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A complexity view on the future of work. Meta-modelling exploration of the multi-sector K+S agent based model.

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A complexity view on the future of work. Meta-modelling exploration of the multi-sector K+S agent based model.*

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Abstract

When complexity meets economics, complexity economics turns out to be something more than simple interactions across individuals/entities, it turns into what has been labelled the *bicycle postulate* made of two components, coordination and change. Granted the "Complex evolving system approach", we provide an example of the effectiveness of the complexity view in economics applied to the context of the current debate on *the future of work* drawing upon the agent-based "Schumpeter meeting Keynes" multi-sector model (Dosi et al., 2022) and the meta-modelling approach developed in Dosi et al. (2018). The complexity approach proves to be an alternative, useful lens to address the technical change vs employment relationship modulated by demand patterns, income distribution, structural change and labour market organizations. It allows to enlarge the scope of investigation beyond production functions of tasks, relative prices of capital vs labour, inputs substitutability, comparative advantages of workers in their skill levels, the latter elements upon which the dominant neoclassical approach on the employment-technology nexus is rooted.

JEL classification: J51, E02, E24, C63

Keywords: Complexity, Meta-modelling, Future of work

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1 Introduction

The notion of multiple paths and threshold points in the development of both socio-economic and natural complex systems involves the idea that history is an essential part of the interpretation of many dynamic phenomena. History-dependence is both shaped by initial conditions and by the effects of particular unfolding events, e.g., crises, regime changes, tipping points. In turn, at their origin there are feedback mechanisms related to coordination failures/successes, and amplification processes stemming from good/bad dynamic increasing returns. Those properties characterize what has been labelled "Economies as complex evolving systems" (Kirman, 2010; Dosi and Roventini, 2019; Arthur, 2021; Dosi, 2022, among others).

Complexity is a term that has seen flourishing and multiple definitions from asymmetry breaking and structures of hierarchies in physics (Anderson, 1972) and in geometry (Mandelbrot, 1982) to behaviours of business organizations (Simon, 1991), from social systems and collective organizations (Page, 2015) to meteorology and climate dynamics (Lorenz, 2000), just to mention a few representative contributions across disciplines.[1] All approaches and definitions of complexity however tend to converge at least on four characteristics: (i) a complex system is made up of the interactions of single units/agents giving rise to system level properties different from individual properties; (ii) emergence is the collective result of local interactions; (iii) structures and hierarchical orders are widespread and in that they influence the interaction across individual entities and represent propagation and amplification mechanisms; (iv) the system might reach threshold points and limit behaviours that whenever crossed give rise to the birth of a new system configuration.

When complexity meets economics, complexity economics turns out to be something more than simple interactions across individuals/entities, it turns into what has been labelled the *bicycle postulate* made of two components, coordination and change (Dosi and Virgillito, 2021). Both micro and macro level phenomena enter into the scene, and the problem of interactions turns into the problem of strategic interactions, such as setting quantities, defining clients, deciding the amount of R&D expenses, hiring and firing, quitting and searching for a new job. These sets of micro level rules, although far from perfect rationality and equilibrium outcomes, still appear in many configurations to be coordinated inside a system characterized by continuous evolution brought about the arrival of the new. Economies in fact are not only complex, in the meaning above discussed, but are also evolving. Evolution is indeed the central attribute of capitalism, here intended as dynamic change, and quite distinct from any attribute of progress.

Change in economics, the opposite of a notion of an equilibrium point requiring no deviation, occurs for many reasons, but primarily on the one hand because of technological and organizational innovation, and on the other hand because of conflict over distribution of resources, definition of property rights and ultimately attribution of power and hierarchies over the division of labour (Dosi, 2022; Dosi and Virgillito, 2019). Conflict between the two macro categories of capital and labour is the clearest example, but conflict over spaces of intervention, authority, roles and functions of individuals are typical traits of modern organizations and societies. Conflict is not the only driver of change: in capitalism, competition is the other driving force of transformation, in this case act-

[1] For a complementary and extensive discussion on complexity and human matter see Bellomo et al. (2021).

ing for the definition and appropriation of market power of some firms/sectors vis-à-vis others. In addition, entry and exit phenomena shape the competition landscape, with some new actors arriving and some others dying. Last, but not least, capitalism cannot be understood without considering processes of accumulation of knowledge and learning under dynamic increasing returns, which are the ultimate essence, together with division of labour, of technical change, the essential engine of capitalism (Dosi and Nelson, 2010).

In the following, granted the "Complex evolving system approach" above sketched, we provide an example of the effectiveness of the complexity view in economics applied to the context of the current debate on *the future of work* (Allen, 2017), earlier framed by evolutionary scholars as the technology-employment nexus (Freeman et al., 1982). The latter topic has been mostly addressed by means of neoclassical static partial equilibrium frameworks (Acemoglu and Restrepo, 2018, 2019) lacking any role attributed to newly emerging and/or disappearing sectors, interdependence, demand and tastes, and ultimately to feedback loops from income distribution to patterns of labour creation and destruction. Mechanisms of tasks reinstatement and displacement are separated from demand creation/destruction and from structural change. Therefore employment dynamics turns out to be orthogonal to system level processes and entirely explained by production functions of tasks and workers comparative advantage in terms of skills.

Distinct from a neoclassical perspective, we draw upon the agent-based "Schumpeter meeting Keynes" multi-sector model (Dosi et al., 2022). It is a simulation laboratory composed of two dynamically coupled domains, namely a Schumpeterian engine encompassing an endogenous growth process driven by innovations and their adoption and diffusion, and a Keynesian engine entailing an aggregate demand process driven by firms investments and workers' consumption. The core model has been recently extended to include: (i) decentralised labour markets characterized by different institutional dynamics of employment relations regimes (Dosi et al., 2020); ii) the arrival of new technological paradigms upstream; iii) the endogenous emergence of new sectors downstream; iv) a class-based consumption dynamics shaped by a hierarchical satisfaction of needs.[2]

Agent-based models are large-scale, computational models which allow the simulation of artificial economies wherein ensembles of heterogeneous agents interact on the ground of simple behavioural rules. Aggregate-level outcomes are the emergent properties from the interactions of such boundedly rational agents. The models may display path-dependent fluctuations across multiple equilibria emerging out of alternative configurations (or dynamic paths) as well as tipping points leading to regime shifts due to parameter changes. Therefore they require both to be empirically validated but also to be largely explored in the parametric space. In fact, as models grow in size and complexity, the "naive" efforts to accurately explore their behaviour by "brute force" or "one factor at a time" approaches quickly show their severe limitations in terms of computational times required and the poor expected accuracy (Helton et al., 2006, Saltelli and Annoni, 2010). Hence, the search for mathematically "well behaved" approximations of the inner relations of the original simulated model, frequently denominated *surrogate models* or *meta-models*, has become increasingly common (Kleijnen and Sargent, 2000, Roustant et al., 2012). The meta-model is a simplified version of the original model that can be more parsimoniously explored – at reasonable computational costs – to evaluate the ef-

[2] A germane agent-based model embracing a multilevel perspective on the future of work scenarios is Vermeulen et al. (2018).

fect of inputs/parameters on the latter and (likely) also on the former. Usual techniques employed for meta-modelling are linear polynomial regressions, neural networks, splines and Kriging. Drawing on large scale sensitivity analysis, we will therefore explore the model behaviour with reference to some variables of interest, related to the future of work scenarios.

In the following, drawing upon Dosi et al. (2022) and Dosi et al. (2018), we first present the basic model structure and its main properties; we then move to the meta-modelling exploration with specific reference to the Sobol decomposition, the response surfaces and the isolevel curves. We conclude the chapter by discussing the results and some avenues of future research.

2 The multi-sector K+S model addressing the future of work

We present a *general disequilibrium*, stock-and-flow consistent, agent-based model, populated by heterogeneous workers, firms, and banks which behave according to heuristic rules.[3]

In brief, the economy is composed by five populations of heterogeneous agents, namely, L^S workers/consumers, F^1_t capital-good firms, F^2_t consumption-good industries, $F^2_{h,t}$ consumption-good firms in each industry h, and B banks, plus the central bank and the government.[4] The basic structure of the model is depicted in Figure 1.

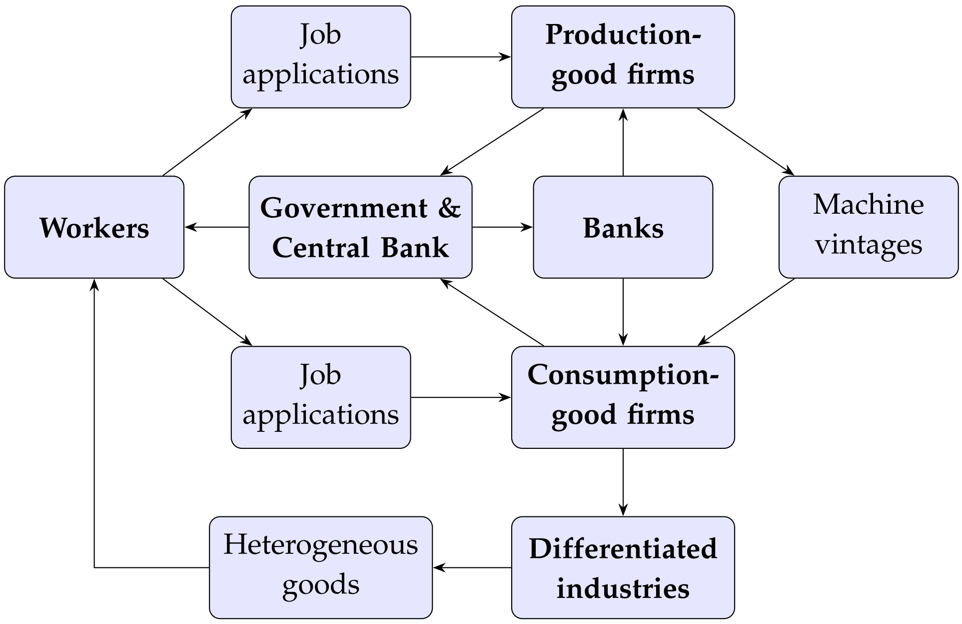


Figure 1: The model overall structure. Boxes in bold style represent the model's agents.

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

[3]The section draws upon Dosi et al. (2022).

[4]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.

capital-good firms and labour in order to produce quality-differentiated goods for final consumers. Across industries, 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 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 decentralised, 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 organised 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.

Figure 2 provides a graphical representation of the structure linking consumption needs, the dual macro-sector division downstream, and technological change upstream.

In Appendix A, we present the behavioural rules characterizing agents. For in-depth details, see Dosi et al., 2010, 2017, 2022. The model's parameters, initial conditions and stock-flow matrix are presented in Appendix B.

2.1 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 (indexation or bargaining) 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.

