Economic forecasting with an agent-based model

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ABSTRACT

We develop the first agent-based model (ABM) that can compete with benchmark VAR and DSGE models in out-of-sample forecasting of macro variables. Our ABM for a small open economy uses micro and macro data from national accounts, sector accounts, input–output tables, government statistics, and census and business demography data. The model incorporates all economic activities as classified by the European System of Accounts (ESA 2010) and includes all economic sectors populated with millions of heterogeneous agents. In addition to being a competitive model framework for forecasts of aggregate variables, the detailed structure of the ABM allows for a breakdown into sector-level forecasts. Using this detailed structure, we demonstrate the ABM by forecasting the medium-run macroeconomic effects of lockdown measures taken in Austria to combat the COVID-19 pandemic. Potential applications of the model include stress-testing and predicting the effects of monetary or fiscal macroeconomic policies.

1. Introduction

This study presents a novel agent-based model (ABM) that derives macroeconomic aggregates of a national economy from the micro-founded behaviour of heterogeneous agents based on detailed macroeconomic (national accounting) and microeconomic datasets. To validate the ABM, we compare its forecast performance to that of a standard Bayesian dynamic stochastic general equilibrium (DSGE) model and time series models. To the best of our knowledge, our model is the first ABM that can compete with such standard models in economic forecasting of main macro variables. In addition, its detailed structure also allows economic forecasting and policy analysis at a more disaggregated level. To demonstrate this potential of our framework, we apply it to assess the medium-run macroeconomic effects of the COVID-19 pandemic and political measures to address the ensuing economic crisis for a small open economy. The model's empirical success suggests that ABMs now constitute a promising direction for economic

modelling—adding to the toolbox available to macroeconomists and potentially complementing DSGE models. Thus, a key objective of this paper is to introduce ABMs to a wide readership. Therefore, we provide a mostly non-technical description of the model, focusing on conveying the key concepts and intuition behind the choice of model features. Nonetheless, to make this model class accessible to interested readers, we provide a detailed model description and documentation of replication codes in the Online Appendix. Finally, we discuss how our ABM overcomes some of the disadvantages of earlier contributions and discuss the strengths and weaknesses of the various approaches considered.

Macroeconomic ABMs explain the evolution of an economy by simulating the micro-level behaviour of heterogeneous individual agents to provide a macro-level picture (Haldane and Turrell, 2018). Farmer and Foley (2009) suggest that, in principle, it might be possible to conduct economic forecasts with a macroeconomic ABM, although some drawbacks need to be overcome. ABMs have well-known pros and cons. One advantage that has often been put forward is that they allow the modelling of more realistic agent behaviour – often characterized by simple rules of thumb – as micro behaviour in an ABM is not constrained by unrealistic assumptions about fully rational agents who optimize individual behaviour under perfectly rational expectations.[1] Paradoxically, this advantage immediately led to what has perhaps been the most important critique of ABMs: they have too many degrees of freedom and too many parameters to calibrate. Indeed, it has been argued that due to this "wilderness of bounded rationality" (Sims, 1980), ABMs have so many parameters that any observed pattern in real data can be matched to an ABM (Fagiolo and Roventini, 2017). Another important disadvantage that has been noted is that ABMs lack the forecasting power of macroeconomic variables. To date, ABMs have mainly been used to generate so-called stylized facts that are observed in macro data (e.g. boom and bust cycles, bubbles and crashes, technological growth, wealth inequality, fat-tailed firm size distributions, and so forth). Our ABM is an attempt to overcome these drawbacks using four key approaches: (1) building an ABM around publicly available macro and microdata of a small open economy, (2) disciplining the individual behaviour of agents (consumers, firms, and banks) through simple heuristics that are calibrated using microdata, (3) using a simple adaptive learning model of expectations through the learning of optimal autoregressive (AR) forecasting rules consistent with macro data, and (4) adopting an empirical validation strategy based on out-of-sample forecasting of macro variables. Furthermore, our detailed ABM contains all sectors of an open economy and can therefore be used for policy analysis.

We benchmark the forecasting performance of our ABM to that of other state-of-the-art approaches. In particular, after the seminal work of Smets and Wouters (2003, 2007), New Keynesian DSGE models that employ Bayesian estimation techniques have been shown to exhibit a similar forecast performance as comparable time series models (Del Negro and Schorfheide, 2013). These DSGE models have become the workhorse framework for economic forecasting and policy analysis on a sound theoretical basis by central banks and other institutions and should be considered to be the minimum standard when it comes to studying business cycles in a general equilibrium framework (Christiano et al., 2018; Brunnermeier et al., 2013). Our benchmark DSGE model is an open-economy version of a typical medium-scale model in the style of Smets and Wouters (2007) extended to a two-region setting that studies the Austrian economy in a currency union with the euro area based on Breuss and Rabitsch (2009).[2] We consider this DSGE model to be a very standard, state-of-the-art model to be benchmarked against. Nonetheless, we emphasize that we do not claim that the DSGE model we adopt cannot be improved upon. In particular, we see room for improvement in at least three important dimensions, all of which have been active areas of research in the DSGE literature in the recent past and could possibly bring the DSGE model closer to our ABM in some dimensions, as these features are all (naturally) present in the ABM model. These are: (1) a role for financial market imperfections; (2) the departure from rational expectations; (3) the departure from the representative agents set up. We discuss the progress made in each of these areas in the DSGE literature in turn.

First, the financial crisis of 2007–2008 and the subsequent Great Recession made apparent that pre-crisis vintages of DSGE models rather neglected the financial sphere.[3,4] However, work that empirically evaluates the performance of DSGE models with financial frictions finds that their inclusion does not necessarily substantially improve the performance of the benchmark model (see, e.g. Lindé et al. (2016) and Brzoza-Brzezina and Kolasa (2013)). Del Negro et al. (2016) investigate the relative forecasting performance of DSGE models with and without financial frictions, finding that models with financial frictions produce superior forecasts in periods

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[1] This approach is related to the large literature on robust policy, see, e.g. Taylor and Williams (2010) and Deak et al. (2022). A common finding in this literature is that simple rules are more robust and perform well in a wide variety of models, while optimal rules can break down if the reference model is misspecified.

[2] Both regions are characterized by a number of real and nominal frictions, such as sticky nominal prices and wages, habit formation in consumption, investment adjustment costs, and price and wage indexation. The model is estimated on the same set of macroeconomic variables as Smets and Wouters (2007), i.e. on real GDP, hours worked, consumption, investment, real wages, and prices for both Austria and the euro area, together with a joint nominal interest rate. For the short-term interest rate, we estimate versions of the DSGE model with either the 3-month Euribor or, alternatively, with the shadow rate, the latter potentially being more appropriate for the estimation period considered in that the policy rate was constrained by an effective lower bound and that monetary policy actions constituted a range of unconventional measures. Model dynamics are driven by Austrian and euro area total factor productivity shocks, wage and price markup shocks, risk premium and investment-specific technology shocks, government expenditure shocks, and a joint monetary policy shock.

[3] While the literature on financial imperfections had already existed pre-crisis (c.f. Kiyotaki and Moore (1997) and Bernanke et al. (1999)), it experienced a huge revival and credit market imperfections were quickly incorporated into the more modern vintages of macroeconomic models for policy analysis. The incorporation of financial frictions allowed DSGE models a role for financial markets, both as a propagator ("financial accelerator") and as a source of fluctuations through shocks originating in the financial sector itself. While earlier contributions placed financial constraints on non-financial firms, more recent work emphasizes balance sheet constraints of highly leveraged banks or households (the literature is enormous and cannot possibly be reviewed here; for recent surveys, see, e.g. Gertler and Kiyotaki (2010), Brunnermeier et al. (2013), and Gertler and Gilchrist (2018)).

[4] As a response, several prominent voices within the economic profession critically reassessed the DSGE approach, e.g. Vines and Wills (2018). For earlier critiques, see, e.g. Canova and Sala (2009), Colander et al. (2009), Kirman (2010), Edge and Gurkaynak (2010), Krugman (2011), Stiglitz (2011, 2018), Blanchard (2016), and Romer (2016). See also the recent response defending DSGE models by Christiano et al. (2018).

of financial distress but do not perform as well in tranquil periods. Second, the DSGE literature has also increasingly considered deviations from the rational expectations hypothesis and informational frictions as important for understanding macroeconomic dynamics. While the assumption of full information rational expectations (FIRE) has been the workhorse approach for the past several decades, bounded rationality, particularly in the form of adaptive learning, has increasingly been implemented in DSGE models.[5,6] Examples of estimated medium-scale macroeconomic models that relax the rational expectations assumption find that some of the persistence observed in macroeconomic time series is no longer attributed to structural parameters but to the expectations formation process or that the model version with rational expectations can be outperformed (c.f. Milani (2007, 2012), Slobodyan and Wouters (2012), and Hommes et al. (2022)). Third, another vivid area of economic research explores the effects of agent heterogeneity in a general equilibrium framework, which has led to the development of heterogeneous agent New Keynesian (HANK) models.[7] HANK models have been used to show that household and firm heterogeneity affect macroeconomic aggregates, but they have rarely been used to forecast economic aggregates, whereas representative agent New Keynesian (RANK) models have, so far, remained the benchmark (Kaplan and Violante, 2018; Christiano et al., 2018; Del Negro and Schorfheide, 2013).[8] The developments discussed above in these three dimensions make it clear that the incorporation of some of these features into our DSGE comparison model could bring it closer to our ABM model and possibly lead to improved forecasting performance. Nonetheless, it is less clear that the inclusion of features along these dimensions has evolved into a new standard for estimated DSGE models used for forecasting—let alone the inclusion of all three dimensions at the same time. Instead, also in more recent contributions to the literature on medium-scale macro DSGE models, models close in spirit to Smets and Wouters (2007) continue to serve as *the* canonical benchmark DSGE model for forecasting (see, e.g. An and Schorfheide (2007), Del Negro and Schorfheide (2013), Schorfheide (2013), Fernández-Villaverde et al. (2016) and Fernández-Villaverde and Guerrón-Quintana (2021)).

The main aim of this paper is then to develop an ABM that matches the historical evolution of variables and can compete with benchmark vector autoregressive (VAR) and DSGE models in out-of-sample forecasting of macro variables. The model is based on Assenza et al. (2015), who developed a stylized ABM with households, firms (upstream and downstream), and a bank, that replicates a number of stylized facts. Our ABM includes all institutional sectors (financial firms, non-financial firms, households, and a general government), where the firm sector is composed of 64 industries according to national accounting conventions and the structure of input–output tables. These four institutional sectors make up the total domestic economy and interact with the rest of the world through imports and exports, where we suppose the demand for exports and the supply of imports to be given exogenously. The model is based on micro and macro data from national accounts, sector accounts, input–output tables, government statistics, census data, and business demography data. The model parameters are either taken directly from data or are calculated from national accounting identities. For exogenous processes, such as imports and exports, parameters are estimated. The model furthermore incorporates all economic activities, as classified by the European System of Accounts (ESA) (productive and distributive transactions), and all economic entities; namely, all juridical and natural persons are represented by heterogeneous agents. The model thus includes a complete GDP identity, where GDP as a macroeconomic aggregate is calculated from the market value of all final goods and services produced by individual agents, and market value emerges from trading or, alternatively, according to the aggregate expenditure or income of individual agents. Markets are fully decentralized and characterized by a continuous search-and-matching process, which allows for trade frictions.

In our model, a number of agents' decision heuristics depend on the expected growth rate and expected inflation, for which agents must form expectations about the (log) level of output and inflation. Agents' expectations are modelled by a parsimonious form of adaptive learning, in which agents act as econometricians who estimate the parameters of their model and make forecasts using their estimates (Evans and Honkapohja, 2001). We follow the approach of Hommes and Zhu (2014), where agents learn the optimal parameters of simple parsimonious AR rules of lag order one in a complex environment where they are not able to understand the actual laws of motion of this economy.[9] In such an environment, despite its complexity, the economy may settle into an equilibrium, where agents learn the optimal (univariate) linear forecasting rule to approximate the unknown complex stochastic actual law of motion of the economy. This type of equilibrium with approximate optimality for expectation formation seems to be

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[5] Again, it is impossible to review the entire literature here, but select articles that survey this large literature include Evans and Honkapohja (2001, 2009), Milani (2012), Woodford (2013), Eusepi and Preston (2018), Berardi and Galimberti (2017), Coibion et al. (2018), Manski (2018), and Evans and McGough (2005).

[6] Alternatively, there exist other popular approaches incorporating behavioural aspects into decision making, such as rational inattention (Sims, 2003, 2010; Maćkowiak et al., forthcoming, 2022) or sticky information (Mankiw and Reis, 2002; Reis, 2006).

[7] A non-exhaustive list of prominent examples includes Kaplan et al. (2018), Kaplan and Violante (2014), McKay and Reis (2016), Khan and Thomas (2008), and Chatterjee et al. (2007).

[8] The properties inherent to DSGE models due to their grounding in general equilibrium theory have led to criticism that HANK DSGE models – in contrast to ABMs – are restricted to a mild form of heterogeneity and, for example, maintain the assumption of rational expectations (Fagiolo and Roventini, 2017). This may be best explained by the way how HANK models depict agent heterogeneity. A restriction here is the necessity to keep a certain amount of information commonly known to the heterogeneous agents in a HANK model in order to be able to solve it. This so-called "approximate aggregation" result uncovered by Krusell and Smith (1998) assumes that agents know the mean of the wealth distribution in the stationary stochastic equilibrium to solve the underlying dynamic programming problem to derive the long-run equilibrium steady-state growth path, which can then be subjected to different exogenous shocks to describe business cycles. The framework of Krusell and Smith (1998) still underlies most HANK models (Fagiolo and Roventini, 2017). In ABMs, in contrast, heterogeneity is fundamental with heterogeneous boundedly rational agents at the micro-level whose interactions create emergent behaviour and endogenous macroeconomic dynamics (Hommes and LeBaron, 2018).

[9] Brayton et al. (1997) discuss the role of expectations in FRB/US macroeconomic models. One approach is that expectations are given by small forecasting models such as a VAR model. Our choice of an AR(1) model is simply the most parsimonious yet empirically relevant choice, where, for each relevant variable, agents learn the parameters of an AR(1) rule consistent with the observable sample mean and autocorrelation.

a natural starting point to address the problem of the "wilderness of bounded rationality," and as indicated, similar applications of learning have taken place in the DSGE literature. With this approach, out-of-sample forecasts of our ABM are performed as follows: parameters and initial conditions of the ABM are calibrated to economic statistics up to a reference quarter so that the model reproduces exactly the state of the economy in that quarter in terms of aggregate GDP, GDP components, industry sizes, etc. For each reference quarter, the model is then solved recursively for a number of periods using Monte Carlo methods, whereby in each period, expectations on output and inflation are formed based on the AR(1) rules, and random shocks to these expectations are drawn together with random disturbances to the model's exogenous variables. Agents' actions are then governed by behavioural rules, some of which depend on these expectations and are followed by interactions between agents in the various markets governed by search and matching processes. The simulation period ends with accounting to update state and flow variables. Fluctuations are driven by the endogenous propagation mechanism that our model's belief dynamics, behavioural rules, and search and matching algorithms induce when departing from last quarter's realizations and observing the exogenous shocks of this period.

