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Scaling and forecasting in a data-driven agent-based model: Applications to the Italian macroeconomy[☆]

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ABSTRACT

Agent-based models typically replicate stylized facts but lack macroeconomic forecasting capabilities. Recent advancements aim to make these models data-driven, enabling predictive applications in macroeconomics. Using data primarily from Eurostat (1996–2019), we calibrate an increasingly popular data-driven model to the Italian economy and evaluate the forecasting performance of macroeconomic variables for both Austria and Italy across various model scales. Our findings show that scale has no impact on forecast accuracy. To enhance the model we test modifications to agents' expectations and firms' production plans, and run long-term simulations to explore model dynamics and identify areas for refinement. The results demonstrate the model's adaptability to different country specifications, with forecasting performance comparable to basic econometric models. Scale analysis and long-term analysis reveal unexplored heterogeneity and suggest that the model should further leverage the potential of agent-based microfoundations to improve forecasting.

1. Introduction

The Great Recession prompted extensive theoretical discussions on the shortcomings affecting mainstream models and their empirical ability to forecast macroeconomic crises. Wickens (2014) states that standard macroeconomic empirical approaches, such as, Dynamic Stochastic General Equilibrium (DSGE) models, time series models, or official forecasts failed to predict the 2007 recession, and all continued to perform poorly even after it had begun. This perspective led to a demand for improved capabilities in capturing key characteristics that played a crucial role in generating the crisis, such as agent heterogeneity, adaptive expectations, domino effects, systemic risk, speculative bubbles, and credit crunches (Colander et al., 2010; Colasante et al., 2017; Dosi, 2011; Kirman, 2010; Krugman, 2011; Stiglitz, 2011).

In this context, agent-based macroeconomic models (ABMs) emerged as a viable alternative to the neoclassical framework (Cincotti et al., 2022; Dawid and Delli Gatti, 2018). Mainstream models rely on general equilibrium, where price adjustments balance markets. In contrast, ABMs depict uncoordinated agent decisions, leading to market disequilibria and imbalances. ABMs represent the economy as a complex, evolving system in which macro and meso dynamics arise from micro-level interactions among bounded rational agents. They are particularly suitable for studying phenomena where heterogeneity, interactions, and nonlinearities are prominent in forecasting and anticipating economic fluctuations.

Due to their flexibility, ABMs have been applied in various domains to address the pressing challenges in today's economies, including the impacts of the fourth industrial revolution (Bertani et al., 2021; Fierro et al., 2022), environmental sustainability transitions (Di Domenico et al., 2023; Lamperti et al., 2021; Raberto et al., 2019; Safarzynska et al., 2023), the economic consequences of pandemics (Hommes et al., 2022), and financial institution interactions leading to financial contagion and systemic crises (Catullo et al., 2021; Riccetti et al., 2016, 2018; Teglio et al., 2012).

Given their strengths and the extensive literature now available, it is highly desirable and potentially very fruitful to integrate ABMs into macroeconomic forecasting. The adoption of ABMs aligns with the call for a plurality in macroeconomic forecasting, as proposed by Haldane and Turrell (2019), who explain that a set of models is more effective than a single methodology and there is the need for a "'Cambrian Explosion' in macroeconomic modeling. From forecasting,

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there is evidence that combining two or more models leads to greater predictive power than using one model alone".

However, since their development, the most significant outstanding challenge for ABMs has been their tendency to provide only qualitative analyses. The calibration and the estimation of ABMs have thus far been conducted in a loose and static manner (Fagiolo et al., 2019; Windrum et al., 2007), and they still fall short of providing reliable quantitative forecasts (Buchanan, 2009; Dosi and Roventini, 2019; Gaffard and Napoletano, 2012). Calibration and estimation of ABMs have thus far been conducted replicating "stylized facts" both at the macroeconomic time series level (e.g., irregular fluctuations in GDP during business cycles) and at the microeconomic cross-sectional level (e.g., the power law distribution of firm size) (Assenza et al., 2015; Dosi et al., 2013).

The most promising path forward involves starting from quantitative empirical evidence and transforming ABMs into data-driven models, as has already occurred with mainstream models such as Computable General Equilibrium (CGE) (Ghaith et al., 2021; Socci et al., 2021) and DSGE models (for instance, Christiano et al., 2018). Recent improvements have been made in all aspects of the validation process, including input validation (calibration or estimation), output validation (checking the empirical reasonableness of model outcomes), and parameter space exploration (Fagiolo et al., 2019). Calibration has benefited from simulation-based methods and Bayesian techniques adapted from machine learning (Lamperti et al., 2018; Grazzini et al., 2017). For example, Delli Gatti and Grazzini (2020) proposed a Bayesian approach to estimate ABM parameters and a simulation-based methodology to forecast macroeconomic time series. Zhang et al. (2023) developed a sequential Bayesian inference to mitigate the estimation error.

An new data-driven approach for ABMs can be seen in the groundbreaking work developed by Poledna et al. (2023) which introduced the first ABM, 1 to 1 reproduction of the Austrian economy, capable of competing with benchmark Vector Autoregressive (VAR) and DSGE models in out-of-sample forecasting of macro variables. This pioneering effort is now catalyzing a new wave of macroeconomic agent-based models (Bachner et al., 2023; Hommes et al., 2022; Hommes and Poledna, 2023; Poledna et al., 2023, 2024). These models, which are built upon the agent-based framework introduced by Assenza et al. (2015), are calibrated using national, sectoral, and demographic-economic data to provide reliable macroeconomic and disaggregated forecasts as well as scenario analyses. As such, they are rapidly emerging as powerful tools for policy laboratories, offering unparalleled flexibility and insight into the complex dynamics of modern economies. This approach addresses the common critique of 'parameter wilderness'— the variety of parameters that often challenges agent based modelers, especially in large scale models- reducing the arbitrariness of model initialization as the parameter set is data-driven.

Our study aims to enhance the understanding of the core model, specifically the one discussed in Poledna et al. (2023) and applied to the Austrian economy, replicating the methodology and comparing the model forecasting performance with macro-econometric benchmark models. We focus on a detailed analysis of the model's properties and behavior by conducting a series of robustness tests to provide a clearer understanding of the model, in particular stressing the role of the scale and expectations.

Firstly, we replicate the calibrated parameter, initial conditions, and the simulation results for the Austrian economy bridging the gap between data sources and the model structure, i.e., mapping the Eurostat dataset to the variable set required for the initialization.

Secondly, we adapt the model to a larger economy, such as Italy, thereby demonstrating the model's versatility. Our main challenge was adapting the calibration strategy to Eurostat data for the Italian economy, following the general guidelines provided by the authors. Even if the data-set is harmonized for the European countries by Eurostat, this process requires several adaptations, as it was not automatic to switch the country flag from Austria to Italy. The model is calibrated for each quarter from 2010–2016 for Austria and 2010–2019 for Italy. The rolling calibration strategy provides useful information on the specific evolution of the economic structure and allows for country comparison in a robust way.

Thirdly, we adopt Monte-Carlo simulations to test the model on both the Italian and Austrian economies to detect quantitative changes in forecasting performance. We compare the ABM's forecasting performance with that of benchmark econometric models and find that the ABM's performance is comparable. In the medium term (2–3 years), the ABM generally performs better.

Fourthly, we test the model along two dimensions: scale (i.e., the number of agents in the economy) and the time horizon of the simulation. The model encompasses intricate algorithmic behaviors influencing individual decisions on saving, consumption, occupational choices, investment, and entry-exit dynamics. As a result, it becomes analytically intractable. Given its rich structure, the model does not have identifiable equilibria and must be simulated on high-performance computers to gather information on its properties. To gather comprehensive information about the model's macroeconomic performance, we progressively scale the dimension of the model in terms of the number of agents, starting from $1 : 10^5$, moving through intermediate scales such as $1 : 10^4$, $1 : 10^3$, $1 : 10^2$, and $1 : 10$, and ultimately reaching 1:1 for Austria and 1:10 for Italy. The goal was to observe whether increasing the degree of realism would lead to improved economic forecasting, ranging from a scenario with a few representative agents for each institutional sector (low scale) to a realistic representation of the economy with a large, heterogeneous agent population (high scale). The results suggest that the model's performance remains consistent regardless of scale, due to the high level of coordination among agents, low heterogeneity, fluid modeling of the search and matching protocols, and the uniform application of sectoral parameters across agents. In a nutshell, the model structure may be too simple to fully capture the interplay between heterogeneity and interaction.

Moreover, to assess the presence of stable or unstable trends for the different agents/institutional real and financial sectors, we extend the analysis from 12 quarters to 200 quarters (50 years) in a separate test. These long-run simulations provide clear evidence about the driving forces of the model, helping us understand the general behavior. They also highlight some unlikely dynamics and suggest areas for refinement to improve the model's forecasting performance.

The analysis demonstrates that the model is demand-led, with the expectation formation process of the agents playing a significant role in shaping the economy's growth trajectory, and has a short-run perspective, given that population levels, productivity and capital levels are held constant. Although specified in nominal variables, real factors drive the model's dynamics, as prices, nominal profits, and wages grow in a balanced manner through a smooth, homogeneous process of inflation expectation formation. The financial side does not strongly influence the aggregate economy.

Additionally, we test various modifications to the model to assess their impact on the forecasting accuracy. We test targeted changes, such as altering the expectation formation equations based on autoregressive models (AR), using alternative information set, or modifying the agent's production planning process. Our findings, show that while some changes improve forecasts, others had mixed or negligible effects.

To conclude, we demonstrate how (Poledna et al., 2023)'s model for Austria can be adapted to another economy, specifically Italy, and how it retains a fair degree of predictive effectiveness at the macroeconomic level. The model represents a versatile instrument capable of integrating both macro-econometric and agent-based approaches to provide reliable forecasting. Nevertheless, it remains a starting point, functioning primarily as a macroeconometric model, where micro and meso data contribute only marginally to the results. While the ABM component is currently underdeveloped, its introduction marks a significant step forward. The integration of ABM into the field of forecasting holds potential for future advancements.

The paper is organized as follows. Section 2 summarizes the model of Poledna et al. (2023), while Section 3 outlines the replication of the calibration process for the Austrian economy and describes how it was adjusted to suit the Italian case. Section 4 discusses the short-run forecasting performance of the model, explores its behavior with different numbers of agents, and proposes some modifications. Section 5 examines the long-run properties of the model for both economies and suggests ideas for improvement. In Section 6 we have listed some possible suggestions for improving the model. Section 7 concludes with a critical discussion of the results and offers suggestions for future developments.

2. The model

We outline the key components of the reference model for our study, specifically the Poledna et al. (2023) model. The economy is structured into six institutional sectors, namely Households, Firms, Government, Banking Sector, Financial Sector and Rest of the world. We report only some of the equations of the model, but the interested reader can access full information in the online appendix in the supplementary material attached to the cited paper.[1]

Households The household sector consists of H $(h = 1, 2, \dots, H)$ individuals. Each individual belongs to an economic activity status at each time period, which determines their income and participation in the consumption market. Economic activity statuses are divided into H_{act} economically active and H_{inact} economically inactive individuals. The active individuals include H_W workers and I investors. Each time period t, workers may change their labor status, with $H_E(t)$ representing employed individuals and $H_U(t)$ representing unemployed individuals actively seeking jobs. Both $H_E(t)$ and $H_U(t)$ are endogenous, as agents can move between these states through hiring or dismissal. Inactive individuals include those under 15 years of age, students, and retirees. Consequently, household income varies based on their status: employed individuals earn sector-specific wages, unemployed individuals receive unemployment benefits (a fraction of their previous wages), investors receive dividend income from firm ownership, and inactive individuals receive social benefits from the government. If an unemployed person finds a new job, they receive the wage of the firm i that hires them:

$$w_h(t) = \begin{cases} w_i(t) & \text{if employed by firm } i \\ w_h(t-1) & \text{otherwise, i.e., if unemployed.} \end{cases} \tag{1}$$

Household purchase consumption goods and invest in dwellings from the firm sector in markets characterized by search and matching processes. They follow a simple heuristic by consuming and investing a fixed proportion of their expected disposable income, based on the expected economic growth rate and inflation, with expectations computed using AR(1) rules. Expected disposable net income, including social transfers, is determined by the household's activity status and associated income from labor, expected profits, or social benefits, as well as tax payments, the consumer price index from the previous period, and expected inflation rate $\pi^{\text{e}}(t)$:

$$Y_h^{\text{e}}(t) = \begin{cases} \left(w_h(t)\left(1-\tau^{\text{SIW}}-\tau^{\text{INC}}(1-\tau^{\text{SIW}})\right)\right. & \\ \left.\quad + sb^{\text{other}}(t)\right)\bar{P}^{\text{HH}}(t-1)(1+\pi^{\text{e}}(t)) & \text{if employed} \\ \left(\theta^{\text{UB}} w_h(t) + sb^{\text{other}}(t)\right)\bar{P}^{\text{HH}}(t-1)(1+\pi^{\text{e}}(t)) & \text{if unemployed} \\ \left(sb^{\text{inact}}(t) + sb^{\text{other}}(t)\right)\bar{P}^{\text{HH}}(t-1)(1+\pi^{\text{e}}(t)) & \text{if not economically active} \\ \theta^{\text{DIV}}(1-\tau^{\text{INC}})(1-\tau^{\text{FIRM}})\max(0, \Pi_i^{\text{e}}(t)) & \\ \quad + sb^{\text{other}}(t)\bar{P}^{\text{HH}}(t-1)(1+\pi^{\text{e}}(t)) & \text{if investor in firm } i \\ \theta^{\text{DIV}}(1-\tau^{\text{INC}})(1-\tau^{\text{FIRM}})\max(0, \Pi_k^{\text{e}}(t)) & \\ \quad + sb^{\text{other}}(t)\bar{P}^{\text{HH}}(t-1)(1+\pi^{\text{e}}(t)) & \text{if a bank investor} \end{cases}, \tag{2}$$

where $\Pi_i^{\text{e}}(t)$ and $\Pi_k^{\text{e}}(t)$ are the expected profit based on the profit of the previous period of firm i and the banking sector (see Eq. (15)), respectively; τ^{INC} is the income tax rate, τ^{SIW} is the rate of social insurance contributions paid by the employee, θ^{DIV} is the dividend payout ratio, and τ^{FIRM} the corporate tax rate and $sb^{\text{other}}(t)$ is the social benefit; $\bar{P}^{\text{HH}}$ is the consumption goods price index:

$$\bar{P}^{\text{HH}}(t) = \sum_g b_g^{\text{HH}} \bar{P}_g(t), \tag{3}$$

where b_g^{HH} is the household consumption coefficient for product g and $\bar{P}_g(t)$ is the producer price index for the principal good g weighted by produced (Y_i), unsold (S_i) and imported (Q_m) volumes:

$$\bar{P}_g(t) = \frac{\sum_{i \in I_{s=g}} P_i(t)(Y_i(t) + S_i(t)) + P_{m=g}(t) Q_{m=g}(t)}{\sum_{i \in I_{s=g}} (Y_i(t) + S_i(t)) + Q_{m=g}(t)}. \tag{4}$$

The consumption budget (net of VAT) of household h ($C_h^{\text{d}}(t)$) is thus given by:

$$C_h^{\text{d}}(t) = \frac{\psi Y_h^{\text{e}}(t)}{1+\tau^{\text{VAT}}}, \tag{5}$$

where $\psi \in (0,1)$ is the propensity to consume out of expected income and τ^{VAT} is a value added tax rate on consumption. Consumers then allocate their consumption budget to purchase different goods from firms. The consumption budget of the hth household to purchase the gth good is

$$C_{hg}^{\text{d}}(t) = b_g^{\text{HH}} C_h^{\text{d}}(t). \tag{6}$$

Whether an individual firm can meet demand depends (apart from aggregate economic conditions) on its production and inventory stock. Thus, the realized consumption of household h is the outcome of the search-and-matching process where $C_h(t) = \sum_g C_{hg}^{\text{d}}(t)$ if the consumer successfully realized the consumption plan, and $< \sum_g C_{hg}^{\text{d}}(t)$ if all firms visited could not satisfy the consumer's demand.

Firms Each firm i ($i = 1, 2, \dots, I = \sum_s I_s$) is engaged in the production of a primary product g ($g = 1, 2, \dots, G$) utilizing labor, capital, and intermediate goods sourced from other firms, all within an industry s ($s = 1, 2, \dots, S$) consisting of I_s firms. Demand for these products arises from various markets, including those for final goods, capital goods, and intermediate inputs. Firms navigate uncertainties regarding future sales, market pricing, input availability, wages, cash flow, and financing access, leading them to form expectations that may not correspond to actual outcomes.

Firms set their production levels and pricing based on expectations of macroeconomic growth rates and inflation, utilizing AR(1) rules for formulation. Thus, the supply decision of firm i is determined by the anticipated rate of real economic growth ($\gamma^{\text{e}}(t)$) and the previous period's demand for its product $Q_i^{\text{d}}(t-1)$:

$$Q_i^{\text{s}}(t) = Q_i^{\text{e}}(t) = Q_i^{\text{d}}(t-1)(1+\gamma^{\text{e}}(t)). \tag{7}$$

Expectations for economic growth are generated using an autoregressive model with a one-period lag (AR(1)):

$$\log(Y^{\text{e}}(t)) = \alpha^{\text{Y}}(t)\log\left(\sum_i Y_i(t-1)\right) + \beta^{\text{Y}}(t) + \epsilon^{\text{Y}}(t), \tag{8}$$

where the parameters $\alpha^{\text{Y}}(t)$, $\beta^{\text{Y}}(t)$, and $\epsilon^{\text{Y}}(t)$ are re-estimated each period based on the time series of aggregate output.

During each period t, firm i (which belongs to industry s) produces output $Y_i(t)$ (in real terms) of the principal product g using labor inputs $N_i(t)$ (the number of employees), intermediate goods/services and raw materials $M_i(t)$, alongside capital $K_i(t-1)$. We assume a Leontief production function with separate nests for intermediate goods, labor, and capital—each representing upper bounds on production:

$$Y_i(t) = \min\left(Q_i^{\text{s}}(t), \beta_i M_i(t-1), \alpha_i(t) N_i(t), \kappa_i K_i(t-1)\right), \tag{9}$$

[1] https://doi.org/10.5281/zenodo.7271552.

where $\alpha_i(t)$ indicates firm i's labor productivity and β_i and κ_i are productivity coefficients for intermediate goods and capital, respectively. The actual output of firm i may fall short of the desired scale of activity $Q_i^s(t)$. Output can be constrained by labor availability, the quantity of intermediate goods, or the capital required in production.

Goods produced are sold via the search and matching mechanism, either to households or to other firms (as intermediate inputs or capital goods investments), or they may be exported.

Investments are made with consideration of the anticipated depreciation of capital. New capital goods[2] acquired at time t will only contribute to the capital stock in the subsequent period $t+1$, implying that capital is a durable and sticky input. The desired investment in capital stock during period t is expressed as:

$$I_i^{\mathrm{d}}(t) = \frac{\delta_i}{\kappa_i} \min\left(Q_i^s(t), \kappa_i K_i(t-1)\right) \tag{10}$$

where δ_i denotes the firm's capital depreciation rate.

The capital stock is homogeneous across all firms, with fixed weights b_g^{CF}, indicating that each firm i—regardless of its sector s—demands $b_g^{\mathrm{CF}} I_i^{\mathrm{d}}(t)$ as its real investment in goods g:

$$I_{ig}^{\mathrm{d}}(t) = b_g^{\mathrm{CF}} I_i^{\mathrm{d}}(t). \tag{11}$$

However, firms may face challenges in obtaining the desired investment goods in the capital goods market. Thus, the amount of realized investment is contingent on the search-and-matching dynamics within the capital goods market $I_i(t) = \sum_g I_{ig}^{\mathrm{d}}(t)$ if the firm successfully executes its investment plan, and $< \sum_g I_{ig}^{\mathrm{d}}(t)$ if none of the firms visited could satisfy its demand. If firm i is unable to implement its investment strategy, it will have to reduce its future operations, as outlined in Eq. (9).

The capital stock, reflecting the total of all goods g, evolves according to a law of motion that encompasses depreciation and investment, where only the capital actively employed in production is subject to depreciation:

$$K_i(t) = K_i(t-1) - \frac{\delta_i}{\kappa_i} Y_i(t) + I_i(t). \tag{12}$$

In the intermediate goods market, the volume of actual purchases is similarly affected by a search-and-matching mechanism. $\Delta M_i(t) = \sum_g \Delta M_{ig}^{\mathrm{d}}(t)$ if the firm successfully realized its plan, and $< \sum_g \Delta M_{ig}^{\mathrm{d}}(t)$ if all firms visited could not satisfy its demand. If firm i is unable to obtain the materials it aimed to purchase, its production capacity will be restricted. The inventory of good g held by firm i changes based on the material utilized in the production process necessary to achieve the actual output ($Y_i(t)$) and the newly acquired intermediate goods:

$$M_i(t) = M_i(t-1) - \frac{Y_i(t)}{\beta_i} + \Delta M_i(t). \tag{13}$$

Firm i utilizes its workforce $N_i(t)$ as labor input for production, representing the total number of employees. Each period, the firm determines its planned employment level $N_i^{\mathrm{d}}(t)$ based on its desired activity level ($Q_i^{\mathrm{s}}(t)$) and its average labor productivity ($\bar{\alpha}_i$): $N_i^{\mathrm{d}}(t) = \max\left(1, \mathrm{round}\left(\frac{Q_i^{\mathrm{s}}(t)}{\bar{\alpha}_i}\right)\right)$. If the number of employees at the start of period t ($N_i(t-1)$), meaning those employed in period $t-1$, exceeds the firm's desired workforce, the firm will randomly lay off $N_i(t-1) - N_i^{\mathrm{d}}(t)$ workers (considering production constraints that may arise from capital shortages). Conversely, if the labor demand to achieve the desired level of activity surpasses the current workforce, the firm will advertise job vacancies, which signifies a need for additional labor. The filling of these vacancies relies on the search-and-matching process within the labor market.