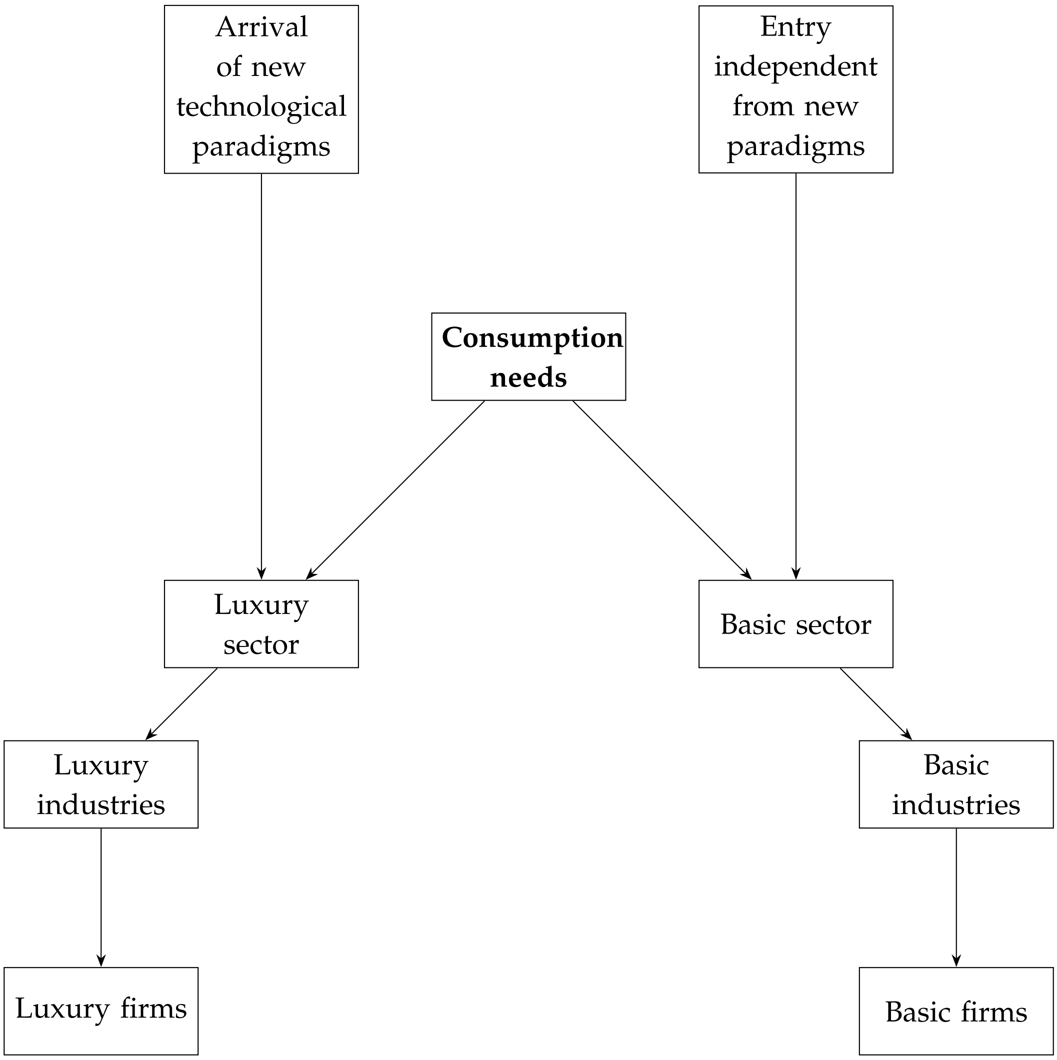


Figure 2: Graphical structure of consumption needs, dual macro-sector division downstream, and technological change upstream.

K+S Model

$\Downarrow$

Microfoundation of the labour market: institutional regimes (Fordist vs Competitive)

$\Downarrow$

Endogenous arrival of new paradigmatic technologies

$\Downarrow$

Endogenous emergence/collapse of industries

$\Downarrow$

Consumption driven by hierarchical satisfaction of needs

Figure 3: Strategy of implementation.

2.2 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 1 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.

The validation procedure follows the so called "output validation" approach according to Fagiolo et al. (2019), which is progressively becoming the most adopted empirical validation strategy in macro agent-based models. According to such an approach the model properties at different levels of disaggregation are contrasted with the empirical evidence. Notice that such an approach rather than *matching-moments* and following strict parameter calibration, is more helpful to study the model functioning and avoid the trap of ex-post fitting of ex-ante strictly calibrated models.

The model, building on the labour-augmented K+S according to the strategy of implementation below presented (Figure 3), 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, under a set-up of the labour market and of labour relations

MICROECONOMIC STYLISED FACTS	MACROECONOMIC STYLISED 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
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	Unemployment and inequality correlation
Cross-sectional Engel's law	Pro-cyclical workers skills accumulation
Heterogeneous propensity to save and consume	Beveridge curve
	Okun curve
	Wage curve
	Matching function
	Engel's law
	Non-satiation in luxury goods
TECHNOLOGY-LEVEL STYLISED FACTS	SECTORAL-LEVEL STYLISED 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 1: Stylised facts matched by the K+S model at different aggregation levels. In bold newly added SFs.

which guarantees a relatively fair and stable income distribution, warranted by a high pass-through of productivity growth to wage growth, 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 characterized by an increasing complexity and by high income elasticity of demand. A counterfactual experiment comparing a Fordist and a Competitive (Post-Fordist) regime shows that a more concentrated income distribution lowers both labour absorption in more technologically advanced industries and radical innovative opportunities. A remarkably higher level of unemployment rate is the end result of the mismatching across production and redistributive forces. Therefore, in this set-up the labour shedding effect of process innovation tends to prevail over the job-creating effect of product innovation.

We now give a glimpse of some properties and patterns that the model is able to replicate.[5] Figures 4.a and 4.b show the diffusion curves, whose estimates give back a strong fit with a Gompertz model (Franses, 1994), capturing therefore an S-shaped behaviour. The pattern characterizes both basic (black) and luxury (blue) products, and the ensuing labour demand, although the humped-shaped curves look more visible for the former, due

[5]The full set of stylized facts and model properties is presented in Dosi et al. (2022).

to a different peak dynamics. The structure of consumption and demand dynamics arising in the two labour market set-ups affect the peak of effective luxury products acquired, but also market concentration. Indeed, according to Figure 4.c and 4.d, the space of products and markets is by far more concentrated in the Competitive rather than in the Fordist set-up (bottom-left corner). Such relationship results into a stronger negative inclination of the market concentration vs the allocated wallet share to buy each product. Income concentration is then reflected into a more skewed distribution of desired consumption in luxury goods, in which only the highest echelons of income distribution (ninth and tenth deciles) are able to save enough to spend money on luxury goods when compared to the Fordist set-up (Figures 4.e. and 4.f). Ultimately, the Competitive setting is characterized by a lower rate of radical innovation (Figure 4.g) that also impacts on the overall unemployment rate (Figure 4.h). Indeed, the two regimes exhibit strong statistically different average values, with the Competitive unemployment average across 100 MC runs at 22% while at 7% in the Fordist.

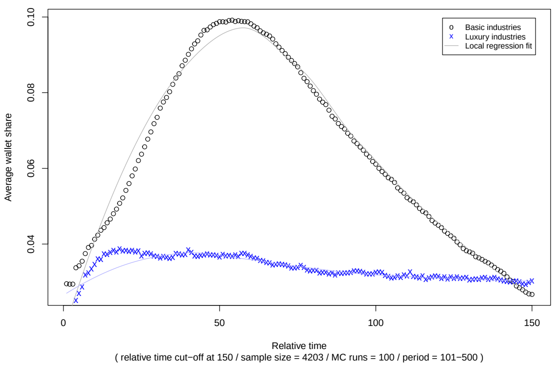
3 Meta-modelling and global sensitivity analysis

Kriging (or Gaussian process regression) is a simple but efficient method for investigating the behaviour of simulation models (see Van Beers and Kleijnen, 2004 or Kleijnen, 2009). Kriging meta-models came originally from the geosciences (Krige, 1951, Matheron, 1963). In essence, it is a spatial interpolation method for the prediction of a system response on unknown points based on the knowledge of such response on a set of previously known ones (the observations) to fit a real-valued random field. Under some set of assumptions, the Kriging meta-model can be shown to provide the best linear unbiased prediction for such points (Roustant et al., 2012). The intuition behind it is that the original model response for the unknown points can be predicted by a linear combination of the responses at the closest known points, similarly to an ordinary multivariate linear regression, but taking the spatial information into consideration. Recent advancements extended the technique, by removing the original assumption that the samples are noise free, made Kriging particularly convenient for the meta-modelling of stochastic computer experiments (Rasmussen and Williams, 2006).

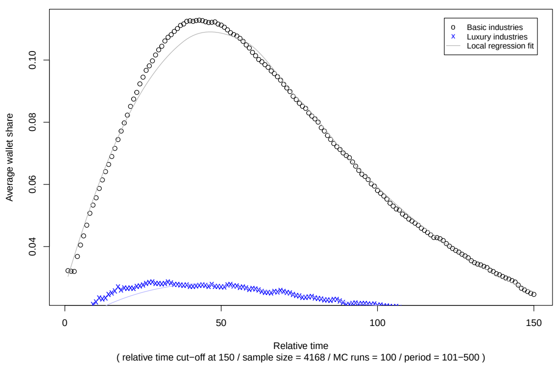
Kriging, as any meta-modelling methodology, is based on the statistical estimation of coefficients for specific functional forms based on data observed from the original system or model. Kriging meta-models are frequently estimated over a near-orthogonal Latin hypercube (NOLH) design of experiments[6] (McKay et al., 2000, and nearer to our concerns here Salle and Yildizoglu, 2014). The NOLH is a statistical technique for the generation of plausible sets of points from multidimensional parameter distributions with good space-filling properties (Cioppa and Lucas, 2007a). It significantly improves the efficiency of the sampling process in comparison to traditional Monte Carlo approaches, requiring far smaller samples – and much less (computer) time – to the proper estimation of meta-model coefficients (Helton et al., 2006, Iooss et al., 2010).

The proposed steps are:

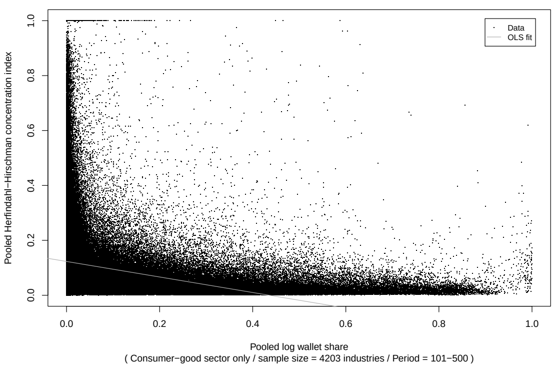
[6]In the present case it may be more appropriate to call the choice of the sampling points in the parameters space as *quasi-experiment*, as the conditions imposed for selecting the observations for the sample are specified by the NOLH.



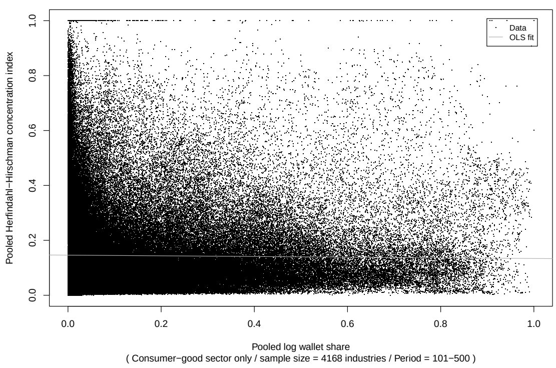
(a) Product diffusion curves - Competitive



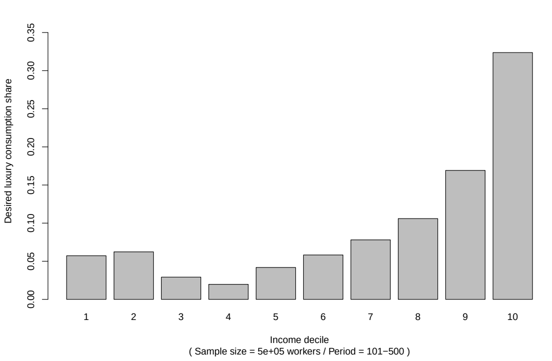
(b) Product diffusion curves - Fordist



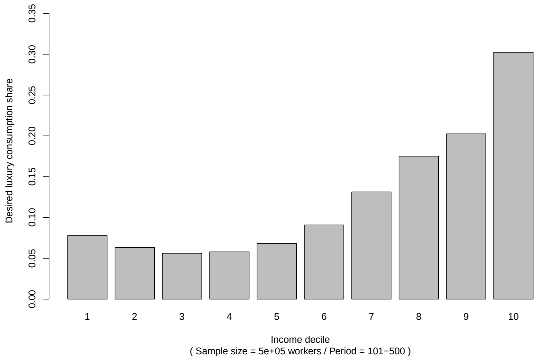
(c) Product expenditure and market concentration - Competitive



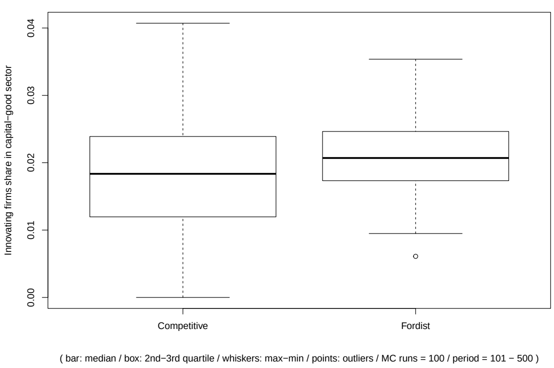
(d) Product expenditure and market concentration - Fordist



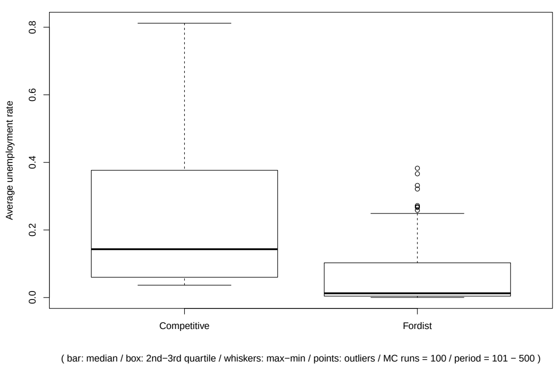
(e) Desired luxury consumption by income level - Competitive



(f) Desired luxury consumption by income level - Fordist



(g) Radical innovation - Competitive vs Fordist



(h) Unemployment rate - Competitive vs Fordist

Figure 4: Competitive vs Fordist labour markets. Source Dosi et al. (2022).

