UNIVERSITÄT BIELEFELD

Faculty of Business Administration and Economics

Working Papers in Economics and Management

No. 04-2024
October 2024

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Herbert Dawid Domenico Delli Gatti Luca Eduardo Fierro

Sebastian Poledna

Bielefeld University
P.O. Boxx 10 01 31
33501 Bielefeld - Germany

ISSN 2196-2173

www.wiwi.uni bielefeld.de

Implications of Behavioral Rules in Agent-based Macroeconomics*

Herbert Dawid[a], Domenico Delli Gatti[b], Luca Eduardo Fierro[c], and Sebastian Poledna[c]

[a]Department of Business Administration and Economics and Center for Mathematical Economics, Bielefeld University, PO Box 100131, 33501 Bielefeld, Germany
[b]Department of Economics and Finance and Complexity Lab in Economics, Università Cattolica del Sacro Cuore, Milano, Italy
[c]International Institute for Applied Systems Analysis, Schlossplatz 1, 2361 Laxenburg, Austria

October 3, 2024

Abstract

In this paper we examine the role of the design of behavioral rules in agent-based macroeconomic modeling. Based on clear theoretical foundations, we develop a general representation of the behavioral rules governing price and quantity decisions of firms and show how rules used in four main families of agent-based macroeconomic models can be interpreted as special cases of these general rules. We embed the four variations of these rules into a calibrated agent-based macroeconomic framework and show that they all yield qualitatively very similar dynamics in business-as-usual times. However, the impact of demand, cost, and productivity shocks differ substantially depending on which of the four variants of the price and quantity rules are used.

Keywords: agent-based macroeconomics, behavioral rules, pricing, forecasting

1 Introduction

Since the development of the first agent-based macroeconomic models in the early 2000s[1], this approach has become an important part of the toolbox for macroeconomic analysis, which features strong behavioral foundations and the potential for versatile policy analysis. Axtell and Farmer (2024); Dosi and Roventini (2019) or Dawid and Delli Gatti (2018) provide extensive surveys and discussions of the merit and the potential of the agent-based approach, as well as of different streams of literature that have flourished in this field of research. A noteworthy recent development is the emergence of a substantial stream of ABM literature focusing on the economic impact and potential policy responses for major challenges, such as green transition (e.g., Filatova and Akkerman (2024); Hötte (2020); Lamperti et al. (2020, 2024); Turco et al. (2023)) or the outbreak of a pandemic like COVID-19 (e.g., Delli Gatti and Reissl (2022); Pichler et al. (2022); Basurto et al. (2023); Poledna et al. (2023)). Several of these papers highlight the value of integrating macro ABMs with dynamic models developed in other disciplines, such as climate research or epidemiology (see also Savin et al. (2023)). In term of policy impact, ABMs are being used increasingly by central banks for analysing issues such as systemic risk, housing market dynamics and inflation (see e.g., the survey by Borsos et al. (2024)).

*This article will be a contributed chapter to the Santa Fe Institute edited volume: "The Economy as a Complex Evolving System, Part IV". We gratefully acknowledge helpful comments from Doyne Farmer and participants of the MacroABM Workshop at IIASA (April 2024), the CEF 2024 conference and WEHIA 2024.

[1]Predecessors closely related in spirit to the agent-based approach, have however been developed substantially earlier. A main example in this respect is the MOSES model, see Eliasson (2023) for an extensive discussion of its development and main results.

On a more conceptual and methodological level, recent work by Poledna et al. (2023); Hommes et al. (2024a) demonstrates that ABMs are not only suitable tools for improving our understanding of the general mechanisms that determine how interactions on the micro level generate macro-level phenomena, but also perform well in terms of short term forecasting capability. Using calibrations based on Austrian (Poledna et al. (2023)) and Canadian (Hommes et al. (2024a)) data, Poledna, Hommes and co-authors show that the out-of-sample forecasting performance of the agent-based macroeconomic model is competitive with that of vector auto-regressive (VAR) and DSGE models. The rich microstructure of the model allows also to make sector-specific forecasts and also in this respect the ABM is fully competitive with forecasts based on VARs.