Firms might require external financial resources to cover current or anticipated expenses. Consequently, each firm i projects its future cash flow $\Delta D_i^{\mathrm{e}}(t)$, which represents the expected variation in its deposits $D_i(t)$:

$$\begin{aligned}\Delta D_i^{\mathrm{e}}(t) = {} & \underbrace{\Pi_i^{\mathrm{e}}(t)}_{\text{Exp. profit}} - \underbrace{\theta L_i(t-1)}_{\text{Debt instalment}} - \underbrace{\tau^{\mathrm{FIRM}} \max(0, \Pi_i^{\mathrm{e}}(t))}_{\text{Corporate taxes}} \\ & \underbrace{- \theta^{\mathrm{DIV}}(1-\tau^{\mathrm{FIRM}}) \max(0, \Pi_i^{\mathrm{e}}(t))}_{\text{Dividend payout}},\end{aligned} \tag{14}$$

where

$$\Pi_i^{\mathrm{e}}(t) = \Pi_i(t-1)(1+\gamma^{\mathrm{e}}(t))(1+\pi^{\mathrm{e}}(t)). \tag{15}$$

The expected profit $\Pi_i^{\mathrm{e}}(t)$ for firm i is projected based on the profit from the previous period. The variable θ represents the debt repayment rate on the firm's existing loans $L_i(t-1)$, τ^{FIRM} denotes the corporate tax rate, and θ^{DIV} signifies the dividend payout ratio. When a firm's internal financial resources fall short of covering its expenditures, it will seek a bank loan, or new credit $\Delta L_i^{\mathrm{d}}(t)$, to bridge its financing gap.

$$\Delta L_i^{\mathrm{d}}(t) = \max(0, -\Delta D_i^{\mathrm{e}}(t) - D_i(t-1)). \tag{16}$$

The deposits of firm i are updated by adding the net cash flow to the previous deposit balance:

$$D_i(t) = D_i(t-1) + \Delta D_i(t). \tag{17}$$

Firms' debt update as follows:

$$L_i(t) = (1-\theta)L_i(t-1) + \Delta L_i(t). \tag{18}$$

Finally, the equity of the firm, $E_i(t)$, changes as the residual component on the firm's balance sheet, where all assets and liabilities are valued at their current market prices:

$$E_i(t) = D_i(t) + \sum_g a_{sg} \bar{P}_g(t) M_i(t) + P_i(t) S_i(t) + \bar{P}^{\mathrm{CF}}(t) K_i(t) - L_i(t) \quad \forall i \in I_s, \tag{19}$$

where $\bar{P}^{\mathrm{CF}}(t)$ is the capital goods price index (CGPI) defined as $\bar{P}^{\mathrm{CF}}(t) = \sum_g b_g^{\mathrm{CF}} \bar{P}_g(t)$.

When a firm experiences both cash-flow insolvency ($D_i(t) < 0$) and balance-sheet insolvency ($E_i(t) < 0$) simultaneously, it is declared bankrupt and a new firm takes its place in the market. The bankrupt firm's real capital stock is transferred to the incoming firm at no cost, but the new firm inherits part of the bankrupt firm's liabilities. A portion of the loans taken by the bankrupt firm is written off, ensuring that the remaining liabilities amount to a fraction ζ^{b} of the real capital stock. This partial cancellation of debt allows the remaining liabilities to be transferred to the new firm's balance sheet.

Firms are owned by only one investor per firm, who receives dividends.

Commercial bank The banking sector is represented by a single bank. This bank obtains deposits from households and firms (that are net savers), remunerated at the policy rate, and provides loans to firms by determining interest rates with a fixed markup on the policy rate $\bar{r}$. Moreover, the banks interacts with the central bank for reserves and advances. Bank profits are determined as the difference between interest received on firm loans and interest paid to deposit holders plus write-offs from credit defaults (see the Eq. (20)).

$$\begin{aligned}\Pi_k(t) = {} & \underbrace{r(t)\sum_{i=1}^{I}\left(L_i(t-1) + \max(0, -D_i(t-1))\right) + r(t)\sum_{h=1}^{H}\max(0, -D_h(t-1)) + \bar{r}(t)\max(0, D_k(t-1))}_{\text{Interest received}} \\ & \underbrace{- \bar{r}(t)\sum_{i=1}^{I}\max(0, D_i(t-1)) - \bar{r}(t)\sum_{h=1}^{H}\max(0, D_h(t-1)) - \bar{r}(t)\max(0, -D_k(t-1))}_{\text{Interest payments}}\end{aligned} \tag{20}$$

[2] In the model, there is no distinction between investment (or capital) goods, consumption goods, and intermediate goods, but each product g is applicable for all these demand categories based on production needs and consumer preferences.

General government The government collects income taxes, capital taxes, corporate taxes, value-added tax on household consumption, and other sector-specific taxes. Other government revenues include social security contributions by employees and employers and other net transfers such as revenues from government sales and services.

Government expenditures are composed of final government consumption, interest payments on government debt, social benefits, subsidies, and other current expenditures.

Individual government entities j ($j = 1, 2, \ldots, J$) participate in the goods market as consumers. Government consumption is assumed to be exogenous and attributed to individual government entities. Real demand for final government consumption $C^G(t)$ is modeled as an autoregressive process of order one (AR(1)), with time-invariant coefficients (α_G and β_G) throughout the simulation:

$$\log(C_G(t)) = \alpha_G \log(C_G(t-1)) + \beta_G + \epsilon_G(t-1).$$

where $\epsilon_G(t-1)$ is a random shock with zero mean and variance σ_G^2.

The government deficit (or surplus) resulting from its redistributive activities is

$$\Pi^{\mathrm{G}}(t) = \underbrace{\sum_{h\in H^{\mathrm{inact}}} \bar{P}^{\mathrm{HH}}(t) sb^{\mathrm{inact}}(t) + \sum_{h\in H^{\mathrm{U}}(t)} \bar{P}^{\mathrm{HH}}(t)\theta^{\mathrm{UB}} w_h(t) + \sum_{h} \bar{P}^{\mathrm{HH}}(t) sb^{\mathrm{other}}(t)}_{\text{Social benefits and transfers}} + \underbrace{\sum_j C_j(t)}_{\text{Government consumption}} + \underbrace{r^{\mathrm{G}} L^{\mathrm{G}}(t-1)}_{\text{Interest payments}} - \underbrace{Y^{\mathrm{G}}(t)}_{\text{Government revenues}}. \tag{21}$$

The government debt as a stock variable is determined by the year-to-year deficits/surpluses of the government sector:

$$L^{\mathrm{G}}(t) = L^{\mathrm{G}}(t-1) + \Pi^{\mathrm{G}}(t). \tag{22}$$

The **Central bank** (CB) determines the policy interest rate $\bar{r}(t)$ according to its targets for inflation and economic growth. It supplies liquidity to the banking system by offering advances to banks and accepts deposits from banks in the form of reserves held at the central bank. Additionally, the central bank acquires external assets, such as government bonds, effectively positioning itself as a creditor to the government.

To determine the policy interest rate, the central bank adopts a "growth" Taylor-rule:

$$\bar{r}(t) = \max\left(0, \rho\bar{r}(t-1) + (1-\rho)\left(r^* + \pi^* + \xi^\pi\left(\pi^{\mathrm{EA}}(t) - \pi^*\right) + \xi^\gamma \gamma^{\mathrm{EA}}(t)\right)\right), \tag{23}$$

where ρ indicates the degree of gradual adjustment in the policy rate, r^* represents the real equilibrium interest rate, π^* is the inflation target set by the central bank, while ξ^π and ξ^γ denote the weights assigned to inflation targeting and economic growth, respectively. We assume that inflation ($\pi^{\mathrm{EA}}(t)$) and economic growth ($\gamma^{\mathrm{EA}}(t)$) within the monetary union adhere to an autoregressive process of order one (AR(1)).

The profits of the central bank, denoted $\Pi^{\mathrm{CB}}(t)$, are calculated as the net result of revenues from interest payments on government debt, along with revenues ($D_k(t) < 0$) or costs ($D_k(t) > 0$) arising from its net position in advances or reserves against the banking sector:

$$\Pi^{\mathrm{CB}}(t) = r^{\mathrm{G}} L^{\mathrm{G}}(t-1) - \bar{r}(t) D_k(t-1). \tag{24}$$

The equity of the central bank, represented as $E^{\mathrm{CB}}(t)$, changes based on its profits or losses and its previous equity.

$$E^{\mathrm{CB}}(t) = E^{\mathrm{CB}}(t-1) + \Pi^{\mathrm{CB}}(t). \tag{25}$$

Rest of the world We include a set of agents that are based abroad and trade with the domestic economy. For simplicity's sake, a representative foreign firm for each sector supplies goods on domestic markets for intermediate, capital, and consumption goods (imports), while foreign consumers demand products on these domestic markets (exports). The total supply of imports $Y^{\mathrm{I}}(t)$ (in real terms) is assumed to follow an autoregressive process of lag order one (AR(1))

$$\log\left(Y^{\mathrm{I}}(t)\right) = \alpha^{\mathrm{I}} \log\left(Y^{\mathrm{I}}(t-1)\right) + \beta^{\mathrm{I}} + \epsilon^{\mathrm{I}}(t-1), \tag{26}$$

Moreover, a representative foreign firm for each sector imports goods from the RoW and supplies them to domestic markets. Thus the mth ($m = 1, 2, \ldots, S$), foreign firm representing an industry s imports the principal product g:[3]

$$Y_m(t) = c^{\mathrm{I}}_{g=s} Y^{\mathrm{I}}(t), \tag{27}$$

where c^{I}_g is the fraction of imported goods of type g as part of total imports. The prices for these import goods are assumed to develop in line with the average sectoral domestic price level. The foreign firm thus sells its products at the inflation-adjusted average sectoral domestic price level. Consequently,

$$P_m(t) = \bar{P}_g(t-1)(1 + \pi^{\mathrm{e}}(t)), \tag{28}$$

where m produces the principal product g.

Finally, The lth ($l = 1, 2, \ldots, L$) foreign consumer, be it a foreign firm, household, or government entity, participates in the domestic goods market as a consumer.

The lth foreign consumer (whether a foreign firm, household, or government entity) participates in the domestic goods market as a buyer. Total sales to these foreign consumers are considered exports to the rest of the world. Similar to imports, the total demand for exports $C^E(t)$ follows an autoregressive process of order one with time-invariant coefficients (α_E and β_E) during the simulation:

$$\log(C^E(t)) = \alpha_E \log(C^E(t-1)) + \beta_E + \epsilon_E(t-1)$$

where $\epsilon_E(t-1)$ is a random shock with zero mean and variance. The shock reflects the relationship between economic growth in the monetary union and the movement of imports and exports.

Search and matching In the model, interactions between agents occur in decentralized markets through search and matching mechanisms. This process takes place not only in the goods market (intermediates, investment, and consumption) but also in the labor and financial markets. The likelihood of a firm being selected depends on its price (with lower prices attracting more customers) and its size (with larger firms having a higher probability of being chosen). The quantity purchased is then determined by the consumer's budget and the seller's available supply.

3. Calibration

The calibration process is crucial for generating precise forecasts and involves the use of empirical data alongside estimation techniques to determine appropriate values for key parameters. The primary dataset utilized is Eurostat, which encompasses a range of sources including censuses, input–output tables, government statistics, and national accounts. The detail of data sources is reported in Table 1. Parameters in the model are categorized based on their source and the method used for calibration.

Census and Business Demography: parameters concerning the number of agents are directly obtained from census data. This includes calibrating specific values such as the number of inactive households. Additionally, census data helps in defining the number of firms, industries and products included in the model.

Input–Output Tables: parameters related to productivity and technology – such as those for capital formation and consumption – are derived from input–output tables. These annual tables provide the

[3] As for domestic firms, we assume that there is a one-to-one correspondence between the sets of industries s and products g, meaning that the nth sector produces only the nth good, and $S = G$.

Table 1
Eurostat data tables.

Name	Code
Population by current activity status, NACE Rev. 2 activity and NUTS 2 region	cens 11an r2
Business demography by legal form (from 2004 onwards, NACE Rev. 2)	bd 9ac l form r2
Symmetric input–output table at basic prices (product by product)	naio 10 cp1700
Cross-classification of fixed assets by industry and by asset	nama 10 nfa st/fl
Government revenue, expenditure and main aggregates	gov 10a main
General government expenditure by function (COFOG)	gov 10a exp
Quarterly non-financial accounts for general government	gov 10q ggnfa
Quarterly government debt	gov 10q ggdebt
Financial balance sheets	nasq 10 f bs
Non-financial transactions (annually)	nasa 10 nf tr
Non-financial transactions (quarterly)	nasq 10 nf tr
GDP and main components (output, expenditure and income)	namq 10 gdp
Money market interest rates - quarterly data	irt st q

necessary data to calibrate sector-specific coefficients accurately.
Government Statistics and Sector Accounts: tax rates and marginal propensities are calculated based on national accounting identities. This ensures that the financial flows observed in the tables and statistics are accurately reflected in the model.
Statutory Guidelines and Financial Regulations: some parameters, including the unemployment benefit replacement rate and capital ratio, are set according to established statutory guidelines and financial regulations.
Exogenously Estimated from National Accounts: parameters for imports, exports, and government final consumption are estimated from national accounts and money market interest rates. These parameters are determined using autoregressive models based on historical time series data, providing a dynamic calibration approach.

The methodology for deriving the models' parameters is data-driven. For example, the parameters obtained from input–output, census tables, and government Statistics, which are central to the model, are derived by inverting the linear static behavioral equations that the model employs.

The model includes two types of parameters: those estimated using time series methods, such as AR parameters defining expectations, and those derived from a snapshot of the data, without considering historical trends. The first type is calculated at the macro level and uniformly assigned to individual agents. In contrast, the second type includes parameters calculated at the meso level and distributed across individuals, such as technology and preferences, while others are derived directly at the micro level, such as agents' numerosity and their employment/unemployment status. As a result, not all parameters reflect real heterogeneity, and for example, two firms belonging to the same sector will share the same technological parameters.

Below, we explain some of the key parameters derived from cross-sectional calibration at each initialization quarter; for full details on the calibration process, we refer to the reference paper.

Productivity coefficients for labor, intermediate inputs and capital ($\alpha_s, \beta_s, \kappa_s$), are derived by dividing the empirical sectors' ($s = 1, \ldots, S$) total outputs ($output_s$) by respectively, the numbers of employees ($employees_s$), the total amounts of intermediate consumption ($\sum intermediate\_consumption_s$) and by their capital stocks, net of the residential assets ($fixed\_assets\_other\_than\_dwellings_s$) in those sectors:

$$\alpha_s = \frac{output_s}{employees_s},$$

$$\beta_s = \frac{output_s}{\sum intermediate\_consumption_s},$$

$$\kappa_s = \frac{output_s}{\frac{fixed\_assets\_other\_than\_dwellings_s}{\omega_s}}.$$

The sectoral depreciation rates (δ_s) are calculated by dividing the sectors's capital consumption ($capital\_consumption_s$) by their capital stocks, net of the residential assets ($fixed\_assets\_other\_than\_dwellings_s$), adjusted for the theoretical rates of capital utilization:

$$\delta_s = \frac{capital\_consumption_s}{\frac{fixed\_assets\_other\_than\_dwellings_s}{\omega_s}}.$$

The sectoral nominal wages per employee (w_s) are calculated by dividing the total wages in the sector ($wages_s$) by the number of employees in that sector ($employees_s$):

$$w_s = \frac{wages_s}{employees_s}$$

The household propensity to consume out of income (ψ) is derived from the ratio of the aggregate household consumption ($household\_consumption$) and taxes on products ($taxes\_products\_household$) to disposable income:

$$\psi = \frac{household\_consumption + \sum taxes\_products\_household}{disposable\_income}$$

where the $disposable\_income$ is the income available to households after taxes and mandatory charges.

The household propensity to invest in dwellings out of income (ψ_H) is calculated as the ratio of the investments in dwellings and related taxes to disposable income:

$$\psi_H = \frac{\sum capital\_formation\_dwellings_s + \sum taxes\_products\_capital\_formation\_dwellings_s}{disposable\_income}$$

where $\sum capital\_formation\_dwellings_s$ is the total amount spent by households on residential buildings across sectors, and $taxes\_products\_capital\_formation\_dwellings_s$ are the taxes on products used for capital formation related to dwellings.

3.1. The calibration for the Italian economy

With the European database serving as the primary data source in Poledna et al. (2023), the calibration process can theoretically be reproduced for any European economy. Nevertheless, there are two primary concerns that need to be resolved:

1. Poledna et al. (2023) discloses the data sources utilized, as well as the calibration strategy, which refers to the procedure through which the parameters and initial conditions are determined, starting from the empirical values of the variables. However, the linkage between data sources and the empirical value of individual variables is missing. Therefore, it is necessary to determine

the mapping between Eurostat sources and the needed variable. For example, we need to find intermediate consumption sectoral observations in the set of Eurostat tables (*Naio-10-cp-1700*) for Italy, in the 2010Q1:2019Q4 quarters, as defined in euro current prices.
2. Addressing country-specific data differences.

To address the first set of challenges, we begin by replicating the specific parameters and initial conditions used for Austria by the cited authors. This was crucial to identify the appropriate data sources and the precise query for each individual variable. Since some data were not fully available (for instance, some items coming from the input and output table regarding the 2018, such as the household consumption) we restricted the analysis of the Austrian economy to each quarter from beginning 2010 to end 2016.

The tasks undertaken were as follows: (i) Collect the bulk dataset[4] and conduct a comparison with the database distributed in supplementary materials of Poledna et al. (2023)[5]; (ii) querying the dataset given the appropriate linkage between data sources and variables; (iii) obtain the parameters and initial conditions.

As shown in the Appendix in Figs. B.4 and B.5, we successfully reproduced the original model initialization. This validates the precision of our querying process, as well as the replication of the database and the calibrated parameters and initial conditions. Next we moved on to the Italian data, showing the adaptability of the model albeit with the necessary adjustments that will be explained in the next section.

The second set of challenges was related to the country-specific nature of the data. Below, we summarize the adjustments required for Italy due to data differences with respect to the Austrian economy:

- For Italy, data necessary to calibrate new investment goods is not available, resulting in a lack of data on the demand and supply of dwellings. Therefore, the flow of formation of dwellings from the "L" sector (real estate activities) in the national accounts $nama\_10\_nfa\_fl$ tables is assumed to be fully produced by the CPA_F (Construction) sector. Moreover, all the stock of dwellings is attributed to the household sector.
- For Italy, the stock of fixed assets data is available at a higher level of aggregation (less sector than required by the model (47 sectors against 62 needed). To address this issue, we used value added as a key metric for disaggregating the data and achieving the desired level of granularity.
- We use the gross operating surplus and the gross mixed income, rather than the corresponding net entries, which are missing for some sectors (e.g., CPA L68 A and CPA L68B), to ensure internal consistency and theoretical soundness, particularly when calculating consumption propensities.
- As in Austria, the business demography data for Italy do not include the agriculture, forestry and fishing sector (A01-A03), or the public administration, defense, and compulsory social security sector (O64). The number of firms in industries A01-A03 is set according to the "Registro Asia Agricoltura" (www.istat.it/it/archivio/278807),

Moreover, as for Austria, we have to perform some assumptions following (Poledna et al., 2023):

- Products are classified according to the Classification of Products by Activity (CPA), fully aligned with NACE, with a breakdown of 64 activities. However, entries for "Services provided by extraterritorial organizations and bodies" (CPA U) contain only zeros and are excluded. Similarly, entries for "services of households as employers, undifferentiated goods and services produced by households for own use" (CPA T) are insignificant (less than 1% of the total labor factor) and are excluded.
  The number of firms in industry O64 is set as in Poledna et al. (2023).
- While a representative foreign firm for each sector is assumed to provide goods on domestic markets (imports), the number of foreign consumers, represented by the parameter L, is assumed to be 50 percent of domestically producing firms, aligning with the share of exports in total value added.
- The number of government entities (J) is set to 20 percent of domestically producing firms, corresponding to the share of government consumption in total value added.
- The distribution of firms, which in turn shapes the distribution of employment, is assumed to follow a power law distribution, matching the empirical distribution observed in Italy.

The calibration period for the Italian economy goes from the first quarter of 2010 to the last quarter of 2019. Given that the input output tables are published only in 2010 and from 2015 to 2019, we have filled the database using the moving average, and we have then verified the coherence of such a procedure.