1. **NOLH DoE**: construct an appropriate design of experiments (DoE) performing efficient sampling via the NOLH approach.
2. **Kriging meta-modelling**: estimate and choose among alternative Kriging meta-model specifications.
3. **Global sensitivity analysis**: analyse the meta-model sensitivity to each parameter of the model using Sobol (variance) decomposition.
4. **Response surface**: graphically map the meta-model response surface (2D and 3D) over the more relevant parameters and identify critical areas.

In a nutshell, the Kriging meta-model Y is intended to predict the response of a given (scalar) output variable y of the original simulation model:[7]

$$Y(\mathbf{x}) = \lambda(\mathbf{x}) + \delta(\mathbf{x}) \tag{1}$$

where $\mathbf{x} \in D$ is a vector representing any point in the parametric space domain $D \subset \mathbb{R}^k$, being $x_1, \ldots, x_k \in \mathbb{R}$ the $k \geq 1$ original model parameters and $\lambda(\mathbf{x}) : \mathbb{R}^k \to \mathbb{R}$, a function representing the global trend of the meta-model Y under the general form:

$$\lambda(\mathbf{x}) = \sum_{i=1}^{l} \beta_i f_i(\mathbf{x}), \quad l \geq 1 \tag{2}$$

being $f_i(\mathbf{x}) : \mathbb{R}^k \to \mathbb{R}$ fixed arbitrary functions and $\beta_1, \ldots, \beta_l$ the l coefficients to be estimated from the sampled response of the original model over the image of y. The trend function λ is assumed here, for simplicity, to be a polynomial of order $l-1$, more specifically of order zero (β_1 is the trend intercept) or one (β_2 is the trend line inclination). This is usually enough to fit even complex response surfaces when coupled with an appropriate design of experiment (DoE) sampling technique.

In Eq. (1), $\delta(\mathbf{x}) : \mathbb{R}^k \to \mathbb{R}$ models the stochastic process representing the local deviations from the global trend component λ. δ is assumed second-order stationary with zero mean and covariance matrix $\tau^2 R$ (to be estimated), where τ^2 is a scale parameter and R is a $n \times n$ matrix (n is the number of observations) whose (i, j) element represents the correlation among $\delta(\mathbf{x}_i)$ and $\delta(\mathbf{x}_j)$, $\mathbf{x}_i, \mathbf{x}_j \in D$, $i, j = 1, \ldots, n$. The Kriging meta-model assumes a close correspondence between this and the correlation across $y(\mathbf{x}_i)$ and $y(\mathbf{x}_j)$ in the original model. Different specifications can be used for the correlation function, according to the characteristics of the y surface. For example, one of the simplest candidates is the power exponential function:

$$\operatorname{corr}(\delta(\mathbf{x}_i), \delta(\mathbf{x}_j)) = \exp\left[-\left(\sum_{g=1}^{k} \psi_g |x_{g,i} - x_{g,j}|\right)^p\right] \tag{3}$$

where $x_{g,i}$ denotes the value of parameter x_g at the point $\mathbf{x}_i$, $\psi_1, \ldots, \psi_k > 0$ are the k coefficients to be estimated and $0 < p \leq 2$ is the power parameter ($p = 1$ for the ordinary exponential correlation function). They quantify the relative weight of parameter x_g, $g = 1, \ldots, k$, on the overall correlation between $\delta(\mathbf{x}_i)$ and $\delta(\mathbf{x}_j)$ and, hopefully, among $y(\mathbf{x}_i)$ and $y(\mathbf{x}_j)$. Notice that a higher ψ_g represents a smaller influence of parameter x_g over δ.[8]

[7] In this section we loosely follow the formalization proposed by Roustant et al. (2012), Salle and Yildizoglu (2014) and Dosi et al. (2018).

[8] Definitions for other correlation function alternatives can be found in Roustant et al., 2012.

Therefore, the Kriging meta-model requires $l + k + 1$ coefficients to be estimated over the n observations selected by an appropriate design of experiments (DoE).[9] As discussed before, $l = 1$ or 2 is adopted. k is determined by the number of parameters of the original model. In practical terms, we constrained the experimental domain to ranges of the parameters that are empirically reasonable and respect minimal technical restrictions of the original model.[10]

Sensitivity analysis (SA) aims at "studying how uncertainty in the output of a model (numerical or otherwise) can be apportioned to different sources of uncertainty in the model input" (Saltelli et al., 2008). Due to the high computational costs of performing traditional SA on the original model (e.g., ANOVA), authors like Kleijnen and Sargent (2000), Jeong et al. (2005) or Wang and Shan (2007) argue that the meta-model SA can be a reliable *proxy* for the original model behaviour. Building on this assumption, one can propose the *global* SA analysis of the Kriging meta-model – as we attempt here – to evaluate the response of the original model over the entire parametric space, providing measurements of the direct and the interaction effects of each parameter. Following Saltelli et al. (2000), for the present analysis we selected a Sobol decomposition form of variance-based global SA analysis. It decomposes the variance of a given output variable of the model in terms of the contributions of each input (parameter) variance, both individually and in interaction with every other input by means of Fourier transformations. This method is particularly attractive because it evaluates sensitivity across the whole parametric space – it is a global approach – and allows for the independent SA analysis of multiple output models while being able to deal with non-linear and non-additive models (Saltelli and Annoni, 2010).

4 Results

Global sensitivity analysis (SA) is performed for $t \in [200, 400]$ on a set of primary output variables (the "metrics") more relevant to the current discussion, namely the overall *Gini index*, the *unemployment rate*, and the *hiring/firing rates*. Additionally, SA of *market-concentration indicators*, the Herfindahl-Hirschman indexes for both capital- and consumption-goods markets is also performed.[11] All the model's parameters and initial conditions, their calibration values, as well as the key SA tests statistics, are detailed in the following.

The K+S model is calibrated using the values presented in Table 4 below (column VALUE) for the parameters and initial conditions. SA is performed across the entire parametric space, inside the closed region defined by Table 4 (columns MIN. and MAX.), and the synthetic results are reported (columns μ^*, DIRECT and INTERACTION) for the most sensitive among the tested output variables (results for the remaining variables can be

[9]The Kriging correlation function (kernel) coefficients are estimated by means of numerical maximum likelihood. For the details on the technical implementation applied, see Roustant et al., 2012.

[10]The technical feasibility criterion adopted was the minimally "normal" operation of the market, measured by the survival of at least two firms during the majority of simulation time steps. Also, some of the parameters' test ranges limit, in practice, the possible ranges of variation for other parameters (e.g., the distribution average μ must be lower than the upper support of distributions μ_{max}).

[11]Other relevant metrics, like the macro aggregates' growth rates, the inequality measures, and the industrial performance indicators were already evaluated in previous papers based on the labour-augmented K+S model and are not be replicated here. The general results from these past analyses indicate a relatively small dependence of the model qualitative results on the chosen parametrization.

requested to the authors). Two SA methodologies are employed, elementary effects (EE) and Sobol variance decomposition (SVD).

As a first step, EE analysis[12] is summarized by the μ^* statistic in Table 4, which is a measure of the direct (absolute) effects of each factor (parameter or initial condition) on the chosen output variable. The parametric space is re-scaled to the $[0, 1]$ interval, on each dimension, for the estimation of μ^*, so the resulting statistics are directly comparable. The statistical significance of the statistic, the probability of not rejecting $H_0 : \mu_i^* = 0$ is also evaluated and indicated by the usual asterisk convention. The EE computation was performed directly over model samples from a coverage-optimized, ten-trajectory, one-at-a-time design of experiments (DoE). Each EE DoE experimental point was sampled three times, to (minimally) compensate for the stochastic components in the model.

As a second step, in order to more precisely quantify the effect of each influential factor over the selected metrics, directly or in interaction with other factors, we perform a series of Sobol Variance Decompositions (SVDs). The SVD is a variance-based, global SA method consisting in the decomposition of the chosen metrics variance into shares according to the contribution of the variances of the factors selected for analysis. This methodology deals better with non-linear and non-additive interactions than EE. It allows to precisely disentangle both direct and interaction quantitative effects of the factors over the entire parametric space (Sobol, 1993, Saltelli et al., 2008). The SVD analysis for the entire set of variables is reported in Table 4 by two statistics: (DIRECT column) the decomposition of the direct influence of each factor on the variance of the tested output variable (adding up to 1), and (INTERACTION column) its indirect influence share, by interacting with other factors (non-linear/non-additive effects).

The SVD analysis was performed using a Kriging meta-model fitted using samples from a near-orthogonal Latin hypercube DoE. Because of the high computational cost to produce the SVD using the original simulation model, a simplified version of it – a meta-model – was estimated using the Kriging method and employed for the SVD. The meta-model was estimated by numerical maximum likelihood using a set of observations sampled from the original model using a high-efficiency, nearly-orthogonal Latin hypercube (NOLH) DoE (Cioppa and Lucas, 2007b). Each point in the NOLH DoE was sampled from 5 to 20 times, according to the NOLH size, to deal with the model's stochastic components.

Out of the total 93 factors in this K+S version, the EE analysis screened 64, 29, and 12 factors which are significant at 5%, 2%, and 1% levels, respectively, and are responsible for at least 70% of the effects on the selected primary model metrics. This analysis indicates that the Gini index is the most sensitive metric (47/20/8 at 5/2/1% significance) while the hiring rate is the least sensitive (34/6/0 factors at 5/2/1%).[13] In total, 64 (5%), 29 (2%), and 12 (1%) unique *primary* factors were identified, after discarding duplicates, and used to generate three additional NOLH DoEs for the Kriging meta-modeling and the SVD analysis.

The SVD analysis better identified a subset of *important* factors for the chosen metrics. In Table 2 the top ten factors for each selected metric are presented.

[12]Briefly, EE proposes both a specific design of experiments, to efficiently sample the parametric space under a multi-path, one-factor-at-a-time strategy, and a absolute importance statistic to evaluate direct and indirect (non-linear/non-additive) effects of the parameters on model results and their statistical significance (Morris, 1991). EE is usually a more powerful SA method than the traditional (local) derivative-based SA approaches (Saltelli et al., 2008).

[13]The selection criteria was to consider the top 70% EE contributors at 5/2% significances, and 90% at 1%.

As expected, the hiring and firing rates share almost the same important factors, with two differences, and a slightly different ordering. Notably, the most relevant factors, accounting for more than 50% of the two metrics variance, are ω_u (average number of applications sent by an unemployed worker per period), m_1 (relative "capital" productivity in the capital-good sector), κ_{max} (maximum threshold to capital expansion of consumption-good firms), and ι (desired inventories share of consumption-good firms). This result puts light on the relevance of the capital-good (machines) sector dynamics (m_1, κ_{max}) on the labour market performance, even if a relatively small share of jobs is directly generated in this sector. Figure 5(b), presents the effects of the other two parameters (ω_u, ι) on the firing rate. Notice the strong (nonlinear) interaction between the two factors in the region $\omega_u \in [0, 10]$ and $\iota \in [0.05, 0.15]$.

