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Technological paradigms, labour creation and destruction in a multi-sector agent-based model*

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Abstract

This paper presents an agent-based model (ABM) of endogenous arrival of technological paradigms and new sectors entailing different patterns of labour creation and destruction, as well as of consumption dynamics. The model, building on the labour-augmented K+S ABM, addresses the long-term patterns of labour demand emerging from heterogeneous forms of technical change. It provides a multi-level, integrated perspective on so called scenarios of the *future of work*, currently often restricted or to firm-level or to short-time sectoral analyses, and studies the conditions under which labour creation and destruction tend to balance. It is a relatively fair and stable distribution of income granted by a Fordist-type of regulation of the labour market that guarantees that the model never reaches stages of full technological unemployment. Patterns of coordination between technical change and aggregate demand are also ensured by the increasing product complexity which keeps on absorbing the labour force.

JEL classification: J51, E02, E24, C63

Keywords: technical change, technological unemployment, structural change, consumption patterns

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1 Introduction

The arrival of paradigmatic technological changes, their diffusion across industries, the ensuing dynamics of labour demand absorption/expulsion, and finally the patterns of consumption of the produced goods are the driving mechanisms of the overall conditions of macroeconomic development. In general, each of these mechanisms tends to be studied in a separate manner, with technological arrivals at the core of economics of innovation, while industry dynamics and labour demand patterns investigated more by structural change studies. Patterns of consumption and distribution of income are not often considered as pivotal in influencing the overall dynamics of labour demand.

After all, technical change is ultimately about two things: either producing existing commodities or services with fewer inputs (i.e. more efficiently), or producing new commodities and new services. In practice, product innovations of one sector are often process innovations for other sectors which are using them. The distinction, nonetheless, is theoretically fruitful. Process innovations necessarily involve some input saving. More precisely, in capitalist economies where conflict over labour processes, income distribution and power are structural features, labour saving is one of the fundamental dimensions of most technological trajectories. Moreover, any labour-saving upstream, i.e. in the production of inputs required by other commodities, represents an input-saving change, in value terms, downstream.

Developed industrial systems are functionally characterised, in normal conditions, by reproducibility and not scarcity, demand-pulled in terms of macroeconomic activity, and balance of payment constrained. Under these conditions, paramount importance must be attributed to the broad duality of technical change which on the one hand continuously saves labour and, on the other hand, creates new markets or expands existing ones by means of changing costs and prices of commodities and services. The balance between demand creation and labour displacement defines the endogenously generated rates of macroeconomic activities and utilizations of the labour force.

In turn, such a balance is shaped by the coupled dynamics among four domains, namely:

- the nature of the fundamental technological paradigms;
- the patterns of diffusion and adoption of new paradigms across industries;
- the nature of the products generated by those new paradigms, with the associated dynamics in the underling capital and labour input requirements;
- the baskets of consumption, as a function of income levels and of income distribution

The impact of technology upon productivity and through that on labour demand has been one of the thorniest issues at least since David Ricardo's chapter "On Machinery". It is often referred to as the problem of *compensation mechanisms* (Freeman and Soete, 1987). There are at least three channels linking technological change, demand and employment namely, *first*, via productivity growth to lower prices to higher demand (under positive price elasticities of demand); *second*, from productivity growth to growing real wages to higher demand, and *third*, with an opposite sign, from productivity growth to labour displacement to higher unemployment and lower demand.

Moreover, a truly dynamically account of possible tendencies toward technological unemployment has to consider the transmission effects from the sectors where technological advances are generated, generically defined upstream along the industrial structure, toward sectors adopting them in the form of new capital goods and intermediate inputs, generically defined as downstream sectors. Therefore, not only generation but also diffusion of new technological paradigms among adopters is of a paramount importance (Rosenberg, 1972; Silverberg, 1991; Dosi and Nelson, 2010).

What firms produce in terms of final products and the related capital and labour requirements have a major impact on overall labour demand. One of the main features of modern capitalism has been the production of increasingly more complex manufacturing artefacts (Baldwin et al., 2000) requiring higher production stages. Indeed, a higher number of production stages requires a higher number of workers to be employed. This might counter-balance the increasing mechanization because of process innovation.

Finally, the overall demand of labour is influenced by the patterns of consumption and the underlying income distribution determining what people consume and the fraction of income they save. In line with a hierarchical structure of satisfaction of individual needs, first basic needs are satisfied, and climbing the income ladder, more complex products start to be acquired, possibly by means of saved income. Saving, in this respect, rather than being used as a precautionary buffer, occurs to acquire complex products which are initially not affordable. This individual pattern gives rise to aggregate Engel laws which are generically observed both historically and across income levels (Syrquin, 1988). Moreover, preferences are collectively shaped, and individual consumption profiles are influenced by their social status and their position along the income ladder.

This paper is positioned at the intersection between the three broad domains of analysis. The first one concerns the long terms patterns of capitalist development and the role in it of technological discontinuities. The literature of long waves and changes in techno-economic paradigms is germane to it (Clark et al., 1981). A second one addresses the compensation mechanisms in determining the patterns of labour creation and destruction (Vivarelli, 1995; Dosi et al., 2021). A third one studies structural change and sectoral dynamics (Kuznets and Murphy, 1966). In the following we present an agent-based model able to thoroughly account for the mechanisms underlying the relationship between employment, technical change and income distribution. In terms of modelling advances, we build upon the labour-augmented (Dosi et al., 2017, 2020) K+S model (Dosi et al., 2010) enlarged to account for (i) the arrival of new paradigmatic changes, (ii) the endogenous emergence and collapse of industries, (iii) consumption rules modelled by means of a hierarchical satisfaction of needs which map into attributes in the product space.

The model does not only reproduce a wide ensemble of micro, meso and macro stylised facts but mainly provides technology-related pulses of aggregate dynamics at different frequencies and is able to shed new light on the current debate on the *future of work*.[1] It is characterised by a system of interdependences among sectors. Inside the upstream sector both disruptive and incremental innovations can occur. Paradigmatic changes in technologies give

[1]Such debate recurrently emerges along the history: from Luddism in the nineteen century up to the report on the impact of automation on labour demand commissioned by the U.S. government, the National Commission on Technology, Automation, and Economic Progress, released in 1966 and the more recent apocalyptic scenarios on the end of work.

rise to technological discontinuities. Together, the arrival of new technological paradigms entails the possibility of the emergence of new sectors in the downstream aggregate. The higher the technological advancements, the higher the complexity of the products developed. Each new sector absorbs labour demand, but it also deploys more advanced techniques of productions. Both inter-firm and inter-sector competition occurs. Each sector experiences a product life-cycle with labour demand and product dynamics intimately related. Consumption and saving behaviours are modelled by distinguishing between basic and luxury goods.

Consumption and saving decisions interact with the dynamic evolution of sectors and their labour absorbing capacity. In so doing, the model accounts for the labour destruction impact of process innovation, which is reflected in the increasing mechanization of production, and the labour creation effect of product innovation due to the emergence of new sectors.

The properties of the model are studied and validated against a series of newly analysed stylised facts, in addition to those already replicated by previous versions of the model, primarily concerning the existence of long waves in GDP and S-shaped structure in industry behaviours. In particular, the model is able to reproduce historical long cycles emerging from the interaction between the arrival of new technological paradigms embedding higher efficiency in terms of production and the emerging new products. New paradigms arrive discontinuously in time and radical innovation activity out of the advancement of "scientific knowledge" is carried out by few risky innovators, well in tune with the Schumpeterian reading of innovative activity. However such knowledge-technological advancements quickly diffuse and dominate the market of capital-good producers because of productivity improvements in the newly discovered machines. Diffusion occurs in such a way that the new paradigm gets established. The underlying interdependency between the dynamics of knowledge generation upstream and of product innovation downstream results into structural change and long lasting S-shaped waves of product cycles. Such technological engine interacts with the demand of labour input requirements giving rise to cycles in employment dynamics. Product life-cycles in turns are reflected into a geometric distribution of the age of industry/firms. The structure of income distribution affects consumption behaviour, the Engel Law endogenously emerges for basic goods while non-satiation characterizes luxury goods. Non trivial interactions in terms of arrival of new paradigms, new industries, and labour demand arise, with potential technological unemployment mediated by product complexities, income elasticities and Keynesian interactions between process innovation and demand generation.

Our model has to be understood in terms of the coupled dynamics between labour-creation, ensured often by complex-product industries, and labour-destruction, often affecting basic, highly mechanised industries. Indeed, the history of Western Capitalism from WWII until the late seventies is a close empirical analogy. Together with the dynamics of product and process innovations we also consider a *mode of regulation* of the relations between social classes which warrants, among other features, a high indexation of wages to productivity and thus a relatively stable functional income distribution; relatively rigid rules of hiring and firing on the labour market (Dosi et al., 2018b), and on the consumption side, a massive diffusion of consumer durables (white and gray goods) characterised by a high income elasticity of demand. Call it the Fordist political economy (Boyer and Saillard, 2005). Such a socio-economic regime represents an overall resilient macroeconomic system able to internally reabsorb technological shocks which although repeatedly occurring, and notwithstanding ubiquitous hysteresis properties (Dosi et al., 2018a), do not appear to yield deep crises. The lesson is that results should be confined to a given socio-economic regime and not easily generalised to alternative ones, like the current post-Fordist or the First Industrial Revolution, the latter object of Ricardo's worries.

The paper is organised as follows. In Section 2 we discuss the broader issue of the human-machine relationship, addressing both the empirical and the theoretical literature. Then present the model in Section 3 that is validated by the emergent statistical properties discussed in Section 4. In Section 5 we focus on the patterns of labour creation and destruction, while Section 6 concludes.

2 Human-machine relationships and the current debates

It is useful to start from the basics and consider the fundamental features of the human-machine relation.[2] The currently dominant framework relies on the so-called *task-based* approach. Popularized by Autor et al. (2003), it considers the bundle of tasks executed by each worker as the most-important dimension in which technological change shapes the dynamics of occupations. In that, the routine vs. non-routine dichotomy has become mainstream in economic literature. The underlying idea is that some human tasks can be more easily substituted by technological change, by means of computers, others less so. The degree of substitutability, it is suggested, depends on the amount of codified knowledge required to execute a given task. In Autor et al. (2003), which leverages on the U.S. DOT dictionary of occupations, tasks considered to be substitutable by technological change include "setting limits, tolerances, or standards", and "finger dexterity", while tasks involving complementarity in human-machine include "knowledge of mathematics", "direction, control, planning", and "eye hand foot coordination". The first two activities are called "routine cognitive" and "routine manual", while the remaining three are "non-routine analytical", "non-routine interactive", and "non-routine manual" respectively. It is noteworthy that the task-based approach is rooted on the earlier *skill-biased technical change* (SBTC) approach, developed during 1990s mainly by Katz and Murphy (1992) to account for U.S. wage inequality, explained via different *premia* on behalf of low- and college-educated workers.

A few years later, Acemoglu and Autor (2011) proclaimed the defeat of SBTC theory. According to Acemoglu and Autor (2011), although such a framework has the merit of explicitly encompassing the skill-biased nature of technical change, it has the shortcoming of predicting an increase in economy-wide average wage and real wage of each skill group. In this respect, the canonical supply-demand model is not able to account for declining earnings, in absolute term, of low skilled workers, because of the absence of a comparative advantage mechanism. It is also unable to account for the different behaviour of the earning distribution across quantiles, highlighting wage polarization. More fundamentally, being based on skills rather than tasks, SBTC cannot explicitly account for human-machine interactions: while skills are a worker's attribute, tasks depends on the technology in use. Finally, by predicting the ultimate effect of technology as productivity-enhancing, substitution effects by embodied technical change in

[2] This section draws upon Staccioli and Virgillito (2021b).

machines are entirely neglected. Aimed at overcoming these limitations, the *routine-biased technical change* (RBTC) has become dominant, adopting the sectoral share of workers equipped by computer as proxy of penetration of technical change, and versions of the dictionary of occupations or alternatively of O*NET for the U.S., PIAAC for OECD countries, EWCS for Europe, BIBB/IAB for Germany (Biagi and Sebastian, 2020) as tasks' measure.

From computers to robots, automation regained attention after the Great Recession, also popularized by contributions like Brynjolfsson and McAfee (2014) and Ford (2015), which forecast that machines will win the race against humans and suggest dystopian scenarios of human-free workplaces. As a result, a number of recent studies rely on a new variable to account for technical change, namely the sectoral share of robots per number of employees. Indeed, the RBTC framework, previously used to account for digitalization, is reoriented towards the analysis of automation. In this respect, distinctions between computer-human vs. machine-human relationships are never truly investigated. So Acemoglu and Restrepo (2018, 2019, 2020) refine upon Acemoglu and Autor (2011) in order to account for two separate effects of automation: a so called *re-instatement effect*, according to which new tasks are created by automation technologies, to be executed by humans, and a *substitution effect*, where tasks previously attributed to labour move to capital. These industry-level studies, based on local labour markets, generally predict that a higher number of robots per employee decreases wages and occupations for low-wage workers. Nonetheless, a cross-country study at the industry level does find positive impact of robotic adoption on labour productivity, but less clear-cut evidence on employment reduction (Graetz and Michaels, 2018). Labour-shedding effects are found for low-skilled rather than medium-skilled workers.

Studies adopting firm-level data provide a different picture: in general, robotic adoption, or alternatively, imported capital equipment, are not found to produce labour expulsion, but rather employment growth (Koch et al., 2019; Domini et al., 2020). On the contrary, disproportionate figures on employment losses are reported by Frey and Osborne (2017), relying on the Delphi method in defining technological bottlenecks and on the RBTC approach, subsequently reviewed downward by Arntz et al. (2016).

At a first sight, the recent findings on robots/automation adoption against employment patterns mimic an older research tradition in the economics of innovation, which, starting with the seminal work by Chris Freeman and associates in 1980s (Clark et al., 1981; Freeman and Soete, 1987), distinguish between alternative effects of technical change on employment, theoretically discussing different compensation mechanisms balancing labour-saving impacts of innovation (Vivarelli, 1995; Simonetti et al., 2000; Piva and Vivarelli, 2018). In general, survey-based studies conducted during the "pre-robots era" on the impact of process innovation, including robotics and automation, seem to confirm a negative employment impact at the sectoral level. On the contrary, firm-level studies are found to report positive effects of process innovation (Calvino and Virgillito, 2018). The apparently conflicting firm-level evidence derives from the undergoing competitive and selection processes occurring in the market. A firm gaining market share, e.g. because of investments in robotic, automation, and in general of process innovation, might well increase its labour demand because of higher sales. However, the underlying sector might witness an overall decrease in employment growth, if the firm is able to increase its sales just at the expense of the share of its competitors (Dosi and Mohnen, 2019).

There are, however, deeper drawbacks in most current approaches to the analysis. A common underlying feature of both SBTC and the task-based approach is the assumption of some given degree of substitutability between labour and capital along isoquants of a purported production function. The relative cost of labour vs. capital ultimately defines the direction of technical change, whether labour-saving or labour-augmenting.

