms and households select banks to deposit savings.

17. *Bonds market*: the government emits new bonds if needed which are purchased by banks and, for the possible residual part, by the Central Bank.

2.2 Notation

Let us first of all clarify the notation used throughout the paper. We employ x_t^e to refer to the expectation of the generic variable x in period t, formulated at $t-1$. When referring to a generic firm we use the index x. In case we seek to specify whether firm x belongs to the consumption good, capital, or service sector we use instead c, k, and s, respectively. Similarly, an individual bank is indexed by b. A worker of generic skill is identified as σ-skilled. We use instead l, m, and h to indicate low, middle, and high skilled workers. A generic household is indexed by z. Finally the superscript D applied to a variable indicates that we are referring to the 'desired' or target value for that variable for a given agent, which can differ from its actual realisation.

2.3 Households

A key aspect of our model is households' heterogeneity in the skill dimension. In order to curb the level of complexity and adhere to the job polarisation literature, we sort workers in three skill groups: low, middle and high. To every household is assigned a skill level, which remains fixed throughout the simulation.

Accordingly, we define three types of occupations depending on the skills they require, i.e. low, middle, and high-skilled jobs: each worker can take up a job matching her skill level or below: workers employed in an occupation for which they are over-qualified are labeled as 'underemployed'.

2.3.1 Wage setting

Each worker updates her demanded wages at every period t, one different demanded wage for each labour market in which she can potentially participate.

The reservation wage for occupations matching the skill-level of the worker is set following a simple heuristic: if in $t-1$ she has been employed, but not underemployed, she scales up her demanded wage by a random amount, vice-versa she scales it down by the same token.

$$w^{d,\sigma^*}_{z,t} = \begin{cases} w^{d,\sigma^*}_{z,t-1}(1 - FN^1_{z,t}) & \text{If} \quad e^{\sigma^*}_{z,t-1} = 0 \\ w^{d,\sigma^*}_{z,t-1}(1 + FN^1_{z,t}) & \text{If} \quad e^{\sigma^*}_{z,t-1} = 1 \end{cases} \tag{1}$$

Where σ^* is the labour market for occupations matching the skills of household z. $w^{d,\sigma^*}_{z,t}$ is the demanded wage by households z, at time t, in market σ^*. $e^{\sigma^*}_{z,t}$ is a dummy variable taking value 1 if z is employed at period t in market σ^* and 0 otherwise; $FN^1_{z,t}$ is a random draw from a folded normal distribution with mean μ_{FN^1} and variance $\sigma^2_{FN^1}$.

Initial wages are assumed to be homogenous across workers in the same skill group, moreover they are set such that $w^{d,l}_{l,0} < w^{d,m}_{m,0} < w^{d,h}_{h,0}$, see section (3) for details about the calibration exercise.

Workers who do not find an occupation in their preferred labour market try to fill vacancies of lower skill requirements. The wage setting equation for jobs below the preferred skill level follows the same logic as the one expressed in equation 1, however with some minor adjustment discussed below.

We assume that workers acquire private information with respect to labour markets in which they actively participate, otherwise they must rely on public information. In what follows, we will refer only to high-skilled workers, being the most general case, but the described mechanism can readily be extended to middle-skilled workers. Low-skilled workers are obviously not targeted, insofar they can only participate in the labour market matching their skill level.

Labour markets open sequentially, from the highest skill level to the lowest, therefore *active* participation at time t in a σ-labour market implies one of the following conditions:

- a worker is unemployed at time t. Indeed, to be unemployed a worker has surveyed - unsuccessfully - all labour markets within her expertise.

- a worker is employed in an occupation below the skill level σ at time t. Indeed, to have found a job below σ implies an unsuccessful search on the σ-labour market.

- a worker is employed in a σ-occupation

If at time t a worker finds herself in one of the aforementioned conditions, then she has acquired some private information on the σ-labour market, specifically she knows if the demanded σ-wage allowed her to find a job and therefore if such demand was competitive or not.

On the other hand, if a worker did not acquire such private information, then she can only rely on public information, that is the prevailing σ-wage, proxied by the mean σ-wage determined at time t.

Therefore, the m-wage determined by a high-skilled worker z_h is defined as:

$$w^{d,m}_{z_h,t} = \begin{cases} \bar{w}^m_{t-1}(1 + FN^1_{z_h,t}) \quad \text{If} \quad e^h_{z_h,t-1} = 1 \\ w^{d,m}_{z_h,t-1}(1 + FN^1_{z_h,t}) \quad \text{If} \quad e^m_{z_h,t-1} = 1 \\ w^{d,m}_{z_h,t-1}(1 - FN^1_{z_h,t}) \quad \text{If} \quad e^h_{z_h,t-1} = 0 \;\; AND \;\; e^m_{z_h,t-1} = 0 \end{cases} \tag{2}$$

Where $\bar{w}^m_{t-1}$ is the average ms-wage at period $t-1$.

The intuition behind equation 2 is straightforward:

- if at time $t-1$ a high-skilled worker is employed in her preferred labour market, her demanded m-wage at time t, will be the average m-wage at $t-1$ plus a random amount.

- if at time $t-1$ a high-skilled worker is employed in the m-labour market, her demanded m-wage at time t, will be the demanded m-wage at $t-1$ plus a random amount.

- if at time $t-1$ a high-skilled worker is employed in the l-labour market or unemployed, her demanded m-wage at time t, will be the demanded m-wage at $t-1$ minus a random amount.

Similarly, the demanded l-wage determined by a high-skilled worker is defined as:

$$w^{d,l}_{z_h,t} = \begin{cases} \bar{w}^l_{t-1}(1+FN^1_{z_h,t}) & \text{If} \quad e^h_{z_h,t-1}=1 \;\; OR \;\; e^m_{z_h,t-1}=1 \\ w^{d,l}_{z_h,t-1}(1+FN^1_{z_h,t}) & \text{If} \quad e^l_{z_h,t-1}=1 \\ w^{d,l}_{z_h,t-1}(1-FN^1_{z_h,t}) & \text{If} \quad e^h_{z_h,t-1}=0 \;\; AND \;\; e^m_{z_h,t-1}=0 \;\; AND \;\; e^l_{z_h,t-1}=0 \end{cases} \tag{3}$$

The wage paid to employed workers equals their desired one. On the other hand, unemployed workers participate to the labour market by posting their desired wages. Also, underemployed workers participate to the labour market in the attempt to improve their occupations.

Employers observe a subset of job-seekers, rank them according to desired wages and start hiring from those asking the lowest wage up.

Unemployed workers are eligible by the government for unemployment benefits, which are set as percentage of the average low-skill wage:

$$ub_t = \Lambda \bar{w}_{ls,t} \tag{4}$$

Where ub_t is the unemployment benefit at time t, Λ is an exogenous policy parameter, and $\bar{w}_{ls,t}$ is the average wage paid to low-skilled workers in t.

2.3.2 Consumption

Households' consumption is determined in two stages: in the first stage households set their consumption budget, in the second stage they allocate it between manufactured goods and services.

We assume a simple Keynesian consumption function with fixed propensities α_{NI} and α_{NW} out of personal net-income $NI_{z,t}$ and net-wealth inherited from the past $NW_{z,t-1}$.

$$C^D_{z,t} = \alpha_{NI} NI_{z,t} + \alpha_{NW} NW_{z,t-1} \tag{5}$$

where $C^D_{z,t}$ indicates desired nominal consumption at time t of the generic z household, i.e. her consumption budget.

$C^D_{z,t}$ is then allocated between services and goods in fixed shares, $\gamma^\sigma, 1-\gamma^\sigma$. These are assumed to be heterogeneous across household skill-groups: as suggested by the empirical literature (Mazzolari and Ragusa, 2013), high-skilled households dedicate a larger share of their consumption to personal services, compared to lower skilled households:

$$\begin{cases} C^{D,s}_{z,t} = \gamma^\sigma C^D_{z,t} \\ C^{D,c}_{z,t} = (1-\gamma^\sigma) C^D_{z,t} \end{cases} \qquad \text{with} \quad \gamma^h \geq \gamma^m \geq \gamma^l \tag{6}$$

where $C^{D,s}_{z,t}$ and $C^{D,c}_{z,t}$ are desired consumption of services and manufactured goods by generic household z.

For simplicity we will assume throughout the paper $\gamma^h > \gamma^m = \gamma^l$

2.3.3 Net Income

Households receive wages in exchange of labour if employed, otherwise they receive unemployment benefits. They also receive dividends from the private sector[11] and interests on deposits. The sum of those components determines the gross income, once income taxes are subtracted we obtain net income:

$$NI_{z,t} = w_{z,t} + i^d_{z,b,t} D_{z,t} + Div_{z,t} - Tax_{z,t} \tag{7}$$

Where $w_{z,t}$ is the wage received by z at time t if employed, or the unemployed benefit if unemployed. $i^d_{z,b,t}$ is the interest rate paid on deposits by z's bank b and $D_{z,t}$ the stock of z's deposits. $Div_{z,t}$ are total dividends received by z and $Tax_{z,t}$ are total taxes due. Taxes are simply defined as a fixed tax rate τ_{inc} charged on gross incomes.

[11] See Appendix A.2 for profits and dividends determination.

2.4 Firms

2.4.1 Production planning and labour demand

Consumption and capital firms plan their output levels $y^D_{x,t}$ in order to match expected demand[12] $s^e_{x,t}$, and to attain a target stock of inventories. As discussed in Steindl (1976) and Lavoie (1992), firms accumulate inventories as a buffer against unexpected demand upswings and therefore we assume planned inventories to be defined as a share v of expected sales:

$$y^D_{x,t} = (1+v)s^e_{x,t} - inv_{x,t-1} \ \text{ with } \ x = \{c, k\} \tag{8}$$

where $inv_{x,t-1}$ are inventories inherited from the past.

Service firms cannot accumulate inventories, as they provide non-storable intangibles, but nonetheless want to be ready in case actual demand exceeds their expectations to avoid frustrating their customers (Lavoie, 1992). Therefore, they plan production $y^D_{s,t}$ so to be able to deliver services in excess for a share v of their own expected sales:

$$y^D_{s,t} = (1+v)s^e_{s,t} \tag{9}$$

Where, with a slight abuse of notation, $y^D_{s,t}$ now indicates desired *potential* production and v determines the desired excess capacity they want to maintain.

2.4.2 Production and labour demand for service and capital firms

Service and capital firms produce using labour only. In order to produce, these firms require low, middle, and high-skilled workers that they must combine in fixed shares: $\alpha^l_x, \alpha^m_x, \alpha^h_x$, with $\alpha^l_x + \alpha^m_x + \alpha^h_x = 1$ and x being an index identifying the type of firm: $x = (k, s)$.
Let us define the number of workers employed by the generic firm x for each skill-group by N^l_x, N^m_x, N^h_x. Then, firms' production is described by a Leontief production function of the

[12] As in Caiani et al. (2016, 2019, 2020), expectations in the model are always formed in an adaptive way. See section A.1 in the appendix.

type:

$$y_{x,t} = min\left(A_x^l N_{x,t}^l, A_x^m N_{x,t}^m, A_x^h N_{x,t}^h\right) \quad \text{with} \quad x = \{s, k\} \tag{10}$$

Where A_x^σ are the technical parameters of the Leontief production function representing the specific productivities of each labour type.

Therefore, labour demand for each skill group can be defined as:

$$N_{x,t}^{D,\sigma} = \frac{y_{x,t}^D}{A_x^\sigma} \tag{11}$$

However, neither equation 10 nor equation 11 allow to grasp the role played by the labour shares defining the proportions in which workers of different skill-groups should be employed. Through some analytical passages, explained in details in appendix B, we can derive an equivalent formulas for production and labour demand as a function of the shares. This alternative definition allows to better grasp how the different labour shares characterizing the technology of production in each sector impact on their demand for each type of worker, and how shifting demand from one sector to another may impact employment. More precisely, equation 10 can be written as:

$$y_{x,t} = \mu_x min\left(\frac{N_{x,t}^l}{\alpha_x^l}, \frac{N_{x,t}^m}{\alpha_x^m}, \frac{N_{x,t}^h}{\alpha_x^h}\right) \tag{12}$$

where μ_x indicates the output producible with one unit of labour, that is the productivity of total labour, when this is split between different skill groups so to respect the proportions required by the technology of production, i.e. when labour is employed efficiently.

Accordingly, labour demand for each skill group can be expressed as:

$$N_{x,t}^{D,\sigma} = y_{x,t}^D \frac{\alpha_x^\sigma}{\mu_x} \tag{13}$$

Appendix B provides the detailed analytical derivation of these equations.

2.4.3 Production and labour demand for consumption firms

Consumption firms combine capital and labour in production. Capital vintages are heterogeneous, each vintage being indexed by κ and identified by a set of five technical parameters $\Omega = \{\mu_\kappa, \bar{l}_\kappa, \alpha^l_\kappa, \alpha^m_\kappa, \alpha^h_\kappa\}$. μ_κ represents capital productivity, i.e. the output producible by one unit of vintage κ in one unit of time. $\bar{l}_\kappa$ is the global capital-labour ratio, whose inverse gives the total number of workers required to operate one unit of vintage κ. α^l_κ, α^m_κ, and α^h_κ define the proportions of these workers that must perform low, middle, and high-skill tasks to operate one unit of machine κ, with $\alpha^l_\kappa + \alpha^m_\kappa + \alpha^h_\kappa = 1$. To simplify the analysis without loss of generality, $\bar{l}_\kappa$ is assumed to be homogenous across vintages so that they can be unambiguously identified by $\Omega^* = \{\mu_\kappa, \alpha^l_\kappa, \alpha^m_\kappa, \alpha^h_\kappa\}$. This implies that the total number of workers needed to operate a machine is fixed and independent of technological change. Therefore, a unit of vintage κ requires $\frac{\alpha^\sigma_\kappa}{\bar{l}_\kappa}$ σ-skilled workers. Accordingly,

$$N^{\sigma*}_{c,\kappa,t} = \frac{\bar{l}_\kappa}{K_{c,\kappa,t}\alpha^\sigma_k} \tag{14}$$

is the number of σ-skilled workers required to operate $K_{c,\kappa,t}$ units at full capacity.

The maximum output producible by firm c using K_κ units of vintage κ is then:

$$y_{c,\kappa,t} = K_{c,\kappa,t}\mu_\kappa min\left(\frac{N^l_{c,\kappa,t}}{N^{l*}_{c,\kappa,t}}, \frac{N^m_{c,k,t}}{N^{m*}_{c,k,t}}, \frac{N^h_{c,k,t}}{N^{h*}_{c,k,t}}\right) \tag{15}$$

with $N^l_{c,k,t}, N^m_{c,k,t}, N^h_{c,k,t}$ representing the actual number of low, mid and high-skilled workers available in firm c to operate vintage κ and $N^{l*}_{c,k,t}, N^{m*}_{c,k,t}, N^{h*}_{c,k,t}$ the correspondent number that would be necessary to operate at full capacity.

Production is thus constrained by both the quantity of capital available for each vintage, which defines the full capacity of production $K_{c,\kappa,t}\mu_\kappa$ for that vintage, and by labour of each skill-group available to operate that vintage that determines, according to the ratios on the right-hand side of equation 15, the actual rates of capacity utilization.

Since firms can invest in every period and machines lasts δ_k periods, consumption firms

typically own machines of different vintages. Firm c then seeks to produce the target $y^D_{c,t}$ using the combination of vintages which allows to minimise costs.
Let us first define the unit cost of production embedded in a machine of vintage κ at time t as:

$$uc_{\kappa,t} = \frac{\sum_{\sigma} \bar{w}^{\sigma}_{c,t} \alpha^{\sigma}_{\kappa} \bar{l}^{-1}_{\kappa}}{\mu_{\kappa}} \tag{16}$$

Where $\bar{w}^{\sigma}_{c,t}$ is the average σ-wage, paid by firm c, at time t. $\frac{1}{\mu_{\kappa}}$ gives the units of vintage k required to produce a unit of output, and the numerator in equation 16 gives the total labour cost of operating these machines.

If desired output is equal or greater than current capacity, then all vintages are employed at full capacity. Otherwise, firm c orders its available vintages from the most convenient to the least convenient based on their implied unit labour costs of production and starts producing using the most convenient ones first. For each vintage along the ranking firm c compares the amount producible using those machines with the residual amount that must be produced to attain the targeted production level. If this latter is higher, the vintage is employed at full capacity, i.e. the desired utilisation rate $u^D_{c,\kappa,t}$ is set equal to 1, and the firm moves to consider the next vintage in the ranking. When, finally, the production achievable using a given vintage exceeds the amount of output yet to produce, its utilisation rate is set to $u^D_{c,\kappa,t} = \frac{y^D_{c,t} - \sum_{\kappa^* > \kappa} K_{c,\kappa^*,t}\mu_{\kappa^*}}{K_{c,\kappa,t}\mu_{\kappa}}$, where κ^* indicates the vintages which were higher in the ranking compared to κ for which $u^D_{c,\kappa^*,t} = 1$. All the vintages following in the ranking then remain idle and their utilisation rate is hence set to 0.