As the field of agent-based macroeconomics has matured, a relatively small set of *model families* has emerged which can be applied to a large number of topics and policy issues. In this chapter we focus on four families only: the framework developed by Poledna, Hommes, and coauthors (CANVAS[2] Poledna et al. (2023); Hommes et al. (2024a,b)), the family of *Complex Adaptive Trivial Systems* (CATS, Delli Gatti et al. (2011); Riccetti et al. (2013); Assenza et al. (2015)), the *Eurace@Unibi* model (EUBI, Dawid et al. (2018, 2019)) and the *Schumpeter meeting Keynes* framework (KS Dosi et al. (2010, 2015)). The focus on these four families is essentially due to the limits of our knowledge base and to the specificity of our competences. We have therefore been forced to leave out of the present analysis a few important frameworks with which we are less familiar, such as the baseline model in Lengnick (2013), the macroeconomic ABM put forward by Peter Howitt and co-authors (see, e.g., Ashraf et al. (2017)), the Oxford-INET model developed by Doyne Farmer and co-authors (successfully used in Pichler et al. (2022)), the JAMEL model (Salle and Seppecher (2018)), or the recently developed MATRIX model (Ciola et al. (2023)).

The four families of macroeconomic ABMs we analyze share the general interpretation of the economy as a system of interacting heterogeneous agents, whose behavior is determined by rules rather than equilibrium conditions, in which macro-level dynamic patterns are emergent phenomena due to micro-level interactions. They differ quite substantially, however, with respect to the specifications of the interaction structures in different sectors and markets as well as of the behavioral rules used by the different agents. To a large extent, these differences are due to the fact that the frameworks have been developed with slightly different research agendas and theoretical foundations in mind. Nevertheless, the heterogeneity of model assumptions and structures makes it challenging to compare results, such as insights about the impact of certain policies, that have been found in different macro ABM settings. Therefore, it is imperative to systematically analyze the impact of differences in the modeling assumptions for behavioral rules and interaction structures on the dynamics of key economic variables. This analysis would not only foster comparability between ABM-based findings but also generate new insights about the relationship between properties of the micro-level behavior and emergent macro-level phenomena.

Two of us made a first step in this direction in Dawid and Delli Gatti (2018), where the modeling assumptions underlying eight families of macroeconomic ABMs are systematically spelled out and compared. The analysis also highlights that several of the considered behavioral rules in different macro ABM families have a common theoretical basis. In this paper we go one step further. We focus on a specific set of important behavioral rules, namely the rules by which firms[3] decide on the quantity to be produced and the price of their product, and make two main contributions.
First, we derive from a clear theoretical micro-foundation a unified representation for behavioral rules concerning price and quantity setting, and show that the rules used in each of the macro ABM families considered (CANVAS, CATS, EUBI, KS) can be interpreted as a special case of that general representation. By so doing we can clearly highlight how the rules differ with respect to the information that is taken into account and also with respect to the underlying economic rationale. Put differently, our unified representation allows us to identify which "channels" are active under the different rules.
Second, we systematically compare the macro-dynamics across macroeconomic ABMs which differ only with respect to the behavioural rule used for determining quantities and prices of consumption goods. More precisely, we incorporate price/quantity decision rules used in each of the four considered ABM families into a calibrated version of the model as in Poledna et al. (2023), and study how the out-of-sample dynamics of the model under these four types of decision rules compare to each other

[2]CANVAS refers specifically to the version developed by the Bank of Canada. The broader family of models to which CANVAS belongs does not have a formal name, unlike other agent-based model families such as CATS, EUBI, and KS.
[3]Strictly speaking for EUBI and KS the rules we consider govern the behaviour of consumption goods firms only.