Here we take an alternative route. According to the evolutionary theory of technical change and the capability-based theory of the firm, first, the degree of substitutability between humans and machines is shaped and constrained by the existing technological trajectories. Therefore, possible labour displacing or augmenting effects of technology have to be understood not along any isoquant of techniques of production and movements thereof, but rather in light of the introduction of a new technique which requires less labour vis-à-vis capital. Second, technology has to be understood as an ensemble of recipes, consisting of both codified and non-codified knowledge. What regulates the space of human intervention on the production process is not simply the pace of technological change, but rather is modulated by *organizational routines*, that is the ensemble of *if/then* conditions occurring among the members of a given organization in their production problem-solving procedures (Dosi and Nelson, 2010). The routine/non-routine dichotomy poorly explains which tasks are expected ex-ante to be substituted and which to be augmented by technologies, once one also accounts for organizational practices. For instance, the so-called "Toyota-way" of production has always kept a low degree of automation inside Toyota manufacturing plants, independently of recurring innovative waves. Third, it is crucial to make the fundamental distinction between product and process innovation (nowadays rephrased as re-instatement vs. displacement). What innovation creates or destroys is not tasks, but rather products or sectors of activity (Freeman and Soete, 1987) at the macro level, and divisions and units at the firm-level, because of internal product-diversification and economies of scale (Chandler, 1993). After all, labour demand is not divisible by tasks. Fourth, it is the very nature of technical change, whether embodied or disembodied, which bears a major impact upon the overall relationship with employment dynamics (Dosi et al., 2021).

2.1 Related evolutionary agent-based models

The growing agent-based literature (Fagiolo and Roventini, 2017; Dawid and Delli Gatti, 2018; Dosi and Roventini, 2019) has addressed the patterns of technological change, structural change and consumption behaviour in various contributions. Among them, the K+S family (Dosi et al., 2010, 2017, 2020) focuses on the coupling between a Schumpeterian engine of innovation and a Keynesian one of demand generation as the ultimate drivers of economic growth. However, so far, such models have lacked any account for structural change and changing baskets of consumption.

The emergence of a variable number of sectors is at the core of the papers developed by Saviotti and Pyka (2004, 2008) who have also recently contributed to debate on the future of work by means of a multisector perspective, stressing the duality of technical change (Vermeulen et al., 2018). Structural change under a fixed number of sectors, and with consumption behaviour recalling the Engel Law are studied in Lorentz et al. (2016); Ciarli et al. (2019). Different propensities to consume across classes, but exogenously given, are explored in Caiani et al. (2019). A heterogeneous, multi-industry set-up, with constant allocation of consumption shares characterises the multi-country model in Dosi et al. (2019). A three-sector structural change model, modulated via Engel Law, is presented in Gabardo et al. (2020). In general, this stream of ABM literature emphasizes the role of demand and consumption behaviours in shaping structural change.

With reference to product life-cycles and role of complexity in the product space, pivotal modelling explorations are in Marengo and Valente (2010); Frenken (2006). Building upon NK models they map complexity, defined as interdependency across product components, into the properties of the innovation process and its speed.

The Eurace family of ABMs has been recently used to study the impact of new digital technologies on productivity and employment (Bertani et al., 2020), while forms of organization of the labour markets, capital investments and growth has been studied by means of the Eurace@Unibi version (Dawid et al., 2019). The model has been recently adopted to study the relationship between technological regimes, inequality and concentration (Dawid and Hepp, 2021).

Advancing with respect to the extant literature, in the following we present a model which develops and refines upon the "K+S" modelling perspective, expanding its vertical interdependent structure in tune with Pasinetti (1983), accounting for the emergence of new sectors downstream. Both new technologies and new products are subject to diffusion processes. New technologies embodied in new generations of capital goods diffuse through their adoption by downstream firms which produce an expanding variety of final goods, in turn diffusing in consumption baskets. New final goods are characterised by increasing degrees of complexity, entailing a growing number of production stages.

Thus, the model is able to fully account for the patterns of labour creation and labour destruction emerging out of the evolution of changing vertically integrated production structures and changing consumption patterns.

3 The model

We build a *general disequilibrium*, stock-and-flow consistent, agent-based model, populated by heterogeneous workers, firms, and banks which behave according to heuristic rules.

In brief, the economy is composed by five populations of heterogeneous agents, namely, L^S workers/consumers, F_t^1 capital-good firms, F_t^2 consumption-good industries, $F_{h,t}^2$ consumption-good firms in each industry h, and B banks, plus the central bank and the government.[3] The basic structure of the model is depicted in Figure 1.

Capital-good firms invest in R&D and produce heterogeneous machine-tools whose stochastic productivity evolves endogenously over time. Less frequently, new generations of machines are discovered, enabling the emergence of new consumption goods and industries. Downstream consumption-good firms combine machines bought from capital-good firms and labour in order to produce quality-differentiated goods for final consumers. Across industries,

[3]Subscript t stands for (discrete) time $t = 1, 2, ..., T$. Agent-specific variables are denoted by subscript h, in case of industries, i, for capital-good firms, j, for consumption-good firms, k, for banks, and ℓ, for workers.

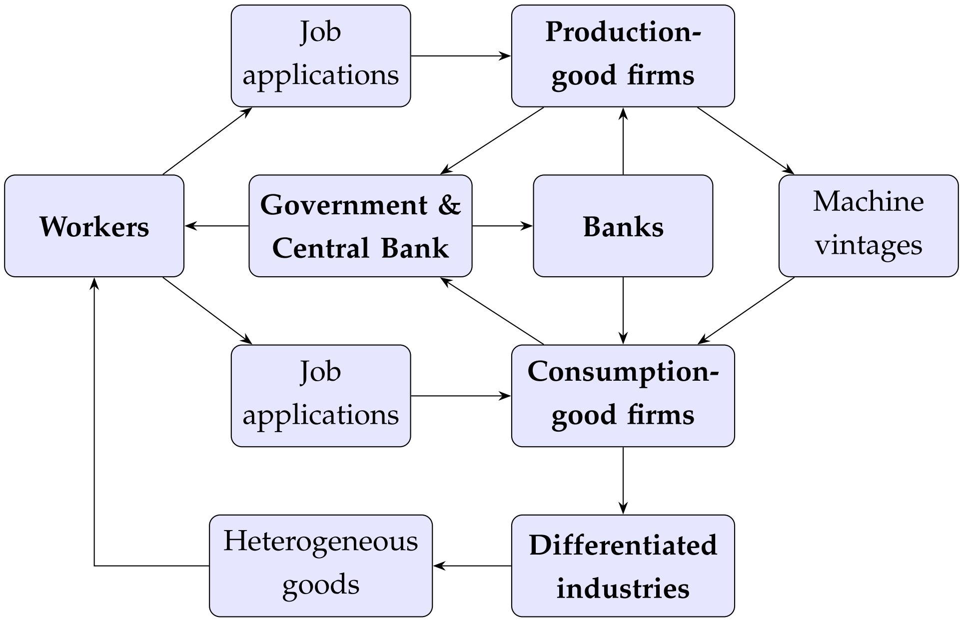


Figure 1: The model overall structure. Boxes in bold style represent the model's agents.

consumption-good firms compete with heterogeneous products for consumers' expenditures. Workers search for jobs, and firms hire workers according to their individual demand expectation. The banking sector is represented by a fixed number of banks which take deposits and provide interest-paying loans to finance firms' production and investment plans. The central bank manages the monetary policy, imposes regulatory reserves to the banks, and bails out the failing ones. The government levies taxes on firm and bank profits, pays unemployment benefits, imposes a minimum wage, absorbs excess profits and losses from the central bank and keeps a non-explosive public debt trajectory in the long run.

Firms on both sectors are associated with a single bank. Banks are heterogeneous under a fixed size distribution, take deposits from firms (corresponding to their net wealth) and workers (corresponding to temporary savings for future consumption), pay interest, and provide credit to firms under the prudential requirements imposed by the central bank (capital and reserves). Available (limited) credit is allocated to clients according to the respective limit and credit score. Firm limits are based on past sales performance, according to a loan-to-value ratio rule, and the score is based on clients' relative solvency index. Total credit supply to the financial sector is elastic and unconstrained by the aggregate supply side, adapting to credit demand and prudential requirements.

The capital-good industry is the locus of endogenous innovation in the model. Capital-good firms innovate by developing new machine-embodied techniques or imitate the ones of their competitors in order to produce and sell more productive and cheaper machinery. Innovation is of two types, "incremental" or "radical". Incremental innovation gradually increases existing technologies' productivity both on new machine construction and usage. Radical innovation introduces a new, qualitatively different generation of machines, associated to a new technological paradigm, which is more productive to use but also more expensive to produce. On demand, capital-good firms supply universal-application machine-tools to consumption-good firms in any downstream industry, producing with labour as the only input. The capital-good market is characterized by imperfect information and Schumpeterian competition driven by technological innovation. Firms signal the price and productivity of their machines to their current customers as well to a subset of potential new ones, and invest a fraction of past revenues in R&D aimed at searching for new machines or copy existing ones. Prices are set using a fixed mark-up over (labour) costs of production.

Consumption-good firms in each industry produce a single, quality-differentiated good, employing capital (composed by different "vintages" of machine-tools) and labour under constant returns to scale. Desired production is determined according to adaptive (myopic) demand expectations. Given the actual inventories, if the current capital stock is not sufficient to produce the desired output, firms order new machines to expand their installed capacity, paying in advance — drawing on their retained past profits or, up to some limits, on bank loans. Moreover, they replace old machines according to a payback-period rule. As new machines embed state-of-the-art technologies, the labour productivity of consumption-good firms increases over time according to the mix of (employed) vintages in the capital stocks. Firms choose the capital-good supplier comparing the price and the productivity of the machines they are aware of. They fix their output prices applying a variable mark-up rule on their (labour) production costs, balancing profit margins and market shares, increasing mark-ups and prices whenever market shares are expanding and vice versa. Imperfect information is also the normal state of the consumption-good markets so consumers do not instantaneously switch to the most competitive producer. Market shares evolve according to a (quasi) replicator dynamics: more competitive firms expand, while firms with relatively lower competitiveness levels shrink, or exit the market.

Consumption-good firms group into different industries. Firms in the same industry produce a homogeneous but quality-differentiated good. From the consumer perspective, there are two broad categories of goods: *basic* (non-durable) and *luxury* (durable). Each industry produces goods from a single category. Products from different industries are heterogeneous in five consumer-relevant attributes: category, price, quality, newness and complexity. Industries compete for the consumer budget ("wallet share") based on these attributes, which are directly derived from the firm-specific product attributes, in the case of price and quality, or are homogeneous for the whole industry, for category, newness and complexity. Firms compete for a fraction (market share) of the wallet share acquired by the industry which they belong to. Therefore, each industry also defines a (separate) market.

The entry-exit process for industries and firms is entirely endogenous. Industries die and firms leave whenever wallet/market shares get close to zero or (total) net assets turn negative (bankruptcy). Residual positive firm net values are collected by the government, and negative proceedings are supported by the defaulted banks. Conversely, there is a positive probability of a new luxury-good industry entering the economy after the introduction of each new machine generation, due to a successful radical innovation in the capital-good sector. New basic-good industries enter randomly, with probability inversely proportional to the number of incumbent basic industries. At the firm level, the (stochastic) number of entrants in an industry depends on the number of incumbents and on the prevailing financial conditions. When the industrial liquidity-to-debt ratio is growing, firm entry gets easier, and vice versa.

The labour market is modelled as a fully decentralized, search-and-hiring process between workers and firms. For simplicity, banks, the central bank and the government occupy no workers. The aggregate supply of labour is fixed and all workers are available to be hired in any period. When unemployed, workers submit a certain number of job applications to a random subset of firms. Employed workers apply for better positions. Larger firms have a proportionally higher probability of receiving job applications, which are organized in separated, firm-specific application queues. The labour market is also characterized by imperfect information as firms only observe workers' skills and wage requests on their own queues, and workers are aware only of the wage offers they may receive from firms where they applied for a job. Firms, on the grounds of received orders (capital-good sector), of the expected demand (consumption-good sector), and the current labour productivity levels, decide whether to (i) hire new workers, (ii) fire part of the existing ones, or (iii) keep the current labour force. Each hiring firm defines a unique wage offer for the best applicant workers, based on firm- and economy-wide productivities. Workers select the best wage offer they get from firms to which they submitted applications, if any. When already employed they may quit the current job if a better offer is received. There are no further rounds of bargaining between workers and firms in the same period. Thus, firms have no guarantee of fulfilling all the open positions, workers may not find a job even when there are still unfilled positions, and no labour market clearing is ever guaranteed. Moreover, there are no firing or hiring transaction costs. The government enforces a minimum wage indexed to the aggregate productivity of the economy.

Consumer splits the income between basic- and luxury-good budgets, entirely allocating her income to basic goods up to a given threshold, corresponding to the median of income distribution, and the excess, if any, to luxury consumption. The budget for (divisible) basic goods is (tentatively) spent every period, and split among basic-good industries according to the respective products attributes (price, quality, newness and complexity). Luxury goods, which are not divisible, are acquired whenever three conditions are met: (i) a minimum period from last acquisition passed, (ii) at least one not-recently-bought good is obtainable, and (iii) the available luxury budget (current plus accumulated) is enough to buy at least one unit of the chosen good. If these conditions are not met, the available luxury budget is saved for the next period. So, the consumption bundle at each period is comprised by a set of heterogeneous basic consumption goods, each one supplied by a different industry and firm, plus possibly one or more units of a single luxury good. If total supply of consumer goods is insufficient to satisfy the resulting demands for basic and luxury goods, the excess is saved in banks and turns into additional consumption demand in the next period(s). Workers cannot get credit from banks for consumption.

See Appendix A for detailed specifications of the behavioural rules outlined above. In the following, we shall highlight mostly new elements vis-à-vis the incumbent K+S family of models.

3.1 Radical innovation and new machine generations

In the vein of Chiaromonte and Dosi (1993), a radical innovation in the capital-good sector is accessed in the set of the notional opportunities i.e. new machine typologies (set of values

$A_{i,t}$), which grows via a stochastic process dependent on exogenous scientific development. The probability of a new technological paradigm be introduced in any period t is given by the parameter $\zeta_g \in \mathbb{R}_+$. If a new machine generation emerges from this process, its initial notional labour productivity A_t^g — for each manufacturing stage of the production of consumer goods — is drawn from a uniform distribution:

$$A_t^g \sim \mathrm{U}\left[\max_i A_{i,t-1}, (1+h)\max_i A_{i,t-1}\right], \tag{1}$$

where $h \in \mathbb{R}_+$ is a parameter capturing the effectiveness of the exploitation of scientific opportunities. The notional capital productivity, i.e., the output per period of one machine used in a single manufacturing stage, is constant (parameter $m_2 \in \mathbb{R}_+$).

Conversely, machines from a new generation are initially more expensive to build, reducing the (labour) productivity B_t^g of capital-good firms exploring the new paradigm:

$$B_t^g \sim \mathrm{U}\left[\frac{\max_i (A_{i,t-1}B_{i,t-1})}{A_t^g}, (1+h)\frac{\max_i (A_{i,t-1}B_{i,t-1})}{A_t^g}\right]. \tag{2}$$

Therefore, B_t^g is drawn symmetrically to A_t^g but lower bounded to the minimum value which keeps the combined labour productivity of the new machine generation competitive vis-à-vis the top incumbent technology (instead of the absolute minimum $B_{i,t-1}$).

Access to radical innovation, if any, at the firm level is modelled as an in-firm, two-step process. Based on the share of workers $IN'_{i,t}$ employed in innovative research and development (R&D) by a capital-good firm, a draw from a Bernoulli distribution with mean $\theta_{i,t}^g$ defines a success or a failure of access at time t:

$$\theta_{i,t}^g = 1 - e^{-\zeta_0 IN'_{i,t}}, \tag{3}$$

$\zeta_0 \in \mathbb{R}_+$ is a parameter. If firm i is successful in accessing the next machine generation, it will consider it when choosing new technology to produce:

$$(A_{i,t}^g, B_{i,t}^g) = \begin{cases} (A_t^g, B_t^g) & \text{if succesfully access new generation} \\ (0,0) & \text{otherwise.} \end{cases} \tag{4}$$

Firm can only access the machine generation immediately above the one currently being produced. Machines are universal in the sense that can be adopted by all downstream industries. However, new luxury good industries require machines belonging to a new family, i.e. a new paradigm. To illustrate, think of a new industry, say automotive, at its beginning which in order to take-off requires, say, a new family of lathes, which thereafter can be adopted also by other final good industries.