In summary, the objectives of this paper are threefold. First, we develop the first ABM that fits micro and macro data of a small open economy and allows out-of-sample forecasting of the aggregate macro variables, such as GDP (including its components), inflation, and interest rates. Second, to perform an empirical validation, we compare the forecast performance of the ABM to those of a VAR, AR, vector error correction model (VECM), and DSGE model. Third, we demonstrate the ABM by assessing the medium-run macroeconomic effects of lockdown measures taken in Austria to combat the COVID-19 pandemic. For the purpose of model validation, we conduct a series of forecasting exercises in which we evaluate the out-of-sample forecast performance of the different model types using a traditional measure of forecast error (root mean squared error). In the first exercise, we validate the ABM against an unconstrained VAR and VECM. In a second exercise, we compare the forecast performance of the ABM to that of the DSGE model for the main macroeconomic aggregates, GDP and inflation, as well as household consumption and investment as the main components of GDP. In a third forecasting setup, we generate forecasts conditional on exogenous paths for imports, exports, and government consumption, corresponding to a small open economy setting and exogenous policy decisions. Overall, the forecasting exercises indicate that the ABM can compete with benchmark VAR and DSGE models in forecasting the macro variables. With these three forecast exercises, we thus achieve comparability of the ABM to the forecasting performance of standard modelling approaches. Finally, we demonstrate the ABM and show that the recovery of the Austrian economy from the steep initial decline in economic activity due to the COVID-19 pandemic and the lockdown measures could take several years. Overall, our results with respect to the COVID-19 pandemic are closely in line with the economic forecasts for the Austrian economy produced by Austria's major forecasting institutions and national accounting data.

The remainder of this manuscript is structured as follows. Section 2 gives a brief summary of the related literature. Section 3 provides an overview of the model and discusses our key modelling choices. Section 4 gives an overview of the parameter calibration. Section 5 describes the forecast performance of the ABM, where we validate the ABM against VAR, VECM, AR, and DSGE models in different forecasting setups. Section 6 presents the application of the ABM in an assessment of the medium-run macroeconomic effects of the COVID-19 pandemic in Austria. Section 7 concludes the paper.

2. Related literature

Since their beginnings in the 1930s,[10] ABMs have found widespread application as an established method in various scientific disciplines (Haldane and Turrell, 2018), for example, in military planning, the physical sciences, operational research, biology, and ecology, but less so in economics and finance. The use of ABMs in the latter two fields to date remains quite limited in comparison to other disciplines. An early exception is Orcutt (1957), who constructed the first simple economically motivated ABM to obtain aggregate relationships from the interaction of individual heterogeneous units via simulation. Other examples include topics such as racial segregation patterns (Schelling, 1969), financial markets (Arthur et al., 1997), or, more recently, the housing market (Geanakoplos et al., 2012; Baptista et al., 2016).

Since the financial crisis of 2007–2008, ABMs have increasingly been applied to research in macroeconomics, and some economists have been pushing ABMs – potentially to complement DSGE models – as a new promising direction for macroeconomic modelling.[11] Farmer and Foley (2009), in particular, suggest that it might be possible to conduct economic forecasts with a macroeconomic ABM, although they consider this to be ambitious. In recent years, several ABMs have been developed that depict entire national economies and are designed to deliver macroeconomic policy analysis. The European Commission (EC) has in part supported this endeavour. One example of a large research project funded by the EC is the Complexity Research Initiative for Systemic Instabilities (CRISIS),[12] an open-source collaboration between academics, firms, and policymakers (Klimek et al., 2015). Another is EURACE,[13] a large micro-founded macroeconomic model with regional heterogeneity (Cincotti et al., 2010).

Both ABMs and DSGE models may be viewed as "bottom-up" models that are based on different forms of micro-foundations. On a spectrum where statistical models lie at one end, ABMs together with micro-founded DSGE models lie at the other. There are two key differences between these two types of models, however: (1) DSGE models assume that agents optimize given their expectations

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[10] The first ABM reportedly was constructed (by hand) by Enrico Fermi in the 1930s to model the problem of neutron transport.

[11] Some examples include Freeman (1998), Gintis (2007), Colander et al. (2008), LeBaron and Tesfatsion (2008), Farmer and Foley (2009), Trichet (2010), Stiglitz and Gallegati (2011), and Haldane and Turrell (2018).

[12] FP7-ICT grant 288501, http://cordis.europa.eu/project/rcn/101350_en.html. (Last accessed November 30th, 2019).

[13] FP6-STREP grant 035086, http://cordis.europa.eu/project/rcn/79429_en.html. See also: http://www.wiwi.uni-bielefeld.de/lehrbereiche/vwl/etace/Eurace_Unibi/ (Last accessed November 30th, 2019).

about the future, while ABMs assume that agents use simple heuristics to consume, produce, invest, work, hire, and conduct all other economic activities. (2) DSGE models, on the one hand, typically feature rational or model-consistent expectations,[14] presuming perfect knowledge by agents about the structure of the economy and thus agents' ability to make correct[15] forecasts about the future evolution of the model economy. ABMs, on the other hand, depict boundedly rational expectations[16] with agents using simple forecasting heuristics to navigate their complex economic environment—the exact structural rules and determinants of which are not known to them, i.e. they are faced with "Knightian" (Knight, 1921) or "fundamental" (Keynes, 1936) uncertainty. Both ABMs and DSGE models are solved numerically. DSGE models, after aggregation, are, mathematically speaking, a system of non-linear difference equations that often is locally approximated (in log-linear terms), especially in Bayesian estimation. Usually, after the aggregation, DSGE models are then log-linearized around the non-stochastic steady state and solved numerically. ABMs are typically solved numerically behavioural rule by behavioural rule.

Macroeconomic ABMs, however, suffer from a number of problems that impede major applications in economics, such as economic forecasting and empirically founded policy evaluation. The relaxation of the rational expectations hypothesis allows for greater flexibility in the design of ABMs since the strong consistency requirements associated with simplistic models – all actions and beliefs must be mutually consistent at all times – are no longer necessary. The lack of a commonly accepted basis for the modelling of boundedly rational behaviour, however, has raised concerns about the "wilderness of bounded rationality" (Sims, 1980). Research on the econometric estimation of ABMs has been growing recently, though most of it still remains at the level of proof of concept (Lux and Zwinkels, 2018). Empirical validation of ABMs remains a difficult task. While DSGE models match the historical evolution of variables, macroeconomic ABMs typically replicate a number of macroeconomic and microeconomic empirical stylized facts, such as time series properties of output fluctuations and growth, as well as cross-sectional distributional characteristics of firms (Dosi et al., 2017; Axtell, 2018). Due to over-parameterization and the corresponding degrees of freedom, almost any simulation output can be generated with an ABM, and thus replication of stylized facts only represents a weak test for the validity of ABMs (Fagiolo and Roventini, 2017).

In a recent overview, Dawid and Delli Gatti (2018) identified seven main families of macroeconomic ABMs[17]: (1) the framework developed by Ashraf et al. (2017); (2) the family of models proposed by Delli Gatti et al. (2011) in Ancona and Milan exploiting the notion of Complex Adaptive Trivial Systems (CATS); (3) the framework developed by Dawid et al. (2018) in Bielefeld as an offspring of the EURACE project, known as Eurace@Unibi; (4) the EURACE framework maintained by Cincotti et al. (2010) in Genoa; (5) the Java Agent based MacroEconomic Laboratory developed by Seppecher et al. (2018); (6) the family of models developed by Dosi et al. (2017) in Pisa, known as the "Keynes meeting Schumpeter" framework; and (7) the LAGOM model developed by Jaeger and coauthors (Wolf et al., 2013). What unites all these families of models is their ability to generate endogenous long-term growth and short- to medium-term business cycles. These business cycles are the macroeconomic outcome of the micro-level interaction of heterogeneous agents in the economy as a complex system subject to non-linearities (Dawid and Delli Gatti, 2018). All these models assume bounded rationality for their agents and thus suppose adaptive expectation in an environment of fundamental uncertainty. Typically, they minimally depict firm, household, and financial (banking) sectors populated by numerous agents of these types (or classes), and agents exhibit additional heterogeneity within one or more of the different classes. All results are obtained by performing extensive Monte Carlo simulations and averaging over simulation outcomes. The great majority of models are calibrated and validated with respect to a (smaller or larger) variety of stylized empirical economic facts (Fagiolo and Roventini, 2017). However, despite their level of sophistication, all these models suffer from one or more impediments: they serve as a theoretical explanatory tool constructed for a hypothetical economy; the choice of the number of agents is arbitrary or left unexplained; time units may have no clear interpretation; validation with respect to stylized empirical facts cannot solve the potential problem of over-parameterization; the choice of parameter values is often not pinned down by clear-cut empirical evidence; most of these models exhibit an extended transient or burn-in phase that is discarded before analysis.

3. An agent-based model for a small open economy

We present an ABM for a small open economy with the aim to use micro and macro data from national sector accounts to allow out-of-sample forecasting of aggregate macro variables and applications involving detailed policy analysis. In this section, we give a short overview of the model and discuss our key modelling choices. For a detailed description of individual agents' behavioural rules, see Online Appendix A. To achieve our aim, we made a number of key modelling choices: First, the structure of the model closely follows conventions from national accounting. It incorporates all economic activities and includes all sectors (financial and non-financial firms, households, the general government, a central bank, and the rest of the world) populated with millions of heterogeneous agents. Second, interactions between agents in the model take place in decentralized markets characterized by search and matching, which allows for trade frictions. Third, agents' expectations are modelled by a simple, parsimonious form of adaptive learning (Hommes and Zhu, 2014). Fourth, economic growth is driven by agents' expectations and their reactions to exogenous shocks and endogenous fluctuations.

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[14] In recent years a large literature on behavioural macro-models with boundedly rational agents and heterogeneous expectations has appeared. See, e.g. the recent contribution of De Grauwe and Ji (2020) or the recent overview in Hommes (2021).

[15] Correct in the sense as, before unknown, exogenous shocks may potentially change economic aggregates and thus move the economy away from the equilibrium path.

[16] A research program that started early on in economics from different perspectives with contributions such as those by Simon (1979), Kahneman and Tversky (1980), and Brock and Hommes (1997).

[17] For another recent overview on macroeconomic ABMs, see Fagiolo and Roventini (2017).

3.1. Basic structure of the model

Following the sectoral accounting conventions of the European System of Accounts (ESA) (Eurostat, 2013), the model economy is structured into six sectors that mirror the structure of institutional sectors as defined by the ESA: *(1) non-financial corporations* (firms); *(2) households*; *(3) the general government*; and *(4) financial corporations* (banks), including *(5) the central bank*. These four sectors make up the total domestic economy and interact with *(6) the rest of the world* (RoW) through imports and exports. Each sector is populated by heterogeneous agents who represent natural persons or legal entities (corporations, government entities, and institutions). All individual agents have separate balance sheets depicting assets, liabilities, and ownership structures. The balance sheets of the agents, and the economic flows between them, are set according to data from national accounts.

Along these lines and following the structure of our dataset, the firm sector (*(1) non-financial corporations*) is made up of 64 industries (NACE/CPA classification by ESA) where each industry produces a perfectly substitutable good. Each firm in the model is part of one industry and produces the industry-specific output by means of labour, capital, and intermediate inputs from other sectors with fixed-coefficients (Leontief) technology.[18] These fixed coefficients are calibrated directly to input–output tables. The firm population of each industry is derived from business demography data, while firm sizes follow a power law distribution, which approximately corresponds to the firm size distribution in Austria. Heterogeneity in the firm sector is thus achieved by industry-specific production functions and varying firm sizes. Similar to other agents in the model, firms are subject to fundamental uncertainty. This uncertainty specifically relates to their future sales, market prices, the availability of inputs for production, input costs, cash flow and financing conditions, which are given by simple heuristics that depend on the two variables they need to form expectations over. In particular, based on partial information about their current status quo and its past development, firms have to form expectations over the (log) output and (producer price) inflation to obtain the expected growth rate and expected inflation. Given these, they estimate future demand for their products, their future input costs, and their future profit margin. According to these expectations – which are not necessarily realized in the future – firms set prices and quantities. In line with our overall approach to expectation formation (see Section 3.3), we assume that firms form these expectations using simple AR(1) rules. Output is sold on respective markets characterized by search and matching to households as consumption goods or investment in dwellings and to other firms as intermediate inputs or investment in capital goods, or it is exported. Firm investment is conducted according to the expected wear and tear on capital. Firms are owned by investors (one investor per firm), who receive part of the profits of the firm as dividend income.

(2) Households earn income and consume (and invest) in markets characterized by search and matching processes. Heterogeneity in the household sector is achieved by the distinction into employed (with sector-specific characteristics), unemployed, investor, and inactive households, with the respective numbers obtained from census data. The source of income is specific for the different household types: employed households supply labour and earn sector-specific wages. Unemployed households are involuntarily idle and receive unemployment benefits, which are a fraction of previous wages. Investor households obtain dividend income from firm ownership. Inactive households do not participate in the labour market and receive social benefits provided by the government. Additional social transfers are distributed equally to all households (e.g. child care payments). All households purchase consumption goods and invest in dwellings which they buy from the firm sector. Similar to firms, some of the households' decision heuristics depend on the expected growth rate of the economy and on expected inflation. Due to fundamental uncertainty, households thus similarly form AR(1) expectations about the future (about the expected growth rate and expected inflation) that are not necessarily realized. For example, expected inflation is needed to calculate their expected net disposable income available for consumption.

The main activities of *(3) the general government* are purchasing goods and services (government consumption) and the redistribution of income to provide social services and benefits to its citizens. The amount and trend of both government consumption and redistribution are obtained from government statistics. The government collects taxes, distributes social as well as other transfers, and engages in government consumption. Government revenues consist of (1) taxes: on wages (income tax), capital income (income and capital taxes), firm profit income (corporate taxes), household consumption (value-added tax), other products (sector-specific, paid by industries), firm production (sector-specific), as well as on exports and capital formation; (2) social security contributions by employees and employers; and (3) other net transfers such as property income, investment grants, operating surplus, and proceeds from government sales and services. Government expenditures are composed of (1) final government consumption; (2) interest payments on government debt; (3) social benefits other than social benefits in kind; (4) subsidies; and (5) other current expenditures. A government deficit adds to its stock of debt, thus increasing interest payments in the periods thereafter.

The banking sector (*(4) financial corporations*) obtains deposits from households as well as from firms and provides loans to firms. Interest rates are set by a fixed markup on the policy rate, which is determined according to a Taylor rule. Credit creation is limited by minimum capital requirements, and loan extension is conditional on a maximum leverage of the firm, reflecting the bank's risk assessment of the potential default by its borrower. Bank profits are calculated as the difference between interest payments received on firm loans and deposit interest paid to holders of bank deposits, as well as write-offs due to credit defaults (bad debt). *(5) The central bank* sets the policy rate according to a generalized Taylor rule based on implicit inflation and growth targets, provides liquidity to the banking system (advances to the bank), and takes deposits from the bank in the form of reserves deposited at the central bank. Furthermore, the central bank purchases external assets (government bonds) and thus acts as a creditor to the government. To model interactions with *(6) the rest of the world*, a segment of the firm sector is engaged in import–export activities. As we model a small open economy, whose limited volume of trade does not affect world prices, we obtain trends of exports and imports from exogenous projections based on national accounts.

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[18] Our choice of Leontief technology is consistent with the data and is in line with the literature (Assenza et al., 2015).