and to the empirical time series. Furthermore, we study how the different rules react to three types of economic shocks, in particular demand, input prices, and productivity shocks. Based on this exercise we can isolate the effect of properties of the firm's behavioural rules on the dynamics of key economic variables and thereby gain important insights about the implications of different modelling assumptions. Furthermore, our exercise also provides insights into the performance of different behavioural assumptions with respect to short-term forecasting.[4]

The paper is organized as follows. In Section 2 we derive a general representation of price-quantity rules for consumption good firms and show how the rule implemented in each of the four considered families of macro ABMs can be interpreted as a special case of this representation. The macroeconomic environment in which the price/quantity rules are embedded is described in Section 3. In Section 4 we present the results of our analysis of the implications of the use of different price/quantity rules. We conclude with a discussion of our results and considerations of how to extend our analysis in Section 5.

2 A general treatment of price-quantity rules in macroeconomic ABMs

2.1 The basic framework

Consider the profit maximization problem of a firm (say firm i, with $i = 1, 2, ...F_C$) in an imperfect competition setting. Using notation similar to Dawid and Delli Gatti (2018)) we write the demand for the good produced by firm i at time t as

$$Q^D_{i,t} = \chi_t s_{i,t}(P_{i,t}, P_{-i,t}, z_{i,t}, z_{-i,t}), \tag{1}$$

where χ_t is the total demand for consumption goods (which in general depends on macroeconomic dynamics, the households' life cycle, the industry's life cycle, etc.) while $s_{i,t}(.)$ captures the market share of firm i. The market share is a function of the firm's own price $P_{i,t}$, the vector of competitors' prices $P_{-i,t}$, the firm's own product characteristics $z_{i,t}$, the vector of product characteristics of competitors $z_{-i,t}$. To be as general as possible, we assume that the functional form of the market share function is firm-specific and time-varying.

A product characteristic is any feature (such as quality, formal appearance, proximity to a given buyer or group of buyers etc.) which might imply differentiation among goods from the consumers' perspective. This differentiation is the source of imperfect competition: Firms produce *varieties* and therefore have price setting power on their captive markets.

Notice that in principle χ_t might depend on the average price level and therefore on the price of the individual firm, inasmuch as the latter contributes to the formation of the aggregate price level. Still, we suppose that firm i assumes that changes in its own price do not affect χ_t, but only its market share $s_{i,t}(.)$.

The firm operates in an uncertain environment. For simplicity, we assume that uncertainty concern (i) the shape of the market share function $s_{i,t}(.)$ and (ii) the vector of competitors' prices $P_{-i,t}$. Hence the firm must estimate the functional form of the market share, that we refer to as the expected market share function and denote with $s^e_{i,t}(.)$ where the superscript e indicates an expectation. Moreover, assuming that the firm's size is "negligible", the vector of competitors' prices can be satisfactorily proxied by the aggregate price level P_t, a weighted average of the individual prices. The firm may be not have sufficient information to determine the actual average price level, hence it has to form the expectation, denoted with P^e_t. For simplicity, we assume that the *expected* average price is uniform across firms. Taking these considerations into account we can write the *expected* demand for the product of firm i as

$$Q^{D,e}_{i,t} = \chi_t s^e_{i,t}(P_{i,t}, P^e_t, z_{i,t}, z_{-i,t}), \tag{2}$$

[4] Our approach here is to compare the different rules with respect to the implications of their use on the macro level. Hence, we do not engage in a comparison of the strength of the empirical foundations, respectively the match with observed data, on the micro level. A discussion of different approaches for developing foundations for decision rules of firms in agent-based models can be found in Dawid and Harting (2012). This paper also explicitly discusses the 'management science approach', i.e., the use of decision heuristics that are documented in the management literature, as the foundation for the decision rules in the EUBI model.