3.2 Technical change and labour productivity

The technology of capital-good firms is defined as (A_i^τ, B_i^τ). A_i^τ is the labour productivity of the machine-tool manufactured by firm i for the consumption-good sector, while B_i^τ is the labour productivity to produce the machine. Superscript τ denotes the technology vintage being produced/used. Given the monetary average wage $w_{i,t}$ paid by firm i, its unit cost of production is:

$$c_{i,t} = \frac{w_{i,t}}{B_i^{\tau}}. \tag{5}$$

Under a fixed mark-up $\mu_1 \in \mathbb{R}_+$ pricing rule, price $p_{i,t}$ of firm i is defined as:

$$p_{i,t} = (1 + \mu_1)c_{i,t}. \tag{6}$$

Firms in the capital-good industry adaptively strive to increase market shares and profits by improving technology via innovation and imitation. Firms invest in R&D a fraction $\nu \in [0, 1]$ of their past sales $S_{i,t-1}$:

$$RD_{i,t} = \nu S_{i,t-1}. \tag{7}$$

R&D activity is performed by workers devoted to this activity, whose demand is:

$$L_{i,t}^{R\&D} = \frac{RD_{i,t}}{w_{i,t}} \tag{8}$$

Firms split their R&D workers $L_{i,t}^{R\&D}$ between innovation ($IN_{i,t}$) and imitation ($IM_{i,t}$) activities according to the parameter $\xi \in [0, 1]$:

$$IN_{i,t} = \xi L_{i,t}^{R\&D}, \tag{9}$$

$$IM_{i,t} = (1 - \xi)L_{i,t}^{R\&D}. \tag{10}$$

In-firm, incremental innovation is a two-step process. The first determines whether a firm obtains or not access to an innovation – irrespectively of whether it will ultimately be a success or a failure – through a draw from a Bernoulli distribution with mean:

$$\theta_{i,t}^{in} = 1 - e^{-\zeta_1 IN'_{i,t}}, \tag{11}$$

with parameter $\zeta_1 \in [0, 1]$ and $IN'_{i,t}$ the normalized share of R&D workers dedicated to innovation. If a firm innovates, it may draw a new machine-embodying technology $(A_{i,t}^{in}, B_{i,t}^{in})$ according to:

$$A_{i,t}^{in} = A_{i,t}\left(1 + x_{i,t}^A\right), \tag{12}$$

$$B_{i,t}^{in} = B_{i,t}\left(1 + x_{i,t}^B\right), \tag{13}$$

where $x_{i,t}^A$ and $x_{i,t}^B$ are two independent draws from a $\mathrm{beta}(\alpha_1, \beta_1)$ distribution, $(\alpha_1, \beta_1) \in \mathbb{R}_+^2$ over the fixed support $[\underline{x}_1, \bar{x}_1] \subset \mathbb{R}$.

Imitation also follows a two-step procedure. The access to imitation comes from sampling a Bernoulli with mean:

$$\theta_{i,t}^{im} = 1 - e^{-\zeta_2 IM'_{i,t}}, \tag{14}$$

being parameter $\zeta_2 \in [0, 1]$ and $IM'_{i,t}$ the normalized share of imitative R&D workers. Firms accessing the second stage may copy technology (A_i^{im}, B_i^{im}) from a close competitor and select the machine to produce using the rule:

$$\min\left[p_{i,t}^m + bc_{A_{i,t}^m}^m\right], \quad m = \tau, g, in, im, \tag{15}$$

where $b \in \mathbb{R}_+$ is a payback parameter.

Firms in consumption-good sector do not conduct R&D, instead they access new technologies incorporating new machines to their existing capital stock $\Xi_{j,t}$. The firm effective productivity $A_{j,t}$ results from both machine (notional) productivity A_i^τ and worker skills $s_{\ell,t}$, as described later, and is computed as:

$$A_{j,t} = \frac{1}{L_{j,t-1}} \sum_{\ell \in \{L_{j,t-1}\}} A_{\ell,t}, \tag{16}$$

where, $L_{j,t}$ is the set of workers at firm j, $\{L_{j,t}\}$, the size of this set, and $A_{\ell,t}$, worker ℓ productivity.

The skill level $s_{\ell,t} \in \mathbb{R}_+$ of worker ℓ evolves in time t as a multiplicative process:

$$s_{\ell,t} = \begin{cases} (1+\tau_T)s_{\ell,t-1} & \text{if employed in } t-1 \\ \dfrac{1}{1+\tau_U} s_{\ell,t-1} & \text{if unemployed in } t-1, \end{cases} \tag{17}$$

where $(\tau_T, \tau_U) \in \mathbb{R}_+^2$ are parameters governing the learning rate while the worker is employed or unemployed, respectively. When hired, a worker acquires the minimum skill level present in the firm, if above her present level. Worker has a fixed working life, retires after a number of periods T_r, and is replaced by a new one with skills equal to the minimum among employed workers.

Worker ℓ current skills $s_{\ell,t}$ define her individual (potential) productivity:

$$A_{\ell,t} = \frac{s_{\ell,t}}{\bar{s}_t} \frac{A_i^\tau}{k_j}, \tag{18}$$

being $\bar{s}_t$ the average overall skill level, A_i^τ the standard notional productivity of the specific machinery vintage the worker operates, and k_j the complexity of the produced good.

3.3 New industry entry and product complexity

The emergence of basic- and luxury-good industries follows two different stochastic processes. The one regulating the entry of basic industries depends on the rate of change of existing industries with respect to the initial ones. The number of basic industries is therefore anchored to its initial number: if the former is higher than the latter, the probability of entry shrinks, while in case the number of existing industries is lower than the initial one, the probability of entry increases. Such a balanced entry dynamics ensures stability in basic-industries and avoids limit behaviours, indeed well in tune with the stable composition of basic needs satisfied by basic products produced by such industries.

The arrival of luxury industries is instead connected with the arrival of new technological paradigms. The higher the jump in productivity efficiency of the new technological paradigm, the higher the probability of arrival of a new luxury industry. In such a way, we explicitly interconnect process innovation upstream and product innovation downstream. Considering the universal usage of new technological paradigms, call them steam engine, electrification, mechanization, automation, digitalization, their arrival will foster the emergence of a new set of products embedding their usage in production. Such industries match an ever increasing set of non basic needs along the history.

At any time t, a new basic-good industry has an entry probability given by:

$$\theta_t^{bas} = 1 - e^{-\zeta_{bas}\left(\frac{F_0^{bas}}{F_{t-1}^{bas}} - 1\right)}, \tag{19}$$

being $\zeta_{bas} \in \mathbb{R}_+$ a parameter, F_{t-1}^{bas} the current number of basic-good industries, and F_0^{bas} the initial number of such industries.

New luxury-good industry emergence is contingent on a new machine generation being introduced by at least one capital-good firm. In each period t after the introduction of a (still unexploited) new generation, the probability of one (and only one) new luxury-good entering the consumption-good sector is:

$$\theta_t^{lux} = \begin{cases} 1 - e^{-\zeta_{lux}\Delta_t^g} & \text{if unexploited generation is available in } t \\ 0 & \text{otherwise,} \end{cases} \tag{20}$$

where $\zeta_{lux} \in \mathbb{R}_+$ is a parameter and Δ_t^g represents the generational improvement of the best machines available in comparison to the last exploited generation:

$$\Delta_t^g = \log\left(\frac{A_t^g B_t^g}{A_{t-u}^g B_{t-u}^g}\right), \tag{21}$$

being $A_t^g B_t^g$ the combined notional labour productivity of the most recent technological paradigm of machines, as explained above, and $A_{t-u}^g B_{t-u}^g$ the equivalent metric for the last paradigm (introduced u periods ago) effectively exploited by a luxury industry.

New industries start with an initial number of new firms, defined by the parameter $F_{min}^2 \in \mathbb{N}$ and evolve according to the entry-exit behavioural rules detailed in Appendix A (as in previous versions of the model). Firms in a new luxury industry can only buy machines from generation A_t^g or newer. New industry's firms always pick the most productive machines from generation A_t^g at the time industry starts.

We introduce a product level attribute, namely complexity. It intends to capture the evolution of more complex products, entailing the integration of many more parts and components in order to be assembled. New consumer goods, introduced by firms in emerging industries, are characterized by a higher notional product complexity, defined as $k_h \in \mathbb{R}_+^*$, drawn from a beta distribution over the average complexity of the same product category:

$$\begin{gathered} k_h = \bar{k}_{t-1}^z \left(1 + \pi_t^z\right) \left(1 + \Delta_t^g\right)^{\gamma_z}, \\ \pi_t^z \sim \text{beta}(\alpha_3, \beta_3), \quad \pi_t^z \in [\underline{x}_3, \bar{x}_3], \quad z = bas, lux, \end{gathered} \tag{22}$$

$\bar{k}_t^z$ are the (weighted) average complexity of existing basic- ($z = bas$) or luxury- ($z = lux$) good industries. π_t^z are random shocks with beta distribution on parameters $(\alpha_3, \beta_3) \in \mathbb{R}_+^2$ over the fixed finite support $[\underline{x}_3, \bar{x}_3] \subset \mathbb{R}$, defined for each industry. Δ_t^g is the generational improvement of the best machines available, as defined above, and $(\gamma_{bas}, \gamma_{lux}) \in \mathbb{R}_+^2$ are technology-intensity parameters, according to the type of industry.

Product complexity k_h defines the notional number of manufacturing stages the firms employ to produce a consumer good in industry h. Each additional stage employs both labour and capital, so complexity affects proportionally the number of workers and machines needed to produce the consumer goods. Therefore, more complex goods present higher average unit (labour) costs:

$$c_{j,t} = k_h \frac{w_{j,t}}{m_2 A_{j,t}}, \tag{23}$$

where $m_2 \in \mathbb{R}_+$ is the (fixed) capital productivity, $w_{j,t}$ is the average wage paid by firm j, and $A_{j,t}$ is the notional (single-stage) average labour productivity j at firm j considering the skill-set ($s_{\ell,t}$) of involved workers. Each machine employed in production has fixed capital productivity m_2, measured as the potential output per period for a single manufacturing stage, and requires (in average) $A_{j,t}$ workers to be operated.

3.4 Labour market under Fordism

Labour demand of firm j in the consumption-good sector $L^d_{j,t}$ is determined by the desired production $Q^d_{j,t}$ and the expected labour productivity $A_{j,t}$:

$$L^d_{j,t} = \frac{Q^d_{j,t}}{A_{j,t}}. \tag{24}$$

Capital-good firms, instead, compute $L^d_{i,t}$ considering orders $Q_{i,t}$ and labour productivity $B_{i,t}$.

Firms decide whether to hire workers according to the expected production $Q^d_{j,t}$ (or $Q_{i,t}$). If it is increasing, $\Delta L^d_{j,t}$ new workers are (tentatively) hired in addition to the existing number $L_{j,t-1}$. Firing occurs only under negative profits (losses). Each firm (expectedly) gets a fraction of the number of applicant workers $L_{a,t}$ in its candidates queue $\{\ell^s_{j,t}\}$, proportional to firm market share $f_{j,t-1}$:

$$\mathrm{E}(L^s_{j,t}) = [\omega\,(1 - U_{t-1}) + \omega_u U_{t-1}]\, L^S f_{j,t-1}, \tag{25}$$

where L^S is the (fixed) total labour supply, U_t is the unemployment rate and $(\omega, \omega_u) \in \mathbb{R}^2_+$ are parameters defining the number of applications each job seeker sends if employed or unemployed, respectively. Considering the set of workers in $\{\ell^s_{j,t}\}$, each firm selects the subset of desired workers $\{\ell^d_{j,t}\}$ to make a job (wage) offer:

$$\{\ell^d_{j,t}\} = \{\ell_{j,t} \in \{\ell^s_{j,t}\} : w^r_{\ell,t} \leq w^o_{j,t}\}. \tag{26}$$

Firms in consumption-good sector target workers that would accept the wage offer $w^o_{j,t}$, considering the wage $w^r_{\ell,t}$ requested by workers, if any. In the capital-good sector, firms top the wages offered by the consumer-good sector ($w^o_{i,t} = \max w^o_{j,t}$). Firm j hires up to the total demand $L^d_{j,t}$ or up to all workers in the queue, whichever is lower. The total number of workers $L_{j,t}$ the firm will employ in t, given the current workforce $L_{j,t-1}$, is bound by:

$$0 \leq L_{j,t} \leq L^d_{j,t} \leq L^s_{j,t}, \qquad L^z_{j,t} = L_{j,t-1} + \#\{\ell^z_{j,t}\}, \quad z = d, s. \tag{27}$$

Firm j offers the wage:

$$w^o_{j,t} = [1 + WP_{j,t} + \mathrm{N}(0, w^o_{err})]\, w^o_{j,t-1} \quad \text{bounded to} \quad p_{j,t-1} A_{j,t-1}, \tag{28}$$

where $w^o_{err} \in \mathbb{R}$ is the standard deviation parameter, that is accepted by the worker if she has no better offer. The wage premium is defined as:

$$WP_{j,t} = \psi_2 \frac{\Delta A_t}{A_{t-1}} + \psi_4 \frac{\Delta A_{j,t}}{A_{j,t-1}}, \qquad \psi_2 + \psi_4 \leq 1, \tag{29}$$

being A_t the aggregate labour productivity, Δ the time difference operator, and $(\psi_2, \psi_4) \in \mathbb{R}^2_+$ parameters. $w^o_{j,t}$ is also applied to existing workers. $w^o_{j,t}$ is bounded to the break-even wage (zero unit profits myopic expectation).

On top of the wage $w_{\ell,t}$ paid to worker ℓ, a firm with above-average profit may distribute bonus $Bon_{j,t}$, equally-divided among workers:

$$Bon_{j,t} = \psi_6(1 - tr)\Pi_{j,t-1}, \tag{30}$$

being $\psi_6 \in [0, 1]$ a sharing parameter, $tr \in [0, 1]$ the tax rate parameter, and $\Pi_{j,t}$ the firm gross profit. Total income of worker ℓ working for firm j in period t is $w_{\ell,t} + Bon_{j,t}/L_{j,t}$.

Table 1 summarizes the features of the Fordist labour market regime.

FIRMS BEHAVIOUR	FORDIST REGULATION
Within firm differentiated wages	no
Wage sensitivity to unemployment	low (rigid)
Wage indexation to average productivity	full
Labour-firing restrictions	under losses only
Worker-hiring rule	higher skills
Worker-firing rule	lower skills
Worker new-job search intensity	low ($\omega = 2$)

Table 1: Characteristics of the Fordist regime.