In turn, the Gini index and the unemployment rate show the significant importance of the market dynamics, at the inter- (χ_c) and intra-industry (χ_2) levels. The replicator equation parameters χ_c and χ_2 define the intensity of the competition, or how fast a competitive advantage turns into more wallet or market share for an industry or firm, respectively. Most of the factors here present an additive behaviour, that is, the interaction between them is relatively weak. However, some interaction can still be recovered, as demonstrated in Figure 6(b), which shows the joint effect of χ_2 and T_{lux} (the average time between luxury goods acquisition) on the Gini index. Notice that the selected calibration values ($\chi_2 = 1$ and T_{lux} = 5, red dot) are close to the minimum value for the index (the yellow dot, about 0.16). As χ_2 increases, so does the inequality measured by the Gini index, potentially achieving almost a 70% increase at the maximum possible setup (blue dot). However, even this significant change does not alter the main qualitative results of the model (societies with a Gini index of 0.16 or 0.27 are both relatively egalitarian).

Last, the market-concentration indicators present, as expected, more unrelated sets of important factors. The Herfindahl-Hirschman standardized index (HHI) for the capital-goods (machines) market was completely and sharply driven by the factors governing the sectoral dynamics, allowing for average values in the $[0.2, 0.6]$ interval. Most important factors are (α_2, β_2), the beta distribution parameters defining the technological imitation opportunities, γ, which sets the intensity of the client-search efforts by firms, ν, the share of revenues applied to R&D, and x_5, the upper limit for the productivity advantage of entrants. In the consumption-goods markets, however, factorial influences are more subtle, with mean HHI around the $[0.05, 0.2]$ range. The most relevant factors are still clearly connected with the sectoral dynamics: the initial entrant cash allocation NW_0^2, the minimum number of basic industries F^{bas}_{min}, the minimum market share for a firm to stay in industry f^c_{min}, the capital productivity m_1, and the share of the firm-level productivity gains passed to wages ψ_4.

Figures 5, 6, 7, 8 present for four variables of interest three plots, namely the Sobol index, the 3D response surface and the isolevel curve (2D). The Sobol index informs about the importance of the most relevant parameters in affecting the kriging meta-model, for one variable at the time; the 3D response surface and the isolevel curves restrict instead the analysis with respect to three and two parameters respectively and indicate the minimum (yellow), the maximum (blue) and the calibration point (red).

Starting with the firing rate (Figure 5), the Sobol index points at the relevance exerted by the ω_u and the ι parameters, both in terms of direct and indirect effects. A strongly non-linear behaviour captures the interaction between those two parameters and the fir-

Relative importance	Gini index		Unemployment rate		Hiring rate		Firing rate		Concentration (capital)		Concentration (consumption)	
1	χ_2	(0.456)	χ_2	(0.225)	ω_u	(0.224)	ι	(0.222)	β_2	(0.376)	NW_0^2	(0.152)
2	χ_c	(0.080)	m_1	(0.145)	m_1	(0.152)	ω_u	(0.213)	γ	(0.287)	F_{min}^{bas}	(0.140)
3	F_{min}^1	(0.066)	ω_u	(0.137)	κ_{max}	(0.137)	m_1	(0.141)	ν	(0.171)	f_{min}^c	(0.126)
4	ω_2	(0.066)	κ_{max}	(0.132)	$\bar{x}_1$	(0.093)	κ_{max}	(0.132)	x_5	(0.151)	m_1	(0.118)
5	m_1	(0.064)	$\bar{x}_1$	(0.095)	ι	(0.070)	$\bar{x}_1$	(0.096)	α_2	(0.070)	ψ_4	(0.114)
6	ψ_4	(0.042)	ι	(0.063)	β_2	(0.049)	ζ_g	(0.051)	μ_1	(0.068)	χ_c	(0.077)
7	T_{lux}	(0.036)	Φ_2	(0.058)	μ_1	(0.048)	α_1	(0.045)	Φ_1	(0.044)	ι	(0.046)
8	β_2	(0.033)	x_5	(0.053)	ζ_g	(0.045)	μ_1	(0.045)	$\bar{x}_2$	(0.038)	κ_{max}	(0.044)
9	f_{min}^c	(0.031)	NW_0^2	(0.049)	NW_0^2	(0.041)	Φ_2	(0.044)	$\underline{x}_1$	(0.026)	F_0^{bas}	(0.044)
10	μ_{res}	(0.031)	ζ_g	(0.046)	α_1	(0.040)	ν	(0.041)	Φ_2	(0.025)	μ_1	(0.036)

Table 2: Top 10 factors for selected model metrics. Relative importance (total effects) from SVD analysis.
In parentheses: average total-effects Sobol indexes of each factor from 93/64/29/12-dimension meta-models.

ing rate, with a deep valley in correspondence of $\iota = 0.12$, which represents a clear threshold point. Higher values of the ι parameter bring again a steep increase in the firing rate. $\omega_u = 10$ represents an other threshold point changing the behaviour of the variable, as visible from the concentric shape of the isolevel curves below the point. Notably, the two parameters refer to model domains ex-ante detached, namely the intensity of accumulation of inventories by firms and the number of applications sent by workers. The two behavioural rules which refer to distinct structures of agents are however both directly influencing the final firing rate.

Going to the second variable, the Gini index (Figure 6) shows as well a non linear dynamics. The most relevant parameters according to the Sobol are χ_2, regulating the intensity of competition in the product market (within-industry replicator dynamics), and T_{lux} affecting the consumption choice of buying a new luxury good. A non-linear behaviour is again present, as visible from the response surface, this time smoother, with a maximum value of the Gini coefficient in correspondence of a very high level of selection intensity. High selection in the product market turns into higher market concentration and dominant positioning of some firms, influencing inequality via "winners take the most" processes. The isolevel curve shows that this dynamics occurs in the range of $\chi_2 \in [2, 3]$ wherein a change in behaviour emerges.

A threshold behaviour due to the interaction between χ_2 and ω_u also characterizes unemployment (Figure 7), again influenced such as inequality by market concentration, mainly as a direct effect. Interaction effects with the number of applications sent by unemployed workers appear after $\omega_u = 5$. Lower market values of market concentration and a higher number of applications sent by unemployed people help in reducing unemployment, while the opposite holds for higher levels of concentration and a number of applications below five. The response surface for unemployment appears to be particularly rugged, with milled isolevel curves and with maximum and minimum values at the opposite corners, the minimum in the upper-left, the maximum in the bottom-right corner. As in the case of inequality, also unemployment rather than being primarily driven by technological parameters inducing eventual technological unemployment, is by far more affected by market concentration, and in that by industry behaviour. These results highlight the importance of investigating the root causes of unemployment primarily with respect to firm performance, survival and growth patterns, rather than over-emphasizing the role of technological variables. Indeed, workers history is tightly linked with firms history.

Lastly, market concentration in the capital-good sector (Figure 8) is mostly driven by innovation and market parameters, namely the number of clients (γ) and the share ν of R&D expenditures, showing the importance of innovative efforts in order to gain/loose market shares. Differently from the other variables, the behaviour of the HHI index in the capital-good sector is linear and it monotonically decreases with lower values of γ and higher values of ν. Indeed, a higher fraction of R&D expenditures by all firms reduces dominant positions and market concentration, making the market more dynamic.

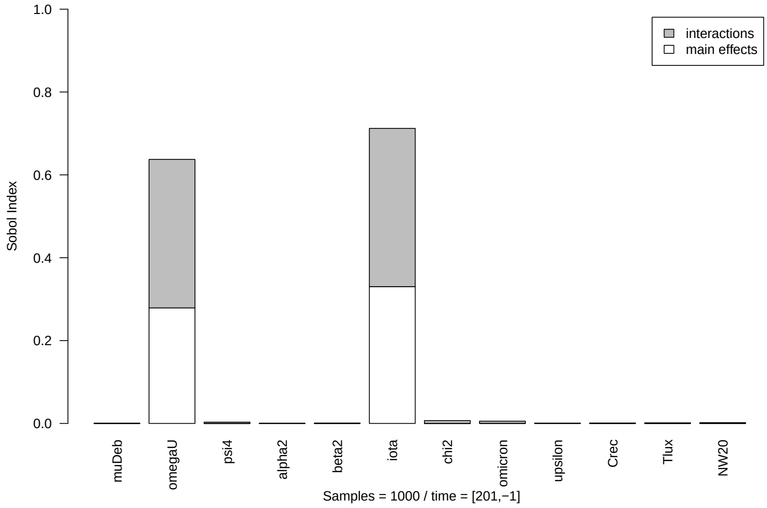
The results inform about the scope and usefulness of meta-modelling techniques which allow to sample the parametric space in an efficient way and to identify tipping points, threshold behaviours and non-linearity in the model. We have presented a range of potential configurations, going from deep threshold points (firing rate), to mild non linear curves (Gini index), to rugged surfaces (unemployment rate), to linear behaviours (concentration index in the consumption-good sector), in order to show an array of model functioning, when looking at different variables. The strength of the approach, together with allowing for a deeper and large scale model exploration, relies also in the possibility to detect the importance of hidden interactions connecting ex-ante detached structures. Indeed, labour market variables as firing, unemployment and inequality rates are intimately linked to product markets and industry dynamics domains, rather than to technological parameters. In that, the model reveals its complex nature, in its ability to allow for propagation, tipping points and non-linearity.

5 Conclusions

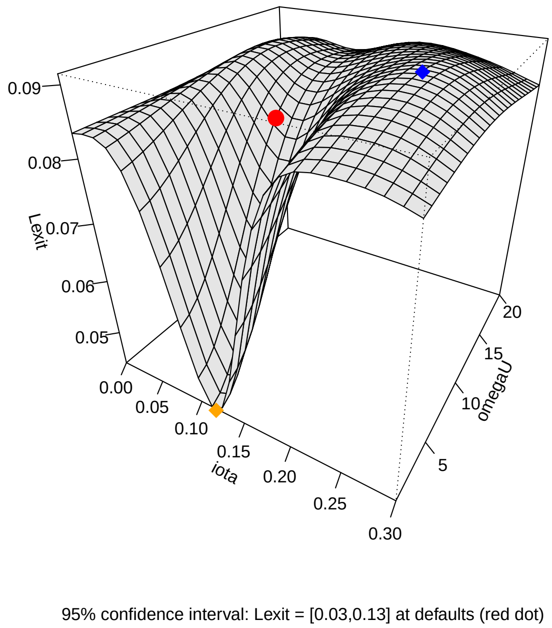
This chapter has addressed the relevance of considering the problem of the future of work embracing a complexity perspective. We have declined complexity as an attribute of both natural and social systems, so called living systems, in which change and coordination shape interactions of individual entities giving rise to macro emergent properties resulting from structures of propagation and hierarchical ordering.

The future of work analysis has been tackled by means of an agent-based model developed upon the K+S family which includes the arrival of new paradigmatic trajectories (product innovation upstream) adopted by downstream firms populating new emerging sectors. The sectoral dynamics is in turn shaped by hierarchical preferences influenced by a class-consumption behaviour. The model offers an integrated, multi-level perspective and it is able to overcome the neoclassical view of the human-machine relationship including the role of demand, income distribution and labour market organizations in affecting the dynamics of employment and unemployment, the latter strongly dependent from the institutional regime regulating labour relations.

