Rational Heuristics? Expectations and Behaviors in Evolving Economies with Heterogeneous Interacting Agents

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ABSTRACT

We analyze the individual and macroeconomic impacts of heterogeneous expectations and action rules within an agent-based model populated by heterogeneous, interacting firms. Agents have to cope with a *complex evolving* economy characterized by deep uncertainty resulting from technical change, imperfect information and coordination hurdles. In these circumstances, we find that neither individual nor macroeconomic dynamics improve when agents replace myopic expectations with less naïve learning rules. In fact, more sophisticated, e.g. recursive least squares (RLS) expectations produce less accurate individual forecasts and also considerably worsen the performance of the economy. Finally, we experiment with agents that adjust simply to technological shocks, and we show that individual and aggregate performances dramatically degrade. Our results suggest that fast and frugal robust heuristics are *not* a second-best option: rather they are "rational" in macroeconomic environments with heterogeneous, interacting agents and changing "fundamentals".

KEY WORDS

Complexity, expectations, heterogeneity, heuristics, learning, agent-based model, computational economics.

JEL

C63, E32, E6, G01, G21, O4.

1 Introduction

In this work we study the individual and macroeconomic impacts of heterogeneous expectations and action rules on individual performance and macroeconomic dynamics by means of an agent-based model populated by heterogeneous, interacting firms. Therein, agents have to cope with an environment characterized by deep uncertainty resulting from technical change, imperfect information and coordination problems.

Expectations have long been central in macroeconomics, from the seminal distinction between risk and uncertainty suggested by Knight (1921), to the description of "animal spirits" playing an important role in generating multiple equilibria and coordination failures in Keynes (1936, 1937), all the way to the rational expectations hypothesis (Muth, 1961; Lucas and Prescott, 1971). Note, however, that before the "rational expectations (RE) revolution", the theory was quite agnostic about the nature of expectations themselves, their origin and their accuracy. And it was also quite agnostic about what agents actually do given their expectations. Only with the RE assumption has (part of) the profession taken expectations to be forward-looking, uniform among agents (take or leave some noise) and on average "true". And, correspondingly, the "action" has been assumed to be "right", that is the one maximizing some objective, conditional on the true expectation on the future. Of course the claims on expectation or action are supported neither by empirical evidence (see e.g. Carroll, 2003; Coibion and Gorodnichenko, 2012, 2015; Gennaioli *et al.*, 2016) nor by experimental studies (see e.g. Tversky and Kahneman, 1974; Schweitzer and Cachon, 2000; Kahneman, 2003; Anufriev and Hommes, 2012). Indeed, "rational" expectations are not viable, even in principle, in presence of Knightian uncertainty, when there are radical changes in policies (Stiglitz, 2011, 2016) and structural breaks in the underlying distributions on which agents form their forecasts (Hendry and Mizon, 2010).[1]

Tentative ways out have been to develop macroeconomic models with learning (e.g. Evans and Honkapohja, 2001) and a somewhat parsimonious use of *bounded rationality*.[2] However, both routes continue to acknowledge Olympic rationality either as something to be learned, or at the very least as the benchmark against which actual expectations ought to be assessed out of the "wilderness of bounded rationality" (Sims, 1980). The "behavioral" approach does introduce meaningful restrictions, but still invokes cognitive limitations, insufficient information, computing power and time assessed against the yardstick of of "full rationality". Observed behaviors would then result from a trade-off between accuracy and effort (a general discussion is in Kahneman, 2003).[3]

Here, we explore an alternative route grounded in the seminal contributions of Simon (1955), March and Simon (1993) and Cyert and March (1992), whereby, first, in complex evolving environments, expectations and behaviors cannot be neatly distinguished, and, second, behavioral patterns are adequately accounted for by *heuristics*, which under Knightian uncertainty and non-stationarity of the fundamentals of the economy, may well be *ecologically rational* (cf. Gigerenzer

[1]For an assessment of risk vs. some form of uncertainty in an econometric perspective, see also Rossi *et al.* (2016).

[2]Since the Great Recession, an increasing number of bounded-rationality DSGE models have appeared. See Dilaver *et al.* (2016) and Fagiolo and Roventini (2016) for surveys from different theoretical perspectives.

[3]Incidentally, notice that the accuracy-effort trade-off is also present in recent rational-expectations models with information frictions, see e.g. Mankiw and Reis (2002), Woodford (2003), and Sims (2003).

and Gaissmaier, 2011; see also Akerlof and Shiller, 2009). A heuristic is "a strategy that ignores part of the information, with the goal of making decisions more quickly, frugally and/or accurately than more complex methods"(Gigerenzer and Gaissmaier, 2011, p. 454).[4] And indeed heuristics match also the so-called "less-is-more" effect, which emerges as a response to the "bias-variance dilemma", well known in machine-learning and statistical inference (see e.g. Geman *et al.*, 1992; Alpaydin, 2004; Hastie *et al.*, 2001). Note that heuristics are not "biases" yielding suboptimal behaviors (as one would gather from Kahneman, 2003 and from a good deal of behavioral economics), but might well be robust "locally optimal" strategies that outperform purported "rational" choices in changing worlds characterized by substantive and procedural uncertainty (Dosi and Egidi, 1991).

In this work, we investigate the validity of such alternative views by studying individual and aggregate performances of different rules of expectation formation and behavior elicitation in an agent-based framework. Agent-based models (ABM) represent the economy as a complex, evolving system populated by heterogeneous, interacting agents (Tesfatsion and Judd, 2006; LeBaron and Tesfatsion, 2008; Farmer and Foley, 2009; Kirman, 2010; Dosi, 2012).[5] More specifically, we extend the Keynes + Schumpeter (K+S) model (Dosi *et al.*, 2010, 2013, 2015, 2016a,b) to account for heterogeneous expectation rules and adaptive learning. The K+S model is a bridge between Keynesian theories of demand generation and Schumpeterian theories of innovation and economic growth, with "Minskian" financial dynamics (Greenwald and Stiglitz, 1993). In that, it represents an economy characterized by endogenous and persistent novelty, imperfect information, where Knightian uncertainty is pervasive and coordination failures are the norm. As imperfect information is ubiquitous, the economy is never in a Pareto equilibrium (Greenwald and Stiglitz, 1986) and agents' behaviors are conditioned by future constraints (Neary and Stiglitz, 1983). The microeconomic foundations of the model are genuinely "behavioral" (Akerlof, 2002): heterogeneous firms and banks behave in tune with what we know from micro-empirical evidence, and they interact without resorting to any ex-ante commitment to the reciprocal consistency of their actions, thus implicitly addressing the call by Solow (2008) for genuine micro-heterogeneity.

Naturally, the very nature of the K+S model rules out the existence of a rational-expectation equilibrium on which fictitious representative agents can coordinate (Kirman, 1992, 2014). Still, we can compare the impact of heterogeneous, more or less "sophisticated", expectations and learning rules on agents' performance, as well as on macroeconomic dynamics. In that, we also address the tension between interpretations based on "biases" and effort/accuracy trade-offs (in tune with behavioral economics) vis-à-vis the hypothesis of ecological rationality of simple heuristics (Gigerenzer and Todd, 1999; Gigerenzer and Selten, 2002). In addition, we evaluate the robustness of our results to alternative heuristic-based rules.

We begin by introducing in the K+S model five expectation rules (based on the experimental findings of Anufriev and Hommes, 2012),[6] allowing firms to switch among them according to their

[4] Among a vast literature, see also Gigerenzer and Todd (1999); Gigerenzer and Brighton (2009); Gigerenzer and Selten (2002); Bröder (2003).

[5] The literature on agent-based macroeconomics has been blossoming in the last years, see e.g. Fagiolo and Roventini (2012, 2016) for recent surveys. See also Sinitskaya and Tesfatsion (2015); Salle (2015) for two recent works investigating non-RE rules in agent-based frameworks.

[6] See also Hommes, 2011; Assenza *et al.*, 2014b; Colasante *et al.*, 2015.

past forecasting performance (Brock and Hommes, 1997). In such a framework, expectations are thus heterogeneous and evolve over time (in line with the empirical evidence in Coibion *et al.*, 2015). We then allow agents to learn by employing more "sophisticated" expectations grounded on recursive least squares (RLS, see e.g. Evans and Honkapohja, 2001), and compare the individual and system-level performances.

Simulation results show that in line with the K+S tradition, the model can account for endogenous growth and business cycles, where mild fluctuations are punctuated by deep downturns (Fagiolo *et al.*, 2008; Stiglitz, 2011, 2016; Ascari *et al.*, 2015), as well as for a wide ensemble of macro and micro empirical regularities (Dosi *et al.*, 2016a). Moreover, we find that compared to simple (benchmark) myopic expectations, somewhat more complex alternatives increase the forecast errors of the agents and do *not* substantially improve the performance of the system (see also Dosi *et al.*, 2006). Altogether, our results suggest that expectations have a limited impact on the dynamics of economies, which are mainly driven by the income constraints affecting agents' choices.

However, both individual and aggregate performance considerably deteriorate when firms abandon "fast and frugal" heuristics and start estimating their future demand via recursive least squares. This is explained by the fact that the forecasting performance of RLS-learning agents — as revealed by their mean squared forecast errors — turns out to be extremely puny in a non-linear environment with Knightian uncertainty. In turn, the errors of RLS agents are amplified by the positive feedbacks introduced by income constraints in the model. This sinks both the short- and long-run performances of the economy, increasing the volatility of business cycles, the unemployment rate, while reducing the growth potential of the economic system. Moreover, and not surprisingly, we find that whenever agents are allowed to choose between RLS-learning and simple invariant rules, they "rationally" adopt the latter.

Our results bring support to the *ecological rationality* of heuristics: in complex, evolving economies characterized by pervasive uncertainty and perpetual structural change, heuristics are not a second-best option, but they provide a more accurate and robust tool for inference and action than more sophisticated forecasting techniques. In turn, macroeconomic models with heterogeneous, interacting agents ought to feature *robust heuristic-driven expectations and behaviors*, because both this is actually observed and they are the most accurate forecasting tool that agents can count on. Notice that the Keynesian nature of heuristics have nothing to do with the purported "frictions" or "rigidities" in the economy. Rather, they are an essential feature of decentralized economies painstakingly coordinating at varying levels of activity. If agents neglect them, they do it at their own peril: we show indeed that both individual and collective performances degrade.

The rest of the paper is organized as follows. In Section 2, we discuss the impact of expectations and agents' interactions on macroeconomic dynamics. In Section 3, we describe the K+S model. We then empirically validate it in Section 4. The impact of heterogeneous expectation rules is studied in Section 5, while learning is introduced in Section 6 and is further investigated in Section 7. In Section 8 we experiment with agents who are like good mainstream economists, i.e. supply-siders responding just to technology shocks. Section 9 discusses in general the properties of heuristic-driven decisions. Finally, our concluding remarks are in Section

10.

2 Expectations, interactions and macroeconomic dynamics: the general problem

In the most general terms, the dynamics of any economy can be seen as an enormously high-dimensional system of difference equations. They describe the "laws of motion" of the system itself and of its multiple constituent agents, driven by the behavioral (and, relatedly, expectational) adjustments of the agents themselves, their interactions, and some (endogenous or exogenous) shocks. In such a "meta-model", agents' individual outcomes depend on i) their expectations based on both their individual and the aggregate histories, ii) their individual histories, iii) the aggregate history, and iv) the individual and aggregate shocks:

$$\begin{aligned}\mathbf{x}(t) = \quad & F\Big(\underbrace{\mathbf{f}\Big[(\mathbf{x}(t-1),\ldots,\mathbf{x}(t-\tau);X(t-1),\ldots,X(t-\tau)\Big]}_{\text{Individual expectations}}; \\ & \underbrace{\mathbf{x}(t-1),\ldots,\mathbf{x}(t-\tau)}_{\text{Individual histories}};\underbrace{X(t-1),\ldots,X(t-\tau)}_{\text{Aggregate history}};\underbrace{\epsilon(t),\varepsilon(t);}_{\text{Shocks}}\Big),\end{aligned} \tag{1}$$

where $\mathbf{x}(t) = [x_1(t),\ldots,x_n(t)]^\intercal$ is a matrix comprising the state variables for all heterogenous $i = 1,\ldots,n$ agents populating the economy (e.g. capital stocks, net worths, sales, prices, etc.), $X(t)$ is the vector of macroeconomic state variables (e.g. GDP, investment, unemployment rate, etc.); $\mathbf{f}(t) = [f_1(t),\ldots,f_n(t)]^\intercal$ is a vector of individual expectation functions which map the individual and system-level histories into forecasts and actions by the agents (i.e. the determination of their "control" variables); and finally $\epsilon(t) = [\epsilon_1(t),\ldots,\epsilon_n(t)]^\intercal$ is the vector of idiosyncratic shocks hitting agents (e.g. their productivity), while $\varepsilon(t)$ are system-wide shocks (affecting e.g. the technological frontier of the economy).

In turn, macroeconomic outcomes (e.g. GDP, total investment...) are either obtained from the aggregation over microeconomic variables or are system-level variables (e.g. inflation, interest rate) determined from microeconomic elements or from other macroeconomic indicators. Note that agents' interactions impact both their state variables as well as the emerging macroeconomic outcomes. And there is also a feedback loop from the macroeconomic aggregates (e.g. demand dynamics, inflation) to agents' forecasts and decisions. In such a framework, agents ought to form their expectations based on the observation of the past, i.e. they are extrapolative, adaptive agents.