2.2 Pricing decision

We assume that technology is linear so that the marginal production cost is constant. We assume moreover that the firm does not know with certainty technology and input prices so that the firm must form expectations of the marginal cost. We denote the *expected* marginal (production) cost at t by $c^e_{i,t}$. We assume finally that the firm incurs fixed costs $F_{i,t}$. The i-th firm sets its own price $P_{i,t}$ in order to maximise expected profits $\Pi^e_{i,t}$:

$$\max_{P_{i,t}} \Pi^e_{i,t} = Q^{D,e}_{i,t} \left(P_{i,t} - c^e_{i,t} \right) - F_{i,t},$$

Note that for simplicity we abstract from capacity constraints in this formulation. From the first order condition we obtain

$$P_{i,t} = (1 + \mu_{i,t}) c^e_{i,t} \tag{3}$$

with the markup given by

$$\mu_{i,t} = \frac{1}{\epsilon^e_{i,t} - 1}, \tag{4}$$

and

$$\epsilon^e_{i,t} = -\frac{\partial Q^{D,e}_{i,t}}{\partial P_{i,t}} \frac{P_{i,t}}{Q^{D,e}_{i,t}} = -\frac{\partial s^e_{i,t} \left(P_{i,t}, P^e_t, z_{i,t}, z_{-i,t} \right)}{\partial P_{i,t}} \frac{P_{i,t}}{s^e_{i,t}(P_{i,t}, P^e_t, z_{i,t}, z_{-i,t})}$$

denoting the (absolute value of the) *expected price elasticity* of the demand for the product of firm i.

The main problem the firm faces in setting the price consists in estimating the price elasticity of demand $\epsilon^e_{i,t}$.[5] Different ABMs use different approaches for addressing this problem.

We envision the following protocol for the firm to estimate the elasticity. The firm believes that its market share is essentially determined by the *ratio* of its own price to the average market price $\frac{P_{i,t}}{P_t}$, a proxy of the *relative* price of the i-th good. Due to the uncertainty surrounding the average price level, the firm forms an expectation of the relative price: $\frac{P_{i,t}}{P^e_t}$. Moreover, the firm assumes that the relationship between the expected market share and the expected relative price is linear. This means that the slope of the expected market share function (with respect to the expected relative price) is independent of the price levels. This is tantamount to assuming that there exist two parameter values $\zeta^e_{i,t}$ and $\bar{\zeta}^e_{i,t}$, both positive, such that the expected market share can be written as follows

$$s^e_{i,t}(P_{i,t}, P^e_t, z_{i,t}, z_{-i,t}) = \bar{\zeta}^e_{i,t} - \zeta^e_{i,t} \left(\frac{P_{i,t}}{P^e_t} - 1 \right).$$

Product characteristics $z_{i,t}$ and $z_{-i,t}$ are "embodied" in the above mentioned parameter values.

Let's assume finally that all firms have identical market shares if they charge the same price. In this case, the intercept of the expected market share function is uniform across firms and equal to $\bar{\zeta}^e_{i,t} = \frac{1}{F_C}$. In the end, therefore, we can write the expected market share as follows:

$$s^e_{i,t} = \frac{1}{F_C} - \zeta^e_{i,t} \left(\frac{P_{i,t}}{P^e_t} - 1 \right), \tag{5}$$

where $\zeta^e_{i,t}$ measures the *sensitivity* of the firm's market share to the relative price of its product.[6]

Using this equation, the expected elasticity of the demand for the product of firm i becomes

$$\epsilon^e_{i,t} = \frac{\zeta^e_{i,t}}{P^e_t} \frac{P_{i,t}}{s^e_{i,t}},$$

Inserting this expression into (4) and solving for $P_{i,t}$ in equation (3) gives the following representation of the firm's optimal price

$$P_{i,t} = c^e_{i,t} + \frac{s^e_{i,t} P^e_t}{\zeta^e_{i,t}}. \tag{6}$$

[5] In principle the firm has to face also potential capacity constraints (respectively: inventory targets), which might imply that an expansion of output induced by a decrease in price leads to an increase in marginal costs. For simplicity this case is not considered in the present setting.