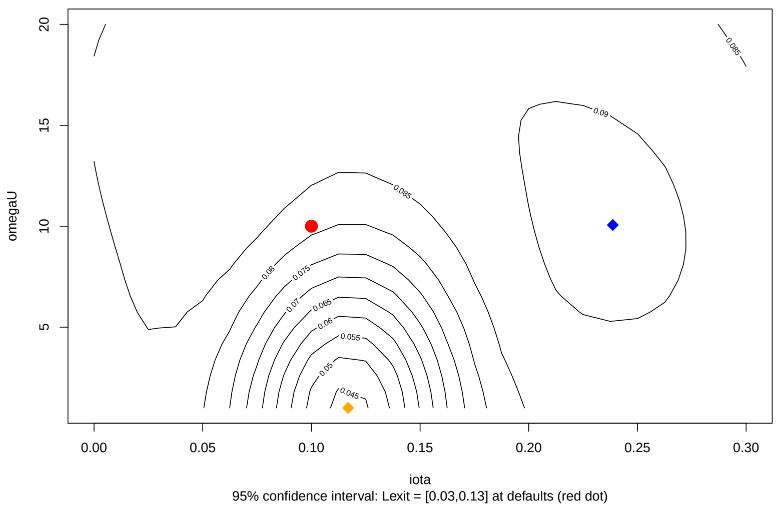
The results obtained in Dosi et al. (2022) are here expanded and further deepened considering the meta-model exploration of the parametric space, performing a global sensitivity analysis on a surrogate model obtained by both elementary effects and Kriging, according to the procedure developed in Dosi et al. (2018). The Sobol Variance Decomposition analysis presented on some selected metrics documents first the presence of a variety of configurations of the model functioning, going from clear threshold points to more linear, well-behaved surfaces. Second, the meta-model results inform about the existing interdependent structures that connect the labour market dynamics with the product markets, the industry dynamics and even with firm-level idiosyncratic choices.



(a) Sobol index

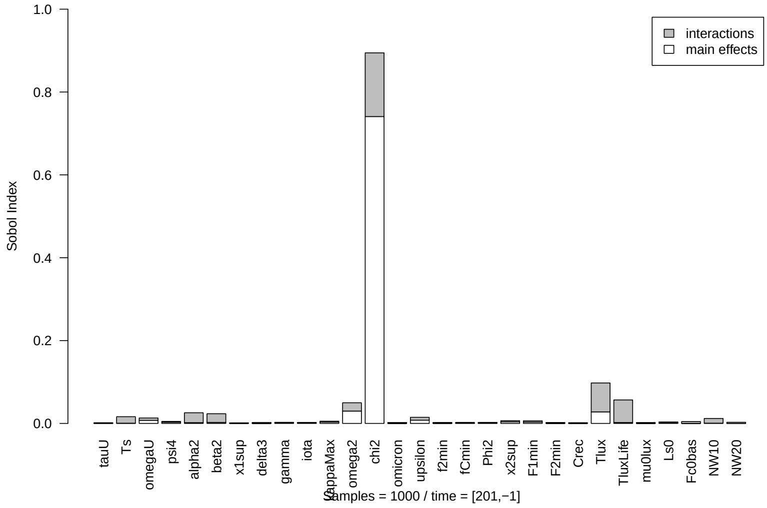


(b) 3D response surface $\chi_2 = 1$

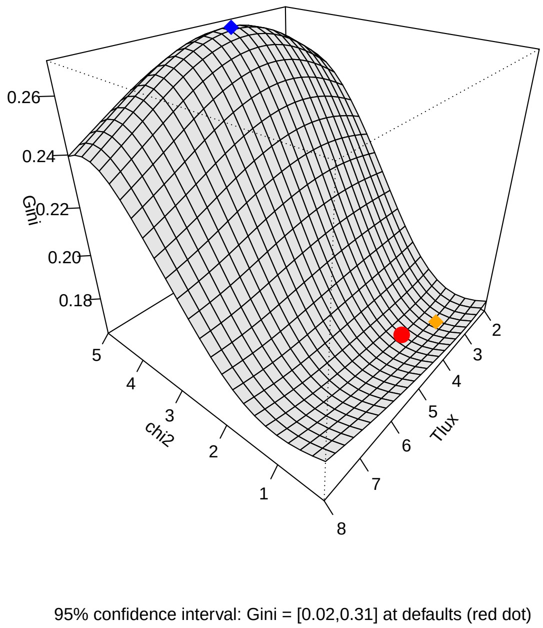


(c) Isolevel response surface $\chi_2 = 1$

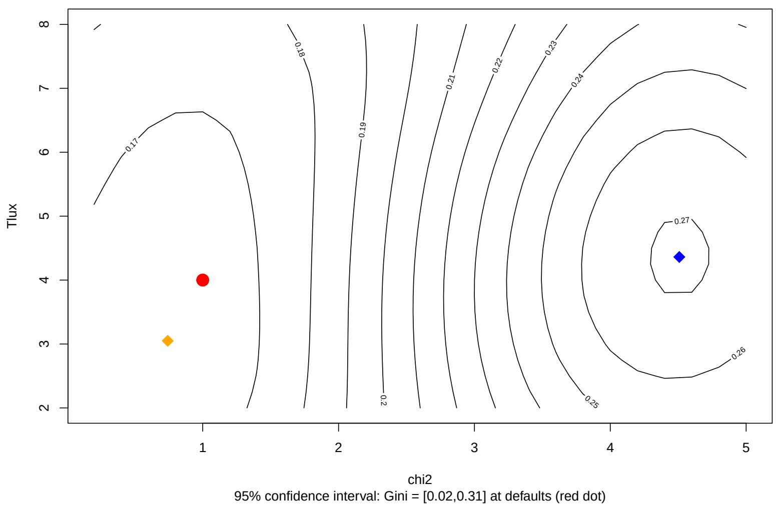
Figure 5: Global sensitivity analysis for Firing rates. Blue dot: maximum; yellow dot: minimum; red dot: calibration value.



(a) Sobol index

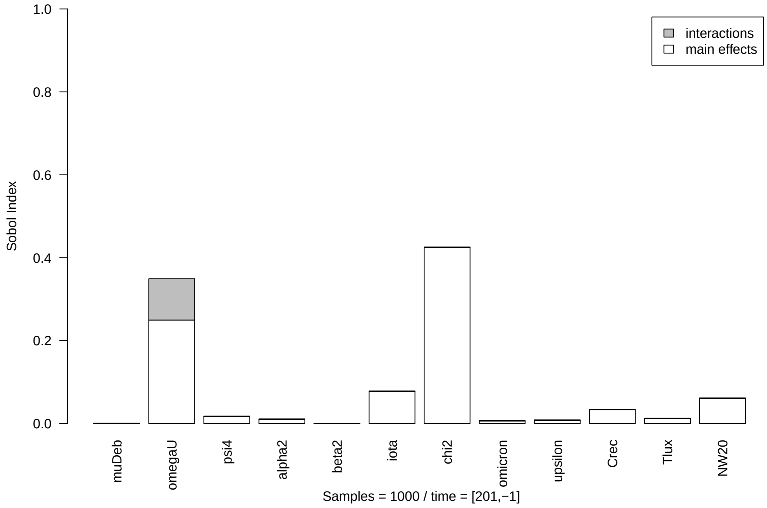


(b) 3D response surface $T_{luxlife} = 8$

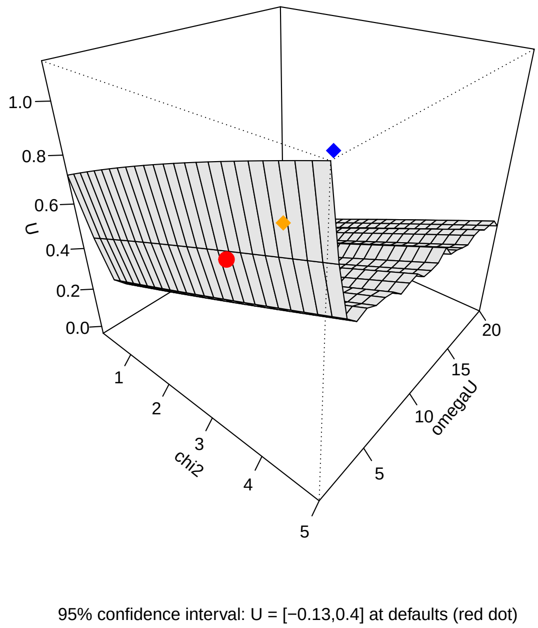


(c) Isolevel response surface $T_{luxlife} = 8$

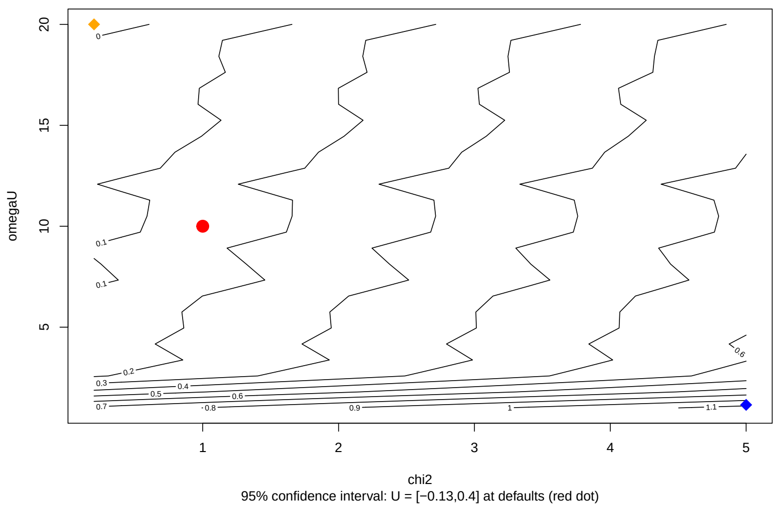
Figure 6: Global sensitivity analysis for Gini index rates. Blue dot: maximum; yellow dot: minimum; red dot: calibration value.



(a) Sobol index

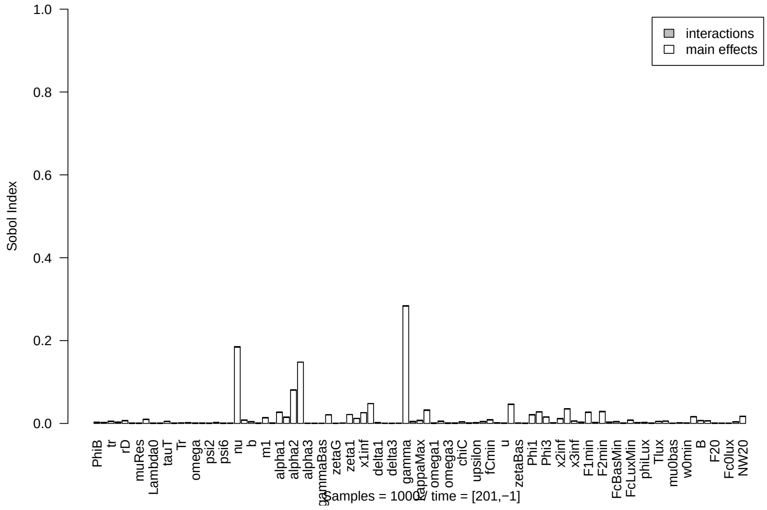


(b) 3D response surface $\iota = 0.1$

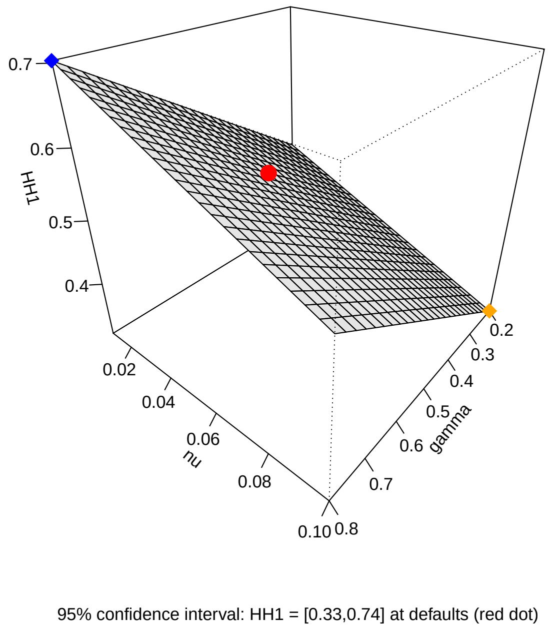


(c) Isolevel response surface $\iota = 0.1$

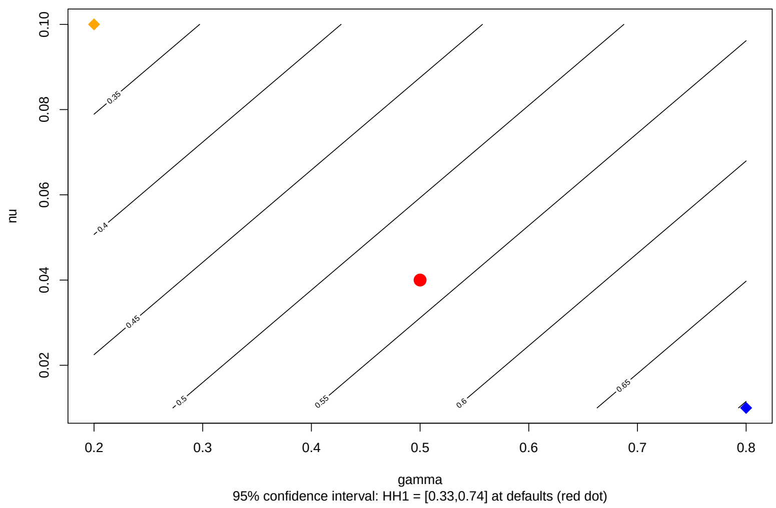
Figure 7: Global sensitivity analysis for Unemployment rates. Blue dot: maximum; yellow dot: minimum; red dot: calibration value.



