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Automation, job polarisation, and structural change

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The increasing automation of tasks traditionally performed by labor is reshaping the relationship between skills and tasks of workers, unevenly affecting labor 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 manufacture-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 polarises the labor market. Finally, we study how labor 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 manufactory sector.

Keywords: agent-based model, automation, structural change, wage polarization, minimum wage

JEL classification: C63, E64, L16

AUTOMATION, JOB POLARISATION, AND STRUCTURAL CHANGE

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Abstract

The increasing automation of tasks traditionally performed by labor is reshaping the relationship between skills and tasks of workers, unevenly affecting labor 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 manufacture-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 polarises the labor market. Finally, we study how labor 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 manufactory sector.

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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 labor or increases the productivity of capital in those tasks[1]. As such, automation can hardly be considered a novelty. However, 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 labor 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 labor 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[2]. Recent influential researches have also warned about the potential disruptive effects of automation in terms of jobs destruction. For example, Frey and Osborne (2017) gained exceptional media 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[3]. This threatening estimate, however, only focuses on one side of the story. Arguably, technological revolutions destroy some jobs as they also generate new ones.

Estimating the net effect of automation on employment and isolating it from other possible

[1]Acemoglu and Restrepo (2020b)

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

[3]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.

contributing factors is extremely difficult. This is pheraps why some of the most convincing steps forward has been done by employing fully-fledged macroeconomic models.[4] 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. According to their estimates 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.

Among the distributional implications of automation, which have been far less investigated, the most obvious regards the type of jobs which are destroyed and generated as a consequence of the wider diffusion of automation, which is one of the main focus of the present paper. A first challenge is to estimate the direct effects of automation on the occupations exposed to it. Novel data on industrial robots provided by the International Federation of Robotics (IFR) has made possible to shed some light on the matter in recent years. Available studies using IFR data suggest that industrial robots are mostly concentrated in the manufactury sector (see Klenert et al. (2020)) and exert a positive contribution in terms of productivity (see Graetz and Michaels (2018)). Moreover, they appear to be skill-biased against low-skilled workers (see Graetz and Michaels (2018) and Borjas and Freeman (2019)))[5]. Based on this evidence, throughout the paper we define automation as a technology which is skill-biased against low-skilled workers, productivity-enhancing, and employed in the manufactory sector only.

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

[4] An incomplete list of paper studying employment effects of automation follows: Acemoglu and Restrepo (2018), Acemoglu and Restrepo (2019), Benzell et al. (2015), Berg et al. (2018), Borjas and Freeman (2019), Caselli and Manning (2017), Chiacchio et al. (2018), DeCanio (2016), Graetz and Michaels (2018), Gregory et al. (2016), and Korinek and Stiglitz (2017)

[5] We shall mention that the skill biased character of automation, although being a widespread hypothesis, is still under researchers' scrutiny. For example, a recent working paper by 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.

on job-polarisation in advanced economies[6], 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. One may be prone to explain this apparent inconsistency as a consequence of the still limited diffusion of robots: according to this interpretation, the skill-biased character of automation would then be outweighed by other factors which happen to polarise the labor market. Although we do not discard such hypothesis, we show that a skill-biased technology can, under plausible conditions, contribute to job polarisation.

More precisely, in this paper we aim at studying automation and its impact on heterogeneous workers, differentiated on the base of the skills they possess. We investigate: (i) which types of jobs/occupations are generated and which ones are suppressed because of automation; (ii) how automation interacts with structural change dynamics and how both contribute to shape aggregate labor demand; (iii) if and how labor market outcomes, in particular relative wages, feed back in the technological dynamics.

To provide an exhaustive analysis of these aspects, one must consider both the *direct* and *indirect* effects of automation. The former refers to the impact on the composition of employment at the firm level, as they proceed in automating their production processes. Such direct effects have been extensively studied on an empirical ground (see citations above), and the stylised facts highlighted by this literature provided guidance to our own analysis. Differently from Acemoglu and Restrepo (2020b), we do not explicitly model tasks, but we focus instead on the overall skill-biased effect of automation on firms' production and labor demand, as highlighted by the available empirical evidence: compared to traditional capital vintages, industrial robots in the model are more productive, require more high-skilled workers to operate, and less low-skilled workers. This approach allows us to embed the analysis of technological change in a Nelson and Winter (1977) typical framework, which is a cornerstone in the AB literature.

The indirect effects are more difficult to assess as they refer to a broad set of systemic adjust-

[6] 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)

ments triggered by automation at the economy-wide level, possibly overlapping and exerting an impact also on sectors of the economy not directly affected by automation processes. Automation changes the cost structure of firms and can affect their profitability, investment behaviour, and the process of market selection. As the composition of labor demand across skill levels changes, automation may affect the distribution of income and wealth. All in all, these processes may affect both the level of aggregate demand and its composition. For example, different types of workers may have different preferences over the pool of goods and services available for their consumption. Changes in the distribution of income would then result in a shift of production across different sectors, possibly triggering a demand-driven process of structural change. Therefore, workers replaced by new machines may relocate to a different firm or sector: job destruction and job creation are indeed both a direct and indirect effect of automation.

In order to account for these pervasive effects, we designed an Agent-Based macroeconomic model encompassing five key ingredients:

1. a multi-sectoral economy composed by Households, Banks, Firms, a Central Bank, and a Government. Firms are differentiated into capital good producers, consumption good producers, and firms providing personal services;

2. workers and jobs heterogeneity: workers are differentiated according to their skill-level. Firms post vacancies for occupations requiring different skill levels, based on the sector they belong to and the machines they employ in production.

3. endogenous skill-biased technological change: capital firms invest in R&D and discover new vintages characterised by different levels of productivity and different requirements for each skill degree. However, the decision to produce a new vintage by capital firms and to adopt it by consumption firms depends also on the relative wages of different skill-groups which concur to determine the capital embedded unit costs of production and therefore the attractiveness associated to each capital vintage.

4. households' heterogeneous preferences: households have differentiated preferences as high-skilled households are assumed to spend a larger portion of their consumption budget on services, compared to middle-skilled and low-skilled households.

Our multi-sectors economy is built upon the classical contribution of Baumol (1967). It indeed comprises a good sector where productivity can grow as the result of technological progress and a service sector where productivity is kept constant by assumption. Baumol's basic multi-sectoral framework has been amended in several ways so to better analyse flows of workers across industries and account in comprehensive way for the modifications induced by automation at the economy-wide level (see section 2).

Accounting for workers and jobs heterogeneity comes as a natural choice to address our main research questions. Moreover, as we will see, assuming free labor mobility across sectors opens up the possibility for structural change to occur and for automation to create and destroy jobs also in sectors not directly affected by it.

Modelling endogenous skill-biased technological change allows us to highlight important feedback dynamics, for example how technological innovations favour structural change, as well as how structural change influence R&D investment and therefore the innovation process itself. But also how technology affects the wage distribution, as well as how changes in relative wages steer the innovation process.

Modelling a multi-sector economy allows us to introduce a double consumption market, where households can buy both (homogenous) goods and (homogenous) services. We are also able to model radically different production technologies across different industries, which in turn impose different labor requirements across industries. Finally, accounting for households' heterogeneous preferences opens up the possibility to study in an integrated framework changes in the employment structure and the distribution of income triggered by technical change, changes in demand patterns, and structural change.

Based on the results of our experiments, the paper also makes two main theoretical contributions: first, we provide a streamlined and data-consistent explanation of how skill-biased technology can bring about job polarisation. A central role is played by the *personal* service sector, which absorbs the shocks originated in the manufacturing sector and provides additional low-skilled occupations for workers expelled by the (endogenous) emergence of automation. This "structural change road to job polarisation" was already put forward by Autor and Dorn (2013), who shows that the growth in low-skilled occupations, so central in the job-polarisation literature, is mostly concentrated in *personal* service occupations. Those are occupations often employed in production of "home substitutes" or similars, like food service workers, janitors, cleaners, and others. Moreover, both Autor and Dorn (2013) and Bárány and Siegel (2018) has already proposed models which formalise 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 labor and high-skilled labor, whereas services are produced by employing low-skilled labor 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 labor substitutability/complementarity is directly exerted. Autor and Dorn show that if the elasticity of substitution between capital and low-skilled labor 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 labor 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-skilled. 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 manufactory grows relative to the other sectors (and services and goods are complements), then workers migrate to the 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. Moreover, we assume, and we think this is far more realistic, that factors of production cannot be substituted at will, as it is the case for CES production functions, where limits to substitutability are only given by economic efficiency concerns. In our framework, technology embedded in machines dictates how much labor and of which kind is needed to operate a particular machine. In other words, we assume a sort of flexible Leontief production function, where technical coefficients evolve endogenously with technological innovation (see sections 2.4.1 and 2.4.6).

Also, differently from previous contributions, in our model heterogenous preferences between goods and *personal* services represent the real trigger for structural change. Following the intuition put forward in Manning (2004) and confirmed by Mazzolari and Ragusa (2013) and Lee and Clarke (2019), we assume consumption spillovers from high-skilled households to low-skilled services. More precisely, we assume that high-skilled households have higher consumption preferences towards personal services relative to other households. Therefore, changes in income distribution, brought about by technological change or otherwise, may modify the aggregate demand composition between goods and services and eventually determine structural change.

Thus, our theoretical framework shows the relevance of wage distribution in explaining various economic adjustments triggered by automation. Moreover, the model does so in accordance with available empirical evidence, which makes it an attractive laboratory to test policies influencing the wage distribution itself.

Our second theoretical contribution is indeed to shed some light on the impact of minimum-wage policies on automation, aggregate productivity, and structural change: we find that minimum wage policies curb structural change. As the wage distribution becomes more equal, the aggregate demand composition shifts less and less towards personal services, and the sectorial composition of the economy settles accordingly. An interesting implication we notice is that constraining structural change allows for higher aggregate productivity. From a theoretical point of view, this is just a version of Baumol's *cost disease*. Furthermore, we think that this result adheres with available empirical evidence, in particular with those studies pointing at structural change as one determinant of productivity slow down [7].

We also find that the minimum wage policy can exert a positive impact on the automation pace and therefore on productivity within manufactory: since automation is skill-biased, productivity gains coming from technological innovations are not necessarily profitable for firms [8], which is all more likely when the wage gap between high and low skilled wages widens excessively, potentially weakening the automation process.

The minimum wage policy can solve this issue by providing the right incentive for productivity enhancing innovations to take place and be employed in production. When the policy is effective, we indeed observe stronger productivity growth within manufactory, along with lower low-skilled employment share and larger high-skilled employment share within manufactory.