Clearly, put that way, there is hardly any way to identify equilibria or dynamical paths of such a system, whose complexity stems from the sheer interdependence among a multitude of heterogenous agents (firms, households, workers, banks). Even neglecting the possibility of changing fundamentals of the economy (due to e.g. technological change), interactions generically entail endemic externalities and non-linearities. And with that come unimmaginably high informational demands on the decision-makers.

Facing all this, the prevailing response of macroeconomic theory, as well known, has been to eliminate complexity at its roots by eradicating interaction altogether and assuming a representative agent of some kind. The radical fallacies of such a reduction have been conclusively argued in Kirman (1992, 2014) at the level of theory, and by Forni and Lippi (1997, 1999) at the level of econometric aggregation.

However, let us leave also all this aside. Now, assuming a representative-agent economy, one does not have to cope with the problem of aggregation, macroeconomics shrinks to microeconomics and we have a much lower dimensional system of the form:

$$X(t) = F\Big(f\Big[X(t-1), \ldots, X(t-\tau)\Big]; X(t-1), \ldots, X(t-\tau); \varepsilon(t)\Big). \tag{2}$$

where the aggregate state variables only depend on the aggregate expectation, the aggregate history and the aggregate shocks. This representation still remains too broad in order to get any full (equilibrium) "antropomorphisation" of the observed dynamics. One at the very least requires the linearization of the $F(\ldots)$ function and, further, the assumption that the "law of motion" of the system is not influenced by (possibly out-of-equilibrium) expectations of the representative agent – who is now, basically, the Central Planner of the economy. This is akin to the basic sketch of e.g. Evans and Honkapohja (1999), where the reduced-form model is a vector of endogenous variables (X), depending on their lagged values, on expectations of next period's values, $f[X]$, and on a vector of exogenous shocks ε

One of the bottom lines of a good deal of the last seventy years of macroeconomics concerns precisely the determination of expectations. We know the story. Even accepting the interpretative legitimacy of the reduction of eq. 1 to eq. 2, the so-called "rational expectation (RE) revolution" further suggests that actual expectations correspond to the "true" statistical conditional expectations. In a nutshell, the forward-looking representative agent — as the macroeconomic theorists — know the "true" model of the economy, $f\Big[X(t-1), \ldots, X(t-\tau)\Big] = E\Big[X(t+1)\Big]$ and the system further simplifies to:

$$X(t) = F\Big(E\Big[X(t+1)\Big]; X(t-1), \ldots, X(t-\tau); \varepsilon(t)\Big). \tag{3}$$

However, even in this reductionist framework, there can be multiple stationary RE equilibria: self-fulfilling expectations can affect the optimal choice of the representative agent and sunspots can arise (among a vast literature, see the seminal contribution of Woodford, 1990 and the survey in Benhabib and Farmer, 1999).

Given such a multiplicity of RE equilibria, the natural natural question is then "where do these expectations come from"? Short of some divine revelation they ought to be plausibly learned. But the literature on learning RE is a very mixed bag, basically ridden of some superficially corroborating models, among which stand out "wrong" learning models, such as OLS, that however may lead to the selection of supposedly "right" outcomes – i.e. some RE equilibria.[7]

At best the results are fragile, even neglecting their econometric inconsistency vis-à-vis any structural break affecting the stochastic process governing the dynamics of the economy. Indeed, as shown by Hendry and Mizon (2010), in such a framework the conditional expectations used by the agents in RE models are neither unbiased nor minimum mean squared error predictors.

[7]Within a wide literature, see Bray (1982), Bray and Kreps (1987), Marcet and Sargent (1988), and the discussions in Evans and Honkapohja (1999, 2001).

In a nutshell, "it is not rational to have rational expectations" (Kirman, 2016, p. 8).

And equally important, the basic theoretical thrust of all, the foregoing stream of theoretical analyses goes against (the little) we know about actual expectation formation by actual economic agents. For instance, using the survey of professional forecasters, Coibion and Gorodnichenko (2012, 2015) reject the RE hypothesis. Similarly, employing survey data on the investment plans of the chief financial officers of large U.S. corporations, Gennaioli *et al.* (2016) find evidence against the RE benchmark, while supporting extrapolative expectations. Finally, the recent evidence stemming from learning-to forecast laboratory experiments show robust and persistent deviations from rational expectations (see e.g. Anufriev and Hommes, 2012; Assenza *et al.*, 2014a).

In the following, we mean to explore a radically alternative route. On the side of the system dynamics, we intend to maintain the complexity of the evolving systems as sketched in the "meta-model" of eq. (1). At the same time, we intend to explore the conjecture that the (sometimes) orderly system-level properties are not the outcome of utterly sophisticated individual forward-looking behaviors, but rather an emergent collective property of relatively simple, inertial behaviors whereby agents learn how to repeatedly swim in an Heraclitus' river in which one is literally unable to ever step in twice.[8]

3 The expectation-enhanced K+S model

This work extends the Keynes+Schumpeter (K+S) family of models (Dosi *et al.*, 2010, 2013, 2015, 2016a,b) by introducing different expectation formation rules. The barebone structure of the model is portrayed in Figure 1.

The economy is composed of F_1 capital-good firms (labelled with index i), F_2 consumption-good firms (denoted by the index j), L^S consumers/workers, B commercial banks (denoted by the index k), a Central Bank and the Government sector. Capital-good firms invest in R&D to increase the productivity of their heterogeneous machine-tools (with product innovation/imitation) and their own production techniques (with process innovation/imitation). Consumption-good firms combine machines bought from capital-good firms and labor in order to produce a homogeneous product for consumers. The banks provide credit to consumption-good firms and buy Government bonds. The public sector levies taxes on firms' and banks' profits, it pays unemployment benefits and bails banks out in case of banking crises. The Government can run deficits by issuing bonds, which are bought by the banking sector. Finally, the Central Bank fixes the baseline interest rate in the economy and the macroprudential regulatory framework.

Let us now sketch the main characteristics and dynamics of the expectation-enhanced K+S model. A detailed description of the model is provided in Appendix B and in Dosi *et al.* (2015, 2016a).

[8] Our work has some (superficial) point of contact with an increasing stream of research which introduce information frictions in rational expectation models. For instance, Mankiw and Reis (2002) assume that information are sticky and agents update them infrequently, while Sims (2003) and Woodford (2003) build noisy-information models, where agents continuously update their beliefs facing a signal extraction problems. However, differently from us, such works assume a fully rational agent and do not account for the "deep" Knigthian uncertainty and possible coordination failures occurring in presence of multiple heterogenous interacting agents.

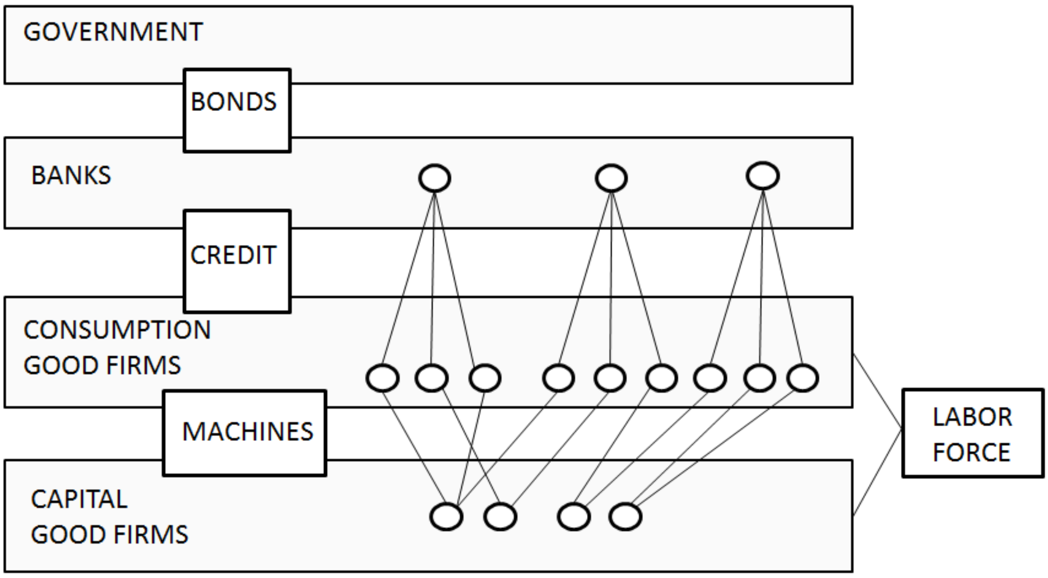

Figure 1: **The structure of the Keynes+Schumpeter model**.

3.1 The timeline of events

In any given time period (t), the following microeconomic decisions take place in sequential order:

1. Policy variables (e.g. capital requirement, tax rate, Central Bank interest rate, etc.) are fixed.

2. Banks determine the potential supply of credit.

3. Capital-good firms perform R&D, trying to discover new products and more efficient production techniques and to imitate their competitors.

4. Consumption-good firms decide how much to produce and invest according to different expectation rules. They apply for bank credit (and may be rationed) if their internal funds are not enough.

5. The capital-good market opens. Given the presence of imperfect information, capital-good firms signal their products to an evolving subset of consumption-good firms, which in turn choose their supplier.

6. Firms in both industries hire workers according to their production plans and start producing.

7. The imperfectly competitive consumption-good market opens. Pervasive imperfect information implies that the market shares of firms evolve according to their price competitiveness.

8. The firms in both sectors compute their profits and pay back their bank loans.

9. Entry and exit take place. In both sectors, firms with near zero market shares or negative net liquid assets are eschewed from the two industries and replaced by new ones.

10. Banks compute their profits and net worth. If the latter is negative they fail and are bailed out by the Government.

11. The Government computes its surplus or deficit, the latter being financed by sovereign debt.

12. Machines ordered at the beginning of the period are delivered and become part of the capital stock at time $t+1$.

At the end of each time step, aggregate variables (e.g. GDP, investment, employment) are computed, summing over the corresponding microeconomic variables. As its direct ancestor (Dosi *et al.*, 2015), the model is stock-flow consistent.

3.2 The capital- and consumption-good sectors

In both capital- and consumption good markets, information are imperfect and firms' price are heterogeneous. As a consequence, the economy is *never* in a constrained Pareto state (Greenwald and Stiglitz, 1986) and the current behavior of firms is conditioned by various constraints (Neary and Stiglitz, 1983).

The *capital-good industry* is the locus of endogenous machine-embodied innovation. The current technology mastered by a capital-good firm is defined by A_i, the labour productivity of the machine it sells to the downstream sector, and by B_i, the efficiency of its production technique. Capital-good firms develop new technologies or imitate the ones of their competitors in order to produce and sell more productive and cheaper machines that are in turn supplied to consumption-good firms. Capital-good firms invest a fraction of their past sales in R&D in order to discover new machines (IN_i) or copy existing ones. The innovation process has two steps: first a random draw from a Bernoulli distribution with parameter $\theta_i^{in}(t) = 1 - e^{-\zeta_1 IN_i(t)}$ determines whether firm i innovates or not. Therefore the frequency of innovations (whether successful or not) depends on $\zeta_1 \leqslant 1$, the firms' *search capabilities*, and the specific amount of R&D they have invested. If an innovation occurs, the firm obtains a new technology, whose labor productivity levels are given by $A_i^{in}(t) = A_i(t)(1 + x_i^A(t))$ and $B_i^{in}(t) = B_i(t)(1 + x_i^B(t))$, where x_i^A and x_i^B are two independent draws from a Beta(α_1, β_1) distribution.[9] Therefore α_1 and β_1 define the extent of *technological opportunities* available to firms, i.e. the magnitude of the innovation leaps. Capital-good firms produce employing only labor and set prices with a fixed mark-up over unit costs of production.

In the *consumption-good industry,* firms produce a homogeneous consumption good employing capital (composed of different vintages of machines) and labor under constant returns to scale. Desired production is fixed according to different adaptive demand expectations (D_j^e):

$$D_j^e(t) = f(D_j(t-1), D_j(t-2), D_j^e(t-1), Y(t-1)), \tag{4}$$

[9] The draws $x_i^A(t)$ and $x_i^B(t)$ may well be negative (i.e. the innovation fails) in that case the firm continues to offer the "old" machine.

where D_j is firm's demand and Y is the gross domestic product. The detailed characterization of firms' expectation formation and dynamics is discussed below (section 3.3).

Desired production (Q^d_j) is then defined based on expected demand and desired inventories (N^e_j):

$$Q^d_j(t) = D^e_j(t) + N^e_j(t), \tag{5}$$

with $N^e_j(t) = N^d_j(t) - N_j(t-1)$ and $N^d_j(t) = \iota D^e_j(t)$, $\iota \in [0;1]$. Given the actual stock of inventories, if the capital stock constrains the production plans of the firm, it invests in new machines in order to expand its production capacity. Thus firms' investment choices are affected by their demand expectations (see on recent evidence Gennaioli *et al.*, 2016).[10] Moreover, firms also invest to acquire state-of-the-art technologies: they replace old and obsolete machines with new ones according to a payback period rule (Dosi *et al.*, 2010).

The capital-good market is characterized by imperfect information and "Schumpeterian" competition (Nelson and Winter, 1982). Upstream firms signal the price and productivity of their machines to their current customers as well as to a set of potential new ones. Consumption-good firms choose their supplier comparing the price and the production costs entailed by the subset of machines they are aware of.