Having determined the combination of vintages employed in production, firm c can compute labour demand for each skill category σ according to the following equation, which makes clear the dependence of firms' labour demand on the technical coefficients of their capital vintages ($\kappa_{c,t}$):

$$N^{\sigma,D}_{c,t} = \sum_{\kappa \in \kappa_{c,t}} u^D_{c,\kappa,t} K_{c,\kappa,t} \left(\frac{\alpha^{\sigma}_{\kappa}}{\bar{l}_{\kappa}} \right) \tag{17}$$

2.4.4 Pricing

Firms set prices applying a non-negative mark-up ι_x (with $x = \{c, k, s\}$) over expected unit labour costs of production, therefore we have:

$$p_{x,t} = (1 + \iota_x) \left(\frac{\sum_\sigma \bar{w}^{e,\sigma}_{x,t} N^{D,\sigma}_{x,t}}{y^D_{x,t}} \right) \tag{18}$$

Where $\bar{w}^{e,\sigma}_{x,t}$ is the expected σ-wage paid by firm x, at time t. Therefore, $\sum_\sigma \bar{w}^{e,\sigma}_{x,t} N^{D,\sigma}_{x,t}$ are the expected total labour costs of production implied by the combination of vintages employed to produce $y^D_{x,t}$. Firm x's mark-up is increased by a stochastic amount drawn from a Folded Normal distribution $FN^2_{x,t}$ when real sales exceeded expected sales, and vice-versa in the opposite case.

$$\iota_{x,t} = \begin{cases} \iota_{x,t-1}(1 + FN^2_{x,t}) & \text{if} \quad s_{x,t-1} > s^e_{x,t-1} \\ \iota_{x,t-1}(1 - FN^2_{x,t}) & \text{if} \quad s_{x,t-1} < s^e_{x,t-1} \end{cases} \tag{19}$$

2.4.5 Investment

Consumption firms invest to attain a desired capacity growth rate $g^D_{c,t}$ which depends on the difference between their normal, or targeted, capacity utilisation rate $\bar{u}$, and the rate of capacity utilisation $u^D_{c,t}$ implied by the production of $y^D_{c,t}$:[13]

$$g^D_{c,t} = \gamma_u \frac{u^D_{c,t} - \bar{u}}{\bar{u}} \tag{20}$$

Where γ_u and $\bar{u}$ are exogenous and equal across firms.

Consumption firms interact with a limited number of capital good producers who supply different capital vintages κ, see section(2.4.6). Therefore, firms must consider, besides the price of acquisition of each vintage, also the operating costs implied by the technology they

[13]Firms' excess capacity is a well-known empirical phenomenon. Steindl (1952) and Lavoie (1992) suggest that excess capacity is held, just as inventories, to accommodate possible unexpected spikes in demand while Spence (1977) argues that excess capacity is employed by incumbent firms as a deterrent to new entrants. See Lavoie (2015) for a detailed discussion.

embed. Therefore, capital supplier i is preferred to capital supplier j if the difference between the unit labour costs associated to vintages i and j over the entire capital life-span δ_κ is smaller than the difference between the price of j and the price of i:

$$\delta_\kappa(uc_{i,t} - uc_{j,t}) < p_{jy} - p_{i,t} \tag{21}$$

where δ_κ is constant and equal across vintages, $uc_{i,t}$ is unit labour costs associated to vintage i, and p_i is its price.

Let us point out that that equation 21 can also be rearranged as:

$$uc_{i,t}\delta_\kappa + p_{i,t} > uc_{j,t}\delta_\kappa + p_{j,t} \tag{22}$$

thereby obtaining a synthetic measure to compare the attractiveness of different vintages.[14]

Once the preferred capital supplier has been determined, consumption firms compute the exact number of machines they need in order to attain $g^D_{c,t}$. Orders placed at time t are delivered at time $t+1$. Obviously, firms have to account for the fact that some machines are approaching their obsolescence limit and will be scrapped from the capital stock at the end of the period.[15] Nominal desired investment $I_{c,t}$ in capital can then be computed by multiplying the number of machines ordered for their price.

2.4.6 R&D

The design of innovation in the model augments the well established evolutionary tradition stemming from the work of Nelson and Winter (1977, 1982) and Winter (1984) with insights from the literature dedicated to *skill-biased* technological change. Such approach has been introduced and popularised in macro ABMs by the seminal contribution of Dosi et al. (2010) and subsequent papers, for instance Dosi et al. (2018) and Dosi et al. (2021) which are among

[14]The right-hand and left-hand sides of equation 22 thus replace the variables P_o and P_n in equation 30 (see appendix A.1) to define the probability of switching from an old supplier i to a new one j in the capital good market.

[15]Notice that $g^D_{c,t}$ may well be negative if firms want to reduce their productive capacity, e.g. as a consequence of a drop in demand. However, real investment in new machines is always non-negative, as we do not model second-hand capital markets or costs imputable to capital items other than sunk costs.

the closest to our contribution.

To simplify the analysis, we assume that capital firms' innovative efforts impact the productivity of a vintage μ_κ and the shares of high and low-skilled workers α^h_κ, and α^l_κ required to operate it, while they leave unaffected the share of middle-skilled workers α^m_κ. This assumption is motivated by the focus on automation and relies on the empirical study by Graetz and Michaels (2018) who, using IFR data, point to two main direct effects of robots: they increase productivity and they increase the share of high-skilled workers, while reducing the share of low-skilled ones. Hence, automation is skill-biased.

Therefore, we model innovation as a process increasing μ_κ and α^h_κ. Moreover, for any increase in α^h_κ, we impose an adjustment on α^l_κ,while α^m_k is left unaltered, such that the condition $\alpha^h_\kappa + \alpha^m_\kappa + \alpha^l_\kappa = 1$ is always satisfied.

Note that in this framework not any realised innovation is economically efficient: an increase in productivity undoubtedly tends to reduce production costs, but it is accompanied by an increase in the parameter α^h_κ, which tends to increase production costs, being high skilled workers more expensive than low-skilled ones. It follows that whether an innovation is adopted in production ultimately depends on the low/high-skill relative wage dynamics. Therefore, productivity growth can come to a halt if the economic conditions are such that, despite increasing productivity, innovations are not profitable from the producers' point of view.

Before proceeding with the exposition, let us clarify that technological innovations affect on the production structure of the consumption good sector, leaving unaffected the capital good sector.

Following Caiani et al. (2019) and a rich literature in the evolutionary tradition[16], we model firms' innovative research and development activity as a two-step stochastic process: first, a draw from a Bernoulli determines whether *R&D* activity has been successful or not, where the probability of success $Pr^{inn}_{k,t}$ depends on resources dedicate to innovative *R&D*.

[16] See Nelson and Winter (1977), Winter (1984), Andersen et al. (1996), Dosi et al. (2010), Caiani (2012), and Vitali et al. (2013).

Formally, the probability of innovating for capital firm k is given by:

$$Pr_{k,t}^{inn} = 1 - e^{-\xi^{inn} N_{k,t}^{h}} \tag{23}$$

where ξ^{inn} is an exogenous time invariant-parameter and $N_{k,t}^{h}$ is the number of workers employed in high-skill occupations by firm k at time t, implicitly assuming that innovation is mainly performed by high-skilled workers. This implies that larger capital firms tend to innovate more than smaller ones, in line with a Schumpeterian Mark II regime which is common to most AB models featuring endogenous growth.
If a capital firm is successful in innovating, it generates a new vintage defined as:

$$\begin{cases} \mu_k^{new} = (1 + FN_{k,t}^{3})\mu_k^{old} \\ \\ \alpha_k^{h,new} = (1 + FN_{k,t}^{4})\alpha_k^{h,old} \end{cases} \tag{24}$$

where μ_k^{new} and $\alpha_k^{h,new}$ are the productivity of the new vintage and the share of high-skilled workers it requires to operate, and where any variation in the value of $\alpha_k^{h,new}$ is mirrored by an equal variation of $\alpha_k^{l,new}$ in the opposite direction, given that $\alpha_k^{m,new}$ is kept constant for simplicity. μ_k^{old} and $\alpha_k^{h,old}$ are the correspondent parameters characterising the vintage currently produced by k. Finally, $FN_{k,t}^{3}$ and $FN_{k,t}^{4}$ indicate two random draws from two folded normal distributions defined over the parameters $\mu_{FN^3}, \sigma^2_{FN^3}$, and $\mu_{FN^4}, \sigma^2_{FN^4}$ respectively.

New vintages are not necessarily put into production and firm k may find more convenient to keep producing the old vintage. Therefore, k switches from the old vintage to the one if and only if the new vintage embeds lower unit costs of production with respect to the old one.

Again, it is worth noting that unit cost of production depends on capital productivity μ_κ, the shares α_k defining the labour requirements for each skill group, as well as on the the evolution of absolute and relative wages. Altogether, these factors concur to steer the direction and strength of technological progress.

Besides innovating, capital firms may also perform $R\&D$ imitative activity that allows them to copy the technology of some competitor. The design of imitation, which generates technological spillovers between firms, does not diverge from the well-established approach presented in the models referenced above.

The probability of imitating Pr^{imi} is determined as:

$$Pr^{imi}_{k,t} = 1 - e^{-\xi^{imi} N^{h}_{k,t}} \tag{25}$$

When successful, capital firms are allowed to observe the technology embedded in the vintages produced by a random subset of N^{imi} competitors and possibly imitate the vintage they find more convenient, when it brings a gain compared to the vintage currently produced.

3 Simulation Setup

3.1 Initial stock, flows and interactions

In order to calibrate the initial conditions of the model we rely on the procedure set out by Caiani et al. (2016) and later employed in Caiani et al. (2019, 2020); Schasfoort et al. (2017). The procedure starts by considering an aggregate parallel version of the model where each sector is characterised by the same behavioural rules of the agents belonging to it (apart from the matching protocols and the other rules which can only apply when there is a multiplicity of agents). This parallel version is then solved in the SS, defined as the situation in which expectations are always met, nominal and real aggregates grow at a constant rate, and unemployment and stock-flow norms remain constant. We identify the features of a reasonable steady state such as the rate of inflation, the rate of growth, and the rate of unemployment. We then set, *ex-ante*, parameters and stocks values for which it was possible to define empirically reasonable values. We then solve the system numerically so to find the values of the remaining parameters, stocks and flows compatible with the desired state and we use them, together with those set *ex-ante*, as initial conditions.

Initial values derived using such procedure can be found in the Transaction Flow matrix 6 and Balance Sheet matrix 5 of the economy. Furthermore, table 7 provides a comprehensive picture of the parameters employed in the simulations, specifying whether their values are set exogenously and then employed to solve numerically the steady state ('pre-SS'), derived from the numerical solution of the steady state ('SS-given'), or set in a way completely disconnected from the stock-flow calibration procedure.[17]

The aggregate values of stocks and flows found through this procedure were then employed to initialise the balance sheet, past values, and expectations of individual agents within each sector-class of agents. For this sake, we assume initial homogeneity across agents belonging to the same class, distributing variables uniformly across agents in a way such that, by aggregating, their initial expectations and personal endowments were consistent with the characteristics of the aggregate steady state.[18]

Besides initial homogeneity, we also assume initial symmetry in terms of economic relationships (e.g. customer-supplier, employer-worker, bank-depositors and debtors): agents are randomly connected but in a way such that, for example, every firm has the same number of workers and customers; every bank has the same number of debtors and depositors, and so on.

Households population sizes are set so that at time 0 every skill group experience the same unemployment level. Also, at time 0 there are no underemployed workers.

Therefore, our calibration procedure initialises agents in a homogenous and symmetric way and let heterogeneity emerge as the simulation unfolds.

[17] In order to ensure the reproducibility of the calibration procedure, the Mathematica (Wolfram) script employed for this purpose is provided with the JMAB code of the model.

[18] As already pointed out in Caiani et al. (2016), as the simulation begins, agents start to interact and adapt their behaviours to the environment, so that the model will start to display its own dynamics. The calibration procedure based on the aggregate Steady State explained above thus serves two main scopes: first, ensuring the plausibility of initial conditions in terms of distribution and relative dimensions of initial stocks and flows; and secondly, providing a parameter configuration capable of limiting the 'wilderness' of the model dynamics in the initial transient phase, which might possibly led our artificial economy on unrealistic-unreasonable paths.

3.2 Technical Parameters calibration

On top of the calibration procedure explained in the previous subsection, particular attention was devoted to the calibration of technical parameters, as they play a central role in driving the dynamics of the model. The technical parameters α's introduced in section 2.4.1, indeed, define sectors employment structure by affecting firms' demand for low, mid and high-skilled workers.

To calibrate these parameters we combine US data taken from the 2017 'industry-occupation matrix' (IOM) and the 'Education and training assignments by detailed occupation table' (ETAO) provided by the Bureau of labour Statistics (BLS). IOM provides the number of workers employed in a given occupation-industry cell[19].ETAO provides information on the typical education requirement for each occupation title contained in IOM.

Following a common practice in the literature, we proxy skills by education and distinguish among three skill groups: low, middle and high-skilled, using a standard classification employed, for example, in Graetz and Michaels (2018).

Roughly speaking, we group jobs requiring no education at all or below high school diploma in the low-skill category; jobs requiring high school diploma or more, but no university degree are considered middle-skill; finally, high-skill jobs require bachelor degree or above. Details are summarised in table 1.

Table 1: Skills definition by educational attainment

Skill level	Qualification
high	"Bachelor's degree","Master's degree", "Doctoral or professional degree"
medium	"High school diploma or equivalent", "Associate's degree", "Some college, no degree","Postsecondary nondegree award"
low	"No formal educational credential"

We then attribute to each job title the correspondent skill group according to the classification proposed in table 1. By combining our jobs-skills classification with IOM it is possible to compute the shares of low, middle, and high-skilled workers required by each

[19]Using this classification we are able to distinguish 819 different occupations distributed across industries disaggregated at NAICS 2-digits.

industry. However, since our model encompasses only three productive sectors, we need to sample sectors in IOM and operate some aggregations across them in order to find a sensible match between our model and the real economy: capital and consumption good producers are assimilated to Manufacturing, Wholesale Trade, and Retail Trade. As for the service sector, coherently with the literature on job polarisation (Autor et al., 2006)) and consumption habits (Mazzolari and Ragusa, 2013), we focus on personal services. Therefore we make them coincide with Accommodation and Food Services and Other Services (except Public Administration), encompassing a wide range of services to households (e.g. Personal Care Services, Personal and Household Goods Repair and Maintenance, Dry cleaning and Laundry Services, Death care Services, etc.). Sectoral employment data in the US in January 2020, i.e. just before the eruption of the Covid-19 crisis, shows that the sectors making up our personal services account to roughly 15.7% of total private employment (that, however, also includes agriculture, not present in our model).[20][21] In our calibration, the initial share of (private) employment in the personal services sector is of approximately 18%.[22] Finally, for the government sector we employed BLS occupational data on Federal, State, and Local Government, excluding state and local schools and hospitals and the U.S. Postal Service (OES Designation). The precise matching between the model and real world sectors is displayed in table 2.

Finally, we can compute the shares of σ-skill occupations in each sector x of our model using the following formula:

$$\alpha_x^\sigma = \frac{\sum\limits_{o \in O^\sigma} Empl_o^x}{totEmpl^x} \tag{26}$$

[20] This estimate was obtained by summing total employment of the Other Services, Accommodation, and Food Services and Drinking Places that make up or personal services sector, that we then compared to employment in the overall Private sector.

[21] The links to the BLS data for these four sectors are the following: https://beta.bls.gov/dataViewer/view/timeseries/CEU8000000001, https://beta.bls.gov/dataViewer/view/timeseries/CES7072100001, https://beta.bls.gov/dataViewer/view/timeseries/CES7072200001, https://beta.bls.gov/dataViewer/view/timeseries/CES0500000001.

[22] In the paper by Mazzolari and Ragusa (2013) itself, outsourced home production jobs include activities like personal services, repair, protective, cleaning, and child care services. From the figures on the employment shares of different sectors by wage decile we can infer that people occupied in the home production substitutes occupations account for a non-negligible portion of total employment, approximately 9% of total wage earners, whereas our personal services sector accounts for 15% of total employment if we include public workers in the denominator.