Also in this case, we believe our results to be supported by empirical evidence: Lordan and Neumark (2018) shows for the US economy that the share of automatable (low-skilled) jobs decrease in response to minimum wage policies, whereas high-skilled workers benefit from it. Moreover, such effect is especially visible in the manufactory sector. We interprete such result as indirect evidence that minimum wage policies can incentivise automation, which in our framework implies higher productivity, lower low-skilled employment share, and larger high-skilled employment share within the manufactory sector.

The rest of the paper is organised as follows: section 2 presents the model; section 3 describes the model calibration and discusses the empirical evidence employed to calibrate

[7] For example Nordhaus (2001) and Duernecker et al. (2017) both show that services, and in particular personal services, relative growth is to some extent responsible for past and future productivity slow down.

[8] Note that labor costs are increasing in the share of high-skilled workers needed to operate a particular machine. Therefore, for given productivity gain, whether an innovation is profitable depends on the level of skill-bias, technological characteristics, and the gap between high and low-skilled wages, endogenous economic condition.

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

Our model comprises four building blocks common in the AB literature and it introduces many significant novelties alongside. The main core is the Agent Based-Stock Flow Consistent (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). This main core is complemented by three major features. The first and probably most important novelty is the addition of a *skill-biased* component coupled with the endogenous R&D innovation process *a lá* Nelson and Winter (1977) which, first revived by Dosi et al. (2010), has become a classical component of macro ABMs[9].

A second innovation is the refinement of the way workers heterogeneity is modelled. In a nutshell, we might disentangle two main strategies employed till now in the ABM literature to deal with workers heterogeneity: the first one (Dawid et al., 2008; Dosi et al., 2018) considers workers performing a homogeneous task but being differentiated in their ability to perform that task. Workers are then assumed to compete on the same labor market for the very same vacancies, but being endowed with different productivity levels. Alternatively, Ciarli et al. (2010) and Caiani et al. (2019) model workers *and* jobs heterogeneity introducing a hierarchical organisational structure where workers perform different tasks and are employed in different tiers of the organisation. Typically, this approach distinguishes between blue and white collars where the former are strictly needed in production, whereas the latter are employed for organisational purposes only.

Our paper builds on this second approach, but incorporates two major departures from pre-

[9]On the other hand, directed technological change is not commonly implemented in ABMs. An example can be found in Fanti (2020) who, differently from us, allows technological innovation to follow either a labor saving trajectory or a labor intensive one.

vious works: (i) we introduce tasks which require different levels of skills to be carried out and which are all directly needed in production; (ii) the efficient mix of tasks (and skills) required by firms depends on the production technology employed. This implies, for example, that different sectors typically require radically different employment structures to carry production. Moreover, where applicable, we assume that different vintages of capital embeds different labor-skill requirements, therefore firms belonging to the same sector, but employing a different production technology will also require a different employment structure in order to carry out production efficiently.

The third key integration with respect to Caiani et al. (2019) is the inclusion of a new sector, namely the *personal* service sector. By the label *personal*, we wish to identify those low-skilled dominated services which provide home substitutes or similar kinds of services to households. We do so in order to integrate the intuition contained in Autor and Dorn (2013) about the link between job polarisation and structural change as well as the consumption spillovers theory put forward by Manning (2004).

The original model, as most of the ABM literature, encompassed two vertically integrated industries: a capital good and a homogenous consumption good sector.[10] In this paper instead, households can consume both manufactured goods and personal services.

Finally, households belonging to different skill groups are further differentiated by assuming that they have heterogeneous preferences between goods and services.

Summing up, our stylised economy is composed of capital good firms, consumption good firms, service firms, banks, households, a government, and a central bank. Capital firms, indexed by k, perform R&D and produce heterogeneous machines out of labor only. Consumption firms, indexed by c, combine machines and workers in order to produce and sell a homogenous product. Service firms, indexed by s employ labor only and provide homogenous services. Households are indexed by h and grouped in three different skill categories: high, middle, and low-skilled. Households sell labor to firms and consume goods and services. The government levies taxes on profit and income, provides unemployment benefits for house-

[10] Exceptions can be found in Caiani et al. (2018), introducing a distinction between tradable vs non-tradable goods, and Ciarli et al. (2010), who allow for differentiated goods in the quality dimension.

holds, hires public workers, and issue bonds. Banks, indexed by b, provide credit to firms, buy government bonds and collect deposits. Finally, the central bank provide cash advances to banks upon request and absorbs unsold government bonds.

With the exception of the labor market (see section, 2.3), every market is modelled 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 random-limited subset with a probability depending on the differences between their prices (or, in the case of capital goods, a combination of prices and technical features of their vintages).[11]

While the following sections focus on the most important features of the model, a complete description is provided in appendix A.

2.1 Sequence of events

In each period of the simulations 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. *Labor demand*: given available technology and desired output levels, firms calculate their labor 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.

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

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

7. *Labor markets*: unemployed workers look for an occupation on the labor market, inelastically supply one unit of labor at the prevailing wage for each type of occupation.

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

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

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

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

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 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 jobs, i.e. low, middle, and high-skilled jobs, and three corresponding segmented labor markets: each worker can take up a job matching her skill level, that is we do not allow for mismatch in the labor market.

Each worker updates her demanded wage at every t following a simple heuristic: if in $t-1$ she has been unemployed, she scales up her demanded wage by a random amount, vice-versa she scales it down by the same token.

$$w^d_{z,t} = \begin{cases} w^d_{z,t-1}(1 - FN^1_{z,t}) \quad \text{If} \quad u_{z,t-1} = 0 \\ w^d_{z,t-1}(1 + FN^1_{z,t}) \quad \text{If} \quad u_{z,t-1} = 1 \end{cases} \tag{1}$$

Where $u_{z,t}$ is dummy variable taking value 1 if z is employed in period t 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 among workers belonging to the same skill group, moreover they are set such that $w^d_{l,0} < w^d_{m,0} < w^d_{h,0}$, see section (3) for details about the calibration exercise.

The wage paid to employed workers equals their desired one. On the other hand, unemployed workers participate to the labor market by posting their desired wages. 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-skilled wage:

$$ub_t = \Lambda \bar{w}_{ls,t} \tag{2}$$

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.

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 $NW_{z,t-1}$.

$$C^D_{z,t} = \alpha_{NI} NI_{z,t} + \alpha_{NW} NW_{z,t-1} \tag{3}$$

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 (Manning, 2004; Mazzolari and Ragusa, 2013; Lee and Clarke, 2019), high-skilled households dedicate a larger share of their consumption to personal services, compared to lower skilled households:

$$\begin{cases} C^{D,s}_{z,t} = \gamma^{\sigma} C^{D}_{z,t} \\ C^{D,c}_{z,t} = (1-\gamma^{\sigma}) C^{D}_{z,t} \end{cases} \qquad \text{with} \quad \gamma^h \geq \gamma^m \geq \gamma^l \tag{4}$$

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

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

2.4 Firms

2.4.1 Production planning and labor 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:

$$y^D_{x,t} = (1+v)s^e_{x,t} - inv_{x,t-1} \;\; \text{with} \;\; x = \{c, k\} \tag{5}$$

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:

$$y^D_{s,t} = (1+v)s^e_{s,t} \tag{6}$$

[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.

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

2.4.2 Production and labor demand for service and capital firms

Service and capital firms produce using only labor. In order to produce, these firms require low, middle, and high-skilled workers that they must combine in fixed shares: $\alpha_x^l, \alpha_x^l, \alpha_x^l$ with $\alpha_x^l + \alpha_x^l + \alpha_x^l = 1$ and x being an index identifying the type of firm: $x = k, s$

Defining the number of workers employed by the generic firm x for each skill-group by N_x^l, N_x^m, N_x^h, firms production function is then described by a Leontief of the type:

$$y_{x,t} = \mu_x min\left(\frac{N_{x,t}^l}{\alpha_x^l}, \frac{N_{x,t}^m}{\alpha_x^m}, \frac{N_{x,t}^h}{\alpha_x^h}\right) \quad \text{with} \quad x = \{s, k\} \tag{7}$$

where μ_x is a sort of total factor productivity referred to different types of workers.[13] Therefore, labor demand by firm x for each skill group σ is determined as:

$$N_{x,t}^{D,\sigma} = y_{x,t}^D \frac{\alpha_x^\sigma}{\mu_x} \tag{8}$$

2.4.3 Production and labor demand for consumption firms

Consumption firms combine capital and labor in production. Capital vintages are heterogeneous, each vintage being indexed by κ and identified by a set of five technical parameters $\Omega = \{\mu_\kappa, \bar{l}_\kappa, \alpha_\kappa^l, \alpha_\kappa^m, \alpha_\kappa^h\}$. 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-labor ratio, defining the total number of workers required to operate one unit of vintage k. α_κ^l, α_κ^m, and α_κ^h define the proportions of these workers that must perform low, middle, and high-skill tasks to operate

[13]Notice that moving μ_x within the brackets we obtain the classical Leontief formulation $y_{x,t} = min\left(\frac{N_{x,t}^l \mu_x}{\alpha_x^l}, \frac{N_{x,t}^m \mu_x}{\alpha_x^m}, \frac{N_{x,t}^h \mu_x}{\alpha_x^h}\right)$ where $\frac{\mu_x}{\alpha_x^\sigma}$ represents the coefficient of production of the generic skill group σ.

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 $\Omega^* = \{\mu_\kappa, \alpha^l_\kappa, \alpha^m_\kappa, \alpha^h_\kappa\}$.

Therefore, a unit of vintage κ requires $\frac{\alpha^\sigma_\kappa}{\bar{l}_\kappa}$ σ-skilled workers.

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

$$y_{c,\kappa,t} = K_{c,\kappa,t}\mu_\kappa min\left(N^l_{c,\kappa,t}\frac{\bar{l}_\kappa}{K_{c,\kappa,t}\alpha^l_k}, N^m_{c,k,t}\frac{\bar{l}_\kappa}{K_{c,\kappa,t}\alpha^m_k}, N^h_{c,k,t}\frac{\bar{l}_\kappa}{K_{c,\kappa,t}\alpha^h_k}\right) \tag{9}$$

With $N^l_{c,k,t}, N^m_{c,k,t}, N^h_{c,k,t}$ representing the number of low, mid and high skill workers available in firm c to operate vintage κ, and the ratios $\frac{\bar{l}_\kappa}{K_{c,\kappa,t}\alpha^l_k}, \frac{\bar{l}_\kappa}{K_\kappa\alpha^m_k}, \frac{\bar{l}_\kappa}{K_\kappa\alpha^h_k}$ giving the amounts that would be necessary to operate $K_{c,\kappa,t}$ units at full capacity.