As we mentioned above, demand expectations play a key role in determining the desired production and investment plans of the firms. At the same time, their actual levels may differ from the desired ones, as firms can face constraints in the availability of external financing. More precisely, in the model, consumption-good firms have to advance worker wages as well as pay the machines they ordered. Thus they may need external financing. As we assume that capital markets are imperfect (e.g. Stiglitz and Weiss, 1981; Greenwald and Stiglitz, 1993; Hubbard, 1998), internal and external sources of finance are imperfect substitutes. To fund their production and investment plans, firms first use their stock of liquid assets, and then they ask credit to banks. Firms pay an interest rate on their loans, which depends on the Central Bank interest rate (r), as well as on their credit rating. However, if banks are unwilling to provide loans, firms can end up being credit constrained. In that case, they first cut their investment and then downscale their production plans. Imperfect capital markets and the possibility of credit rationing represent a first important source of *income constraints* in our model, which contributes to make it different from models where allocative considerations drive the dynamics.

Imperfect information is pervasive also in the consumption-good market (see Rotemberg, 2008, for a survey on consumers' imperfect price knowledge). As a consequence, consumers cannot instantaneously switch to the most competitive producer even if the good is homogeneous. Consumption-good firms fix their prices applying a *variable* idiosyncratic mark-up on their production costs. Such costs are given by the ratio between the nominal wage (w) and the average labor productivity resulting from the machines employed in the production process. Mark-up dynamics are driven by the evolution of firms' market shares (in line with "customer market"

[10] It is important to emphasize that individual agents form expectations on the state variables which are going to affect their performance (e.g. their demand), and building on such expectations, they determine their control variables, e.g. planned production and investments, in a genuine "Keynesian" perspective. Conversely, they do *not* care about system-level variables which might have the outmost importance for the modeler, but exert only a very indirect influence on individual agents (e.g. economy-wide levels of productivity). The two types of forecasts, unfortunately, get confounded when one assumes the representative agent, who is also the Central Planner, who is also the modeler...

models originally described by Phelps and Winter, 1970): firms increase their margins whenever their market share is expanding. In turn, market shares evolve according to a "quasi replicator" dynamics: more competitive firms expand while firms with a relatively lower competitiveness level shrink (see Eqs. 29-31, Appendix B).[11]

At the end of every period, capital- and consumption-good firms compute their profits, pay taxes, and update their stock of liquid assets. If the latter is positive, they increase their bank deposits (consumption-good firms repay their debt first). If a firm's stock of liquid assets is negative or if its market share shrinks to zero, then the firm goes bankrupt and exits the market. As we assume that the number of firms is fixed over time, each dead firm is replaced by a new entrant.[12]

3.3 An ecology of expectation heuristics

In presence of imperfect information (Greenwald and Stiglitz, 1986) and deeply uncertain environments (Knight, 1921; Keynes, 1937), we assume that agents follow behavioral rules, or *heuristics* to form their demand expectations. More specifically, in line with the experimental evidence provided by Anufriev and Hommes (2012), firms can choose among the following repertoire of different rules.[13]

First, firms may follow naïve demand expectations (NA), according to which the past is the best proxy for the future:

$$D^e_{na,j}(t) = D_j(t-1). \tag{6}$$

This is the common expectation assumption in the K+S model (Dosi *et al.*, 2010, 2013, 2015) and it represents our benchmark case.

Second, under adaptive expectations (ADA), firms correct for their past demand forecast mistakes:

$$D^e_{ada,j}(t) = D^e_j(t-1) + \omega_{ada}(D_j(t-1) - D^e_j(t-1)), \tag{7}$$

with $\omega_{ada} = 0.65$.

Third, in the weak (WTR) and strong (STR) trend expectation rules, firms behave like "chartist" traders (see Lux and Marchesi, 2000; Anufriev and Hommes, 2012), trying to ride demand patterns:

$$D^e_{wtr,j}(t) = D_j(t-1) + \omega_{wtr}(D_j(t-1) - D_j(t-2)); \tag{8}$$

$$D^e_{str,j}(t) = D_j(t-1) + \omega_{str}(D_j(t-1) - D_j(t-2)). \tag{9}$$

The only difference between the WTR and STR expectation rules is the value of the parameter weighing past demand changes, i.e. $\omega_{wtr} = 0.4$ and $\omega_{str} = 1.3$.

Finally, firms may react to both their past demand dynamics and to some aggregate "anchor", the GDP. The "anchor and adjustment" expectation rule (AA, see Tversky and Kahneman, 1974)

[11] The competitiveness of firms depends on price as well as on unfilled demand.

[12] Furthermore, in line with the empirical literature on firm entry (Caves, 1998), we assume that entrants are on average smaller than incumbents, with the stock of capital of new consumption-good firms and the stock of liquid assets of entrants in both sectors being a fraction of the average stocks of the incumbents.

[13] See also Dosi *et al.*, 2006; Hommes, 2011; Assenza *et al.*, 2014b; Colasante *et al.*, 2015. Coibion *et al.* (2015) find empirical evidence supporting heterogeneity of beliefs among firms.

is thus:

$$D^e_{aa,j}(t) = [1 + w_{aa}\Delta GDP(t-1) + (1-\omega_{aa})\Delta D_j(t-1)]\, D_j(t-1), \qquad (10)$$

with $\omega_{aa} = 0.5$. The value of the parameters of the expectation rules are calibrated according to the evidence provided by Hommes (2011) and Anufriev and Hommes (2012).

Expectations are heterogeneous and evolve over time (Brock and Hommes, 1997; Hommes, 2011; Anufriev and Hommes, 2012) and are selected by agents on the basis of their predictive performance. Starting from a uniform distribution of the five expectation rules described above, firms switch across heuristics according to their past performance.[14] Notice that firms have indeed strong incentives to forecast future demand correctly so as to avoid costly accumulation of inventories (as in Schweitzer and Cachon, 2000) or conversely to avoid missing sales and profit opportunities.[15]

Following Brock and Hommes (1997), Hommes (2011), and Anufriev and Hommes (2012), and in line with the experimental evidence in Schweitzer and Cachon (2000), firms update the performance (U) of each heuristic $h \in \{na, ada, wtr, str, aa\}$ according to the last demand forecast error:

$$U_{h,j}(t) = -\left(\frac{D_j(t-1) - D^e_{h,j}(t-1)}{D^e_{h,j}(t-1)}\right)^2 + \eta U_{h,j}(t-1), \qquad (11)$$

where $0 \leq \eta \leq 1$ is a memory parameter measuring the relative weight attributed by agents to past errors. Firms adopt a given expectation rule with a probability $n_{h,j}(t)$, which is updated in each period as follows:

$$n_{h,j}(t) = \delta n_{h,j}(t-1) + (1-\delta)\frac{\exp(\beta U_{h,j}(t))}{Z_j(t)}, \qquad (12)$$

with $0 \leq \beta, \delta \leq 1$, and $Z_j(t) = \sum_{h=1}^{H} \exp(\beta U_{h,j}(t))$ being a normalization factor. The parameter δ captures the persistence or inertia of expectation-formation rules, while the parameter β measures the intensity of choice, i.e. how fast firms switch to more successful expectation rules.[16]

In the simulation exercises performed in Section 6, we will also experiment with enhanced degrees of "rationality" and introduce *learning.* More specifically, firms will behave as econometricians, estimating the parameters of the expectation rules via recursive least squares (RLS, Evans and Honkapohja, 2001).

3.4 The banking sector

In the model, money is endogenous as its supply depends on the lending activity of banks (among a vast body of literature, see e.g. Godley and Lavoie, 2007; McLeay *et al.*, 2014). Commercial banks gather deposits and provide credit to firms. The number of banks is fixed.[17]

[14] Entrant firms copy the expectation rule of an incumbent and their probability to adopt any one of them is proportional to its diffusion in the system. Simulation results presented in Section 5 are robust to the assumption that the entrants start with a uniform distribution of expectation rules.

[15] The effects of the two types of forecasting errors are indeed roughly symmetric.

[16] The values of the β and δ parameters are calibrated according to the values provided by Anufriev and Hommes (2012).

[17] For simplicity, we assume that the network linking firms and banks is also fixed over time and the bank-firm relationship holds both for deposits and credit. Following the empirical evidence on the skewness of the bank size

Banks' supply of credit is a function of their equity and is constrained by capital adequacy requirements inspired by Basel-framework rules (see e.g. Delli Gatti *et al.*, 2010; Ashraf *et al.*, 2017; Raberto *et al.*, 2012; Popoyan *et al.*, 2017). Moreover, banks maintain a buffer over the mandatory level of capital, whose magnitude is intentionally altered over the business cycle according to their financial fragility (Bikker and Metzemakers, 2005; Becker and Ivashina, 2014), proxied by the ratio between accumulated bad debt (i.e. loans in default) and bank assets (Adrian and Shin, 2010). Credit supply is thus influenced by changes in a bank's balance sheet, which itself is affected by bank profits net of loan losses. This creates a positive feedback loop from loan losses to changes in banks' equity, with a consequent reduction in the amount of credit supplied to firms in the next period.

Credit demand stems from consumption-good firms' financing needs for investment and production, net of their internal funds (see Section 3.2 above). Banks allocate credit among their clients by ranking the applicants in terms of their creditworthiness, defined by the ratio between past net worth and sales. Banks provide credit up to their credit supply ceiling. Credit rationing (Stiglitz and Weiss, 1981) is an emergent property of the model: firms' ability to obtain credit depends on their financial status, but also on the financial fragility of their bank (see also Greenwald and Stiglitz, 1993; Stiglitz and Greenwald, 2003).

Banks fix the interest rate on loans applying a mark-up on the Central Bank interest rate (r), which is set in each period according to a Taylor rule (Howitt, 1992; Taylor, 1993):

$$r(t) = r^T + \gamma_\pi(\pi(t) - \pi^T), \tag{13}$$

where $\gamma_\pi > 1$, π^T and r^T are the target inflation and interest rates, and $\pi(t)$ is the inflation rate of the period. Banks' loan rates are changing over time, but they are also heterogeneous across borrowers, as they incorporate a spread linked to firms' idiosyncratic credit risk.

Banks experience loan losses whenever one of their clients goes bankrupt and exits the market. Loan losses represent an (endogenous) negative shock to bank profits, which may become negative. If the net worth of the bank is not sufficient to cover such losses, the bank goes bankrupt. Whenever a bank fails, the Government steps in and bails it out providing fresh capital.

3.5 The labor market, consumption and the government sector

The labor market does not feature any imposed clearing condition. The labor supply L^S is fixed and inelastic to the wage rate (w), which is determined by institutional and market factors.[18] As a consequence, both involuntary unemployment and labor rationing may emerge. Wage dynamics depend on the gap between actual and targeted inflation, and on the dynamics of average productivity and of the unemployment rate:

$$\frac{\Delta w(t)}{w(t-1)} = \pi^T + \psi_1(\pi(t-1) - \pi^T) + \psi_2 \frac{\Delta \overline{AB}(t)}{\overline{AB}(t-1)} - \psi_3 \frac{\Delta U(t)}{U(t-1)}, \tag{14}$$

distribution (Berger *et al.*, 1995; Ennis, 2001), banks are assumed heterogeneous in their number of clients, which are drawn from a Pareto distribution.

[18] A detailed microfoundation of the labor market in the K+S models is provided in Dosi *et al.* (2016d,c).

where $\overline{AB}$ is the average labor productivity, U the unemployment rate, and $\psi_{1,2,3} > 0$.

Unemployed workers receive a subsidy (w^u) which is a fraction of the current wage, i.e. $w^u(t) = \varphi w(t)$, with $\varphi \in [0, 1]$. Given the total labor demand L^D, the total amount of unemployment subsidies to be paid by the Government (G) is:

$$G(t) = \max\{w^u(t)(L^S - L^D(t)), 0\}. \tag{15}$$

We assume that workers fully consume their income (which is equivalent to assuming that workers are credit constrained and therefore cannot engage in standard consumption smoothing),[19] while capitalists do not, but only save and invest. Accordingly, aggregate consumption (C) depends on the income of both employed and unemployed workers:

$$C(t) = w(t)L^D(t) + G(t). \tag{16}$$

The tight relation between the dynamics of consumption and income is the second main source of *income constraints* in our model (the other one being the effect of credit constraints of firms' investments, see Section 3.2). Notice that also in this respect our model is very different from other macro-models (e.g. DSGE ones), where consumption is instead determined by an inter-temporal allocative decision driven by the difference between the interest and inter-temporal discount rates.

Taxes on profits paid by firms and banks are gathered by the Government at the fixed tax rate tr. Public expenditures are composed of the cost of public debt ($Debt^{cost}$), of bank bailouts ($Gbailout$) and the unemployment subsidies (G). Public deficit (or surplus) is then equal to:

$$Def(t) = Debt^{cost}(t) + Gbailout(t) + G(t) - Tax(t). \tag{17}$$

In case of public deficit, the Government has to issue new bonds, which are bought by banks according to their share in the total supply of credit.[20] If the demand for bonds from the Government is higher than what banks are able to buy, the Central Bank steps in and buys the remaining debt.[21] If $Def(t) < 0$, the Government uses the surplus to repay its debt.

To repeat, the explicit microfoundation of the dynamics for all aggregate variables of interest (e.g. output, investment, employment, etc.) is nested in the decisions of a multiplicity of heterogeneous, adaptive agents and in their interaction mechanisms (see the meta-model representation of eq. 1). The model satisfies the standard national account identities: the sum of value added of capital- and consumption goods firms (GDP) equals their aggregate production. Total production in turn coincides with the sum of aggregate consumption, investment

[19]The above assumption is also in line with the microeconomic empirical evidence suggesting that the consumption of most households tracks their income as their wealth is close to zero (see e.g. Wolff, 1998). Notice that the conclusions of the paper qualitatively hold as long as, in good Keynesian fashions (see e.g. Kaldor, 1955), the propensity to consume out of profits is lower than that out of wages.