(a) Sobol index



(b) 3D response surface $\beta_2 = 4$



(c) Isolevel response surface $\beta_2 = 4$

Figure 8: Global sensitivity analysis for HHI index (upstream sector). Blue dot: maximum; yellow dot: minimum; red dot: calibration value.

The complexity approach has proven to be therefore an alternative, useful lens to address old and recurrent questions in economics as the technical change vs employment relationship modulated by demand patterns, income distribution, structural change and labour market organizations. It allows to enlarge the scope of investigation beyond production functions of tasks, relative prices of capital vs labour, inputs substitutability, comparative advantages of workers in their skill levels, the latter elements upon which the neoclassical approach on the employment-technology nexus is rooted (Acemoglu and Restrepo, 2018).

Future modelling advances entail the inclusion of alternative set-ups of the labour markets (Fordist vs Competitive) characterizing each specific new emerging industry, therefore allowing for the competition between high-opportunities (e.g., ICT) vs low-opportunities (e.g., meat processing) manufacturing industries. The aim is to study the extent to which the erosion in the employment relations coupled with bad versus good alternative specialization strategies impact upon the overall dynamics of labour demand creation/destruction. In addition, deepening the analysis of the role played by class-based consumption and hierarchical needs satisfaction is another potential path of future research, possibly including imitative behaviours.

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Appendix A - Model description

Radical innovation and new machine generations

New technological paradigms affect the productivity in making machines by workers upstream and the productivity embodied in machines adopted downstream. Therefore, they affect both the efficiency in labour productivity of workers in the machine-producing sector, but also the efficiency embodied in capital, thus the amount of labour required to operate such new machines, impacting on the capital/labour ratio in downstream industries.

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^g_t — for each manufacturing stage of the production of consumer goods — is drawn from a uniform distribution:

$$A^g_t \sim \mathrm{U}\left[\max_i A_{i,t-1}, (1+h)\max_i A_{i,t-1}\right], \tag{4}$$

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^g_t of capital-good firms exploring the new paradigm:

$$B^g_t \sim \mathrm{U}\left[\frac{\max_i\left(A_{i,t-1}B_{i,t-1}\right)}{A^g_t}, (1+h)\frac{\max_i\left(A_{i,t-1}B_{i,t-1}\right)}{A^g_t}\right]. \tag{5}$$

Therefore, B^g_t is drawn symmetrically to A^g_t 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 $\theta^g_{i,t}$ defines a success or a failure of access at time t:

$$\theta^g_{i,t} = 1 - e^{-\zeta_0 IN'_{i,t}}, \tag{6}$$

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

$$(A^g_{i,t}, B^g_{i,t}) = \begin{cases} (A^g_t, B^g_t) & \text{if succesfully access new generation} \\ (0,0) & \text{otherwise.} \end{cases} \tag{7}$$

Firm can only access the machine generation immediately above the one currently being produced. Inside each technological paradigm, 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.

Technical change and labour productivity

The technology of capital-good firms is defined as (A^τ_i, B^τ_i). A^τ_i is the labour productivity of the machine-tool manufactured by firm i for the consumption-good sector, while B^τ_i 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:

$$c_{i,t} = \frac{w_{i,t}}{B^\tau_i}. \tag{8}$$

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

$$p_{i,t} = (1+\mu_1)c_{i,t}. \tag{9}$$

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 $S_{i,t-1}$:

$$RD_{i,t} = \nu S_{i,t-1}. \tag{10}$$

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

$$L^{R\&D}_{i,t} = \frac{RD_{i,t}}{w_{i,t}} \tag{11}$$

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

$$IN_{i,t} = \xi L^{R\&D}_{i,t}, \tag{12}$$

$$IM_{i,t} = (1-\xi) L^{R\&D}_{i,t}. \tag{13}$$

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:

$$\theta^{in}_{i,t} = 1 - e^{-\zeta_1 IN'_{i,t}}, \tag{14}$$

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 $(A^{in}_{i,t}, B^{in}_{i,t})$ according to:

$$A^{in}_{i,t} = A_{i,t}\left(1 + x^A_{i,t}\right), \tag{15}$$

$$B^{in}_{i,t} = B_{i,t}\left(1 + x^B_{i,t}\right), \tag{16}$$

where $x^A_{i,t}$ and $x^B_{i,t}$ are two independent draws from a $\text{beta}(\alpha_1, \beta_1)$ 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:

$$\theta^{im}_{i,t} = 1 - e^{-\zeta_2 IM'_{i,t}}, \tag{17}$$

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^{im}_i, B^{im}_i) from a close competitor and select the machine to produce using the rule:

$$\min\left[p^m_{i,t} + bc^m_{A^m_{i,t}}\right], \quad m = \tau, g, in, im, \tag{18}$$

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^τ_i and worker skills $s_{\ell,t}$, as described later, and is computed as:

$$A_{j,t} = \frac{1}{L_{j,t-1}} \sum_{\ell \in \{L_{j,t-1}\}} A_{\ell,t}, \tag{19}$$

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:

$$s_{\ell,t} = \begin{cases} (1 + \tau_T)s_{\ell,t-1} & \text{if employed in } t-1 \\ \dfrac{1}{1+\tau_U} s_{\ell,t-1} & \text{if unemployed in } t-1, \end{cases} \tag{20}$$

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, 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:

$$A_{\ell,t} = \frac{s_{\ell,t}}{\bar{s}_t} \frac{A^\tau_i}{k_j}, \tag{21}$$

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

The adopted definition of skills implies that the latter are firm-specific rather than industry-specific and accumulate with job tenure. Therefore, whenever workers quit and are hired by a new firm, a new process of firm-level skill acquisition starts. The acquired minimum skill level in the entry period represents an economy-wide minimum floor.

New industry entry and product complexity

We model industry entry and structural change along two dimensions: first we split products into two macro-sectors, basic (non durable) and luxury (durable) goods. Inside each category, single industry evolution occurs, according to a product life-cycle dynamics. The attribute of basic versus luxury of the two macro-sectors derives from the type of "needs" they satisfy. While basic goods reflect needs to which workers allocate the entire fraction of income until a given threshold, luxury goods require savings to be bought.

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:

$$\theta_t^{bas} = 1 - e^{-\zeta_{bas}\left(\frac{F_0^{bas}}{F_{t-1}^{bas}}-1\right)}, \tag{22}$$

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:

$$\theta_t^{lux} = \begin{cases} 1 - e^{-\zeta_{lux}\Delta_t^g} & \text{if unexploited generation is available in } t \\ 0 & \text{otherwise,} \end{cases} \tag{23}$$

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:

$$\Delta_t^g = \log\left(\frac{A_t^g B_t^g}{A_{t-u}^g B_{t-u}^g}\right), \tag{24}$$

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 (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:

$$\begin{gathered} k_h = \bar{k}_{t-1}^z \left(1 + \pi_t^z\right) \left(1 + \Delta_t^g\right)^{\gamma_z} , \\ \pi_t^z \sim \text{beta}(\alpha_3, \beta_3), \quad \pi_t^z \in [\underline{x}_3, \bar{x}_3], \quad z = bas, lux, \end{gathered} \tag{25}$$

$\bar{k}_t^z$ 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:

$$c_{j,t} = k_h \frac{w_{j,t}}{m_2 A_{j,t}}, \tag{26}$$

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.

Labour market under different regimes

We model the labour market under two regimes, a Fordist and a Competitive set-up whose main attributes are summarised in Table 3.

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

$$L_{j,t}^d = \frac{Q_{j,t}^d}{A_{j,t}}. \tag{27}$$

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

Firms decide whether to hire (or fire) workers according to the expected production $Q_{j,t}^d$ (or $Q_{i,t}$). If it is increasing, $\Delta L_{j,t}^d$ new workers are (tentatively) hired in addition to the existing number $L_{j,t-1}$. Each firm (expectedly) gets a fraction of the number of applicant workers $L_{a,t}$ in its candidates queue $\{\ell_{j,t}^s\}$, proportional to firm market share $f_{j,t-1}$:

$$\mathrm{E}(L_{j,t}^s) = \left[\omega \left(1 - U_{t-1}\right) + \omega_u U_{t-1}\right] L^S f_{j,t-1}, \tag{28}$$

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 select the subset of desired workers $\{\ell^d_{j,t}\}$ to make a job (wage) offer:

$$\{\ell^d_{j,t}\} = \{\ell_{j,t} \in \{\ell^s_{j,t}\} : w^r_{\ell,t} \leq w^o_{j,t}\}. \tag{29}$$

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:

$$0 \leq L_{j,t} \leq L^d_{j,t} \leq L^s_{j,t}, \qquad L^z_{j,t} = L_{j,t-1} + \#\{\ell^z_{j,t}\}, \quad z = d, s. \tag{30}$$

The search, wage determination and firing processes differ according to the configuration. When there is no bargaining, firm j offers the wage:

$$w^o_{j,t} = [1 + WP_{j,t} + \mathrm{N}(0, w^o_{err})]\, w^o_{j,t-1} \quad \text{bounded to} \quad p_{j,t-1}A_{j,t-1}, \tag{31}$$

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:

$$WP_{j,t} = \psi_2 \frac{\Delta A_t}{A_{t-1}} + \psi_4 \frac{\Delta A_{j,t}}{A_{j,t-1}}, \qquad \psi_2 + \psi_4 \leq 1, \tag{32}$$

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). When one-round bargaining exists, workers have reservation wages equal to the unemployment benefit, if any, and request a wage $w^r_{\ell,t}$ in the job application:

$$w^r_{\ell,t} = \begin{cases} w_{\ell,t-1}(1+\epsilon) & \text{if employed in } t-1 \\ w^s_{\ell,t} & \text{if unemployed in } t-1, \end{cases}. \tag{33}$$

$w_{\ell,t}$ is the current wage for the employed workers and $\epsilon \in \mathbb{R}_+$, a parameter. Unemployed workers have a shrinking satisfying wage $w^s_{\ell,t}$, accounting for the wage history:

$$w^s_{\ell,t} = \max\left(w^u_t, \frac{1}{T_s}\sum_{n=1}^{T_s} w_{\ell,t-n}\right), \tag{34}$$

being $T_s \in \mathbb{N}_*$, the moving average time-span parameter. An employed worker accepts the best offer $w^o_{j,t}$ she receives if higher than current wage $w_{\ell,t}$. An unemployed worker accepts the best offer if at least equal to the unemployment benefit w^u_t.