3.2. Decentralized markets and trade frictions

Interactions between agents in the model take place on decentralized markets. These markets are characterized by search and matching, e.g. sellers (such as firms) are matched with buyers (such as consumers) using randomized algorithms that allow for trade frictions (see Online Appendix A.1.1). Similar to other macroeconomic ABMs, the interaction of different agents on markets (or other economic structures) is thus governed by explicit behavioural rules or heuristics that depict the micro behaviour and institutional design of the considered economic system. This approach allows ABMs to capture institutional settings of specific markets and to represent shortages of both supply or demand and the occurrence of frictions in markets in a natural way via simulations from the bottom-up (Dawid and Delli Gatti, 2018). Search and matching in the ABM thus replaces mechanisms such as price-driven supply and demand interaction, market clearing (Walras' law) and optimality assumptions that we are familiar with from Computable General Equilibrium (CGE) or DSGE models. The decentralized search and matching mechanism in the ABM of, for example, the goods market relies on the probability of a firm to be visited by a certain agent – which might be a household (private consumption), a firm (intermediate input to production), or the government (public consumption), among others – to purchase a product. The probability of a firm i to be chosen by a customer depends (1) on the offering price of the firm, i.e. higher prices decrease the probability of the firm being visited, and (2) on the size of the firm, i.e. larger firms have a higher probability being visited by a customer. The purchased amount then depends on the consumption budget of the consumer and the supply from the seller. In the aggregate, goods markets in the ABM are efficient in the sense that there is no "frictional" excess demand or supply, i.e. buyers can exhaust their consumption budget as long as aggregate supply is sufficient to match aggregate demand. However, in the case that aggregate demand exceeds aggregate supply, i.e. when the stocks of all visited firms are not sufficient, (some) individual consumption budgets may not be exhausted, and aggregate excess demand is present. The opposite case, of course, can also be relevant, i.e. that (some) firms cannot sell off all their stock, and the firm sector is left with aggregate excess supply. However, in the absence of large endogenous fluctuations or exogenous shocks, the ABM constantly tends towards an approximate equilibrium state (see Section 3.3), and markets, in general, tend to be close to the equilibrium state where demand and supply match.

3.3. Expectations and adaptive learning—Behavioural Learning Equilibrium (BLE)

In our model, there are two variables that agents need to form expectations over. These are the expected (log) output and (producer price) inflation, from which agents compute the economy's expected growth rate and inflation rate. All agents (firms and households) form their expectations over these variables in a homogeneous way. So, how do agents in our ABM form expectations? We assume agents in the ABM are boundedly rational and do not fully understand the complex structure of their economic environment. Rather, they use simple forecasting heuristics, namely parsimonious AR(1) rules, to forecast variables in the model economy. This simple rule is misspecified as it ignores cross-correlations and complex nonlinearities. However, within their complex environment, agents learn and re-estimate the two parameters of each AR(1) rule and therefore learn the optimal AR(1) heuristic consistent with the mean and the persistence (i.e. the first-order autocorrelation coefficients) of all variables governing their expectations. In a complex environment, agents thus learn to use nearly optimal AR(1) forecasting heuristics.

In the complex ABM environment, in the long run, the learning process would settle down to a so-called *misspecification equilibrium*. In particular, learning converges to a behavioural learning equilibrium (BLE) as introduced by Hommes and Zhu (2014). A BLE is one of the simplest types of misspecification equilibria put forth in the literature and arises when agents' perceptions about endogenous economic variables are consistent with the actual realizations of these variables in the sense that the unconditional mean and first-order autocorrelations of the unknown nonlinear stochastic process – which describes the actual law of motion of the economy – coincide with the unconditional mean and autocorrelations of the AR(1) process that agents believe to be the actual law of motion. A BLE is parameter free, as agents employ the optimal (univariate) linear forecasting rule in an unknown nonlinear stochastic economy for each variable to be forecasted. Although a BLE is not a rational expectations equilibrium (REE) – since the linear forecasts do not coincide with the true conditional expectation – along a BLE, forecasting errors are unbiased and uncorrelated. A BLE may therefore be seen as an "approximate rational expectations equilibrium", in which the misspecified perceived law of motion is the *best univariate linear approximation* of the actual (unknown) nonlinear law of motion.

In the ABM, agents continuously learn and update the parameters of their AR(1) forecasting rule. For our forecast variables, persistence is high so that the AR(1) autocorrelations parameters are close to one. The adaptive learning process in our ABM thus leads to near-unit root behaviour consistent with the realized near-unit root autocorrelations of the economy. Thus, while the complex ABM may, in general, not be in equilibrium, agents constantly learn in an approximately optimal way, and in the long run, expectations – unless disturbed by exogenous shocks or endogenous fluctuations – will tend to converge to a BLE. In this sense, the fluctuations in our ABM are close to a BLE to which the adaptive learning process converges.

3.4. Determinants of growth and economic fluctuations

Economic growth in the ABM is an emerging property driven by the aggregated behaviour of agents. In general, in macroeconomic ABMs, GDP tends to self-organize towards a growth path with endogenously generated fluctuations (Dawid and Delli Gatti, 2018). In particular, trend growth at a horizon of 2–3 years in this ABM is driven by agents' expectations and their reactions to exogenous shocks and endogenous fluctuations. For example, supply decisions by firms are based on their expectations of real economic growth, which are formed using an AR(1) rule for log levels of aggregate output. Notice that for a special case of the BLE, with the AR(1) coefficient equal to 1, the growth expectations become self-fulfilling, leading to a constant realized growth

path in the economy as long as firms do not face constraints on production inputs. Our ABM is, in fact, close to having *multiple steady state growth paths*.[19] The adaptive learning process typically leads to near unit root AR(1) coefficients so that the BLE learning process is close to one of these self-fulfilling growth paths. Agents' expectations and their reactions to shocks and fluctuations are dependent on the initial conditions and result in path dependencies caused by externalities and nonlinearities due to interactions between agents. Since agents learn from their past mistakes, they will tend to close the gap between their expectations and the actual realizations of model variables—leading to the tendency to converge to a BLE, as argued above.

In the model, agent behaviour can exacerbate or dampen exogenous shocks and trigger endogenous fluctuations without exogenous shocks. For example, with a government sector, which collects taxes and provides social transfers, the model includes the automatic stabilizing mechanisms associated with a large welfare state. Other agent behaviour exacerbates exogenous shocks and may trigger endogenous fluctuations causing externalities and nonlinearities due to interactions. For example, the bankruptcy and the ensuing default of a particular firm agent is an endogenous event in the model that occurs if a firm has negative equity.[20] The bankruptcy may then cause losses of income both along the supply chain for other firms and for workers that are laid off. Moreover, the write-off of debt might restrict future credit provision by the banking sector due to minimum capital requirements. In turn, these losses of income and credit facilities, among others, might lead to decreased consumption by households and reduced firm investment, and consequently even to additional bankruptcies. This chain of events can exacerbate the initial effects of the bankruptcy for several periods in the model via these multiplier effects, potentially causing medium- or long-term path-dependencies before the model will tend to converge to a (new) BLE.

There are several sources of exogenous fluctuations in our model. Exogenous disturbances that arise to the two variables over which expectations are formed (similar to Assenza et al. (2015)) can be interpreted as aggregate shocks to (the expectations of) the growth rate and inflation rate of the economy. In addition, there are shocks to the five variables that are modelled as exogenous AR(1) processes. These consist of demand shocks from exports and government consumption, supply shocks from imports, and inflation and growth shocks in the euro area. For example, an export shock may cause demand deficiency, and thus some firms might not be able to sell off their production, forcing them to increase inventories. In the next period, with the inventory in stock, these firms will tend to lower current production, leading to layoffs of workers. This increased unemployment can lead to reduced income for a longer duration for several workers, reducing their consumption and thus, in turn, decreasing profits for some firms. Again, a chain of events reducing economic activity due to these multiplier effects might ensue in path dependencies and hysteresis until the model economy will tend to converge to a (new) BLE. However, given the initial conditions, endogenous fluctuations in the ABM are typically moderate, and the model tends to self-organize towards a growth path in the absence of large exogenous shocks.

3.5. Out-of-sample forecasts

By construction, macroeconomic ABMs are recursive sequential models in discrete time. In our ABM, the time unit for one period is a quarter. The sequence of events in each period starts with agents forming expectations, followed by interactions between agents in the various markets governed by search and matching processes, and ends with accounting to update state and flow variables. The exact sequence of events is given implicitly by equations and algorithms in Online Appendix A. The ABM is numerically solved in each period, where endogenous variables are determined one at a time in sequence. To obtain numerical results, Monte Carlo methods are used.

ABM forecasts are constructed in the following way: First, the ABM is calibrated to a reference quarter where a wide range of parameters and initial conditions are calibrated to economic statistics up to the reference quarter so that the model reproduces exactly the state of the economy in that quarter in terms of aggregate GDP, GDP components, and industry sizes, etc. (for details, see Section 4). Second, we conduct 500 Monte Carlo simulations with the calibrated model. For each Monte Carlo simulation, we recursively solve the model for twelve periods (i.e. the maximum forecast horizon). In each period, the sequence of events is the following:

(i) We start by solving the behavioural rules of agents regarding expectation formation, using the assumption that the expected next quarter's level of output and inflation are modelled by parsimonious AR(1) processes. From this, we obtain the expected rate of real economic growth and the expected inflation rate, upon which the decision heuristics for other variables (production, pricing, demand, employment, etc.) depend.

(ii) We draw random numbers from normal distributions for all exogenous shocks of our model. These are shocks to the AR(1) expectations of (log) output and (producer price) inflation, as well as to the other variables modelled as exogenous AR(1) processes (exports, imports, government expenditure, and inflation and growth of the euro area).

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[19] This may be seen from Equation (A.6) in Online Appendix A.1.2. When the AR(1) coefficient on aggregate output equals 1, i.e. $\alpha^Y(t-1) \equiv 1$, as long as firms are not constrained by labour, capital and financial constraints, the production follows a self-fulfilling growth path with a growth rate of $\beta^Y(t-1) \equiv \beta^*$. Under the adaptive learning process, the parameters $\alpha^Y(t-1)$ and $\beta^Y(t-1)$ are slowly time varying, with $\alpha^Y(t-1)$ close to 1, and the ABM with learning closely follows temporary self-fulfilling growth paths.

[20] Negative equity can result from a number of reasons in the model. One example would be unfavourable industry structures, which cause a number of firms in an industry to suffer from negative profit rates. Another reason might be that a firm is unlucky in the matching process when there is insufficient aggregate demand.

(iii) We solve the algorithms for the search and matching processes of the credit and labour market. These algorithms are solved numerically at the transaction level. As part of the algorithms, we draw uniformly distributed random numbers to reshuffle agents in random order. For example, we let firm agents in random order pick applicants in the labour market.

(iv) After search and matching in the credit and labour market is completed, production of firms is carried out, and the search and matching process of the goods market is solved. Here we draw again uniformly distributed random numbers to reshuffle agents on the demand side of the goods market in random order. Such a customer could be a household (private consumption), a firm (intermediate input to production), or the government (public consumption), among others. The probability that a firm and a customer match depends negatively on the firm's price and positively on the firm's size. With these assumptions, we construct an empirical cumulative distribution function in which large firms and firms with a low price are more heavily weighted, from which we then randomly draw the firm that the customer meets.

(v) After the search and matching is completed, behavioural equations regarding accounting are solved, and we update the remaining stock and flow variables of agents.

Third, after the 500 Monte Carlo simulations are completed, we calculate GDP and other macroeconomic aggregates for each simulation according to Online Appendix A.7. Finally, we average model results of the 500 Monte Carlo simulations to obtain the ABM forecasts.

4. Calibration to the Austrian economy

In this section, we discuss the calibration of the model presented in Section 3. We start by giving a short overview of the data sources for the calibration, followed by a brief discussion of the calibration procedure. For a detailed description of how specific parameters are calibrated, see Online Appendix D.

4.1. Data sources for calibration

To calibrate the model presented in Section 3 to the Austrian economy, we use data from Eurostat. Parameters of the model are calibrated so that a period t is one quarter, and each agent in the model represents a natural person or legal entity, such as a corporation, a government entity, or any other institution, in Austria. Austria is a typical example of an advanced small open economy with about 8.8 million inhabitants and more than half a million registered businesses.[21] It is closely integrated into the European economy by extensive trade: the export quota, i.e. the share of exports in GDP, is slightly more than 52 per cent, and the import quota is about 48 per cent. Austria's well-developed service sector constitutes about 71 per cent of the total GDP, while the industry sector takes a smaller share with about 28 per cent of GDP, and the agricultural sector contributes much less (about 1.5 per cent of GDP). Austria has a well-developed social and welfare system, primarily based on social security contributions, as well as taxation of income and consumption. Correspondingly, the ratio of public spending to GDP is about 52 per cent, while the overall tax burden, that is, the ratio of total taxes and social security contributions to GDP, reaches 43 per cent.

The parameters of the model can be broadly classified according to the used data source and the calibration procedure. In general, model parameters are either taken directly from data or are calculated from national accounting identities. For exogenous processes such as imports and exports, parameters are estimated from national accounts. Data sources include *(1) census and business demography*; *(2) input–output tables*; *(3) government statistics and sector accounts*; and *(4) national accounts (GDP and main components) and money market interest rates*. Additionally, a number of parameters are calibrated according to (5) statutory guidelines, financial regulations, and banking practices. Data sources and the respective Eurostat data tables are collected in Table 1.[22] The classification of these parameters according to their data source and calibration method is shown in Table 2. Parameters of the ABM are always calibrated to one reference quarter. For the forecasting exercise in Section 5, parameters were calibrated to *39* different reference quarters from the first quarter of 2010 to the third quarter of 2019. Here we show, as an example, parameter values for 2010:Q4.

4.1.1. Census and business demography data

Parameters that specify the number of agents are taken directly from census and business demography data. This is possible because we use a scale of 1:1 between the model and data so that each agent in the model represents a natural or legal person in reality. This has the advantage that our ABM is directly calibrated to micro and macroeconomic data. Scaling or fine-tuning of parameters is not needed. Rather, parameters are directly taken from data or are calculated from accounting identities. An illustrative and straightforward example for this class of parameters is the number of inactive households (H^{inact}). This parameter is calibrated according to population census data, which provides a numerical picture of the structure of the population, households, and families in a country. Here we use the statistics on *"Population by current activity status, NACE Rev. 2 activity and NUTS 2 region"* (*cens_11an_r2*) to calibrate H^{inact} to the number of inactive persons in Austria in 2011. Since data on population and housing censuses are collected every decade, this parameter is constant for all reference quarters.

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[21] For facts and figures about the Austrian economy, see, e.g. the Austrian Statistical Agency, http://statistik.at/web_en/statistics/index.html (Last accessed November 30th, 2018).

[22] The data are obtained from Eurostat, where they are freely available, see http://ec.europa.eu/eurostat/estat-navtree-portlet-prod/BulkDownloadListing?sort=1&dir=data (Last accessed November 30th, 2018). The codes under which the respective datasets are available from Eurostat (such as e.g. naio_10_cp1700) at this download facility are given in brackets in the description below.

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 (stocks)	nama_10_nfa_st
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

Note: The codes under which the respective datasets are available from Eurostat (such as, e.g. naio_10_cp1700) are shown in the second column.