To summarize the dataset and further check its internal consistency, we build a simplified social accounting matrix (SAM). We report in Table A.13 the theoretical structure of the SAM emerged from the dataset used by Poledna et al. (2023), and in Table A.14 the numerical SAM for both the Italian and the Austrian economy for year 2010.

In Tables A.9, we report the values of the parameters and the initial conditions for Italy and Austria of one specific quarter (2010:Q4) as an example, while in Figs. B.6 and B.7 (Appendix B.2), we collect all the parameters and the initial conditions for Italy and compare them with the Austrian ones. Such figures represent important macroeconomic tendencies reflected by ratios defined by parameters. Some parameters for the Italian economy align with those values of Austria. However, we find some interesting differences besides, of course, the scale parameters representing the number of agents (H_{act}, H_{inact}, J, L, etc.). Indeed, average taxation rates from different sources are slightly higher in Austria. In Austria, the propensity to consume out of income (ψ) ranges around 0.94, while the propensity to invest in dwellings (ψ_H) is around 0.07; instead, in Italy, the calibration strategy displays an adjustment in the considered period over saving-consumption propensities: ψ moves from below 0.88 to around 0.92 and ψ_h reduces from 0.09 to 0.075; therefore, in the first periods Italian households show a lower propensity to consume and an higher propensity to invest in dwellings, while after the Great Recession these propensities have approached Austrian ones. The firm's dividend payout ratio θ_{DIV}, in Italy, has also followed a remarkable change in the analyzed period, reducing from above 0.8 to a value of 0.7, below the Austrian propensity; this could be a signal of financial distress due to the recession related to the sovereign debt crisis.

We also collect the parameters that influence the expectations modeled with AR(1) processes: α_x, β_x and σ_x (with x=$G, E, I, Y^{EA}, \pi^{EA}$, where G is the public expenditure, E is the export, I is the import and Y^{EA} and π^{EA} are the Central Bank expectations on GDP and inflation) are respectively the trend persistence, the intercept and the error variance; Italy shows larger variations during the period, probably due to the deterioration of the economy between the phase before the great recession and the phase after it.

In Table A.12 we collect the main parameters for the sectors of the Italian economy for 2010:Q4.

4. Short-run analysis

We perform for both the Italian and the Austrian Economy 500 Monte Carlo simulations, 12 quarters ahead for each initialization/parameterization. For the Italian economy, we perform a rolling simulation exercise initializing the model from 2010:Q1 to 2019:Q3 for a total

[4] https://ec.europa.eu/eurostat/data/bulkdownload.
[5] https://doi.org/10.5281/zenodo.7271552.

of 39 initializations and with an out-of-sample forecast from 2010:Q2 to 2019:Q4. For the Austrian Economy we perform the same exercise initializing the model from 2010:Q1 to 2016:Q4 with an out-of-sample forecast from 2010:Q2 to 2019:Q4 as in Poledna et al. (2023).

In Figs. 1(a) and 1(b), we show the behaviors of the calibrated models for the main macroeconomic variables. While the Austrian economy is not affected by strong shocks like the Italian economy, allowing the model to better anticipate smoothed trends, the situation is less favorable for the Italian economy. Indeed, for instance, the model is not able to anticipate the debt crisis in 2011–2013. In general, the model quickly converges to the same average forecast, regardless of the initialization period. As a result, it fails to accurately reflect the state of the business cycle, whether in expansion or recession.

One possible explanation is that the model relies on a fixed mechanism for generating agents' expectations, based on an AR(1) process calculated on variables measured in levels, with parameters consistently estimated from 1996, thus exhibiting some persistence in values. Therefore, we believe that the model proposed by Poledna et al. (2023) is a good starting point on which many improvements can be grafted. Some simple experiments to modify the mechanism of expectation formation are proposed in Section 4.2.

4.1. Model validation

Following Poledna et al. (2023), we compute the root mean squared error (RMSE) statistics for various forecasting horizons: 1, 2, 4, 8, 12 quarters ahead. The variables analyzed are: GDP, inflation, household consumption, investments and government consumption. In Tables 2–7 we collect the RMSE over the 500 Monte Carlo exercises, against three benchmarks:

- an auto-regressive (AR) of lag 1 for each variable;
- a vector auto-regressive (VAR) model of lag 1 with the five selected variables;
- an auto-regressive moving avergate (ARMA) process for each variable following the Box-Jenkins procedure (in particular, observing autocorrelations and partial autocorrelations, and information criteria) to select the AR and MA components. The AR and MA components are reported in Tables 4 and 7.

Preliminarily, we can see that the RMSE of AR(1) and ABM for Austria are very similar to the RMSE reported in Poledna et al. (2023), confirming the reliability of our results. Two main facts can be observed in Tables 2–7. First, the forecasting performance of the ABM is in line with that of all proposed econometric models. Indeed, the Diebold–Mariano test shows that very few forecast errors are statistically different between the ABM and the model taken as reference. However, for Austria, the ABM model out-performs the econometric models in forecasting medium run (2–3 years) government consumption and household consumption.

Instead, for Italy, given the high volatility in the Italian macroeconomic cycle, the ABM performs worse than the AR(1) and the VAR in predicting GDP when the forecasting horizon is short (≤4 quarters), while there is a small improvement of the performance, compared to all econometric models, when the forecasting horizon is longer. Same patterns as GDP for household consumption and, albeit with smaller percentages, for investments. In addition, the ABM model shows excellent performance in predicting the consumption of Italian government.

Overall, in the medium term, the model appears to perform slightly better than the econometric models analyzed. One possible explanation for the similarity in the results observed is that the ABM is itself driven by AR(1) processes. However, there are some endogenous feedback processes that may have an impact on improving the forecast in the medium term.

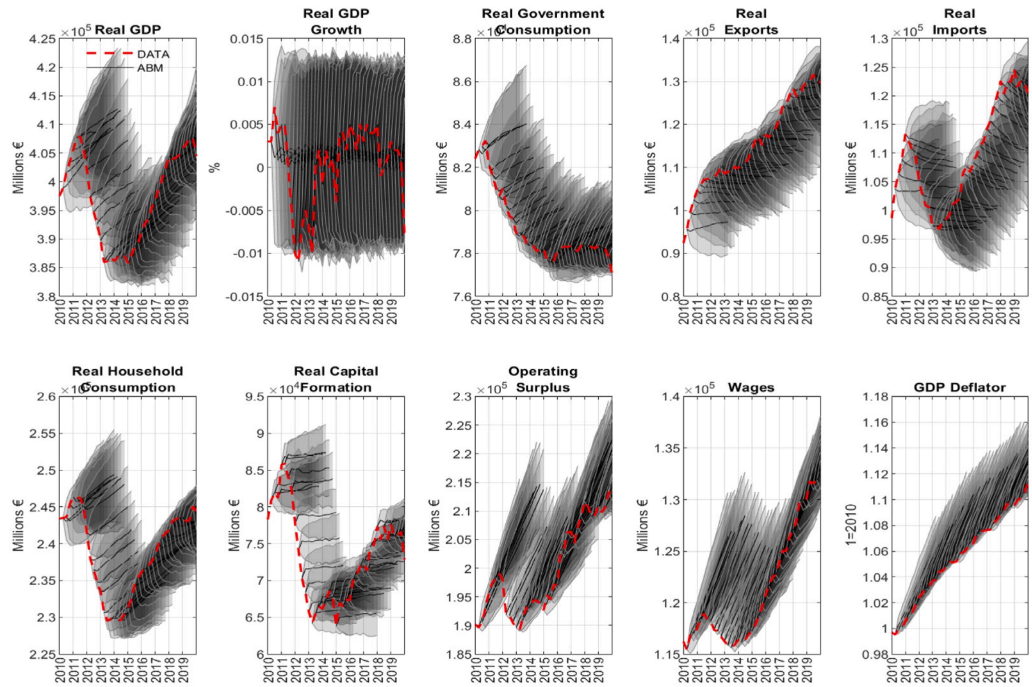
The second important fact is that the model performance is invariant with respect to the scale. This property holds for the two economies and suggests a reflection on the building components of the ABM economy. We propose an investigation on the interaction protocols, on the expectation formation process and on the agents heterogeneity. Indeed, the interaction protocol allows for a smoothed matching, because agents are allowed to search without time and spatial constraints. Moreover, the process of expectation formation is common to all agents, who predict growth rates and prices at the aggregate level and in a coordinated manner, applying the expected trends to the individual variables. Finally, besides homogeneity in expectation formation, agents generally present a low level of heterogeneity. For instance, all firms in an industry have the same calibrated production function, and all households have the same calibrated consumption function. All these aspects, strictly related to the calibration strategy, make the model behave homogeneously at different scales. Perhaps, modifying the assumptions related to these aspects, the scale would matter. However, there is a risk that phenomena of rationing due to decentralized matching, or reduced coordination due to greater heterogeneity in expectations and functions of production and consumption, could lead to a deterioration in forecasting performance, because of frictions that damage the functioning of the simulated economy. This issue is deepened in Section 5 and suggests future investigations. As mentioned above, the model of Poledna et al. (2023) is a starting point on which to work for further refinement.

4.2. Model changes and evaluation of their forecasting performance

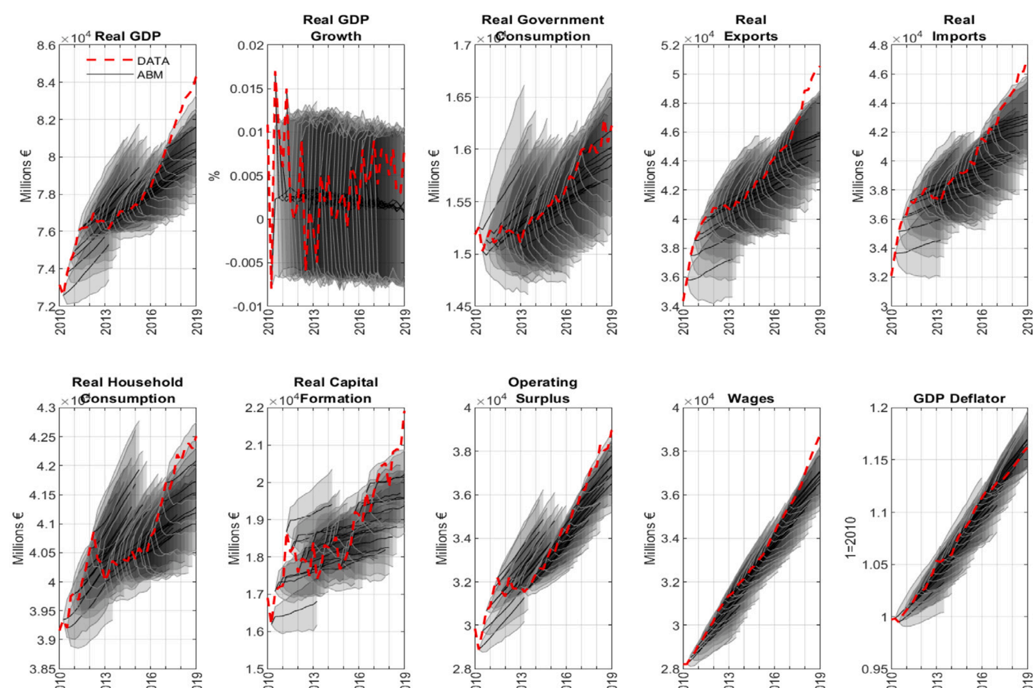
In this section, we resimulated the model by making, one at a time, a number of small changes that, in our opinion, could improve the model or could be interesting variations to test its robustness. For each change, we observed the percentage change in RMSE from the baseline version of the model, shown in Table 8.

The first change concerns AR(1) models used to determine the exogenous components (such as government consumption and exports) and the endogenous components (such as the expected growth rate of the economy and inflation rate). The basic model assumes that agents estimate the parameters of the AR models using data from 1996. The assumption of such a long memory seems to us unreasonable and risks keeping estimates too static in a changing context instead. Therefore, we created three alternative simulations in which we fixed the memory of each econometric process at 3, 5 or 10 years. These alternative models with shorter AR(1) time windows (3 and 5 years) show improvements in inflation forecasts compared to the baseline. There is, however, a worsening of the forecast on GDP and household consumption, although this worsening is not statistically significant. The 10-year time window presents similar results, but the improvement in the inflation forecast is much less pronounced, and the deterioration in the forecast of the other quantities analyzed is more significant. These results seem to suggest the use of a shorter memory and a need for careful calibration to balance accuracy across different variables.

The second change concerns the time series used for the AR(1) process. The baseline model assumes that individuals form expectations using an AR(1) on values in levels of the logarithm of GDP, Export, Import and Government Consumption. The time series, however, are not stationary and therefore the AR processes in levels cannot be applied. Assuming such a systematic error for all agents seems to us an unrealistic assumption. Therefore, we decided to have AR(1) calculated on the series of first differences of the logarithm of GDP, Export, Import and Government Consumption. Such amendments have pertained to the formation of expectations in the private sector, as well as in government and the rest of the world. The model with AR(1) on first differences provides good short-term (1 quarter and 2 quarters) forecasting results for all variables, but its performance deteriorates over the long term. Indeed, in the very short term (1 quarter), the modified model shows a statistically significant improvement in GDP (28.7%), investments (10.4%), and household consumption (30.9%). However, the model shows a decrease in inflation performance (−5%) and a worsening



(a) Italian Economy



(b) Austrian Economy

Fig. 1. Out-of-sample forecasts for the Italian and Austrian economy. The forecast period is 2010:Q2 to 2019:Q4 and the time horizon is 12 quarters. The ABM is initialized in each quarter from 2010:Q1 to 2019:Q3 for Italy and from 2010:Q1 to 2016:Q4 for Austria. Figures show the economy variables on a quarter basis. The black solid line is the average of 500 Monte Carlo simulations, while the shaded gray area represents the 80 per cent confidence interval around the mean trajectory. The red dashed line represents the observed Eurostat data for Italian economy. The economy is modeled at a scale of 1:1000.

Table 2
Out-of-sample forecast performance in comparison to AR(1) model, for the AUSTRIAN economy. The stars represent the significance of the Diebold–Mariano test, which compares the predictive accuracy of two forecasts. The forecast period is 2010:Q2 to 2019:Q4. The AR(1) model is estimated each quarter from 2010:Q1 to 2016:Q3 and the time series data used for estimation begins from 1996:Q1. The ABM results are obtained as an average of 500 Monte Carlo simulations and are initialized in each quarter from 2010:Q1 to 2016:Q3. Percentage improvement (+) or losses (−) relative to AR(1) model.

	GDP	Inflation	Investments	Gov consumption	Household consumption
AR(1) RMSE-statistic for different forecast horizons					
1q	0.59	0.35	1.12	0.67	0.58
2q	0.86	0.32	1.84	0.77	0.81
4q	1.39	0.31	3.04	1.23	1.27
8q	2.25	0.31	4.23	2.02	2.05
12q	2.89	0.25	6.01	2.62	2.74
Scaled 1:100 000 ABM percentage improvements (+) or losses (−) relative to AR(1)					
1q	9 (0.46)	−0.5 (0.36)	0.2 (0.93)	1.9 (0.89)	−0.9 (0.95)
2q	3.2 (0.83)	−3.4 (0.02**)	−0.8 (0.82)	3.3 (0.86)	2.2 (0.92)
4q	−1 (0.97)	−1 (0.15)	−1.8 (0.75)	23.2 (0.46)	9.8 (0.73)
8q	0.3 (1.00)	−1.3 (0.28)	−4.9 (0.72)	29.1 (0.58)	19.7 (0.63)
12q	−4.9 (0.95)	−2.2 (0.50)	−4.5 (0.78)	27.9 (0.67)	20 (0.67)
Scaled 1:10 000 ABM percentage improvements (+) or losses (−) relative to AR(1)					
1q	8.8 (0.48)	−0.1 (0.94)	−0.5 (0.83)	−5.9 (0.70)	1.9 (0.88)
2q	2.5 (0.88)	0.1 (0.92)	−2.1 (0.60)	−2.3 (0.91)	3 (0.89)
4q	−2.1 (0.93)	−1.9 (0.43)	−2.5 (0.67)	20.5 (0.54)	10.9 (0.71)
8q	−1.3 (0.98)	−0.6 (0.53)	−6.4 (0.64)	28.2 (0.61)	20.6 (0.66)
12q	−8.5 (0.93)	0.4 (0.61)	−7.9 (0.66)	27.3 (0.69)	22.3 (0.72)
Scaled 1:1000 ABM percentage improvements (+) or losses (−) relative to AR(1)					
1q	8.1 (0.51)	−0.8 (0.37)	0.1 (0.97)	−8.6 (0.59)	2 (0.86)
2q	4.5 (0.78)	−0.3 (0.76)	−0.7 (0.84)	1.9 (0.92)	4.7 (0.82)
4q	1.2 (0.96)	−0.2 (0.85)	−1.3 (0.82)	23.9 (0.45)	10.7 (0.72)
8q	−0.2 (1.00)	−1.2 (0.15)	−6.4 (0.64)	28.3 (0.60)	19.5 (0.70)
12q	−8.8 (0.92)	2.9 (0.45)	−8.9 (0.63)	27.6 (0.67)	20 (0.77)
Scaled 1:100 ABM percentage improvements (+) or losses (−) relative to AR(1)					
1q	9 (0.46)	−0.5 (0.67)	0 (1.00)	−5.6 (0.70)	1.4 (0.91)
2q	5.6 (0.71)	−0.3 (0.80)	−0.3 (0.93)	0.2 (0.99)	2.7 (0.90)
4q	2.1 (0.93)	−1.9 (0.16)	−0.7 (0.89)	20.3 (0.51)	8.7 (0.78)
8q	3.5 (0.95)	−0.9 (0.31)	−3.5 (0.76)	26.3 (0.62)	19.1 (0.71)
12q	−2.6 (0.98)	−0.8 (0.56)	−5.3 (0.72)	27.9 (0.67)	21.5 (0.75)
Scaled 1:10 ABM percentage improvements (+) or losses (−) relative to AR(1)					
1q	7.6 (0.53)	0.4 (0.44)	−1.5 (0.48)	−2.5 (0.86)	−4.4 (0.77)
2q	3.9 (0.80)	1.3 (0.31)	−2 (0.50)	4.4 (0.81)	−2.2 (0.93)
4q	2.9 (0.89)	−0.1 (0.89)	−1.2 (0.81)	24 (0.44)	7.3 (0.83)
8q	3.3 (0.95)	1.6 (0.31)	−3.8 (0.75)	28.8 (0.59)	17.6 (0.75)
12q	−2.6 (0.98)	0.4 (0.82)	−5.1 (0.73)	28 (0.68)	20.9 (0.77)
Scaled 1:1 ABM percentage improvements (+) or losses (−) relative to AR(1)					
1q	7.8 (0.53)	−0.4 (0.69)	−1.8 (0.45)	−0.3 (0.98)	−8.1 (0.60)
2q	4.3 (0.78)	−0.6 (0.67)	−1.9 (0.60)	4 (0.83)	−4.5 (0.86)
4q	1.9 (0.93)	−4.1 (0.00***)	−1.4 (0.80)	23.8 (0.45)	5.3 (0.88)
8q	3.5 (0.95)	1.3 (0.52)	−4.3 (0.71)	29.6 (0.57)	17 (0.76)
12q	−2.9 (0.97)	−0.8 (0.69)	−5.9 (0.70)	30.8 (0.64)	19.8 (0.79)

(though not statistically significant) of all forecasts over the 2–3 year time horizon.

The third experiment modifies the expectation formation process of firms. In particular, we consider firms following naive expectations or being trend followers (both strong and weak), as suggested by Dosi et al. (2020) that enriched the model presented in Dosi et al. (2010). In the case of naive expectations, firms simply want to produce ($Q_{s,i}$) what they have registered as demand ($Q_{d,i}$) in the previous period:

$$Q_{s,i}(t) = Q_{d,i}(t-1)$$

In the case of trend followers, firms behave like chartist traders, trying to ride demand patterns:

$$Q_{s_i}(t) = Q_{d_i}(t-1) + w * (Q_{d_i}(t-1) - Q_{d_i}(t-2))$$

where w is the value of the parameter weighing past demand changes, with $w_{\text{weak}} = 0.3$ and $w_{\text{strong}} = 1.3$ (Dosi et al., 2020). Models incorporating naive and trend follower expectations obtain results that are in line overall with the basic model, showing how robust it is to the use of different thumb rules adoptable by agents who are not perfectly rational, from naive firms to firms with minimal econometric capabilities and who believe that their sales will increase at the projected rate of GDP growth.

The last experiment is to incorporate the level of inventories when firms define the production plan, as done by Hommes and Poledna (2023). Indeed, it is plausible for firms to consider leftover inventory from the previous period and subtract it from the amount of products they need to produce to reach a predetermined level of output available for sale. This modification alters the production equation to:

$$Q_s(t) = \max\left(Q_d(t-1)(1+\gamma^e) - S(t-1); 0\right).$$

where $S(t-1)$ are the inventories. The inclusion of inventory levels in production planning appears to have a slightly positive impact on forecast of GDP, investments, and household consumption in the short term and in government consumption in the medium term. However, the effects on inflation are mixed.