Table 2: Model sectors - real world match

Sectors	NAICS classification
Capital/Consumption Goods	31-33, 42, 44-45
Personal Services	72, 81
Government	999000 (OES Designation)

Where O^{σ}_{x} is the set of all occupations requiring σ-skills (where $\sigma = \{l, m, h\}$) within sector x, $Empl^{x}_{o}$ is the total number of workers employed in occupation of type o within sector x, and $totEmpl^{x}$ is the total number of workers employed in sector x.[23]

Table 3 displays the values of the calibrated technical parameters.

Table 3: Technical Parameters Calibrated Values

	ls	ms	hs
Manufacture/Capital	0.348287	0.5279909	0.1237221
Service	0.6792776	0.2712603	0.04946206
Government	0.06438509	0.6031763	0.3324386

As a final remark, let us point out that our approach introduces an interesting novelty in the calculation of industries skill-shares. The previous literature derives this measure by simply dividing the number of workers in the industry endowed with a certain education level for industry total employment. This, however, provides a picture of the skill distribution of the workforce, not of the skills needed to perform the different tasks required in the industry. The two measures do not necessarily coincide as one might be prone to think at a first glance. Indeed, they mostly diverge as a consequence of the possible mismatch between workers' skills and occupations type. In advanced economies 'underemployed' workers, having higher educational levels compared to those required to perform the typical tasks implied by their job, are a non-negligible share of the workforce. Our approach, by looking at the education levels required by each occupation type, rather than simply at the education attainments of employed workers', allows to overcome this possible bias, providing a more accurate estimate

[23]Remember from section 2.4.1 that, for service and capital firms, the technical parameters α^{σ} are fixed once and for all. Conversely, in the consumption goods sector the parameters α^{σ} are a property of capital goods and endogenously evolve over time due to R&D. Therefore, we assume that only one capital vintage κ_0 is available at the beginning of the simulation and its embedded technical parameters $\alpha^{l}_{\kappa_0}$, $\alpha^{m}_{\kappa_0}$, and $\alpha^{h}_{\kappa_0}$ are calibrated according to equation 26.

of the demand for low, middle, and high-skilled workers by different sectors.

3.3 Initial wage distribution calibration

Wage distribution across occupations is also a key variable of our model as it determines unit costs of production across sectors (therefore relative prices) as well as aggregate demand composition.

Again, we start by using BLS data on the "Annual mean wage by typical entry-level educational requirement" referring to May 2017. We then use table 1 to map education requirements in BLS data into our three skill-group classification and we then take averages in order to calculate the initial relative wages across groups:

$$w_{t_0}^{\sigma} = \frac{\sum\limits_{educ \in \sigma} w^{educ}}{n^{\sigma}} \tag{27}$$

Where *educ* represents any education level specified in the BLS table (like Bachelor's degree","Master's degree" etc.). Therefore $educ \in \sigma$ represents the education subset such that only education levels classified as σ-skill according to table 1 survive. w^{educ} is the average wage paid to occupations belonging to education level *educ* as indicated by the BLS table. n^{σ} is the number of education levels belonging to the skill category σ.

Finally, we rescale $w_{t_0}^{h}$ to 10 and use relative wages obtained with equation 27 to set low and middle-skill wages. Results are shown in table 4:

Table 4: Initial Wages Calibrated Values

ls	ms	hs
2.8	4.6	10

4 Baseline Results

To analyse the model, we run 25 Monte Carlo repetitions, each simulation lasting 1000 periods. The model is calibrated so that one simulation period represents a quarter.

We carried out a tentative validation by checking the model ability to broadly replicate the empirical properties of main macroeconomic variables (Dosi et al., 2010; Assenza et al., 2015; Caiani et al., 2016; van der Hoog and Dawid, 2017; Fagiolo et al., 2019). The results of this exercise are presented and commented in appendix E.

For explanatory purposes, we refer to a sample simulation to describe the model dynamics in the baseline scenario, however across simulations summaries are available in table 9.

Figures 1-2 show the main dynamics of the model: labour productivity in the consumption good sector follows a stable upward trend, therefore generating real GDP growth (see plots 1a-1b). Real consumption grows for both manufactured goods and services (see plots 1c-1d), even though for different reasons: real goods consumption increases as a result of productivity growth in the consumption goods sector which allows firms to increase their productive capacity and, by reducing unit costs of production and prices relative to wages, households to expand their real consumption demand. On the other hand, growth in services consumption is determined both by the shift in aggregate demand from goods to services documented in plot 2f and by their appreciation relative to consumption goods (plot 1f) which increases their real value, obtained by dividing nominal sales by the consumer price index.

In fact, although overall inflation appears to be rather stable (see plot 1e), consumption goods prices tend to grow at a lower pace than service prices (see plot 1f), reflecting different production cost trends across the two sectors: since there is free labour mobility across sectors wages paid to given skill occupations do not systematically differ across sectors. Services and consumption goods producers may hence be characterised by different trends in their unit variable costs as a consequence of (i) the rise in productivity experienced in manufacture as opposed to the constant productivity of services (ii) differences in the rate of growth of wages across skill-groups, coupled with the different mix of skills required by the two sectors (see section 3.2). In our case, the former effect tends to prevail explaining the downward trend in relative prices, despite the fact that employment in services is characterised by design by a higher share of low-skill occupations, whose wages grow at a lower pace compared to high-skill ones (see later plot 2g).[24]

[24]Note that such tendency in relative prices found support in real data, see for example the empirical

Overall, unemployment tends to decrease and then stabilizes around a low value, approximately equal to 1% (see plot 1g). However, we invite the reader to take this result with a grain of salt and not to regard it as an inherent property of automation. Rather, we believe it to be a side-effect, possibly partly related to the calibration employed, of the shift of final demand from manufacture to services documented in plot 2f. We noticed that unemployment tends to be higher in the simulations when the employment share of services grows slower. One may thus be prone to connect the reduction in unemployment to the difference in productivity levels characterizing the two sectors, affecting their requirement of labour per unit of output, or to the different average wages paid by the sectors, possibly affecting aggregate demand. However, we are reluctant to consider these two factors as the main cause of the declining unemployment, due to the Kaleckian mark-up pricing mechanism assumed in the model (section 2.4.4) that should offset their possible effect on labour demand, at least on average and over a certain time-span. Conversely, we tend to attribute this result to the different tendency of the two sectors to hoard money. This is not a novel results. Post-Keynesian theorists have long insisted on the markup being, in a demand-led economy, the ultimate variable determining the functional distribution of income and the level of demand.[25]

In our model, while the two sectors have the same dividend rate, they are endowed with different initial markups, being the markup of consumption firms calibrated so to give

evidence provided by Boppart (2014).

[25]As a pure matter of example to clarify this aspect we can consider the hypothetical case of two sectors, a and b characterised by different productivity levels A, being $A_a > A_b$, and different markups, being $\iota_a > \iota_b$. Shifting 1 unit of *nominal* demand from a to b will thus cause a reduction of sector a's real demand equal to $1/p_a$ where p_a is the price fixed as a markup over unit variable costs $p_a = (1+\iota_a)\frac{\omega_a}{A_a}$ with ω_a representing the average wage paid by sector a. Therefore the variation of labour demand in sector a is $\Delta N_a = -\frac{1}{\left((1+\iota_a)\frac{\omega_a}{\cancel{A_a}}\right)/\cancel{A_a}} = -\frac{1}{(1+\iota_a)\omega_a}$. Conversely, employment in sector b rises by $\Delta N_b = \frac{1}{(1+\iota_b)\omega_b}$.

However, as a consequence of these changes, profits in sector a decrease by $\Delta\pi_a = -1 - \cancel{\omega_a}\left(\frac{-1}{(1+\iota_a)\cancel{\omega_a}}\right) = -\frac{\iota_a}{1+\iota_a}$ whereas in sector b they increase by $\Delta\pi_b = \frac{\iota_b}{1+\iota_b}$.

Assuming that both wages and profits are completely spent on final demand and no money is hoarded, leads to no change in final demand: $\Delta FD = -\frac{\cancel{\omega_a}}{(1+\iota_a)\cancel{\omega_a}} + \frac{\cancel{\omega_b}}{(1+\iota_b)\cancel{\omega_b}} - \frac{\iota_a}{1+\iota_a} + \frac{\iota_b}{1+\iota_b} = -\frac{\cancel{1+\iota_a}}{\cancel{1+\iota_a}} + \frac{\cancel{1+\iota_b}}{\cancel{1+\iota_b}} = 0$

However, if profits are hoarded for a share equal to $\rho < 1$, then: $\Delta FD = -\frac{1+\rho\iota_a}{1+\iota_a} + \frac{1+\rho\iota_b}{1+\iota_b} > 0$ under the assumption that $\iota_a > \iota_b$.

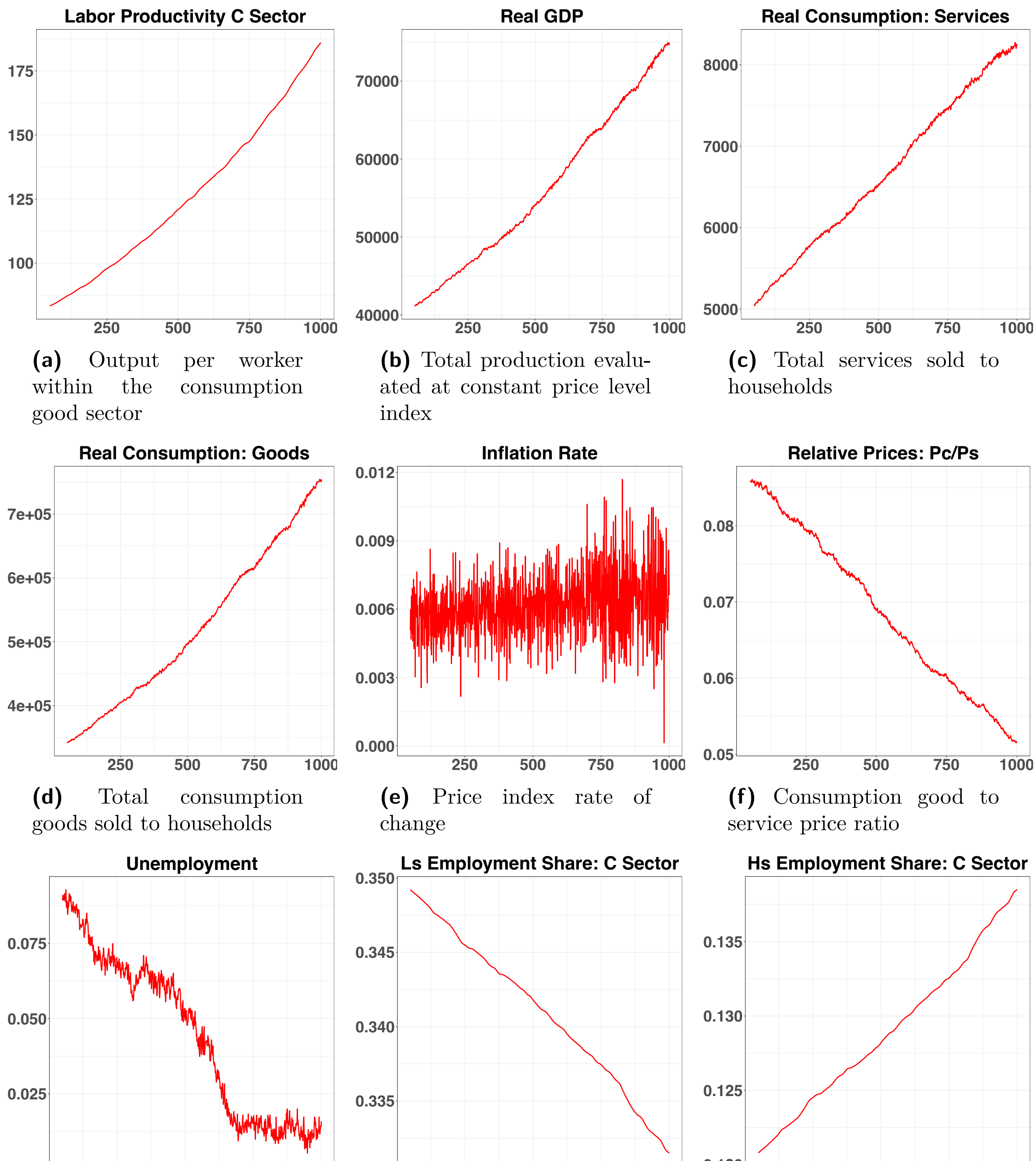
This simplified example clarifies that a shift in nominal demand from a sector with a higher propensity to hoard towards a sector with lower propensity to hoard increases aggregate final demand, whereas differentials in productivity levels and average wages play no role in presence of a markup pricing. One may easily verify that assuming that also wages are partly hoarded does not revert this insight.

them the possibility of funding part of their investment with internal funds, resulting from past undistributed profits. When these funds are actually invested they translate into a demand for the goods produced by the capital sectors thereby sustaining employment, but also profits (that are also partly hoarded), in that sectors. However, firms may frequently abstain from investing when their demand is lower than expected, without reducing for this reason their markup. In this case, revenues will be lower, reducing profits, but the share of them that is hoarded and no longer fuels demand will be higher. In addition, since services are not storable, service firms have to hire some workers in excess compared to their sales expectations, as explained in section 2.4.1, in order to be ready to expand their production if their actual demand proves to be higher than expected.[26] This, per se, may be sufficient to exert a positive effect on employment as demand shifts to services. In addition, this fact also implies that, even when sales expectations prove to be correct, actual profit margins will be lower than the markup applied on expected unit labour costs to set the price because service firms are also paying for workers' idle time. Shifting demand from the manufacturing to the service sector will thus reduce the overall propensity to hoard of the economy, with a positive effect on final demand that, eventually, explains the observe decrease in unemployment levels. Be as it may, our result on employment is in tune with the empirical evidence against robots as job killers (see for example Dauth et al., 2021 and Cords and Prettner, 2022). [27]

[26]There is also a technical reason for assuming this excess capacity: having no inventories, if service firms demanded labour just to the level required to satisfy their expected demand, they would never be able to produce and sell more than expected quantities, and consequently their sales expectations and production levels would never be allowed to grow.

[27]While a different initial markup in the two sectors, or a different excess capacity target for the service sector are unlikely to revert the fundamental properties of our baseline, we cannot exclude that a different, but still plausible, calibration might lead to a different pattern of total unemployment. We would then avoid to put too much emphasis on this results and to connect it to either automation or to the process of structural change undergoing in the model.