[6] A simple microfoundation for this demand structure is presented in Appendix A.

From the pricing rule we retrieve the mark-up:

$$\mu_{i,t} = \frac{s^e_{i,t} P^e_t}{\zeta^e_{i,t} c^e_{i,t}}. \tag{7}$$

Based on (7) we can formulate the following recursive representation of the markup:

$$\mu_{i,t} = \mu_{i,t-1} \times \underbrace{\frac{s^e_{i,t}}{s^e_{i,t-1}}}_{\substack{\text{exp. change}\\ \text{in market share}}} \times \underbrace{\frac{P^e_t}{P^e_{t-1}}}_{\substack{\text{exp. change}\\ \text{in av. price}}} \Big/ \underbrace{\frac{\zeta^e_{i,t}}{\zeta^e_{i,t-1}}}_{\substack{\text{exp. change}\\ \text{in sensitivity}}} \times \underbrace{\frac{c^e_{i,t}}{c^e_{i,t-1}}}_{\substack{\text{exp. change}\\ \text{in marg. cost}}}. \tag{8}$$

It is worth noting that the change of the reciprocal of expected sensitivity, $\frac{1/\zeta^e_{i,t}}{1/\zeta^e_{i,t-1}}$, is closely related to unexpected demand. In the absence of rationing and capacity constraints, actual output would coincide with expected demand: $Y_{i,t} = Q^{D,e}_{i,t}$. Actual demand $Q^D_{i,t}$, in turn, is increasing with the current value of $\zeta_{i,t}$. A lower (higher) realization of $\zeta_{i,t}$ relative to $\zeta^e_{i,t}$ (for given prices), therefore, yields a higher (lower) actual demand relative to expected demand. This results in an increase (reduction) of unfulfilled demand. Based on these considerations, we interpret the ratio $\frac{1/\zeta^e_{i,t}}{1/\zeta^e_{i,t-1}}$ as a proxy for unfulfilled demand expressed as a percentage of output. Hence, we can rewrite and reinterpret the representation of the markup as follows:

$$\mu_{i,t} = \mu_{i,t-1} \times \underbrace{\frac{s^e_{i,t}}{s^e_{i,t-1}}}_{\substack{\text{exp. change}\\ \text{in market share}}} \times \underbrace{\frac{P^e_t}{P^e_{t-1}}}_{\substack{\text{exp. change}\\ \text{in av. price}}} \times \underbrace{\frac{1/\zeta^e_{i,t}}{1/\zeta^e_{i,t-1}}}_{\substack{\text{rate of}\\ \text{excess demand}}} \Big/ \underbrace{\frac{c^e_{i,t}}{c^e_{i,t-1}}}_{\substack{\text{exp. change}\\ \text{in marg. cost}}}. \tag{9}$$

Equation (9) shows that different *channels* might drive a change in the markup, each one identified by a change in a variable: market share, average price, rate of excess demand and marginal cost. This representation can be used as an encompassing basis that may generate different heuristics. The main families of macroeconomic ABMs, in fact, differ with respect to the channels which are embedded in the pricing heuristics they adopt. To compare these heuristics, in what follows we introduce a dummy for each of the variables showing up in (9). These dummies will be denoted with δ^x where x is an element in the set $X = \{s^e_i, P^e, Q^D_i, c^e_i\}$. We therefore will write each of the four growth factors appearing in (9) in the form $(1 + \delta^x \pi^x_t)$ or $(1 + \delta^x \gamma^x_t)$, where δ^x is set to 1 (zero) if the channel corresponding to variable x is active (inactive) in any specific ABM, $\pi^{x_N}_t$ is the growth rate of nominal variables (price level and marginal cost) and $\gamma^{x_R}_t$ denotes the growth rate of real variables (market share and the rate of excess demand). Hence we can write the markup as follows:

$$\mu_{i,t} = (\delta^{rec} + \mu_{i,t-1}) \frac{(1 + \delta^{s^e_i} \gamma^{s^e_i}_{i,t})(1 + \delta^{P^e} \pi^{P^e}_t)(1 + \delta^{Q^D_i} \gamma^{Q^D_i}_{i,t})}{(1 + \delta^{c^e_i} \pi^{c^e_i}_{i,t})} - \delta^{rec} \tag{10}$$

with $\gamma^{s^e_i}_{i,t}$ denoting the growth rate of the firm's expected market share, $\pi^{P^e}_t$ the growth rate of the expected price level, $\gamma^{Q^D_i}_{i,t}$ the unfulfilled demand expressed as a percentage of output, and $\pi^{c^e_i}_t$ the expected growth rate of firm i's marginal cost. In the CATS and CANVAS model families the recursive representation given in (10) is applied to $(1 + \mu_{i,t})$ rather than $\mu_{i,t}$. Formally, we represent this by introducing the dummy δ^{rec}, which is set to one for CATS and CANVAS and to zero for EUBI and KS.

In the implementation of the model the expected growth rates are determined as follows:

$$\begin{aligned}
\gamma_{i,t}^{s_i^e} &= \frac{s_{i,t}^e}{s_{i,t-1}^e} - 1 = \frac{s_{i,t-1}}{s_{i,t-2}} - 1 = \gamma_{t-1}^{s_i} \\
\pi_t^{P^e} &= \frac{P_t^e}{P_{t-1}^e} - 1 = \frac{P_{t-1}}{P_{t-2}}\frac{(1+\pi_t^e)}{(1+\pi_{t-1}^e)} - 1 \\
\pi_{i,t}^{c_i^e} &= \frac{c_{i,t}^e}{c_{i,t-1}^e} - 1 = \frac{c_{i,t-1}}{c_{i,t-2}}\frac{(1+\pi_t^e)}{(1+\pi_{t-1}^e)} - 1 \\
\gamma_{i,t}^{Q_i^D} &= \frac{Q_{i,t-1}^D}{Y_{i,t-1}} - 1.
\end{aligned}$$

We assume that firms have naive expectations about the growth rate of their market share, so that the expected growth rate of the market share in t is equal to the actual growth rate of the market share in t-1: $\gamma_t^{s_i^e} = \gamma_{t-1}^{s_i}$. As to expectations of the average market price, we assume that $P_t^e = P_{t-1}(1+\pi_t^e)$ with π_t^e the expected overall inflation rate estimated using an AR(1) model applied to the time series of the producer price index (PPI), which is re-estimated every period.[7] Similarly, we assume that expectations of the nominal marginal costs are updated using the expected inflation rate:

$$c_{i,t}^e = c_{i,t-1}(1+\pi_t^e). \tag{11}$$

Finally, as discussed above, $\gamma_{i,t}^{Q_i^D}$ proxies the ratio $\frac{1/\zeta_{i,t}^e}{1/\zeta_{i,t-1}^e}$ under the assumption of naive expectations about $\zeta_{i,t}$, i.e., $\zeta_{i,t}^e = \zeta_{i,t-1}$.

Using this notation, we can write the general pricing rule as in (3) with $\mu_{i,t}$ given by (10) and $c_{i,t}^e$ given by (11).

2.3 Quantity decision

Generally speaking, in macroeconomic ABMs, firms are assumed to set the desired scale of production $Y_{i,t}^*$ in order to satisfy the demand they expect to receive:

$$Y_{i,t}^* = Q_{i,t}^{D,e}. \tag{12}$$

When inventories of final goods can be stored, desired production must take into account that the stock of accumulated inventories up to the previous period $\Delta_{i,t}$ can be used to satisfy current demand. In this case desired production is $\tilde{Y}_{i,t}^* = \max[0, Q_{i,t}^{D,e} - \Delta_{i,t}]$.[8]