In conclusion, some changes that may be useful to make the model theoretically more consistent (such as using AR on stationary series) or richer (such as considering inventories in firms' production plans), can be made without detriment to the model's forecasting performance.

Table 3
Out-of-sample forecast performance in comparison to VAR(1) model, for the AUSTRIAN economy. The stars represent the significance of the Diebold–Mariano test, which compares the predictive accuracy of two forecasts. The forecast period is 2010:Q2 to 2019:Q4. The AR(1) model is estimated each quarter from 2010:Q1 to 2016:Q3 and the time series data used for estimation begins from 1996:Q1. The ABM results are obtained as an average of 500 Monte Carlo simulations and are initialized in each quarter from 2010:Q1 to 2016:Q3. Percentage improvement (+) or losses (−) relative to VAR(1) model.

	GDP	Inflation	Investments	Gov consumption	Household consumption
VAR(1) RMSE-statistic for different forecast horizons					
1q	0.6	0.36	1.34	0.72	0.57
2q	0.86	0.34	2	0.78	0.8
4q	1.4	0.31	3.23	1.25	1.21
8q	2.27	0.31	4.45	2.06	2.03
12q	2.91	0.25	6.26	2.66	2.73
Scaled 1:100 000 ABM percentage improvements (+) or losses (−) relative to VAR(1)					
1q	10.9 (0.41)	0.8 (0.92)	16.4 (0.17)	9 (0.47)	−2.4 (0.88)
2q	3.9 (0.81)	1.8 (0.46)	7.4 (0.42)	3.5 (0.85)	0.4 (0.99)
4q	−0.1 (1.00)	−1.9 (0.01***)	4.2 (0.62)	24.4 (0.45)	5.4 (0.85)
8q	1.1 (0.98)	−1.5 (0.34)	0.3 (0.98)	30.5 (0.57)	19 (0.64)
12q	−4 (0.96)	−2.6 (0.47)	−0.3 (0.98)	29 (0.67)	19.5 (0.68)
Scaled 1:10 000 ABM percentage improvements (+) or losses (−) relative to VAR(1)					
1q	10.7 (0.42)	1.2 (0.89)	15.9 (0.18)	1.8 (0.90)	0.5 (0.97)
2q	3.2 (0.85)	**5.2 (0.02**)**	6.2 (0.48)	−2 (0.92)	1.1 (0.96)
4q	−1.2 (0.96)	−2.8 (0.29)	3.6 (0.67)	21.7 (0.52)	6.6 (0.83)
8q	−0.5 (0.99)	−0.9 (0.31)	−1.1 (0.93)	29.6 (0.60)	19.9 (0.66)
12q	−7.6 (0.93)	−0.1 (0.93)	−3.6 (0.82)	28.4 (0.68)	21.8 (0.73)
Scaled 1:1000 ABM percentage improvements (+) or losses (−) relative to VAR(1)					
1q	10 (0.45)	0.5 (0.95)	16.3 (0.17)	−0.7 (0.96)	0.5 (0.97)
2q	5.2 (0.76)	**4.8 (0.04**)**	7.5 (0.43)	2.2 (0.91)	2.9 (0.89)
4q	2.1 (0.93)	−1.1 (0.24)	4.7 (0.59)	25.1 (0.44)	6.4 (0.84)
8q	0.7 (0.99)	−1.4 (0.16)	−1.1 (0.94)	29.7 (0.58)	18.9 (0.71)
12q	−7.9 (0.93)	2.5 (0.47)	−4.6 (0.78)	28.7 (0.66)	19.5 (0.78)
Scaled 1:100 ABM percentage improvements (+) or losses (−) relative to VAR(1)					
1q	10.9 (0.41)	0.7 (0.93)	16.2 (0.17)	2.1 (0.88)	−0.1 (0.99)
2q	6.3 (0.70)	**4.8 (0.06*)**	7.9 (0.39)	0.4 (0.98)	0.9 (0.97)
4q	3 (0.89)	−2.8 (0.10*)	5.2 (0.52)	21.5 (0.49)	4.3 (0.89)
8q	4.3 (0.94)	−1.2 (0.16)	1.6 (0.89)	27.7 (0.60)	18.4 (0.72)
12q	−1.8 (0.98)	−1.2 (0.42)	−1.1 (0.94)	29 (0.66)	21 (0.76)
Scaled 1:10 ABM percentage improvements (+) or losses (−) relative to VAR(1)					
1q	9.5 (0.46)	1.7 (0.84)	14.9 (0.21)	4.9 (0.71)	−6 (0.72)
2q	4.6 (0.78)	**6.3 (0.02**)**	6.2 (0.51)	4.7 (0.81)	−4.2 (0.86)
4q	3.9 (0.86)	−1 (0.42)	4.8 (0.54)	25.2 (0.43)	2.8 (0.94)
8q	4.1 (0.94)	1.4 (0.32)	1.4 (0.90)	30.2 (0.58)	16.9 (0.75)
12q	−1.8 (0.98)	0 (0.99)	−0.9 (0.94)	29.1 (0.67)	20.4 (0.78)
Scaled 1:1 ABM percentage improvements (+) or losses (−) relative to VAR(1)					
1q	9.8 (0.46)	0.9 (0.91)	14.8 (0.21)	7 (0.58)	−9.8 (0.58)
2q	5 (0.77)	**4.5 (0.02**)**	6.4 (0.49)	4.3 (0.82)	−6.5 (0.79)
4q	2.8 (0.90)	−5 (0.00***)	4.6 (0.58)	25 (0.43)	0.7 (0.98)
8q	4.3 (0.94)	1 (0.62)	0.9 (0.94)	31 (0.56)	16.3 (0.77)
12q	−2 (0.98)	−1.2 (0.60)	−1.7 (0.90)	31.8 (0.63)	19.3 (0.79)

5. Longer forecasting exercise

In this section, we analyze the dynamics that emerge in the model once the forecasting horizon is extended to more than 12 quarters. Although we are fully aware that the model has a short-run perspective because forecasting is meaningful only in the short-run, this exercise is interesting in order to get a clue of the driving forces of the model. In other words, we can understand which dynamics determine the "short-run" forecasting results. Consequently, we also check if the elements embedded in the model are enough to describe realistic economic dynamics or if some other theoretical elements have to be added in order to have results grounded in a more comprehensive economic model.

Similar to the short-run analysis, also in this case, we use the revolving approach to study the model responses to the different initialization. The time horizon (T) is settled to 200 periods (50 years). Because of the massive computational effort, we run 100 Monte Carlo simulations for each initialization quarter and the scale of the model is set at 1:1000. In order to better visualize the results, we will plot the average of the Monte Carlo simulations, selecting only one initialization per year and, specifically, the first quarter. We will show simulations referred both to the Italian and the Austrian economy.

As is easily understandable from the Figs. 2(a)–3(a), the model is demand-led and the autonomous components, namely public expenditures, exports and imports (panel e, f, g of Figs. 2(a) and 2(b)), play a relevant role in determining the growth path of the economy. The dynamic of these autonomous components (except for the zero mean stochastic error shock) is settled from the very beginning of the simulation period. Indeed, the coefficients of the AR processes (α, β and σ), which define the level of expenditures over time, are time invariant and depend only on the time series recorded before the simulation quarter of initialization. As in Poledna et al. (2023), the starting year is

Table 4
Out-of-sample forecast performance in comparison to ARMA(p,q) model, for the AUSTRIAN economy. The stars represent the significance of the Diebold–Mariano test, which compares the predictive accuracy of two forecasts. The forecast period is 2010:Q2 to 2019:Q4. The ARMA(p,q) model is estimated each quarter from 2010:Q1 to 2016:Q3 and the time series data used for estimation begins from 1996:Q1. The ABM results are obtained as an average of 500 Monte Carlo simulations and are initialized in each quarter from 2010:Q1 to 2016:Q3. Percentage improvement (+) or losses (−) relative to ARMA(p,q) model.

	GDP	Inflation	Investments	Gov consumption	Household consumption
ARMA(p,q) specification					
AR	12	4,11,14	2	3	1 12
MA	1,2	–	–	–	–
ARMA RMSE-statistic for different forecast horizons					
1q	0.54	0.39	1.16	0.63	0.59
2q	0.77	0.37	1.91	0.77	0.84
4q	1.34	0.37	3.18	1.1	1.3
8q	2.21	0.31	4.31	1.84	2.1
12q	2.89	0.26	6.06	2.39	2.79
Scaled 1:100 000 ABM percentage improvements (+) or losses (−) relative to ARMA					
1q	0.4 (0.96)	9.1 (0.32)	3.5 (0.53)	−4.5 (0.70)	1.4 (0.92)
2q	−7.5 (0.67)	9.9 (0.23)	3.1 (0.67)	2.9 (0.84)	5 (0.81)
4q	−4.3 (0.88)	**14.4 (0.07*)**	2.4 (0.79)	14.2 (0.63)	11.8 (0.68)
8q	−1.5 (0.98)	0.2 (0.99)	−3 (0.86)	22.4 (0.64)	21.5 (0.60)
12q	−4.8 (0.95)	0.8 (0.91)	−3.7 (0.85)	21 (0.74)	21.4 (0.63)
Scaled 1:10 000 ABM percentage improvements (+) or losses (−) relative to ARMA					
1q	0.2 (0.98)	9.4 (0.30)	2.9 (0.60)	−12.7 (0.37)	4.1 (0.75)
2q	−8.3 (0.64)	13 (0.10)	1.9 (0.81)	−2.6 (0.88)	5.8 (0.78)
4q	−5.4 (0.86)	13.7 (0.14)	1.8 (0.84)	11.1 (0.73)	12.9 (0.67)
8q	−3.2 (0.96)	0.8 (0.94)	−4.5 (0.79)	21.4 (0.67)	22.3 (0.63)
12q	−8.4 (0.93)	3.3 (0.68)	−7 (0.74)	20.3 (0.75)	23.7 (0.69)
Scaled 1:1000 ABM percentage improvements (+) or losses (−) relative to ARMA					
1q	−0.6 (0.93)	8.7 (0.33)	3.4 (0.54)	−15.6 (0.30)	4.1 (0.71)
2q	−6 (0.73)	12.6 (0.13)	3.2 (0.66)	1.6 (0.92)	7.5 (0.72)
4q	−2 (0.95)	**15.1 (0.05**)**	2.9 (0.75)	15 (0.62)	12.7 (0.68)
8q	−2 (0.97)	0.3 (0.98)	−4.4 (0.79)	21.6 (0.66)	21.3 (0.67)
12q	−8.7 (0.92)	5.8 (0.46)	−8.1 (0.70)	20.6 (0.73)	21.4 (0.75)
Scaled 1:100 ABM percentage improvements (+) or losses (−) relative to ARMA					
1q	0.4 (0.96)	9 (0.33)	3.3 (0.55)	−12.3 (0.36)	3.6 (0.78)
2q	−4.8 (0.77)	12.6 (0.15)	3.6 (0.62)	−0.2 (0.99)	5.5 (0.80)
4q	−1.1 (0.97)	13.7 (0.11)	3.5 (0.69)	10.9 (0.70)	10.7 (0.73)
8q	1.7 (0.97)	0.6 (0.96)	−1.6 (0.91)	19.3 (0.69)	20.9 (0.68)
12q	−2.5 (0.98)	2.2 (0.63)	−4.5 (0.80)	21 (0.73)	22.8 (0.73)
Scaled 1:10 ABM percentage improvements (+) or losses (−) relative to ARMA					
1q	−1.2 (0.88)	9.8 (0.28)	1.9 (0.73)	−9.1 (0.49)	−2.1 (0.89)
2q	−6.8 (0.70)	**14 (0.09*)**	1.9 (0.78)	4.1 (0.79)	0.7 (0.98)
4q	−0.2 (0.99)	**15.2 (0.09*)**	3 (0.72)	15 (0.60)	9.3 (0.78)
8q	1.6 (0.98)	3.1 (0.76)	−1.8 (0.90)	22.1 (0.65)	19.4 (0.72)
12q	−2.5 (0.98)	3.4 (0.31)	−4.3 (0.81)	21.1 (0.74)	22.3 (0.75)
Scaled 1:1 ABM percentage improvements (+) or losses (−) relative to ARMA					
1q	−0.9 (0.91)	9.1 (0.33)	1.6 (0.77)	−6.8 (0.57)	−5.7 (0.71)
2q	−6.3 (0.72)	12.4 (0.16)	2.1 (0.77)	3.7 (0.80)	−1.5 (0.95)
4q	−1.3 (0.96)	11.8 (0.14)	2.8 (0.75)	14.8 (0.61)	7.4 (0.83)
8q	1.8 (0.97)	2.7 (0.83)	−2.4 (0.87)	23 (0.63)	18.9 (0.73)
12q	−2.8 (0.97)	2.2 (0.78)	−5.1 (0.78)	24.1 (0.70)	21.2 (0.77)

1996. Therefore, the long time span used to estimate the AR coefficients implies long memory and explains the general upward trend of the simulations, even in the middle of downturns.

The endogenous element of the demand side of the economy is represented by the actions of the private sector, which quarterly estimates, using an updated dataset with the last simulated observation in the previous period, both the coefficients and the variance of the AR processes. This affects both the final consumption and the investment level of the economy, as reported in panel h and i of Figs. 2(a) and 2(b). As shown in Figs. 3(a) and 3(b) panel b, the unemployment rate is closely connected to the real GDP.

Also, the supply side can play a role in the long-term: economic growth can be constrained by the unavailability of necessary supply factors. Given the model short-term nature, population and productivity levels are held constant, and the capital stock is fixed with no provision for net investments (as shown in Eq. (10)). This becomes evident in some Austrian simulations where the economy reaches full employment, as shown in Fig. 3(b) panel b.

Figs. 2(a) and 2(b) panel c, j, k, l show that the nominal component dominate the growth trajectory. However, the nominal variables do not play a crucial role because prices, profits, and wages tend to grow symmetrically and contemporaneously, driven by a smooth and homogeneous process of inflation expectations formation. As prices and

Table 5
Out-of-sample forecast performance in comparison to AR(1) model, for the ITALIAN economy. The stars represent the significance of the Diebold–Mariano test, which compares the predictive accuracy of two forecasts. The forecast period is 2010:Q2 to 2019:Q4. The AR(1) model is estimated each quarter from 2010:Q1 to 2019:Q3 and the time series data used for estimation begins from 1996:Q1. ABM results are obtained as an average of 500 Monte Carlo simulations and are initialized in each quarter from 2010:Q1 to 2019:Q3. Percentage improvement (+) or losses (−) relative to AR(1) model.

	GDP	Inflation	Investments	Gov consumption	Household consumption
AR(1) RMSE-statistic for different forecast horizons					
1q	0.37	0.34	1.46	0.61	0.42
2q	0.73	0.3	2.58	1.04	0.83
4q	1.51	0.32	4.95	1.88	1.72
8q	3.07	0.33	9.93	3.5	3.72
12q	4.22	0.36	13.69	4.98	5.18
Scaled 1:100 000 ABM percentage improvements (+) or losses (−) relative to AR(1)					
1q	−32.8 (0.02**)	**2.9 (0.00***)**	−5.9 (0.12)	**32.5 (0.00***)**	−43 (0.00***)
2q	−21.5 (0.15)	−0.4 (0.72)	−3.1 (0.45)	**30 (0.01**)**	−25.8 (0.07*)
4q	−2.4 (0.83)	−0.1 (0.94)	2.2 (0.68)	**26 (0.09*)**	−6.9 (0.67)
8q	13.7 (0.43)	−2 (0.11)	8.1 (0.22)	27.2 (0.26)	11.2 (0.49)
12q	17.8 (0.52)	−1 (0.30)	11.2 (0.19)	30.5 (0.35)	18 (0.52)
Scaled 1:10 000 ABM percentage improvements (+) or losses (−) relative to AR(1)					
1q	−32.8 (0.01**)	1.3 (0.38)	−5.7 (0.12)	**32 (0.02**)**	−35.5 (0.01***)
2q	−22 (0.14)	−1.2 (0.41)	−3.1 (0.47)	**32.9 (0.01**)**	−23.9 (0.10)
4q	−3.2 (0.79)	−0.4 (0.72)	2.1 (0.71)	**27.7 (0.09*)**	−6.9 (0.67)
8q	13.3 (0.39)	−0.5 (0.87)	7.9 (0.19)	27.4 (0.26)	10.1 (0.44)
12q	17.3 (0.45)	1.4 (0.42)	10.9 (0.12)	30.1 (0.36)	16.9 (0.47)
Scaled 1:1000 ABM percentage improvements (+) or losses (−) relative to AR(1)					
1q	−38.6 (0.01**)	0.2 (0.80)	−7.1 (0.08*)	**31.7 (0.01**)**	−44.5 (0.00***)
2q	−24.4 (0.13)	−1 (0.45)	−3.7 (0.39)	**31.9 (0.01**)**	−27.4 (0.06*)
4q	−5 (0.68)	−3.2 (0.00***)	1.4 (0.79)	**28.1 (0.08*)**	−8.6 (0.61)
8q	10.2 (0.37)	0.4 (0.70)	7 (0.15)	27.3 (0.26)	8.3 (0.41)
12q	15.1 (0.35)	−2 (0.22)	**10.2 (0.02**)**	30.3 (0.35)	15.2 (0.42)
Scaled 1:100 ABM percentage improvements (+) or losses (−) relative to AR(1)					
1q	−33.6 (0.01**)	**2.5 (0.02**)**	−6.1 (0.12)	**31.7 (0.01***)**	−41.5 (0.00***)
2q	−25.2 (0.12)	0.5 (0.72)	−4 (0.35)	**31.7 (0.01**)**	−26.5 (0.06*)
4q	−8 (0.55)	−0.3 (0.81)	0.6 (0.91)	**26.8 (0.09*)**	−9.1 (0.58)
8q	8.3 (0.36)	0.1 (0.96)	6.5 (0.13)	26.8 (0.26)	8.1 (0.39)
12q	13.7 (0.29)	−1.1 (0.31)	9.9 (0.00***)	29.7 (0.35)	15.1 (0.41)
Scaled 1:10 ABM percentage improvements (+) or losses (−) relative to AR(1)					
1q	−38.2 (0.01**)	−2.6 (0.47)	−7.2 (0.09*)	**30.7 (0.01***)**	−50.1 (0.00***)
2q	−23.7 (0.15)	−3.3 (0.00***)	−3.8 (0.40)	**29.1 (0.02**)**	−26.6 (0.06*)
4q	−5.7 (0.67)	1.2 (0.16)	1.2 (0.83)	**26.8 (0.09*)**	−8.1 (0.63)
8q	8.5 (0.38)	−1.4 (0.26)	6.5 (0.15)	27 (0.25)	7.8 (0.45)
12q	13.8 (0.32)	−2 (0.04**)	**9.8 (0.01***)**	29.9 (0.35)	15.1 (0.44)

wages increase at the same pace following expectations, real wages do not accelerate, even in the presence of a low unemployment, as observed for the Austrian economy. This results in a flat Phillips curve.

The expected increase in the price level is homogeneous across all agents in the private sector and affects all nominal variables (expected profits, loans, investments, expected income and then demand for consumption). Moreover, inflation grows mainly because of the built-in inflation which depends on the expectation that firms have in terms of inflation, while the cost-push inflation (reported in Figs. 3(a)–3(b) panel g) does not play a very relevant role and the demand-pull inflation (added in the model presented in Hommes and Poledna, 2023) is not included. All this, also prevents strong heterogeneity in sectoral inflation dynamics, thus eliminating the need for adjustments in the reshuffling of the consumption basket (such as shifts in consumer preferences or substitution effects between goods), which would be complicated in this model, where the allocation of expenditures among goods from different sectors is fixed in nominal terms.

In general, homogeneous expectations are a key feature of the model, indeed, they are also applied to the expected growth rate of the economy used by households and firms to set the desired consumption and the desired production respectively. In other words, all private sector agents share identical expectations regarding the economy's growth rate and inflation. These expectations are determined based on all available past GDP and inflation values, which are assumed to be common knowledge among all agents.

As already explained, the financial sphere is highly simplified, and it is composed of a single commercial bank and the central bank (CB), whose relationship is limited to the amount of interest-bearing reserves/advances, which emerge as a difference between the liabilities and the assets in the commercial bank balance sheet. The commercial bank grants loans and allows negative deposits, as well as ensuring that agents can deposit their savings.

However, the financial side does not strongly influence the aggregate economy. Indeed, at least in Poledna et al. (2023) (and differently from Hommes and Poledna (2023), where a financial accelerator is introduced), the loan granting does not affect significantly the total supply. If lending is constrained (due to banking system conditions or because of the firm financial conditions), firms continue with their production plans and, in case internal cash is not enough (for financing investments, wages, or other expenses), negative deposits are granted. Credit conditions only influence the probabilities of default, because firms default when both equity and deposits are negative. This appears clear when looking at the equity of the banking system. When the forecasting horizon is stretched, as shown in Figs. 3(a) and 3(b) panel

Table 6
Out-of-sample forecast performance in comparison to VAR(1) model, for the ITALIAN economy. The forecast period is 2010:Q2 to 2019:Q4. The AR(1) model is estimated each quarter from 2010:Q1 to 2019:Q3 and the time series data used for estimation begins from 1996:Q1. ABM results are obtained as an average of 500 Monte Carlo simulations and are initialized in each quarter from 2010:Q1 to 2019:Q3. Percentage improvement (+) or losses (−) relative to VAR(1) model.