Baseline I



(a) Output per worker within the consumption good sector

(b) Total production evaluated at constant price level index

(c) Total services sold to households

(d) Total consumption goods sold to households

(e) Price index rate of change

(f) Consumption good to service price ratio

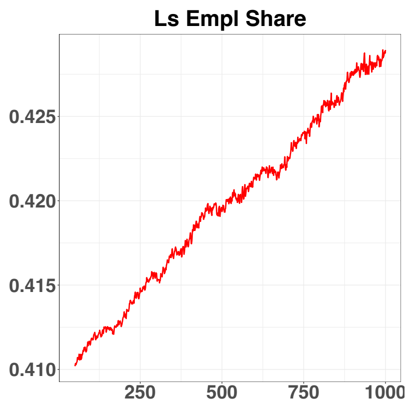
(g) Unemployment rate

(h) Low-skilled occupations share within the consumption good sector

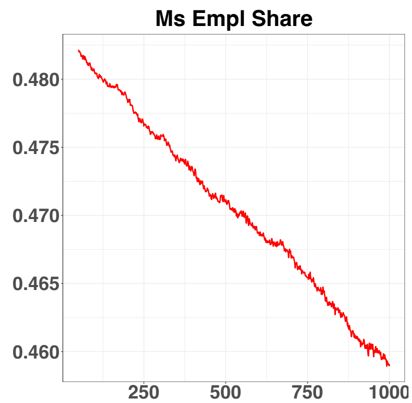
(i) High-skilled occupations share within the consumption good sector

Figure 1: Time series refers to a single simulation run

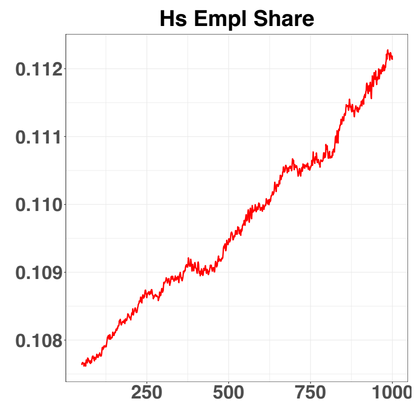
Baseline II



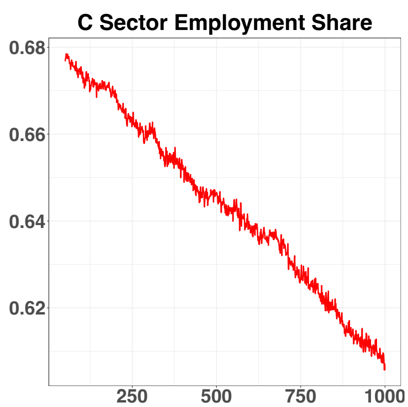
(a) Low-skilled occupations share within the private sector



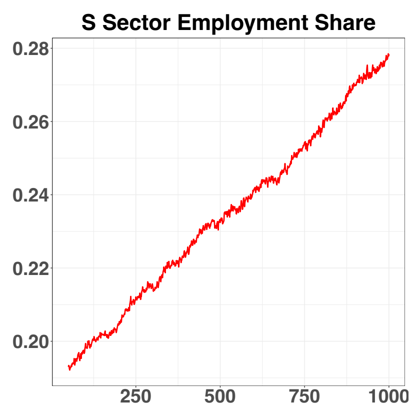
(b) Middle-skilled occupations share within the private sector



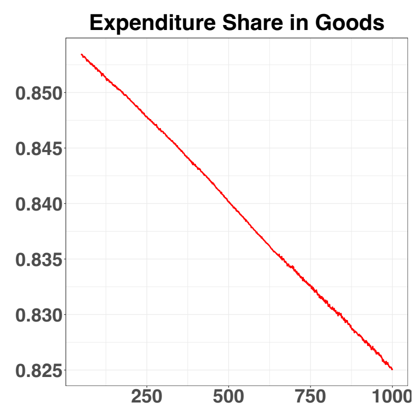
(c) High-skilled occupations share within the private sector



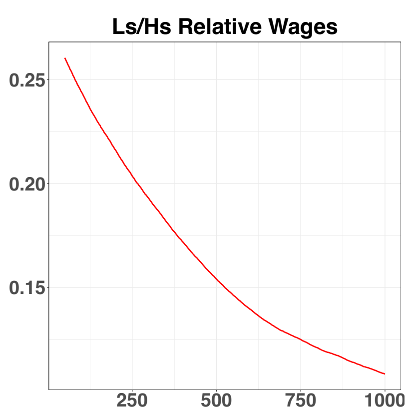
(d) Employment share accruing to the consumption good sector



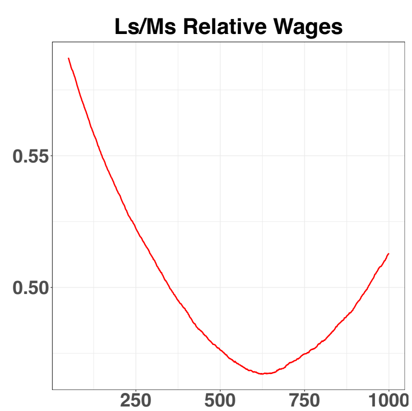
(e) Employment share accruing to the service sector



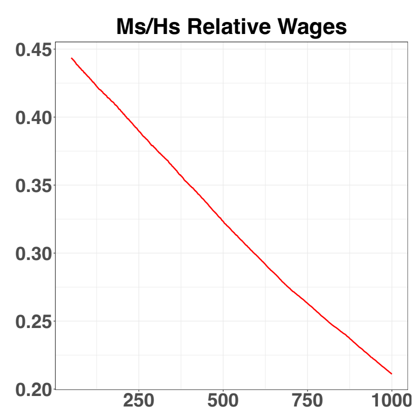
(f) Aggregate nominal demand share allocated to consumption goods



(g) Low-to-high skill average wage ratio



(h) Low-to-middle skill average wage ratio



(i) Middle-to-high skill average wage ratio

Figure 2: Time series refers to a single simulation run

In section 2.4.6 we clarified how technological change embedded in new machines reshapes the employment structure of consumption firms with respect to the skills required for production. Technological change is assumed to be skill-biased: R&D leads to new and more productive machines which, however, require more high-skilled workers and less low-skilled ones.

Thus, consistently with raising productivity within manufacturing, the share of high-skilled workers employed in the consumption good sector increases at the expense of low-skill employment (see plots 1h-1i).

Yet, when we consider the wider economy we observe job-polarisation, that is the growth in the shares of high and low-skill occupations at the expense of middle-skill jobs (see plots 2a to 2c).

The share of high-skill jobs increases as a direct consequence of the skill-biased nature of technological change and the rise of robots. Instead, the growth in the share of low-skill occupations is a consequence of the rise of the employment levels in the personal service sector, relative, in particular, to consumption good producers (plots 2d and 2e). This result is consistent with the empirical observation of Autor and Dorn (2013), according to most of the growth of low-skill occupations in US happened with the personal service sector.

As discussed in section 3.2, personal services are in fact characterised by design by a higher share of low-skilled workers compared to consumption and capital firms. The retrenchment of manufacture and the rise of personal services originates from a shift of part of the final demand from the former to the latter, as documented in plot 2f. This shift, in turn, can be related to the skill-biased nature of the process of automation that enhances job opportunities for high-skilled workers, thereby improving their employment conditions and allowing their their wages to grow faster, relative to middle and low-skilled workers. In turn, as high-skilled workers devote a larger share of their consumption to personal services (equation 6), a distribution of income more favourable to high-skilled eventually shifts aggregate consumption from goods to services. The greater consumption of high-skilled on personal services thus spills over to the employment of low-skilled, along the lines suggested by Mazzolari and Ragusa (2013); Manning (2004); Lee and Clarke (2019). Also, note that automation in the manufacturing sector has been found to generate employment spill-overs in the personal service sector, therefore even this result is consistent with empirical observations.[28]

The model thus generates almost by design job polarisation and structural change as a result of an endogenous process of skill-biased technological progress.

Job polarisation is accompanied by wage polarisation:[29] plots 2h and 2i show that both low and high-skill wages grow relative to middle-skilled ones, at least, from a certain point onwards. Note that σ-wage always refers to the wage paid to σ-occupations, and not necessarily to σ-skilled workers.

Wages in high-skill occupations improve in absolute and relative terms thanks to the growing demand for high-skilled workers coming with automation. Wages of low-skilled, instead, initially decline relative to middle-skilled, as the additional competition coming from middle (and possibly high)-skilled workers who could not find an occupation matching their skills tends to dampen the growth of wages in lower skill labour markets. However, as the rise of low-skill jobs in the service sector progressively improves their employment conditions, wages of low-skilled start to gain ground and the plot represented in 2i displays an increasing trend.[30].

In our model, wage polarisation and job polarisation both emerge from the skill-biased character of automation and the spillovers originated from the consumption of high-skilled workers fostering a process of structural change of the economy from manufactured goods to personal services that eventually creates additional job opportunities for low-skilled expelled by manufacture, but not for middle-skilled.

Plots 3a to 3c show that underemployment represents a sizeable feature of our economy.

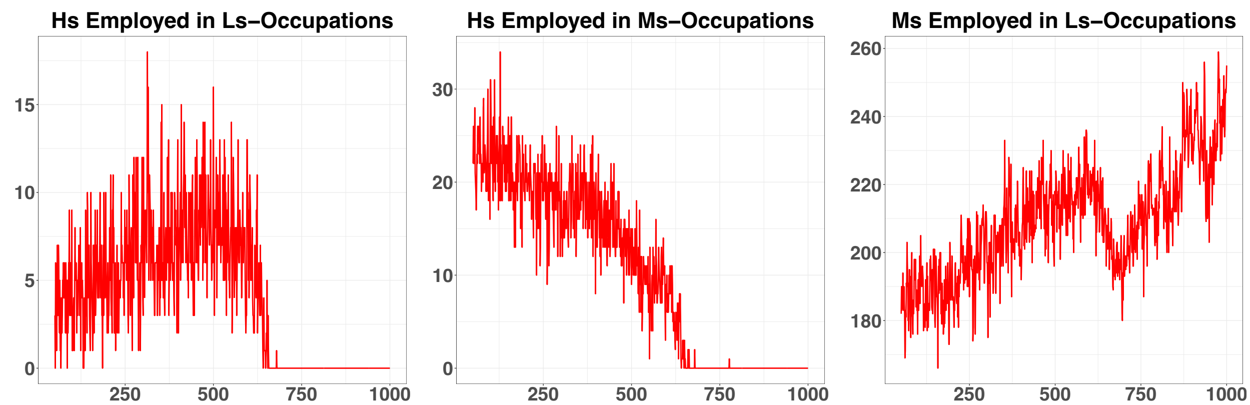
[28]This result can be found in Dauth et al. (2021). For the sake of completeness, we shall add that this type of spill-over has also been found, and even to a larger extent, for the business service sector.

[29]From an empirical point of view, wage polarisation is a well established stylised fact for the US economy (see Acemoglu and Autor, 2011 and Firpo et al., 2011). Wage polarisation has also been found in the UK and continental Europe (see Machin, 2011, Antonczyk et al., 2018, and Dustmann et al., 2009), although admittedly for European countries the evidence is somehow weaker (see Naticchioni et al., 2014).

[30]Wage polarisation seems to be also accompanied by a rise in personal income inequality. Figure 10 in Appendix C reports the wage Lorenz curves for selected points in time. It shows that Lorenz curves move further from the perfect equality line as time elapses, accompanied by a rise in the Gini index that passes from 0.29 of period 200 to 0.48 of period 1000.

Not surprisingly, high-skilled workers seldom rely on labour markets below their preferred one being the growth of high-skill jobs strong and increasing. On the other hand, middle-skilled workers participate in good number on the low-skilled labour market. We observe an upward trend in the number of underemployed middle-skilled workers, which is an effect of job-polarisation: as the demand for middle-skilled workers shrinks, more and more middle-skilled workers are displaced from their preferred occupations. The growth in the service sector however, generates new low-skilled jobs, part of which are taken up by displaced middle-skilled workers.

Baseline III



(a) Number of high-skilled workers employed in low-skilled occupations

(b) Number of high-skilled workers employed in middle-skilled occupations

(c) Number of middle-skilled workers employed in low-skilled occupations

Figure 3: Time series refers to a single simulation run

5 Sensitivity

As a consistency check for the baseline dynamics of the model, we perform a sensitivity analysis on two key parameters, $\sigma^2_{FN^4}$ and γ^h. $\sigma^2_{FN^4}$ determines the skill-bias strength of the innovation process, that is to larger values of $\sigma^2_{FN^4}$ is associated a stronger skill-bias.

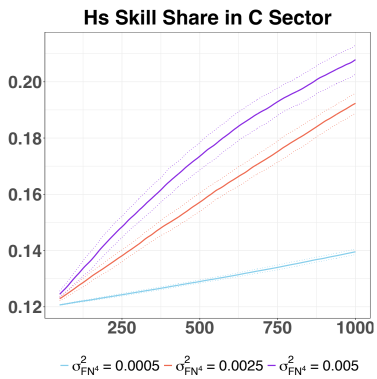
γ^h represents the share of consumption budget allocated to services by high-skilled households. To a larger γ^h is associated a stronger preference for services by high-skilled consumers.

5.1 Skill-bias Sensitivity: $\sigma^2_{FN^4}$

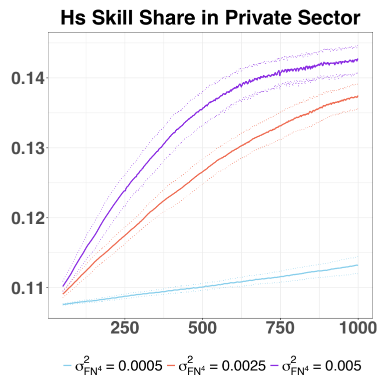
In this sensitivity exercise, we experiment with different $\sigma^2_{FN^4}$, taking values (0.0005, 0.0025, 0.005), with 0.0005 being the baseline value. Each parameter configuration has been run 25 times for 1000 periods.

For the ease of exposition, Figure (4) shows the main time series obtained as means across simulation accompanied by the relative standard deviations. Moreover, table (10) in Appendix F presents the across simulations summary statistics.

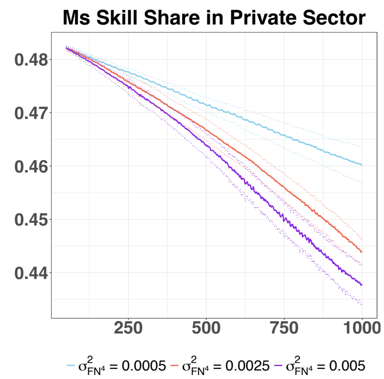
Figure 4: Sensitivity $\sigma^2_{FN^4}$



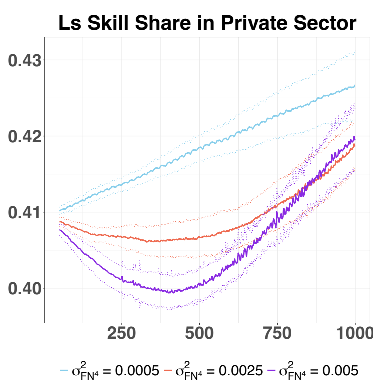
(a) High-skilled occupations share within the consumption good sector



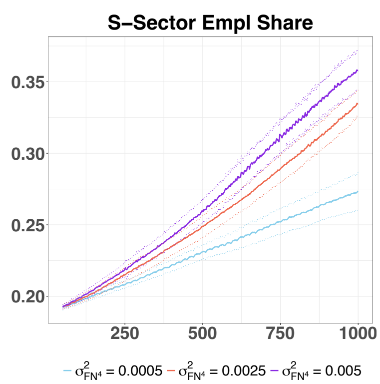
(b) High-skilled occupations share within the private sector



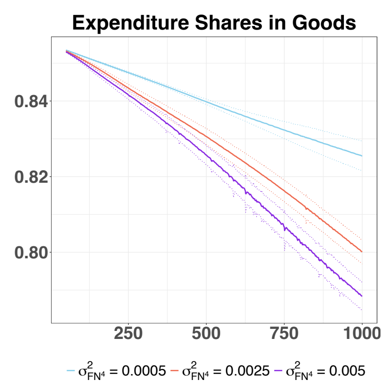
(c) Middle-skilled occupations share within the private sector



(d) Low-skilled occupations share within the private sector



(e) Employment share accruing to the service sector



(f) Aggregate nominal demand share allocated to consumption goods

Each solid line within a plot refers to a particular level of the parameter $\sigma^2_{FN^4}$. Time series are means across Montecarlo simulations. Dotted lines represents ± 1 standard deviations.

Our sensitivity exercise directly influences the share of high-skilled workers pertaining to the consumption good sector, which unsurprisingly turns out to be increasing in $\sigma^2_{FN^4}$ (see plot 4a).

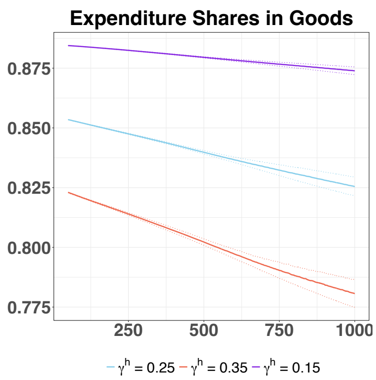
The strength of structural change is also positively related to $\sigma^2_{FN^4}$. For larger parameter values we observe faster growth of the service sector (plot 4e) due to a faster aggregate demand shift from goods to services (plot 4f).

By looking at the aggregate skill-employment composition (plots 4b-4d) we observe that large growth in high-skill employment within manufacturing tends to outweigh the positive structural change effect on low-skill employment. Indeed, for the first part of the simulation, we observe a dynamics consistent with the classical skill-bias adjustment of the labour market. However, as the service sector picks up, the job polarisation dynamics is re-established also in large $\sigma^2_{FN^4}$ scenarios.

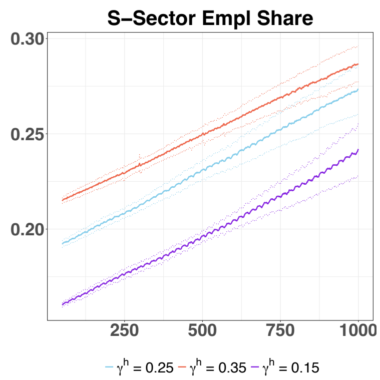
5.2 Consumption Sensitivity: $(\gamma^h, \gamma^m, \gamma^l)$

In this sensitivity exercise we experiment with three different γ^h values: (0.15, 0.25, 0.35), with 0.25 being the baseline configuration.