[20]Sovereign bonds are endogenously supplied by the Government according to its deficit, while banks' demand for bonds is accommodating supply, in the spirit of e.g. Krishnamurthy and Vissing-Jorgensen (2012). Banks buy Government bonds employing only their net profits.

[21]As the model has been designed to account for both small fluctuations and large crises, we think that it is reasonable and in line with the current practices (see e.g. Bernanke, 2011) to let the Central Bank buy sovereign bonds, especially when banking crises force the Government to bailout banks, considerably increasing the public debt.

Stylized facts		Empirical studies (among others)
Macroeconomic stylized facts		
SF1	Endogenous self-sustained growth with persistent fluctuations	Burns and Mitchell (1946); Kuznets and Murphy (1966); Zarnowitz (1985); Stock and Watson (1999)
SF2	Fat-tailed GDP growth-rate distribution	Fagiolo *et al.* (2008)
SF3	Recession duration exponentially distributed	Ausloos *et al.* (2004); Wright (2005)
SF4	Relative volatility of GDP, consumption and investment	Stock and Watson (1999); Napoletano *et al.* (2006)
SF5	Cross-correlations of macro variables	Stock and Watson (1999); Napoletano *et al.* (2006)
SF6	Pro-cyclical aggregate R&D investment	Walde and Woitek (2004)
SF7	Cross-correlations of credit-related variables	Lown and Morgan (2006); Leary (2009)
SF8	Cross-correlation between firm debt and loan losses	Mendoza and Terrones (2014); Foos *et al.* (2010)
SF9	Banking crises duration is right skewed	Reinhart and Rogoff (2009)
SF10	Fiscal costs of banking crises to GDP distribution is fat-tailed	Laeven and Valencia (2008)
Microeconomic stylized facts		
SF11	Firm (log) size distribution is right-skewed	Dosi (2007)
SF12	Fat-tailed firm growth-rate distribution	Bottazzi and Secchi (2003, 2006)
SF13	Productivity heterogeneity across firms	Bartelsman and Doms (2000); Dosi (2007)
SF14	Persistent productivity differential across firms	Bartelsman and Doms (2000); Dosi (2007)
SF15	Lumpy investment rates at firm-level	Doms and Dunne (1998)
SF16	Firm bankruptcies are counter-cyclical	Jaimovich and Floetotto (2008)
SF17	Firm bad-debt distribution fits a power-law	Di Guilmi *et al.* (2004)

Table 1: Stylized facts replicated by the K+S models.

and change in inventories.

4 Empirical validation

The K+S model can jointly account for a large number of *macro* and *micro* stylized facts. The ability of the model to reproduce *at the same time* a wide set of empirical regularities, holding the set of parameter values fixed, is a procedure that both empirically validates the model, and disciplines the parametrization used in the simulation experiments (much more details on these results in Dosi *et al.*, 2010, 2013, 2015).

We briefly recall the micro- and macro regularities reproduced by the model in Table 1. On the macroeconomic side, self-sustained growth is endogenously generated by the model (see left plot in Figure 2) together with emergent business cycles (see the bandpass-filtered GDP, right plot in Figure 2). Mild economic fluctuations are punctuated by *deep downturns* (Stiglitz, 2016). As a consequence, the GDP growth-rate distribution generated by the model exhibits fat tails (cf. Figure 3) well in tune with the empirical evidence (Fagiolo *et al.*, 2008).[22] At the business cycle frequencies, the relative volatility of fluctuations between output, investment and consumption and the comovements between GDP and the main macroeconomic time series are in line with the empirical evidence (for the empirics and discussion cf. Stock and Watson, 1999; Napoletano *et al.*, 2006). In particular, aggregate R&D investment is pro-cyclical (see e.g. Walde and Woitek, 2004).

[22] Note that DSGE models are not able to match such empirical regularities even if they are fed with fat-tailed shocks (Ascari *et al.*, 2015).

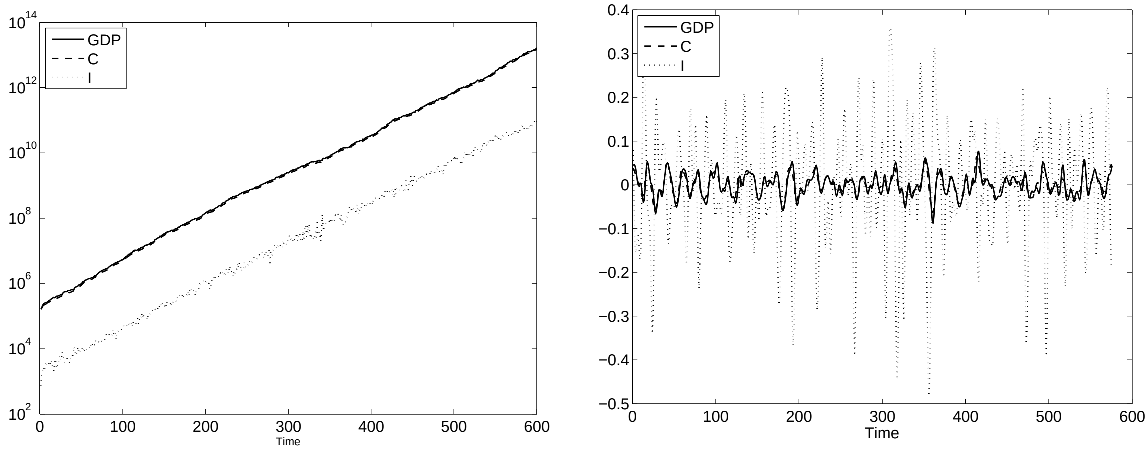

Figure 2: Model-generated GDP, consumption and investment time series.

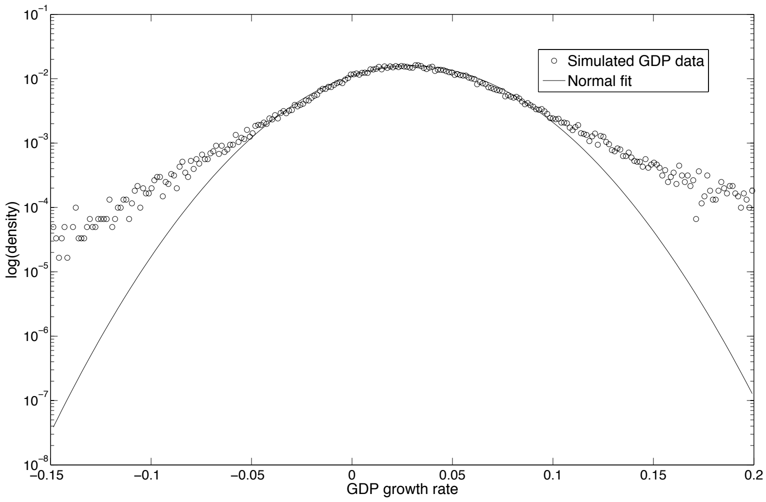

Figure 3: GDP growth-rate distribution. Simulated data vs. Normal fit.

Furthermore, the model also matches the major business cycle stylized facts concerning *credit* (Bikker and Metzemakers, 2005; Mendoza and Terrones, 2014) and *banking crises* (Laeven and Valencia, 2008; Reinhart and Rogoff, 2009). In particular, credit booms lead to higher firm default rates, which often trigger banking crises. The impact of banking crises on the public budget is severe, much higher than those of "standard" recessions, and not limited to bailout costs (Reinhart and Rogoff, 2013).

Finally, the model is also able to replicate several *microeconomic* empirical regularities. Note that the properties described herafter are emerging from the simulations; all firms are initialized in the first period of the model with the same size and productivity level. To begin with, firms are extremely heterogeneous in terms of size, growth rate and productivity: firm size distributions are right skewed; firm growth-rate distributions are fat tailed; productivity differentials among firms are persistent over time (see e.g. Bartelsman and Doms, 2000; Dosi, 2007). Moreover, firms invest in a lumpy fashion (Doms and Dunne, 1998).

Note that the capability of agent-based models to replicate both macro and micro stylized facts is one of the major advantages vis-à-vis DSGE ones, which by building on the fiction of the representative agent cannot account for any meaningful heterogeneity at the microeconomic level (Fagiolo and Roventini, 2016).

5 The impact of heterogeneous expectation formation rules

After having showed the explanatory capabilities of the K+S model in the baseline scenario with naïve expectations (NA), let us compare the performance of the economy under alternative expectation formation scenarios. More specifically, we assess the impact of different expectation heuristics on variables capturing the long-run performance of the economy (average GDP growth), as well as short-run fluctuations (output volatility, average unemployment rate, economic crises - i.e. the likelihood of GDP drops higher than three percent). We also study the forecast mistakes of firms in alternative expectation regimes, measured as follows:

$$Error_j(t) = \left[\frac{D_j(t) - (D_j^e(t) + N_j^e(t))}{D_j^e(t) + N_j^e(t)}\right]^2, \tag{18}$$

which include also expected inventories (N^e).[23] Then, we compute the *mean squared forecast error (MSFE)*, built by aggregating consumption-good firms' demand forecast mistakes. Note that MSFEs map directly into firms' profitability, thus affecting their evolution and survival probability. Indeed, the correlations between MSFEs and firms' profit margins are significantly negative, especially when they accumulate losses (see Table 2). If firms underestimate their demands, they lose competitiveness and market shares, while in case of overproduction, they have to pay wages and accumulate inventories without getting revenues.

The results of our Monte Carlo simulation analyses are presented in Table 3, where we report, for all the variables, the ratio between alternative expectation rules and the baseline

[23]The expectation mistakes of consumption-good firms are computed at the end of the period, once realized demand is observed. As they account also for expected inventories (N^e), firms with correct expectations make no mistakes. Expectational errors are normalized to be independent from firms' size. The $MSFE$ is then the Monte-Carlo average of the mean over all agents' squared errors for all periods in each independent run.

	Avg. correlation	Std. dev.
Unconditional	-0.147	0.023
Conditional on firms with negative profits	-0.758	0.021

Table 2: Average correlation between mean squared forecast errors and firms' profits. Average over 50 MC runs.

myopic heuristic (NA), and mean-difference t-tests. The first four scenarios (ADA, WTR, STR and AA) assume that all the firms in the economy follow the same expectation rule. This allows us to understand the forecast errors of each rule as well as their impact on the economic system, *independently* of other heuristics.

The mean squared forecast errors reported in Table 3 are significantly different from zero in all expectation scenarios (in line with a rich body of empirical evidence, see e.g. Coibion and Gorodnichenko, 2012; Gennaioli *et al.*, 2016). The MSFEs of myopic NA expectations are significantly lower than those of most other heuristics (WTR, STR, AA), with the exception of the adaptive expectation (ADA) regime (although not significantly different). Note, however, that the quality of the forecasts of alternative expectations rules does not necessarily map into the "goodness" of macroeconomic performances (cf. Table 3), as such another piece of evidence on the lack of isomorphism between micro expectations/behaviors and system-level dynamics. So, for example, with strong trend heuristics (STR), higher MSFEs translate into lower long-run growth and higher short-run instability. This result is explained by the destabilizing role in model dynamics of additional positive feedbacks resulting from STR rule (see e.g. Heemeijer *et al.*, 2009; Anufriev *et al.*, 2013). Similarly, when firms take into account both their own demand and GDP dynamics as in the AA case, both MSFEs and output volatility and the likelihood of economic crises significantly *increase*.[24] However, the MSFE of the weak trend rule (WTR) is higher than those of myopic expectations, but the unemployment rate falls (while the performance of other variables is not significantly different from the benchmark case). Finally, with respect to the benchmark scenario, the adaptive expectation rule (ADA) reduces GDP volatility and the likelihood of crises without increasing MSFEs.

[24]The worse performance of AA expectations is confirmed also when firms consider only GDP growth ($w_{aa} = 1$) in forecasting their demand. The results are available from the authors upon request.

Expectation rules	Avg. GDP growth	GDP volatility	Unemployment rate	Likelihood of crises	Mean squared forecast error
Average value, NA					
NA	0.030	0.042	0.047	0.066	0.072
Ratio wrt. NA					
ADA	0.996	0.858**	1.304	0.611**	0.960
WTR	1.005	1.060	0.691*	1.049	1.842**
STR	0.966**	2.879**	2.341**	3.082**	7.731**
AA	1.000	1.563**	0.890	1.775**	1.321**
SWITCH	1.008	0.947	0.395**	0.765*	1.773**

Table 3: Expectation heuristics and macroeconomic performance. Average values in the baseline (NA) and ratio with respect to the baseline, myopic expectations (NA). *: significant difference wrt. baseline (NA) at 1% level (**) and 5% level (*).

Let us now consider the SWITCH scenario, where expectations are heterogeneous as agents can switch across heuristics according to their past performance (cf. Section 3.3), thus "learning" from experience. Figure 4 depicts the evolution of the share of each heuristic followed by agents over time. With the exception of the strong trend rule (STR), the share of the other heuristics is similar and fluctuates around a relatively stable value: firms do not converge to a single dominant expectation rule, but rather the system grows on an ecology of them. Such a result is robust to different values of the parameters affecting firms' choice of the expectation heuristic (cf. η, δ and β, in Eqs. 11 and 12) and it is in line with the evidence of Coibion *et al.* (2015) supporting the existence of persistently heterogeneous beliefs among firms. In presence of such an ecology of expectation heuristics, the mean squared forecast errors are considerably and significantly higher than in the benchmark myopic case (cf. Table 3). If agents try to improve their forecast performance switching among different heuristics according to their past performance, they indeed *worsen* it. the performance of the economy is *not* worse than the one observed under the myopic (NA) rule: on the contrary, the unemployment rate and occurrence of crises are significantly lower (see Table 3). Again, higher MSFEs do not appear to significantly affect the performance of the economy: the unemployment rate and occurrence of crises are significantly lower that those observed under myopic (NA) rule (see Table 3).