	GDP	Inflation	Investments	Gov consumption	Household consumption
VAR(1) RMSE-statistic for different forecast horizons					
1q	0.41	0.31	1.25	0.65	0.4
2q	0.67	0.31	1.96	1	0.8
4q	1.29	0.31	3.77	1.77	1.67
8q	2.71	0.33	8.74	3.32	3.69
12q	3.9	0.35	12.9	4.75	5.19
Scaled 1:100 000 ABM percentage improvements (+) or losses (−) relative to VAR(1)					
1q	−20.1 (0.31)	−5.3 (0.06*)	−24 (0.22)	**36.5 (0.01**)**	−47.5 (0.00***)
2q	−32.3 (0.26)	2.3 (0.26)	−35.4 (0.19)	27.5 (0.12)	−29.6 (0.05**)
4q	−19.8 (0.50)	−0.4 (0.67)	−28.2 (0.34)	21.2 (0.29)	−9.9 (0.57)
8q	2.5 (0.77)	−2.4 (0.02**)	−4.5 (0.63)	23.3 (0.35)	10.4 (0.47)
12q	11 (0.36)	−1.3 (0.16)	5.7 (0.25)	27 (0.41)	18.3 (0.50)
Scaled 1:10 000 ABM percentage improvements (+) or losses (−) relative to VAR(1)					
1q	−20.2 (0.30)	−7 (0.02**)	−23.8 (0.22)	**36.1 (0.03**)**	−39.7 (0.00***)
2q	−32.8 (0.25)	1.5 (0.58)	−35.3 (0.19)	30.5 (0.10)	−27.7 (0.07*)
4q	−20.8 (0.49)	−0.7 (0.48)	−28.4 (0.34)	23 (0.27)	−10 (0.58)
8q	2.1 (0.81)	−0.9 (0.75)	−4.7 (0.65)	23.5 (0.36)	9.4 (0.40)
12q	10.5 (0.13)	1.1 (0.53)	5.4 (0.29)	26.6 (0.41)	17.1 (0.43)
Scaled 1:1000 ABM percentage improvements (+) or losses (−) relative to VAR(1)					
1q	−25.4 (0.22)	−8.2 (0.00***)	−25.5 (0.20)	**35.8 (0.03**)**	−49 (0.00***)
2q	−35.4 (0.24)	1.7 (0.46)	−36.2 (0.19)	29.5 (0.11)	−31.3 (0.04**)
4q	−22.9 (0.47)	−3.5 (0.00***)	−29.2 (0.34)	23.3 (0.26)	−11.7 (0.53)
8q	−1.4 (0.87)	−0.1 (0.95)	−5.7 (0.64)	23.4 (0.36)	7.5 (0.34)
12q	8.1 (0.31)	−2.3 (0.17)	4.7 (0.37)	26.8 (0.41)	15.4 (0.38)
Scaled 1:100 ABM percentage improvements (+) or losses (−) relative to VAR(1)					
1q	−20.9 (0.30)	−5.6 (0.01**)	−24.3 (0.21)	**35.9 (0.02**)**	−45.9 (0.00***)
2q	−36.4 (0.23)	**3.1 (0.08*)**	−36.6 (0.19)	29.3 (0.11)	−30.4 (0.04**)
4q	−26.4 (0.45)	−0.6 (0.68)	−30.3 (0.34)	22 (0.28)	−12.2 (0.51)
8q	−3.6 (0.46)	−0.3 (0.91)	−6.2 (0.64)	22.9 (0.36)	7.3 (0.31)
12q	6.6 (0.40)	−1.4 (0.20)	4.4 (0.41)	26.2 (0.41)	15.3 (0.36)
Scaled 1:10 ABM percentage improvements (+) or losses (−) relative to VAR(1)					
1q	−25 (0.23)	−11.2 (0.02**)	−25.6 (0.20)	**34.9 (0.02**)**	−54.8 (0.00***)
2q	−34.7 (0.25)	−0.5 (0.78)	−36.3 (0.19)	26.6 (0.13)	−30.5 (0.04**)
4q	−23.7 (0.48)	0.9 (0.48)	−29.6 (0.35)	22 (0.29)	−11.2 (0.55)
8q	−3.3 (0.71)	−1.8 (0.05*)	−6.2 (0.63)	23.1 (0.35)	7 (0.39)
12q	6.7 (0.39)	−2.3 (0.03**)	4.3 (0.41)	26.4 (0.40)	15.3 (0.39)

c, the effect of the insolvency is piled up over time and the bank equity becomes negative because of the non-performing loan. However, the economy keeps growing even if the conditions for loan granting are prevented, given the negative value of the bank equity.

In this model, money supply is completely endogenous, following the circuitist approach. There is no portfolio allocation; the only financial asset in the model is represented by the deposits which also serve as the source of final financing when loans are prevented.

The European central bank follows the Taylor rule with expectations exogenously driven because computed with an AR(1) process on European inflation and GDP growth. While the European CB sets the reference interest rate, the national central bank (CB) buys interest-bearing government bonds. The CB presents an equity led by its profits that, in turn, are mainly driven by the interests received on the public debt. In Austria, except for the simulations starting in 2010, the public debt shows a declining dynamic (see Fig. 3(b), panel a) that leads the debt to cancel out, and, therefore, the CB equity (panel d) often decreases in the second part of the simulations. Conversely, in Italy, the high level of public debt leads to continuous capital growth of the CB.

The model presents some "stabilization" mechanisms in addition to expectation coordination and the dynamics of the autonomous components. In particular, since the matching rounds are as many as needed, the total aggregate demand is always met if there is enough aggregate supply. Prioritization is observed within the matching mechanism, with input markets being satisfied first, followed by investment and consumption goods markets. There is also a well-defined hierarchy of priorities within the consumption sphere (state first and then households). Moreover, the excess demand is registered only by those firms that have spare capital so that in the following periods higher production is possible.

The investment function in the model relies on the "utilization rate" and is set at its equilibrium levels. In other words, firms acquire only the capital they expect to be depreciated. This can lead to underestimating investment when the capital has to be increased, because the capital growth is not included in the computation, and overestimating in the opposite case. Moreover, the capital good is uniform across all firms (for productive capital goods) and households (for dwellings).

Finally, the entry-exit mechanism operates smoothly, with one firm entering the market when another exits. Bankrupted firms maintain balance sheet continuity, except for the write-off of loans and negative deposits. Indeed, firms capital remains in the balance sheet of the entrant firm. Instead, the write-offs recorded by the banking system reduce the bank equity. Moreover, the equity of the new enterprise is taken from the bank's previous loan, functioning as a bail-in mechanism.

6. Some suggestions for improving the model

As already mentioned in Section 4, the model does not fully exploit the possibilities associated with agent heterogeneity. First, the calibration of the model relies on sectoral and macroeconomic data, which are assumed to remain invariant across a multitude of agents

Table 7
Out-of-sample forecast performance in comparison to ARMA(p,q) model, for the ITALIAN economy. The forecast period is 2010:Q2 to 2019:Q4. The ARMA(p,q) model is estimated each quarter from 2010:Q1 to 2019:Q3 and the time series data used for estimation begins from 1996:Q1. ABM results are obtained as an average of 500 Monte Carlo simulations and are initialized in each quarter from 2010:Q1 to 2019:Q3. Percentage improvement (+) or losses (−) relative to the associated ARMA(p,q) model.

	GDP	Inflation	Investments	Gov consumption	Household consumption
ARMA(p,q) specification					
AR(p)	–	1	1	2	1,2
MA(q)	1,2	–	–	–	–
ARMA RMSE-statistic for different forecast horizons					
1q	0.5	0.34	1.46	0.53	0.42
2q	0.92	0.3	2.58	0.89	0.82
4q	1.73	0.32	4.95	1.7	1.69
8q	3.2	0.33	9.93	3.27	3.71
12q	4.28	0.36	13.69	4.73	5.19
Scaled 1:100 000 ABM percentage improvements (+) or losses (−) relative to ARMA					
1q	0.7 (0.86)	**2.9 (0.00***)**	−5.9 (0.12)	**22.2 (0.02**)**	−42.4 (0.00***)
2q	3.8 (0.54)	−0.4 (0.71)	−3.1 (0.45)	**18.5 (0.05**)**	−26.8 (0.07*)
4q	10.8 (0.33)	−0.1 (0.94)	2.2 (0.68)	17.9 (0.15)	−8.4 (0.63)
8q	17.2 (0.35)	−2 (0.11)	8.1 (0.22)	22.2 (0.29)	10.8 (0.47)
12q	19 (0.47)	−1 (0.30)	11.2 (0.19)	26.8 (0.37)	18.3 (0.52)
Scaled 1:10 000 ABM percentage improvements (+) or losses (−) relative to ARMA					
1q	0.6 (0.87)	1.3 (0.38)	−5.7 (0.12)	**21.7 (0.08*)**	−34.9 (0.01***)
2q	3.5 (0.61)	−1.2 (0.41)	−3.1 (0.47)	**21.9 (0.04**)**	−24.9 (0.11)
4q	10.1 (0.34)	−0.4 (0.72)	2.1 (0.71)	19.8 (0.14)	−8.5 (0.64)
8q	16.8 (0.30)	−0.5 (0.87)	7.9 (0.19)	22.3 (0.30)	9.8 (0.40)
12q	18.5 (0.40)	1.4 (0.42)	10.9 (0.12)	26.5 (0.38)	17.2 (0.46)
Scaled 1:1000 ABM percentage improvements (+) or losses (−) relative to ARMA					
1q	−3.7 (0.30)	0.2 (0.80)	−7.1 (0.08*)	**21.3 (0.07*)**	−43.9 (0.00***)
2q	1.5 (0.79)	−1 (0.45)	−3.7 (0.39)	**20.7 (0.05**)**	−28.4 (0.06*)
4q	8.5 (0.35)	−3.2 (0.00***)	1.4 (0.79)	20.2 (0.13)	−10.1 (0.58)
8q	13.9 (0.25)	0.4 (0.70)	7 (0.15)	22.2 (0.29)	7.9 (0.35)
12q	16.3 (0.29)	−2 (0.22)	**10.2 (0.02**)**	26.7 (0.38)	15.5 (0.42)
Scaled 1:100 ABM percentage improvements (+) or losses (−) relative to ARMA					
1q	0.1 (0.99)	**2.5 (0.02**)**	−6.1 (0.12)	**21.4 (0.05*)**	−40.9 (0.00***)
2q	0.9 (0.86)	0.5 (0.72)	−4 (0.35)	**20.5 (0.05**)**	−27.6 (0.06*)
4q	5.9 (0.41)	−0.3 (0.81)	0.6 (0.91)	18.8 (0.14)	−10.7 (0.56)
8q	12.1 (0.20)	0.1 (0.96)	6.5 (0.13)	21.7 (0.30)	7.7 (0.31)
12q	14.9 (0.23)	−1.1 (0.31)	**9.9 (0.00***)**	26 (0.37)	15.4 (0.41)
Scaled 1:10 ABM percentage improvements (+) or losses (−) relative to ARMA					
1q	−3.4 (0.33)	−2.6 (0.48)	−7.2 (0.09*)	**20.1 (0.05**)**	−49.4 (0.00***)
2q	2.1 (0.72)	−3.3 (0.00***)	−3.8 (0.40)	**17.5 (0.07*)**	−27.6 (0.07*)
4q	7.9 (0.36)	1.2 (0.16)	1.2 (0.83)	18.8 (0.15)	−9.7 (0.60)
8q	12.3 (0.23)	−1.4 (0.26)	6.5 (0.15)	21.9 (0.29)	7.4 (0.39)
12q	15 (0.26)	−2 (0.04**)	**9.8 (0.01***)**	26.2 (0.37)	15.3 (0.43)

and during the same simulation. We suggest that households could exhibit an increasing propensity to consume as disposable income declines. Conversely, firms could have increasing returns to scale as size increases, balanced by higher costs for certain labor units, such as those representing top management.

Another area where the heterogeneity of agents should be increased is the formation of expectations. In Section 4.2, we have implemented some changes in the model, but additional improvements can be considered (for example, sectoral expectations could be modeled). Moreover, expectations, as introduced in Section 4.2, could be calculated in a rolling window with a shorter historical dataset.

Wages and prices rise according to the demand for labor and goods. Therefore, a demand-pull inflation mechanism should be incorporated. Of course, this opens up further issues to be resolved, especially if the model is not simulated for a very short period: if each sector has different inflation because sectoral demands are not aligned, then the consumption basket should be rebalanced using elasticities of substitution between goods.

The investment function of firms should be revised with the inclusion of the ability to raise capital in response to an increase in demand, without increasing (to its possible saturation) the rate of capital utilization.

Additionally, investment should also be linked to the financial situation of the firm: the assumption that credit is always granted anyway, either directly or through negative deposits, is not realistic. Firms should have an internal leverage target and face constraints from the financial system.

The financial system is oversimplified. It would be good to have more banks, and more importantly, banks should lend according to the capital held (following Basel rules), without the current negative deposit-granting mechanism. For loans, banks should fix a spread on the policy rate high enough to make positive profits. A spread that, as in reality, increases in crisis phases due to the increased risk premium. In addition, in the event that a bank's capital falls below the minimum required by financial supervision, recapitalization mechanisms should be introduced, because maintaining negative capital as is the case in simulations for the Austrian economy, shown in Fig. 3(b) panel c, is unrealistic in an economic model.

More broadly, the entry-exit mechanism could be improved. Indeed, the assumption for firms of one-to-one replacement can be replaced by a mechanism that decouples entries from exits, where entries are positively correlated with the business cycle.

Finally, the SAM that emerges from the model has the secondary income redistribution part moving smaller values than the empirical

Table 8
Out-of-sample forecast performance of the baseline Agent-Based Model (ABM) compared with various modifications, for the Italian economy. The stars represent the significance of the Diebold–Mariano test, which compares the predictive accuracy of two forecasts. The forecast period is 2010:Q2 to 2019:Q4. ABM results are obtained as an average of 500 Monte Carlo simulations and are initialized in each quarter from 2010:Q1 to 2019:Q3. AR_roll_3, AR_roll_5, and AR_roll_10 refer to shorter fixed AR(1) time windows of 3, 5, and 10 years, respectively. AR_rate corresponds to AR(1) calculated on the series of first differences of the logarithm of the data. EX_naive, EX_Strend, and EX_Wtrend refer to experiments where expectations are modeled as naive or as trend followers, with both strong and weak trends. The final experiment includes the level of inventories in firms' production planning.

	GDP	Inflation	Investments	Gov consumption	Household consumption
AR_roll_3 ABM percentage improvements (+) or losses (−) relative to baseline ABM					
1q	−6.2 (0.61)	**27.3 (0.00***)**	7 (0.10)	−17.2 (0.17)	−9.6 (0.44)
2q	−5.7 (0.73)	**17 (0.01**)**	**10.4 (0.10*)**	1.2 (0.92)	−9.9 (0.58)
4q	−6.5 (0.72)	**23 (0.01***)**	10.9 (0.13)	12.9 (0.26)	−14.3 (0.50)
8q	−3.1 (0.92)	**26.5 (0.01**)**	9.5 (0.33)	15.8 (0.26)	−16.7 (0.61)
12q	−10.8 (0.84)	**28.7 (0.08*)**	8.6 (0.48)	12.5 (0.37)	−7.3 (0.83)
AR_roll_5 ABM percentage improvements (+) or losses (−) relative to baseline ABM					
1q	−3.4 (0.69)	**31.6 (0.00***)**	2.5 (0.36)	−14.6 (0.07*)	−3.4 (0.70)
2q	−4.3 (0.74)	**21 (0.00***)**	2.6 (0.52)	−1.2 (0.88)	−7.3 (0.60)
4q	−7.9 (0.64)	**25.3 (0.01***)**	1.7 (0.78)	7.9 (0.49)	−12.2 (0.51)
8q	−14.3 (0.56)	**22.6 (0.00***)**	0.7 (0.92)	10.6 (0.28)	−11.9 (0.62)
12q	−15.5 (0.49)	**23.7 (0.03**)**	−1.6 (0.80)	6.3 (0.74)	−13.7 (0.60)
AR_roll_10 ABM percentage improvements (+) or losses (−) relative to baseline ABM					
1q	−7.3 (0.19)	**14.3 (0.00***)**	−0.8 (0.65)	−25.9 (0.00***)	−16.2 (0.01**)
2q	−11.8 (0.08*)	**13.4 (0.03**)**	−2.3 (0.34)	−2.5 (0.86)	−13.9 (0.10*)
4q	−14.3 (0.14)	**13 (0.06*)**	−3.4 (0.35)	10.5 (0.56)	−16.2 (0.08*)
8q	−15.2 (0.41)	7.6 (0.27)	−3.7 (0.43)	16.1 (0.42)	−15.2 (0.13)
12q	−20.5 (0.46)	7.9 (0.14)	−4.8 (0.48)	18.7 (0.47)	−17.2 (0.16)
AR_rate ABM percentage improvements (+) or losses (−) relative to baseline ABM					
1q	**28.7 (0.01**)**	−5 (0.07*)	**10.4 (0.02**)**	−3.9 (0.51)	**30.9 (0.00***)**
2q	14.8 (0.18)	−1.5 (0.67)	6.7 (0.11)	−6.7 (0.53)	21 (0.11)
4q	−15.2 (0.34)	3.5 (0.11)	−3.4 (0.50)	−22.3 (0.20)	−0.8 (0.94)
8q	−43 (0.33)	−1.7 (0.05**)	−10.9 (0.42)	−32.5 (0.30)	−24.4 (0.35)
12q	−51.6 (0.44)	−0.1 (0.97)	−12.5 (0.54)	−41.3 (0.37)	−32.4 (0.47)
EX_naive ABM percentage improvements (+) or losses (−) relative to baseline ABM					
1q	6.5 (0.23)	−2.5 (0.05**)	3.3 (0.12)	−0.9 (0.65)	−3.6 (0.43)
2q	3.6 (0.58)	2.6 (0.30)	2.2 (0.37)	−0.1 (0.96)	0 (1.00)
4q	1.7 (0.82)	**3.4 (0.01**)**	1.2 (0.67)	−0.3 (0.90)	0.7 (0.92)
8q	1.3 (0.89)	−0.9 (0.43)	0.6 (0.83)	0 (0.98)	1 (0.90)
12q	−0.7 (0.95)	1.5 (0.19)	0.1 (0.99)	0.2 (0.90)	0.7 (0.94)
EX_Strend ABM percentage improvements (+) or losses (−) relative to baseline ABM					
1q	6.5 (0.23)	−2.5 (0.05**)	3.3 (0.12)	−0.8 (0.70)	−3.7 (0.42)
2q	3.7 (0.54)	1.8 (0.47)	2.6 (0.35)	−0.4 (0.87)	0.1 (0.99)
4q	4 (0.46)	1.8 (0.30)	2 (0.39)	−1.4 (0.61)	2 (0.69)
8q	0.3 (0.95)	0.5 (0.79)	0.8 (0.64)	**9.3 (0.03**)**	−0.9 (0.50)
12q	−5.6 (0.87)	**7.7 (0.08*)**	−0.2 (0.98)	**14.7 (0.06*)**	−1.6 (0.92)
EX_Wtrend ABM percentage improvements (+) or losses (−) relative to baseline ABM					
1q	6.5 (0.23)	−2.5 (0.05**)	3.3 (0.12)	−0.8 (0.70)	−3.7 (0.42)
2q	3.7 (0.56)	1.8 (0.47)	2.2 (0.36)	−2.9 (0.30)	0.5 (0.92)
4q	2.3 (0.71)	**5.5 (0.01***)**	1.2 (0.61)	−3.6 (0.33)	1.1 (0.83)
8q	−0.6 (0.88)	−2.1 (0.00***)	0 (0.98)	−2.3 (0.44)	−0.4 (0.89)
12q	−2.7 (0.17)	0.1 (0.93)	−0.6 (0.41)	−2.4 (0.44)	−1.1 (0.64)
Inventories ABM percentage improvements (+) or losses (−) relative to baseline ABM					
1q	**2.8 (0.02**)**	−2.5 (0.05**)	**0.8 (0.03**)**	−2.4 (0.12)	**3.9 (0.00***)**
2q	2.7 (0.56)	0.4 (0.79)	1.3 (0.42)	**7.1 (0.06*)**	1.8 (0.30)
4q	4.7 (0.67)	1.2 (0.25)	2 (0.58)	**10.5 (0.01***)**	2 (0.68)
8q	5.3 (0.76)	0.5 (0.11)	1.8 (0.72)	**7.9 (0.03**)**	2.9 (0.73)
12q	2.2 (0.91)	−0.7 (0.51)	1 (0.86)	**6 (0.03**)**	2.1 (0.81)

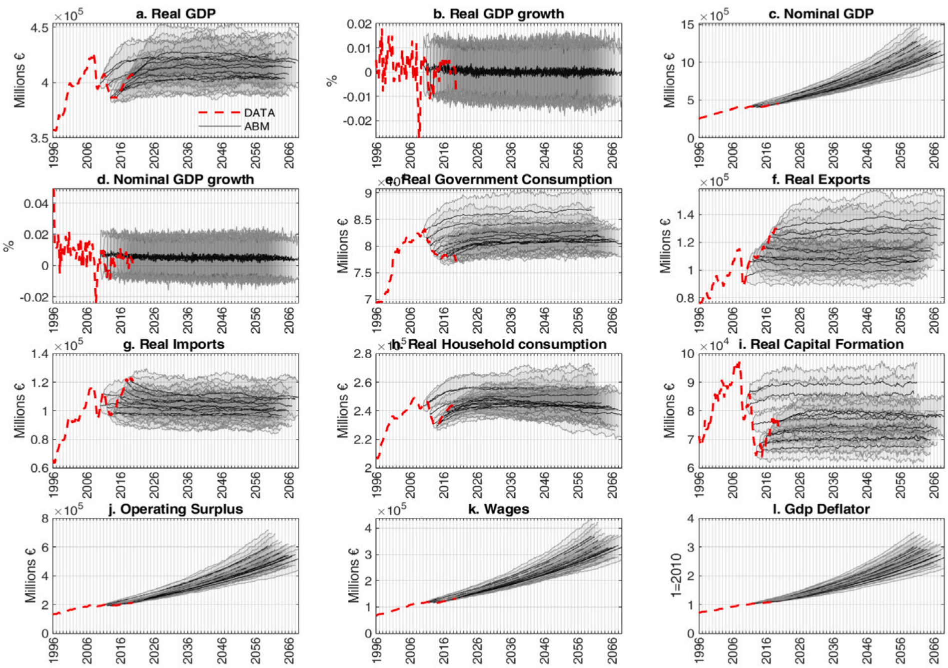
SAM, thus indicating the possibility of model improvement in the representation of redistribution mechanisms.