3.5 Consumption across income groups

Workers income $In_{\ell,t}$ is originated from the wage $w_{\ell,t}$ paid by firms to employed workers, or the unemployment subsidy w^u_t, paid by the government, plus the eventual outstanding bonus $Bon_{\ell,t-1}$:

$$In_{\ell,t} = \begin{cases} w_{\ell,t} + Bon_{\ell,t-1} & \text{if employed in } t \\ w^u_t + Bon_{\ell,t-1} & \text{if unemployed in } t, \end{cases} \tag{31}$$

At time t, consumer ℓ distributes her income between basic and luxury goods. Below a certain threshold, consumers allocate all their income to basic goods in order to satisfy their basic needs. Above it, the distribution of relative shares depends on the quantile to which they belong. In a such a way, we assume that the satisfaction of basic needs is equal across classes, while luxury preferences expand with income.

$$C^{d,bas}_{\ell,t} = \begin{cases} In_{\ell,t} & \text{if } In_{\ell,t} \leq \underset{n}{\text{perc}}\left(\phi_{lux}, In_{n,t-1}\right) \\ \underset{n}{\text{perc}}\left(\phi_{lux}, In_{n,t-1}\right) & \text{otherwise,} \end{cases} \tag{32}$$

where $\text{perc}_n(\cdot)$ is the percentile function determining the income share $In_{n,t-1}$ of the worker n spending $\phi_{lux} \in [0, 1]$. Consumers (tentatively) spend the entire basic good budget every period, splitting it among available products according to their relative competitiveness $E_{h,t}$ (details below). Consumption is contingent on available (total) supply of goods, so desired consumption may not materialize into effective consumption ($C^{bas}_{\ell,t} \leq C^{d,bas}_{\ell,t}$), and the excess demand may be force-saved for the next period(s). Any income in excess to the basic products budget is directed to the consumption of luxury goods:

$$C^{d,lux}_{\ell,t} = \begin{cases} In_{\ell,t} - C^{d,bas}_{\ell,t} & \text{if } In_{\ell,t} > \underset{n}{\text{perc}}\left(\phi_{lux}, In_{n,t-1}\right) \\ 0 & \text{otherwise.} \end{cases} \tag{33}$$

Basic goods are perfectly divisible and more than one type of basic good can be bought at a single period. Conversely, luxury goods are not perfectly divisible and require the consumption of at least one unit. Additionally, individual consumers accumulate (save) the luxury budget for T_{lux} periods before effectively buying ($T_{lux} \in \mathbb{N}$, a parameter), and do not buy the same (durable) luxury product before its lifetime ($T^{max}_{lux} \in \mathbb{N}$) is over. Therefore, the successful allocation of the consumer savings to luxury $Sav^{lux}_{\ell,t}$ depends on three conditions: (i) the (unit) price $p_{h,t}$ of at least one product unit fits the budget for luxury goods (current plus savings, $C^{d,lux}_{\ell,t} + Sav^{lux}_{\ell,t-1}$), (ii) a number of at least T_{lux} periods has passed from the last luxury acquisition, and (iii) there exists at least one specific good which she has not consumed in the past T^{max}_{lux} periods. If any of the conditions is not met, the budget for luxury is saved:

$$Sav^{lux}_{\ell,t} = \begin{cases} 0 & \text{if } \min\limits_{h} p^{*}_{h,t} \leq C^{d,lux}_{\ell,t} + Sav^{lux}_{\ell,t-1} \text{ and } t \geq t^{*}_{\ell} + T_{lux} \\ Sav^{lux}_{\ell,t-1} + C^{d,lux}_{\ell,t} & \text{otherwise or if supply shortage,} \end{cases} \tag{34}$$

where t^{*}_{ℓ} is the last time consumer ℓ bought a luxury product, and $p^{*}_{h,t}$ is the price of the cheapest luxury good the consumer does not already own. Exceptionally, savings for luxury goods can be expended in basic goods when worker is unemployed. In this case, an amount equal to $Sav^{lux}_{\ell,t}/T_{lux}$ is transferred to the basic-goods budget $C^{d,bas}_{\ell,t}$ every period while unemployment and savings last. Additionally, in case of a shortage in the selected luxury-good industry, consumer may be forced to save and try again to buy, the same or other product, in next period.

3.6 Inter-industry competition

In standard consumer choice theory, inter-industry allocation of demands would be assumed to depend on explicit well-behaved utility functions. Conversely, in our world of adaptive preferences and social conformity, the ranking order of basic goods is equal across consumers, that is they all satisfy the basic needs with the same order of preferences. However, budget constraints deriving from different wages will define heterogeneous ex-post consumption bundles. Thus, it is more appropriate to think of competing industries for consumption budgets over populations of potential consumers.

Competition among industries for the consumers' budgets takes place inside the two subsectors defined by the consumption goods categories, basic and luxury. The relative competitiveness $E_{h,t}$ of each industry is defined by a weighted combination of four components: average product price $\bar{p}'_{h,t}$, quality $\bar{q}'_{h,t}$, newness $\bar{n}'_{h}$ (industry age), and complexity $\bar{k}'_{h}$.

$$E_{h,t} = \delta_1 \left(1 - \bar{p}'_{h,t-1}\right) + \delta_2 \bar{q}'_{h,t-1} + \delta_3 \left(1 - \bar{n}'_{h}\right) + \delta_4 \bar{k}'_{h}, \tag{35}$$

where $(\delta_1, \delta_2, \delta_3, \delta_4) \in \mathbb{R}_+^4$ are parameters. All competitiveness components are log-normalized to the interval $[0.1, 0.9]$.

Basic-good industries' wallet shares evolve according to their relative competitiveness. They share the sub-sectoral (monetary) demand of basic goods following a replicator dynamics:

$$f_{h,t} = f_{h,t-1}\left(1 + \chi_c \frac{E_{h,t} - \bar{E}_t^{bas}}{\bar{E}_t^{bas}}\right), \qquad \bar{E}_t^{bas} = \frac{1}{F_t^{bas}} \sum_{h \in bas} E_{h,t} f_{h,t-1}, \tag{36}$$

with $\chi_c \in \mathbb{R}_+$ the replicator selectivity parameter, $\bar{E}_t^{bas}$, the average relative competitiveness among basic-good industries, and F_t^{bas}, the current number of basic industries.

Luxury-good industries compete on a consumer-by-consumer basis. As consumers have tight budgets, do not buy luxury every period, and do not acquire the same good before some time. A search-and-match algorithm is required to model the process. It tries to connect each prospective consumer ℓ to an industry-product h and to a supplier-firm j at every time t, operating as follows. In the first step, willing-to-buy consumers identify the set of luxury-good industries offering products satisfying their particular requirements (maximum price $p_{h,t}$ less or equal to $C_{\ell,t}^{d,lux} + Sav_{\ell,t-1}^{lux}$ and not consumed before or out of useful life). Second, from the set qualified industry-product pairs, consumers draw one with probabilities given by the corresponding industry relative competitiveness $E_{h,t}$, and fill a generic buying order to the chosen industry indicating the desired expense amount. Third, consumer orders for each industry are tentatively allocated to supplier firms according to their relative competitiveness in that industry (see Appendix A for details), until all demand or supply is fulfilled. Next, if there is excess demand, some consumers will have their orders rejected and budgets force-saved for the next period ($Sav_{\ell,t}^{lux} = Sav_{\ell,t-1}^{lux} + C_{\ell,t}^{d,lux}$), or excess supply turns into firm inventories. Last, accepted orders may have quantities adjusted to account for differences between average industry price $p_{h,t}$ and the allocated firm price $p_{j,t}$.

In Appendix A, we present the remaining behavioural rules characterizing agents. For in-depth details, see Dosi et al., 2010, 2017. The model's parameters, initial conditions and stock-flow matrix are presented in Appendix B.

3.7 Timeline of events

In each simulation period the following sequence of events takes place:

1. Science advances occur and new machine technological generations may be discovered;
2. Workers (employed and unemployed) update their skills;
3. Machines ordered in the previous period (if any) are delivered;
4. Capital-good firms perform R&D and signal machines to consumption-good firms;
5. Consumption-good firms determine desired production, investment and workforce;
6. Firms allocate cash-flows and (if needed) borrow from banks to operate and invest;
7. Capital-good firms send their brochures and receive machine-tool orders for the next period (if applicable);
8. Job-seeking workers send job applications to firms;
9. Wages are set and job vacancies are partly or totally filled;
10. Firms pay wages/bonuses and government pays unemployment benefits;

11. Consumer-workers define the consumption bundles for basic and luxury goods;
12. Wallet shares are allocated among industries according to relative competitiveness;
13. Market shares in each industry are allocated according to relative competitiveness;
14. Firms and banks compute their profits, pay taxes and repay (part of) their debt;
15. Exit takes place, near-zero share and bankrupt industries and firms leave the market;
16. Prospective entrant industries may enter when new machine generation emerges;
17. Prospective entrant firms stochastically enter according to market conditions;
18. Aggregate variables are computed.

4 Model properties and validation

Let us discuss the properties of the simulation results. Our primary focus here is on the dynamics of disruptive technological change, that is the arrival of new paradigms together with the compensation effects of the demand side. Table 2 presents the list of stylised facts that the model is able to replicate. With respect to previous model versions, we now include technology-level and industry-level stylised facts, while we add consumption properties to micro- and macro-level stylised facts and long-term output properties.[4]

In Table 3, MC descriptive statistics of main variables of interest including average GDP growth rate, unemployment, wage and productivity standard deviation, inflation are listed. Wages present a remarkable heterogeneity, with dispersion on average at 17%, which is by far higher than the number recorded in previous single-industry version of the model under the Fordist set-up (for reference see Dosi et al., 2017, 2018b). This means that the bulk of wage heterogeneity comes from sectoral differences. Indeed, productivity standard deviation stands in the downstream aggregate at 26%. Sectoral heterogeneity in productivity transfers into sectoral heterogeneity in wages. Additionally, unlike previous models, a genuine inflation dynamics emerges, with an average value of 2.7% with maximum recorded values at 4%. Inflation is the result of the introduction of complexity attributes in the product space: more complex goods, both basic and luxury, are more costly to be produced and more expensive to be acquired.

By construction, there always exists a distance between the notional opportunity set of technological advancement, say scientific research, and the actual access by innovators to this knowledge. Figure 2.a presents the distance between the potential technological frontier and the technology actually in use. Empirically, our description of the knowledge space goes back to the distinction between basic science and technological applications put forward in the linear model (Bush, 1945; Furnas, 1948) which still represents a useful first approximation to broadly interpret the relationship between science and technology (Balconi et al., 2010).

A stepwise dynamics in the evolution of technological frontier is presented in Figure 2.b wherein one history of simulation is shown. The vertical edge of each step represents the discrete advancement brought about the advancements in Δ_t^g of new machine families. In line with the empirical evidence, the share of radical innovative firms investing in the new generation of machines is relatively small, around 2%, with respect to those firms doing incremental innovation and imitation, both approximately around 25% (Figure 2.c). Although the share

[4]For a critical discussion on ABM validation see Fagiolo et al. (2019), while for large scale sensitivity analysis see Dosi et al. (2018).

of innovators is tiny, successful new-generation capital-goods rapidly diffuse also across other firms. Therefore, each paradigm actually represents a true shift in the technique of production which easily tends to become dominant. However, inside each simulation history, not all new discovered technologies are able to dominate the market: some failing technologies reach 80% or 60% of the share of overall capital-equipments and then fade away, overridden by new ones (Figure 2.d).

Capital-equipments are sold to industries downstream whose entry dynamics is differentiated between basic and luxury goods. While basic industries emerge with a probability influenced by the actual number of industries in the market, the emergence of a new luxury industry is a more rare event and linked to the new emerging paradigms. Whenever a new generation of capital-goods is actually accessed by a firm upstream, a new luxury sector downstream might emerge. Luxury products have a higher level of complexity vis-à-vis basic industries and to be produced require more advanced techniques of productions. Complexity is subject to an ever-growing dynamics, in line with the literature documenting increasing combinations of parts (Baldwin et al., 2000), or stages of production in our case (Figure 3.a).

The process of entry-exit at the industry level exhibits an exponential age distribution as shown by the log-linear fit (Figure 3.b) in line with empirical evidence. At the industry level, the exponential age distribution reflects a higher fraction of short-lasting industries and a small fraction of long-lasting ones. The empirical analysis has still left open whether age distribution follows a pure geometric or a state-dependent Weibull distribution, however there is broad agreement about the negative log-linear relationship as a first approximation (Calvino et al., 2020; Coad, 2018, 2010).

Product attributes, in terms of complexity, newness (product age), price and quality affect final consumer demand of each of the two macro-categories of goods. Figure 3.c shows a typical life-cycle, hump-shaped dynamics in the average wallet share, resulting from 100 MC runs. Notably, the fraction of basic goods is by far much higher than that of luxury ones. Moreover, the peak of diffusion of basic products occurs at a later stage than luxury ones and their cycle duration is longer. The industry life-cycle is the combined interaction of supply and demand effects. On the one hand, firm entry depends on the number of existing firms in a given sector (cf. Equation 42), implying higher entry in the rising up phase of the cycle followed by a "shake-out". On the other hand, the product cycle evolves, consumer demand saturates due to less appealing older products, yielding a declining phase (Klepper, 1997).

A non trivial question regards the relationship between industry concentration and product demand. Looking at the distribution of the share of products by industry versus industry concentration a clear negative non-linear pattern emerges: the space is extremely dense in the lower-triangular part (higher fraction of products acquired in low-concentrated sectors), while it becomes very sparse for increasing values of market concentration (Figure 3.d). This negative relationship highlights how in the final part of the product life-cycle, the one characterised by higher concentration, the share of consumption shares gets rarefied.

Consumption patterns are presented in Figure 4. First of all, in Figure 4.a we recover the Engel Law over time, in line with old-lasting empirical evidence (Syrquin, 1988). Along the simulation period, the share of basic goods over total income decreases, signalling satiation in the consumption of those products. Once satisfied basic needs, workers, according to a hierarchical lexicographic order between basic and luxury products (Aversi et al., 1999; Chai and Moneta, 2013), start saving. Savings are only spent for the desired luxury products. Over time, the gap between savings and consumption in luxury goods keeps constant, signalling *non-satiation* (Figure 4.b). Recall that according to our consumption rule, saving is socially determined in the sense that only those workers above a given income percentile start doing it to buy luxury products. The latter also symbolize status goods, *conspicuous consumption* in Veblen theory (Trigg, 2001).

Figure 4.c and 4d show the dynamics of cross-sectional Engel Law across income deciles. While basic consumption starts to decline by income level after the sixth percentile (recall that our consumption/saving parameter is fixed at $\phi_{lux} = 0.5$), the fraction of desired luxury consumption steadily increases across percentiles. Note that across income deciles basic products are always bought because necessary to satisfy basic needs, while the first percentile, which also includes unemployed people, shows a share of desired basic expenditure (vis-à-vis income) even higher than one, signalling non-satiation for the poorest fraction of the population.

With respect to S-shaped curve predicted by the life-cycle model, Table 4 shows the estimate of a Gompertz's model (Franses, 1994), with the following specification:

$$\log(\Delta \log x_t) = -\gamma t + \log(\beta e^{\gamma} - \beta) + \epsilon_t \tag{37}$$

Table 4 provides results for both demand of products and labour. In both cases the predicted correlation and the high R^2 yield a strong fitting, confirming the (asymmetric with respect to standard logistic curve) S-shape nature of the life-cycle according to Figure 3.c.

In a nutshell, the model is able to robustly replicate the rich thread of long-term changes in both production and consumption structures empirically observed. But, what is the impact upon the dynamics of the macroeconomy?