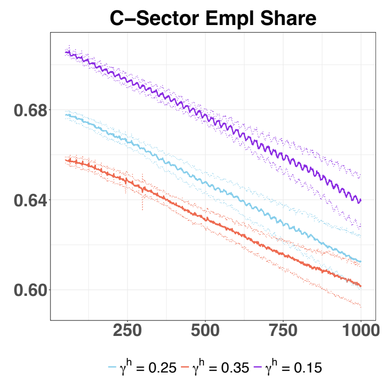
Figure 5: Sensitivity γ^h



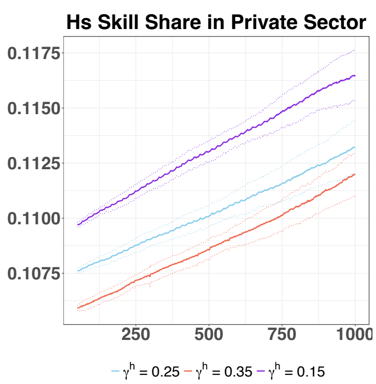
(a) Aggregate nominal demand share allocated to consumption goods



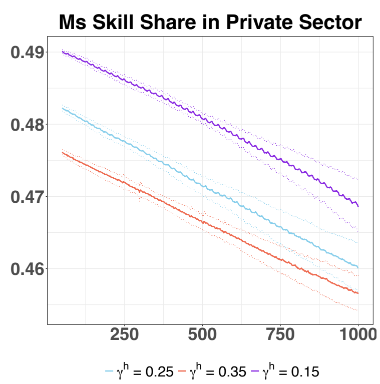
(b) Employment share accruing to the service sector



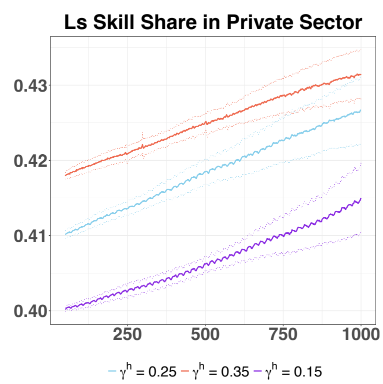
(c) Employment share accruing to the consumption good sector



(d) High-skilled occupations share within the private sector



(e) Middle-skilled occupations share within the private sector



(f) Low-skilled occupations share within the private sector

Each solid line within a plot refers to a particular level of the parameter γ^h. Time series are means across Montecarlo simulations. Dotted lines represents ± 1 standard deviations.

The most direct channel through which γ^h affects the model dynamics is the aggregate demand composition. Lower values of γ^h translates to larger shares of nominal good consumption (see plot 5a).

As aggregate demand shifts away from services, the structural change dynamics slows down: a stronger demand for consumption goods relative to services reduces the growth in the service employment share, favouring the consumption good sector (see plots 5b-5c).

As discussed in section 4, structural change is one of the main engines behind job polarisation. This sensitivity exercise confirms it: to lower service employment shares are associated larger high *and* middle-skill employment shares (see plots 5d-5f). We therefore conclude that low γ^h values tame job polarisation by hampering the structural change effect.

6 Policy Experiment: Introducing a Minimum Wage

As discussed in previous sections, changes in relative wages play a pivotal role in shaping the economy wide response to automation. In this section we will investigate the point more closely, as well as studying possible feedbacks running from relative wages to the automation process and aggregate productivity dynamics.

In order to do so, we experiment a minimum wage policy defined as a peg to the larger wages paid in the economy, that is hs-wages:

$$\begin{cases} w_{z,t} & = max\left(w^d_{z,t}, w^{policy}_t\right) \\ w^{policy}_t & = \psi_p \bar{w}_{hs,t-1} \text{ with } \psi_p \in (0,1) \end{cases} \tag{28}$$

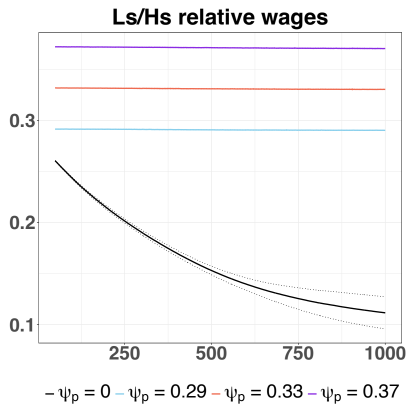
Where w^{policy}_t is the legal minimum wage, ψ_p is an exogenous policy peg, and $\bar{w}_{hs,t-1}$ is the average wage paid to high-skilled workers in the previous period. Let us also remark that $w^d_{z,t}$ is computed as usual, that is by means of equation 1.

Although the policy virtually applies to every worker in the economy, it is very unlikely to affect individuals employed in hs-occupations. On the other hand, it directly affects ls-workers and, for large enough ψ_p, ms-workers. This is not by chance, as the policy design is intended primarily to reduce the spread between ls and hs-wages, given the influence this variable exerts on the aggregate productivity dynamics as well as the pace and strength of automation.

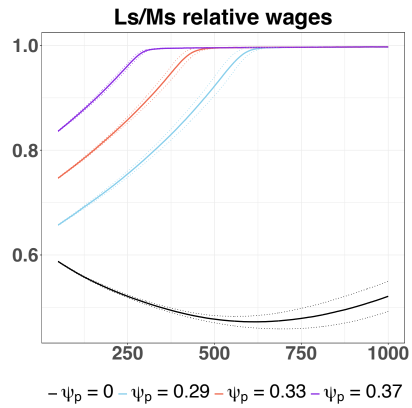
We experiment three policy scenarios where $\psi_p = (0.29, 0.33, 0.37)$, for each scenario we run a Montecarlo experiment of 25 simulations, each of them lasting 1000 periods, as in the baseline scenario discussed in section 4.

The first set of results is described in Figure 6, where we plot the main time series obtained as means across simulation $+/-$ one standard deviation. Summary statistics for these experiments are also reported in table 12.

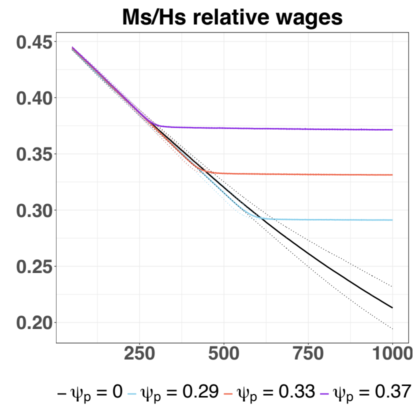
Figure 6: Policy I



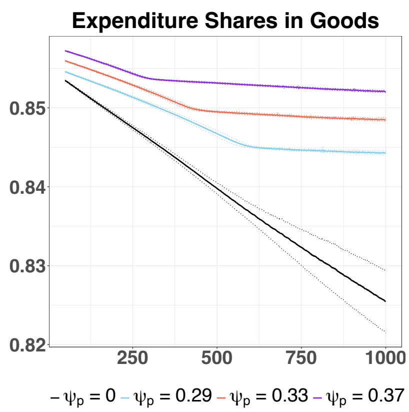
(a) Low-high skill average wage ratio



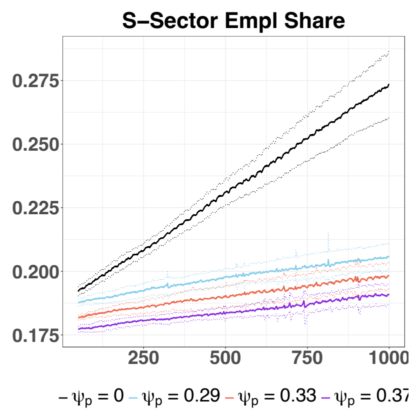
(b) Low-Middle skill average wage ratio



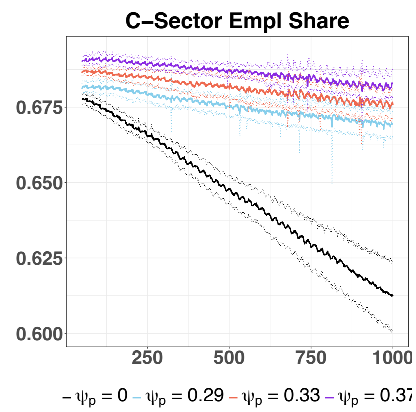
(c) Middle-high skill average wage ratio



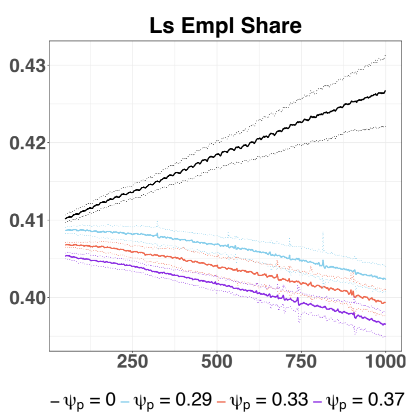
(d) Aggregate nominal demand share allocated to consumption goods



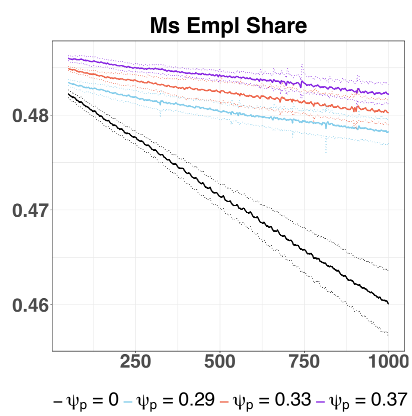
(e) Employment share accruing to the service sector



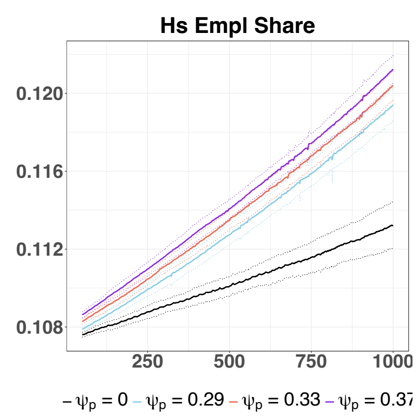
(f) Employment share accruing to the consumption good sector



(g) Low-skilled occupations share within the private sector



(h) Middle-skilled occupations share within the private sector



(i) High-skilled occupations share within the private sector

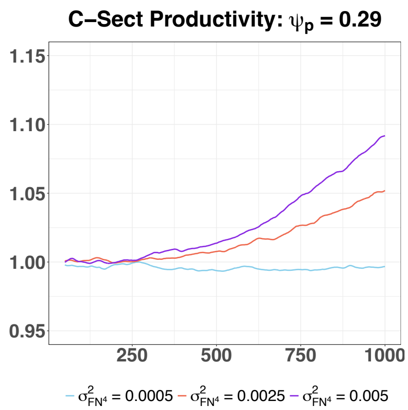
Each solid line within a plot refers to a particular level of the policy ψ_p. Time series are means across Montecarlo simulations. Dotted lines represents ± 1 standard deviations.

6.1 Minimum Wage, Skill-Bias, and Productivity

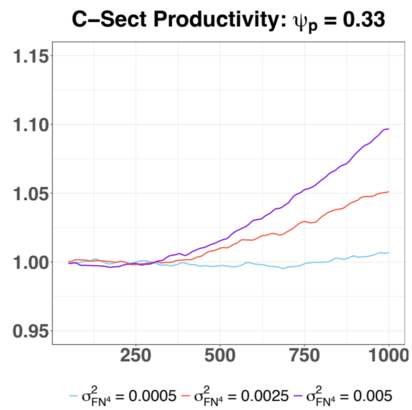
The most direct effect exerted by the policy is on the ls/hs and ms/hs relative wages, which by design turn out to be larger in policy scenarios relative to the baseline and linearly increasing in ψ_p (plots 6a-6c). These changes in relative wages tend to dampen the speed at which aggregate demand shifts from manufactured goods to services (plot 6d). This in turn affects the strength of the structural change process from high-productivity manufacturing to low-productivity personal services: indeed in the baseline scenario the service employment share grows at a faster pace than in policy scenarios, moreover larger values of ψ_p are associated to lower service employment shares (plots 6e-6f).

A slower structural change process has important repercussions on the labour market, in particular as far as job-polarisation is concerned: as the service sector growth shrinks - relative to the baseline scenario - so does the share of low-skill employment. As a result, the labour market ceases to polarise and shows the usual skill-biased shape (plots 6g-6i).

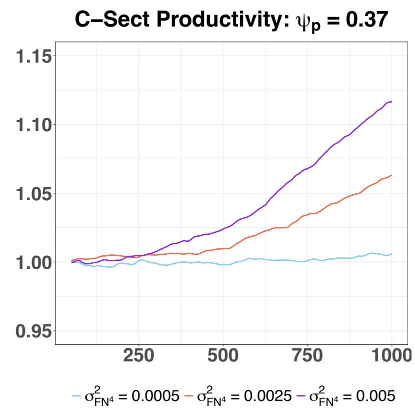
Figure 7: Policy II



(a)

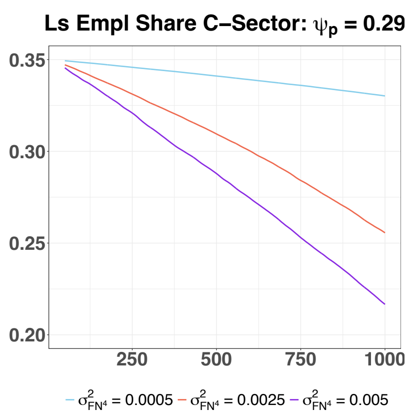


(b)

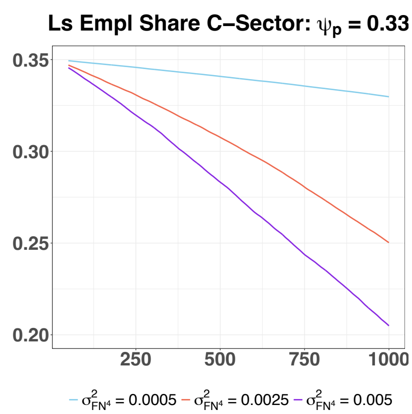


(c)

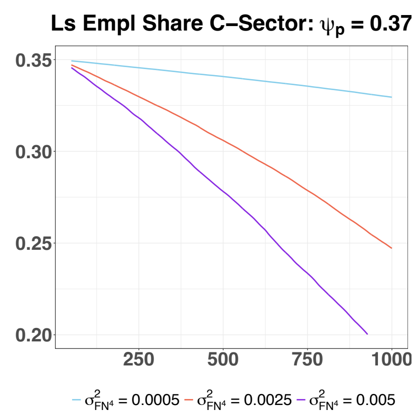
Output per employed worker within the consumption good sector



(d)



(e)



(f)

Share of low-skilled occupations within the consumption good sector

Each plot refers to a particular level of the policy ψ_p and contains one time series for each skill-bias parameter value $\sigma^2_{FN_4}$ employed.
Time series are means across Montecarlo simulations.
Time series are expressed as ratios between policy vs policy free experiments.

Besides the effects on the sectoral composition of demand and employment, the analysis of the impact exerted by a minimum wage on labour productivity is particularly interesting. We analyse it both in terms of aggregate productivity, that is real GDP per employed worker, and in terms of productivity within manufacture, measured as output per employed worker within the consumption good sector.

In order to explore these effects, we intersect the sensitivity exercise on the skill-biased parameter $\sigma^2_{FN_4}$ proposed in section 5.1, with the minimum wage policy. In this way, we are able to better characterise the policy effect and to link it with a central characteristics of the innovation process, that is the skill-bias strength of automation.

Why should the minimum wage constitute a push for automation? Recall that technological innovations occurs following a random process, but they are not necessarily sold by capital good producers or adopted by manufacturing firms. This is so, because an innovation is not automatically efficient from a production view point. Increasing productivity is an obvious positive feature for manufacturing firms, however it comes with the cost of larger hs-skill labour requirement. In a way, automation reduces and increases unit costs of production at the same time and what matters for firms is which effect dominates the other. Moreover, the very same innovation, which is a capital vintage embedding a given productivity gain and given skill-bias, might be efficient or not depending on economic conditions and in particular on relative wages. As a matter of fact, when the distance between low and high skill wages increases, economically efficient innovations are harder to be discovered, since for a given level of skill-bias, larger productivity leaps are required. Therefore, if the cost of high-skilled is very high relative to low-skilled, it might be the case that an automated technology, though more productive, entails greater unit labour costs to be operated and hence it is not adopted. A minimum wage policy, by reducing wage dispersion, makes this circumstance more unlikely to occur (by making high-skilled relatively cheaper or, vice-versa, low-skilled more expensive) and favours the adoption of new technologies and the rise in productivity levels. Such a microeconomic effect has been also identified in the recent empirical literature, see for example Lordan and Neumark (2018)) who find that minimum wage stimulates the adoption of automated technologies (to replace low-skilled workers) or Deng et al. (2021) who find that manufacturing plants impacted by the introduction of a minimum wage in 2015 were more prone to adopt robots.