In general, the forecasting exercise should be evaluated with broader caveats in mind. Firstly, many dimensions of the model are treated as exogenous, particularly when considering the expectations of various goods and prices, with its specification relying on a simple AR(1) process. This choice may constrain the model's dynamic behavior and forecasting performance.

Secondly, recent advancements have introduced methods for estimating such models in a more empirically consistent manner (Alfarano et al., 2008; Grazzini and Richiardi, 2015). However, it is important to acknowledge that the model reconsidered here does not pursue this objective. Instead, it explicitly prioritizes an almost fully calibrated approach to parameter estimation, driven by data. Future research should focus on developing strategies for consistent estimation, calibration, and initialization, incorporating a broader historical dataset to enrich the model with a deeper understanding of historical economic and structural data generation processes.

Thirdly, another significant topic in recent literature is the challenge of approximating the true model through reduced-form representations (Barde, 2020; Lamperti, 2017). Such approaches aim to estimate the parameters of the model while ensuring econometric consistency.

(a) Italian Economy



(b) Austrian Economy

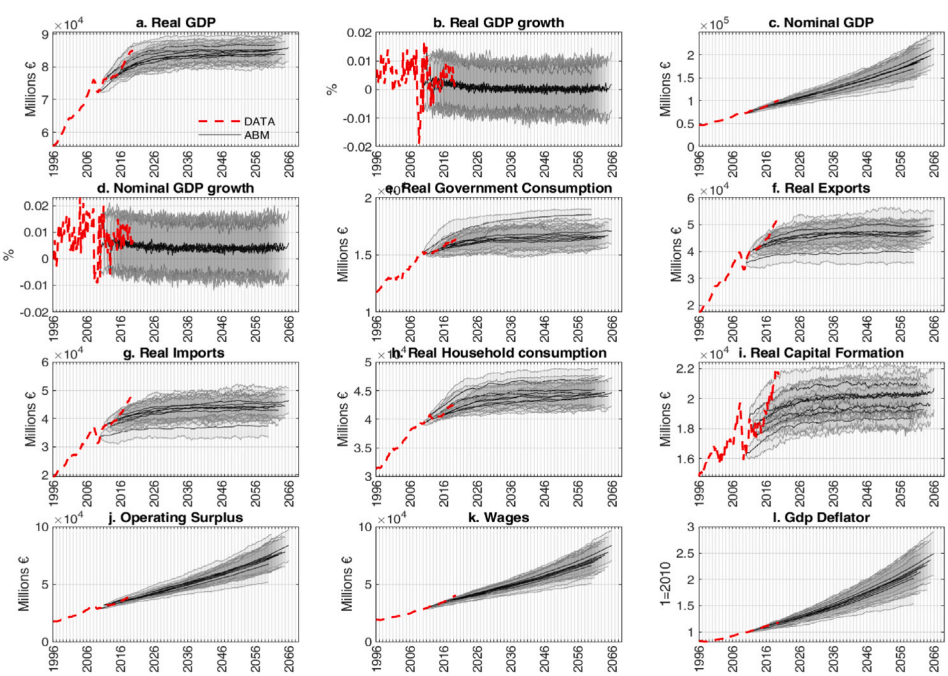
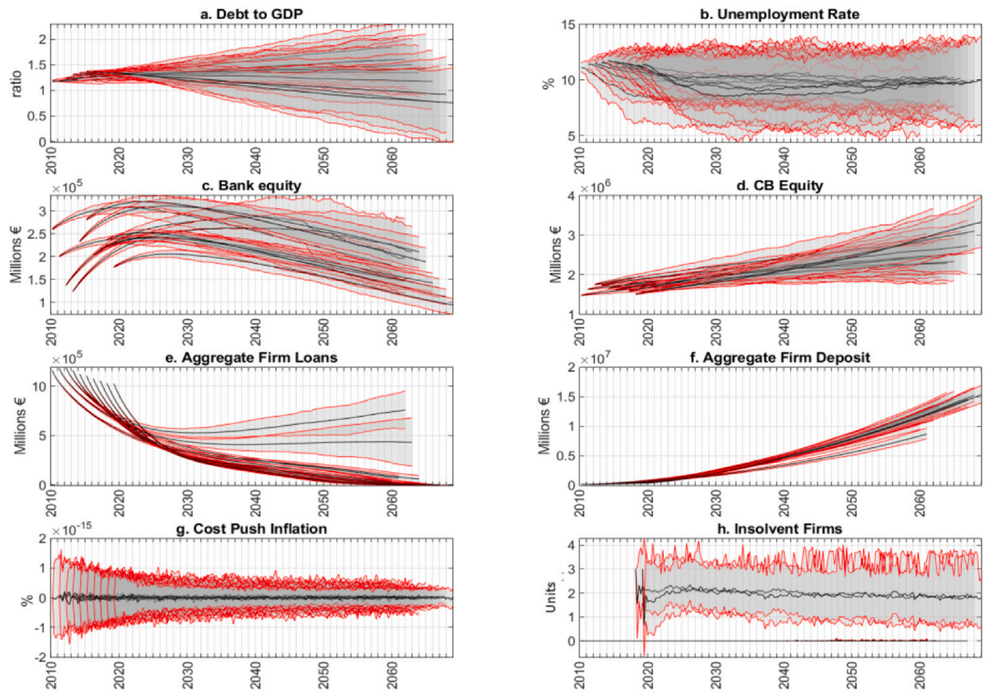


Fig. 2. Long-term simulations for the Italian and Austrian economies, spanning 200 quarters. The ABM is initialized from 2010 to 2019 for Italy, and from 2010 to 2016 for Austria. The graphs display the variables estimated in the simulations, with the results averaged over 100 Monte Carlo simulations. The red dotted line represents the empirical data, while the gray shaded area indicates the 10th to 90th percentile range of the Monte Carlo simulations. The black line represents the mean of the Monte Carlo simulations. The scale used is 1:1000.

7. Conclusions and future work

Agent-based macroeconomic models are flexible models, able to represent complex evolving systems. Due to their flexibility, ABMs have been applied in various domains and are particularly suitable for studying economic phenomena where heterogeneity, interactions, and nonlinearities are prominent (for instance, in the presence of domino effects, systemic risk, speculative bubbles, and credit crunches).

(a) Italian Economy



(b) Austrian Economy

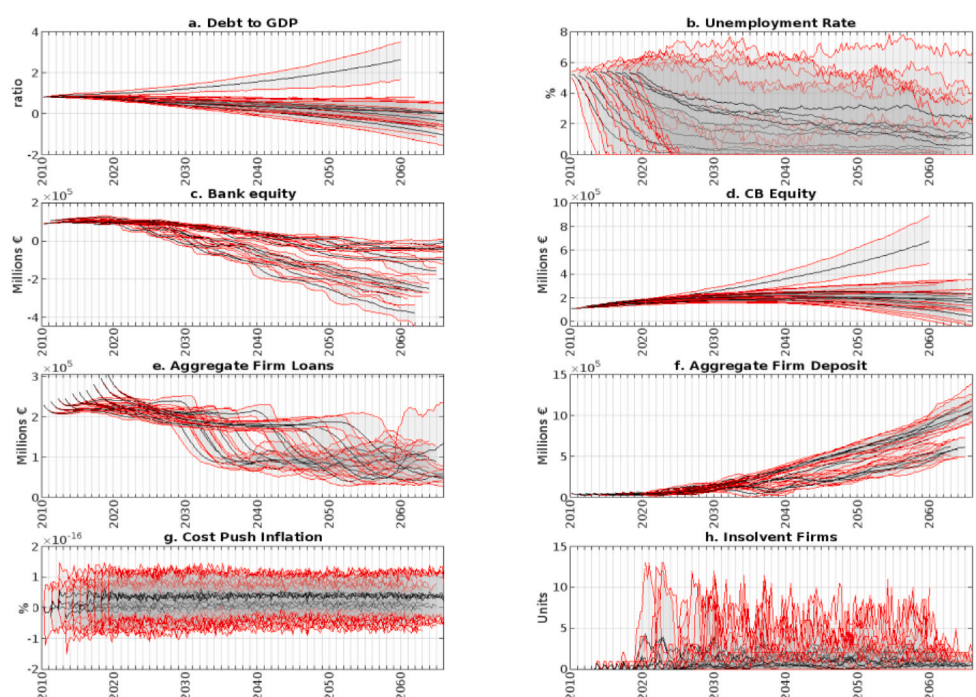


Fig. 3. Long-term simulations for the Italian and Austrian economies, spanning 200 quarters. The graphs display the variables estimated in the simulations, with the results averaged over 100 Monte Carlo simulations. The red shaded area indicates the 10th to 90th percentile range of the Monte Carlo simulations. The black line represents the mean of the Monte Carlo simulations. The scale used is 1:1000.

However, ABMs usually provide qualitative analysis only. ABM developers often validate their models by replicating "stylized facts" both at macroeconomic and microeconomic levels using artificial data generated by simulations based on calibrated parameters. A first attempt to provide a reliable quantitative forecast is performed by Poledna et al. (2023). They have the great merit to calibrate a macroeconomic ABM on a large set of empirical Austrian data. Using their model, we develop a data-driven ABM for the Italian economy. As a preliminary step, we replicate the simulations on the Austrian economy. Then, we calibrate the model parameters and initial conditions for the Italian economy.

We explore the forecasting performances of the model comparing the out of sample root mean square error of the model to the root mean square error of an AR(1) a VAR(1) and some ARMA models, using a rolling window forecast exercise from 2010 to 2019, with horizons equal to 1, 2, 4, 8, 12 quarters ahead. We find that, overall, the forecasting performance of the ABM is in line with that of all proposed econometric models and, in the medium term (2–3 years) the ABM seems to be able to do generally slightly better, while, given the high volatility in the Italian macroeconomic cycle, the ABM performs worse than the AR(1) when the forecasting horizon is short (≤4 quarters).

Here the question arises as to whether it is useful to forecast with an ABM, given that forecasts of the same level of accuracy can be obtained using econometric models that are much less complex than an ABM containing thousands or millions of agents. We think the answer is positive for a number of reasons. First of all, "a patchwork of models will be more resilient than a single methodology" as explained by Haldane and Turrell (2019) (see also the citation reported in the Introduction).

Second, ABMs, in their Monte Carlo replications, are able to create a range of possible trajectories and thus can provide a probability of crisis occurrence. Quoting (Haldane and Turrell, 2019) again, they said about DSGE models: "The most important point here is not that this set of models did not forecast the precise timing of the crisis. Almost by definition, costly financial crises cannot be forecast because, if they could, central banks and governments would take actions to prevent them. The real problem was that these models said nothing about the probability of a serious crisis arising endogenously at any time, or about the downstream consequences for the economy of a crisis once it had struck. The absence of nonrational expectations, heuristics and non-linear amplification channels was probably key in explaining these problems.", while they explain that "An ABM is a way to generate many possible, plausible realizations of variables".

Third, again following Haldane and Turrell (2019)'s reasoning, we need "models to handle fluctuations far from equilibrium", on which policy experiments can be run to figure out how to reduce the frequency or severity of crises, and ABMs allow experiments to be performed. They think that there are models better equipped than ABMs to perform forecasts, but "ABMs are better placed to produce conditional forecasts, where a particular policy is being explored".

Fourth, ABMs are able to incorporate both the macro level and the meso and micro levels. Thus, they can provide, in a single model, a set of predictions at various levels that are consistent with each other.

Finally, we are currently unable to say whether macro- and meso-level economic forecasting done with ABMs is capable of being more accurate than that done with other models. ABMs offer great flexibility and many possibilities for improvement, and already in many scientific fields forecasting is based on simulation models (think, for example, of meteorology). We believe, therefore, that a promising strand of studies can be developed on the real forecasting capabilities of ABM in macroeconomics. The Poledna et al. (2023) model can be one of the starting points for a number of possible improvements. However, it remains a starting point, functioning primarily as a macroeconomic model with real variables (lacking an adequately developed financial part), where microeconomic heterogeneity contributes only marginally to the results.

In fact, another important result found in our analyses is that the forecasting performance is invariant with respect to the scale. This property holds for the two economies and suggests a reflection on the interaction protocols and on the agents heterogeneity. Indeed, the interaction protocol allows for a smoothed matching and agents present a low level of heterogeneity. Perhaps, modifying the assumptions related to these aspects, the scale would matter, and an optimal scale (i.e., one that uses the smallest number of agents without affecting the dynamics of the simulations) could be found. This issue suggests further future investigations.

In Section 5, even if we know that the model has a short-run perspective because forecasting is meaningful only in the short-run, we evaluate the dynamic properties of the model extending the simulation to a long-run horizon. The long-run simulation shows the driving force of the model, that is generally demand-driven, and in particular is determined by expectations on the autonomous components of demand. Nominal component of the growth is the preponderant dimension, but it does not play a relevant role because prices, profits, and wages grow contemporaneously through a homogeneous process of inflation expectations. This is one of the stabilization mechanisms present in the model. Again, using heterogeneous expectations could modify the economic dynamics.

Moreover, we observe some dynamics that can be improved. Indeed, especially for financial variables, some non-stationary trends are detected. In addition, as already said, the financial sphere is very simplified and does not strongly influence the simulations. To improve this aspect, some behavioral rules could be modified.

In conclusion, we think the model developed by Poledna et al. (2023) is very promising because addresses the common critique of ABM "parameter wilderness", is quite robust to the change in geographic area over which it is applied (we show it can be quite easily extended to another EU country), and opens the field to the use of agent models in macroeconomics with a forecasting purpose, where the integration of macro, meso and micro levels could potentially lead to better forecasting. However, the short and long-run analyses show how the multitude of agents used is probably not fully exploited. Therefore, we suggest refining the model in order to increase heterogeneity and to increase frictions in coordination mechanisms, as well as changing some behavioral rules.

CRediT authorship contribution statement

Jacopo Di Domenico: Conceptualization, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft. **Michele Catalano:** Conceptualization, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft. **Luca Riccetti:** Supervision, Project administration, Funding acquisition, Conceptualization, Software, Validation, Formal analysis, Investigation, Writing – original draft.

Declaration of competing interest

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Appendix A. Tables

A.1. Parameters and initial conditions

See Tables A.9–A.12.

Table A.9
Replication of scalar parameters for Austrian economy in the fourth quarter of 2010.

Parameter	Description	Value
G/S	Number of products/industries	62
H^{act}	Number of economically active persons	4 729 215
H^{inact}	Number of economically inactive persons	4 130 385
J	Number of government entities	152 820
L	Number of foreign consumers	305 639
τ^{INC}	Income tax rate	0.2134
τ^{FIRM}	Corporate tax rate	0.0762
τ^{VAT}	Value-added tax rate	0.1529
τ^{SIF}	Social insurance rate (employers' contributions)	0.2122
τ^{SIW}	Social insurance rate (employees' contributions)	0.1711
τ^{EXPORT}	Export tax rate	0.0029
τ^{CF}	Tax rate on capital formation	0.0876
τ^{G}	Tax rate on government consumption	0.0091
r^{G}	Interest rate on government bonds	0.0091
μ	Risk premium on policy rate	0.0293
ψ	Fraction of income devoted to consumption	0.9394
ψ^{H}	Fraction of income devoted to investment in housing	0.0736
θ^{DIV}	Dividend payout ratio	0.7768
θ^{UB}	Unemployment benefit replacement rate	0.3586
θ	Rate of instalment on debt	0.05
ζ	Banks' capital ratio	0.03
ζ^{LTV}	Loan-to-value (LTV) ratio	0.6
ζ^{b}	Loan-to-capital ratio for new firms after bankruptcy	0.5
π^{*}	Inflation target of the monetary authority	0.005
α^{G}	Autoregressive coefficient for government consumption	0.9845
β^{G}	Scalar constant for government consumption	0.1515
σ^{G}	Standard deviation of government consumption	0.0112
α^{E}	Autoregressive coefficient for exports	0.9693
β^{E}	Scalar constant for exports	0.3261
α^{I}	Autoregressive coefficient for imports	0.974
β^{I}	Scalar constant for imports	0.2762
$\alpha^{Y^{EA}}$	Autoregressive coefficient for euro area	0.9673
$\beta^{Y^{EA}}$	Scalar constant for euro area GDP	0.4817
$\alpha^{\pi^{EA}}$	Autoregressive coefficient for euro area inflation	0.3834
$\beta^{\pi^{EA}}$	Scalar constant for euro area inflation	0.0026
$\sigma^{\pi^{EA}}$	Standard deviation of euro area inflation	0.0025
ρ	Adjustment coefficient of the policy rate	0.9263
r^{*}	Real equilibrium interest rate	−0.0034
ξ^{π}	Weight of the inflation target	0.3214
ξ^{γ}	Weight of economic growth	1.2994

Table A.10
Scalar parameters for Italian economy in the fourth quarter of 2010.

Parameter	Description	Value
G/S	Number of products/industries	62
H^{act}	Number of economically active persons	26 412 486
H^{inact}	Number of economically inactive persons	33 448 449
J	Number of government entities	1 233 828
L	Number of foreign consumers	1 233 828
τ^{INC}	Income tax rate	0.1958
τ^{FIRM}	Corporate tax rate	0.0479
τ^{VAT}	Value-added tax rate	0.1202
τ^{SIF}	Social insurance rate (employers' contributions)	0.386
τ^{SIW}	Social insurance rate (employees' contributions)	0.0884
τ^{EXPORT}	Export tax rate	0.0019
τ^{CF}	Tax rate on capital formation	0.1725
τ^{G}	Tax rate on government consumption	0.002
r^{G}	Interest rate on government bonds	0.0099
μ	Risk premium on policy rate	0.0177
ψ	Fraction of income devoted to consumption	0.8837
ψ^{H}	Fraction of income devoted to investment in housing	0.0944
θ^{DIV}	Dividend payout ratio	0.8072
θ^{UB}	Unemployment benefit replacement rate	0.4032
θ	Rate of instalment on debt	0.05
ζ	Banks' capital ratio	0.03
ζ^{LTV}	Loan-to-value (LTV) ratio	0.6

(*continued on next page*)

Table A.10 (*continued*).

Parameter	Description	Value
ζ^b	Loan-to-capital ratio for new firms after bankruptcy	0.5
π^*	Inflation target of the monetary authority	0.005
α^G	Autoregressive coefficient for government consumption	0.9658
β^G	Scalar constant for government consumption	0.3837
σ^G	Standard deviation of government consumption	0.0081
α^E	Autoregressive coefficient for exports	0.9448
β^E	Scalar constant for exports	0.6413
α^I	Autoregressive coefficient for imports	0.943
β^I	Scalar constant for imports	0.6377
$\alpha^{Y^{EA}}$	Autoregressive coefficient for euro area	0.9673
$\beta^{Y^{EA}}$	Scalar constant for euro area GDP	0.483
$\alpha^{\pi^{EA}}$	Autoregressive coefficient for euro area inflation	0.3999
$\beta^{\pi^{EA}}$	Scalar constant for euro area inflation	0.0025
$\sigma^{\pi^{EA}}$	Standard deviation of euro area inflation	0.0025
ρ	Adjustment coefficient of the policy rate	0.9279
r^*	Real equilibrium interest rate	−0.0036
ξ^π	Weight of the inflation target	0.2816
ξ^γ	Weight of economic growth	1.3327

Table A.11
Initial conditions for the Austria and Italian economy in the fourth quarter of 2010.