For the classification of industries, we use the statistical classification of economic activities in the European Community (NACE).[23] Several consolidated tables including input–output tables, demographic data, and cross-classification tables are compiled for the euro area and European Union with a breakdown of 64 activities/products. We, therefore, set the number of industries (S) and the number of products (G) to 62, as we do not include the sectors *"Services of households as employers and services produced by households for own use"* (T) and *"Services provided by extraterritorial organizations and bodies"* (U) in the model, which have zero or close to zero output in Austria. Parameters concerning the numbers of firms in the sth industry (I_s) are calibrated to the respective numbers in business demography data (*bd_9ac_l_form_r2*). Business demography data shows the characteristics and demography of the business population and is available annually. We, therefore, calibrate I_s to the annual values for each reference quarter of a calendar year. Similarly, the total number of active persons (H^{act}) is derived from business demography data. The number L of foreign firms that import goods from Austria is not available from business demography data. As a simplifying assumption, this number is assumed to be 50 per cent of domestically producing firms, which approximately corresponds to the share of exports in total value added. Similarly, the number of government entities (J) is set to 25 per cent of domestically producing firms, which roughly equals the share of government consumption in total value added. This corresponds to a realistic depiction of public entities comprising municipalities, public schools, social insurance carriers, and districts, among others, in Austria according to their participation in the Austrian economy.

4.1.2. Input–output tables

Model parameters concerning productivity and technology coefficients, as well as capital formation and consumption coefficients, are taken directly from input–output tables or are derived from them. These parameters are industry-specific (NACE/CPA classification by ESA) and are calibrated to the annual values for each reference quarter of a calendar year. The input–output framework of the ESA consists of supply and use tables in current prices and the prices of the previous year. Supply and use tables are matrices describing the values of transactions in products for the national economy categorized by product type and industry; see Eurostat (2013). We use the symmetric input–output table at basic prices (product by product) (*naio_10_cp1700*) to calibrate the technology, consumption and capital formation coefficients (a_{sg}, b_g^{CF}, b_g^{HH}, b_g^{CFH}, c_g^{G}, c_g^{E} and c_g^{I}) and the productivity coefficient of intermediate inputs and net tax rates (β_i, τ_i^{Y} and, τ_i^{K}). For example, to calibrate the technology coefficients a_{sg}, we compile a matrix of intermediate consumption. To obtain the technology coefficients a_{sg}, the entries are then normalized column-wise.

For some parameters, we need to combine the logic of sectoral accounts and input–output tables. The information by the institutional sector in the sector accounts and the information by industry or product in the supply and use tables can be linked by cross-classification tables. We use cross-classification tables and structural business statistics (business demography) to complement symmetric input–output tables to calibrate the productivity coefficients for labour and capital ($\bar{\alpha}_i$, κ_i), the depreciation rate (δ_i), and the average wage rate ($\bar{w}_i$). For example, we combine data from input–output tables with business demography data to calibrate the average productivity of labour for firm i ($\bar{\alpha}_i$), which is assumed to be equal across firms in each industry s, but different between industries ($\bar{\alpha}_i = \alpha_s \quad \forall i \in I_s$). It is defined by the output in the industry divided by the number of persons employed in the population of active enterprises in that industry.[24] Similarly, the productivity coefficients of capital (κ_i) and the depreciation rate (δ_i) are calibrated by using the cross-classification table of fixed assets by industry and by asset (*nama_10_nfa_st*).

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[23] Products are classified according to the classification of products by activity (CPA), which is fully aligned with NACE.

[24] In the context of the Labour Force Survey (LFS), an employed person is a person aged 15 and over (or 16 and over in Iceland and Norway) who, during the reference week, performed work – even if just for one hour a week – for pay, profit or family gain. For further information, see http://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:Employed_person_-_LFS (Last accessed November 30th, 2018).

Table 2

Model parameters.

Parameter	Description	Value	Source
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	Census data, business demography data
J	Number of government entities	152 820	
L	Number of foreign consumers	305 639	
I_s	Number of firms/investors in the sth industry	See Online Appendix D	
$\bar{\alpha}_i$	Average productivity of labour of the ith firm		
κ_i	Productivity of capital of the ith firm		
β_i	Productivity of intermediate consumption of the ith firm		
δ_i	Depreciation rate for capital of the ith firm		
$\bar{w}_i$	Average wage rate of firm i		
a_{sg}	Technology coefficient of the gth product in the sth industry		
b_g^{CF}	Capital formation coefficient of the gth product (firm investment)		
b_g^{CFH}	Household investment coefficient of the gth product	Parameters are firm/sector specific;	Input-output tables
b_g^{HH}	Consumption coefficient of the gth product of households	See Online Appendix D	
c_g^{G}	Consumption of the gth product of the government in mln. Euro		
c_g^{E}	Exports of the gth product in mln. Euro		
c_g^{I}	Imports of the gth product in mln. Euro		
τ_i^{Y}	Net tax rate on products of the ith firm		
τ_i^{K}	Net tax rate on production of the ith firm		
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	Government statistics, sector accounts
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	Basel III, ECB statutes, banking practices, literature
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	
$\alpha^{\text{Y}^{\text{EA}}}$	Autoregressive coefficient for euro area GDP	0.9673	
$\beta^{\text{Y}^{\text{EA}}}$	Scalar constant for euro area GDP	0.4817	National accounts (exogenously estimated)
$\alpha^{\pi^{\text{EA}}}$	Autoregressive coefficient for euro area inflation	0.3834	
$\beta^{\pi^{\text{EA}}}$	Scalar constant for euro area inflation	0.0026	
$\sigma^{\pi^{\text{EA}}}$	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^{Y}	Weight of economic growth	1.2994	
C	Covariance matrix of euro area GDP and imports and exports		

Note: Model parameters for the reference quarter 2010:Q4. Exogenous autoregressive coefficients and parameters of the Taylor rule are estimated over the sample 1997:Q1 to 2010:Q4.

4.1.3. Government statistics and sector accounts

Tax rates and marginal propensities to consume or invest are calculated from national accounting identities. These tax rates are approximated by average rates and are calibrated such that the financial flows observed in input–output tables, government statistics, and sector accounts are matched. In the context of the model, we define an average tax rate as the aggregate tax flow paid by an institutional sector (firms, households, etc.) in a calendar year divided by the corresponding aggregate monetary flow that serves as the base for the tax and that is received by the same institutional sector (such as income, profit, output, fixed assets,

etc.). This annual average tax rate obtained from macroeconomic aggregates is then applied to every individual agent in our model in the corresponding economic context.[25] We, thus, calibrate tax rates and marginal propensities to consume or invest to the annual values for each reference quarter of a calendar year. For example, the tax rate on income (τ^{INC}) from both labour and capital is calibrated such that tax payments on wages received by employees and taxes on dividends received by investors sum up to the total income tax payments by the household sector, according to government statistics (*gov_10a_main*).[26] Similarly, the firm profit tax rate (τ^{FIRM}) is calibrated to the ratio of total corporate tax flows, which are obtained from sector accounts (non-financial transactions (*nasa_10_nf_tr*)), to total operating surplus and mixed income, which we directly take from input–output tables. Rates for social security contributions both for employers (τ^{SIF}) and employees (τ^{SIW}) are calibrated in a similar way to input–output tables and government statistics. Likewise, value added tax rates (τ^{VAT}, τ^{CF}, τ^{G}, τ^{EXPORT}) are calibrated to input–output tables.

Households' marginal propensity to consume (ψ) and invest (ψ^{H}) is calibrated such that consumption out of disposable income equals actual household consumption and investment in dwellings as obtained from input–output tables for Austria provided by Statistik Austria.[27] Firms' dividend payout ratio (θ^{DIV}) is calibrated to match interest and dividend receipts plus mixed income[28] by the household sector in the sector accounts (non-financial transactions (nasa_10_nf_tr)) in relation to total net operating surplus and mixed income as obtained from input–output tables. The risk premium (μ) paid on firms' outstanding debt is obtained from sector accounts. It is calibrated such that total interest payments in our model financial market, where firm debt constitutes the only financial asset held by the banking sector, matches empirically observed interest payments paid by non-financial and financial corporations in the sector accounts (non-financial transactions (*nasq_10_nf_tr*)). Therefore, the risk premium (μ) is calculated by the difference between the 3-month Euribor interest rate obtained from money market interest rates (*irt_st_q*) and the observed interest payments divided by the liabilities of non-financial corporations, which is obtained from sector accounts (financial balance sheets (*nasq_10_f_bs*)). Similarly, the interest rate on government debt (r^{G}) is obtained from government statistics (*gov_10q_ggdebt*, *gov_10q_ggnfa*) and is calibrated to the interest due per quarter by the general government as a proportion of the total government debt.

4.1.4. Statutory guidelines, financial regulation (Basel III), and banking practices

A number of parameters are calibrated according to statutory guidelines, financial regulation (Basel III), and banking practices. Since the statutory guidelines and regulations did not change during the calibration period, these parameters are assumed to be constant for all reference quarters. For example, the replacement rate for unemployment benefits (θ^{UB}) is chosen according to the statutory replacement rate of 55 per cent of net income, which amounts to a replacement rate on the gross income of $\theta^{\text{UB}} = 0.55(1 - \tau^{\text{INC}})(1 - \tau^{\text{SIW}})$. The capital ratio ($\zeta$) and the inflation target of the monetary authority (π^*) are set according to financial regulation (Basel III) and the statutes of the ECB (2 per cent inflation target). The rate of debt instalment (θ) is set such that firms repay 5 per cent of their total outstanding debt every quarter. The bank's maximum loan-to-value (LTV) ratio (ζ^{LTV}) is set to 60 per cent. LTV is one of the most common ratios considered for secured loans, and loans with an LTV ratio below 60 per cent are typically considered low- or medium-risk loans. Finally, the loan-to-value ratio for a new firm replacing a bankrupt firm (ζ^{b}) is set to be equal to 0.5.

4.1.5. Exogenously estimated from national accounts (GDP and main components) and money market interest rates

For exogenous processes such as imports and exports, parameters are estimated from national accounts (main aggregates, *namq_10_gdp*) and money market interest rates (*irt_st_q*). Imports, exports, and the final consumption expenditure of the general government, as well as inflation and GDP growth of the euro area, are assumed to follow an autoregressive process of lag order one (AR(1)). The coefficients of these AR(1) models (α^{G}, β^{G}, α^{E}, β^{E}, α^{I}, β^{I}, α^{YEA}, β^{YEA}, $\alpha^{\pi\text{EA}}$, $\beta^{\pi\text{EA}}$) are estimated from the observable time series of real government consumption, real exports, and real imports of Austria, and real GDP and inflation (GDP deflator) of the euro area. These parameters are estimated over the sample from the first quarter of 1997 to the respective reference quarter of the calibration. The sample 1996:Q2 to 1996:Q4 is used as a pre-sample period. Similarly, parameters of the Taylor rule (ρ, r^*, ξ^π, ξ^γ), see Online Appendix A.5.1, are also estimated over the sample from the first quarter of 1997 to the respective reference quarter of the calibration.[29]

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[25] For reasons of model parsimony, we abstract from the progressivity of the Austrian tax system (e.g. regarding income taxes) and secondly from other tax regulations (deductions, exemptions, etc.) relevant for some agents due to specific features of the Austrian tax code.

[26] From national accounting data alone, it is not possible to distinguish between the amount of income taxes due to incomes from labour and capital, respectively. For this distinction, it would be necessary to resort to the Austrian tax code and household surveys.

[27] See https://www.statistik.at/web_en/statistics/Economy/national_accounts/input_output_statistics/index.html (Last accessed November 30th, 2018) for more information on input–output tables provided by Statistik Austria. More detailed input–output tables for Austria, which include a breakdown of investment into different investment purposes (dwellings, other buildings and structures, machinery, transport equipment, cultivated assets, and intangible fixed assets), can be purchased. This is the only case where we do not rely upon publicly and freely available data from the Eurostat bulk download facility.

[28] In the logic of input–output tables, the self-employed are attributed to firm sectors. Thus, the operating surplus of industries includes mixed income, which directly flows to households in the depiction of our model and is thus treated as dividend income.

[29] Formally, the estimated Taylor rule is an AR(1) process of the 3m-Euribor with inflation and output growth as additional exogenous regressors. There is a wide literature on the estimation of Taylor rules that varies widely in the precise specification and method of estimation. Our estimated coefficients are roughly in line with the literature on euro area estimates of that sample period, in that the coefficient on economic activity comes out as relatively important and that the estimated coefficient on inflation tends to be low, see, e.g. Blattner and Margaritov (2010), Rivolta (2018) and the references therein.

5. Forecast performance

To validate the ABM, we conduct a series of forecasting exercises in which we evaluate the out-of-sample forecast performance of the ABM in comparison with standard macroeconomic modelling approaches.[30] The purpose of the first comparison in Section 5.1 is to compare the ABM to a VAR and a VECM. The purpose of the second comparison in Section 5.2 is to benchmark the ABM to a DSGE model as an alternative modelling paradigm that is rooted in economic theory.[31] Here, the AR model serves as a benchmark model for the forecast performance of both the ABM and the DSGE model. In the third forecast exercise in Section 5.3, we test the ABM against a VAR with exogenous variables (i.e. a VARX) and the DSGE model in a conditional forecasting setup.

5.1. Comparison with VAR and VECM

In this section, we compare the out-of-sample forecast performance of the ABM to that of an unconstrained (non-theoretical) VAR model and a VECM in a traditional out-of-sample root mean squared error (RMSE)[32] forecast exercise. To test whether the ABM and the VECM forecasts are significantly different in accuracy than the VAR(1) forecasts, we conduct (modified) Diebold–Mariano tests (Harvey et al., 1997) correcting for the overall length of the forecasting horizon. Observable time series include real GDP, inflation, real government consumption, real exports and real imports of Austria, real GDP and inflation of the euro area (EA), and the Euro Interbank Offered Rate (Euribor). The VAR and the VECM are initially estimated over the sample 1997:Q1 to 2010:Q1 (the sample 1996:Q2 to 1996:Q4 is used as a pre-sample period) and are then used to forecast the eight time series from 2010:Q2 to 2019:Q4; the models being re-estimated every quarter for the periods 2010:Q2 to 2019:Q3. In the VAR model, we enter GDP, government consumption, exports, imports, and GDP of the euro area in the first differences of the logged variables. For the inflation of Austria and the euro area, we use the first differences of the log GDP deflator, and the Euribor is entered in quarterly rates. To determine the optimal lag length of the VAR models, we use Akaike's and the Bayesian Information Criterion (AIC and BIC). For the entire period from 2010:Q1 to 2019:Q3, VAR models of lag order one minimize both the AIC and BIC. For the optimized log-likelihoods and the forecast performance of VAR models of different lag orders, see Tables G.1 and G.2 in the Online Appendix. Similarly, for the VECM, we use the AIC to determine the optimal lag length and the Johansen test to infer the cointegration rank. For the entire period from 2010:Q1 to 2019:Q3, we thus estimate a VECM of lag order zero and rank three. ABM forecasts are constructed analogously to the VAR and the VECM: the ABM is calibrated to 39 different reference quarters of the calibration period 2010:Q1-2019:Q3. Then, we let the model run for up to 12 quarters from each of these starting points (i.e. in the last eleven simulations up until 2019:Q4), where we average ABM model results of 500 Monte Carlo runs before we evaluate the forecasting accuracy.[33]

Table 3 reports the out-of-sample RMSEs for different forecast horizons of 1, 2, 4, 8, and 12 quarters over the period 2010:Q2 to 2019:Q4. RMSEs of GDP, government consumption, exports, imports, and GDP of the euro area are reported in log levels. For the inflation of Austria and the euro area, RMSEs are shown as the first differences of the respective log GDP deflators, and the error of the Euribor is reported in quarterly rates. In parentheses, we show the *p*-values of (modified) Diebold–Mariano tests, where we test whether the ABM forecasts are significantly different in accuracy than the VAR(1) forecasts (the null hypothesis of the test is that the ABM and the VECM have the same accuracy as the VAR(1)). These out-of-sample forecast statistics demonstrate the good forecast performance of the ABM relative to the VAR(1) model. Overall, however, as the p-values of the (modified) Diebold–Mariano tests show, the forecasting performance of the ABM and the VECM is not significantly different in terms of accuracy from the VAR(1) model. While the RMSE of the ABM and the VECM tend to be substantially lower, e.g. for GDP forecasts, especially in the longer run, the difference is, however, not significant.