The first general conclusion from this battery of simulation exercises is that *fast and frugal* heuristics can forecast better than more sophisticated rules (in line with the results in Gigerenzer and Brighton, 2009; Gigerenzer and Todd, 1999). Second, compared to the latter, more sophisticated rules involving learning from experience (such as in the SWITCH regime) yield *worse* forecasts. Third, such worsened individual performance, however, is not reflected by any deterioration of the performance of the system: on the contrary, stochastic micro transitions within ecologies of rules seem to somewhat stabilize it, *thus possibly improving macroeconomic dynamics.* Of course, this lack of isomorphism between micro and aggregate behaviors witnesses the illegitimacy of the use of any "representative agent" as explanatory device of macro dynamics (all this fully in line with Kirman, 2010).

Finally, expectations do have some effect on the dynamics of the economy but not too much

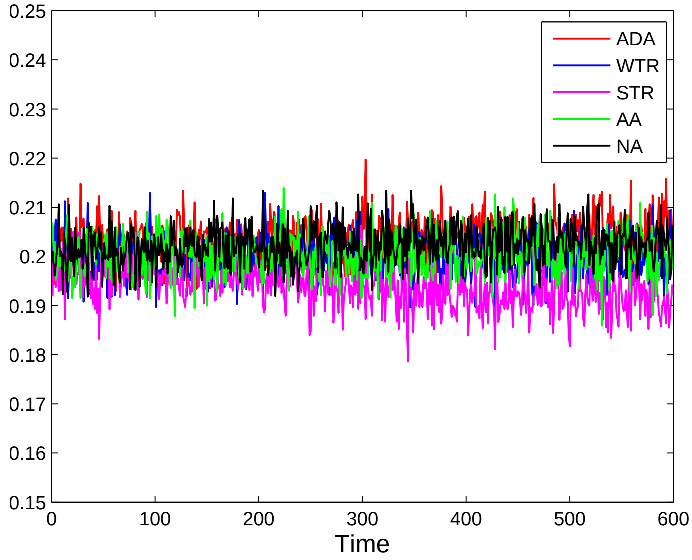

Figure 4: Average share of each expectation heuristic over time. Average over 50 simulations.

(see also Dosi *et al.*, 2006). They are not the main drivers and source of fluctuations: rather, *income constraints* appear to have a fundamental role and *co-evolve* with them. This is revealed by the relative stable performance of the economy in different expectation scenarios. In the exercises so far, agents just switch between fixed parameter heuristics. Let us now explore how further increasing the sophistication of firms' expectation formation process affects individual and macroeconomic performance.

6 From heuristics to learning expectations

Let us now relax the assumption of common and stable parameters in the expectation heuristics followed by firms, and make agents learn *as if* they were econometricians. While it is not possible to implement forward-looking calculations in agent-based models because the latter follow the arrow of time as the real world does (Macy and Flache, 2002), one may introduce a learning process which tries to capture "a boundedly rational model of how rational expectations can be achieved" (Evans and Honkapohja, 1999, p. 452). More specifically, agents are assumed to predict their future demand estimating the parameter of their expectation rule via *recursive least squares* (RLS, see e.g. Evans and Honkapohja, 2001).

We will introduce RLS learning in the adaptive expectation (ADA) scenario (cf. Section 5 above). In such a setting, the parameter (ω_{ada}) of the expectation heuristic now varies cross-sectionally and over time, according to firms' estimations over their own demand time series ($\hat{\omega}_{rls,j}$). As the ADA was the regime with the lowest mean squared forecast error, we will also test whether RLS learning further reduces it vis-à-vis heuristics rules. Together we shall assess the impact of learning on macroeconomic dynamics. The results presented below also hold when firms estimate the parameter of the trend expectation rule.[25]

In the RLS-learning adaptive expectations scenario, firms can now estimate Equation 7 by

[25] Under the RLS-learning scenario, the "weak" and "strong" trend rules collapse into a unique one.

recursive least squares (Evans and Honkapohja, 2001):

$$D_j(t-1) - D_j^e(t-2) = const + w_{rls,j}(D_j(t-2) - D_j^e(t-2)) + \epsilon(t), \tag{19}$$

where the estimation sample size is between $T_{rls}^{min} = 5$ and $T_{rls}^{max} = 40$ observations. To account for agents' limited memory, when the sample reaches the maximum size T_{rls}^{max}, the firm replaces the oldest observation with the newest one.[26]

Notice that the very presence of exit and entry processes leads to the joint presence of two types of agents: *heuristic-guided* and *sophisticated* firms (Haltiwanger and Waldman, 1985).[27] The first type of firms are entrants, which cannot (yet) rely on past demand observations to estimate $\hat{w}_{rls,j}$. In such a case, we assume that for the first periods, young firms follow a heuristic, setting the parameter as in Equation 7 (i.e. $\hat{\omega}_{rls,j} = \omega_{ada} = 0.65$). Once incumbent firms gather enough observations (T_{rls}^{min}), they become "sophisticated" and start performing RLS. Note that the relative share of heuristic vs. sophisticated firms (which, as shown below, impacts both the micro- and macroeconomic performance in the system) depends on entry and exit processes, and on the minimum number of observations required to perform RLS (T_{rls}^{min}).

Further important insights can be gained by experimenting the evolutionary competition between "adult" heuristic and RLS agents within the same environment. Thus, we check their relative "fitness" proxied by, first, the revealed profitabilities of the two behavioural types, and, second, their survival rates. In order to do that, when firms become old enough to perform RLS regressions (i.e. 8-periods old in the benchmark case), they continue to be heuristic with probability one half, or conversely become of the RLS type and start estimating their adaptive parameter.

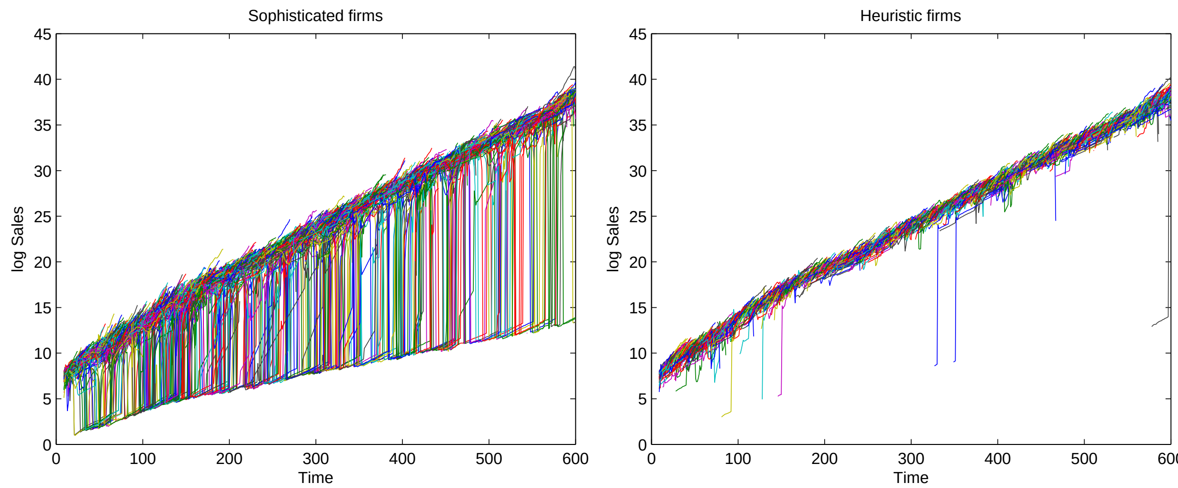

Figure 5: Evolution of the logarithm of sales of RLS agents (left) and heuristic-guided agents (right) over one simulation run.

In terms of profitabilities, the greater forecasting errors make more sophisticated firms less

[26] After the estimation we bound the parameters such that $\hat{\omega}_{rls,j,t} \in [-2; 2]$. The presented results are robust also in the unbounded case.

[27] As pointed pointed out by Haltiwanger and Waldman (1985), when there is a fraction of agents which have no previous experience with a specific situation, learning does not converge to a rational expectation equilibrium. Similarly, in our model, learning cannot jettison heuristic-guided firms from the economy.

Expectation rules	Avg. GDP growth	GDP volatility	Unemployment rate	Likelihood of crises	Mean squared forecast error
Ratio wrt. to NA					
ADA + RLS learning	0.961**	1.242**	4.553**	1.623**	7.529**
Ratio wrt. to ADA					
ADA + RLS learning	0.965**	1.448**	3.492**	2.657**	7.847**

Table 4: Macroeconomic performance under RLS-learning ADA expectations, $T_{rls}^{min} = 5$. Ratio with respect to the baseline (NA, ADA). Average over 50 MC runs. Significant difference wrt. baseline at 1% level (**) and 5% level (*).

profitable (see also Table 2). Conversely, median age at death of the two types are not statistically different. Recall that firms die when either their market shares go to zero, or their net worth become negative, so that also firms with negative profits survive as long as they have a positive accumulated cash balances from the past. In addition, both types display means of age at death much higher than the medians - as such evidence of a fat right-tail of firms which happen to live much longer, either because they are technologically more competent or simply luckier in their forecast and investment decisions. However, more "sophisticated" firms seem to live a more precarious and marginal life. The volatility of their size is much higher (see Figure 5) and they represent 97% of the firms in the bottom decile of the market share distribution (average over 50 Montecarlo runs). Finally, we experimented with different selection intensities (proxied by the parameter χ governing the replicator equation, eq. 31 in the Appendix): as the latter increases, the median and mean age at death of RLS agents falls faster than heuristic ones.

In Table 4, we compare our target indicators under RLS learning in the adaptive expectation scenario vis-à-vis the baseline (myopic expectations, NA) as well as the simple heuristic ADA. Simulation results show that RLS learning has both short- and long-run *destabilizing* effects on macroeconomic dynamics, as it increases output volatility, the unemployment rate and the likelihood of economic crises, while reducing average GDP growth.

Why does the introduction of RLS-learning considerably worsen the performance of the economy? Overall, firms make considerably larger forecasting mistakes (cf. Table 4, last column).[28] Let us consider separately the mean squared demand forecast errors of heuristic-guided and sophisticated agents. Table 5 presents such statistics. The surge in the MSFE is mainly driven by sophisticated agents, whose errors are eight times larger than heuristic ones. Moreover, the presence of sophisticated agents also inflates the forecast errors of heuristic-guided firms, from 0.069 to 0.082 (the relation between the relative share of the two types of firms and their MSFEs will be further studied below).

What can explain the huge mistakes of sophisticated firms, and the consequent lower performance of the RLS-learning scenario vis-à-vis the myopic and ADA ones? There are two alternative hypotheses. A straightforward explanation is simply that fast and frugal heuristic

[28]Note that when RLS-learning is introduced, the increases in MSFEs are much higher than the differences across alternative heuristic-expectation scenarios. And this comes together with worse macroeconomic performances.

Expectation rule	all agents	sophisticated agents	heuristic-guided agents
NA	0.072	-	-
ADA	0.069	-	-
ADA + RLS learning	0.544	0.685	0.082

Table 5: Mean squared demand forecast errors under the different expectation scenarios. Average over 50 MC runs.

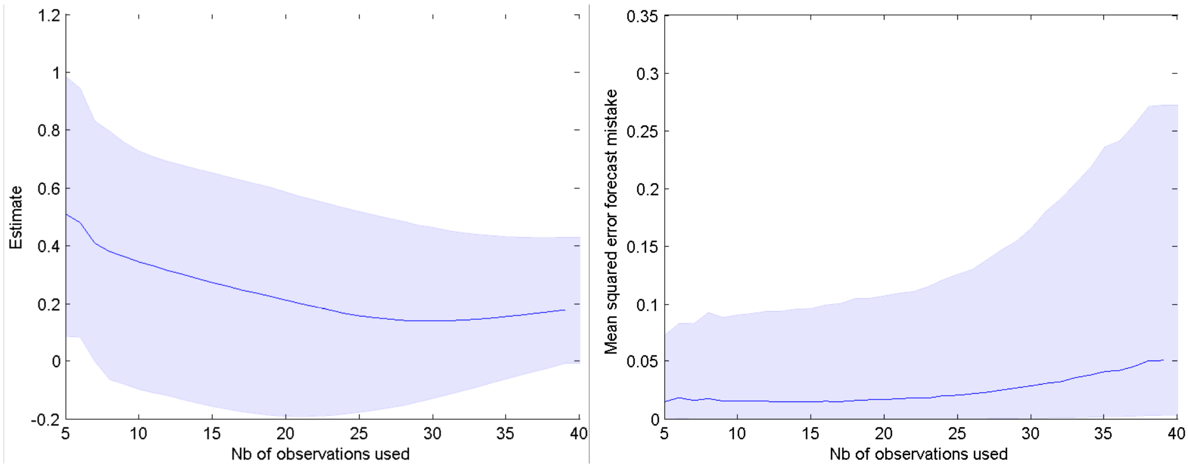

Figure 6: Cross-sectional performance across agents using different number of observations required to perform RLS. Left: Binned plot relating sample size and estimated coefficients. Right: Binned plot relating sample size and demand forecast mistakes.

expectations outperform RLS-learning ones in an economic environment characterized by deep uncertainty and technical change (in line with Heiner, 1983; Gigerenzer and Todd, 1999; Bröder, 2003; Gigerenzer and Brighton, 2009). In such a framework, heuristics can allow one to get more accurate forecasts than complex procedures, because they are robust to changes in the fundamentals of the economy. This is the *less-is-more* principle emerging when agents must take decisions or form forecasts in complex environment (Gigerenzer and Brighton, 2009). The alternative hypothesis is that the larger forecast errors of sophisticated agents are due to an insufficient number of observations employed in the estimations, and/or to the noise created by heuristic-guided firms.