Since firms can invest in every period and machines lasts δ_k periods, consumption firms typically owns machines of different vintages. Firm c then seeks to produce the target $y^D_{c,t}$ using the combination of vintages which allows to minimize costs.

Let us first define the unit cost of production embedded in a machine of vintage κ at time t as:

$$uc_{\kappa,t} = \frac{\sum_\sigma w^\sigma_t \alpha^\sigma_\kappa \bar{l}^{-1}_\kappa}{\mu_\kappa} \tag{10}$$

Where $\frac{1}{\mu_\kappa}$ gives the units of vintage k required to produce a unit of output, and the numerator in equation 10 gives the total labor 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 labor 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 utilization 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 labor demand for each skill category σ according to the following equations which makes clear the dependence of firms' labor demand on the technical coefficients of their capital vintages ($\kappa_{c,t}$):

$$N^{\sigma,D}_{c,t} = \sum_{\kappa \in \kappa_{c,t}} u^D_{c,\kappa,t} K_{c,\kappa,t} \left(\frac{\alpha^\sigma_\kappa}{\bar{l}_\kappa} \right) \tag{11}$$

2.4.4 Pricing

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

$$p_{x,t} = (1 + \iota_x) \left(\frac{\sum_\sigma w^\sigma_t N^{D,\sigma}_{x,t}}{y^D_{x,t}} \right) \tag{12}$$

where the $\sum_\sigma w^\sigma_t N^{D,\sigma}_{x,t}$ is total labor costs 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. To avoid excessive variance, we impose an upper and lower bound to markups, $(1+\zeta)\iota_{x,0}$ and $(1-\zeta)\iota_{x,0}$ respectively, where $\iota_{x,o}$ is the calibrated initial value of the markup for firms belonging to sector $x = \{c, k, s\}$, and ζ is an exogenous parameter, homogeneous across sectors, determining the corridor width.

$$\iota_{x,t} = \begin{cases} Min\left\{\iota_{x,t-1}(1 + FN^2_{x,t}), (1+\zeta)\iota_{x,0}\right\} & \text{if} \quad s_{x,t-1} > s^e_{x,t-1} \\ Max\left\{\iota_{x,t-1}(1 - FN^2_{x,t}), (1-\zeta)\iota_{x,0}\right\} & \text{if} \quad s_{x,t-1} < s^e_{x,t-1} \end{cases} \tag{13}$$

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 $y^D_{c,t}$:[14]

$$g^D_{c,t} = \gamma_u \frac{u^D_{c,t} - \bar{u}}{\bar{u}} \tag{14}$$

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 embed. Therefore, capital supplier i is preferred to capital supplier j if the difference between the unit labor 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:

$$\delta_\kappa(uc_{i,t} - uc_{j,t}) < p_{jy} - p_{i,t} \tag{15}$$

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

Let us point out that that equation 15 can also be rearranged as:

$$uc_{i,t}\delta_\kappa + p_{i,t} > uc_{j,t}\delta_\kappa + p_{j,t} \tag{16}$$

thereby obtaining a synthetic measure to compare the attractiveness of different vintages.[15]

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

[14]Firms' excess capacity is 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.

[15]The right-hand and left-hand sides of equation 16 thus replace the variables P_o and P_n in equation 24 (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.

end of the period.[16] 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 (1983) with insights from the literature dedicated to *skill-biased* technological change.

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 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, insofar an increase in productivity undoubtedly reduces production costs, but an increase in the parameter α^h_κ typically increases production costs[17]. It follows that whether an innovation will be adopted in production ultimately depend on the low/high-skilled relative wage dynamics, therefore productivity growth can come to an halt if the economic conditions are such that, despite increasing productivity, innovations are not profitable from the producers' point of view.

Following Caiani et al. (2019) and a rich literature in the evolutionary tradition[18], we model

[16] 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.

[17] This is so, because high-skilled wages are higher than low-skilled ones.

[18] See Nelson and Winter (1977), Winter (1983), Andersen et al. (1996), Dosi et al. (2010), Caiani (2012),

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 $R\&D$.
Formally, the probability of innovating for capital firm k is given by:

$$Pr^{inn}_{k,t} = 1 - e^{-\xi^{inn} N^h_{k,t}} \tag{17}$$

where ξ^{inn} is an exogenous time invariant-parameter and $N^h_{k,t}$ is the number of workers employed in high-skilled occupations by firm k at time t, implicitly assuming that innovation is mainly performed by high-skilled workers. This implies that larger capital firms tends 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:

$$\begin{cases} \mu^{new}_k = (1 + FN^3_{k,t})\mu^{old}_k \\ \\ \alpha^{h,new}_k = (1 + FN^4_{k,t})\alpha^{h,old}_k \end{cases} \tag{18}$$

where μ^{new}_k and $\alpha^{h,new}_k$ 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 $\alpha^{h,new}_k$ is mirrored by an equal variation of $\alpha^{l,new}_k$ in the opposite direction, given that $\alpha^{m,new}_k$ is kept constant for simplicity. μ^{old}_k and $\alpha^{h,old}_k$ are the correspondent parameters characterizing the vintage currently produced by k. Finally, $FN^3_{k,t}$ and $FN^4_{k,t}$ 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.

and Vitali et al. (2013).

Again, please notice that unit costs of production depends on capital productivity μ_κ, the shares α_k defining the labor 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:

$$Pr_{k,t}^{imi} = 1 - e^{-\xi^{imi} N_{k,t}^{h}} \tag{19}$$

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 characterized by the same behavioral rules of the agents belonging to it (apart from the matching protocols and the other rules which only makes sense when there is a multiplicity of agents), which we solve in the steady state. This was 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 value was 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.[19]

The aggregate values of stocks and flows found for 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.[20]

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.

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

[19] 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.

[20] As already pointed out in Caiani et al. (2016), as the simulation begins, agents start to interact and adaptivity enters the drama, so that the model will start to display its own dynamics. The calibration procedure based on the factious 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 Labor Statistics (BLS). IOM provides the number of workers employed in a given occupation-industry cell[21].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

[21]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 (Manning, 2004; Mazzolari and Ragusa, 2013; Lee and Clarke, 2019), 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, Drycleaning and Laundry Services, Death care Services, etc.). 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.

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)

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

$$\alpha_x^\sigma = \frac{\sum\limits_{o \in O^\sigma} Empl_o^x}{totEmpl^x} \tag{20}$$

Where O_x^σ is the set of all occupations requiring σ-skills (where $\sigma = \{l, m, h\}$) within sector x, $Empl_o^x$ 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.[22]

[22] 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 $\alpha_{\kappa_0}^l$, $\alpha_{\kappa_0}^m$, and $\alpha_{\kappa_0}^h$ are calibrated according to equation 20.

Table 3 displays the values of the calibrated technical parameters.

Table 3: Technical Parameters Calibrated Values

	ls	ms	hs
Manufactory/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 of the demand for low, midlle,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 we all as aggregate demand composition.

Again, we use data provided by the BLS, this time the table named "Annual mean wages by typical entry-level educational requirement" referring to May 2017. As the name suggest, this table contains information about average wages earned by occupations grouped by education requirements. We use table 1 to further aggregate education requirements in our skill-group classifications and take averages in order to calculate relative wages at time 0:

$$w^{\sigma}_{t_0} = \frac{\sum\limits_{educ \in \sigma} w^{educ}}{n^{\sigma}} \tag{21}$$

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-skilled 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 normalise $w^{h}_{t_0}$ to 10 and use relative wages obtained with equation 21 to set low and middle-skilled wages. Results are shown in table 4:

Table 4: Initial Wages Calibrated Values

ls	ms	hs
2.8	4.6	10

4 Main 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. The first periods of each simulation must be interpreted as the 'transient' or 'burn-in' phase, that is the period required for an AB model to start displaying regular and stable properties. Therefore, this burn-in phase is discarded from the analysis. In the present model, after approximately 50 periods, the economy stabilises around a 'quasi'-steady state, that is a situation in which main economic aggregates, stock-flow norms, and the rate of growth of nominal and real variables, fluctuate around relatively stable values.

Before analysing the dynamics of the model, 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; van der Hoog and Dawid, 2017; Caiani et al., 2016). The results of this exercise are presented and commented in appendix C.

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 1a to 1l show that labor productivity in the consumption good sector follows a stable upward trend, therefore generating real GDP growth. Real consumption grows both for goods and services, even though for different reasons. Real goods consumption increases as a result of productivity growth in the consumption goods sector, which, reducing unit costs of production and prices relative to wages, allows households to expand their real goods consumption. On the other hand, growth in services consumption is mostly determined by the shift in aggregate demand from goods to services documented in figure 2i.

Linked to the aggregate demand shift just introduced, it is the structural change process documented in figures (1g, 1h, 1i). These figures indeed show a stark different employment dynamics across sectors: shrinking in the consumption and capital goods sector, expanding in the service sector. Moreover, since the latter outweighs the former, the aggregate effect turns out to be a constant reduction in the unemployment rate.

Finally, let us point out that, although overall inflation appears to be rather stable, consumption goods prices tend to grow at a lower pace than service prices, reflecting different production cost trends across the two sectors: since we assume free labor mobility across sectors, we also imply that wages - for given skill level - do not systematically differ across sectors. It follows that two sectors show different unit costs trends if (i) they experience different productivity growth and (ii) wages grow at different rates across skill-groups (recall that different sectors employ a different mix of skilled-workers, see section 3.2). In our case, differentials in productivity growth is the main driver and explanation for the downward trend in relative prices documented in figure 1l[23].