Microeconomic stylized facts	Macroeconomic stylized facts
Skewed firm size distribution	Endogenous self-sustained growth with persistent fluctuations
Fat-tailed firm growth rates distribution	Fat-tailed GDP growth rate distribution
Heterogeneous productivity across firms	Endogenous volatility of GDP, consumption and investment
Persistent productivity differentials	Cross-correlation of macro variables
Lumpy investment rates of firms	Pro-cyclical aggregate R&D investment and net entry of firms in the market
	Long-term memory process in GDP
	Typical power spectrum
Heterogeneous skills distribution	Persistent and counter-cyclical unemployment
Fat-tailed unemployment time distribution	Endogenous volatility of productivity, unemployment, vacancy, separation and hiring rates
Fat-tailed wage growth rates distribution	
Cross-sectional Engel's law	
Heterogeneous propensity to save and consume	Unemployment and inequality correlation
	Pro-cyclical workers skills accumulation
	Beveridge curve
	Okun curve
	Wage curve
	Matching function
	Engel's law
	Non-satiation in luxury goods
Technology-level stylized facts	Sectoral-level stylized facts
Stepwise increase in technological frontier	**Product life-cycle**
Lower rate of radical versus incremental innovation	**Exponential age distribution**
Fast diffusion of dominant techniques	**Sectoral wage and productivity differentials**

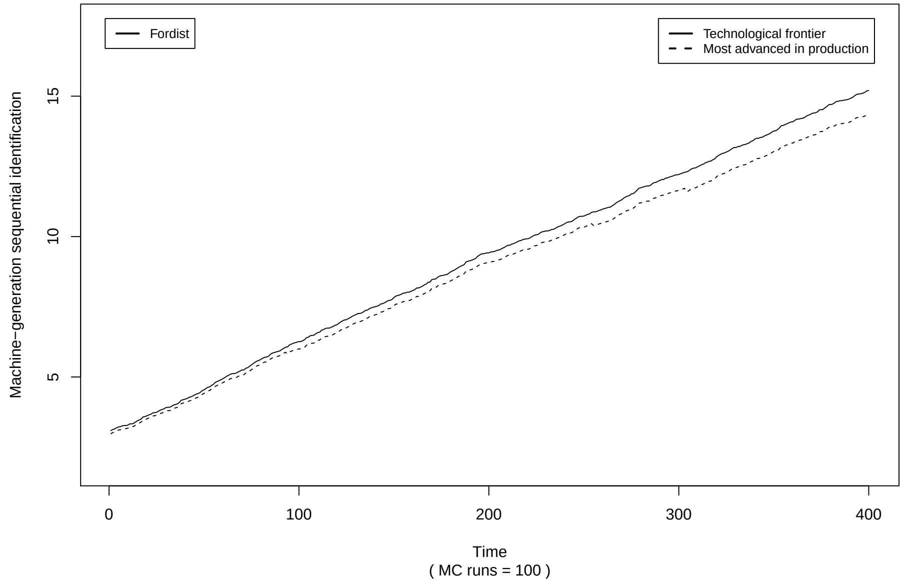
Table 2: Stylized facts matched by the K+S model at different aggregation levels. In bold newly added SFs.

	Avg	SD	Min	Max
GDP growth	0.0256	0.0035	0.0127	0.0297
Volatility of GDP growth	0.0636	0.0255	0.0341	0.1585
Inflation	0.0271	0.009	0.0068	0.0490
Full employment frequency	0.410	0.120	0.1275	0.625
Unemployment	0.0727	0.1084	0.000	0.549
Vacancy	0.468	0.1175	0.1684	0.6639
Entry rate of labour	0.1142	0.0128	0.059	0.132
Wages dispersion	0.175	0.0314	0.1224	0.2579
Bonus to wage ratio	0.0382	0.014	0.0249	0.0995
Income concentration	0.0961	0.0157	0.0683	0.1352
Productivity growth	0.0264	0.0032	0.0129	0.030
Productivity dispersion	0.2607	0.0464	0.183	0.357
Quality	1.654	0.0728	1.393	1.771
Incremental innovation	0.2614	0.0391	0.0902	0.3041
Radical innovation	0.0208	0.0076	0	0.0384
Imitation	0.2593	0.0149	0.2107	0.2990
Market concentration	0.2579	0.0734	0.1302	0.5545
Mark-ups	0.3881	0.0696	0.3353	0.7475
Net entry of firms	0.0165	0.0047	0.009	0.0346

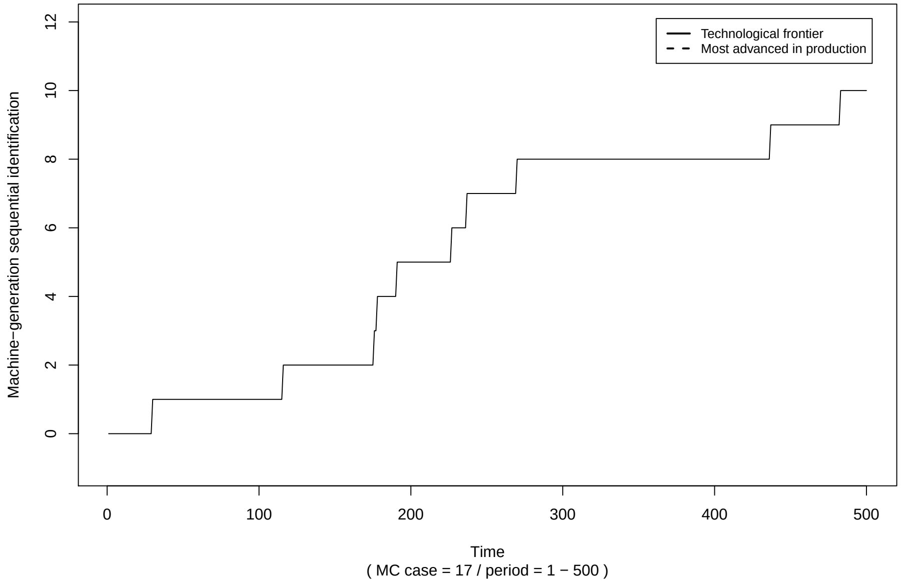
Table 3: Monte Carlo descriptive statistics. MC runs = 100 | period = 101 – 500

	Demand.Bas.	Demand.Lux.	Labour.Bas.	Labour.Lux.
beta	1.29	0.59	1.26	0.63
(s.e.)	0.14	0.06	0.12	0.06
(p-val.)	0.00	0.00	0.00	0.00
gamma	0.09	0.13	0.09	0.12
(s.e.)	0.01	0.01	0.01	0.01
(p-val.)	0.00	0.00	0.00	0.00
Pred.Corr.	0.91	0.94	0.91	0.95
R^2	0.82	0.89	0.83	0.90
Periods	400.00	400.00	400.00	400.00
Industries	2878.00	1092.00	2878.00	1092.00

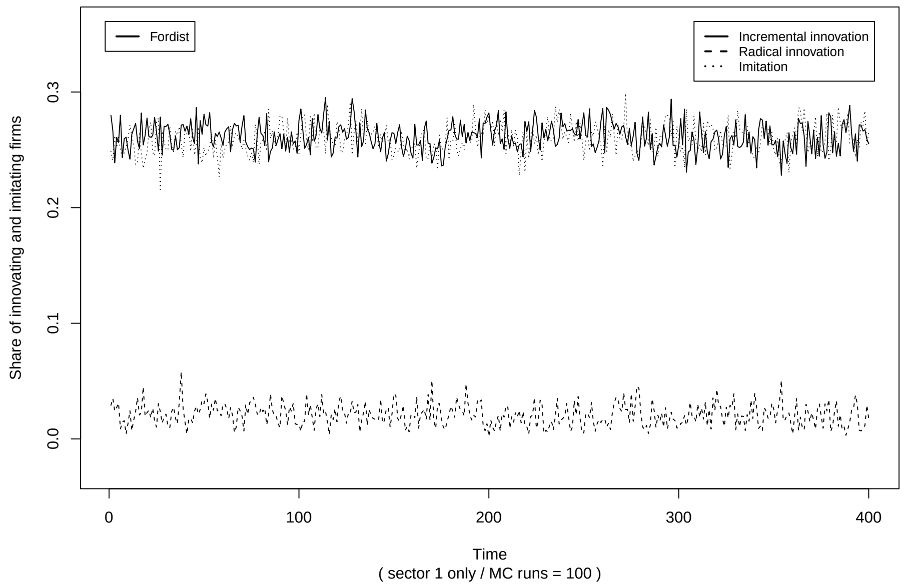
Table 4: Estimation of the Gompertz' growth model



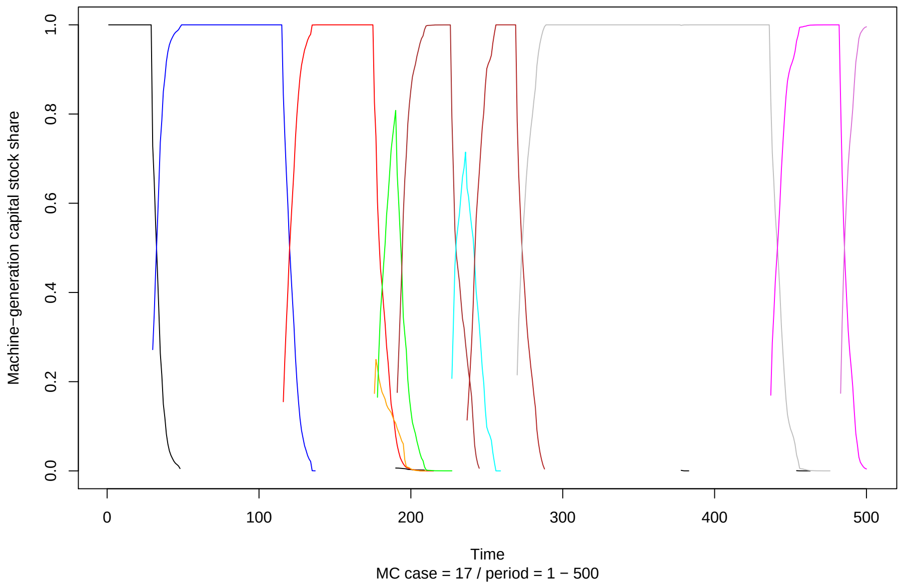
(a) Technological frontier and most advanced firms in production



(b) Evolution of technological frontier – one sample path

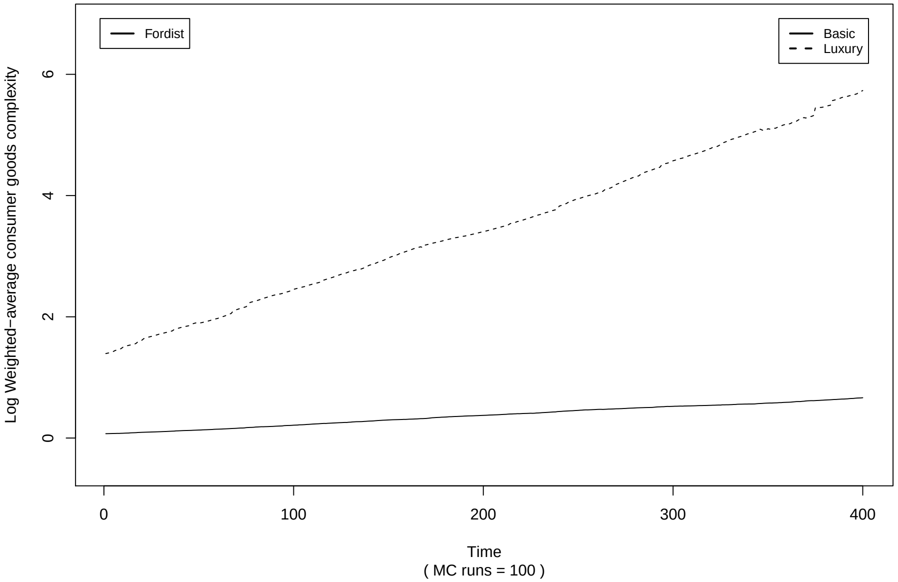


(c) Radical innovation, incremental innovation and imitation rates

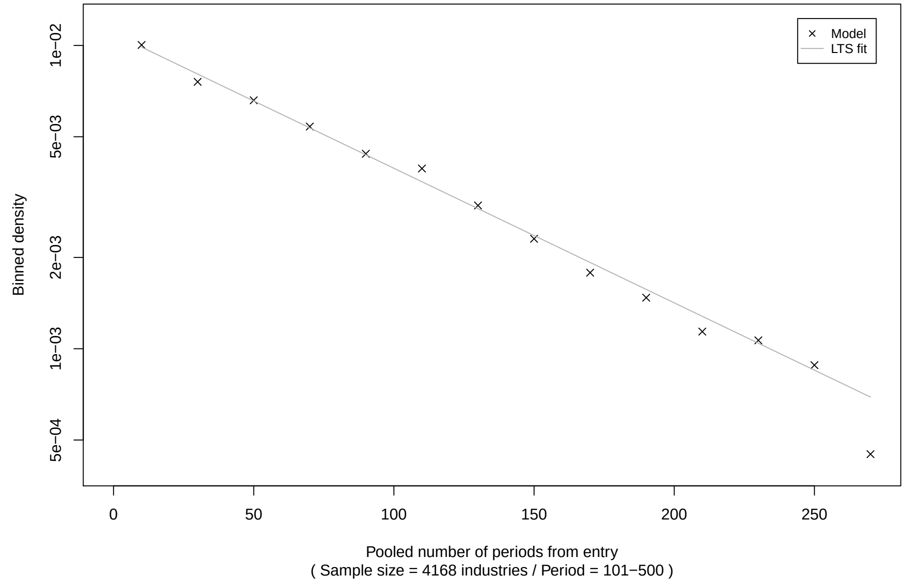


(d) Diffusion of new technological paradigms – one sample path

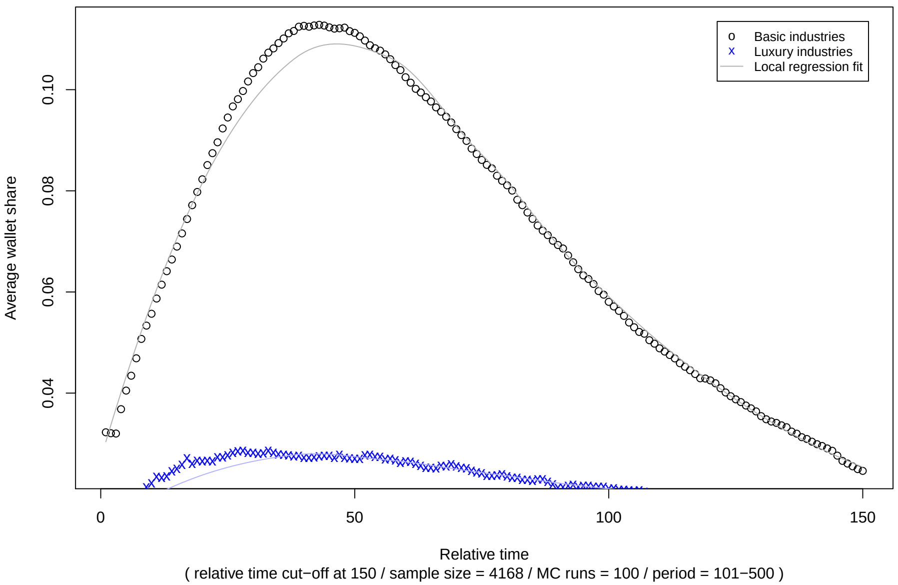
Figure 2: Technological frontier, diffusion of new paradigms, innovators and imitators