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

$$w^{min}_t = w^{min}_{t-1}\left(1 + \psi_2 \frac{\Delta A_t}{A_{t-1}}\right). \tag{35}$$

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:

$$Bon_{j,t} = \psi_6(1 - tr)\Pi_{j,t-1}, \tag{36}$$

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 3: Characteristics of the two types of regimes

LABOUR MARKET ATTRIBUTES	FORDIST	COMPETITIVE
Wage sensitivity to unemployment	low (rigid)	high (flexible)
Wage indexation to average productivity	full	partial
Labour-firing restrictions	under losses only	under downsizing
Worker-hiring rule	higher skills	lower wage-to-skill ratio first
Worker-firing rule	lower skills	higher wage-to-skill ratio first

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 $Bon_{\ell,t}$:

$$In_{\ell,t} = \begin{cases} w_{\ell,t} + Bon_{\ell,t-1} & \text{if employed in } t \\ w^u_t + Bon_{\ell,t-1} & \text{if unemployed in } t, \end{cases} \tag{37}$$

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 such a way, we assume that the satisfaction of basic needs is equal across classes, while luxury preferences expand with income.

$$C^{d,bas}_{\ell,t} = \begin{cases} In_{\ell,t} & \text{if } In_{\ell,t} \leq \underset{n}{\mathrm{perc}}\left(\phi_{lux}, In_{n,t-1}\right) \\ \underset{n}{\mathrm{perc}}\left(\phi_{lux}, In_{n,t-1}\right) & \text{otherwise,} \end{cases} \tag{38}$$

where $\mathrm{perc}_n(\cdot)$ 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:

$$C^{d,lux}_{\ell,t} = \begin{cases} In_{\ell,t} - C^{d,bas}_{\ell,t} & \text{if } In_{\ell,t} > \underset{n}{\mathrm{perc}}\left(\phi_{lux}, In_{n,t-1}\right) \\ 0 & \text{otherwise.} \end{cases} \tag{39}$$

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_{lux}^{max} periods. If any of the conditions is not met, the budget for luxury is saved:

$$Sav_{\ell,t}^{lux} = \begin{cases} 0 & \text{if } \min_h p_{h,t}^* \leq C_{\ell,t}^{d,lux} + Sav_{\ell,t-1}^{lux} \text{ and } t \geq t_\ell^* + T_{lux} \\ Sav_{\ell,t-1}^{lux} + C_{\ell,t}^{d,lux} & \text{otherwise or if supply shortage,} \end{cases} \tag{40}$$

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 $Sav_{\ell,t}^{lux}/T_{lux}$ is transferred to the basic-goods budget $C_{\ell,t}^{d,bas}$ 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.

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 sub-sectors 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 $\bar{k}'_h$.

$$E_{h,t} = \delta_1 \left(1 - \bar{p}'_{h,t-1}\right) + \delta_2 \bar{q}'_{h,t-1} + \delta_3 \left(1 - \bar{n}'_h\right) + \delta_4 \bar{k}'_h, \tag{41}$$

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:

$$f_{h,t} = f_{h,t-1}\left(1 + \chi_c \frac{E_{h,t} - \bar{E}_t^{bas}}{\bar{E}_t^{bas}}\right), \qquad \bar{E}_t^{bas} = \frac{1}{F_t^{bas}} \sum_{h \in bas} E_{h,t} f_{h,t-1}, \tag{42}$$

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 $C^{d,lux}_{\ell,t} + Sav^{lux}_{\ell,t-1}$ 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, 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 ($Sav^{lux}_{\ell,t} = Sav^{lux}_{\ell,t-1} + C^{d,lux}_{\ell,t}$), 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 $p_{j,t}$.

The model can run just with the basic-good sector driven by a life-cycle dynamics involving saturation of old industries and emergence of new ones. However, the absence of the luxury sector prevents any link between supply and demand dynamics by which more complex needs, arising along the income ladder, are satisfied by new emerging industries. More importantly, the luxury sector is populated by durable goods which are bought only out of saving decisions. Therefore, in line with the Engel curve, the dynamics of such sector is driven by higher than median consumers.

Note that product variety inside each industry was already embedded in previous versions of the model in terms of quality level (proxied by better produced goods out of more skilled labour, see Equation 55). However the inclusion of luxury goods entails distinct income elasticities of demand: while basic-goods are all desired with the same share across workers, luxury goods are individual specific.

Investment and entry

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

$$D^e_{j,t} = \mathrm{g}\left(D_{j,t-1}, D_{j,t-2}, D_{j,t-n}\right), \quad 0 < n < t, \tag{43}$$

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:

$$Q^d_{j,t} = (1+\iota)D^e_{j,t} - N_{j,t-1}, \tag{44}$$

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:

$$EI^d_{j,t} = K^d_{j,t} - K_{j,t-1}. \tag{45}$$

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:

$$RS_{j,t} = \left\{ A^\tau_i \in \Xi_{j,t} : \frac{p^*_{i,t}}{c^{A^\tau_i}_{j,t} - c^*_{j,t}} \leq b \right\}, \tag{46}$$

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:

$$b^z_{h,t} = \max\left[\left(o\pi^z_t + (1-o)MA^z_{h,t}\right) F^z_{h,t-1}, 0\right], \qquad z = 1, 2, \tag{47}$$

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:

$$MA^z_{h,t} = MC^z_{h,t} - MC^z_{h,t-1} \qquad \text{(bounded to } [\underline{x}^z_2, \bar{x}^z_2]), \tag{48}$$

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):

$$MC^z_{h,t} = \log NW^z_{h,t-1} - \log Deb^z_{h,t-1}. \tag{49}$$

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:

$$f_{j,t} = f_{j,t-1}\left(1 + \chi\frac{E_{j,t} - \bar{E}_{h,t}}{\bar{E}_{h,t}}\right), \qquad \bar{E}_{h,t} = \frac{1}{F^2_{h,t}}\sum_{j\in h} E_{j,t} f_{j,t-1}, \tag{50}$$

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 $q'_{j,t}$:

$$E_{j,t} = \omega_1\left(1 - p'_{j,t-1}\right) + \omega_2\left(1 - l'_{j,t-1}\right) + \omega_3 q'_{j,t-1}, \tag{51}$$

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 $c_{j,t}$:

$$p_{j,t} = (1 + \mu_{j,t})\, c_{j,t}. \tag{52}$$

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

$$\mu_{j,t} = \mu_{j,t-1}\left(1 + \upsilon\frac{f_{j,t-1} - f_{j,t-2}}{f_{j,t-2}}\right), \tag{53}$$

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:

$$l_{j,t} = \max\left[D_{j,t} - (Q_{j,t} + N_{j,t}), 0\right]. \tag{54}$$

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

$$q_{j,t} = \frac{1}{L_{j,t-1}}\sum_{\ell\in\{L_{j,t-1}\}} \log\left[s_{\ell,t-1}\right], \tag{55}$$

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 ($BadDeb_{k,t}$):

$$\Pi^b_{k,t} = r_{deb} Loans_{k,t} + r_{res} Res_{k,l} - r_D Depo_{k,t} - BadDeb_{k,t}, \tag{56}$$

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

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

$$Tax_t = \left(\Pi^1_t + \Pi^2_t + \Pi^b_t\right) tr, \tag{57}$$

where Π^1_t, Π^2_t and Π^b_t 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^u_t which is a fraction of the current average wage $\bar{w}_t$:

$$w^u_t = \psi \bar{w}_{t-1}, \tag{58}$$

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

$$G_t = \left(L^S - L^D_t\right) w^u_t. \tag{59}$$

$$Def_t = G_t - Tax_t, \tag{60}$$

The stock of public debt is updated as in:

$$Deb_t = Deb_{t-1} + Def_t - \Pi^{cb}_t + G^{bail}_t, \tag{61}$$

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

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

$$C^{d,bas}_t + C^{d,lux}_t = C^d_t = \sum_\ell In_{\ell,t} + C^d_{t-1} - C_{t-1}. \tag{62}$$

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

$$C_t = \min\left(C^d_t, Q^2_t\right), \quad Q^2_t = \sum_j Q_{j,t}. \tag{63}$$

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^1_t and Q^2_t, 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:

$$Q^1_t + Q^2_t = Y_t = C_t + I_t + \Delta N_t. \tag{64}$$

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

Appendix B - Parameters setting and stock and flow consistency

Symbol	Description	Value	Min.	Max.	μ^*	Direct	Interaction
Policy and credit market							
Φ^b	Bail-out reference as share of incumbent net wealth	0.500	0.200	1.000	0.033*	0.000	0.001
ϕ	Unemployment subsidy rate on average wage	0.400	0.100	0.900	0.066	0.000	0.001
tr	Tax rate	0.150	0.050	0.300	0.058*	0.010	0.001
r	Prime interest rate	0.010	0.005	0.030	0.041*	0.006	0.001
r_D	Interest rate on bank deposits	0.000	0.000	0.005	0.065*	0.000	0.001
μ_{deb}	Mark-up of interest on debt over prime rate	0.300	0.100	0.500	0.037**	0.014	0.001
μ_{res}	Mark-up of interest on reserve to prime rate	-0.500	-0.200	-0.800	0.042*	0.030	0.001
Λ	Prudential limit on debt (sales multiple)	2.000	1.000	3.000	0.055*	0.007	0.001
Λ_0	Prudential limit on debt (initial fixed floor)	1000.00	500.000	2000.00	0.042	0.004	0.001
Labour market							
ϵ	Minimum desired wage increase rate	0.020	0.005	0.100	0.039*	0.016	0.001
τ_T	Skills accumulation rate on tenure	0.010	0.002	0.050	0.043*	0.013	0.001
τ_U	Skills deterioration rate on unemployment	0.010	0.002	0.050	0.052*	0.003	0.001
T_r	Number of periods before retirement (work life)	120	80	160	0.045*	0.003	0.001
T_s	Number of wage memory periods	0	0	4	0.047*	0.002	0.001
ω	Number of firms to send applications (employed)	1	0	10	0.042*	0.003	0.001
ω_u	Number of firms to send applications (unempl.)	10	1	20	0.161*	0.048	0.001
ψ_2	Aggregate productivity pass-through	1.000	0.950	1.050	0.060*	0.005	0.000
ψ_4	Firm-level productivity pass-through	0.500	0.000	1.000	0.032**	0.015	0.000
ψ_6	Share of firm free cash flow paid as bonus	0.200	0.000	0.500	0.063	0.003	0.000
Technology							
η	Maximum machine-tools useful life	19	10	30	0.033*	0.004	0.000
ν	R&D investment propensity over sales	0.040	0.010	0.100	0.057*	0.010	0.000
ξ	Share of R&D expenditure in imitation	0.500	0.200	0.800	0.046	0.002	0.000
b	Payback period for machine replacement	8.000	3.000	12.00	0.042*	0.004	0.000
h	Effectiveness of opportunities exploitation	0.100	0.050	0.200	0.032*	0.005	0.000
m_1	Capital productivity in capital-good sector	1.000	0.200	5.000	0.086*	0.084	0.000
m_2	Capital productivity in consumer-good industries	100.0	20.00	500.0	0.041*	0.006	0.000
(α_1, β_1)	Beta distribution parameters (innovation process)	(3.000,3.000)	(1.000,1.000)	(5.000,5.000)	(0.044*,0.021*)	(0.016,0.021)	(0.000,0.000)
(α_2, β_2)	Beta distribution parameters (entrant productivity)	(2.000,4.000)	(1.000,1.000)	(5.000,5.000)	(0.096**,0.079**)	(0.001,0.038)	(0.000,0.001)
(α_3, β_3)	Beta distribution parameters (industry complexity)	(2.000,4.000)	(1.000,1,000)	(5.000,5.000)	(0.031*,0.037*)	(0.000,0.001)	(0.000,0.000)
$(\gamma_{bas}, \gamma_{lux})$	Technology intensity in industry (basic, luxury)	(0.250,1.000)	(0.000,0.500)	(0.500,2.000)	(0.060*,0.053)	(0.007,0.001)	(0.000,0.000)
(ζ_g, ζ_0)	Likelihood of emergence/access to new generation	(0.030,0.020)	(0.010,0.010)	(0.100,0.050)	(0.027*,0.050*)	(0.005,0.022)	(0.000,0.000)
(ζ_1, ζ_2)	Search capabilities for innovation/imitation	(0.100,0.100)	(0.050,0.050)	(0.200,0.200)	(0.026**,0.038*)	(0.005,0.000)	(0.000,0.000)
$[\underline{x}_1, \bar{x}_1]$	Beta distribution support (innovation process)	[-0.150,0.150]	[-0.300,0.100]	[-0.100,0.300]	(0.032*,0.063*)	(0.013,0.021)	(0.000,0.000)

(continue...)