[23]Note that such tendency in relative prices found support support in real data, see for example the empirical evidence provided by Boppart (2014)

Baseline I

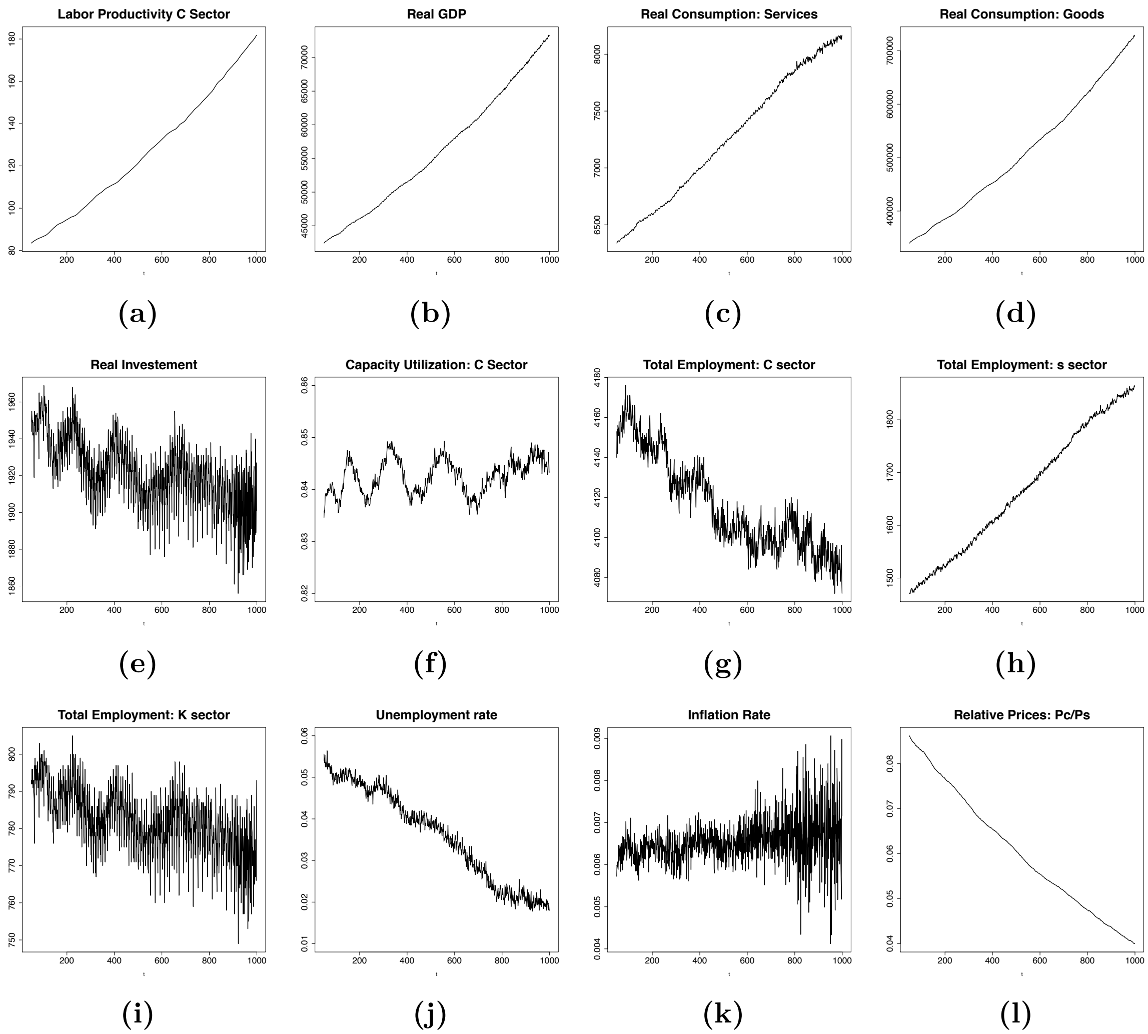


Figure 1: Time series refers to a single simulation run (seed=10)

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. Since productivity growth occurs at the cost of employment readjustment towards more expensive labor, market conditions, i.e. relative wages dynamics, can slow down new technologies adoption, as more productive machines do not necessarily imply lower production costs.

Having said that, we do observe productivity growth throughout the simulation, meaning

Baseline II

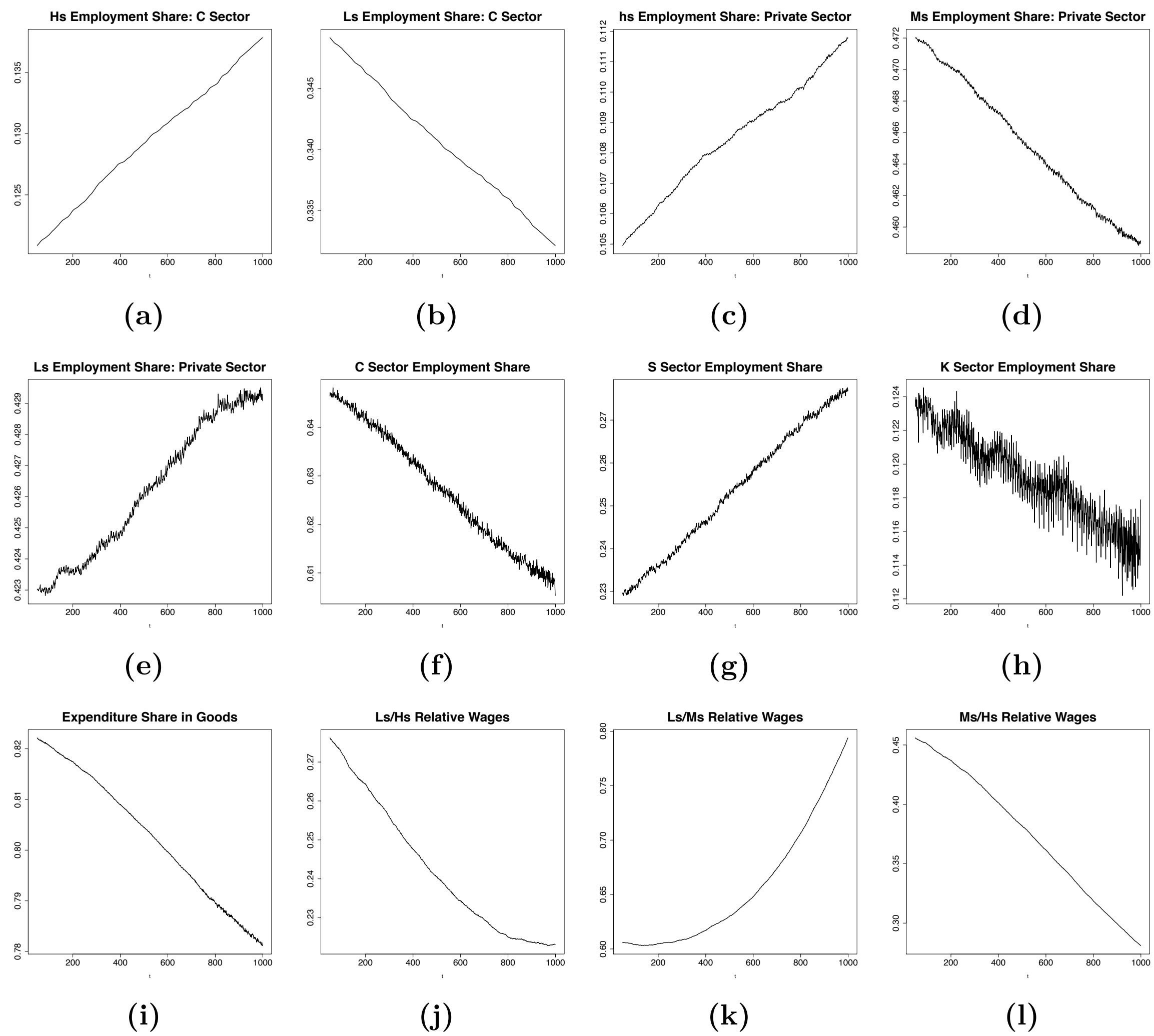


Figure 2: Time series refers to a single simulation run (seed=10)

that the incentives to invest in productivity enhancing machines on average prevail. Consistently, the share of high-skilled workers employed in the consumption good sector increases at the expense of low-skilled employment.

And yet, when we consider the wider economy we do observe job-polarisation, the growth in the share of high-skilled workers pertaining to the whole private sector goes hand in hand with a growing low-skilled employment share. The share of high-skilled 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-skilled employment is less trivial, being only indirectly linked to technological change: figures 2f to 2h show that employment in the service sector grows relative to other sectors, in particular to consumption good producers.

Remind that, as discussed in section 3.2, personal services are characterised, in accordance with empirical evidence, by a higher share of low-skilled workers compared to consumption and capital firms. It then follows that when employment in services grows relative to other sectors, also the share of low-skilled occupations in the whole economy grows, thus explaining the dynamics displayed in figure 2e.

However, what is the trigger of this structural change process characterised by the rise of personal services? In our model, this is mainly explained by a change in the composition of aggregate demand for consumption: as documented in figure 2i, the share of households' nominal consumption directed to manufactured goods drops in favour of services. This shift, in turn, can be related to technological change through two distinct channels. First, in equation 4 we posited that higher skill groups have a higher propensity to consume services relative to manufactured goods. Any increase in the income of high-skilled households relative to other groups then partly shifts aggregate consumption from goods to services. The rise in the demand for high-skilled workers, caused by the process of automation, increases the share of income of high skill households as it allows their wages to grow faster, relative to middle and low-skill workers.

Second, as new high-skilled jobs are created, a larger share of high-skilled workers is employed at each point in time, thereby contributing to increase their group's income and consumption shares.

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

Finally, we also show that the job polarisation is accompanied by wage polarisation, indeed figures 2k and 2l show that both low and high-skilled wages grow relative to middle-skilled ones. On one hand, this is to be expected given the model dynamics and the wage equation (eq 1). Indeed, as a particular skill group experience larger employment rates relative to another, its members revise up their reservation wages more frequently than other workers. It follows, that the average wage of skill groups featuring larger employment rates necessarily grows at faster pace than for skill groups featuring lower employment rates.

On the other hand, wage polarisation seems to characterise many economies, although somehow stronger evidence is provided for US than Europe for example[24]. Admittedly, from an empirical point of view it is not clear the extent of such wage polarisation trend, neither, and this is maybe more relevant, its causes, that is whether it is technological innovation triggering it or something else[25].

In our particular case the dynamics which polarise wages is the same which polarise jobs: skill-biased technological innovations coupled with structural change, which determines stronger supply pressures on low and high-skill labor markets relative to the middle-skill labor market.

5 Sensitivity

We have argued that the root causes of our results are essentially two: skill-biased technological change and heterogenous consumption preferences. However, we wish to better substantiate such claim by exploring different parameter configurations and analyse how the main results change accordingly.

The natural candidates for a sensitivity exercise of this kind are the parameters $\sigma^2_{FN^4}$ and γ^h. The former represents the variance of the folded normal distribution FN^4, from which new α^h_κ's are drawn within the innovation process. Larger $\sigma^2_{FN^4}$'s imply higher probabilities of drawing big new α^h_κ's, or, in other words, the larger $\sigma^2_{FN^4}$ the *more* skill-biased the technological process.

On the other hand, γ^h represents the share of consumption budget allocated to services by high-skilled households, playing a pivotal role in the structural change dynamics. Larger γ^h are associated to stronger preferences towards services by high-skilled households.