Additionally, in Table G.3 in the Online Appendix, we report the mean forecast biases of ABM and the VECM in comparison to the VAR(1) for different forecast horizons of 1, 2, 4, 8, and 12 quarters over the period 2010:Q2 to 2019:Q4. To test whether the models have a significant forecast bias, we conduct Mincer and Zarnowitz (1969) tests and show the respective *p*-values in Table G.3 in the Online Appendix. Overall, the ABM and the VAR(1) have a similar low forecast bias for almost all variables and forecast horizons. These mean biases are, in general, significant according to the Mincer and Zarnowitz (1969) test except for inflation. Notable exceptions are imports and exports, where the VAR(1) has a substantial bias compared to the other models. The VECM, in comparison, has, in general, a lower forecast bias than the VAR(1), which is also not significant for the variables GDP and imports.

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[30] This out-of-sample prediction performance evaluation is constructed along the lines of Smets and Wouters (2007), who compare a Bayesian DSGE model to unconstrained VAR as well as Bayesian VAR (BVAR) models. As Smets and Wouters (2007) and for reasons of data availability, we are restricted to using final-revised data as available from Eurostat at the time of model estimation. For example, it is a well-known fact that input–output tables are produced with a lag of usually several years (for Austria, the lag is about 4 to 5 years). Clearly, vintage data, that is, data that was available at the period to which the model is calibrated, would, in general, be preferable for a pseudo-out-of-sample forecast exercise with expanding sample as we conduct below in Section 5. However, similar to Smets and Wouters (2007), in this study, we are primarily interested in how well the ABM fits data of the Austrian economy and not in benchmarking the forecast performance of the ABM with potentially inconsistent real-time data. Conducting a real-time forecast evaluation along the lines of, e.g. Diebold et al. (2017) is subject to future research.

[31] As discussed above, to benchmark the forecasting performance of our ABM, we choose a two-region DSGE model of Austria and the euro area in the style of Smets and Wouters (2007), which is the canonical DSGE model used for forecasting.

[32] The root mean squared error is defined as follows: $RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{T}(\hat{x}_t - x_t)^2}$, where $\hat{x}_t$ is the forecast value and x_t is the observed data point for period t.

[33] To check the robustness with respect to the number of Monte Carlo simulations, we recomputed the results presented in Table 3 for 400 and 600 Monte Carlo simulations and confirmed that the results are almost identical.

Table 3
Out-of-sample forecast performance.

	GDP	Inflation	Government consumption	Exports	Imports	GDP EA	Inflation EA	Euribor
VAR(1)	*RMSE-statistic for different forecast horizons*							
1q	0.45	0.33	0.66	1.53	1.66	0.41	0.17	0.05
2q	0.82	0.3	0.67	2.83	2.66	0.79	0.15	0.08
4q	1.78	0.28	1	6.18	5.67	1.85	0.16	0.18
8q	4.06	0.28	1.61	13.46	11.96	4.08	0.18	0.42
12q	5.83	0.25	2.1	18.93	16.08	5.36	0.19	0.57
VECM	*Percentage improvements (+) or losses (−) relative to VAR(1) model*							
1q	11.9 (0.29)	4.1 (0.72)	−9.5 (0.45)	24.6 (0.04**)	5.8 (0.67)	18.5 (0.25)	−1.2 (0.89)	−3.8 (0.84)
2q	37.7 (0.02**)	−5.1 (0.66)	−39.7 (0.17)	45.6 (0.00***)	30.4 (0.03**)	32.3 (0.02**)	−6.8 (0.50)	2.8 (0.87)
4q	56.6 (0.04**)	−24.9 (0.04**)	−44.5 (0.34)	65.5 (0.01**)	54 (0.01***)	41.9 (0.15)	−15.8 (0.20)	27.4 (0.02**)
8q	67.1 (0.15)	−21 (0.00***)	−40.6 (0.52)	74.8 (0.06*)	71.6 (0.06*)	47.5 (0.33)	−13.7 (0.55)	66.8 (0.01***)
12q	64.6 (0.26)	−8 (0.73)	−39.9 (0.56)	74.4 (0.11)	72.8 (0.12)	42.9 (0.50)	−16.2 (0.13)	74.6 (0.01**)
ABM	*Percentage improvements (+) or losses (−) relative to VAR(1) model*							
1q	−13 (0.36)	9.8 (0.21)	−14.1 (0.31)	10 (0.45)	7.5 (0.54)	−1.1 (0.94)	11.5 (0.12)	25.6 (0.16)
2q	4.3 (0.82)	7 (0.02**)	−14.5 (0.06*)	28.8 (0.04**)	16.8 (0.24)	2.6 (0.90)	−4.7 (0.64)	17.7 (0.35)
4q	25.6 (0.40)	0.1 (0.99)	3.6 (0.71)	47.4 (0.06*)	35.6 (0.12)	19.8 (0.60)	−4.8 (0.59)	37.7 (0.00***)
8q	46 (0.39)	−0.4 (0.92)	15.9 (0.13)	60.5 (0.16)	50.3 (0.23)	32.1 (0.63)	5.3 (0.58)	62.5 (0.02**)
12q	49.2 (0.50)	−0.5 (0.90)	13.4 (0.49)	62.2 (0.26)	48.1 (0.37)	25 (0.79)	5.8 (0.14)	64.2 (0.01**)

Note: The forecast period is 2010:Q2 to 2019:Q4. The VAR(1) and the VECM are estimated starting in 1997:Q1 and are re-estimated each quarter. The ABM is calibrated to 39 different reference quarters from 2010:Q1 to 2019:Q3. ABM results are obtained as an average of 500 Monte Carlo simulations. In parentheses, we show *p*-values of (modified) Diebold–Mariano tests (Harvey et al., 1997), where we test whether forecasts are significantly different in accuracy than the VAR(1) (the null hypothesis of the test is that the ABM and the VECM have the same accuracy as the VAR(1)). *, **, and *** denotes significance at the 10 per cent, 5 per cent, and 1 per cent levels, respectively.

5.2. Comparison with a standard DSGE model

In this section, we benchmark the ABM to a standard DSGE model by comparing their out-of-sample forecast performances. In general, the ABM and the DSGE model forecast different variables due to the inherent methodological differences between these model types. Therefore, we choose as variables for comparison the major macroeconomic aggregates: real GDP, inflation, and the main components of GDP—real household consumption and real investment, as well as interest rates, which can be forecasted with both models. As discussed above, to conduct this comparison, we employ a version of the standard DSGE model of Smets and Wouters (2007), which is a widely cited New Keynesian DSGE model for the US economy with sticky prices and wages, adapted to the Austrian economy. Specifically, we use a two-region model similar to Breuss and Rabitsch (2009), which is a New Open Economy Macro model for Austria as part of the European Monetary Union (EMU) constructed along the lines of Smets and Wouters (2007). It is a modified version of the two-country DSGE model as put forth in Breuss and Rabitsch (2009). See Online Appendix F for a detailed description of the DSGE model.

The model by Smets and Wouters (2007) has been generalized to the open economy as follows. The two-country economy is normalized to one, where the size of the home economy equals n, and the size of the foreign economy equals $(1 − n)$. Firms in each region produce goods using capital and labour according to a Cobb–Douglas production function. Each of the two countries specializes in the production of one region-specific good, i.e. there are both domestic and foreign tradable goods. These domestic and foreign tradable goods come in several varieties, over which producers have some degree of power in price setting. Investment is assumed to be a constant elasticity of substitution (CES) index over domestic and foreign investment goods. Financial markets are assumed to be complete; that is, a full set of Arrow–Debreu securities is assumed to exist. Households receive utility from consumption and disutility from working. They also own the economy's capital stock, which they rent to firms as means of production, and supply a variety of differentiated labour services, over which they have some degree of power in wage setting. Furthermore, household consumption is assumed to be a CES index over domestic and foreign consumption goods, which is possibly different from the CES investment index. In line with recent literature on DSGE models, a number of both real and nominal frictions are assumed. First, costs for capital adjustment and habit formation are imposed. Second, some degree of stickiness for both prices set by firms and wages demanded by households is assumed according to Calvo (1983) staggered price and wage-setting mechanisms. Both prices and wages are partially indexed; that is, they are to some degree inflation-adjusted in the event that price or wage changes are not possible. The DSGE model is estimated using Bayesian methods on quarterly time series as observable variables.[34]

As a benchmark model for the forecast performance of both the ABM and the DSGE model, we use AR models. As above, we use the AIC and BIC to determine the optimal lag length for the AR models. For details see, Tables G.4 and G.5 in the Online Appendix. For the entire period from 2010:Q1 to 2019:Q3 and for all variables, AR models of lag order one minimize both the AIC

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[34] The observed variables in the DSGE model are (see Online Appendix F for further information): log difference of real GDP (dY^{obs}, dY^{obs*}), real consumption (dC^{obs}, dC^{obs*}), real investment (dX^{obs}, dX^{obs*}) and the real wage (dW^{obs}, dW^{obs*}), log hours worked ($EMPL^{obs}, EMPL^{obs*}$), the log difference of the GDP deflator (Π^{obs}, Π^{obs*}) (six each for Austria and the euro area, where the euro area is indicated with *), as well as the three-month Euribor (R^{obs}).

Table 4

Out-of-sample forecast performance in comparison to DSGE model.

	GDP	Inflation	Household consumption	Investment	Euribor
AR(1)	*RMSE-statistic for different forecast horizons*				
1q	0.52	0.3	0.52	1.18	0.03
2q	0.77	0.28	0.73	1.78	0.06
4q	1.26	0.28	1.14	2.91	0.11
8q	2.12	0.29	1.93	4.26	0.16
12q	2.89	0.25	2.74	6.01	0.2
DSGE	*Percentage improvements (+) or losses (−) relative to AR(1) model*				
1q	1.1 (0.93)	−13.6 (0.05**)	7.7 (0.25)	−1.6 (0.87)	−147.8 (0.00***)
2q	−5.7 (0.70)	−10.9 (0.19)	12.5 (0.40)	2.4 (0.90)	−183.4 (0.00***)
4q	−8.2 (0.76)	−9.6 (0.09*)	30.5 (0.21)	−10.5 (0.74)	−201.3 (0.00***)
8q	−2 (0.97)	2.7 (0.80)	38.5 (0.30)	−19.4 (0.57)	−210 (0.00***)
12q	3.7 (0.97)	−14.9 (0.18)	49 (0.30)	0.4 (0.98)	−180.4 (0.00***)
ABM	*Percentage improvements (+) or losses (−) relative to AR(1) model*				
1q	1.7 (0.88)	−0.2 (0.80)	−16.1 (0.26)	−3.7 (0.12)	−3.6 (0.44)
2q	−1.8 (0.90)	−0.7 (0.52)	−13.1 (0.56)	−4.3 (0.23)	−2.6 (0.69)
4q	−5.5 (0.81)	1.5 (0.03**)	−2 (0.95)	−4.6 (0.40)	2.1 (0.85)
8q	−3.4 (0.95)	1.2 (0.53)	11.8 (0.83)	−6.9 (0.56)	0.6 (0.98)
12q	−2.7 (0.97)	0.2 (0.80)	19.7 (0.79)	−5.7 (0.71)	−0.3 (0.99)

Note: The forecast period is 2010:Q2 to 2019:Q4. The AR(1) and the DSGE model are estimated starting in 1997:Q1 and are re-estimated each quarter. The ABM is calibrated to 39 different reference quarters from 2010:Q1 to 2019:Q3. ABM results are obtained as an average of 500 Monte Carlo simulations. In parentheses, we show *p*-values of (modified) Diebold–Mariano tests (Harvey et al., 1997), where we test whether forecasts are significantly different in accuracy than the AR(1) (the null hypothesis of the test is that the ABM and the DSGE have the same accuracy as the AR(1)). *, **, and *** denotes significance at the 10 per cent, 5 per cent, and 1 per cent levels, respectively.

and BIC. Thus, as a standard time series model for comparing the forecast performance of the ABM and DSGE models, we estimate AR(1) models on the log first differences of real GDP, real household consumption, real investment, the log difference of the GDP deflator (inflation), and the Euribor (in quarterly rates). The DSGE model and the AR models are initially estimated over the sample 1997:Q1 to 2010:Q1, and the models are then used to forecast the five time series from 2010:Q2 to 2019:Q4, with the models being re-estimated every quarter for the periods 2010:Q2 to 2019:Q3. Analogously, the ABM is again calibrated to 39 different reference quarters of the calibration period 2010:Q1-2019:Q3. ABM results are obtained as an average of 500 Monte Carlo simulations, and the DSGE model is estimated using Bayesian methods.[35]

Table 4 shows comparisons between the ABM and the DSGE and AR(1) models for forecast horizons of 1, 2, 4, 8, and 12 quarters over the period 2010:Q2 to 2019:Q4. Here, RMSEs of GDP, household consumption, and investment are reported in log levels. RMSEs of inflation are again shown as the first differences of the log GDP deflator, and the error of the Euribor is reported in quarterly rates. Overall, for more or less all macroeconomic variables, the forecast performances of the ABM, DSGE, and AR(1) models are not significantly different from each other. This is also reflected in the *p*-values of the (modified) Diebold–Mariano tests, which show no significant differences of any model compared to the AR(1) for any variable and forecast horizon except for inflation and the Euribor of the DSGE model.[36] Interesting results are obtained by comparing across Tables 3 and 4: while the forecast performance for inflation of all models, except for the DSGE model, is similar in Tables 3 and 4, the ABM, the VECM, and the AR(1) improve on the VAR(1). This is not too surprising, as it is known that AR models are hard benchmarks and overparameterized VARs typically perform poorly in out-of-sample forecast exercises (Smets and Wouters, 2007).

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[35] DSGE estimations are done with Dynare, see http://www.dynare.org/ (Last accessed November 30th, 2018). A sample of 250,000 draws was created (neglecting the first 50,000 draws).