Symbol	Description	Value	Min.	Max.	μ^*	Direct	Interaction
Industrial dynamics							
δ_1	Industry competitiveness weight for price	1.000	0.500	2.000	0.055*	0.028	0.000
δ_2	Industry competitiveness weight for quality	1.000	0.500	2.000	0.032*	0.002	0.000
δ_3	Industry competitiveness weight for newness	1.000	0.500	2.000	0.046*	0.014	0.000
δ_4	Industry competitiveness weight for complexity	1.000	0.500	2.000	0.048*	0.002	0.000
γ	Share of new customers for capital-good firm	0.500	0.200	0.800	0.047*	0.008	0.000
ι	Desired inventories share	0.100	0.000	0.300	0.064*	0.000	0.000
κ_{max}	Maximum threshold to capital expansion	0.500	0.100	1.000	0.115*	0.067	0.000
μ_1	Mark-up in capital-good sector	0.100	0.010	0.200	0.057*	0.003	0.000
ω_1	Firm competitiveness weight for price	1.000	0.500	2.000	0.032*	0.029	0.000
ω_2	Firm competitiveness weight for unfilled demand	1.000	0.500	2.000	0.080*	0.106	0.000
ω_3	Firm competitiveness weight for quality	1.000	0.500	2.000	0.044*	0.004	0.000
χ_2	Replicator dynamics coefficient (inter-firm)	1.000	0.200	5.000	0.111*	0.051	0.000
χ_c	Replicator dynamics coefficient (inter-industry)	0.250	0.100	1.000	0.058*	0.154	0.001
o	Weight of market conditions for entry decision	0.500	0.000	1.000	0.059**	0.001	0.000
υ	Mark-up adjustment coefficient	0.040	0.010	0.100	0.074**	0.012	0.000
f^2_{min}	Min share to firm stay in consumption-good industry	10^{-5}	10^{-6}	10^{-4}	0.064	0.004	0.000
f^c_{min}	Min wallet share to industry stay in sector	0.010	0.001	0.1	0.046*	0.044	0.000
n_c	Min periods to evaluate industry exit	10	5	20	0.069*	0.005	0.000
u	Planned utilization by consumption-good entrant	0.750	0.500	1.000	0.036*	0.001	0.000
x_5	Max technical advantage of capital-good entrant	0.300	0.000	0.600	0.102*	0.005	0.000
$(\zeta_{bas}, \zeta_{lux})$	Opportunities weight for new basic/luxury industry	(0.050,0.050)	(0.020,0.020)	(0.100,0.100)	(0.026*,0.029*)	(0.004,0.000)	(0.000,0.000)
$[\Phi_1, \Phi_2]$	Min/max capital ratio for consumer-good entrant	[0.100,0.900]	[0.000,0.500]	[0.500,1.000]	(0.064*,0.065*)	(0.002,0.001)	(0.000,0.000)
$[\Phi_3, \Phi_4]$	Min/max net wealth ratio for capital-good entrant	[0.100,0.900]	[0.000,0.500]	[0.500,1.000]	(0.037*,0.039)	(0.001,0.010)	(0.000,0.000)
$[\underline{x}_2, \bar{x}_2]$	Entry distribution support for entrant draw	[-0.150,0.150]	[-0.300,0.100]	[-0.100,0.300]	(0.034*,0.101*)	(0.011,0.040)	(0.000,0.000)
$[\underline{x}_3, \bar{x}_3]$	Entry distribution support for complexity draw	[0.000,0.050]	[-0.100,0.030]	[0.020,0.100]	(0.049*,0.046*)	(0.015,0.011)	(0.000,0.000)
$[F^1_{min}, F^1_{max}]$	Min/max number of capital-good firms	[1,100]	[1,20]	[20,50]	(0.128*,0.038*)	(0.039,0.001)	(0.000,0.000)
$[F^2_{min}, F^2_{max}]$	Min/max number of consumer-good firms in industry	[1,100]	[1,20]	[20,400]	(0.045*,0.022*)	(0.000,0.001)	(0.000,0.000)
$[F^{bas}_{min}, F^{bas}_{max}]$	Min/max number of consumer basic-good industries	[3,10]	[1,5]	[5,20]	(0.033*,0.041*)	(0.006,0.004)	(0.000,0.000)
$[F^{lux}_{min}, F^{lux}_{max}]$	Min/max number of consumer luxury-good industries	[1,10]	[0,3]	[3,10]	(0.051*,0.039*)	(0.000,0.001)	(0.000,0.000)
Consumption							
ϕ_{lux}	Percentile of income to spend in luxury goods	0.500	0.200	0.700	0.058*	0.013	0.000
C_{rec}	Unfilled past consumption recover limit	0.200	0.100	0.500	0.046**	0.001	0.000
T_{lux}	Time between acquisition of luxury goods	4	2	8	0.049**	0.005	0.000
T^{life}_{lux}	Lifetime of a luxury good	8	4	16	0.049*	0.016	0.000

(continue...)

SYMBOL	DESCRIPTION	VALUE	MIN.	MAX.	μ^*	DIRECT	INTERACTION
Initial conditions							
$(\mu_0^{bas}, \mu_0^{lux})$	Initial mark-up in basic/luxury-good industries	(0.300,0.500)	(0.200,0.300)	(0.500,0.800)	(0.041*,0.045*)	(0.005,0.003)	(0.000,0.000)
w_0^{min}	Initial minimum wage and social benefit floor	0.500	0.200	0.800	0.108*	0.001	0.000
L^S	Number of workers	2.5×10^5	1.3×10^5	5.0×10^5	0.025*	0.000	0.000
B	Number of banks	10	5	15	0.034*	0.003	0.000
(F_0^1, F_0^2)	Initial number of capital/consumption-good firms	(20,50)	(10,20)	(40,200)	(0.032**,0.023**)	(0.001,0.002)	(0.000,0.000)
(F_0^{bas}, F_0^{lux})	Initial number of basic/luxury-good industries	(5,1)	(1,0)	(10,5)	(0.050*,0.045*)	(0.008,0.000)	(0.001,0.001)
(NW_0^1, NW_0^2)	Multiple on initial net wealth for capital/consumption	(1.000,2.000)	(0.000,0.000)	(5.000,5.000)	(0.054*,0.059**)	(0.010,0.000)	(0.001,0.001)

Table 4: Model parameters and initial conditions, calibration values, minimum-maximum range for sensitivity analysis, elementary effects μ^* statistic and Sobol decomposition direct and interaction effect indexes.
μ^* statistic estimated using factors rescaled to $[0, 1]$. μ^* significance: *** 0.1% | ** 1% | * 5% | (no asterisk) not significant at 5% level ($n = 2820$ samples).
Sobol decomposition based on Kriging meta-model with 1st order polynomial trend and Matern 5/2 covariance kernel ($n = 2560$ samples).
Sensitivity analysis statistics relative to Gini index (the most sensitive variable) and Baseline values.

	Workers (households)	**Firms** *capital-good*	*consumption-good*	**Banks**	**Central bank**	**Government**	$\sum$
Fixed capital			$+K_t^{nom}$				$+K_t^{nom}$
Equities	$+Eq_t$	$-Eq_t^1$	$-Eq_t^2$				0
Deposits	$+Sav_t$	$+NW_t^1$	$+NW_t^2$	$-Depo_t$			0
Loans		$-Deb_t^1$	$-Deb_t^2$	$+Loans_t$			0
Monetary base				$+MB_t$	$-MB_t$		0
Reserves (required)				$+Res_t$	$-Res_t$		0
Excess reserves				$+ExRes_t$	$-ExRes_t$		0
Liquidity facilities				$-Loans_t^{cb}$	$+Loans_t^{cb}$		0
Government bonds				$+Bonds_t^b$	$+Bonds_t^{cb}$	$-Deb_t$	0
Government deposits					$-Depo_t^g$	$+Depo_t^g$	0
Balance	$-Bal_t$	$-Bal_t^1$	$-Bal_t^2$	$-Bal_t^b$	$-Bal_t^{cb}$	$-Bal_t^g$	$-K_t^{nom}$
$\sum$	0	0	0	0	0	0	0

Table 5: Stock-flow consistency: balance-sheet matrix.

	Workers	Capital-good firms		Consumption-good firms		Banks		Central bank	Government	$\sum$
	(households)	*current*	*capital*	*current*	*capital*	*current*	*capital*			
Transactions										
Consumption	$-C_t$			$+S_t^2$						0
Investment		$+S_t^1$			$-I_t^{nom}$					0
Government expenditure	$+G_t$								$-G_t$	0
Wages	$+W_t$	$-W_t^1$		$-W_t^2$						0
Taxes	$-Tax_t^w$	$-Tax_t^1$		$-Tax_t^2$		$-Tax_t^b$			$+Tax_t$	0
Profits, firms and banks		$-$ net Π_t^1	$+$ net Π_t^1	$-$ net Π_t^2	$+$ net Π_t^2	$-$ net Π_t^b	$+$ net Π_t^b			0
Op. result, central bank								$-\Pi_t^{cb}$	$+\Pi_t^{cb}$	0
Bonuses	$+Bon_{t-1}$				$-Bon_{t-1}^2$					0
Dividends	$+Div_{t-1}$		$-Div_{t-1}^1$		$-Div_{t-1}^2$		$-Div_{t-1}^b$			0
New equity	$-cEntry_{t-1}$		$+cEntry_{t-1}^1$		$+cEntry_{t-1}^2$					0
Liquidation equity	$+cExit_{t-1}$		$-cExit_{t-1}^1$		$-cExit_{t-1}^2$					0
Bad debt			$+BadDeb_{t-1}^1$		$+BadDeb_{t-1}^2$	$-BadDeb_{t-1}$				0
Bail-out							$+G_t^{bail}$	$-G_t^{bail} + G_{t-1}^{bail}$	$-G_{t-1}^{bail}$	0
Interest, deposits	$+r_{t-1}^D Sav_{t-1}$	$+r_{t-1}^D NW_{t-1}^1$		$+r_{t-1}^D NW_{t-1}^2$		$-r_{t-1}^D Depo_{t-1}$				0
Interest, loans		$-r_{t-1}^{deb} Deb_{t-1}^1$		$-r_{t-1}^{deb} Deb_{t-1}^2$		$+r_{t-1}^{deb} Loans_{t-1}$				0
Interest, reserves						$+r_{t-1}^{res} Res_{t-1}$		$-r_{t-1}^{res} Res_{t-1}$		0
Interest, liq. facilities						$-r_{t-1} Loans_{t-1}^{cb}$		$+r_{t-1} Loans_{t-1}^{cb}$		0
Interest, gov. bonds						$+r_{t-1}^{bonds} Bonds_{t-1}^b$		$+r_{t-1}^{bonds} Bonds_{t-1}^{cb}$	$-r_{t-1}^{bonds} Deb_{t-1}$	0
Interest, gov. deposits								$-r_{t-1}^{res} Depo_{t-1}^g$	$+r_{t-1}^{res} Depo_{t-1}^g$	0
Flow of funds										
Change, deposits	$-\Delta Sav_t$		$-\Delta NW_t^1$		$-\Delta NW_t^2$		$+\Delta Depo_t$			0
Change, loans			$+\Delta Deb_t^1$		$+\Delta Deb_t^2$		$-\Delta Loans_t$			0
Change, monetary base							$+\Delta MB_t$	$-\Delta MB_t$		0
Change, reserves							$-\Delta Res_t$	$+\Delta Res_t$		0
Change, excess reserves							$-\Delta ExRes_t$	$+\Delta ExRes_t$		0
Change, liq. facilities							$+\Delta Loans_t^{cb}$	$-\Delta Loans_t^{cb}$		0
Change, gov. bonds							$-\Delta Bonds_t^b$	$-\Delta Bonds_t^{cb}$	$+\Delta Deb_t$	0
Change, gov. deposits								$+\Delta Depo_t^g$	$-\Delta Depo_t^g$	0
$\sum$	0	0	0	0	0	0	0	0	0	0

Table 6: Stock-flow consistency: transaction-flow matrix.
$\Delta X_t = X_t - X_{t-1}$. net $\Pi_t^z = \Pi_t^z - Tax_t^z, z = 1, 2, b$.