[24]See Acemoglu and Autor (2011), Firpo et al. (2011), Machin (2011), Antonczyk et al. (2018), and Dustmann et al. (2009) for example

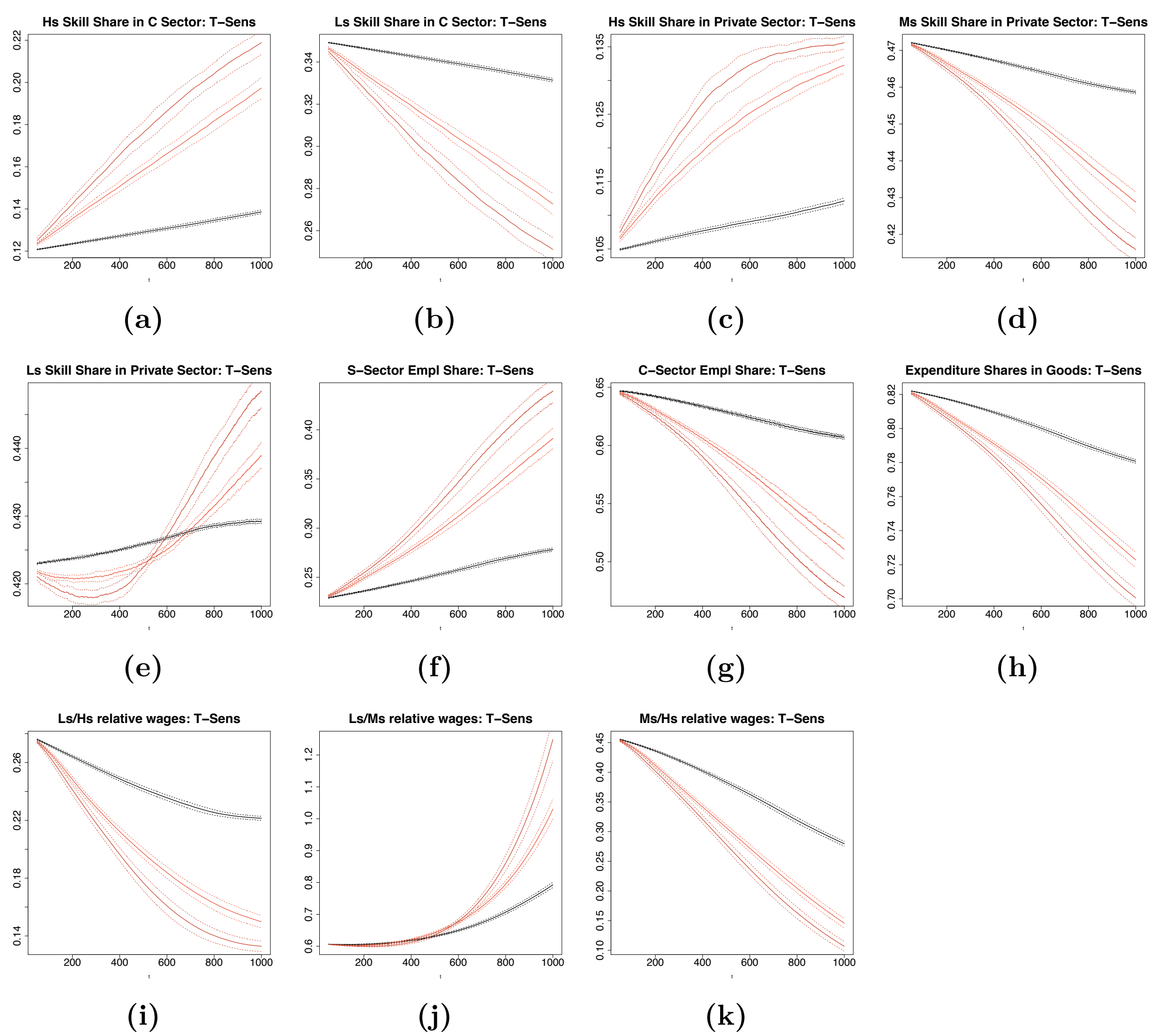
[25]See Naticchioni et al. (2014) for an insightful discussion on this point

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

In this sensitivity exercise, we run the model using the exact same baseline parameter configuration except for the parameter $\sigma^2_{FN^4}$ 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, as in the baseline configuration.

For the ease of exposition, panel (3) shows the main time series obtained as means across simulation accompanied by the relative standard deviations. Moreover, table (10) in Appendix D presents the across simulations summary statistics.

Figure 3: Sensitivity $\sigma^2_{FN^4}$



Black time series refer to the baseline configuration, whereas coloured time series refers to sensitivity configurations. Darker shades of orange refers to larger $\sigma^2_{FN^4}$ values.
Solide lines refers to means across simulation, dotted lines depict $\pm$ 1 standard deviation.

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 $\sigma^2_{FN^4}$: the more skill-biased is automation, the larger the share of high-skilled workers (and the lower the share of low-skilled workers) employed in the consumption good sector.

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, as well as faster decline of the consumption good sector (see figures 3f and 3g). Such effect is mediated by the relative wage dynamics: larger values of $\sigma^2_{FN^4}$ determine better employment performances of high-skilled workers relative to other workers, which therefore increase their wages relative to low and middle-skilled workers. It follows, that for large $\sigma^2_{FN^4}$ the aggregate demand shift towards services is faster, explaining the associated stronger structural change dynamics.

Job polarisation is also positively associated to $\sigma^2_{FN^4}$, indeed for larger $\sigma^2_{FN^4}$ we observe: (i) larger aggregate high-skilled employment shares, which directly mirrors the stronger high-skilled share growth within the consumption good sector; (ii) faster decrease in the middle-skilled employment share; (iii) larger low-skilled employment shares, which is also a side effect of structural change. Note that in a first period the low-skilled employment share is lower for large values of $\sigma^2_{FN^4}$, meaning that the employment loss within manufactory outweighs the gain coming from structural change. However, as the simulation unfold the structural change effect prevails and the low-skilled employment share recovers relative to the baseline scenario.

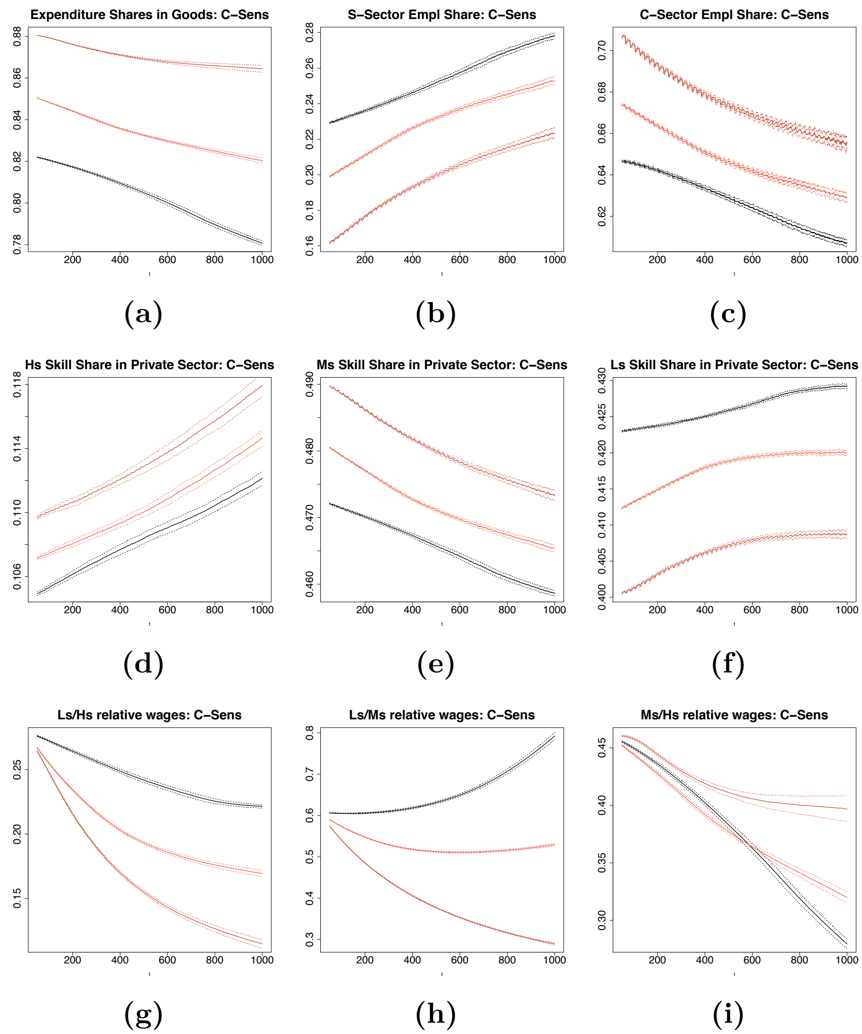
5.2 Consumption Sensitivity: $(\gamma^h, \gamma^m, \gamma^l)$

In this sensitivity exercise we experiment with three different γ^h values: (0.48, 0.38, 0.28), with 0.48 being the baseline configuration.

The most direct channel through which γ^h affects the model dynamics is the aggregate demand composition. Lower values of γ^h translates in larger shares of nominal good consumption.

As aggregate demand shifts away from services, the structural change dynamics slows down:

Figure 4: Sensitivity γ^h



Black time series refer to the baseline configuration, whereas coloured time series refers to sensitivity configurations. Darker shades of orange refers to lower γ^h values.
Solide lines refers to means across simulation, dotted lines depict $\pm$ 1 standard deviation.

a stronger demand for consumption goods relative to services reduces the growth in the service employment share, favouring the consumption good sector.

As discussed in section 4, structural change is one of the main engines behind job polarisation. This sensitivity exercise confirms it, indeed to lower service employment shares are associated larger high and middle-skilled employment shares as well as low low-skilled employment shares. We therefore conclude that low γ^h values tame job polarisation by hampering the structural change effect.

Finally, we also observe a seizable effect on relative wages: low γ^h are associated to lower low-skilled wages relative to both middle and high-skilled wages, which is a direct consequences of the employment outcomes described above.