In order to test the latter interpretation, we begin by exploiting the cross-sectional heterogeneity in the size of the samples employed by the sophisticated agents to estimate their expected demand. Indeed, depending on their age, firms rely on a variable number of observations bounded between T_{rls}^{min} and T_{rls}^{max}. Figure 6 (left) shows that, as the size of the sample increases and approaches $T_{rls}^{max} = 40$, the estimates become more and more similar across firms, but the demand forecast errors steadily *rise* (cf. Figure 6, right). This means that long-lasting incumbents make larger mistakes than novel RLS-learning firms. This is a first indication that more information does *not* yield more accuracy in such a setting.

We then consider whether the underperformance of sophisticated agents is due to the "noise" created by heuristic-based ones. By tuning the parameter T_{rls}^{min}, which defines the minimum

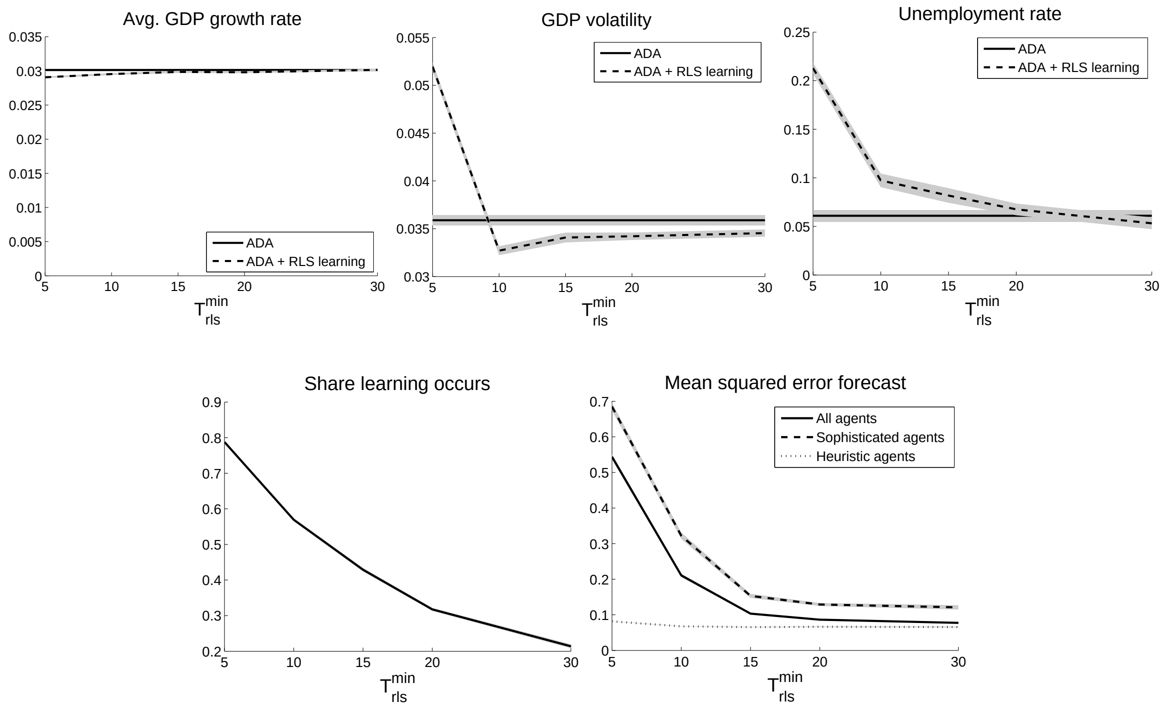

Figure 7: Effect of changing the minimum number of observations to perform RLS, T_{rls}^{min}. Average over 50 MC runs.

number of observations required for RLS estimation, we exogenously change the relative share of sophisticated and heuristic firms in the economy. Figure 7 (bottom, left) shows that the share of RLS learners decreases from 79% to 20% as T_{rls}^{min} rises from five to thirty. At the same time, as more heuristic followers populate the economy, output volatility and the unemployment rate steadily *fall* (see Figure 7, top row). Furthermore, the analysis of the MSFEs of the two types of agents suggests that two effects are responsible for such improvement in the performance of the economy (cf. Figure 7, bottom right). First, as heuristic agents make lower mistakes than sophisticated ones, the increase in their relative share automatically reduces the average forecast error, due to a sheer *composition effect*. At the same time, an *interaction effect* is at work, as both types of agents (and especially the sophisticated ones) reduce their mistakes when the fraction of sophisticated firms is lower. The RLS-learning firms turn out to be the source of noise as they destabilize the forecasting performance of all agents. The model shows that the presence of firms following simple heuristics *stabilizes* the economy. In contrast, the introduction of firms endowed with sophisticated expectation "learning" decreases both individual and collective performance, yielding more market turbulence, higher output volatility and unemployment, and lower long-run growth.

The puny performance of expectations formed with RLS learning boils down to the fact that it is not possible to bend complex, non-linear worlds into a linear framework. This is the case in this model, and it is also the typical situation in contemporary economies where the stream of innovations and the resulting perpetual structural change coevolve with Knightian uncertainty, making the typical econometric tools employed in standard macroeconomics (see e.g. Evans and Honkapohja, 2001) useless or even misleading. In such a framework, the less-is-more principle holds (Gigerenzer and Brighton, 2009) and more information deteriorates the quality of the forecasts (cf. Figure 6, see also Geanakoplos, 1992). Indeed, in line with Box and Jenkins (1976), more sophisticated models, even when they fit better the data, are worse predictors. Thus, in a complex evolving economy, the adoption of fast and frugal heuristics is the "rational" response of agents (Gigerenzer and Todd, 1999; Gigerenzer and Brighton, 2009), and regulators and policy makers too (Haldane, 2012).

7 Structural breaks, uncertainty and expectations

In order to provide further support to this conclusion, we perform two additional sets of experiments. First, we study how RLS-learning expectations fare in an environment presenting a lower level of uncertainty and complexity (*low-innovation* regime). This first robustness test will allow us to evaluate the concept of ecological rationality (Gigerenzer and Todd, 1999; Gigerenzer and Selten, 2002), i.e. expectation rules may perform differently depending on the environment. As discussed above, the poor performance of the RLS-learning rule might be related to the complex evolving nature of the environment, as driven by innovation leaps. It follows that such result might be affected by an exogenous change in the size and frequency of innovation leaps.

Second, we allow RLS learners to choose whether they want to use the heuristic or the sophisticated rule, either based on their relative performance (*choosing-RLS* scenario), or due to the presence of structural breaks that could affect the results of their estimation (*structural-break* regime). Indeed, "smarter" agents than the RLS-learners might be able to detect when to use RLS-learning and when to choose heuristics, depending on their relative fitness.

We exogenously reduce the uncertainty and complexity of the environment by limiting the Schumpeterian engine of the K+S model, scaling down the frequency and magnitude of the micro-shocks that characterize the innovation process. More specifically, we consider a *low-innovation* scenario where both firm search capabilities and technological opportunities are lower with respect to the baseline parametrization (see Section 3.2, Appendix B and the experiments in Dosi *et al.*, 2010).[29] Let us compare the performance of the economy under the baseline and the low-innovation regimes under the ADA and ADA + RLS expectation formation. The results are presented in Table 6. Irrespectively of the mechanisms of expectation formation, slowing down the Schumpeterian engine negatively affects both the short- and long-run performance of the economy (in accordance with Dosi *et al.*, 2010) (see Table 6, first row). Interestingly, and somewhat puzzlingly, under the low innovation regime the economy seems to become *more* volatile. Put the other way round, it seems that, other things being equal, the stronger the innovative drive of the economy, the higher the rate of growth of the economy and the lower its volatility. Conversely, with a milder innovative push the coordination hurdles become more pronounced[30]

[29] The parameters impacting search capabilities in the innovation and imitation processes (ζ_1 and ζ_2), are reduced from 0.3 to 0.05, and the Beta distribution governing technological opportunities is modified from a Beta$(3,3)$ to a Beta$(2.7,3.3)$.

[30] This is what in another work (Dosi and Virgillito, 2017), one caricaturally calls "the bicycle theorem": it is much easier to stand up when you steadily cycle...

Expectation rules	Avg. GDP growth	GDP volatility	Unemployment rate	Likelihood of crises	Mean squared forecast error
Ratio wrt to ADA					
ADA, low-innovation regime	0.541**	1.211**	1.365**	2.896**	1.128**
Ratio wrt ADA+RLS					
ADA+RLS, low-innovation regime	0.542**	0.967**	0.687**	1.261**	0.830**

Table 6: Effect of low-innovation regime. Ratio with respect to the benchmark Schumpeterian regime. Significant difference wrt. baseline at 1% level (**) and 5% level (*).

Equally interestingly, under the low-innovation regime, when firms adopt RLS-learning expectations, the short-run performance of the economy improves, rendering it less volatile (even if it grows at a lower rate, see Table 6, second row). This comes from the fact that in a less complex environment, recursive least squares work relatively better, resulting also in a significantly lower MSFE. In particular, the demand forecast errors of sophisticated firms fall (from 0.69 to 0.58 on average), more than compensating the surge in output volatility and unemployment due to the feebler process of technical change.

The conclusion of the foregoing exercise is that the performance of RLS-learning expectations is improved if the economy is less subject to innovation shocks, and is thus more predictable. This result corroborates the notion that expectation rules can only be assessed in relation to the features of the environment where they are formed, as argued by Gigerenzer and Todd (1999).

What happens instead if firms try to account for the relative accuracy of the heuristic and RLS-learning expectations, or if they account for structural breaks when they select their forecasting rules?

In the *choosing-RLS* scenario, we allow firms to choose between the heuristic and sophisticated expectation rules, on the basis of the comparison of the ex-post MSFEs of the two rules in the previous period. Simulation results show that agents *rationally* choose to follow heuristics most of the time. Indeed, in 56% of cases, firms decide not to employ RLS, reducing the population of RLS-learning agents from 79% to 31%.[31] As a consequence, the mean squared forecast error considerably contracts and the performance of the economy improves (i.e. higher GDP growth, lower GDP volatility, unemployment rate and likelihood of crises than in the ADA+RLS scenario; cf. Table 7, first row).

Furthermore, as RLS learning assumes a linear relationship between past and future individual performance, it is inadequate if the relationship under study is characterized by sudden changes and breaks (more on that in Hendry and Mizon, 2010). In the *structural-break* scenario, we allow firms to decide whether or not to use RLS expectations after performing a Chow test for structural breaks. More specifically, once a firm has accumulated enough past observations ($T_{rls}^{chow} = 24$), it performs a Chow test, dividing the most recent T_{rls}^{chow} observations into two equal subsamples. If the test rejects the null hypothesis of structural stability, the agent *rationally* chooses to revert to the heuristic rule. If no structural break is found, it keeps on with RLS-learning expectations. We find that the Chow test does not accept the null hypothesis 25%

[31] More detailed simulation results are available from the authors upon request.

Expectation rules	Avg. GDP growth	GDP volatility	Unemployment rate	Likelihood of crises	Mean squared forecast error
Ratio wrt ADA+RLS					
ADA+RLS cum choosing-RLS	1.038**	0.641**	0.185**	0.284**	0.119**
Ratio wrt to ADA					
ADA+RLS and structural break test	0.978**	1.021	1.974**	1.209*	3.517**
Ratio wrt ADA+RLS					
ADA+RLS and structural break test	1.014*	0.705**	0.565**	0.455**	0.448**

Table 7: Effect of choosing between the heuristic and sophisticated rules. Ratio with respect to the ADA regime with RLS learning. Significant difference wrt. baseline at 1% level (**) and 5% level (*).

of the times, resulting in a lower share of sophisticated agents in the system (on average, 56% of firms perform RLS, against 79% when the Chow test was not present). As a consequence, when firms can "rationally choose" to switch to heuristics when they detect a structural break, the relative MSFE falls and all the macroeconomic indicators *improve* (see the last row in Table 7). However, in such a case, even if firms can employ sophisticated econometric procedures, the short- and long-run performance of the economy is still worse than when fast and frugal adaptive heuristic rules are employed (see Table 7, second row)! Our findings, again, confirm that in an uncertain, complex world, characterized by frequent structural breaks, "less-is-more procedures" lead to more accurate forecasts and heuristic expectations are *rational* (Gigerenzer and Todd, 1999; Gigerenzer and Brighton, 2009).