Using $Q_{i,t-1}^D = (1+\gamma_{i,t}^{Q_i^D})Y_{i,t-1}$, we can write expected demand in t as

$$Q_{i,t}^{D,e} = (1+\gamma_{i,t}^{Q_i^D})(1+\gamma_{i,t}^{Y_i})Y_{i,t-1}, \tag{13}$$

where $\gamma_{i,t}^{Y_i}$ is the expected growth rate of demand of firm i. In line with the existing literature, we assume that firms use the estimated growth rate of *aggregate* demand as a proxy for this rate: $\gamma_{i,t}^{Y_i} = \gamma_t^Y$ for all i, with γ_t^Y estimated on the basis of an AR(1) model applied to past demand data (which might be proxied by sales). Since supply is set to satisfy expected demand – see (12) – desired output changes (relative to output in the previous period) if the firm adjusts (i) the quantity produced following a market disequilibrium (excess demand or supply) and/or (ii) its expectation of aggregate demand. In symbols:

$$Y_{i,t}^* = \left(1 + (1-\delta^{Q_i^D})\gamma_{i,t}^{Q_i^D}\right)(1+\delta^{Y_i}\gamma_t^Y)Y_{i,t-1}. \tag{14}$$

where $\delta^{Q_i^D}$ is the dummy already used in the markup rule (10). Quantity adjustment is not active if $\delta^{Q_i^D} = 1$ (hence $1-\delta^{Q_i^D} = 0$). In this case, in fact, the firm reacts to excess demand or supply with a

[7] Inflation expectations are computed in every period as $\log(1+\pi_t^e) = \alpha_{t-1}^\pi \pi_{t-1} + \beta_{t-1}^\pi + \epsilon_{t-1}^\pi$. Where α_{t-1}^π and β_{t-1}^π are re-estimated every period on the time series of inflation $\pi_{t'}$ where $t' = -T', -T'+1, -T'+2, \ldots, 0, 1, 2, \ldots, t-1$. ϵ_{t-1}^π is a random shock with zero mean and variance re-estimated every period from past observations over the last $T'+t-1$ periods.

[8] In some of the considered macroeconomic ABMs firms include positive inventory targets in their production planning. Since this seems to have little relevance for our analysis we abstract from such inventory planning here.

price change and does not adjust quantities. On the contrary, for $\delta^{Q_i^D} = 0$ (hence $1 - \delta^{Q_i^D} = 1$) only the quantity is adjusted in response to a difference between demand and supply and the price does not change.
Furthermore, the firm takes into account the expected change in aggregate demand in its production planning if $\delta^{Y_i} = 1$. If $\delta^{Y_i} = 0$, desired output does not react to changes in aggregate demand.

2.4 Application to key ABM families

In this subsection we show how the price/quantity heuristics in the CANVAS, CATS, EUBI and KS families of macroeconomic ABMs can be interpreted as special cases of our general model formulation.

Model	$\delta^{\mathbf{s_i^e}}$	$\delta^{\mathbf{P^e}}$	$\delta^{\mathbf{Q_i^D}}$	$\delta^{\mathbf{c_i^e}}$	$\delta^{\mathbf{rec}}$	$\delta^{\mathbf{Y_i}}$
CANVAS	0	0	cond.	0	1	1
CATS	0	0	cond.	1	1	0
EUBI	1	1	0	1	0	1
KS	1	0	0	0	0	0

Table 1: Price-quantity rules in four main families of macroeconomic ABMs

The relationship between these models and our general formulation is summarized in Table 1. Whereas the first five columns refer to dummies describing different (strategic) aspects of firm's pricing strategy, the last one indicates in how far firms have naive expectations about future demand, or anticipate future changes based on past data. We briefly discuss the different entries in this table, column-wise, i.e., going through the different dummy variables governing which of the different channels present in our general formulation are active in each model.

The *market power channel* (captured by $\delta^{s_i^e}$), is most explicitly present in KS, where markups are adjusted in parallel to changes in the market share. In EUBI the channel is present implicitly, due to the fact that firms choose profit maximizing prices based on the estimated[9] sensitivity of its demand with respect to price changes. As can also be seen in (7), this procedure implies a positive relationship between price and market share. The price adjustment rules in CATS and CANVAS do not incorporate any dependence of price on market share, and therefore $\delta^{s_i^e} = 0$ for these models.