[36] At this point, however – since this might catch the eye of any professional forecaster – we would like to comment on the limited performance of the DSGE model with regard to interest rate forecasts. On the one hand, we should emphasize that the AR(1) forecasts we adopt as our benchmark are very hard to beat and are considerably more competitive benchmarks than a VAR(1), which is the example benchmark used in Smets and Wouters (2007). This particularly holds true for the interest rate. When we compare our forecasts to those of a VAR(1) (see Online Appendix F), the DSGE forecast performance is closer to the one obtained by Smets and Wouters (2007), despite the fact that our model forecasts almost twice as many variables (Austrian and euro area variables) and the more demanding forecasting period post-Great Recession. It could, however, also be argued that the forecasting performance is compromised because our DSGE model does not account for a possibly binding zero lower bound. To address this issue – without explicitly having to adopt estimation methods capable of addressing occasionally binding constraints – we also estimate a version of the DSGE model where we replace the (possibly constrained) 3m-Euribor series with the euro area shadow rate of Wu and Xia (2016). Shadow rates are fictional short-term rates that are constructed from the observed yield curve and are therefore not restricted by the effective lower bound. By using such a policy rate as a proxy for the central bank's policy stance, one can assess the effect of monetary policy without introducing non-linearity to the model (Wu and Xia, 2016). The forecasts of such a version of our DSGE model do, however, not improve. Therefore, we continue to report results with the baseline of having the 3m-Euribor as an observable. Online Appendix F discusses in detail the intricacies of estimating DSGE models in ZLB times, the progress made in the recent literature in addressing this methodologically (in solution and estimation methods), and presents our results from our DSGE model estimated on the Wu and Xia (2016) shadow rate.

Table 5
Conditional forecast performance.

	GDP	Inflation
VARX(1)	*RMSE-statistic for different forecast horizons*	
1q	0.45	0.31
2q	0.55	0.3
4q	0.83	0.3
8q	1.2	0.31
12q	1.44	0.28
VECMX	*Percentage improvements* (+) *or losses* (−) *relative to VARX(1) model*	
1q	3.2 (0.80)	−0.3 (0.98)
2q	−8.7 (0.66)	10.3 (0.27)
4q	6.2 (0.83)	7.6 (0.41)
8q	18.3 (0.52)	5.8 (0.62)
12q	23 (0.13)	−4.5 (0.74)
ABM	*Percentage improvements* (+) *or losses* (−) *relative to VARX(1) model*	
1q	1.1 (0.93)	1.5 (0.89)
2q	−2.5 (0.89)	10 (0.28)
4q	8.7 (0.71)	7.8 (0.43)
8q	13.9 (0.63)	6 (0.64)
12q	12.3 (0.66)	−6.4 (0.64)

Note: The forecast period is 2010:Q2 to 2019:Q4. The VARX(1) and the VECMX are estimated starting in 1997:Q1 and are re-estimated each quarter. The ABM is calibrated to 39 different reference quarters from 2010:Q1 to 2019:Q3. ABM results are obtained as an average of 500 Monte Carlo simulations. In parentheses, we show p-values of (modified) Diebold–Mariano tests (Harvey et al., 1997), where we test whether forecasts are significantly different in accuracy than the VARX(1) (the null hypothesis of the test is that the ABM and the VECMX have the same accuracy as the VARX(1)). *, **, and *** denotes significance at the 10 per cent, 5 per cent, and 1 per cent levels, respectively.
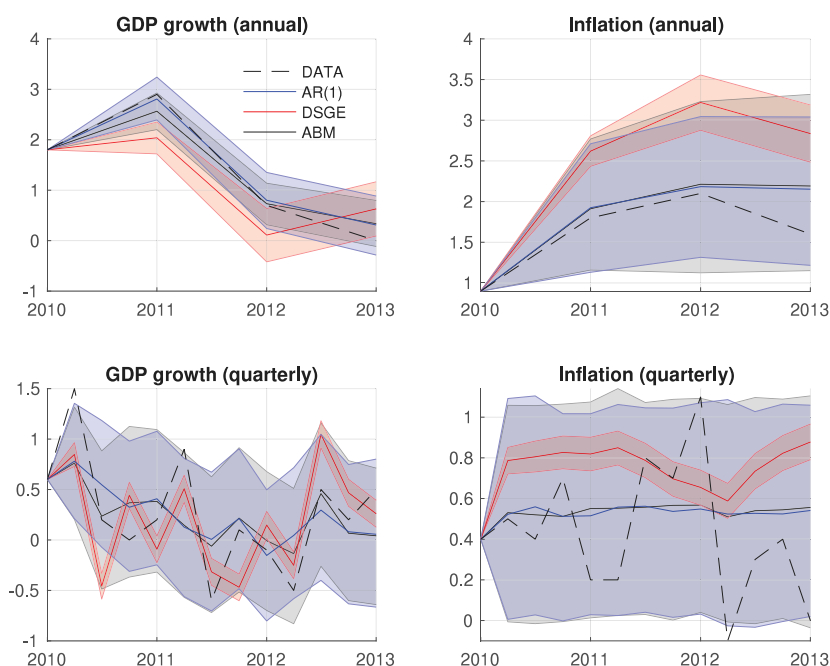
5.3. Conditional forecasts

As a further validation exercise, we test the conditional forecast performance of the different model classes (ABM, DSGE, VARX, VECMX and ARX models).[37] In this exercise, we generate forecasts from the three models conditional on the paths realized for the following three variables: real exports, real imports, and real government consumption (conditional forecasts of the DSGE model are subject to the exogenous paths for exports and imports only). The exogenous predictors can be included in the VARX, VECMX and ARX models and the ABM (conditional forecasts) in a straightforward way; for details, see Online Appendix B. Conditional forecasts in the DSGE model are achieved by controlling certain shocks to match the predetermined paths of the exogenous predictors. In particular, we control the consumption preference shocks for Austria and the euro area, which are the major drivers for Austrian exports and imports in the two-country setting of the DSGE model.[38] Again, we use the period 1997:Q1–2010:Q1 to initially estimate the DSGE, VARX, and VECMX. In the VARX model, we enter GDP and the exogenous variables government consumption, exports, and imports in the first differences of the logged variables. For the inflation of Austria, we again use the first differences of the log GDP deflator. The ABM is again calibrated to 39 different reference quarters of the calibration period 2010:Q1-2019:Q3. We then forecast real GDP, inflation, and nominal household consumption and investment from 2010:Q2 to 2019:Q4, with the DSGE, VARX, and VECMX being re-estimated every quarter for the periods 2010:Q2 to 2019:Q3. Thus, together with the real exports, real imports, and real government consumption, we account for all main components of GDP.[39]

Tables 5 and 6 show that the forecast performance of all models considered (VARX, VECMX, ARX; ABM and DSGE model with conditional forecasts) improves pronouncedly for GDP (Tables 5 and 6), as well as for household consumption and investment (Table 6) when exogenous predictors are included. Similarly, with the predictors, the mean forecast bias of all models is also pronouncedly lower, which can be seen in Tables G.9 and G.12 in the Online Appendix. Again, the performance of the ABM (conditional forecasts), the VARX(1), the VECMX, and the ARX(1) models are relatively similar for all variables and forecast horizons as indicated by the p-values of the (modified) Diebold–Mariano tests. Table 6 shows that the forecast performance of the DSGE model (conditional forecasts) deteriorates for household consumption (in the long-run significantly so) and investments for all horizons as compared to unconditional forecasting, while it stays about the same for GDP as compared to the ARX and ABM models. This

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[37] Again, we use the AIC and BIC to determine the optimal lag length for the VARX and ARX models and the AIC and Johansen test to determine the optimal lag length and cointegration rank for the VECMX. For details on the ARX model, see Tables G.10 and G.11 in the Online Appendix. As above, for the entire period from 2010:Q1 to 2013:Q4 and for all variables, models of lag order one minimize both the AIC and BIC.

[38] In fact, we control the shocks to household bond holdings (ε_t^b, ε_t^{b*}), which enters the consumption decision by households; see Online Appendix F on the DSGE model for details.

[39] Another note on interest rate forecasts: since interest rates are determined exogenously for the Austrian economy (which makes up only 3 per cent of the total GDP of the euro area) and are assumed to remain constant in the conditional forecasting setup, we do not report on Euribor forecasts here. For readers interested in the interest rate forecast performance of the two-country DSGE model in the conditional forecasting setup, please refer to Online Appendix F on the DSGE model.

Table 6

Conditional forecast performance in comparison to DSGE model.

	GDP	Inflation	Household consumption	Investment
ARX(1)	*RMSE-statistic for different forecast horizons*			
1q	0.44	0.31	0.49	1.19
2q	0.54	0.3	0.64	1.57
4q	0.82	0.3	0.98	2.5
8q	1.19	0.31	1.54	3.98
12q	1.44	0.28	2.19	5.59
DSGE	*Percentage improvements (+) or losses (−) relative to ARX(1) model*			
1q	−20.8 (0.22)	−18 (0.13)	−187.6 (0.01***)	−2.7 (0.84)
2q	−11.7 (0.48)	−13.2 (0.22)	−185.8 (0.01**)	−16 (0.43)
4q	4.5 (0.82)	−24.8 (0.21)	−220.9 (0.01***)	−41.8 (0.27)
8q	17.2 (0.29)	−51.4 (0.24)	−251.1 (0.03**)	−56.6 (0.38)
12q	32.6 (0.01**)	−152.8 (0.00***)	−246.5 (0.12)	−47.2 (0.54)
ABM	*Percentage improvements (+) or losses (−) relative to ARX(1) model*			
1q	−0.4 (0.97)	1.5 (0.90)	−29.8 (0.03**)	3.3 (0.76)
2q	−4.2 (0.82)	10.7 (0.24)	−10.6 (0.63)	−2.4 (0.80)
4q	7.8 (0.73)	8 (0.42)	6 (0.83)	−1.7 (0.87)
8q	13.2 (0.63)	6.5 (0.61)	40 (0.39)	9.8 (0.39)
12q	12.3 (0.65)	−7.1 (0.58)	50.5 (0.37)	11.5 (0.24)

Note: The forecast period is 2010:Q2 to 2019:Q4. The ARX(1) and the DSGE model are estimated starting in 1997:Q1 and are re-estimated each quarter. The ABM is calibrated to 39 different reference quarters from 2010:Q1 to 2019:Q3. ABM results are obtained as an average of 500 Monte Carlo simulations. In parentheses, we show *p*-values of (modified) Diebold–Mariano tests (Harvey et al., 1997), where we test whether forecasts are significantly different in accuracy than the ARX(1) (the null hypothesis of the test is that the ABM and the DSGE have the same accuracy as the ARX(1)). *, **, and *** denotes significance at the 10 per cent, 5 per cent, and 1 per cent levels, respectively.

Fig. 1. Forecast performance from 2011:Q1–2013:Q4. ABM conditional forecasts (black line), DSGE conditional forecasts (red line), ARX(1) forecasts (blue line), and observed Eurostat data for Austria (dashed line). Top figures show year-average growth and inflation (percentage change on the previous year); bottom figures depict quarterly growth and inflation rates (percentage change on the previous quarter). A 90 per cent confidence interval is plotted around the mean trajectory. Model results are obtained as an average of 500 Monte Carlo simulations. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

deterioration for household consumption and investment, however, is mostly due to methodological reasons, that is, the need to control exogenous shocks such that the exogenous paths of the predictors are matched in the DSGE model. This clearly has the most pronounced implications for the forecast of household consumption (to a lesser extent also for forecasts of investment) in the DSGE model, where forecast errors increase to a large extent when compared to the ARX(1) model for these variables.
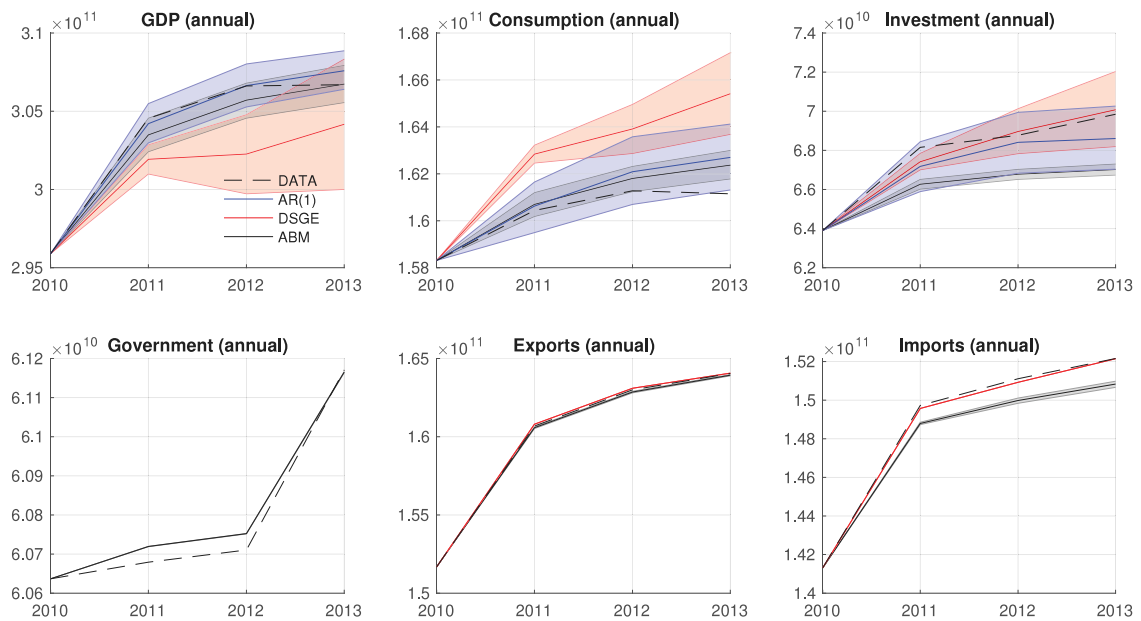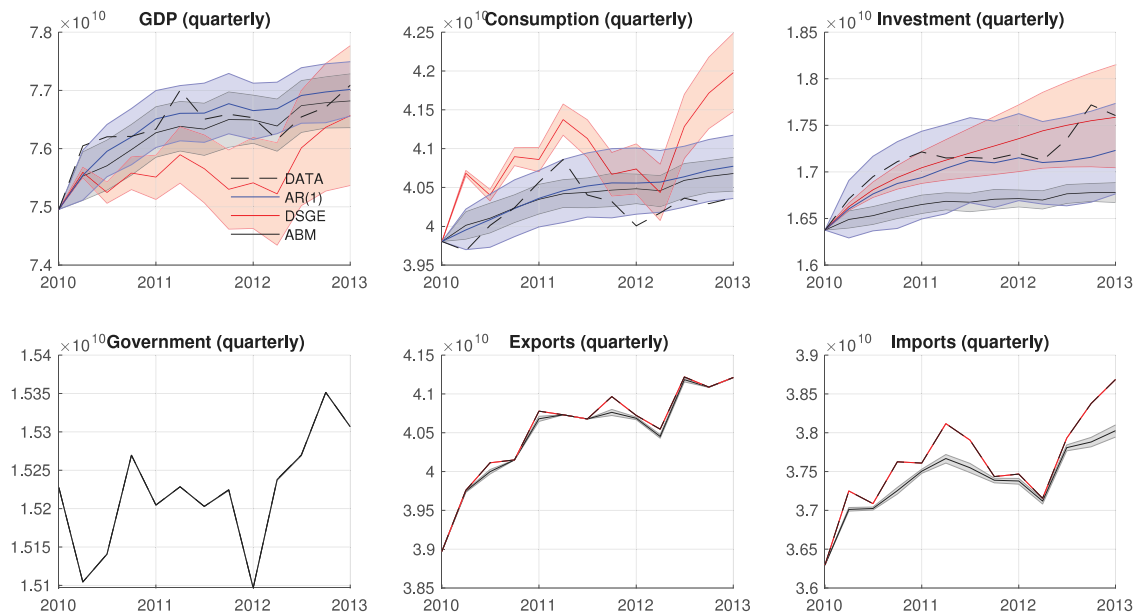
Fig. 2. Forecast performance from 2011:Q1–2013:Q4. GDP (annually, in euro and real terms with the base year 2010), household consumption (annually, in euro and real terms with the base year 2010), fixed investment (annually, in euro and real terms with the base year 2010), government consumption (annually, in euro and real terms with the base year 2010), exports (annually, in euro and real terms with the base year 2010), and imports (annually, in euro and real terms with the base year 2010). ABM conditional forecasts (black line), DSGE conditional forecasts (red line), ARX(1) forecasts (blue line), and observed Eurostat data for Austria (dashed line). A 90 per cent confidence interval is plotted around the mean trajectory. Model results are obtained as an average of 500 Monte Carlo simulations. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 3. Forecast performance from 2011:Q1–2013:Q4. GDP (quarterly, in euro and real terms with the base year 2010), household consumption (quarterly, in euro and real terms with the base year 2010), fixed investment (quarterly, in euro and real terms with the base year 2010), government consumption (quarterly, in euro and real terms with the base year 2010), exports (quarterly, in euro and real terms with the base year 2010), and imports (quarterly, in euro and real terms with the base year 2010). ABM conditional forecasts (black line), DSGE conditional forecasts (red line), ARX(1) forecasts (blue line), and observed Eurostat data for Austria (dashed line). A 90 per cent confidence interval is plotted around the mean trajectory. Model results are obtained as an average of 500 Monte Carlo simulations. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

To further illustrate our results, Figs. 1–3 provide a graphical comparison between conditional forecasts with the ABM and results from an ARX(1) model, and between conditional forecasts with the DSGE model and actual time series data reported by Eurostat.