Initial condition	Description	Value
Austria		
D^H	Initial personal assets (deposits) of the household sector	222 933
D^I	Initial liquidity (deposits) of the firm sector (in mln. Euro)	52 141
D^{RoW}	Initial net creditor/debtor position of the national economy to RoW (in mln. Euro)	0
E^{CB}	Initial central banks' equity (in mln. Euro)	107 627.8
E_k	Initial banks' equity (in mln. Euro)	106 948
K^H	Initial capital (dwellings) of the household sector (in mln. Euro)	405376,9
L^G	Initial government debt (in mln. Euro)	244 696.8
L^I	Initial debt of the firm sector (in mln. Euro)	244 953
ω	Desired capacity utilization rate	0.85
sb^{inact}	Initial pension/social benefits in mln. Euro	0.002
sb^{other}	Initial social benefits received by all households in mln. Euro	0.0004
w^{UB}	Initial unemployment benefits (in mln. Euro)	0.004
C^G	Consumption of the government (in mln. Euro)	15 336
C^E	Exports (in mln. Euro)	35 493
Y^I	Imports (in mln. Euro)	34 455
Italy		
D^H	Initial personal assets (deposits) of the household sector	1 142 204
D^I	Initial liquidity (deposits) of the firm sector (in mln. Euro)	240 052
D^{RoW}	Initial net creditor/debtor position of the national economy to RoW (in mln. Euro)	0
E^{CB}	Initial central banks' equity (in mln. Euro)	1 573 874.2
E_k	Initial banks' equity (in mln. Euro)	189 493
K^H	Initial capital (dwellings) of the household sector (in mln. Euro)	2 571 723.9
L^G	Initial government debt (in mln. Euro)	1 920 620.2
L^I	Initial debt of the firm sector (in mln. Euro)	1 225 003
ω	Desired capacity utilization rate	0.85
sb^{inact}	Initial pension/social benefits in mln. Euro	0.00139
sb^{other}	Initial social benefits received by all households in mln. Euro	0.000279
w^{UB}	Initial unemployment benefits (in mln. Euro)	0.00106
C^G	Consumption of the government (in mln. Euro)	71 429
C^E	Exports (in mln. Euro)	113 201
Y^I	Imports (in mln. Euro)	73 878

A.2. Social accounting matrices tables

See Tables A.13–A.14.

Table A.12

Sectoral parameters. Value for Italy 2010:Q4. I_s is the number of firms/investors in the sth industry, N_s is the employment in the sth industry, α_s is the average productivity of labor of the sth industry, β_s is the productivity of intermediate consumption of the sth industry, κ_s is the productivity of capital of the ith firm, δ_s is the depreciation rate for capital of the sth industry, w_s is the average wage rate of the sth industry, τ_s^Y si the net tax rate on products of sth industry, τ_s^K is the net tax rate on production of the sth industry, b_g^{CF} is the capital formation coefficient of the gth product (firm investment), b_g^{CFH} is the household investment coefficient of the gth product, b_g^{HH} is the consumption coefficient of the gth product of households, c_g^G is the consumption of the gth product of the government in mln. Euro, c_g^E is the exports of the gth product in mln. Euro, c_g^I is the imports of the gth product in mln. Euro.

	I_s	N_s	α_s	β_s	κ_s	δ_s	w_s	τ_s^Y	τ_s^K	b_g^{CF}	b_g^{CFH}	b_g^{HH}	c_g^G	c_g^E	c_g^I
A01	389 063	769 030	0.0164	2.7536	0.0924	0.0187	0.0014	0.0069	−0.043	0.0018	0	0.017	0	0.0118	0
A02	5 849	14 143	0.0257	11.7412	0.1138	0.0269	0.0066	0.0037	0.0286	0	0	0.0005	0.0014	0.0002	0.0001
A03	8 540	25 923	0.0209	3.4497	0.0836	0.0107	0.003	0.0093	−0.0185	0.0002	0	0.0026	0	0.0004	0.002
B	2 538	34 872	0.0714	2.2888	0.0878	0.0129	0.0062	0.0074	0.0201	0.0004	0	0.0127	0	0.0021	0.1635
C10–12	57 953	435 554	0.0646	1.3373	0.6166	0.0296	0.0046	0.0047	0.0052	0	0	0.0765	0	0.0415	0.052
C13–15	65 833	517 848	0.0336	1.4729	0.7969	0.0324	0.0037	0.0102	0.007	0.0014	0	0.0338	0	0.0665	0.061
C16	33 805	139 290	0.024	1.5922	0.4562	0.0298	0.0027	0.0093	0.0086	0.0037	0	0.0009	0	0.0027	0.0087
C17	13 579	97 817	0.0553	1.4047	0.7015	0.0402	0.0053	0.0036	0.0079	0	0	0.0032	0	0.011	0.0141
C18	7 680	77 453	0.0398	1.7129	0.3886	0.0254	0.0053	0.0044	0.0057	0	0	0.0004	0	0.0017	0
C19	328	16 353	0.7995	1.1217	0.5103	0.0192	0.021	0.0069	0.0032	0	0	0.0201	0	0.0243	0.0252
C20	3 645	108 453	0.1088	1.391	0.4282	0.0303	0.0082	0.0154	0.006	0	0	0.0068	0	0.041	0.0827
C21	1457	69 254	0.0688	1.7237	0.4147	0.0333	0.0082	0.0052	0.0115	0	0	0.0037	0.0183	0.025	0.0447
C22	11 023	184 583	0.0483	1.4824	0.4663	0.0292	0.0054	0.008	0.009	0.0008	0	0.0058	0	0.0234	0.0155
C23	22 801	216 632	0.036	1.6116	0.3964	0.031	0.0046	0.0088	0.0074	0.0011	0	0.002	0	0.0158	0.0043
C24	29 219	177 657	0.0668	1.265	1.1157	0.0615	0.0049	0.0032	0.0039	0.0001	0	0	0	0.0425	0.0727
C25	48 205	514 636	0.0382	1.5929	0.4184	0.0249	0.0049	0.005	0.008	0.0354	0	0.0029	0	0.0299	0.0099
C26	5 472	112 684	0.0456	1.7882	0.3389	0.0318	0.0056	0.0046	0.0085	0.0481	0	0.0099	0	0.0214	0.1025
C27	9 955	171 650	0.0524	1.4756	0.5249	0.0308	0.0056	0.0045	0.0054	0.0146	0	0.0057	0	0.0367	0.0311
C28	24 817	462 776	0.0462	1.5101	0.584	0.0298	0.0057	0.0054	0.0065	0.1079	0	0.0016	0	0.1152	0.0696
C29	3 437	158 126	0.0584	1.4107	0.3813	0.0264	0.0054	0.0046	0.0039	0.036	0	0.0226	0	0.0431	0.0903
C30	1 758	106 440	0.0449	1.5499	0.335	0.027	0.0054	0.0069	0.0038	0.032	0	0.0033	0	0.023	0.0246
C31_32	52 392	293 276	0.0336	1.5886	0.6591	0.0382	0.0041	0.0094	0.0088	0.0218	0	0.0145	0	0.0351	0.0235
C33	39 207	167 088	0.0384	1.7906	0.5457	0.0404	0.0055	0.0101	0.0099	0.071	0	0	0	0	0.007
D	4 097	86 595	0.2187	1.6621	0.0987	0.0135	0.0087	−0.0089	0.0126	0	0	0.0159	0.0001	0.0179	0
E36	1 251	29 467	0.0512	2.2967	0.1662	0.0297	0.006	0.0553	0.0203	0	0	0.0044	0.0007	0.0024	0
E37–39	7 523	151 520	0.053	1.5394	0.2833	0.0204	0.006	0.0209	0.0139	0	0	0.0082	0	0.0024	0.0027
F	619 911	1 845 391	0.0297	1.5502	0.9678	0.0337	0.0031	0.007	0.0099	0.256	1	0.0085	0.0039	0.0004	0.0236
G45	120 582	405 361	0.0221	1.7596	0.6666	0.0275	0.0028	0.0077	0.0152	0.0155	0	0.0288	0	0.0023	0
G46	415 233	1 212 358	0.0304	1.899	0.5328	0.0285	0.0035	0.008	0.0118	0.0571	0	0.0647	0.003	0.0185	0
G47	658 262	1 922 113	0.0153	2.437	0.437	0.0258	0.0024	0.0093	0.0125	0.0389	0	0.1123	0.0101	0.0196	0
H49	110 105	560 080	0.0376	2.2665	0.1305	0.0092	0.0051	0.0387	0.0031	0.0056	0	0.0315	0.0021	0.0154	0
H50	1 609	29 128	0.0806	1.8204	0.2614	0.0668	0.0051	0.0065	−0.0279	0.0003	0	0.0029	0	0.0108	0
H51	235	24 088	0.0589	1.2774	0.6885	0.0125	0.0062	0.0052	−0.0008	0	0	0.0061	0	0.0026	0.0166
H52	22 651	342 123	0.0468	2.0578	0.1816	0.0248	0.0055	0.0101	0.017	0	0	0.0082	0.0172	0.0223	0
H53	2121	163 441	0.0075	2.4715	0.3705	0.0133	0.0024	0.0289	0.005	0	0	0.0008	0	0.0004	0.0002
I	301 485	1 287 210	0.0201	2.2747	0.2909	0.0197	0.0031	0.0133	0.0097	0	0	0.1023	0.0028	0.0097	0
J58	6 415	42 122	0.0823	1.7797	0.5045	0.0249	0.0115	0.006	0.0122	0.0101	0	0.0069	0	0.0027	0.0028
J59_60	8 762	62 615	0.0598	1.9385	0.3955	0.0457	0.0061	0.0034	−0.0004	0.0051	0	0.0054	0	0.0027	0
J61	3 878	100 093	0.1068	2.2791	0.3015	0.0258	0.0077	0.0017	0.0131	0	0	0.0214	0	0.0089	0
J62_63	81 634	369 792	0.0343	2.2812	0.6258	0.065	0.0056	0.0116	0.0134	0.0783	0	0.0001	0.0014	0.003	0.0057
K64	3 807	381 637	0.0476	3.1302	0.3323	0.0146	0.0104	0.0319	0.0326	0	0	0.0187	0	0.0042	0
K65	212	43 289	0.0952	1.522	0.9651	0.0195	0.0104	0.0576	0.0212	0	0	0.0158	0	0.0025	0.0052
K66	83 403	170 933	0.0427	2.7366	0.2722	0.0067	0.007	0.0346	0.0225	0.0006	0	0.0022	0	0.0033	0.0049
L68A	223 086	348 646	0.1799	8.8812	0.3735	0.0824	0.0017	0.003	0.0088	0.0457	0	0.1783	0.0046	0.1174	0
M69_70	324 817	622 133	0.0282	2.7627	0.9846	0.0253	0.0028	0.0087	0.0112	0.0118	0	0.0044	0	0.0031	0.0039
M71	228 899	324 837	0.0321	2.2545	1.1888	0.051	0.0028	0.0086	0.0092	0	0	0.0014	0.0006	0.0045	0
M72	8 662	25 056	0.2649	2.1993	0.1481	0.0127	0.0555	0.0178	0.0147	0.0958	0	0.0002	0.0005	0.0032	0.0141
M73	20 681	62 062	0.0959	1.5477	2.023	0.064	0.0089	0.0088	0.0067	0	0	0	0	0.0031	0.0032
M74_75	139 091	211 674	0.0268	2.3144	0.911	0.0345	0.0023	0.0087	0.0096	0	0	0.0024	0.0018	0.0041	0.0036
N77	16 620	48 102	0.1544	2.075	0.3155	0.0534	0.0114	0.0086	0.0127	0	0	0.0014	0	0.0064	0
N78	1 261	218 817	0.0064	7.0993	5.4788	0.1292	0.0037	0.0052	0.0037	0	0	0.0006	0.0003	0.0017	0.0021
N79	14 410	49 485	0.0573	1.1946	1.0995	0.0121	0.0035	0.0022	0.0001	0	0	0.0063	0.0009	0.0025	0.004
N80–82	119 627	808 202	0.0154	2.0062	0.4371	0.0184	0.003	0.0122	0.0117	0	0	0.0041	0.0051	0.006	0.0021
O	10 000	251 139	0.142	5.5942	0.0605	0.0107	0.0436	0.0225	0.0251	0	0	0.0017	0.4003	0.0557	0
P	25 181	89 573	0.1906	7.442	0.524	0.0161	0.0998	0.0136	0.0273	0	0	0.014	0.1809	0.0045	0
Q86	236 485	466 458	0.0581	3.059	0.3895	0.0207	0.0155	0.0356	0.0264	0	0	0.02	0.2772	0.0126	0
Q87_88	10 635	269 813	0.0194	2.3429	0.7097	0.0247	0.0056	0.0347	0.0138	0	0	0.0048	0.0485	0.0016	0
R90–92	35 198	79 554	0.0738	2.0025	0.2676	0.0194	0.0082	0.0338	0.0072	0.0015	0	0.0136	0.0126	0.0022	0
R93	27 050	87 740	0.0316	1.8229	0.4249	0.0359	0.0042	0.027	0.0085	0	0	0.0049	0.0037	0.0021	0
S94	36 588	123 919	0.0111	1.9605	1.6561	0.065	0.0024	0.0391	0.0127	0	0	0.0031	0.0016	0.0005	0
S95	19 982	35 867	0.0214	2.0955	0.5873	0.0335	0.0024	0.0087	0.0124	0.0009	0	0.0017	0	0.0002	0.0005
S96	145 305	285 748	0.0194	3.2449	0.3807	0.0189	0.0024	0.0139	0.0098	0	0	0.0256	0.0002	0.0024	0

Table A.13
General Social Accounting Matrix emerging from the model.

	Commodities	Labor factor	Gross operating surplus	Net taxes on commodities	Net taxes on activities	Taxes on income	Household	Corporation	Government	ROW	Gross capital formation
Commodities	Intermediate consumption						Household consumption		Government consumption	Exports	Capitalformation (inventory changes+fixed capital formation -dwellings + other)
Labor factor	Compensation employees										
Gross operating surplus	Operating surplus+capital consumption										
Net taxes on commodities	Taxes products										
Net taxes on activities	Taxes production										
Taxes on income							Income tax	Corporate tax+capital taxes			
Household		Compensation employees	Operating surplus+capital consumption				Property income+mixed income		Unemployment benefits+pension benefits+social benefits		
Corporation											
Government				Taxes products	Taxes production	Income tax+corporate tax+capital taxes	Social contributions-(compensation employees-wages)	Compensation employees-wages			
ROW	Imports										
Gross capital formation							Residually	Residually	Residually		

Table A.14
Social Accounting Matrix. Austria, year 2010. Italy, year 2010.

Austria (2010)	Commodities	Labor factor	Gross operating surplus	Net taxes on commodities	Net taxes on activities	Taxes on income	Household	Corporation	Government	ROW	Gross capital formation	TOT
Commodities	677 699.79	0	0	0	0	0	141 936.6	0	59 503.92	137 526.32	63 767.38	1 080 434.01
Labor factor	138 728.42	0	0	0	0	0	0	0	0	0	0	138 728.42
Gross operating surplus	119 459.83	0	0	0	0	0	0	0	0	0	0	119 459.83
Net taxes on commodities	6697.6	0	0	0	0	0	0	0	0	0	0	6697.6
Net taxes on activities	3950.45	0	0	0	0	0	0	0	0	0	0	3950.45
Taxes on income	0	0	0	0	0	0	37 520.8	5799.8	0	0	0	43 320.6
Household	0	138 728.42	119 459.83	0	0	0	54 200	0	98 253.1	0	0	410 641.35
Corporation	0	0	0	0	0	0	0	0	0	0	0	0
Government	0	0	0	6697.6	3950.45	43 320.6	19 587.67	24 280.33	0	0	0	97 836.65
ROW	133 897.95	0	0	0	0	0	0	0	0	0	0	133 897.95
Gross capital formation	0	0	0	0	0	0	157 396.28	−30 080.13	−59 920.37	−3628.37	0	63 767.41
TOT	1 080 434.04	138 728.42	119 459.83	6697.6	3950.45	43 320.6	410 641.35	0	97 836.65	133 897.95	63 767.38	2 098 734.27
Italy (2010)	Commodities	Labor factor	Gross operating surplus	Net taxes on commodities	Net taxes on activities	Taxes on income	Household	Corporation	Government	ROW	Gross capital formation	TOT
Commodities	3 521 307.73	0	0	0	0	0	869 306.79	0	326 990.25	375 855.27	314 224.43	5 407 684.47
Labor factor	624 335.28	0	0	0	0	0	0	0	0	0	0	624 335.28
Gross operating surplus	764 410.83	0	0	0	0	0	0	0	0	0	0	764 410.83
Net taxes on commodities	39 805.39	0	0	0	0	0	0	0	0	0	0	39 805.39
Net taxes on activities	36 494	0	0	0	0	0	0	0	0	0	0	36 494
Taxes on income	0	0	0	0	0	0	226 675	39 676	0	0	0	266 351
Household	0	624 335.28	764 410.83	0	0	0	580 393	0	527 161	0	0	2 496 300.11
Corporation	0	0	0	0	0	0	0	0	0	0	0	0
Government	0	0	0	39 805.39	36 494	266 351	39 802.53	173 876.47	0	0	0	556 329.39
ROW	421 331.24	0	0	0	0	0	0	0	0	0	0	421 331.24
Gross capital formation	0	0	0	0	0	0	780 122.79	−213 552.47	−297 821.86	45 475.97	0	314 224.43
TOT	5 407 684.47	624 335.28	764 410.83	39 805.39	36 494	266 351	2 496 300.11	0	556 329.39	421 331.24	314 224.43	10 927 266.14

Appendix B. Figures

B.1. Replication of the parameters of the model of Poledna et al. (2023) for Austria

The figures show the values of the initial conditions and parameters for Austria, for any rolling window of calibration 2010:Q1-2016:Q4, found by Poledna et al. (2023) and by us. As can be seen, the series coincide and thus the lines in the figures overlap.

B.2. Parameters and initial conditions for Austrian and Italian economies

In the following we show the initial conditions and parameters value for any rolling window of calibration 2010:Q1-2016:Q4 for Austria and 2010:Q1-2019:Q4 for Italy.

B.3. Parameters value for different scales

See Fig. B.8.

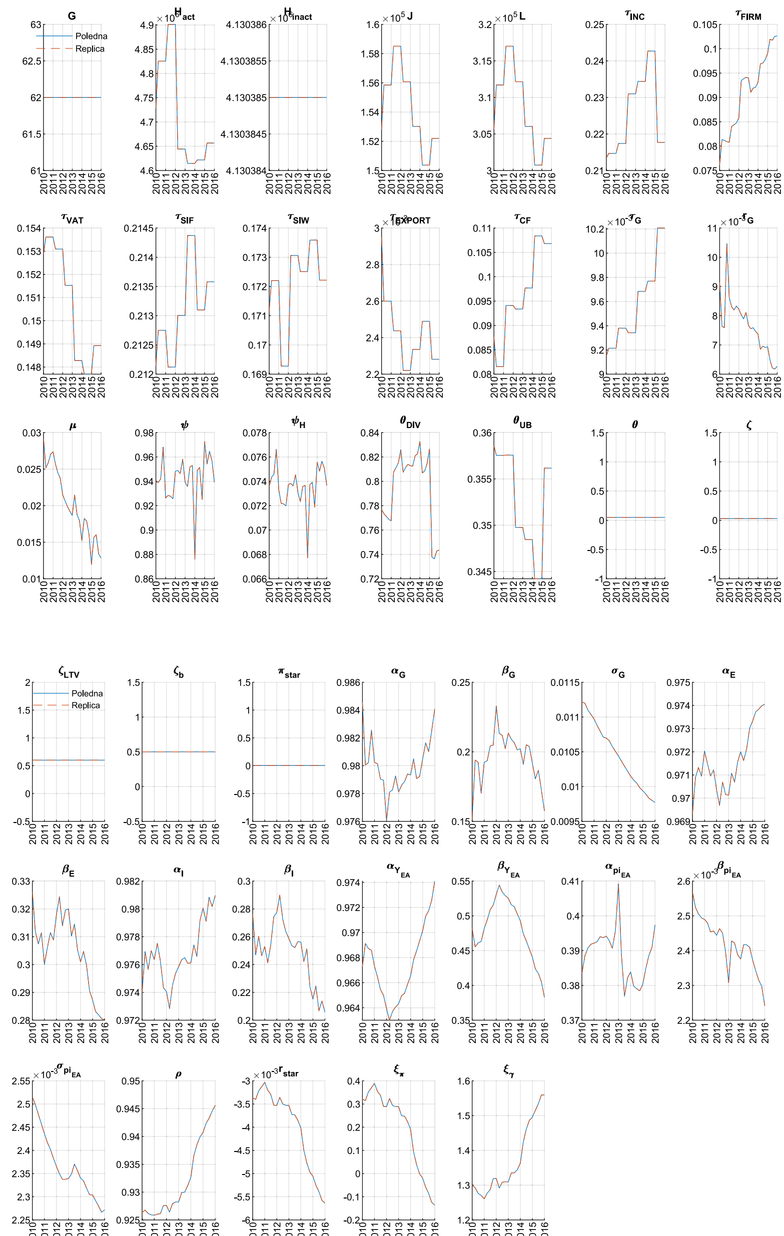

Fig. B.4. Parameters as reported in Table A.9, except for constant parameters set by Poledna et al. (2023) according to Basel III, ECB statutes, banking practices and literature. Solid blue lines represent parameters fixed by Poledna et al. (2023) while dotted red lines represent our values. See Table A.9 for the description of each variable.