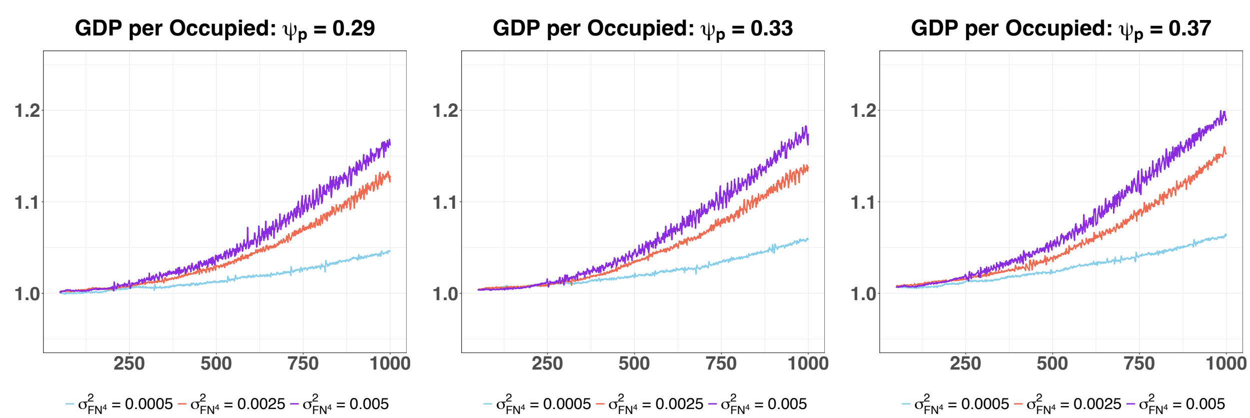
Another channel through which the minimum wage policy can affect productivity is via its demand composition effect: by shifting demand in favour of manufacturing goods, investment on capital items should increase and, since the frequency of discoveries is a positive function of investment, this might accelerate the overall innovation process.

Plots 7a-7c show that the minimum wage policy is associated with larger productivity within the manufacturing sector. Moreover, such effect is more visible when the skill-bias is stronger, which is consistent with our previous discussion. Indeed, when innovations entail larger increases in the share of hs-workers for given productivity gain, relatively small deviations between hs and ls wages can undermine the economic efficiency of newly discovered capital vintages, which are therefore discovered but never diffused.

Also, let us point out that the result on productivity is not just a random occurrence, that is a series of lucky draws as far as productivity gains are concerned. Faster productivity growth reflects indeed the faster pace of automation, which is in turn reflected by lower (larger) low (high) skill employment shares within the manufacturing sector (plots 7d-7f). Notice indeed, that to faster productivity growth are associated lower low-skill employment shares, moreover when the policy is not able to affect productivity, neither it affects the employment composition within the manufacturing sector.

Therefore, our minimum wage policy can help the diffusion of productivity enhancing technologies where decentralised market outcomes fail to provide the incentives for firms to adopt them.

Figure 8: Policy III



(a) **(b)** **(c)**

GDP produced per employed worker in the whole economy

Each plot refers to a particular level of the policy ψ_p and contains one time series for each skill-bias parameter value $\sigma^2_{FN_4}$ employed.
Time series are means across Montecarlo simulations.
Time series are expressed as ratios between policy vs policy free experiments.

Not surprisingly, the faster automation pace associated with the minimum wage policy translates in larger aggregate productivity, measured by GDP per employed worker. By comparison of Figures 7 and 8, however, two non obvious observations emerge: the effect on aggregate productivity is larger than the effect on productivity within manufacture and a non negligible positive effect on aggregate productivity is detected also when there is no effect on productivity within manufacture.

Those facts suggest that technological innovation is not the sole force behind stronger aggregate productivity growth and that the minimum wage policy operates also trough another channel. As often in this paper, such channel is a structural change type of mechanism. Recall, that the minimum wage policy reshapes the aggregate demand composition, by curbing the shift from goods to services. Also, manufacture is assumed to be the relatively higher productivity sector. It follows that a larger share of GDP produced by manufacture implies larger aggregate productivity.

To conclude, a minimum wage policy has the potential to boost aggregate productivity: first and foremost, because of its positive effect on technological innovations, or, to be more precise, on its positive effect on the *adoption* of technological innovations. Secondly, the minimum wage policy redirects aggregate demand towards high productive sectors, which has an obvious positive effect on aggregate productivity.

6.2 Minimum Wage, Consumption Preferences, and Productivity

Up to now, we have interacted the minimum wage policy with the skill-bias parameter, finding a positive effect on productivity. Such effect can be disentangled in two distinct mechanisms: a supply-driven mechanism regarding the economic efficiency of innovations, and a demand-driven mechanism linking income distribution, demand composition and structural change.

In this section we wish to isolate the demand-driven mechanism in order to show its stand-alone relevance. This time, we interact the minimum wage policy with different values for the parameters (γ^l, γ^m), for a given skill bias $\sigma^2_{FN_4}$[31].

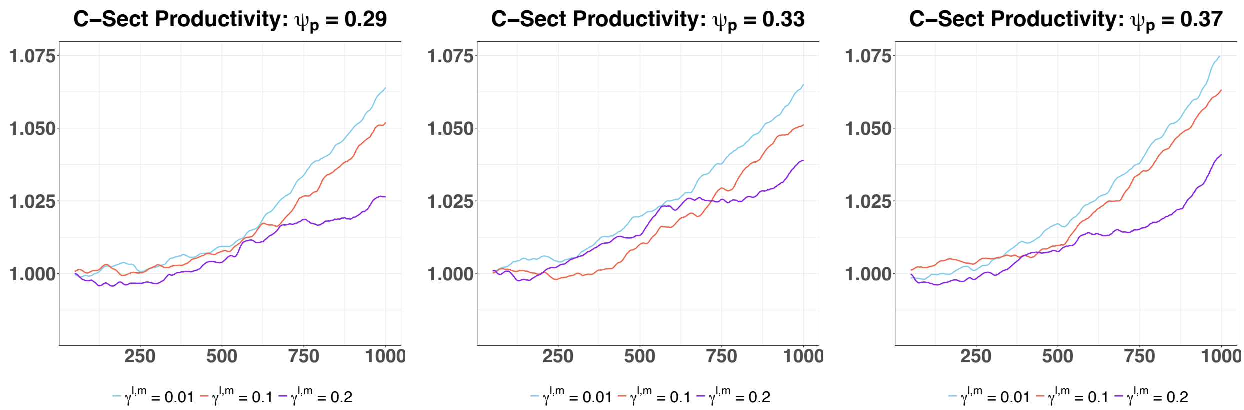
[31] In the presented battery of experiments we fixed $\sigma^2_{FN_4}$ to the value 0.0025.

By fixing $\sigma^2_{FN_4}$, we, to some extent, control for the supply-driven effect. On the other hand, by varying the parameters (γ^l, γ^m) we modulate the demand composition effect. Indeed, for given relative wages, lower values of (γ^l, γ^m) are associated to aggregate demand shifts towards goods (relative to services) and vice-versa.

The condition $\gamma^l = \gamma^m$ holds across the sensitivity exercise, the values assigned to (γ^l, γ^m) are (0.01, 0.10, 0.20), with 0.10 being the value set outside this sensitivity exercise. For each (γ^l, γ^m) value, we run a policy-free scenario and the usual three policy scenarios, where $\psi_p = (0.29, 0.33, 0.37)$.

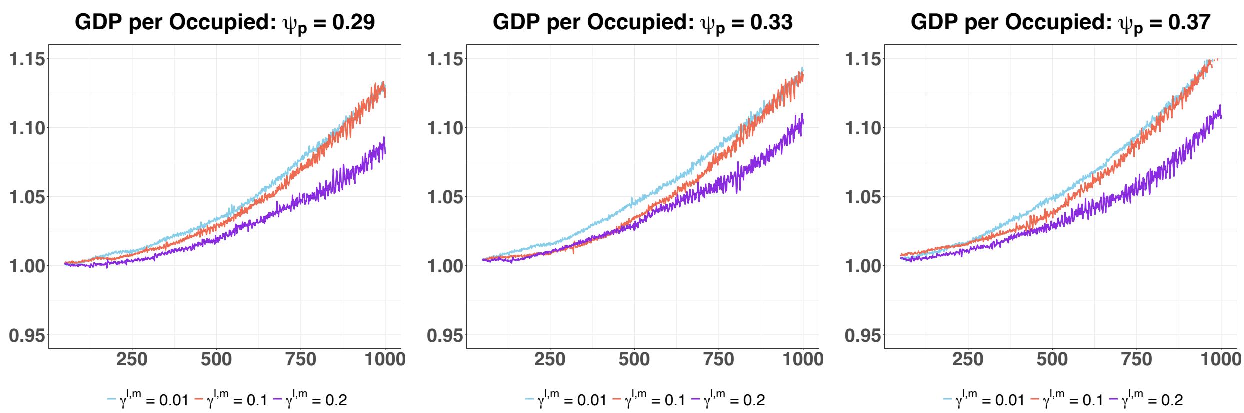
Figure 9 reports results for productivity within manufacture and aggregate productivity, time series refers to means across 25 Montecarlo simulations, each lasting 1000 periods. For the ease of exposition, productivities are expressed as ratios with respect to the policy free scenarios.

Figure 9: Policy IV



(a) (b) (c)

Output per employed worker within the consumption good sector



(d) (e) (f)

GDP produced per employed worker in the whole economy

Each plot refers to a particular level of the policy ψ_p and contains one time series for each service preference parameter value (γ^l, γ^m) employed.
Time series are means across Montecarlo simulations.
Time series are expressed as ratios between policy vs policy free experiments.

Plots 9d- 9f shows that GDP per employed worker (i.e. aggregate productivity) tends to be larger for larger values of the policy parameter ψ_p and for smaller (γ^l, γ^m), that is when ls and ms-households have stronger preferences towards goods with respect to services. Similarly, we observe a stronger policy effect on productivity within manufacturing for lower (γ^l, γ^m) (plots 9a-9c).

Results show that the policy is less effective when middle and low-skilled workers dedicate a greater shares of their consumption to personal services, which makes them more similar to high-skilled and thus reduces the ability of the policy to counteract, by shifting the distribution of income in favour of middle and low-skilled, the fall in the demand for manufactured goods. Conversely, a minimum wage tends to be more effective when middle and low-skilled workers dedicate lower share to personal services and a greater one to manufactured goods, and shifting the distribution of income thus generates a greater effect on the sectoral composition of demand.

To recap, our policy experiments show that a minimum wage policy can in principle boost productivity, both within manufacturing and in the aggregate. However, such positive effect operates through two distinct channels, a supply-driven and a demand-driven types of mechanism. It follows that, for the minimum wage policy to be effective, technological innovations must be sufficiently skill-bias and of the kind assumed in the paper. From the demand side perspective, instead, policy effectiveness requires larger propensity to consume manufactured good for low/middle-income households relative to higher income ones.

7 Conclusions

Our paper proposes a rich and coherent framework for studying issues related to structural change, technological innovations and labour market adjustments. It contributes to various strands of literature, ranging from Agent-Based macroeconomics, job polarisation, evolutionary technical change, skill-biased technical change, automation, and demand-driven structural change.

Model design and calibration were driven by available empirical evidence and, besides the standard validation exercises, our simulations seem able to replicate and explain several important stylised facts within these strands of literature: (i) the emergence of job polarisation as a by product of automation; (ii) how automation can trigger a demand-driven structural change process from manufacturing to personal services; (iii) how a structural change of this type can feedback in the labour demand and complement the automation process in determining labour market polarisation.

From the modelling side, our work introduces several interesting novel aspects compared to the previous literature: (i) we introduce heterogenous consumption preferences. As suggested by the consumption spill-over literature (Mazzolari and Ragusa, 2013), we assumed high-skilled workers to be endowed with stronger preferences for personal services than the rest of the population; (ii) we introduce a personal service sector, generating low-skill employment growth (see Autor and Dorn, 2013). Consistently, we assume the service sector to disproportionately employ low-skill labour, as suggested by BLS data presented in the paper; (iii) we show how these dynamics are often mediated by changes in the wage-distribution, which are at the same time effects and causes of the aforementioned aggregate dynamics.

The key role played by wage distribution gave us the opportunity to experiment with minimum wage policies and investigate some related effects. Minimum wage policies can exert a positive effect both on aggregate productivity and the automation process. The former effect simply uncloaks an implication of structural change, which, being weaker under the minimum wage policy regime, favours a more productive sectorial composition of the economy.

The latter effect, consistently with the empirical findings of Lordan and Neumark (2018) and Deng et al. (2021), highlights that by narrowing the spread between low and high-skill wages, we actually make automation more attractive and therefore set the right incentives for stronger productivity growth within manufacture.

However, our paper remains almost silent on several relevant issues linked to automation, among which technological unemployment undoubtedly stands out. The reason lies in a set of limitations affecting the current framework, which are essential to appreciate how automation affects total employment and which we hope to overcame in the future: (i) we assumed no labour barriers across sectors; (ii) individuals in the model are exogenously assigned to a skill level, that is they neither have the opportunity of learning new skills, nor they face the risk of loosing those acquired; (iii) we do not model explicitly the link between automation and functional distribution, the former being central in determining aggregate demand and therefore aggregate employment in the model.

To conclude, we believe such limitations to be much relevant when studying the effects of automation on aggregate employment. However, our focus is on employment composition, for which such abstractions seem to be less harmful. Indeed, our model, despite the limitations, is able to replicate stylised facts concerning job polarisation and structural change, bridge them through a common technological root, and shed some light on the positive effect of minimum wage on productivity.

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A Appendix: Completing the Model

This appendix completes the description of the model. The behavioural equations presented hereafter are taken from the parent models Caiani et al. (2016) and Caiani et al. (2019), although slight modification are introduced in order to accommodate for service firms.

A.1 Expectations and market interactions

As in the original models we started from (Caiani et al., 2016, 2019, 2020), expectations are formed in an adaptive way, following:

$$x_t^e = x_{t-1}^e + \lambda \left(x_{t-1} - x_{t-1}^e \right) \tag{29}$$

where λ defines an exogenous and time-invariant parameter, homogenous across agents.

With the exception of the labour market (see section, 2.3), every market is modelled through a decentralised matching mechanism, where demanders observe prices and use them to select suppliers. The mechanism is the same employed in previous versions of the model: following Riccetti et al. (2015), we assume that any demander observes prices offered by her previous suppliers and a subset of the population of χ potential suppliers.

In the consumption, service, and credit markets, among the χ selected potential suppliers, the demander singles out the agent offering the lower price and compare it with the price offered by her previous supplier. If the price offered by the new supplier, P_n, is lower than the price offered by the old one, P_o, the demander switches to the new supplier with a probability defined as an increasing, non-linear function of the difference between the two prices:

$$Pr_s = \begin{cases} 1 - e^{\epsilon\left(\frac{P_n - P_o}{P_n}\right)} & \text{if } \; P_n < P_o \\ 0 & \text{Otherwise} \end{cases} \tag{30}$$

Where ϵ is an intensity of choice exogenous parameter. In the deposit market, since the price (the interest rate) corresponds to a rate of return, demanders prefer suppliers offering higher interests and equation 30) thus becomes:

$$Pr_s = \begin{cases} 1 - e^{\epsilon\left(\frac{P_o - P_n}{P_o}\right)} & \text{if } \; P_o < P_n \\ 0 & \text{Otherwise} \end{cases} \tag{31}$$

The selection of suppliers in the capital good market, which should consider also the technical features of the vintage, besides its price, follows the slightly more complex rule already described in section 2.4.5.

A.2 Firms

A.2.1 Profits and dividends

Consumption firms pre-tax profits are the sum of revenues from sales, interest received, and the nominal variation of inventories, minus wages, interest paid on loans, and capital amortization:

$$\pi_{c,t} = s_{c,t}p_{c,t} + i^d_{b,t-1}D_{c,t-1} + \Delta ninv_{c,t} - \sum_{\sigma} w^{\sigma}_t N^{\sigma}_{c,t} - ipayments_{c,t} - amcosts_{c,t} \tag{32}$$

Where $\pi_{c,t}$ are pre-tax profits realised at time t, $s_{c,t}$ are realised sales, $i^d_{b,t-1}$ is the interest rate paid on deposits by c's bank b, $D_{c,t-1}$ is c's total amount of deposits, $\Delta ninv_{c,t}$ is the variation in nominal inventories, $ipayments_{c,t}$ are c's interest payment due in t, and $amcosts_{c,t}$ are capital amortization costs. More specifically we have:

$$\begin{cases} \Delta ninv_{c,t} = inv_{c,t}uc_{c,t} - inv_{c,t-1}uc_{c,t-1} \\ \\ ipayments_{c,t} = \sum_{j=t-\eta}^{t-1} i^l_j L_{c,j} \frac{\eta - [(t-1)-j]}{\eta} \\ \\ amcosts_{c,t} = \sum_{\kappa \in \kappa_{c,t}} (K_{c,\kappa,t} p_{\kappa}) \frac{1}{\delta_{\kappa}} \end{cases}$$

Where η is the exogenous loans duration, i^l_j the interest rate charged on loan $L_{c,j}$, which in turn represent the credit obtained by firm c at time j, and p_κ is the price paid for one unit of capital belonging to vintage κ.