8 "Real-Business-Cycle" agents: supply-driven expectation dynamics

Throughout the work, we have modelled agents - no matter the expectation rules - as somewhat "Keynesian", in that the object of their expectation is basically demand and, based on that, they compute their desired investment. Relatedly, we have explored the impact of different degrees of "sophistication" and "rationality" in such demand forecasting attempts. In this last exercise we turn to a different, even more radical, approach to supposedly increase the rationality of firms. We assume that consumption-good firms take their desired production and investment decisions by always forecasting a demand level corresponding to their full capacity utilization. In addition, they perfectly foresight the rate of potential productivity growth, as determined by productivity shocks in the capital-good sector. Notice that the latter assumption is possible because, although productivity shocks are endogenous and idiosyncratic in the model, their realizations are known before production and investment in the consumption-good sector take place. The foregoing assumptions are equivalent to a framework in which - from the viewpoint of agents' expectations - the economy is fully supply-driven. Notice that this is also the typical situation in Real Business Cycle (RBC) models (see King and Rebelo, 1999, as well as the barebone of New Keynesian DSGE models), where the economy is always at full capacity

Expectation rules	Avg. GDP growth	GDP volatility	Unempl. rate	Likelihood of crises
Ratio wrt to NA				
RBC agents (no inventories)	0.815**	3.658**	2.765**	2.390**
RBC agents (inventories)	0.894**	3.125**	3.059**	2.444**

Table 8: Effect of RBC agents. Ratio with respect to the baseline (NA). Significant difference wrt. baseline at 1% level (**) and 5% level (*).

utilization and the dynamics is entirely driven by aggregate productivity shocks. For this reason, we label agents in this economy "RBC agents".

We implement the notion in two different scenarios. In the first one ("no inventories" scenario), consumption-good firms do not consider inventories, and they set their desired production to a level equal to their productive capacity:

RBC agents (no inventories):
$$Q_j^d(t) = K_j(t). \tag{20}$$

In the second scenario ("inventories" scenario), firms account for the feedback from demand on production by adjusting downwards their desired production in presence of inventories inherited from the past period:

RBC agents (inventories):
$$Q_j^d(t) = K_j(t) - N_j(t-1). \tag{21}$$

Moreover, in the model used in the paper, consumption-good firms define their desired capital based on desired production and the capacity utilization rate u as follows:

Baseline:
$$K_j^d(t) = \frac{Q_j^d(t)}{u}, \tag{22}$$

with u=0.75. We assume that RBC agents define their desired production by adjusting their current level of capital to the potential aggregate productivity growth in the capital-good sector, $A_1^{potential}(t)$:

RBC agents:
$$K_j^d(t) = \frac{Q_j^d(t)}{u} * (1 + A_1^{potential}(t)), \tag{23}$$

where $A_1^{potential}(t)$ is the weighted average of productivity growth in the capital-good sector.

Table 8 presents the aggregate indicators for these two experiments, compared to our benchmark myopic expectations scenario (NA). The differences with respect to the baseline are dramatic. In the scenario without inventories, 45% of simulations end in a collapse of the consumption-good sector (100% of failures, in which case the simulations are stopped). In the remaining simulations, the economy performs significantly worse than in the baseline, both in the long-term (lower GDP growth) as well as in the short-term (higher GDP volatility, unemployment and crises). In the second scenario, with inventories, an indirect feedback from lack of demand to production and investment is added. Yet, the aggregate performance of the economy

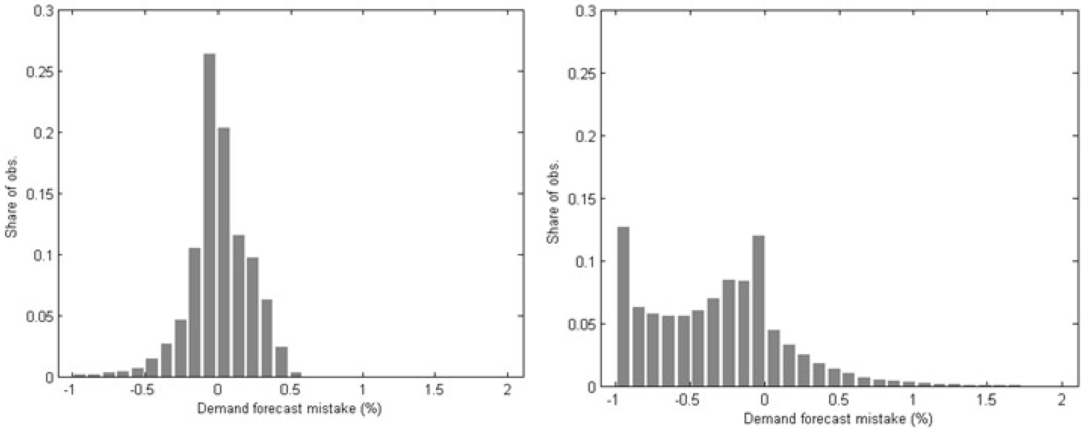

Figure 8: Distribution of demand forecast mistake with RBC agents, scenario without inventories. Left: NA; Right: RBC, no inventories. Average over 50 MC runs. The forecasting errors are not squared in order to emphasize over-production (negative values) as well as under-production (positive-values).

does not improve much.

How can one explain the significantly worse performance of the economy in presence of RBC agents? In a world without income constraints, having all firms coordinating their demand expectations on full-capacity utilization levels would be enough for the achievement of a full-employment-full-capacity state at the aggregate level. This is not the case in this model, where income constraints arise both from uncertainty in the distribution of demand across firms and from financial market imperfections limiting the investment and consumption of, respectively, firms and households. In particular, the possibility that some firms are credit rationed implies in general that *actual* aggregate investment will be lower than *desired* aggregate investment. In its turn, lower rates of actual investment map into lower levels of employment and of final consumption demand. The result is that many RBC firms will end up over-producing, accumulating inventories, and making losses. The neglect of these endogenous demand effects by RBC agents is revealed by the analysis of the distribution of their forecast errors (see Figure 8, right plot), whose mass is much more skewed to the left compared to the baseline (see Figure 8, left plot). These over-production mistakes are further amplified in the model via the adverse effects that bankruptcy has on the supply of credit to firms. Indeed, persistent accumulation of inventories and losses will map into higher rates of bankruptcy. This results in higher rates of bad debt that reduce banks' net worth, and in turn, the available supply of credit.

In conclusion, the above analysis is a robust confutation of the standard "supply-side model". In fact, RBC agents are "right" on the supply side part of the model and on their structural understanding of the stochastic productivity process. Yet, the overall impact is largely negative because they neglect the "Keynesian" endogeneity of demand. Notice that the results strengthen the notion that financial market imperfections play a key role in generating aggregate coordination failures (see Greenwald and Stiglitz, 1993).

9 The properties of heuristic-driven decisions

It is crucial to emphasize that in complex evolving worlds, *even the analyst*, as well as any agent with the same knowledge of the analyst, with the "true" model of the world, would not do any better than the "heuristic agent". Consider the "analyst" who happens to be the "constructor" of the world, that is us authors of the model: we "know" the true model and we can simulate it up to time t. Are we able to predict what a state variable will be, say demand, of agent i at time $t+1$, better than any heuristic agent? The answer, which is quite revolutionary, is in general negative. Of course we would be very good at "predicting the past" - as Balzac once wrote -, that is in fitting, but probably poor in forecasting.

To see this, recall that the model is a very high dimensional system: in its bare-bone structure, it has $N1+N2$ firms, hit by endogenously-generated idiosyncratic shocks (capital-embodied productivity improvements) which affect the competitiveness of the firms via their unit costs, and through that, the dynamics of the market shares and survival probabilities. Therefore, the minimum dimensionality of the system is $(N1+N2)\times c$ (i.e the number of control variables of each firm) $\times s$ (the system-level state variables). Furthermore, besides being high dimensional, the system is also highly non-linear.

First, micro technological shocks painstakingly propagate in the economic system. Second, different degrees of competitiveness introduce system-level correlations in the dynamics of firms' market shares. Third, of course, there is yet another Keynesian system-level correlation, because the individual demands are the market shares multiplied by the size of the whole market, but the latter (endogenously) sums up over all employed workers multiplied by their wages. Fourth, pervasive financial imperfections imply that firms can be constrained in their production and investment decisions by the credit supply of banks, which endogenously evolve according to their equities, possibly leading to emergent banking crises, leading to deep downturns. The emerging outcome is a system which, at the level of the individual components - that is, the firms that make decisions - is a combination between some complex non-linear dynamics and seemingly random walks.

Here, it is fundamental to track the sources of prediction errors. As formalized by Gigerenzer and his colleagues (within a long tradition in the learning literature), total forecast errors, averaged across all possible data samples of a given size, can be written as:

$$\text{total forecast error} = (\text{bias})^2 + \text{variance} + \text{noise},$$

> "The bias is defined as the difference between the true underlying function and the mean function, derived from the estimating algorithm. Thus, a zero bias is achieved if the mean function induced by the algorithm is precisely the underlying function. Variance captures how sensitive the induction algorithm is to the content of these individual samples, and is defined as the sum of the square differences between the mean functions and the individual functions induced from each of the samples" (Gigerenzer and Brighton, 2009, p. 117).

Thus, even in a stationary world, "an unbiased algorithm may suffer from high variance because the mean function may be precisely the underlying function, but the individual functions may suffer from excess variance and hence high errors" (*ibid*). And agents, in the real world, only observe *one* sample path, their own history. Moreover, in our case, the point is further exacerbated by the intrinsic non-stationarity and non-linearity of the world as a whole, and of the fate of each agent in such environments. Indeed, most likely (individual) dynamics diverge. We are not able yet to dissect non-linear deterministic processes vs. the seemingly stochastic components. However, the ontology of our world is fully opposite to those who claim agents can learn "rational expectations" (see Marcet and Sargent, 1989). On the contrary, the world is too complex, and too much changing, in order to be able to learn its fine structure, let alone its parameters. Thus, there is in most cases of complex environments, no accuracy/efforts trade-offs in information gathering. In such a framework, heuristics outperform OLS learning in forecasting because their forecast are certainly biased as compared to those which an omniscient Laplacian God would make, but have a much lower variance than those which finite agents could make on the grounds of all their available information.

10 Concluding remarks

In this work we have extended the Keynes+Schumpeter (K+S) family of models to account for the impact of heterogeneous expectations and learning processes on the performance of the economy. In particular, firms can forecast their future demand either by choosing among an ensemble of different heuristics or via recursive least square estimations.

Simulation results show that under alternative heuristics, significantly different mean squared forecast errors do *not* considerably affect macroeconomic performance (below a certain threshold). This invariance suggests the relative minor role of expectations in environments where income constraints largely drive the dynamics of the economy. Furthermore, none of the heuristic rules disappear from the market, in line with the evidence of persistent heterogeneity in firms' beliefs (see Coibion *et al.*, 2015).

However, when "sophisticated" firms are allowed to estimate their future demand via recursive least squares, expectations do matter. And they matter for the worse: their forecast errors skyrocket and the performance of the economy significantly worsens. In addition, agents "rationally" choose heuristics vis-à-vis RLS-learning of expectations whenever they are allowed to select among the two. The conclusion is that heuristics should *not* be considered as a second-best approximation, trading-off accuracy for effort in presence of cognitive limitations and biases. Instead, the less-is-more principle holds, and "[we] can rely on heuristics because they are accurate, not because they require less effort at the cost of some accuracy" (Gigerenzer and Brighton, 2009, p. 135).

Why does RLS learning spectacularly fail in the K+S model? The huge forecast errors made by RLS-learning firms come from the fact that it is not possible to bend complex, non-linear worlds into a linear econometric framework. By the same token, trying to bend a world that is intrinsically keynesian, into a fully supply side one - alike RBC and DSGE - worsens both individual and aggregate performances. In presence of imperfect information (Greenwald and Stiglitz, 1986), deep uncertainty (Knight, 1921) and technical change, the best "evolutionary" response of firms seem to be the adoption of *heuristics*. "Fast and frugal" heuristics perform relatively better in more uncertain settings, with large innovation leaps and structural breaks.

The *ecological rationality* of heuristics (Gigerenzer and Todd, 1999; Gigerenzer and Selten, 2002) thus appears to be an emergent property in complex evolving economies, captured by the K+S model. If the rationality of decision rules is evaluated according to their ability to reach their goal given the environment, rather than by their use of more information, computation and time (Bröder, 2003), then our results suggest that *robust heuristic expectations* are indeed "rational".

In contemporary macroeconomic theory the role of expectations has been almost certainly overstated. For sure expectations matter in influencing business cycle dynamics - in the real world and also in the K+S family of models, but they are not the main source of fluctuations. Other, more fundamental mechanisms such as firms' heterogeneous innovation performance, productivity dynamics and financial conditions (Greenwald and Stiglitz, 1993) interact with demand expectations to trigger growth waves, avalanches of bankruptcies, as well as mild and deep recessions (Stiglitz, 2011, 2016). In all that, simple and robust heuristics may not only be better in terms of performance of individual agents, but turn out to be also a source of predictability of behaviors (Heiner, 1983), and a "collective stabilizer", allowing for easier coordination among heterogeneous interacting agents.

There are different ways forward in this research path. One of them, and a very challenging one indeed, is to contribute to the current debate about the robustness of macroeconomic policy across different expectation frameworks. One way to do it would be to employ the K+S model with alternative heuristic expectations to study the impact of different combinations of monetary and fiscal policies (e.g. as in Dosi *et al.*, 2015, 2016b), finally pushing the policy analysis beyond and away from the dire straits of the "Lucas critique".