6 Policy Experiment: 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 with a minimum wage policy defined as a peg to the larger wages paid in the economy, that is hs-wages:

$$\begin{cases} w_{z,t} & = max\left(w^{d}_{z,t}, w^{policy}_{t}\right) \\ w^{policy}_{t} & = \psi_p \bar{w}_{hs,t-1} \text{ with } \psi_p \in (0,1) \end{cases} \tag{22}$$

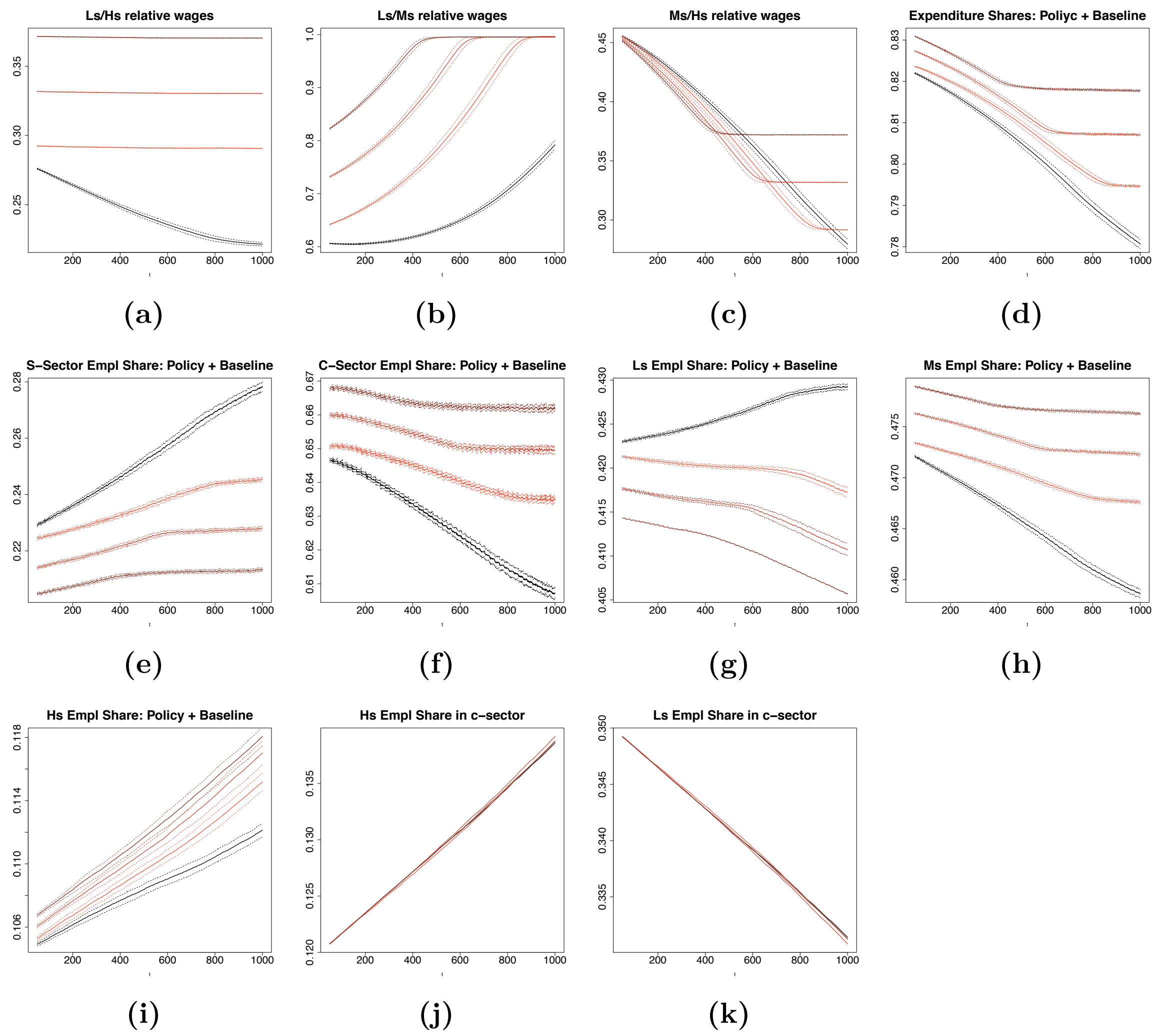
Where w^{policy}_{t} is the legal minimum wage, ψ_p is an exogenous policy peg, and $\bar{w}_{hs,t-1}$ is the average wage paid to high-skilled workers in the previous period. Let us also remark that $w^{d}_{z,t}$ is computed as usual, that is by means of equation 1.

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, since, as we will see, such spread determines the aggregate productivity dynamics as well as the pace and strength of automation.

We experiment with 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 panel 5, where we plotted the main time series obtained as means across simulation $+/-$ one standard deviation. Moreover across experiment summary statistics are reported in table 12.

Figure 5: Policy I



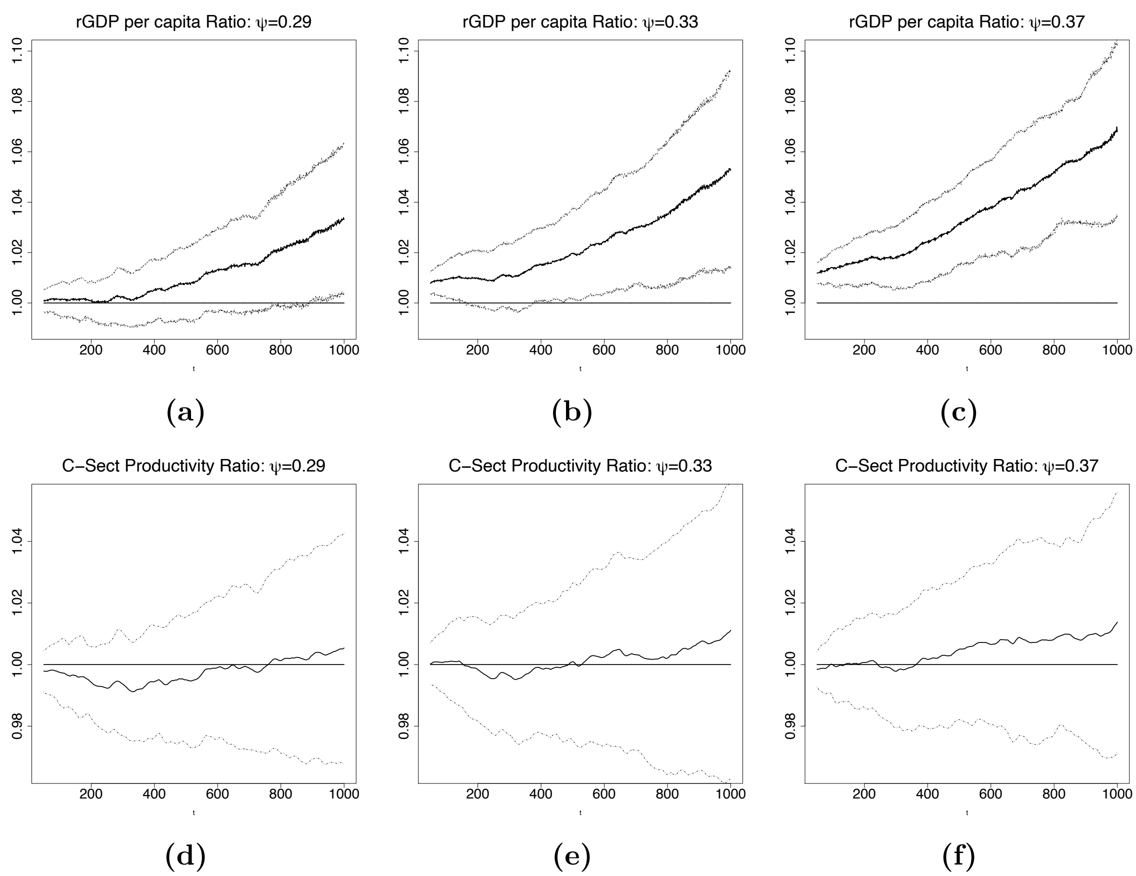
Black time series refer to the baseline configuration, whereas coloured time series refers to policy scenarios. Darker shades of orange are associated to larger ψ_p values.
Solid lines refer to means across simulation, dotted lines depict $\pm$ 1 standard deviation.

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. These changes in relative wages determine a shift in aggregate demand towards goods relative to the baseline scenario, or, to put it differently, the long run tendency of aggregate demand to shift from goods to services is slower when the policy is in place and it comes to a halt when all relative wages align. This affects the structural change dynamics, 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.

A slower structural change process has important repercussions on the labor market, in particular as far as job-polarisation is concerned. As already pointed out, job-polarisation is partly driven by structural change, therefore as the service sector growth shrinks - relative to the baseline scenario - so does the share of low-skilled employment. On the other hand, middle and high-skilled employment shares benefit from the fact the manufactory grows in relative terms when the policy is in place.

Finally, we note that the policy does not affect skill-employment shares within manufactory, suggesting that in this context the policy neither promote, nor discourage automation.

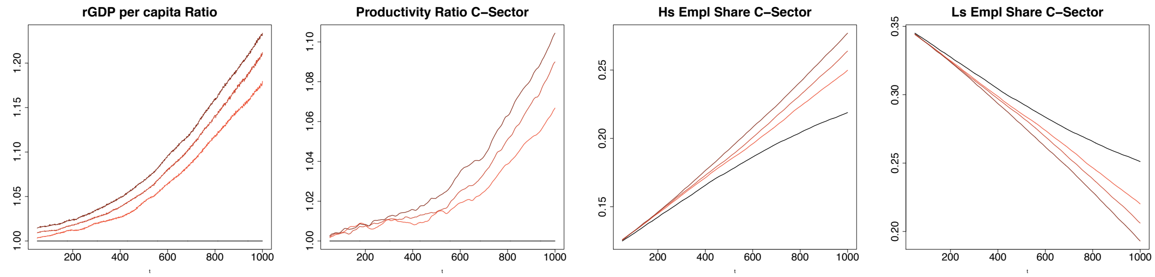
Figure 6: Policy II



Each figure contains baseline Vs policy configuration ratios.
Solid lines refer to means across simulation, dotted lines depict $\pm$ 1 standard deviation.

Having discussed some general impacts of the minimum wage, we now want to turn on a

Figure 7: Policy III



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

Black time series refer to the baseline configuration, whereas coloured time series refers to policy scenarios.
Darker shades of orange are associated to larger ψ_p values.
Solid lines refer to means across simulation.
Note the figures 7a-7b refer to policy Vs baseline ratios.

more specific issue: the effect of minimum wage on productivity, both in terms of aggregate productivity, that is GDP per employed worker, and within-manufactory productivity, that is automation pace/innovation dynamics.

Let us start by clarifying the two main determinants of aggregate productivity in our model: obviously, aggregate productivity is driven by sectors specific productivities and their trajectories, which in our case boil down to productivity in the manufactory sector. The second main determinant is the sectorial composition of the economy. Since we have assumed different productivities across sectors, it follows that when more (less) productive sectors grow relative to others, aggregate productivity must increase (decreases) accordingly.

Panel 6 shows that overall the policy exerts a positive effect on aggregate productivity and that to larger values of ψ_p are associated larger productivity gains. On the other hand, productivity within manufactory hardly improves because of the policy. We can therefore conclude that the policy exert a positive, although limited, effect on aggregate productivity exclusively through the structural change channel, as technological innovation does not respond to the policy in any meaningful way.

This last fact may seem puzzling, since automation, i.e. productivity within manufactory, is essentially determined by two factors: (i) the innovation frequency, that is the number of successful innovations per unit of time; (ii) the likelihood for a given innovation to be economically efficient, that is to bear lower unit costs of production with respect to already existing vintages.