We assume that capital items stored as capital firms' inventories do not depreciate, therefore capital firms compute pre-tax profits using a slightly modified version of equation (32), where the term *amcosts* is not accounted for. We assume that service firms do not hold capital items and inventories, therefore the service firms' profit equation is obtained by getting rid of the terms $\Delta ninv$ and *amcosts* from equation (32).

If pre-tax profits turn out to be positive, firms pay taxes to the government which are set as $Tax_{x,t} = max\,(\tau_\pi \pi_{x,t}, 0)$. Where τ_π is the exogenous time-invariant tax rate on profits. Moreover, whenever profits are positive dividends are distributed to households as described in section 2.3. The total amount of redistributed profits is given by $Div_{x,t} = max\,(\rho_{\Phi_x} \pi_{x,t}(1 - \tau_\pi), 0)$, where ρ_{Φ_x} is the exogenous, time-invariant, sector specific share of distributed profits.

A.2.2 Credit Demand and Bankruptcies

Following Fazzari et al. (1988) empirical evidence about the pecking order theory of finance set out by Myers (1984), we assume that firms resort to expensive external financing only when internal funding are not enough to cover financial needs. Moreover, we assume that firms wish to retain a certain share Υ of total wage disbursement for precautionary reasons:

$$L^D_{x,t} = I^D_{x,t} + Div^e_{x,t} + \Upsilon W_{c,t} - OCF^e_{x,t} \tag{33}$$

Where $L^D_{x,t}$ is credit demanded by firm x at time t, $Div^e_{x,t}$ are expected dividends, $W_{c,t}$ is total labour costs[32], and $OCF^e_{x,t}$ are total expected cash flows.

[32]Note that unlike in the parents model, labour costs at this stage are not expected, but actual. This is because in the current model wages are not determined by a decentralised mechanism and at the stage in which credit demand needs to be formulated both labour demand and wages are known. However, in

Note the since capital and service firms do not invest, the term $I^D_{x,t}$ in equation (33) is always set to 0 for $x = s, k$.

Any time firms runs out of the liquidity needed to pay wages, interest coming due or taxes they are forced into bankruptcy and bailed out by households following the same mechanism described in Caiani et al. (2016).

A.3 Banks

A.3.1 Credit Supply

Banks assess each credit demand coming from firms and decide whether to satisfy the demand in full, to satisfy only part of the demand, or to outright reject the loan request.

In the first stage banks evaluate the probability of default at each point in time for the whole duration of the loan requested, which is given by the parameter η and set exogenously to 20 periods. Let us define the debt service variable as the first tranche of payment associated to the hypothetic loan as $ds^{L^D} = \left(i^l_{b,t} - \frac{1}{\eta}\right) L^D$. The probability of a default in each of the 20 periods ahead is then computed using a logistic function, based on the percentage difference between borrowers' cash flows and debt service:

$$Pr^d_{x,t} = \frac{1}{1 + exp\left(\frac{OCF_{x,t} - \zeta_{\Phi_x} ds^{L^D}}{ds^{L^D}}\right)} \tag{34}$$

Where ζ_{Φ_x} is an exogenous, time-invariant, sector specific risk aversion parameter, the higher ζ_{Φ_x} the more banks are risk averse with respect to firms belonging to sector Φ_x.

Using $Pr^d_{x,t}$ banks are able to calculate the expected return to each requested loan.Banks are willing to satisfy agents' demand for credit whenever the expected return is greater or equal than zero. Otherwise, the bank may still be willing to provide some credit, if there exists an amount LD^* for which the expected return is non-negative.

principle there still exists a source of uncertainty at this stage, indeed labour markets have not opened yet, therefore firm x maybe labour constrained so that its labour demand may not coincide with its labour force. Since in our simulation firms are never labour constrained we decided to disregard such source of uncertainty.

A.3.2 Interests Setting

Banks set interest rates on loans and deposits, in the former case they use their own capitalization as reference variable: When banks are more capitalized than desired, they offer an interest rate lower than their competitors' average thus trying to expand further their balance sheet by attracting more customers on the credit market. In the opposite case firms want to reduce their exposure: a higher interest rate has the twofold effect of making bank's loans less attractive while increasing banks' margins. Therefore:

$$i^l_{b,t} = \begin{cases} \bar{l}^l_{b,t}\left(1 + FN^5_{b,t}\right) & \text{if} \quad CR_{b,t} < CR^T_t \\ \\ \bar{l}^l_{b,t}\left(1 - FN^5_{b,t}\right) & \text{Otherwise} \end{cases} \tag{35}$$

Where $CR_{b,t}$ is the b's current capital ratio and CR^T_t is the common target, defined as the past period sector average. $\bar{l}^l_{b,t}$ is the past period average interest rate on loans and $FN^5_{b,t}$ is a random draw from a folded normal distribution $(\mu_{FN^5}, \sigma_{FN^5})$.

The interest rate on deposits is set following a similar logic, where the liquidity ratio $LR_{b,t}$ is the reference variable. We assume a compulsory lower bound for liquidity ratio equal to 8%. Besides the mandatory lower bound, a common liquidity target LR^T_t defined as the sector average in the last period. When the liquidity ratio is below the target banks set their interest on deposits as a stochastic premium over the average interest rate in order to attract customers, and vice-versa when banks have plenty of liquidity:

$$i^d_{b,t} = \begin{cases} \bar{i}^d_{t-1}\left(1 + FN^5_{b,t}\right) & \text{if} \quad LR_{b,t} \geq LR^T_t \\ \\ \bar{i}^d_{t-1}\left(1 - FN^5_{b,t}\right) & \text{Otherwise} \end{cases} \tag{36}$$

Where $\bar{l}^d_{b,t}$ is the past period average interest rate on deposits and $FN^6_{b,t}$ is a random draw from a folded normal distribution $(\mu_{FN^5}, \sigma_{FN^5})$.

A.3.3 Bonds Demand, Dividends, and Bankruptcies

We assume that banks use their reserves in excess of their target (after repayment of previous bonds by the government) to buy government bonds.

Banks pre-tax profits $\pi_{b,t}$ are given by the sum of the interests received on loans and bonds, minus interests paid on deposits and cash advances. Banks' taxes are calculated as $Tax_{b,t} = max\left(\tau_\pi \pi_{b,t}, 0\right)$. Moreover, whenever profits are positive dividends are distributed to households as described in section 2.3. The total amount of redistributed profits is given by $Div_{b,t} = max\left(\rho_{\Phi_b}\pi_{x,t}(1-\tau_\pi), 0\right)$, where ρ_{Φ_b} is the exogenous, time-invariant, sector specific share of distributed profits.

Whenever a bank's net-wealth turns out to be negative, such bank is forced into bankruptcy and it's bailed out by households as in Caiani et al. (2016).

B Appendix: Service/Capital Sector Production Function

Let us recall the Leontief production function characterizing the capital and service sectors (equation 10):

$$y_{x,t} = min\left(A^l_x N^l_{x,t}, A^m_x N^m_{x,t}, A^h_x N^h_{x,t}\right) \quad \text{with} \quad x = \{s, k\}$$

Given the Leontief technology, different types of labour are employed efficiently when:

$$y_{x,t} = A^l_x N^l_{x,t} = A^m_x N^m_{x,t} = A^h_x N^h_{x,t} \tag{37}$$

This occurs when labour is employed so to respect the labour shares that characterise the technology (the recipe of production), that is if:

$$\frac{N^l_{x,t}}{N^l_{x,t}+N^m_{x,t}+N^h_{x,t}}=\alpha^l_x \quad ; \quad \frac{N^m_{x,t}}{N^l_{x,t}+N^m_{x,t}+N^h_{x,t}}=\alpha^m_x \quad ; \quad \frac{N^h_{x,t}}{N^l_{x,t}+N^m_{x,t}+N^h_{x,t}}=\alpha^h_x \tag{38}$$

We can then divide the identities in 37 by $\left(N^l_{x,t}+N^m_{x,t}+N^h_{x,t}\right)$, obtaining:

$$\frac{y_{x,t}}{N^l_{x,t}+N^m_{x,t}+N^h_{x,t}}=A^l_x\underbrace{\frac{N^l_{x,t}}{N^l_{x,t}+N^m_{x,t}+N^h_{x,t}}}_{=\alpha^l_x}=A^m_x\underbrace{\frac{N^m_{x,t}}{N^l_{x,t}+N^m_{x,t}+N^h_{x,t}}}_{=\alpha^m_x}=A^h_x\underbrace{\frac{N^h_{x,t}}{N^l_{x,t}+N^m_{x,t}+N^h_{x,t}}}_{=\alpha^h_x} \tag{39}$$

We indicate the left-hand term of these identities by $\mu_x=\frac{y_{x,t}}{N^l_{x,t}+N^m_{x,t}+N^h_{x,t}}$

Therefore, μ_x represents the output producible by jointly employing α^l_x units of low-skill labour, α^m_x units of middle-skill labour, and α^h_x units of high-skill labour. Given that $\alpha^l_x+\alpha^m_x+\alpha^h_x=1$ by definition, μ_x can be interpreted as the output producible with one unit of labour, that is the productivity of total labour, when this is split between different skill groups so to respect the proportions required by the technology of production, i.e. when labour is employed efficiently.

Solving the identities 39 for productivities, we have:

$$A^l_x=\frac{\mu_x}{\alpha^l_x} \quad ; \quad A^m_x=\frac{\mu_x}{\alpha^m_x} \quad ; \quad A^h_x=\frac{\mu_x}{\alpha^h_x} \tag{40}$$

Substituting 40 into equations 10 and 11 we obtain the formulas for the production function and firms' labour demand as functions of the labour shares displayed by equations 12 and 13.

$$y_{x,t}=\mu_x min\left(\frac{N^l_{x,t}}{\alpha^l_x},\frac{N^m_{x,t}}{\alpha^m_x},\frac{N^h_{x,t}}{\alpha^h_x}\right)$$

$$N^{D,\sigma}_{x,t}=y^D_{x,t}\frac{\alpha^\sigma_x}{\mu_x}$$

C Lorenz Curves

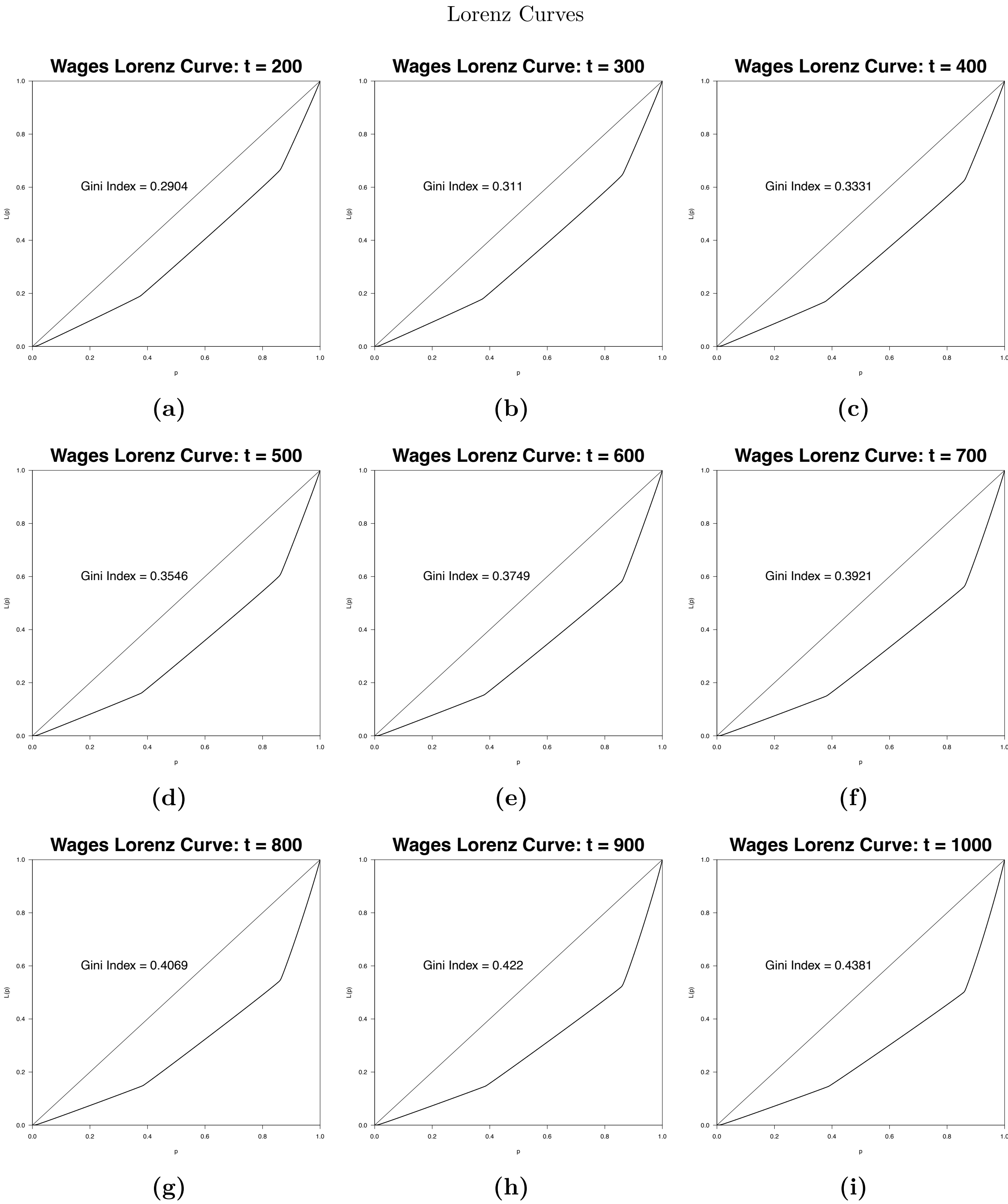


Figure 10

D Parameters and stock-flow calibration

Table 5: Aggregate balance sheet matrix at t=0

	Hh	cFirms	sFirms	kFirms	Banks	Gov	CB	$\sum$
Deposits	34006.2	18472	3828.3	3694.4	-60000.9	0	0	0
Loans	0	-40689.1	-515.3	-1288	42492.3	0	0	0
c Goods	0	2213	0	0	0	0	0	2213
k Goods	0	39613.6	0	369.4	0	0	0	39983.1
Bonds	0	0	0	0	16138.4	-23442.8	7304.4	0
Reserves	0	0	0	0	7304.4	0	-7304.4	0
Advances	0	0	0	0	0	0	0	0
Net Worth	34006.2	19609.6	3313	2775.9	5934.1	-23442.8	0	42196.1

Table 6: Aggregate transaction flow matrix at t=0 (cells have been round to 1 decimal digit)

	HH	c Firm		s Firm		k Firm		Banks		Gov	CB		$\sum$
		CA	KA	CA	KA	CA	KA	CA	KA		CA	KA	
Cons	-28332.9	24198.3	0	4134.6	0	0	0	0	0	0	0	0	0
Wages	33018.8	-18472	0	-3828.3	0	-3694.4	0	0	0	-7024.1	0	0	0
Dole	990.1	0	0	0	0	0	0	0	0	-990.1	0	0	0
CG on inventories	0	16.5	-16.5	0	0	2.7	-2.7	0	0	0	0	0	0
Investments	0	0	-3953	0	0	3953	0	0	0	0	0	0	0
Capital Amortization	0	-3658.1	3658.1	0	0	0	0	0	0	0	0	0	0
Taxes	-7332	-388	0	-65.6	0	-54.9	0	-39.1	0	7879.7	0	0	0
Dep. Interests	84.4	45.8	0	9.5	0	9.2	0	-148.9	0	0	0	0	0
Bonds Interest	0	0	0	0	0	0	0	40	0	-58.2	18.1	0	0
Loans Interests	0	-282.7	0	-3.9	0	-8.9	0	295.2	0	0	0	0	0
Advances Interests	0	0	0	0	0	0	0	0	0	0	0	0	0
Profits	1824.8	-1459.8	146	-246.6	24.7	-206.6	20.7	-147.2	44.2	0	0	0	0
CB Profits	0	0	0	0	0	0	0	0	0	18.1	-18.1	0	0
Δ Deposits	-253.1	0	-137.5	0	-28.5	0	-27.5	0	446.7	0	0	0	0
Δ Reserves	0	0	0	0	0	0	0	0	-54.4	0	0	54.4	0
Δ Bonds	0	0	0	0	0	0	0	0	-120.1	174.5	0	-54.4	0
Δ Loans	0	0	303	0	3.8	0	9.6	0	-316.3	0	0	0	0
$\sum$	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 7: Parameters Table