Table 7

Out-of-sample forecast performance of sectoral gross value added (GVA).

	A	B, C, D and E	F	G, H and I	J	K	L	M and N	O, P and Q	R and S
VAR(1)	*RMSE-statistic for different forecast horizons*									
1q	5.25	1.2	1.49	0.8	1.66	3.29	0.41	1.17	0.46	0.62
2q	7.32	1.71	1.93	1.15	2.01	3.63	0.6	1.57	0.61	0.83
4q	9.9	2.24	3.35	1.83	2.96	5.03	0.9	2.28	0.88	1.19
8q	10.76	2.83	5.99	2.96	2.75	4.58	1.22	3.75	1.46	1.86
12q	13.67	3.31	8.06	3.79	3.63	4.45	1.72	5.04	1.94	2.63
ABM	*Percentage improvements (+) or losses (−) relative to VAR(1) model*									
1q	0.5 (0.95)	−2.3 (0.82)	23.9 (0.04**)	−6.8 (0.40)	4.9 (0.47)	14.8 (0.04**)	−39.1 (0.01***)	−15.7 (0.24)	−1.3 (0.87)	12.3 (0.32)
2q	2.6 (0.36)	7.3 (0.18)	8.8 (0.04**)	−7.4 (0.61)	2.5 (0.82)	0.6 (0.90)	−90.2 (0.00***)	−14.1 (0.33)	−15.1 (0.34)	10.4 (0.52)
4q	8.4 (0.08*)	5.8 (0.17)	8.5 (0.01***)	−3.6 (0.88)	−2.8 (0.74)	1.8 (0.45)	−150.8 (0.00***)	−24.3 (0.36)	−34.3 (0.36)	14.5 (0.47)
8q	8.1 (0.44)	7.6 (0.16)	7.8 (0.00***)	15.6 (0.66)	−48.2 (0.01***)	5.8 (0.35)	−250 (0.00***)	−24.2 (0.51)	−54.4 (0.41)	28.7 (0.35)
12q	9.1 (0.39)	6.8 (0.21)	10.2 (0.09*)	38.4 (0.56)	−64.6 (0.00***)	5.4 (0.62)	−271 (0.00***)	−31.3 (0.51)	−74.1 (0.43)	27.5 (0.46)

Note: GVA is shown for the sectors Agriculture, forestry and fishing (A); Industry (except construction) (B, C, D and E); Manufacturing (C); Construction (F); Wholesale and retail trade, transport, accommodation and food service activities (G, H and I); Information and communication (J); Financial and insurance activities (K); Real estate activities (L); Professional, scientific and technical activities, as well as administrative and support service activities (M and N); Public administration, defence, education, human health and social work activities (O, P and Q); Arts, entertainment, and recreation, as well as other service activities (R and S). The forecast period is 2010:Q2 to 2019:Q4. The VAR(1) model is estimated starting in 1997:Q1 and is re-estimated each quarter. The ABM is calibrated to 39 different reference quarters from 2010:Q1 to 2019:Q3. ABM results are obtained as an average of 500 Monte Carlo simulations. In parentheses, we show *p*-values of (modified) Diebold–Mariano tests (Harvey et al., 1997), where we test whether forecasts are significantly different in accuracy than the VAR(1) (the null hypothesis of the test is that the ABM is less accurate than the VAR(1)). *, **, and *** denotes significance at the 10 per cent, 5 per cent, and 1 per cent levels, respectively.

Fig. 1 shows aggregate GDP growth and inflation (measured by GDP deflator) rates—annually (top) and quarterly (bottom). One can see at first glance that the ABM tracks the data very well for GDP growth (left panels). For annualized (top left) and quarterly (bottom left) model results, almost all data points are within the 90 per cent confidence interval (grey shaded area)—except for two outliers (2011:Q1,2012:Q1), where the Austrian growth rates picked up quite sharply. It is especially interesting to note how the ABM catches trends in the data somewhat better than the ARX(1) model. In particular, the ABM reacts directly to a fall in exports in 2013:Q1 (see Fig. 3)—which reflects a slowdown in economic growth for some of Austria's European trading partners during the European debt crisis—that drags down GDP growth in the ABM. Similar to the ABM, the DSGE in a conditional forecasting setup seems to catch upward and downward trends in the data quite well but tends to "overreact" by taking the trend too far. This overshooting might deteriorate the forecasting performance of the DSGE somewhat and is most probably connected to the way in which controlling the shocks for the conditional forecasting procedure influences the mechanics of the DSGE model. While both the AR model and the ABM seem to follow rather smooth trajectories in comparison to the data (see Fig. 1, bottom left), it is quite interesting to see how the DSGE model rather mirrors the developments of the data—showing the strengths of this theory-based model also in the conditional forecasting setup.

A similar picture arises when the conditional forecasts for the main macroeconomic aggregates in levels (GDP, household consumption, investment) of the ABM are compared to the other models; see Figs. 2 (annual) and 3 (quarterly). Looking at GDP at annual levels (top left in Fig. 2) and quarterly levels (top left in Fig. 3), it is evident that the ABM closely follows the data, as do the growth rates in Fig. 1, and that all data points are within the confidence interval. The ARX(1) model delivers a comparable forecasting performance to the ABM. The DSGE model at first consistently underestimates both annual and quarterly GDP levels and then overestimates the upward trend starting in 2013:Q2. Both the ABM and the ARX(1) model seem to smooth out the changes in household consumption to approximately match the average trend, with the ABM being somewhat closer to the data. Again, the DSGE model seems to follow the trends in the data quite accurately but consistently overestimates the level, which might be responsible for the overall deterioration of the forecasting performance of the DSGE model for household consumption.

5.4. Sectoral decomposition

The previous sections have demonstrated that the ABM can compete with benchmark VAR and DSGE models in out-of-sample forecasting of macroeconomic aggregates. An important advantage of our approach is that the detailed structure of the ABM allows macroeconomic forecasts to be disaggregated with varying levels of detail, offering insights into the composition of overall macroeconomic trends. Thus, as a last validation exercise, we test the sectoral out-of-sample forecast performance of the ABM. In this exercise, we decompose ABM forecasts from Sections 5.1 and 5.2 for different sectors by economic activities. Specifically, sectoral gross value added (GVA) is disaggregated for ten economic activities according to the statistical classification of economic activities in the European Community (NACE Rev. 2). As a benchmark, we use a VAR model estimated on the log differences of sectoral GVA, where we determine the optimal lag length with the AIC and BIC. For details see, Tables G.13 and G.14 in the Online Appendix. For the entire period from 2010:Q1 to 2019:Q3, models of lag order one minimize both the AIC and BIC. The VAR model is initially estimated over the sample 1997:Q1 to 2010:Q1 and is then used to forecast the ten time series from 2010:Q2 to 2019:Q4, with the model being re-estimated every quarter for the periods 2010:Q2 to 2019:Q3. The ABM is again calibrated to 39 different reference quarters of the calibration period 2010:Q1-2019:Q3, and results are obtained as an average of 500 Monte Carlo simulations.
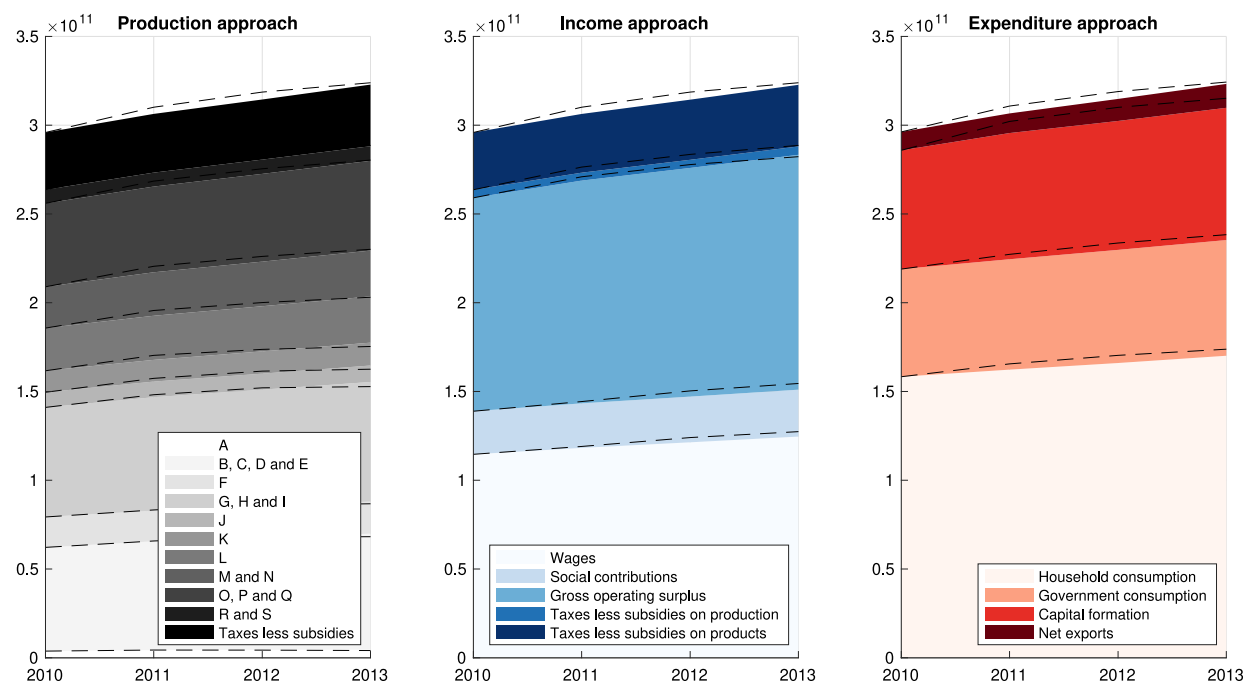
Fig. 4. Components of GDP according to production, income and expenditure approaches. The coloured areas indicate ABM simulation results for one selected period (2011:Q1–2013:Q4), again as an average of 500 Monte Carlo simulations. The dashed line shows the corresponding values obtained from the data. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 7 shows the sectorally disaggregated forecast performance of the ABM in comparison to a VAR(1) model. At first glance, it becomes apparent that the ABM improves on the forecast performance of the VAR(1) in some sectors and does worse in others. These performance gains or losses are, in general, significant according to the (modified) Diebold–Mariano tests. Results have confirmed our intuition that ABM forecasts would tend to perform better for larger sectors that are closely connected to economic developments in Austria and do worse for sectors that are subject to processes or policy decisions, which are exogenous to our model. Particular but non-exhaustive examples for such sectors driven by exogenous factors are: (1) the agricultural sector (A), which is to a large extent dominated by the subsidy policies of the Austrian government and the EU, (2) the real estate sector (L), which reflects how rents are imputed for national accounting data, or (3) activities of head offices (M), which might reflect changes in ownership structures of large companies (holdings) more than economic developments in Austria. Additionally, in Table G.15 in the Online Appendix, we report the mean forecast biases of ABM in comparison to the VAR(1). Overall, the ABM and the VAR(1) have a similar forecast bias for most sectors and forecast horizons. These mean biases are, in general, significant according to the Mincer and Zarnowitz (1969) test.

5.5. Components of GDP

In the previous sections, we have shown that the ABM delivers a competitive forecasting performance to standard models for macroeconomic aggregates and allows macroeconomic forecasts to be broken down with varying levels of detail. Another important advantage of our approach is that forecasts can be decomposed in a stock-flow consistent way according to the rules and conventions of national accounting (ESA). In particular, we can forecast *all* economic activities depicted in the model consistent with national accounting rules and relate them to the main macroeconomic aggregates. Most importantly, for all forecasts, our model preserves the principle of double-entry bookkeeping. This consistency implies that all financial flows within the model are explicit and are recorded as an outflow of money (use of funds) for one agent and as an inflow of money (source of funds) for another agent. In principle, we can thus consistently report on the economic activity of every single agent at the micro-level. This multitude of results consists of all components of GDP on a sectoral level: among others, wages, operating surplus, investment, taxes and subsidies of different kinds, intermediate inputs, exports, imports, final consumption of different agents (household, government), employment, and also economic indicators such as productivity coefficients for capital, labour, and intermediate inputs.

Probably the simplest example indicative of this model structure is that it breaks down simulation results into the larger components of GDP according to the different approaches for determining GDP. Fig. 4 is a graphical representation of the ABM out-of-sample forecasts from Section 5.4. The components are shown according to the production, income, and expenditure approaches to determine GDP, which are defined within the framework of our model along ESA lines, as laid out in Online Appendix A.7. With the fine-grained detail incorporated into our model, we can demonstrate how the development of macroeconomic aggregates such as

GDP relates to trends in different industries (production approach), the distribution of national income (income approach), and the composition of final uses in the economy (expenditure approach). Here, the coloured fields indicate ABM simulation results for the different components of GDP, while the dashed line refers to the values reported in the data. Our results show that ABM forecasts of these components of GDP, where the ABM does not predict major structural changes for the Austrian economy, correspond closely to the developments in the data.

6. An agent-based approach to assess the economic effects of the COVID-19 pandemic

Finally, we use the detailed ABM to assess the medium-run macroeconomic effects of lockdown measures taken in Austria to combat the COVID-19 pandemic.[40] Pausing the activity of several economic sectors in the country for a period of more than two months not only had adverse consequences on the sectors that were directly affected but caused ripple-through effects that can be assessed using appropriate modelling tools considering inter-industry linkages such as our ABM. The level of detail of our model allowed for the measurement of economic reactions to the COVID-19 related lockdown measures within particular industries, as well as tracking the propagation of these measures through the economic system of the country.