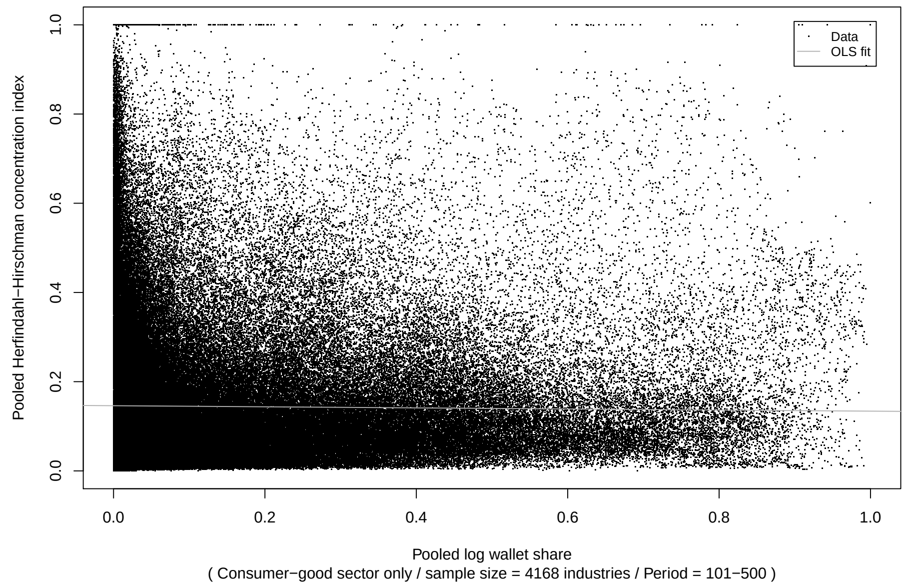
(a) Product complexity



(b) Industry age distribution

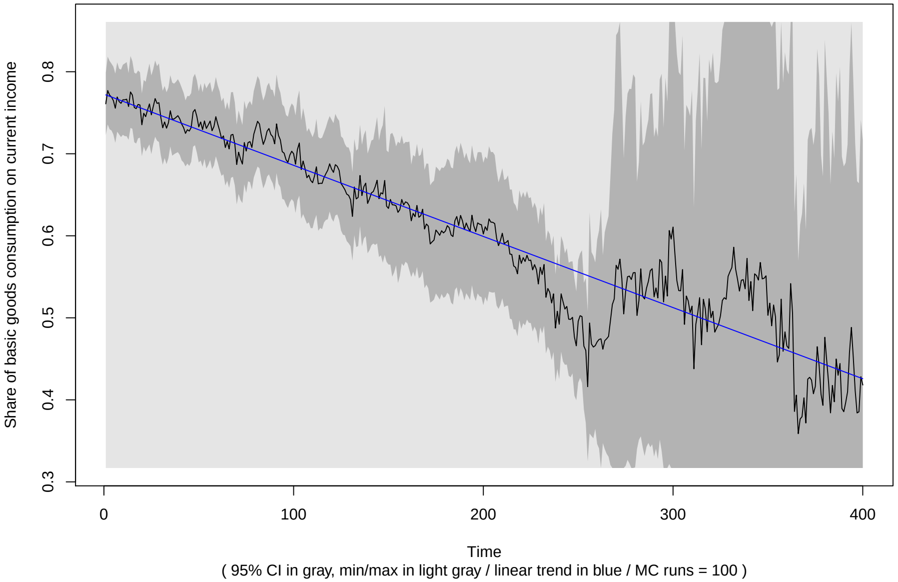


(c) Average industry consumption share

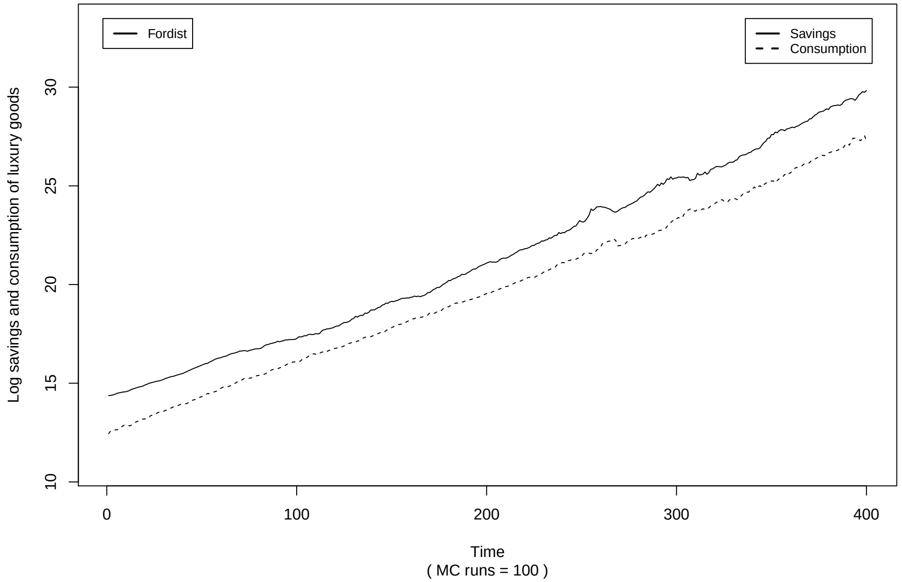


(d) Industry consumption share vs. concentration

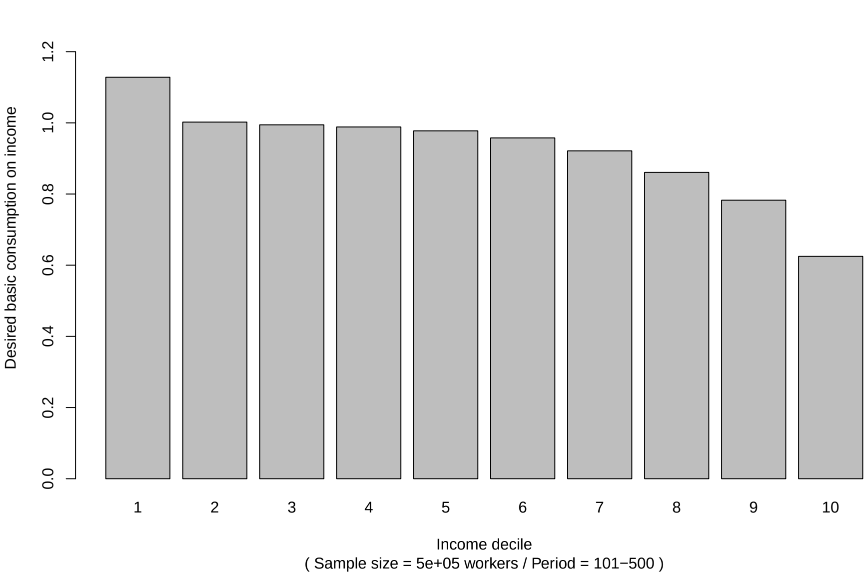
Figure 3: Product attributes and industry analysis



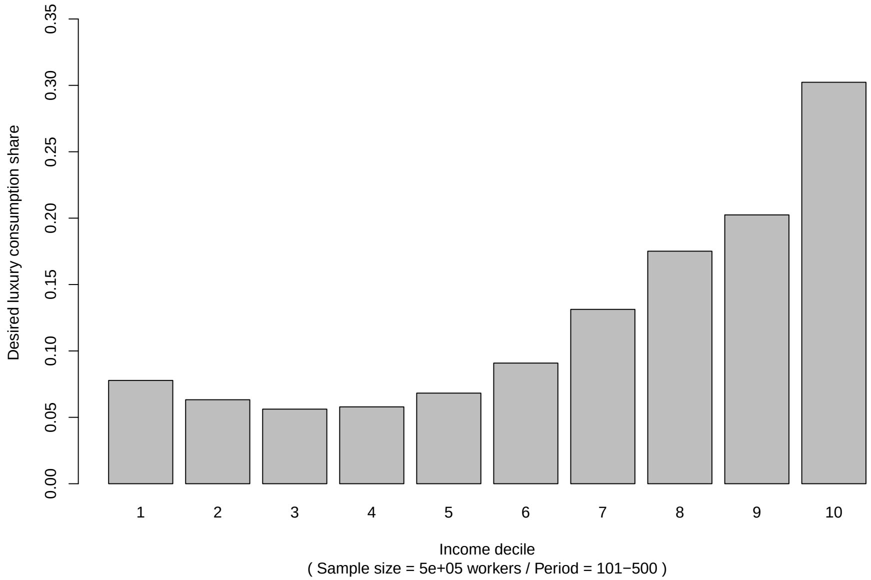
(a) Engel Law



(b) Savings and Consumption in luxury industries



(c) Desired basic consumption by income



(d) Desired luxury consumption by income level

Figure 4: Consumption patterns

5 Macroeconomic dynamics, labour creation and labour destruction

In this section we present the long run macroeconomic properties of the model, the dynamics of labour demand and the impact of product and process innovation upon unemployment.

Let us start with the long-term autocorrelation in GDP shown in Figure 5.a. Indeed, the auto-correlogram reveals a quite persistent structure, with a positive statistical significant autocorrelation coefficient up to 100 periods under our baseline parametrization. The latter long memory process is supportive of long-waves in GDP. Evidence of long range persistence in GDP has been empirically detected in Diebold and Rudebusch (1989) and Prados De La Escosura and Rodríguez-Caballero (2020), among others.

The frequencies of such a persistent signal can be detected by means of a spectral density analysis. The latter is a technique that allows to move from the time to the frequency domain, in such a way to distinguish at each frequency the energy spectral density of the signal. On the vertical axis of Figure 5.b the average spectral density of real GDP is shown, while in the horizontal axis GDP frequencies are plotted. It clearly emerges how the concentration of the density function is higher at very low frequencies, less than 0.1. The spectral density gradually decades, with very low values at high frequencies (0.5). The shape of the power spectrum is well in tune with the one detected by Granger (1966).[5] The overall monotonic declining pattern of the spectral density confirms that the waves behind GDP move over long periods, indeed in line with the literature emphasizing the role of changes in techno-economic systems as drivers of the long term dynamics (Clark et al., 1981; Silverberg, 2007).[6]

What are the underlining forces behind long waves in output? Figures 5.c and 5.d present the growth of labour demand, pooling all sectors, distinguishing for basic and luxury products: the hump-shaped structure reflects the underlying Gompertz's growth model above discussed. Labour demand cycle spreads approximately along 150 time periods. Indeed, cycles in labour absorption/expulsion underlie cycles in the overall produced output. In turn, long cycles in labour demand are the joint result of technical change, from the one hand, and consumption patterns on the other.

What is the average dynamics of the capital/labour ratio across sectors, as such a proxy of sectoral heterogeneity in terms of capital intensity? Figure 6.a illustrates it. Industries are born, often but not always, with low degrees of mechanization which accelerates around the time of the peak in output and labour demand. That corresponds also to a shake-out in the industry-structure. Note that such patterns in the life-cycle of industries have nothing to do with movements along production functions but are instead genuine emergent properties, with the acceleration of mechanization due to the fast diffusion of more efficient machines. Such diffusion is fast because demand grows and, with that, investment in new vintages of machine raises. Initially-born high capital-intensive industries tend to be offset by less capital intensive industries up to $t = 50$. After that point, new industries are all characterised by increasing

[5]Notably, according to the latter, the trend component, which we retain in the analysed time series, only affects the intensity of the power spectrum, not its shape, which has been defined by Granger (1966) as the "typical spectral shape of an economic variable".

[6]Empirical detection of long-waves in GDP and other economic variables has been more recently addressed by means of wavelet analysis, a time-frequency representation which allows to overcome the problem of detection of long waves in non-stationary time series (Gallegati, 2019; Charpe et al., 2020; Staccioli and Virgillito, 2021a).

capital/labour ratios. The U-shape is therefore emerging from the variety of capital intensive industries the model generates, say heavy metal industries vs clothing.[7]

Notably, product attributes, in particular complexity, strongly influence the actual effect of process innovation. In fact, Figures 6.b and 6.c present the relationship between labour productivity and the capital/labour ratio for each of the two industry categories. Notice that here all entities are measured in physical terms, that is number of machines, unit of output and number of workers. So, even if productivity grows ubiquitously, as it should, proportionally to the degree of mechanization, basic industries, at equal capital/labour ratio, show a level of labour productivity in physical terms by far higher than luxury ones. This is the result of the different degrees of complexity that, as discussed above, is higher for luxury products as compared to basic ones. Indeed, a higher complexity level, corresponding to more stages of production, entails a lower labour physical productivity, for a given constant capital/labour ratio. Not surprisingly, the labour input required to produce a car is higher than that for a loaf of bread. Indeed, in our set-up, the increasing product complexity is a fundamental compensatory mechanism against the labour saving effect of process innovation.

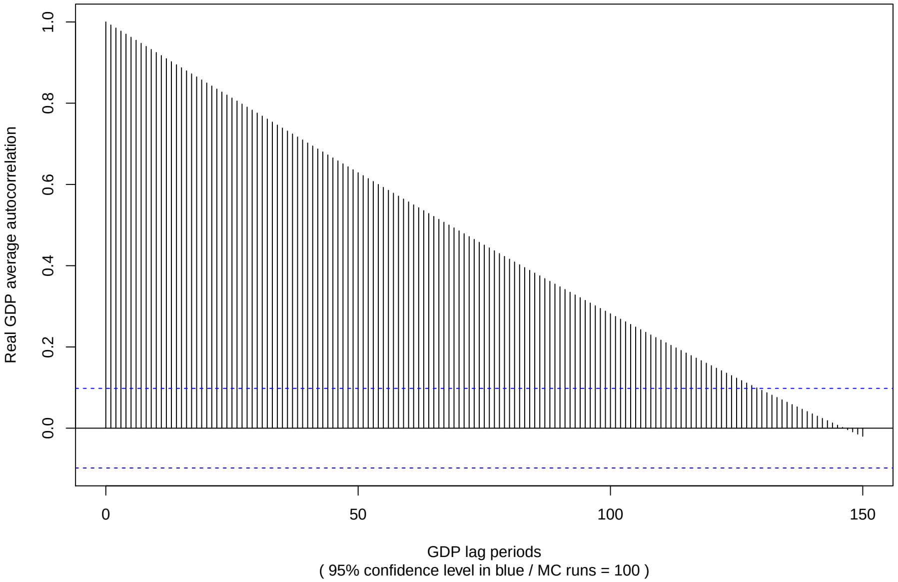
Table 5 completes the picture about the relationship between heterogeneous forms of technological change and labour demand. The correlation structure clarifies that (i) the acquisition of new machines is positively correlated with labour demand, with capital and labour *complementary inputs* rather than substitute; (ii) product demand is positively correlated with labour demand, in line with the usual Keynesian properties of the model, and also with the proximate synchronization of product and labour demand cycles; (iii) productivity upstream in producing machines is labour displacing as well as the new generation of machines embedding dominant, more efficient, techniques of production, (iv) productivity downstream positively correlates with labour demand implying that, overall, labour-shedding effects tend to be counterbalanced by the transfers of productivity gains to price decreases and therefore higher demand, and by the indexation of wages to productivity fostering output sales. The correlation structure does not allow to detect which effect, price, income elasticities or productivity to wages pass-through, dominate, however the analysis of consumption patterns highlighted the increasing share of luxury goods in higher income deciles as such ensuring labour absorption for their production.

If overall labour creation and destruction experience a relatively stable dynamics, this is also ensured by income distribution. In the Fordist set-up unemployment stands at 7% and *full employment* is reached in 40% of the cases (cf. Table 3), on average across 100 MC, which entail sustained aggregate demand deriving from an overall equal distribution of productivity gains to wages. Figure 6.d shows the cumulative distribution of income: it presents a relatively small support and almost fits a log-normal distribution except for top-incomes with a Pareto tail. Corroborating evidence of a different behaviour for top-incomes is in Shaikh (2017). As such the interaction between the Keynesian engine and the Fordist wage-labour nexus counteract the Schumpeterian forces driving labour shedding.