As a matter of fact, our minimum wage policy unambiguously proves to be beneficial for both aspects, indeed it exerts a positive impact on the innovation frequency [26] as well as it increases the likelihood for a given innovation to be economically efficient[27].

However, the advantages provided by the minimum wage policy remain small as long as the innovation path does not hit some thresholds which systematically reduce the likelihood for new vintages to be economically efficient.

To better substantiate our claim, we propose a trivial experiment: since the cost of automation is given by the difference between productivity gains and the skill-bias extent of innovations, we introduce the exact same policies, but in a scenario where we keep fixed the productivity gain parameter, $\sigma^2_{FN^3}$, and increase the skill-bias parameter, $\sigma^2_{FN^4}$. For the ease of exposition we employ a parameter value[28] already used in the sensitivity experiment discussed in section 5.1, that is $\sigma^2_{FN^4} = 0.005$.

Panel 7 shows that in this scenario both GDP per employed worker and productivity within manufactory are positive and largely impacted by the policy. In the most favourable case, the policy delivers a gain of about +20% and +10% respectively for aggregate and within manufactory productivity relative to the no-policy scenario. Moreover, in all cases we observe clear upward trends in the policy gains for aggregate and within-manufactory productivity.

Growth in productivity within manufactory is an unambiguous indication of faster automation, which is also reflected in the skill employment shares within manufactory. We indeed observe larger shares of high-skilled workers within manufactory, compensated by lower shares of low-skilled employment.

We conclude that the minimum wage policy exerts a positive effect both on aggregate productivity and on the automation/innovation dynamics. However, such effect is stronger, the

[26]This is the structural change channel: growth in the consumption good sector spills over the capital sector. Larger employment in the capital sector implies larger probability of innovation and imitation: see equations (17, 19) in section 2.4.6.

[27]This is the incentive channel: for given productivity gain and skill bias, the larger the gap between ls and hs-wages the more likely the innovation is discarded by firms because not convenient in terms of unit costs of production, see discussion in section 2.4.6. It follows that closing the gap between ls and hs-wages increases the probability of adoption for more productive vintages

[28]This experiment has to be considered preliminary, indeed we planned to run a more comprensive set of experiments intersecting our policy scenarios with the whole tech sensitivity

more skill-biased is the innovation process, relative to the productivity gains it delivers.

7 Conclusions

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

Using this framework, we showed a number of interesting macroeconomic dynamics, informally validated by inspection of external empirical evidence. Our key assumptions are also thoroughly motivated by external empirical evidence, or direct ones when possible.

As the parent models, this model is able to replicate a wide range of well known macro stylised facts: relative volatilities, auto-correlation, and cross-correlation of the main macroeconomic aggregates. To these stylised facts, we added many more, specific to our research question: (i) we showed the emergence of job polarisation as a by product of automation; (ii) we showed how automation can trigger a demand-driven structural change process from manufactory to personal services; (iii) we showed how a structural change of this type can feedback in the labor demand and complement the automation process in determining labor market polarisation.

We provided abundant empirical evidence consistent with the aforementioned results, as well as with the main novelties proposed in the paper. In a nutshell, these can be summarised as: (i) we introduced heterogenous consumption preferences. As suggested by the consumption spill-over literature (Manning, 2004, Mazzolari and Ragusa, 2013,Lee and Clarke, 2019), we assumed high-skilled workers to be endowed with stronger preferences for personal services than the rest of the population; (ii) we introduced a personal service sector, generating low-skilled employment growth (see Autor and Dorn, 2013). Consistently, we assumed the service sector to disproportionately employ low-skilled labor, as suggested by BLS data presented in the paper; (iii) we showed 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. We noticed that 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. From a theoretical standpoint, the result is a slight variation of Baumol's *costs disease* argument, corroborated by empirical studies investigating the link between structural change and productivity slow down.

The latter effect highlights that by narrowing the spread between low and high-skilled wages, we actually reduce the cost of automation and therefore set the right incentives for stronger productivity growth within manufactory. We also maintain that, beside being logically consistent, this result is coherent with empirical evidence pointing at minimum wage as a risk factor for automatable jobs.

Given our research question, we tried to keep the model as concise as possible, however our framework can be amended along several dimensions, allowing for study a wider range of economic issues. Let us therefore highlight at least three possible additions to the current framework, which we hope to account for in the future: (i) we simplified the skill distribution of the labor force by compressing it in three categories, proxied by education. Although this is common practise in the literature, we are aware that the links among skills and tasks are far more complex and that in order to analyse more precisely the effect of automation on the labor market we shall make an effort in this direction; (ii) on one hand we assumed no labor barriers across sectors, on the other we assumed perfect rigid segmented labor market in the skill dimension. Both assumptions appear to be rather strong: although occupations in different sectors may demand the same education attainments, they typically require different skills. Moreover, there is abundant empirical evidence of labor market skill mismatch, suggesting that labor markets differentiated by skills are more fluid than assumed in the model; (iii) finally, we want to stress that individuals 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. In other words, at the present stage, there is no room for studying education policies of any kind. This is probably a major pitfall of our framework, so it is important to stress that our results hold only *ceteris paribus*, that is given a time invariant skill distribution of the workforce. Moreover, keeping fixed the workforce skill distribution preempts us from studying a wide range of relevant economic issues, the most important of which being the effect of automation on unemployment. Indeed, in a skill-biased world, aggregate employment outcomes crucially depend on the availability of workers possessing determined skills demanded by firms and therefore on the ability to adjust the skill supply, in the face of technological shocks.

To conclude, we believe that there are vast avenues for future research and much room for improvements in our framework. However none of these would alter in any fundamental way the main results contained in the present paper, but they would certainly allow to widen the scope of analysis of our framework.

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A Appendix: Complete 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:

$$x_t^e = x_{t-1}^e + \lambda \left(x_{t-1} - x_{t-1}^e \right) \tag{23}$$

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

With the exception of the labor market (see section, 2.3), every market is modeled 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:

$$Pr_s = \begin{cases} 1 - e^{\epsilon\left(\frac{P_n - P_o}{P_n}\right)} & \text{if } \; P_n < P_o \\ 0 & \text{Otherwise} \end{cases} \tag{24}$$

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 24) thus becomes:

$$Pr_s = \begin{cases} 1 - e^{\epsilon\left(\frac{P_o - P_n}{P_o}\right)} & \text{if } \; P_o < P_n \\ \\ 0 & \text{Otherwise} \end{cases} \tag{25}$$

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:

$$\pi_{c,t} = s_{c,t} p_{c,t} + i^d_{b,t-1} D_{c,t-1} + \Delta ninv_{c,t} - \sum_{\sigma} w^{\sigma}_t N^{\sigma}_{c,t} - ipayments_{c,t} - amcosts_{c,t} \tag{26}$$

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:

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

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_{kappa} is the price paid for one unit of capital belonging to vintage κ.

We assume that capital items stored as capital firms' inventories does not depreciate, therefore capital firms compute pre-tax profits using a slightly modified version of equation (26), 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 (26).

If pre-tax profits turn out to be positive, firms pay taxes to the government which are set as $Tax_{x,t} = max\left(\tau_\pi \pi_{x,t}, 0\right)$. 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 $Div_{x,t} = max\left(\rho_{\Phi_x}\pi_{x,t}(1-\tau_\pi), 0\right)$, 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. (1987) 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:

$$L^D_{x,t} = I^D_{x,t} + Div^e_{x,t} + \Upsilon W_{c,t} - OCF^e_{x,t} \tag{27}$$

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 labor costs[29], and $OCF^e_{x,t}$ are total expected cash flows.

[29]Note that unlike in the parents model, labor 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 labor demand and wages are known. However, in principle

Note the since capital and service firms do not invest, the term $I^D_{x,t}$ in equation (27) 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:

$$Pr^d_{x,t} = \frac{1}{1 + exp\left(\frac{OCF_{x,t} - \zeta_{\Phi_x} ds^{L^D}}{ds^{L^D}}\right)} \tag{28}$$

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.

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

$$i^l_{b,t} = \begin{cases} \bar{l}^l_{b,t}\left(1 + FN^5_{b,t}\right) & \text{if} \quad CR_{b,t} < CR^T_t \\ \\ \bar{l}^l_{b,t}\left(1 - FN^5_{b,t}\right) & \text{Otherwise} \end{cases} \tag{29}$$

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:

$$i^d_{b,t} = \begin{cases} \bar{i}^d_{t-1}\left(1 + FN^6_{b,t}\right) & \text{if} \quad LR_{b,t} \geq LR^T_t \\ \\ \bar{i}^d_{t-1}\left(1 - FN^6_{b,t}\right) & \text{Otherwise} \end{cases} \tag{30}$$

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 $(\mu_{FN^6}, \sigma_{FN^6})$.

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 $Tax_{b,t} = max\,(\tau_\pi \pi_{b,t}, 0)$. 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 $Div_{b,t} = max\,(\rho_{\Phi_b}\pi_{x,t}(1-\tau_\pi), 0)$, 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 Parameters and stock-flow calibration