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A Parameters

Description	Symbol	Value
Benchmark parameters		
Montecarlo replications	MC	50
Time sample	T	600
Number of firms in capital-good industry	F_1	50
Number of firms in consumption-good industry	F_2	200
Number of banks	B	10
Capital-good firms' mark-up	μ_1	0.04
Consumption-good firm initial mark-up	$\overline{\mu}_0$	0.20
Banks deposits interest rate mark-up	r^D	-1
Banks reserve interest rate mark-up	μ^{res}	-0.33
Bond interest rate mark-up	μ^{bonds}	0
Loan interest rate mark-up	μ^{deb}	0.30
Bank capital adequacy rate	τ^b	0.08
Wage setting $\Delta\overline{AB}$ weight	ψ_1	1
Wage setting Δcpi weight	ψ_2	0.05
Wage setting ΔU weight	ψ_3	0.05
Shape parameter of bank client distribution	$pareto_a$	0.08
Desired inventories	ι	0.10
Beta distribution parameters (innovation process)	(α_1, β_1)	(3,3)
Firm search capabilities parameters	$\zeta_{1,2}$	0.30
Policy parameters		
Inflation adjustment parameter (TR_π)	γ_π	1.10
Target interest rate	r^T	0.025
Target inflation rate	π^T	0.02
Tax rate	tr	0.10
Unemployment subsidy rate	φ	0.40
Expectation parameters		
ADA adjustment	w_{ada}	0.65
WTR adjustment	w_{wtr}	0.4
STR adjustment	w_{str}	1.3
LAA adjustment	w_{aa}	0.5
Memory parameter	η	0.7
Intensity of choice	β	0.4
Inertia parameter	δ	0.9

Table 9: Parameters

B The K+S Model

In this appendix we present the full formal structure of the model described in Section 3. We detail the equations characterising the decision rules in the capital- and consumption-good industries and we elaborate on the rules governing the firm-bank interactions. The model is stock-flow consistent. More details can be found in Dosi *et al.* (2015).

The capital- and consumption-good industries, complements

The capital-good industry

The technology of capital-good firms (identified with the subscript i) is defined by their labour productivity B_i^τ and that of the machine they sell to the consumption-good sector firms A_i^τ, wihere τ is the technology vintage. Their price is then defined by applying a fixed mark-up ($\mu_1 > 0$) on their unit cost of production c. The latter is computed as $c_i(t) = \frac{w(t)}{B_i^\tau}$, where $w(t)$ is the nominal wage.

Both types of productivity (B_i^τ and A_i^τ) evolve as an outcome of (costly) innovation and imitation, which require capital-good firms to invest in R&D. The value of R&D expenses (equally split between innovation IN_i and imitation IM_i) is defined by a simple heuristic: it is a fixed share of past sales $\nu = 0.04$. Innovation is risky: not all firms innovate, and the resulting innovation may be unsuccessful. The probability to innovate is defined by a random draw from a Bernoulli distribution of parameter $\theta_i^{in}(t) = 1 - e^{-\zeta_1 IN_i(t)}$, with $\zeta_1 \leqslant 1$, and increases with the amount of R&D allocated to innovation (IN_i). Conditional on innovating, the firm draws a new technology with the following characteristics:

$$A_i^{in}(t) = A_i(t)(1 + x_i^A(t))$$
$$B_i^{in}(t) = B_i(t)(1 + x_i^B(t)),$$

where x_i^A and x_i^B are two independent draws from a Beta(α_1, β_1) distribution over the support $[\underline{x}_1, \overline{x}_1]$ with $\underline{x}_1 \in [-1, 0]$ and $\overline{x}_1 \in [0, 1]$. As discussed in Section 3, and shown in Section 6, α_1 and β_1 impact the technological opportunities of capital-good firms.

Similarly, access to imitation depends on imitation expenses IM_i, such that the probability to imitate follows a Bernoulli draw ($\theta_i^{im}(t) = 1 - e^{-\zeta_2 IM_i(t)}$). Conditional on imitation, the firm copies the technology from another incumbent firm, chosen in consideration with its technological distance from the imitating firm (in Euclidean terms), and obtains the new values $A_i^{im}(t)$ and $B_i^{im}(t)$. The firm chooses between its current (τ) and new technology (obtained from innovation or imitation) as follows:

$$\min \left[p_i^h(t) + bc^h(A_i^h(t)) \right], \qquad h = \tau, in, im, \tag{24}$$

where $b = 3$ is the payback period parameter (see Eq. 27 below). Once the productivity of their current product is defined, capital-good firms seek customers by sending information about their machine's price and productivity to a subset of consumption-good firms. Thus the latter have imperfect information about the available machines on the market. This subset includes their historical clients (HC_i) and a random sample of potential new clients $NC_i(t) = \varpi HC_i(t)$, with $\varpi = 0.5$.

The consumption-good industry

Consumption-good firms (identified with the subscript j) produce a homogeneous good using labor and capital under constant returns to scale. They define their desired level of production Q_j^d using adaptive demand expectations $D_j^e = f(D_j(t-1), D_j(t-2), \ldots, D_{j,t-h})$, desired inventories ($N_j^d$) and stock of inventories (N_j):

$$Q_j^d(t) = D_j^e(t) + N_j^d(t) - N_j(t-1), \tag{25}$$

with $N_j^d(t) = \iota D_j^e(t), \iota \in [0, 1]$. Such desired level of production is associated with a desired capital stock (K_j^d). If needed, they thus have to expand their current capital stock (K_j) through (desired) expansionary investment (EI_j^d):[32]

$$EI_j^d(t) = K_j^d(t) - K_j(t). \tag{26}$$

Besides expansionary investment, consumption-good firms may have to invest in order to replace old (of age$> \eta$ periods, $\eta = 20$) or obsolete machines, considering new machines' prices. Indeed, the stock of capital comprises different vintages of machines, each with different productivity $A_i^\tau \in \Xi_j$ (the productivity associated with their supplier i when they bought the machine). Machines are scrapped according to the following payback routine:

$$RS_j(t) = \left\{ A_i^\tau \in \Xi_j(t) : \frac{p^*(t)}{c(A_i^\tau(t)) - c^*(t)} \leq b \right\}, \tag{27}$$

where p^* and c^* are the price and unit cost of production of new machines. The unit labour cost associated with the machine of vintage τ is $c(A_i^\tau, t) = \frac{w(t)}{A_i^\tau}$. Replacement investment aggregates at firm level the number of old

[32] Such expansionary investment is limited by a fixed maximum threshold, as found in the empirical literature on firm investment patterns (e.g. Doms and Dunne, 1998).

machines and those satisfying Equation 27. Finally, the *actual* level of investment will depend on firms' ability to use internal finance, or obtain external finance (see below).

Consumption-good firms' price is chosen by applying a variable mark-up (μ_j) on unit costs of production (c_j):

$$p_j(t) = (1 + \mu_j(t))c_j(t). \tag{28}$$

where the unit cost at the firm level $c_j(t)$ is the average over all their current machines.

The variable mark-up is adjusted with respect to the evolution of firms' market shares (f_j), where market share expansion allows firms to apply a higher mark-up:[33]

$$\mu_j(t) = \mu_j(t-1)\left(1 + \upsilon \frac{f_j(t-1) - f_j(t-2)}{f_j(t-2)}\right), \tag{29}$$

with $\upsilon = 0.01$.

Given the heterogeneous price but homogeneous good, do all final-good consumers switch to the cheapest supplier? This is not the case because they have imperfect information regarding the available prices (see Rotemberg, 2008). Still, market shares are positively associated with consumption-good firms' *competitiveness* (E_j), which reflects both their price and their amount of unfilled demand (l_j) as inherited from the previous period:

$$E_j(t) = -p_j(t) - l_j(t), \tag{30}$$

where the unfilled demand $l_j(t)$ is the difference between actual demand and production of the period. A firm's market share is then driven by its relative competitiveness compared to the weighted average ($\overline{E}$),[34] following a "quasi" replicator dynamics:

$$f_j(t) = f_j(t-1)\left(1 - \chi \frac{E_j(t) - \overline{E}(t)}{\overline{E}(t)}\right), \tag{31}$$

with $\chi = 1$.

The banking sector, complements

Consumption-good firms can access credit to finance their production and investment from B commercial banks (identified with the subscript k), so that they are proportional to the number of firms in the downstream sector: $B = \frac{F_2}{a}$, with $a = 20$.[35] Each firm is paired with a bank for the entire simulation, so that the distribution of banks' number of clients follows a power law of parameter $\alpha = 0.08$, reflecting the empirical descriptions in Berger *et al.* (1995); Ennis (2001). We identify a bank's portfolio of clients Cl_k, with clients listed as $cl = 1, ..., Cl_k$.

Credit quantity

Besides the initial heterogeneity in terms of number of clients, banks endogenously evolve and grow apart in terms of their supply of credit and balance sheet characteristics. More precisely, credit supply is constrained by capital adequacy requirements inspired by Basel-framework rules (see e.g. Delli Gatti *et al.*, 2010; Ashraf *et al.*, 2017; Raberto *et al.*, 2012). The regulatory limit depends on banks' equity in the previous period ($NW_k^b(t-1)$). In addition to the mandatory level of capital, we assume, following the empirical evidence (BIS, 1999), that banks maintain a counter-cyclical buffer over the regulatory limit. The latter depends on their financial fragility, defined by their past leverage $Lev_k(t-1)$ (the accumulated bad debt to assets ratio). Credit supply is set as:

$$TC_k(t) = \frac{NW_k^b(t-1)}{\tau^b(1 + Lev_k(t-1))}, \tag{32}$$

[33] As based on "customer market" models, see Phelps and Winter (1970).

[34] It is computed using the market shares of the previous period: $\overline{E}(t) = \sum_{j=1}^{F_2} E_j(t) f_j(t-1)$.

[35] Capital-good firms do not need credit because they are paid in advance, before production starts, and do not invest. a can be taken as a proxy for the level of competition in the banking market and is set according to the empirical literature on topologies of credit markets (e.g. De Masi and Gallegati, 2007; De Masi *et al.*, 2010).

with macroprudential parameter $\tau^b = 0.08$. Banks' availability of credit thus depends on the negative shocks to their balance sheet (from clients' past defaults, see below) as well as the regulatory environment, common to all banks.

After banks have defined their supply f credit, and consumption-good firms their demand for loans (see above), the allocation of credit is based on a pecking-order basis, where loan applicants are ranked according to a proxy for their credit-worthiness (their past net worth to sales ratio ($\frac{NW_j(t-1)}{S_j(t-1)}$). Banks allocate credit to firms until they run out of funds or they satisfy all their applicants' needs. Credit rationing emerges as a consequence of a firm's low ranking (ie. firms' low credit-worthiness) or the bank's low availability of credit (ie. banks' financial fragility or tight macroprudential framework).

Interest rates

The interest rates on loans r_j^{deb} paid by a particular firm depends on i) the central bank base rate r, ii) a (homogeneous) bank mark-up and iii) a firm-specific risk permium. The base rate is fixed in each period according to a conservative Taylor rule (Taylor, 1993), targeting inflation:

$$r(t) = r^T + \gamma_\pi(\pi(t) - \pi^T), \qquad \gamma_\pi = 1.1 \tag{33}$$

where $\pi(t)$ is the inflation rate of the period, $r^T = 0.025$ is the target interest rate and $\pi^T = 0.02$ is the inflation target.[36]

Firms' risk premium depends on their credit class, which corresponds to the quartiles q of the distribution of their bank's ranking of applicants. The loan rate is thus:

$$r_j^{deb}(t) = (1 + \mu^{deb})r(t)\,(1 + (q-1)k_{const}) \qquad q = 1, 2, 3, 4 \tag{34}$$

with $\mu^{deb} = 0.3$ the bank mark-up, and $k_{const} = 0.1$ a scaling parameter.

Besides revenues on interest on loans, banks receive interest on their stock of sovereign debt bonds at the rate $r^{bonds}(t) = r(t)$[37] and on their stock of reserves at the central bank at the rate $r^{res}(t) = (1 + \mu^{res})r(t)$, with $\mu^{res} = -0.33$.

Bank net worth, failure and bailout policies

As described above, the evolution of banks' balance sheets has an important impact on credit. Bank profits (Π_k^b) evolve as follows:

$$\Pi_k^b(t) = \sum_{cl=1}^{Cl_k} r_{cl}^{deb}(t)Deb_{cl}(t) + r^{res}Cash_k(t) + r^{bonds}(t)Bonds_k(t) - r^D Dep_k(t) - BadDebt_k(t) \tag{35}$$

where Deb_{cl} is the stock of debt of client cl, $Cash_k$ are the liquidities of the bank, $Bonds_k$ is the stock of sovereign bonds, and $BadDebt_k$ the non-performing loans of the period. The latter correspond to the stock of debt of clients of the bank which exit the market. Banks then pay taxes on their positive profits at the rate $tr = 0.1$. Note that profits ca be negative if loan losses are important.

Banks' net worth are adjusted for the new net profits as follows:

$$NW_k^b(t) = Loans_k(t) + Cash_k(t) + Bonds_k(t) - Depo_k(t) + Net\Pi_k^b(t) \tag{36}$$

where $Loans_k(t)$ is the stock of loans and $Depo_k(t)$ clients' deposits.

A bank goes bankrupt if its net worth turns negative (due to important loan losses). When this happens, the Government always intervenes to bail banks out and provides fresh capital, of amount $Gbailout_k$. The size of the saved bank is set as a fraction of the smallest incumbent's equity, provided it respects the capital adequacy ratio.

[36] See experiments on various Taylor rules in Dosi *et al.* (2015).
[37] See alternative rules for the setting of sovereign debt bonds in Dosi *et al.* (2015).

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