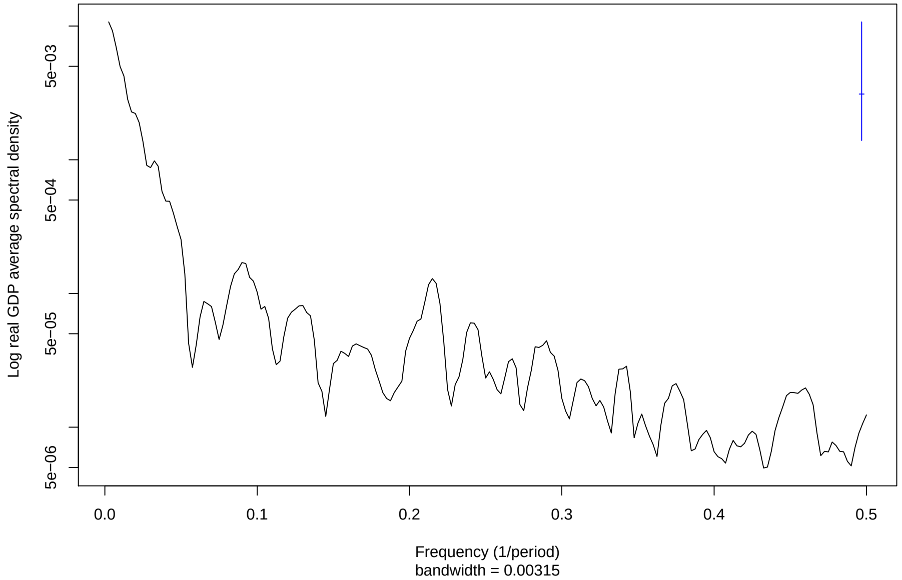
[7] For a theoretical controversy about the historical evolution of the capital/labour ratio across sectors and over time see Reubens (1964) vs. Fei and Ranis (1964). An over increasing capital/labour ratio represents the second stylised fact of economic growth, according to Kaldor (1961).

	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4
Labour demand (s.1)	-0.14	0.14	0.52	0.86	1.00	0.86	0.52	0.14	-0.14
(s.e.)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Labour demand (s.2)	-0.01	0.21	0.52	0.82	1.00	0.82	0.52	0.21	-0.01
(s.e.)	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.01
Machine demand (s.1)	-0.12	0.12	0.45	0.73	0.84	0.72	0.44	0.13	-0.11
(s.e.)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Goods demand (s.2)	-0.07	-0.05	0.01	0.10	0.17	0.20	0.19	0.14	0.09
(s.e.)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Productivity (s.1)	0.01	-0.04	-0.11	-0.17	-0.21	-0.20	-0.16	-0.09	-0.02
(s.e.)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Productivity (s.2)	0.08	0.08	0.07	0.05	0.04	0.05	0.06	0.06	0.05
(s.e.)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Machine technology (s.2)	0.00	0.00	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.00
(s.e.)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

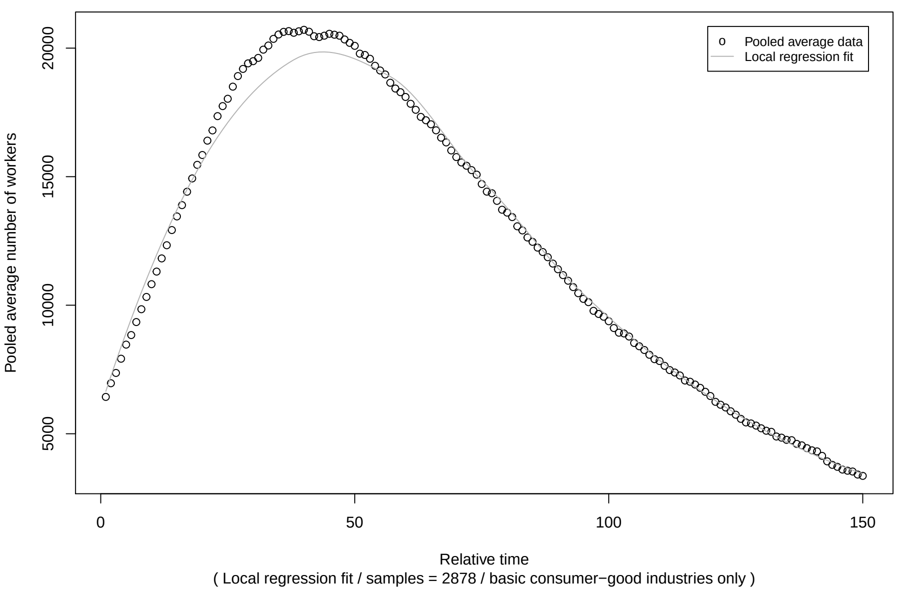
Table 5: Correlation structure to labour demand. MC standard errors | sample size = 4168 industries | MC runs = 100 | period = 101500.



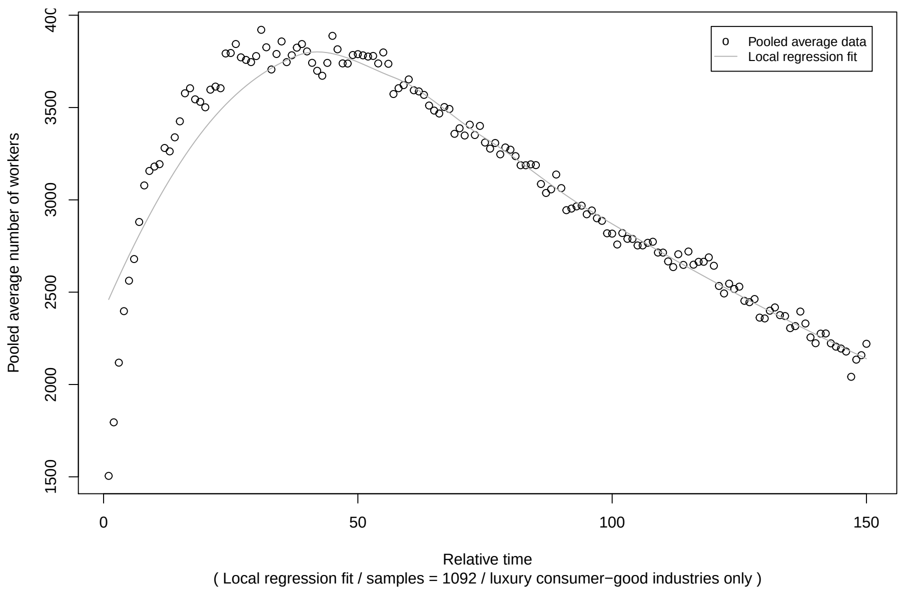
(a) Long-term GDP autocorrelation



(b) GDP spectral density

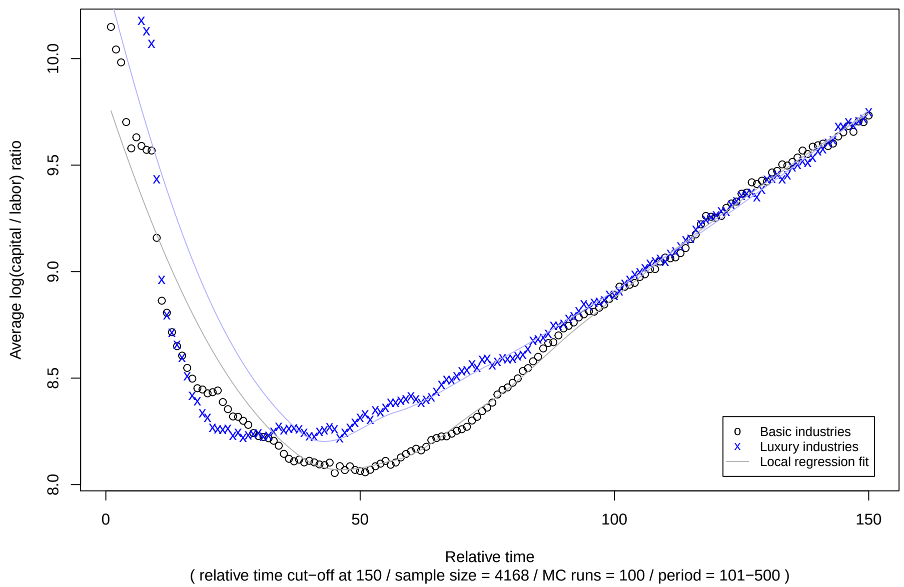


(c) Average basic industry labour growth curve

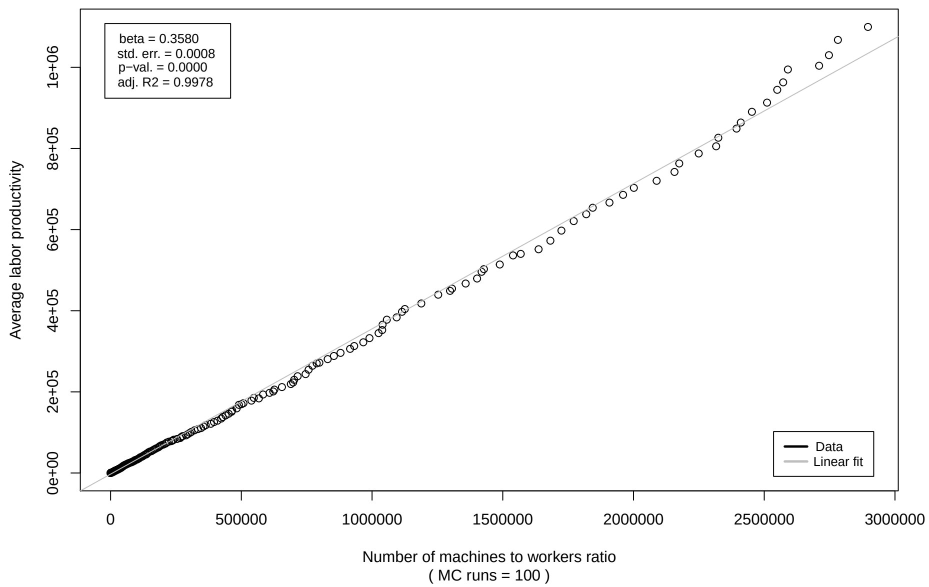


(d) Average luxury industry labour growth curve

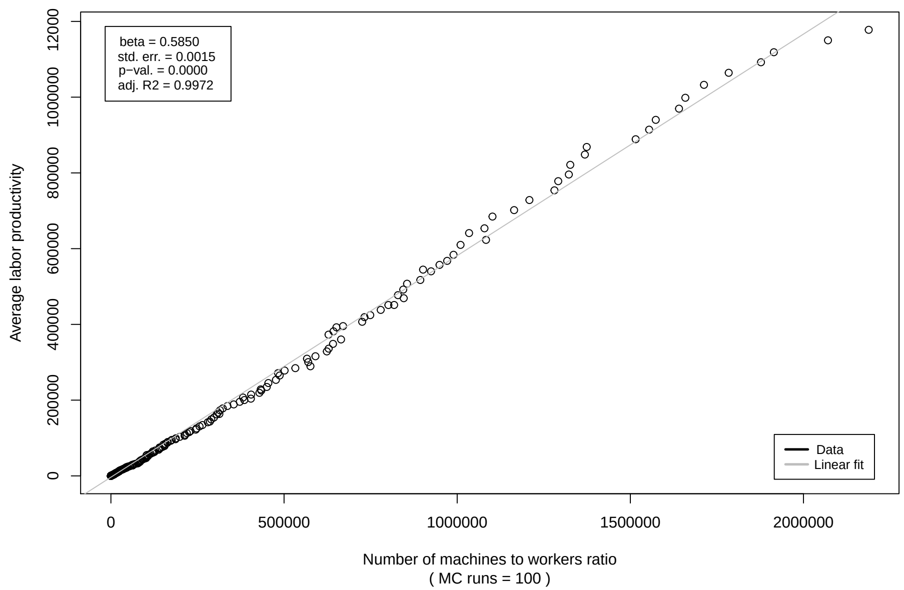
Figure 5: Long range memory processes in GDP, long waves and cycles in labour demand



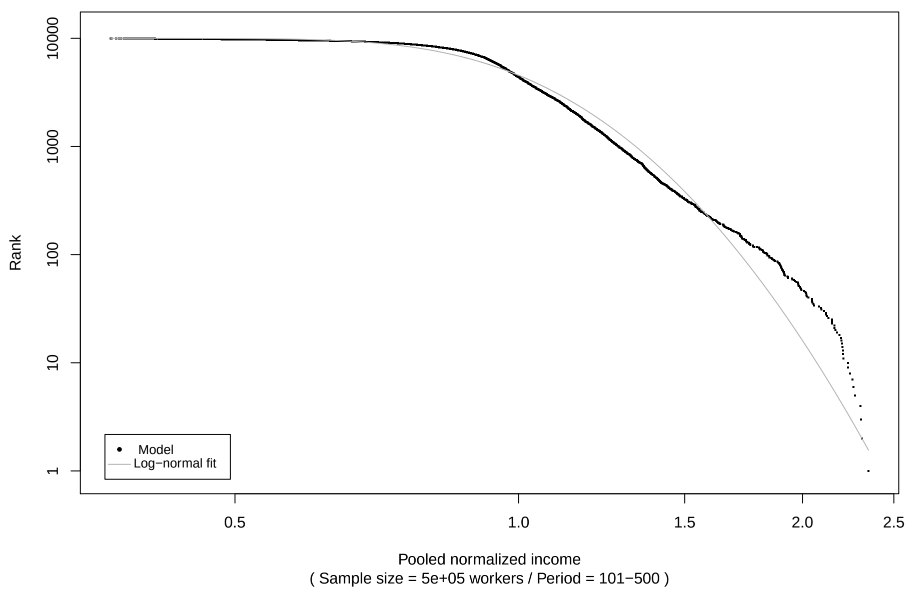
(a) Average industry capital to labour ratio



(b) Process innovation in basic industries



(c) Process innovation in luxury industries



(d) Income distribution

Figure 6: Process innovation and income distribution

6 Conclusions

We presented an ABM of endogenous arrival of technological paradigms, and together of new sectors. The model, building on the labour-augmented K+S, is meant to analyse the long-term patterns of labour demand under the fundamental duality of technical change between the labour shedding effects of efficiency-enhancing process innovation and the job-creating ones of product innovation. The ABM perspective allows to tackle such a duality under conditions of *general disequilibrium*, thus avoiding any ex-ante commitment to the idea that the two effects will compensate in the aggregate.

Process innovation is represented by the arrival of new techniques of production embedded in new capital-goods, that are product innovations, which diffuse across producers and among users, for which they are process innovations. Product innovation in final goods here is modelled by means of the emergence of new sectors.

Consumers demand goods in hierarchical order starting from basic and moving to luxury ones. Ubiquitous emergent regularities are humped-shaped diffusion of new products along the industry life-cycle and Engel-type evolution of consumption baskets. New final goods are also more complex in that they also require more stages of production and thus more workers per unit of output: white and gray goods are more complex than breads or pairs of trousers.

On the institutional side, we employ a set-up of the labour market and of labour relation which guarantees a relatively fair and stable income distribution, warranted by a high pass-through of productivity growth to wage growth. Under such Fordist regime an overall compensation between the dual effect of technical change tends to apply and no episode of deep technological unemployment occurs. Notice, however, that is made possible by the contemporaneous presence of, first, socio-relational conditions which ensure a high elasticity of wages to productivity, and, second, a sustained arrival of new final goods characterised by an increasing complexity and by high income elasticity of demand.

These conditions yield a virtuous matching between the Schumpeterian machine of innovation and the Keynesian machine of demand generation. This model has therefore to be understood as able to account for the long run productive forces behind capitalism until the eighties. After that historical turning point, both the erosion of wage labour and the changing nature of new products are more or less gradually putting under pressure the ability of the macroeconomy to self-organize into stable configuration phases. We leave for future research the coupling of a changing regulation of the labour market and decreasing product complexity, because e.g. of miniaturization or consolidation, as two directions to study eventual jobless scenarios.