Table 5: Aggregate balance sheet matrix at t=0

	Households	c Firms	s Firms	k Firms	Banks	Government	CB	$\sum$
Deposits	40601.5	18472	5140.86	3694.4	-67908.7	0	0	0
Loans	0	-39857.5	-1288.3	-1295.26	42441.1	0	0	0
c Goods	0	2213.01	0	0	0	0	0	2213.01
k Goods	0	39613.6	0	369.44	0	0	0	39983.1
Bonds	0	0	0	0	25601.3	-32183.9	6582.6	0
Reserves	0	0	0	0	6582.6	0	-6582.6	0
Advances	0	0	0	0	0	0	0	0
Net Worth	40601.5	20441.1	3852.56	2768.58	6716.25	-32183.9	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	-29791.4	24290.7	0	5500.72	0	0	0	0	0	0	0	0	0
Wages	34584.5	-18472	0	-5140.9	0	-3694.4	0	0	0	-7277.2	0	0	0
Dole	1164.8	0	0	0	0	0	0	0	0	-1164.8	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	-7686.1	-404.5	0	-76.2	0	-54.8	0	-44.3	0	8265.9	0	0	0
Dep. Interests	100.7	45.8	0	12.8	0	9.2	0	-168.5	0	0	0	0	0
Bonds Interest	0	0	0	0	0	0	0	63.5	0	-79.9	16.3	0	0
Loans Interests	0	-296.7	0	-9.6	0	-9.6	0	316	0	0	0	0	0
Advances Interests	0	0	0	0	0	0	0	0	0	0	0	0	0
Profits	1929.8	-1521.7	152.2	-286.8	28.7	-206.1	20.7	-166.7	50	0	0	0	0
CB Profits	0	0	0	0	0	0	0	0	0	16.3	-16.3	0	0
Δ Deposits	-302.2	0	-137.5	0	-38.3	0	-27.5	0	505.5	0	0	0	0
Δ Reserves	0	0	0	0	0	0	0	0	-49	0	0	49	0
Δ Bonds	0	0	0	0	0	0	0	0	-190.6	239.6	0	-49	0
Δ Loans	0	0	296.7	0	9.6	0	9.6	0	-316	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}	labor productivity (service sector)	5
μ_{κ_0}	capital productivity (initial vintage)	10
$\bar{l}_\kappa$	capital-labor ratio	8
$\iota_{\Phi_c,0}$	initial mark-up (consumption sector)	0.315
$\iota_{\Phi_s,0}$	initial mark-up (service sector)	0.07
$\iota_{\Phi_k,0}$	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}	labor 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	0.65
	SS-given	
μ_k	labor productivity (capital setor)	2.5
α_{NI}	consumption propensity out of income	0.85
ζ_{Φ_c}	banks' risk aversion (consumption firms)	2.59131
ζ_{Φ_s}	banks' risk aversion (service firms)	7.43604
ζ_{Φ_k}	banks' risk aversion (capital firms)	7.37521
γ_0	Initial aggregate service consumption share	0.185
γ^l	service consumption share (low-skilled)	0.48
γ^m	service consumption share (middle-skilled)	0.05
γ^h	service consumption share (high-skilled)	0.05
	free	
ζ	mark-up corridor	0.05
$\bar{u}$	normal capacity utilization	0.8
μ_u	investment sensitivity to capacity utilization	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	(0.002, 0.0)
$(\sigma^4_{FN}, \mu^4_{FN})$	FN^4 parameters	(0.0005, 0.0)

Table 8: Agents Class Sizes

Description	value
low-skilled workers	2939
middle-skilled workers	3911
high-skilled workers	1149
consumption firms	49
service firms	49
capital firms	9
banks	5

C Volatilities, Auto and Cross-correlations

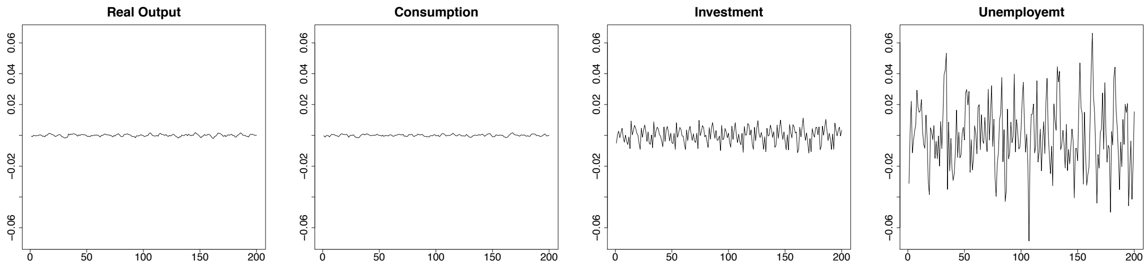
Following Dosi et al. (2010), Assenza et al. (2015), van der Hoog and Dawid (2017), and Caiani et al. (2016), we compare the properties of our simulated data with an ensemble of empirical stylized facts. For the sake of brevity, we focus on the cyclical properties of main economic variables.[30] We separate 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.

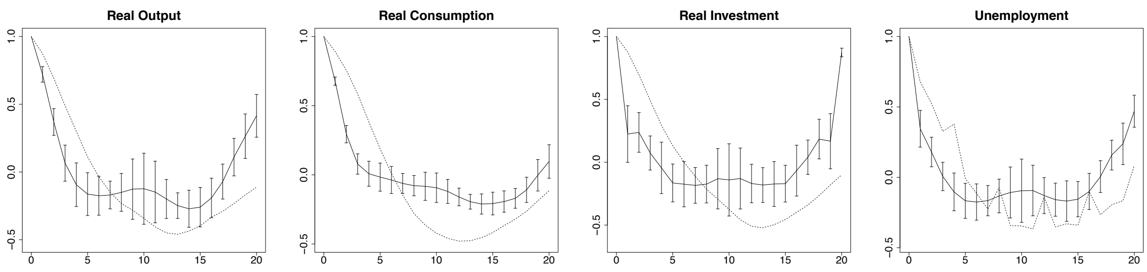
[30] A more extensive analysis of the cyclical components of other economic variables, of the distributions characterizing firm and bank size, and of the properties of the networks generated by agents' interactions on different markets was discussed, for the 'parent' model, in Caiani et al. (2016). The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

Figure 8: Volatilities simulation 1



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

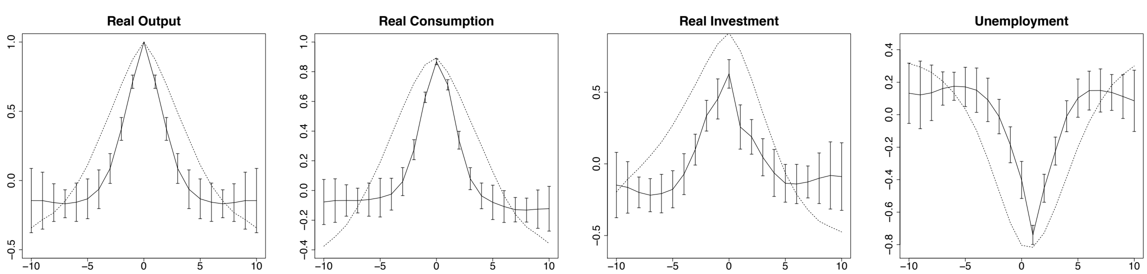
Figure 9: Auto-Correlations



(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 10: 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.

D Summary Statistics Across MC

Table 9: Main Growth Rates: Baseline

	Mean	SD
GDP	0.7530	0.0333
productivity C-sector	1.2332	0.0559
relativePrices	-0.5455	0.0115
cHsShare	0.1442	0.0071
hsShare	0.0671	0.0040
lsShare	0.0146	0.0007
msShare	-0.0280	0.0009
cEmplShare	-0.0605	0.0018
sEmplShare	0.2102	0.0067
kEmplShare	-0.0737	0.0052
expenditureSharesInGoods	-0.0494	0.0013
lsHsrelativeWages	-0.1951	0.0051
msHsrelativeWages	-0.3806	0.0091
lsMsrelativeWages	0.2996	0.0133

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	-0.0494	0.0013
sens_0025	-0.1176	0.0053
sens_005	-0.1439	0.0061
lsHsrelativeWages	-0.1951	0.0051
sens_0025	-0.4505	0.0156
sens_005	-0.5118	0.0138
msHsrelativeWages	-0.3806	0.0091
sens_0025	-0.6718	0.0175
sens_005	-0.7575	0.0185
lsMsrelativeWages	0.2996	0.0133
sens_0025	0.6767	0.0495
sens_005	1.0209	0.1057
cEmplShare	-0.0605	0.0018
sens_0025	-0.2053	0.0133
sens_005	-0.2684	0.0152
sEmplShare	0.2102	0.0067
sens_0025	0.6818	0.0436
sens_005	0.8815	0.0521
kEmplShare	-0.0737	0.0052
sens_0025	-0.2050	0.0137
sens_005	-0.2612	0.0187
lsShare	0.0146	0.0007
sens_0025	0.0401	0.0045
sens_005	0.0650	0.0060
msShare	-0.0280	0.0009
sens_0025	-0.0894	0.0057
sens_005	-0.1162	0.0067
hsShare	0.0671	0.0040
sens_0025	0.2359	0.0111
sens_005	0.2536	0.0127
cHsShare	0.1442	0.0071
sens_0025	0.5835	0.0382
sens_005	0.7297	0.0487

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: μ Sensitivity

	Mean	SD
expenditureSharesInGoods	-0.0494	0.0013
sens_62	-0.0347	0.0014
sens_72	-0.0179	0.0019
lsHsrelativeWages	-0.1951	0.0051
sens_62	-0.3579	0.0088
sens_72	-0.5582	0.0131
msHsrelativeWages	-0.3806	0.0091
sens_62	-0.2876	0.0107
sens_72	-0.1369	0.0243
lsMsrelativeWages	0.2996	0.0133
sens_62	-0.0986	0.0048
sens_72	-0.4881	0.0038
cEmplShare	-0.0605	0.0018
sens_62	-0.0652	0.0027
sens_72	-0.0717	0.0034
sEmplShare	0.2102	0.0067
sens_62	0.2651	0.0097
sens_72	0.3737	0.0163
kEmplShare	-0.0737	0.0052
sens_62	-0.0714	0.0060
sens_72	-0.0770	0.0071
lsShare	0.0146	0.0007
sens_62	0.0183	0.0006
sens_72	0.0200	0.0012
msShare	-0.0280	0.0009
sens_62	-0.0309	0.0011
sens_72	-0.0328	0.0014
hsShare	0.0671	0.0040
sens_62	0.0683	0.0043
sens_72	0.0733	0.0062
cHsShare	0.1442	0.0071
sens_62	0.1486	0.0082
sens_72	0.1556	0.0110

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

	Baseline	policy_29	policy_33	policy_37
productivity				
MEAN	1.2332	1.2480	1.2526	1.2624
SD	0.0559	0.0633	0.0761	0.0681
lsHsrelativeWages				
MEAN	-0.1951	-0.0057	-0.0042	-0.0031
SD	0.0051	0.0008	0.0005	0.0003
msHsrelativeWages				
MEAN	-0.3806	-0.3575	-0.2655	-0.1730
SD	0.0091	0.0009	0.0015	0.0014
lsMsrelativeWages				
MEAN	0.2996	0.5476	0.3557	0.2054
SD	0.0133	0.0017	0.0027	0.0019
expenditureSharesInGoods				
MEAN	-0.0494	-0.0349	-0.0242	-0.0155
SD	0.0013	0.0003	0.0002	0.0003
sEmplShare				
MEAN	0.2102	0.0917	0.0638	0.0411
SD	0.0067		0.0027	0.0026
cEmplShare				
MEAN	-0.0605	-0.0244	-0.0156	-0.0090
SD	0.0018	0.0008	0.0010	0.0011
lsShare				
MEAN	0.0146	-0.0093	-0.0162	-0.0204
SD	0.0007	0.0012	0.0015	0.0013
msShare				
MEAN	-0.0280	-0.0121	-0.0083	-0.0055
SD	0.0009	0.0003	0.0003	0.0002
hsShare				
MEAN	0.0671	0.0918	0.1010	0.1035
SD	0.0040	0.0047	0.0068	0.0054

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