To implement the COVID-19 related shocks in the model, we made four modifications with respect to the model presented in Section 3. Specifically, we model the COVID-19 pandemic by (1) a domestic supply shock caused by the restrictions of economic activities due to the lockdown measures; (2) an export demand shock; (3) a supply shock from a decrease in imports; and (4) we implement a short-time work policy instrument. This policy instrument represented one of the main economic relief measures of the government and allowed Austrian companies to keep their employees at a salary of up to 90 per cent of the net remuneration received before short-time work, which was refunded by the Austrian government to the companies in full instead of potentially laying them off. The scenario assumptions are calibrated with labour market data collected by the Austrian Public Employment Service (AMS) and with scenarios from Oxford Economics.[41] To calibrate the domestic supply shock, we use AMS data on the net inflow of unemployed persons by sector as of March 2020 and assume that approximately 65 per cent of companies would use the short-time work policy instrument. To account for the effects of the COVID-19 pandemic in the RoW, we use the March 2020 Coronavirus pandemic scenario projected by Oxford Economics for Austrian imports and exports to calibrate the export demand and import supply shocks. For details on the implementation of the COVID-19 related shocks, see Online Appendix C.

6.1. Impact of the shutdown until mid-may on macroeconomic variables

The projections show that due to the shutdown until mid-May 2020 (as announced by Austrian politics at that time), the Austrian economy would suffer from a sharp initial contraction and then experience a gradual recovery. In total, our simulations show that Austrian GDP would contract by more than 6 per cent in 2020 as a yearly average (almost seven percentage points below the benchmark scenario), followed by a pronounced recovery thereafter, especially in 2021 (see Fig. 5, lower left panel). At the time of writing, the recovery of the economy has already begun after restrictions on economic activity have ended for most sectors—which has occurred during the middle of the year 2021 in Austria, while the further development of the pandemic is yet unclear and renewed restrictions in fall 2021 are not unlikely. In any case, the transition to the original growth path would take a considerable amount of time for several reasons. First of all, not all employees who were previously laid off would be rehired immediately. Second, post-crisis investment would be limited by the financial conditions of companies. Third, the demand for consumption and intermediate goods is likely to remain below pre-crisis levels for some time. Three aspects of the model primarily drive the results: (1) the large supply shock caused by the restrictions of economic activities due to the lockdown measures; (2) the supply shock from a decrease in imports and the export demand shock; (3) the adaptive learning process that pulls the model economy back towards the approximate (BLE) equilibrium path. Additionally, due to policy intervention (short-time work) and automatic fiscal stabilizers (from the well-developed social security system in Austria), a part of the shock is absorbed. While GDP growth can be expected to return to trend levels after approximately two to three years, GDP levels would remain considerably lower than in the baseline scenario until then (see Fig. 5, upper left panel). As can be expected, the effects of the pandemic on labour markets are tremendous. Even if a significant proportion of companies institute short-time work instead of laying off their workforce, the unemployment rate is expected to rise to more than 10 per cent in 2020 (see Fig. 5, upper right panel). It is particularly compelling to note that the labour market takes a longer time to recover than GDP: unemployment does not return to levels before the COVID-19 pandemic until the end of the simulation period (winter 2022). As in other countries around the globe, the implementation of measures to

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[40] Results of this analysis, together with an alternative scenario for the duration of the lockdown, have been released as a policy brief in April 2020 (Poledna et al., 2020). This policy brief has enriched the academic and policy debate about the economic consequences of the COVID-19 pandemic in Austria. Despite the uncertainty surrounding the duration of the then-implemented lockdown measures and the potential implementation of additional lockdowns thereafter, our analysis (conducted in the spring of 2020) showed how our ABM provided insights into likely trajectories of a small open economy when confronted with a large shock. Moreover, our detailed quantitative analysis has revealed mechanisms through which the political measures put in place have affected economic activity for different sectors. In particular, despite these high uncertainties both regarding the model and the assumptions, our results quite closely matched the actual economic effects of the COVID-19 pandemic in Austria 2020 at the time of writing. Our simulations predicted a reduction by slightly more than 6 per cent for the lockdown until mid-May 2020. The actual reduction of the Austrian economy amounted to a total of 6.6 per cent for 2020 as an annual average. Similarly, our forecasts in 2020 of GDP growth rates of more than 2.5 per cent for the year 2021 were very much in line with the economic forecasts for the Austrian economy by Austria's major forecasting institutions IHS (2.6 per cent, see Bittschi et al. (2021)) and WIFO (2.3 per cent, see Ederer (2021)) at that time.

[41] For details see https://www.oxfordeconomics.com/country-economic-forecasts.
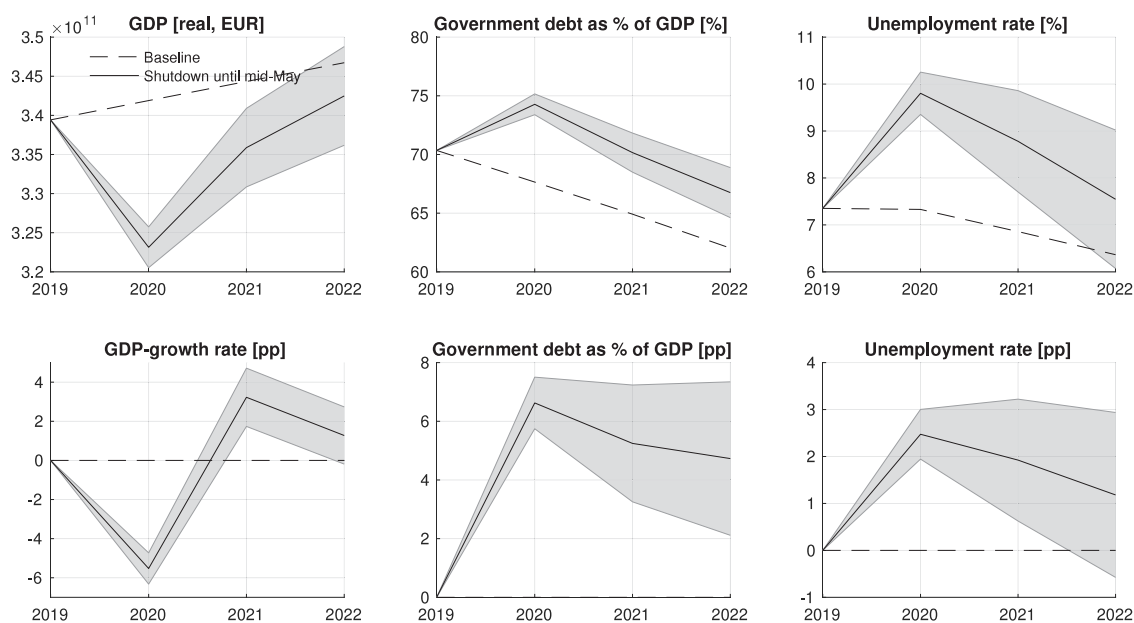
Fig. 5. Impact of the shutdown until mid-May on annual macroeconomic variables with respect to the baseline scenario. The top figures show the macroeconomic variables under the shutdown scenario in levels at an annualized basis; the bottom figures with respect to the baseline scenario in percentage points [pp]. One standard deviation is plotted around the mean trajectory. Model results are obtained as an average of 500 Monte Carlo simulations.

support companies and people required massive amounts of additional government funding to keep the Austrian economy afloat. According to our simulations, this additional funding increased the national debt by about 7 pp to more than 75 per cent of GDP (from an initial value of about 70.5 per cent in 2019) until the end of 2020 (see Fig. 5, middle panels).

6.2. Impacts differentiated by industries and components of GDP

Based on our scenario assumptions, highly differentiated output effects are expected for different economic sectors, depending on their relative sensitivity to the lockdown of economic and social activities. This can be clearly seen in Fig. 6 (top left), which presents the contribution of individual sectors to the total changes in GDP due to the COVID-19 pandemic (the stacked area under the line diagrams) and relates them to the total shares of these sectors in the economy (the pie diagram in the right lower corner). The sectoral decomposition of GDP dynamics in this projection shows that those sectors that offer products of final demand: construction (F), wholesale and retail trade (G), transportation (H), accommodation and food services (I), as well as arts, entertainment, recreation, and other activities (R and S). These sectors are most directly affected by the shutdown and thus experience a steep decrease in output. Output in some sectors fell sharply during the time of the lockdown. The accommodation and food services sector, for instance, experienced a decline of more than 50 per cent during the lockdown (second quarter of 2020) and only partially started to recover in 2021. The decline in output is only partially compensated for by the subsequent expansion in the three-year simulation period, so that sectoral output, especially for construction, wholesale and retail trade, transportation, as well as accommodation and food services, remains below the trend until the end of 2022. The decomposition into expenditure components shown in Fig. 6 (bottom centre) reveals that household consumption is hit hardest by an almost 4 pp reduction in 2020 due to the lockdown measure. On the other hand, it is interesting to note that according to the breakdown in GDP income components, see Fig. 6 (top right), this reduction in household consumption then translates into a higher loss in operating surplus of about 4 pp, which in relative term is almost twice as large as the loss in wage income. Clearly, in this result, one can identify the government intervention, i.e. the short-time work policy instrument, which alleviates the burden of the crisis that has to be borne by the household sector.

7. Conclusions

We developed an ABM of a small open economy that fits micro and macro data from national accounts, sector accounts, input–output tables, government statistics, census data, and business demography data. The model is very detailed and is the first ABM that can compete with standard VAR, VECM, AR, and DSGE models in out-of-sample forecasting. An advantage of our detailed ABM is that it allows for a breakdown of the forecasts of aggregate variables in a stock-flow-consistent manner to generate forecasts of disaggregated sectoral variables and the main components of GDP.

At this point, we stress that the purpose of this study was not to indicate whether an ABM at such high resolution as ours can forecast better than an AR or DSGE model for a particular variable or time horizon. Rather, we believe that the benchmarking
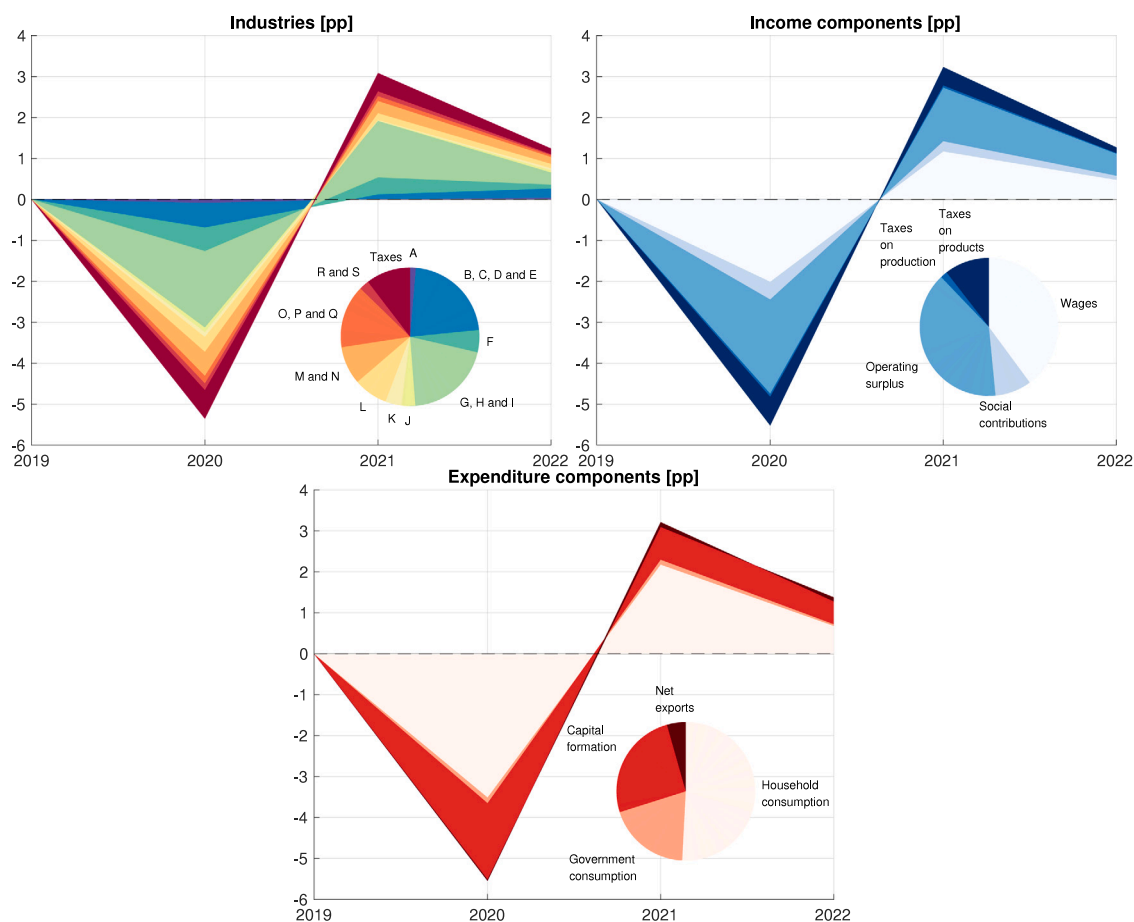
Fig. 6. Contribution of industries (top left), income components (top right), and expenditure components (bottom centre) to GDP growth with shutdown until mid-May with respect to the baseline scenario in percentage points [pp]. The stacked areas under the line diagram show the respective contributions of individual sectors to the total change in GDP growth due to the shutdown. The pie charts in the lower right corners show the relative shares of these sectors in GDP. The contribution of industries is shown for the sectors Agriculture, forestry and fishing (A); Industry (except construction) (B, C, D, and E); Manufacturing (C); Construction (F); Wholesale and retail trade, transport, accommodation, and food service activities (G, H and I); Information and communication (J); Financial and insurance activities (K); Real estate activities (L); Professional, scientific and technical activities, as well as administrative and support service activities (M and N); Public administration, defence, education, human health, and social work activities (O, P and Q); Arts, entertainment, and recreation, as well as other service activities (R and S). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

and validation procedure for an ABM, as presented here, is the first major and necessary step in turning an ABM into a mature forecasting and policy evaluation tool. For these reasons, our main aim was to develop the simplest prototype of an ABM where the macro-economy emerges bottom-up from the micro-level and which has a forecast performance comparable to that of standard approaches.

The ABM is tailor-made for the small open economy of Austria, but it can easily be adapted to the economies of larger countries, such as the UK and the US or to larger regions such as the EU. In addition, it would be interesting to calibrate it to other periods beyond the ones presented here, e.g. for the run-up to the financial crisis of 2007–2008, to investigate whether parameter values and forecasts change significantly for other periods.[42] By also including long-term trends, such as productivity growth or demographics, this ABM could become a highly detailed long-run simulator of different national economies or larger economic regions. Such extensions are currently being explored.

Our model has been used to forecast the medium-run macroeconomic effects of different scenarios for lockdown measures taken in Austria to combat the COVID-19 pandemic. The dynamic properties and the detailed structure of our model enabled us to assess their overall macroeconomic impact, including labour market effects of the COVID-19 pandemic, making detailed projections on sectoral impacts and presenting a realistic outlook on the timing and shape of economic recovery thereafter. Other potential applications of the model include stress-testing exercises or predicting the effects of changes in monetary, fiscal, and other macroeconomic policies.

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[42] For this study, we were restricted by the data availability as discussed above. Most notably, for our present analysis, the sectoral definitions for input–output tables were changed between the years 2009 and 2010.

A grand challenge and possible long-term objective for future work would be to create a "Big Data ABM" research program to develop ABMs for larger economies and regions based on available micro and macro data to eventually monitor the macro-economy in real-time on supercomputers. Such detailed ABMs have the potential for improved macro forecasting and more reliable policy scenario analysis; they could revolutionize the way we monitor and forecast economic activity in the short, medium, and long runs.

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Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.5281/zenodo.7271552.

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