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Appendices

Appendix A

Investment and firm entry

Firm j invests according to expected demand $D^e_{j,t}$, computed by an adaptive rule:

$$D^e_{j,t} = \mathrm{g}\left(D_{j,t-1}, D_{j,t-2}, D_{j,t-n}\right), \quad 0 < n < t, \tag{38}$$

where $D_{j,t-n}$ is the actual demand faced by firm at time $t-n$. $n \in \mathbb{N}_*$ is a parameter and $\mathrm{g} : \mathbb{R}^n \to \mathbb{R}_+$ is the expectation function, usually an unweighed moving average over 4 periods. The corresponding desired level of production $Q^d_{j,t}$, considering the actual inventories $N_{j,t}$ from previous period, is:

$$Q^d_{j,t} = (1+\iota)D^e_{j,t} - N_{j,t-1}, \tag{39}$$

being $N^d_{j,t} = \iota D^e_{j,t}$ the desired inventories and $\iota \in \mathbb{R}_+$ a parameter.

If the desired capital stock K^d_j – computed as a linear function of the desired level of production $Q^d_{j,t}$ – is higher than the current $K_{j,t}$, firm invests $EI^d_{j,t}$ to expand capacity:

$$EI^d_{j,t} = K^d_{j,t} - K_{j,t-1}. \tag{40}$$

Replacement investment $SI^d_{j,t}$, to substitute a set $RS_{j,t}$ of existing machines by more productive ones, is decided according to a fixed payback period $b \in \mathbb{R}_+$. Machines $A^\tau_i \in \Xi_{j,t}$ are evaluated by the ratio between the price of new machines and the corresponding cost savings:

$$RS_{j,t} = \left\{ A^\tau_i \in \Xi_{j,t} : \frac{p^*_{i,t}}{c^{A^\tau_i}_{j,t} - c^*_{j,t}} \leq b \right\}, \tag{41}$$

where $p^*_{i,t}$ and $c^*_{j,t}$ are the price and unit cost of production upon the selected new machine, among the ones known to the firm.

Prospective firms in both sectors decide on entry based on the number $F^z_{h,t-1}$ $(z = 1,2)$ of firms in industry and the financial conditions of incumbents. The number of entrants in industry h of sector z is:

$$b^z_{h,t} = \max\left[\left(o\pi^z_t + (1-o)MA^z_{h,t}\right) F^z_{h,t-1}, 0\right], \qquad z = 1,2, \tag{42}$$

being $o \in [0,1]$ a mix parameter and π^z_t a uniform random draw on the fixed support $[\underline{x}^z_2, \bar{x}^z_2]$ representing the idiosyncratic component in the entry process. The industry market attractiveness $MA^z_{h,t}$ is evaluated based on the dynamics of firms' balance sheets:

$$MA^z_{h,t} = MC^z_{h,t} - MC^z_{h,t-1} \qquad (\text{bounded to } [\underline{x}^z_2, \bar{x}^z_2]), \tag{43}$$

defined as the (log) ratio between the industry-aggregated stocks of liquid assets $NW^z_{h,t-1}$ (bank deposits) and debt $Deb^z_{h,t-1}$ (bank loans):

$$MC^z_{h,t} = \log NW^z_{h,t-1} - \log Deb^z_{h,t-1}. \tag{44}$$

Competition, prices, and quality

In the consumer-good sector, firm j compete according to their relative competitiveness in its industry h. Market share evolves following a replicator dynamics:

$$f_{j,t} = f_{j,t-1}\left(1 + \chi \frac{E_{j,t} - \bar{E}_{h,t}}{\bar{E}_{h,t}}\right), \qquad \bar{E}_{h,t} = \frac{1}{F^2_{h,t}} \sum_{j \in h} E_{j,t} f_{j,t-1}, \tag{45}$$

where $\chi \in \mathbb{R}_+$ is a parameter, $F^2_{h,t}$ is the current number of firms in industry h, and $\bar{E}_{h,t}$ is the average competitiveness in industry. Firm relative competitiveness $E_{j,t}$ is defined by the individual, industry-normalized price $p'_{j,t}$, unfilled demand $l'_{j,t}$ and product quality $q'_{j,t}$:

$$E_{j,t} = \omega_1\left(1 - p'_{j,t-1}\right) + \omega_2\left(1 - l'_{j,t-1}\right) + \omega_3 q'_{j,t-1}, \tag{46}$$

being $(\omega_1, \omega_2, \omega_3) \in \mathbb{R}^3_+$ parameters.

Consumption-good prices are set by firm j applying a variable mark-up $\mu_{j,t}$ on average unit cost $c_{j,t}$:

$$p_{j,t} = (1 + \mu_{j,t})\, c_{j,t}. \tag{47}$$

Firms have a heuristic mark-up rule driven by the evolution of individual market shares:

$$\mu_{j,t} = \mu_{j,t-1}\left(1 + \upsilon \frac{f_{j,t-1} - f_{j,t-2}}{f_{j,t-2}}\right), \tag{48}$$

with parameter $\upsilon \in \mathbb{R}_+$.

Unfilled demand $l_{j,t}$ is the difference between actual demand $D_{j,t}$ firm j gets and its effective production $Q_{j,t}$ plus existing inventories $N_{j,t}$ from past periods, if any:

$$l_{j,t} = \max\left[D_{j,t} - \left(Q_{j,t} + N_{j,t}\right), 0\right]. \tag{49}$$

The quality of consumer-good produced by firm j is determined by its average (log) skill level, considering each worker ℓ skills $s_{\ell,t}$:

$$q_{j,t} = \frac{1}{L_{j,t-1}} \sum_{\ell \in \{L_{j,t-1}\}} \log\left[s_{\ell,t-1}\right], \tag{50}$$

being $\{L_{j,t}\}$ the set of workers employed by firm, and $L_{j,t}$ the number of workers in the set.

Banks, government, and consumption

There are B commercial banks (subscript k) which take deposits and provide credit to firms. Bank-firm pairs are set randomly and are stable along firms' lifetime. Bank profits come from interest received on loans ($Loans_{k,t}$) and on reserves at the central bank ($Res_{k,t}$) deducted from interest paid on deposits ($Depo_{k,t}$) and from losses from defaulted loans ($BadDeb_{k,t}$):

$$\Pi^b_{k,t} = r_{deb} Loans_{k,t} + r_{res} Res_{k,l} - r_D Depo_{k,t} - BadDeb_{k,t}, \tag{51}$$

being $(r^{deb}, r, r_D) \in \mathbb{R}^3_+$ the interest rates on debt, bank reserves, and deposits, respectively.

Government taxes firms and banks profits at a fixed rate $tr \in \mathbb{R}_+$:

$$Tax_t = \left(\Pi^1_t + \Pi^2_t + \Pi^b_t\right) tr, \tag{52}$$

where Π_t^1, Π_t^2 and Π_t^b are the aggregate total profits of the capital-good, the consumer-good and the banking sectors, respectively. It pays to unemployed workers a benefit w_t^u which is a fraction of the current average wage $\bar{w}_t$:

$$w_t^u = \psi \bar{w}_{t-1}, \tag{53}$$

where $\psi \in [0, 1]$ is a parameter. The recurring total public expenditure G_t and the public primary deficit (or surplus) are:

$$G_t = \left(L^S - L_t^D\right) w_t^u. \tag{54}$$

$$Def_t = G_t - Tax_t, \tag{55}$$

The stock of public debt is updated as in:

$$Deb_t = Deb_{t-1} + Def_t - \Pi_t^{cb} + G_t^{bail}, \tag{56}$$

where Π_t^{cb} is the operational result (profits/losses) of the central bank and G_t^{bail} is the cost of rescuing (bail-out) the banking sector during financial crises, if any.

Government may impose a minimum wage w_t^{min} on firms, indexed on aggregate productivity A_t:

$$w_t^{min} = w_{t-1}^{min}\left(1 + \psi_2 \frac{\Delta A_t}{A_{t-1}}\right). \tag{57}$$

Workers fully consume their income (when possible) and do not take credit. Accordingly, desired aggregate consumption C_t^d depends on the income $In_{\ell,t}$ of both employed and unemployed workers plus the unsatisfied desired aggregate consumption from previous periods:

$$C_t^{d,bas} + C_t^{d,lux} = C_t^d = \sum_\ell In_{\ell,t} + C_{t-1}^d - C_{t-1}. \tag{58}$$

The effective consumption C_t is bound by the real production Q_t^2 of the consumption-good sector:

$$C_t = \min\left(C_t^d, Q_t^2\right), \quad Q_t^2 = \sum_j Q_{j,t}. \tag{59}$$

The model applies the standard national account identities by the aggregation of agents' stocks and flows. The aggregate value added by capital- and consumption-good firms Y_t equals their aggregated production Q_t^1 and Q_t^2, respectively (there are no intermediate goods). That is equal to the sum of the effective consumption C_t, the total investment I_t and the change in firm's inventories ΔN_t:

$$Q_t^1 + Q_t^2 = Y_t = C_t + I_t + \Delta N_t. \tag{60}$$

For further details, see Dosi et al. (2010, 2017).

Appendix B

SYMBOL	DESCRIPTION	VALUE
Policy and credit market		
ϕ	Unemployment subsidy rate on average wage	0.400
tr	Tax rate	0.100
r	Prime interest rate	0.010
r_D	Interest rate on bank deposits	0.000
μ_{deb}	Mark-up of interest on debt over prime rate	0.300
μ_{res}	Mark-up of interest on reserve to prime rate	-0.500
Λ	Prudential limit on debt (sales multiple)	3
Labour market		
w^o_{err}	SD of error when evaluating the market wage	0.100
ϵ	Minimum desired wage increase rate	0.020
τ_T	Skills accumulation rate on tenure	0.010
τ_U	Skills deterioration rate on unemployment	0.010
T_r	Number of periods before retirement (work life)	120
T_s	Number of wage memory periods	4
ω	Number of firms to send applications (employed)	5
ω_u	Number of firms to send applications (unempl.)	10
ψ_2	Aggregate productivity pass-trough	1.000
ψ_4	Firm-level productivity pass-trough	0.500
ψ_6	Share of firm free cash flow paid as bonus	0.200
Technology		
η	Maximum machine-tools useful life	19
ν	R&D investment propensity over sales	0.040
ξ	Share of R&D expenditure in imitation	0.500
b	Payback period for machine replacement	9
h	Effectiveness of opportunities exploitation	0.100
m_1	Worker output scale in capital-good units	0.100
m_2	Machine-tool unit production capacity	40
(α_1, β_1)	Beta distribution parameters (innovation process)	(3,3)
(α_2, β_2)	Beta distribution parameters (entrant productivity)	(2,4)
(α_3, β_3)	Beta distribution parameters (industry complexity)	(2,4)
(ζ_g, ζ_0)	Likelihood of emergence/access to new generation	(0.030,0.020)
(ζ_1, ζ_2)	Search capabilities for innovation/imitation	(0.100,0.100)
$[\underline{x}_1, \bar{x}_1]$	Beta distribution support (innovation process)	[-0.150,0.150]

(continue...)

SYMBOL	DESCRIPTION	VALUE
Industrial dynamics		
δ_1	Industry competitiveness weight for price	1.000
δ_2	Industry competitiveness weight for quality	1.000
δ_3	Industry competitiveness weight for newness	1.000
δ_4	Industry competitiveness weight for complexity	1.000
γ	Share of new customers for capital-good firm	0.500
ι	Desired inventories share	0.100
κ_{max}	Maximum threshold to capital expansion	0.500
μ_1	Mark-up in capital-good sector	0.100
ω_1	Firm competitiveness weight for price	1.000
ω_2	Firm competitiveness weight for unfilled demand	1.000
ω_3	Firm competitiveness weight for quality	1.000
χ	Replicator dynamics coefficient (inter-firm)	1.000
χ_c	Replicator dynamics coefficient (inter-industry)	1.000
υ	Mark-up adjustment coefficient	0.040
f^2_{min}	Min share to firm stay in consumption-good industry	10^{-5}
f^c_{min}	Min wallet share to industry stay in sector	0.010
n_c	Min periods to evaluate industry exit	10
o	Weight of market conditions for entry decision	0.500
u	Planned utilization by consumption-good entrant	0.750
x_5	Max technical advantage of capital-good entrant	0.300
$(\zeta_{bas}, \zeta_{lux})$	Opportunities weight for new basic/luxury industry	(0.050,0.500)
$[\Phi_1, \Phi_2]$	Min/max capital ratio for consumer-good entrant	[0.100,0.900]
$[\Phi_3, \Phi_4]$	Min/max net wealth ratio for capital-good entrant	[0.100,0.900]
$[\underline{x}_2, \bar{x}_2]$	Entry distribution support for entrant draw	[-0.150,0.150]
$[\underline{x}_3, \bar{x}_3^{bas/lux}]$	Entry distribution support for complexity draw	[0.0,1.0/2.0]
$[F^1_{min}, F^1_{max}]$	Min/max number of capital-good firms	[1,100]
$[F^2_{min}, F^2_{max}]$	Min/max number of consumer-good firms in industry	[1,100]
$[F^{bas}_{min}, F^{bas}_{max}]$	Min/max number of consumer basic-good industries	[3,10]
$[F^{lux}_{min}, F^{lux}_{max}]$	Min/max number of consumer luxury-good industries	[1,10]
Consumption		
C_{rec}	Unfilled past consumption recover limit	0.200
ϕ_{lux}	Percentile of income to spend in luxury goods	0.500
T_{lux}	Time between acquisition of luxury goods	4
T^{life}_{lux}	Lifetime of a luxury good	8
Initial conditions		
μ^2_0	Initial mark-up in consumption-good sector	0.200
k^{lux}_0	Initial average complexity of luxury goods	2
K_0	Initial capital stock in consumer-good sector	2500
w^{min}_0	Initial minimum wage and social benefit floor	0.500
L^S	Number of workers	2.510^5
Sav^{lux}_0	Initial savings for luxury goods acquisition	5.010^5
Λ_0	Prudential limit on debt (initial fixed floor)	10^6
B	Number of banks	10
NW^b_0	Initial net wealth of banking sector	1.010^6
(F^1_0, F^2_0)	Initial number of capital/consumption-good firms	(20,50)
(F^{bas}_0, F^{lux}_0)	Initial number of basic/luxury-good industries	(5,1)
(NW^1_0, NW^2_0)	Initial net wealth capital/consumption-good ind.	(1000,0)

Table 6: Model parameters and initial conditions, calibration values.

	Workers	Capital-good firms		Consumption-good firms		Bank		Government	$\sum$
		current	capital	current	capital	current	capital		
Consumption	$-C$	$+C$							0
Investment		$+I$			$-I$				0
Govt. expenditures	$+G$							$-G$	0
Wages	$+W$	$-W^1$		$-W^2$					0
Profits, firms		$-\Pi^1$	$+\Pi^1$	$-\Pi^2$	$+\Pi^2$				0
Profits, bank						$-\Pi^b$	$+\Pi^b$		0
Debt interests		$-rDeb^1_{t-1}$		$-rDeb^2_{t-1}$		$+rDeb_{t-1}$			0
Deposits interests		$+rNW^1_{t-1}$		$+rNW^2_{t-1}$		$-rNW_{t-1}$			0
Taxes		$-Tax^1$		$-Tax^2$				$+Tax$	0
Change in debt			$+\Delta Deb^1$		$+\Delta Deb^2$		$-\Delta Deb$		0
Change in deposits			$-\Delta NW^1$		$-\Delta NW^2$		$+\Delta NW$		0
$\sum$	0	0	0	0	0	0	0	$\approx 0^*$	$\approx 0^*$

Table 7: Stock-and-flow consistency: transaction flow matrix.
(*) Government deficit/superavit is close to zero in the long run.