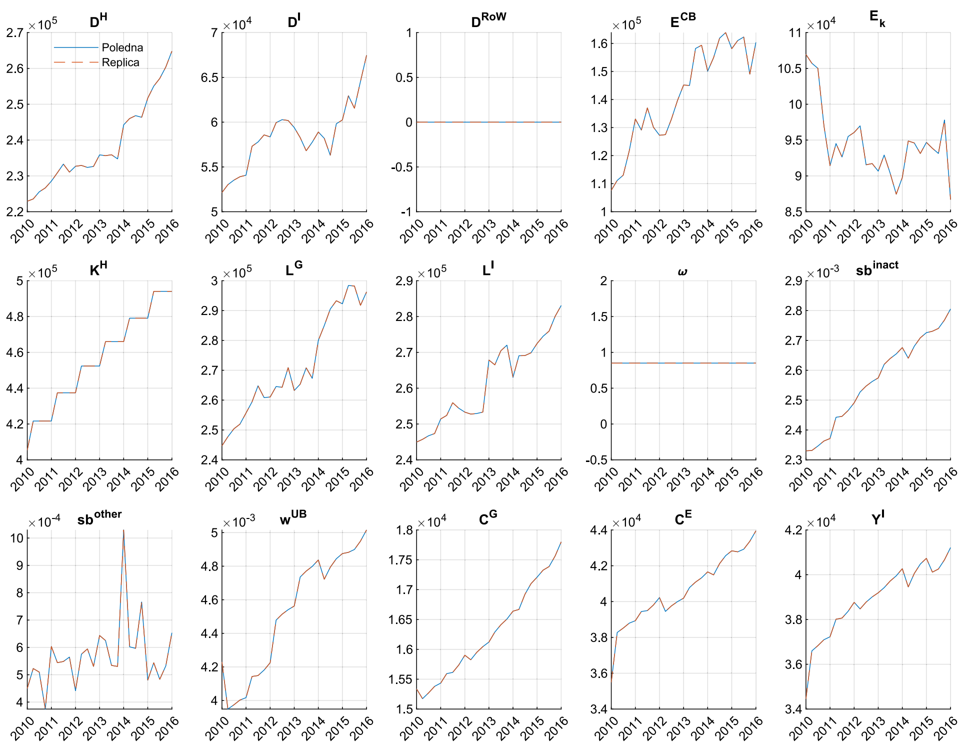

Fig. B.5. Solid blue lines represent the initial conditions fixed by Poledna et al. (2023) while dotted red lines represent our values. See Table A.11 for the description of each variable.

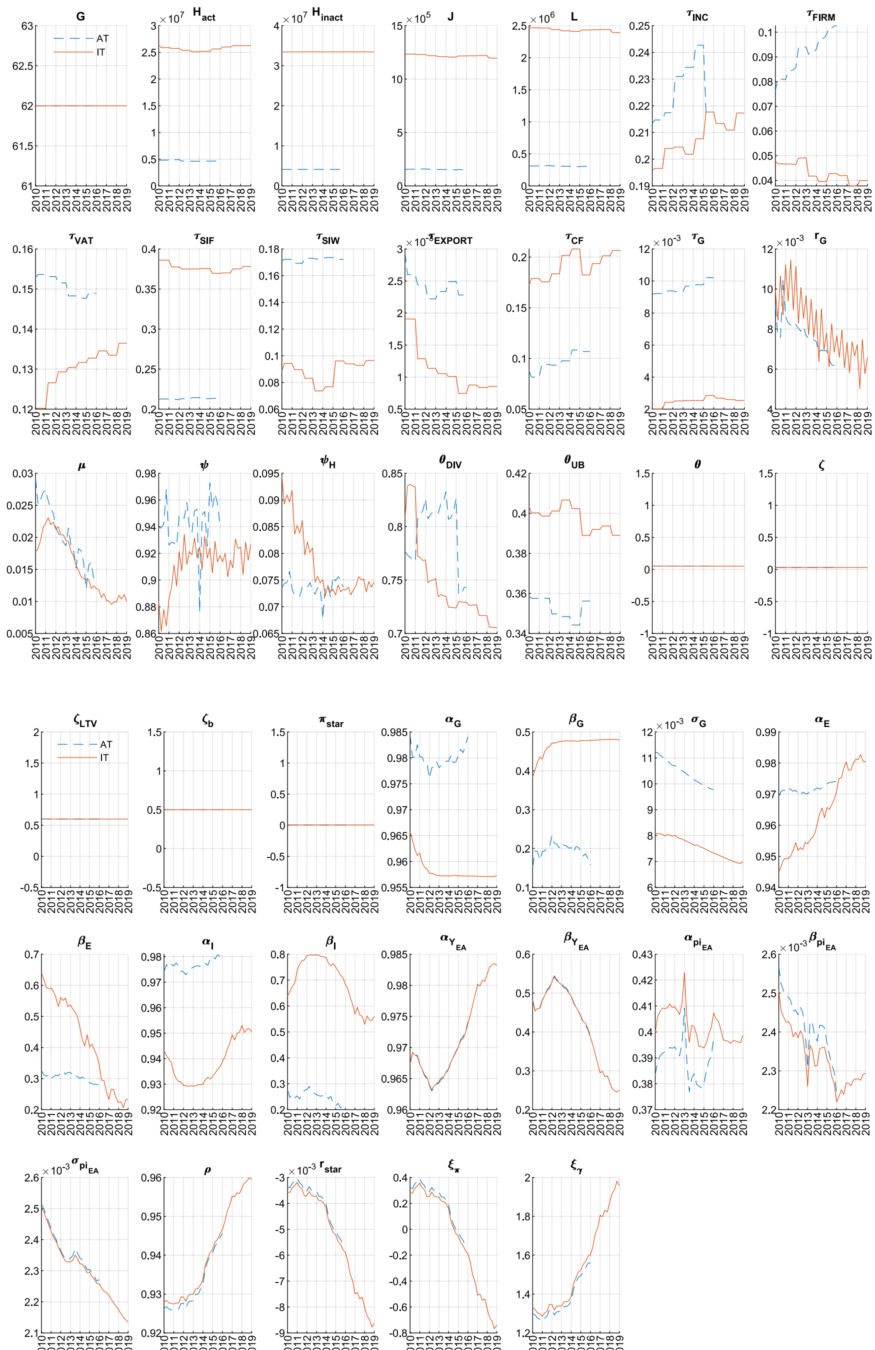

Fig. B.6. Parameters value. Austria dotted blue lines. Italy red solid lines. See Table A.9 for the description of each variable.

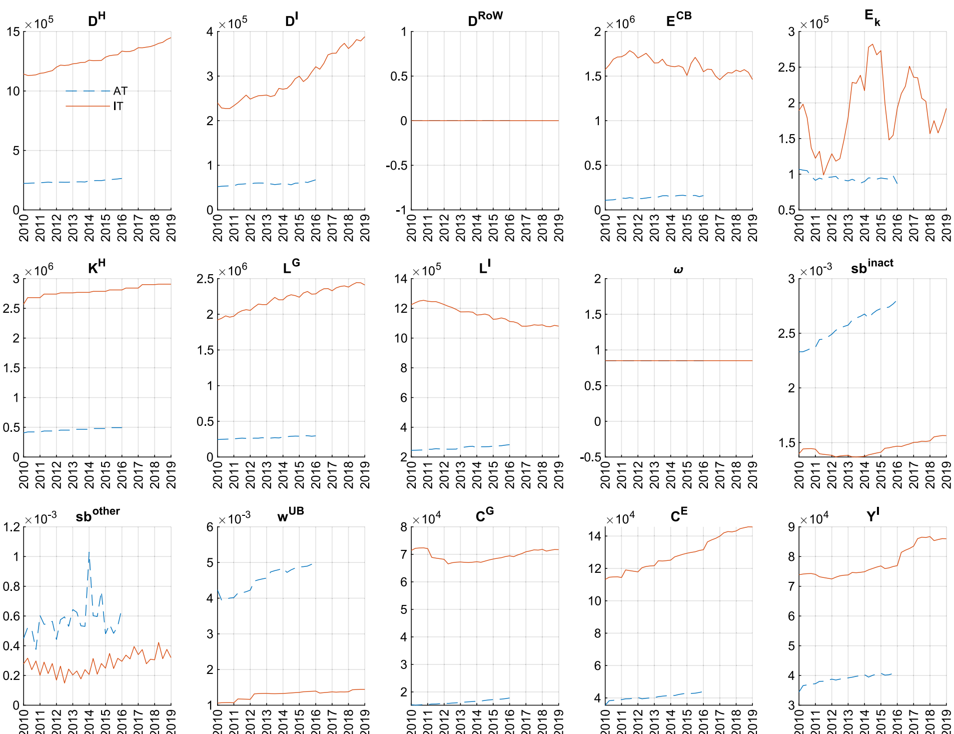

Fig. B.7. Initial conditions. Austria dotted blue lines. Italy red solid lines. See Table A.11 for the description of each variable.

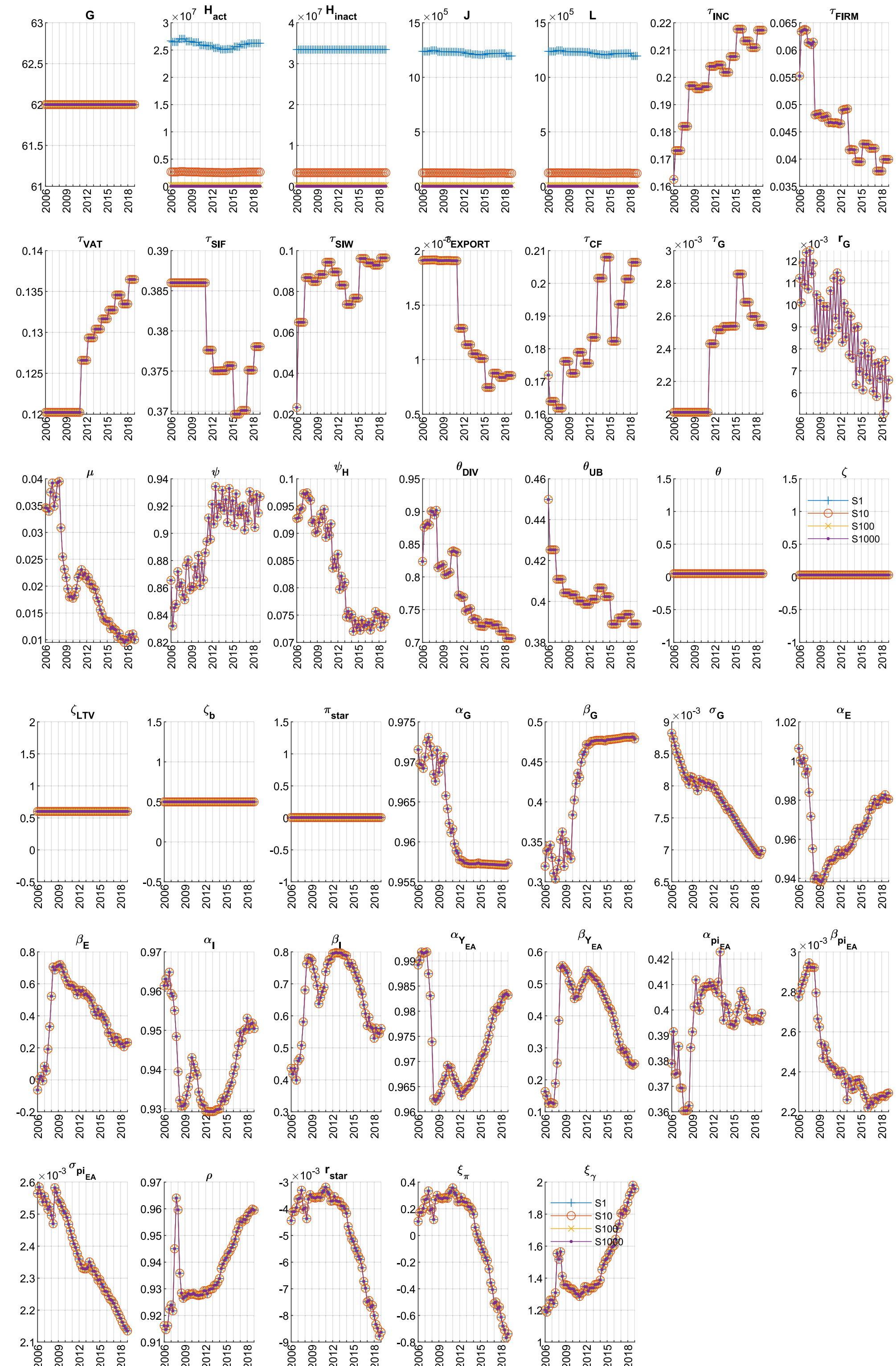

Fig. B.8. Parameters value for the Italian economy, according to the different scales. See Table A.9 for the description of each variable.

Data availability

The simulation data is available upon request from the authors.

References

Alfarano, S., Lux, T., Wagner, F., 2008. Estimation of agent-based models: The case of an asymmetric herding model. Comput. Econ. 32 (4), 317–336.

Assenza, T., Delli Gatti, D., Grazzini, J., 2015. Emergent dynamics of a macroeconomic agent based model with capital and credit. J. Econom. Dynam. Control 50 (C), 5–28.

Bachner, G., Knittel, N., Poledna, S., Hochrainer-Stigler, S., Reiter, K., 2023. Revealing indirect risks in complex socioeconomic systems: A highly detailed multi-model analysis of flood events in Austria. Risk Anal. 44 (1), 229–243.

Barde, S., 2020. Macroeconomic simulation comparison with a multivariate extension of the Markov information criterion. J. Econom. Dynam. Control 111, 103–115.

Bertani, F., Ponta, L., Raberto, M., Teglio, A., Cincotti, S., 2021. The complexity of the intangible digital economy: an agent-based model. J. Bus. Res. 129, 527–540.

Buchanan, M., 2009. Meltdown modeling. Nature 460, 680–682.

Catullo, E., Giri, F., Gallegati, M., 2021. The economic impact of complex interconnections: Agent-based models as a laboratory for policy experiments. Macroecon. Dyn. 25 (5), 1227–1246.

Christiano, L.J., Eichenbaum, M.S., Trabandt, M., 2018. On DSGE models. J. Econ. Perspect. 32 (3), 113–140.

Cincotti, S., Raberto, M., Teglio, A., 2022. Why do we need agent-based macroeconomics? Rev. Evol. Political Econ. 3.

Colander, D., Goldberg, M., Haas, A., Kirman, A., Juselius, K., Sloth, B., Lux, T., 2010. The financial crisis and the systemic failure of academic economics. Vopr. Èkon. 6, 10–25.

Colasante, A., Palestrini, A., Russo, A., Gallegati, M., 2017. Adaptive expectations versus rational expectations: Evidence from the lab. Int. J. Forecast. 33 (4), 988–1006.

Dawid, H., Delli Gatti, D., 2018. Agent-based macroeconomics. In: Handbook of Computational Economics, vol. 4, Elsevier, pp. 63–156.

Delli Gatti, D., Grazzini, J., 2020. Rising to the challenge: Bayesian estimation and forecasting techniques for macroeconomic Agent Based Models. J. Econ. Behav. Organ. 178, 875–902.

Di Domenico, L., Raberto, M., Safarzynska, K., 2023. Resource scarcity, circular economy and the energy rebound: A macro-evolutionary input-output model. Energy Econ. 128, 107155.

Dosi, G., 2011. What Makes Economic Complexity Grow? The Role of Eco-Systems and of Inductive Learning. Technical Report, Institute for New Economic Thinking.

Dosi, G., Fagiolo, G., Napoletano, M., Roventini, A., 2013. Income distribution, credit and fiscal policies in an agent-based Keynesian model. J. Econom. Dynam. Control 37 (8), 1598–1625.

Dosi, G., Fagiolo, G., Roventini, A., 2010. Schumpeter meeting Keynes: A policy-friendly model of endogenous growth and business cycles. J. Econom. Dynam. Control 34 (9), 1748–1767.

Dosi, G., Napoletano, M., Roventini, A., Stiglitz, J.E., Treibich, T., 2020. Rational heuristics? Expectations and behaviors in evolving economies with heterogeneous interacting agents. Econ. Inq. 58 (3), 1487–1516.

Dosi, G., Roventini, A., 2019. More is different... and complex! the case for agent-based macroeconomics. J. Evol. Econ. 29, 1–37.

Fagiolo, G., Guerini, M., Lamperti, F., Moneta, A., Roventini, A., 2019. Validation of agent-based models in economics and finance. In: Beisbart, C., Saam, N.J. (Eds.), Computer Simulation Validation: Fundamental Concepts, Methodological Frameworks, Philosophical Perspectives. Springer International Publishing, Cham, pp. 763–787.

Fierro, L.E., Caiani, A., Russo, A., 2022. Automation, job polarisation, and structural change. J. Econ. Behav. Organ. 200, 499–535.

Gaffard, J.-L., Napoletano, M. (Eds.), 2012. Agent-Based Models and Economic Policy, vol. 124, pp. 7–447.

Ghaith, Z., Kulshreshtha, S., Natcher, D., Cameron, B.T., 2021. Regional Computable General Equilibrium models: A review. J. Policy Model. 43 (3), 710–724.

Grazzini, J., Richiardi, M., 2015. Estimation of ergodic agent-based models by simulated minimum distance. J. Econom. Dynam. Control 51, 148–165.

Grazzini, J., Richiardi, M., Tsionas, M., 2017. Bayesian estimation of agent-based models. J. Econom. Dynam. Control 77 (C), 26–47.

Haldane, A.G., Turrell, A.E., 2019. Drawing on different disciplines: macroeconomic agent-based models. J. Evol. Econ. 29 (1), 39–66.

Hommes, C., He, M., Poledna, S., Siqueira, M., Zhang, Y., 2022. CANVAS: A Canadian Behavioral Agent-Based Model. Staff Working Papers 22–51, Bank of Canada.

Hommes, C., Poledna, S., 2023. Analyzing and Forecasting Economic Crises with an Agent-Based Model of the Euro Area. Tinbergen Institute Discussion Papers 23-013/II, Tinbergen Institute.

Kirman, A., 2010. The economic crisis is a crisis for economic theory. CESifo Econ. Stud. 56, 498–535.

Krugman, P., 2011. The profession and the crisis. East. Econ. J. 37, 307–312.

Lamperti, F., 2017. Empirical validation of simulated models through the GSL-div: An illustrative application. Comput. Econ. 50 (1), 149–172.

Lamperti, F., Bosetti, V., Roventini, A., Tavoni, M., Treibich, T., 2021. Three green financial policies to address climate risks. J. Financ. Stab. 54, 100875.

Lamperti, F., Roventini, A., Sani, A., 2018. Agent-based model calibration using machine learning surrogates. J. Econom. Dynam. Control 90 (C), 366–389.

Poledna, S., Miess, M.G., Hommes, C., Rabitsch, K., 2023. Economic forecasting with an agent-based model. Eur. Econ. Rev. 151 (C).

Poledna, S., Strelkovskii, N., Conte, A., Goujon, A., Linnerooth-Bayer, J., Catalano, M., Rovenskaya, E., 2024. Economic and labour market impacts of migration in Austria: an agent-based modelling approach. Comp. Migr. Stud. 12 (1), 1–27.

Raberto, M., Ozel, B., Ponta, L., Teglio, A., Cincotti, S., 2019. From financial instability to green finance: the role of banking and credit market regulation in the Eurace model. J. Evol. Econ. 29 (1), 429–465.

Riccetti, L., Russo, A., Gallegati, M., 2016. Financialisation and crisis in an agent based macroeconomic model. Econ. Model. 52, 162–172.

Riccetti, L., Russo, A., Gallegati, M., 2018. Financial regulation and endogenous macroeconomic crises. Macroecon. Dyn. 22 (4), 896–930.

Safarzynska, K., Di Domenico, L., Raberto, M., 2023. The circular economy mitigates the material rebound due to investments in renewable energy. J. Clean. Prod. 402, 136753.

Socci, C., Felici, F., Pretaroli, R., Severini, F., Loiero, R., 2021. The multisector applied computable general equilibrium model for Italian economy (MACGEM-IT). Ital. Econ. J. 7, 109–127.

Stiglitz, J.E., 2011. Rethinking macroeconomics: What failed, and how to repair it. J. Eur. Econ. Assoc. 9 (4), 591–645.

Teglio, A., Raberto, M., Cincotti, S., 2012. The impact of banks' capital adequacy regulation on the economic system: An agent-based approach. Adv. Complex Syst. 15.

Wickens, M., 2014. How useful are DSGE macroeconomic models for forecasting? Open Econ. Rev. 25 (1), 171–193.

Windrum, P., Fagiolo, G., Moneta, A., 2007. Empirical validation of agent-based models: Alternatives and prospects. J. Artif. Soc. Soc. Simul. 10 (2), 8.

Zhang, J., Zhang, Q., Li, Y., Wang, Q., 2023. Sequential Bayesian inference for agent-based models with application to the Chinese business cycle. Econ. Model. 126, 106381.