Symbol	Description	Value
	pre-SS	
α_{NW}	consumption propensity out of wealth	0.1
v	inventories share	0.1
μ_{Φ_s}	labour productivity (service sector)	5
$\mu_{\kappa 0}$	capital productivity (initial vintage)	10
$\bar{l}_{\kappa}$	capital-labour ratio	8
$\iota_{\Phi_c,0}$	initial mark-up (consumption sector)	0.31
$\iota_{\Phi_s,0}$	initial mark-up (service sector)	0.188
$\iota_{\Phi_k,0}$	initial mark-up (capital sector)	0.07
δ_{κ}	capital life span	20
η	loans duration	20
τ_{π}	profit tax rate	0.21
τ_{GI}	labour income tax rate	0.21
ρ_{Φ_b}	dividend rate (bank sector)	0.7
$\rho_{\Phi_c}, \rho_{\Phi_s}, \rho_{\Phi_k}$	dividend rate (real sector)	0.9
Υ	wage retainment share	1
Λ	unemployment benefit	0.34
	SS-given	
μ_k	labour productivity (capital setor)	2.5
α_{NI}	consumption propensity out of income	0.87
ζ_{Φ_c}	banks' risk aversion (consumption firms)	1.91527
ζ_{Φ_s}	banks' risk aversion (service firms)	25.0961
ζ_{Φ_k}	banks' risk aversion (capital firms)	7.70672
γ^l	service consumption share (low-skilled)	0.1
γ^m	service consumption share (middle-skilled)	0.1
γ^h	service consumption share (high-skilled)	0.25
	free	
$\bar{u}$	normal capacity utilisation	0.8
μ_u	investment sensitivity to capacity utilisation	0.015
ξ^{inn}	innovation parameter	0.005
ξ^{imi}	innovation imitation	0.2
λ	adaptive parameter	0.25
δ_{κ}	capital life span	20
$(\sigma^1_{FN}, \mu^1_{FN})$	FN^1 parameters	(0.0095, 0.0)
$(\sigma^2_{FN}, \mu^2_{FN})$	FN^2 parameters	(0.015, 0.0)
$(\sigma^3_{FN}, \mu^3_{FN})$	FN^3 parameters	(0.02, 0.0)
$(\sigma^4_{FN}, \mu^4_{FN})$	FN^4 parameters	(0.0005, 0.0)
$(\sigma^5_{FN}, \mu^5_{FN})$	FN^5 parameters	(0.03, 0.0)
$\epsilon^{cr} = \epsilon^d$	intensity choice credit/deposit market	4.62
$\epsilon^k = \epsilon^{cons} = \epsilon^s$	intensity choice capital/good/service market	1
$\chi^{cr} = \chi^d$	potential suppliers credit/deposit market	3
$\chi^k = \chi^{cons} = \chi^s$	potential suppliers capital/good/service market	2

Table 8: Agents Class Sizes

Description	value
low-skilled workers	2828
middle-skilled workers	4015
high-skilled workers	1156
consumption firms	49
service firms	49
capital firms	9
banks	5

E Volatilities, Auto and Cross-correlations

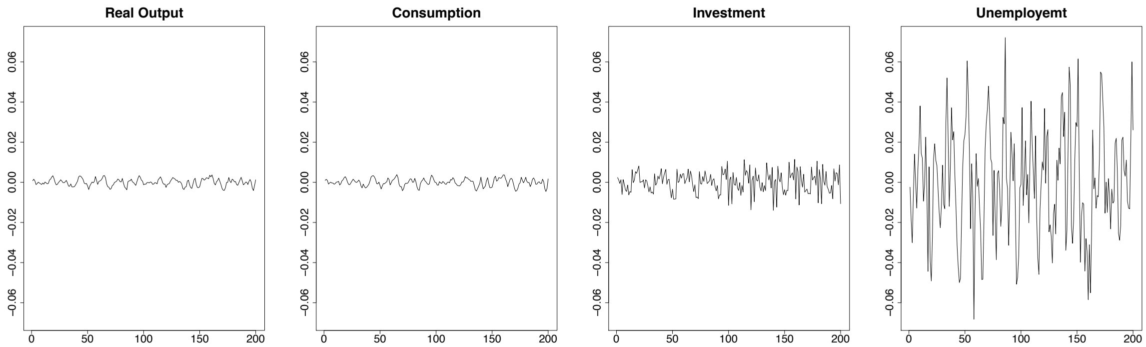
Following Dosi et al. (2010), Assenza et al. (2015), van der Hoog and Dawid (2017), and Caiani et al. (2016), we compare the properties of our simulated data with an ensemble of empirical stylised facts. For the sake of brevity, we focus on the cyclical properties of main economic variables.[33] We separate the trend and cyclical components of our artificial time series by mean of the Hodrick–Prescott filter and compare their properties to the correspondent time series for the US economy starting from the first quarter of 1948.

As expected, real investment is much more volatile than consumption and GDP, whereas unemployment is more volatile than investment. The auto-correlations of consumption, investment, GDP, and unemployment generated by the model display a good approximation of their empirical counterparts. All have a strong first order auto-correlation which rapidly fades away as the lag order increases, though real GDP, investment and unemployment display a non-negligible positive auto-correlation at the 20^{th} lag. This is likely a consequence of the assumption that real capital has a duration of 20 periods that may introduce a significant cyclical component in real investment, which ends ups affecting also unemployment and total output.

Also, artificial cross-correlations provide an acceptable approximation of the properties displayed by empirical time series: as expected, real investment and consumption are pro-cyclical and coincident, whereas unemployment is counter-cyclical and lagging by one period.

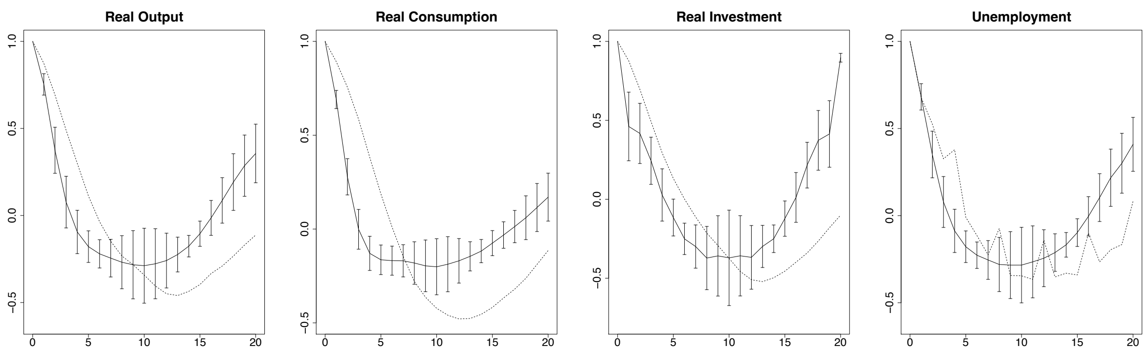
[33] A more extensive analysis of the cyclical components of other economic variables, of the distributions characterising firm and bank size, and of the properties of the networks generated by agents' interactions on different markets was discussed, for the 'parent' model, in Caiani et al. (2016). The present version of the model does not seem to diverge in any significant way from the qualitative properties discussed there.

Figure 11: Volatilities simulation 1



(a) **(b)** **(c)** **(d)**

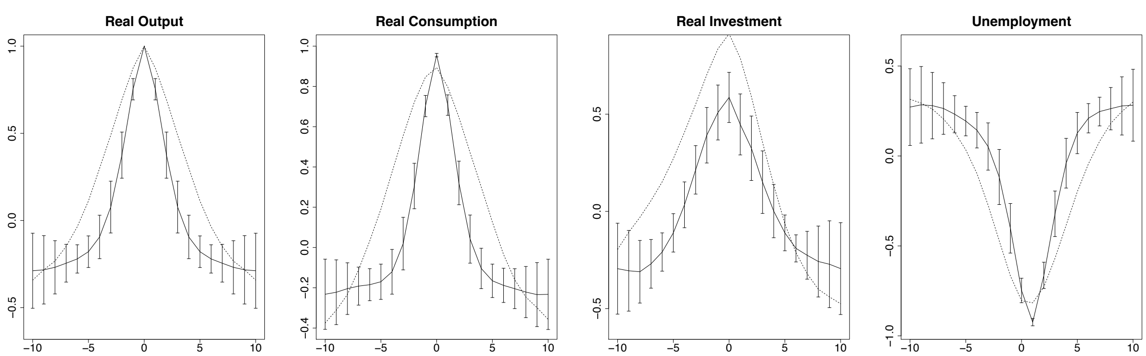
Figure 12: Auto-Correlations



(a) **(b)** **(c)** **(d)**

Average simulated (continuous) and real (dashed) auto-correlations of the de-trended series up to the 20th lag. Bars are standard deviations of Monte Carlo average auto-correlations.

Figure 13: Cross-Correlations



(a) **(b)** **(c)** **(d)**

Average simulated (continuous) and real (dashed) cross-correlations of the de-trended series up to the 10th lag. Bars are standard deviations of Monte Carlo average cross-correlations.

F Summary Statistics Across MC

Table 9: Main Growth Rates: Baseline

	Mean	SD
GDP	0.9038	0.0531
productivity	1.3379	0.0702
unemployment	-0.8933	0.0584
relativePrices	-0.4383	0.0296
cHsShare	0.1529	0.0083
hsShare	0.0512	0.0107
lsShare	0.0393	0.0103
msShare	-0.0448	0.0067
cEmplShare	-0.0953	0.0160
sEmplShare	0.4108	0.0630
kEmplShare	-0.1142	0.0124
expenditureSharesInGoods	-0.0322	0.0045
lsHsrelativeWages	-0.5646	0.0606
msHsrelativeWages	-0.5124	0.0419
lsMsrelativeWages	-0.1107	0.0485

Growth rates are calculated for each simulation run taking as the starting point the first 20 periods average of the simulation and as the ending point the last 20 periods average of the simulation. The table reports across simulations means and standard deviations for each macroeconomic aggregate.

Table 10: Main Growth Rates: $\sigma^2_{FN^4}$ Sensitivity

	Mean	SD
expenditureSharesInGoods	-0.0322	0.0045
$\sigma^2_{FN^4} = 0.0025$	-0.0610	0.0036
$\sigma^2_{FN^4} = 0.005$	-0.0745	0.0042
lsHsrelativeWages	-0.5646	0.0606
$\sigma^2_{FN^4} = 0.0025$	-0.8103	0.0176
$\sigma^2_{FN^4} = 0.005$	-0.8770	0.0181
msHsrelativeWages	-0.5124	0.0419
$\sigma^2_{FN^4} = 0.0025$	-0.7214	0.0249
$\sigma^2_{FN^4} = 0.005$	-0.7965	0.0235
lsMsrelativeWages	-0.1107	0.0485
$\sigma^2_{FN^4} = 0.0025$	-0.3189	0.0295
$\sigma^2_{FN^4} = 0.005$	-0.3972	0.0333
cEmplShare	-0.0953	0.0160
$\sigma^2_{FN^4} = 0.0025$	-0.1732	0.0113
$\sigma^2_{FN^4} = 0.005$	-0.2010	0.0170
sEmplShare	0.4108	0.0630
$\sigma^2_{FN^4} = 0.0025$	0.7214	0.0470
$\sigma^2_{FN^4} = 0.005$	0.8397	0.0713
kEmplShare	-0.1142	0.0124
$\sigma^2_{FN^4} = 0.0025$	-0.1718	0.0122
$\sigma^2_{FN^4} = 0.005$	-0.2061	0.0212
lsShare	0.0393	0.0103
$\sigma^2_{FN^4} = 0.0025$	0.0240	0.0082
$\sigma^2_{FN^4} = 0.005$	0.0296	0.0102
msShare	-0.0448	0.0067
$\sigma^2_{FN^4} = 0.0025$	-0.0779	0.0049
$\sigma^2_{FN^4} = 0.005$	-0.0907	0.0075
hsShare	0.0512	0.0107
$\sigma^2_{FN^4} = 0.0025$	0.2535	0.0192
$\sigma^2_{FN^4} = 0.005$	0.2857	0.0193
cHsShare	0.1529	0.0083
$\sigma^2_{FN^4} = 0.0025$	0.5516	0.0319
$\sigma^2_{FN^4} = 0.005$	0.6496	0.0410

Growth rates are calculated for each simulation run taking as the starting point the first 20 periods average of the simulation and as the ending point the last 20 periods average of the simulation. The table reports across simulations means and standard deviations for each macroeconomic aggregate.
Full variable names in bold refers to baseline.

Table 11: Main Growth Rates: γ^h Sensitivity

	Mean	SD
expenditureSharesInGoods	-0.0322	0.0045
$\gamma^h = 35$	-0.0505	0.0069
$\gamma^h = 15$	-0.0117	0.0018
lsHsrelativeWages	-0.5646	0.0606
$\gamma^h = 35$	-0.4660	0.0693
$\gamma^h = 15$	-0.7111	0.0418
msHsrelativeWages	-0.5124	0.0419
$\gamma^h = 35$	-0.5118	0.0312
$\gamma^h = 15$	-0.5127	0.0521
lsMsrelativeWages	-0.1107	0.0485
$\gamma^h = 35$	0.0897	0.0825
$\gamma^h = 15$	-0.4094	0.0233
cEmplShare	-0.0953	0.0160
$\gamma^h = 35$	-0.0835	0.0128
$\gamma^h = 15$	-0.0924	0.0152
sEmplShare	0.4108	0.0630
$\gamma^h = 35$	0.3257	0.0416
$\gamma^h = 15$	0.4887	0.0783
kEmplShare	-0.1142	0.0124
$\gamma^h = 35$	-0.1215	0.0128
$\gamma^h = 15$	-0.1021	0.0157
lsShare	0.0393	0.0103
$\gamma^h = 35$	0.0315	0.0075
$\gamma^h = 15$	0.0353	0.0108
msShare	-0.0448	0.0067
$\gamma^h = 35$	-0.0402	0.0049
$\gamma^h = 15$	-0.0425	0.0069
hsShare	0.0512	0.0107
$\gamma^h = 35$	0.0562	0.0093
$\gamma^h = 15$	0.0607	0.0104
cHsShare	0.1529	0.0083
$\gamma^h = 35$	0.1525	0.0088
$\gamma^h = 15$	0.1585	0.0100

Growth rates are calculated for each simulation run taking as the starting point the first 20 periods average of the simulation and as the ending point the last 20 periods average of the simulation. The table reports across simulations means and standard deviations for each macroeconomic aggregate.
Full variable names in bold refers to baseline.

Table 12: Main Growth Rates: Policy

	$\psi_p = 0$	$\psi_p = 29$	$\psi_p = 33$	$\psi_p = 37$
productivity				
MEAN	1.3379	1.3326	1.3527	1.3487
SD	0.0702	0.0639	0.0626	0.0729
lsHsrelativeWages				
MEAN	-0.5646	-0.0040	-0.0042	-0.0046
SD	0.0606	0.0005	0.0005	0.0007
msHsrelativeWages				
MEAN	-0.5124	-0.3391	-0.2494	-0.1597
SD	0.0419	0.0013	0.0012	0.0013
lsMsrelativeWages				
MEAN	-0.1107	0.5069	0.3266	0.1846
SD	0.0485	0.0029	0.0020	0.0018
expenditureSharesInGoods				
MEAN	-0.0322	-0.0119	-0.0085	-0.0059
SD	0.0045	0.0003	0.0002	0.0001
sEmplShare				
MEAN	0.4108	0.0929	0.0873	0.0738
SD	0.0630		0.0275	0.0232
cEmplShare				
MEAN	-0.0953	-0.0181	-0.0160	-0.0122
SD	0.0160	0.0063	0.0063	0.0056
lsShare				
MEAN	0.0393	-0.0153	-0.0182	-0.0215
SD	0.0103	0.0040	0.0040	0.0038
msShare				
MEAN	-0.0448	-0.0104	-0.0092	-0.0074
SD	0.0067	0.0027	0.0026	0.0022
hsShare				
MEAN	0.0512	0.1045	0.1095	0.1135
SD	0.0107	0.0071	0.0071	0.0060

Growth rates are calculated for each simulation run taking as the starting point the first 20 periods average of the simulation and as the ending point the last 20 periods average of the simulation. The table reports across simulations means and standard deviations for each macroeconomic aggregate.