The *competitors' prices channel* (δ^{P^e}), is directly present in the EUBI model, due to the fact that firms communicate the (last period) prices of the competitors to the consumers participating in the surveys they use to estimate demand. Hence, the derived optimal price is an approximation of a best reply to competitors' price setting decisions, which points to a positive correlation between the individual price and the prices charged by the firm's competitors. In KS the competitors' prices have no direct influence on the firm's price. In the CATS and CANVAS models the average market price does not directly influence the level of the firm's price, but determines whether the latter is adjusted upwards (in case of excess demand and underpricing in the previous period) or downwards (in case of excess supply and overpricing).[10] The level of the average market price in CATS and CANVAS determines whether the *excess demand channel* (captured by $\delta^{Q_i^D}$) is active or not. In particular, $\delta^{Q_i^D} = 1$ if either the firm's price in $t-1$ was below the average market price in case of excess demand or $P_{i,t-1} > \bar{P}_t$ in case of excess supply. In KS no direct relationship between excess supply/demand and pricing can be established, although there is an indirect effect through a potential change in the

[9]Firms use consumer surveys as the basis of this estimation in EUBI.
[10]Underpricing (overpricing) occurs when the firm's price is lower (higher) than the average price.

firm's market share. In EUBI excess supply has no impact on future prices, and excess demand would affect the price only if capacity expansion is too costly for the firm to be carried out. In light of this we set $\delta^{Q_i^D} = 0$ for KS and EUBI, although some effect of excess demand on pricing is possible in EUBI.

The *cost absorption channel* ($\delta^{c_i^e}$) describes to which extent firms reduce (increase) their markup if their (marginal) production costs go up (down). When $\delta^{c_i^e} = 1$ the markup decreases at the same rate with which the marginal cost increases, so that cost increases are fully absorbed and the firm's profit margin is independent of the size of the cost. This is equivalent to assuming zero pass-through from cost to price. This is the case in CATS, where pricing does not directly depend on the size of the production costs. On the contrary, both in CANVAS and KS the markup does not depend on the cost level, such that cost increases are fully passed through to consumers. In EUBI firms take into account the estimated production costs in t when determining their optimal price, such that, in accordance with (7), the markup is inversely related to the cost level, such that $\delta^{c_i^e} = 1$.

As discussed above, the dummy δ^{rec} expresses whether changes induced by the four channels apply only to the mark-up $\mu_{i,t}$, or to the entire price-cost ratio $(1 + \mu_{i,t})$. For EUBI and KS the former holds ($\delta^{rec} = 0$), while the latter applies for CANVAS and CATS ($\delta^{rec} = 1$). Finally, the last column of Table 1 refers to the formation of demand expectation of the firms. In CATS and KS firms have naive expectations about the size of total demand in t ($\delta^{Y_i} = 0$), whereas in CANVAS and EUBI firms choose their production quantity using an estimate of the change in demand from $t-1$ to t.

3 The macroeconomic environment

In this section we give a brief overview over the macroeconomic model in which these price-quantity rules are embedded. Similarly to most MABMs, our framework comprises 5 classes of agents: Firms, households, banks, a government and a central bank, whose relations are summarised in Figure 1.

Each firm belongs to a sector g ($g = 1, 2, \ldots, G$), sectors are organised in an Input-output (IO) network, with each sector having size I_g. Firms belonging to sector g produce a single homogeneous good also indexed by g, and the economy as a whole produces G heterogeneous goods. We index firms using i ($i = 1, 2, \ldots, I = \sum_g I_g$) and use the notation $g(i)$ to indicate i's sector. Firms produce using labour, capital, and intermediate goods.

The household sector comprises H ($h = 1, 2, \ldots, H$) persons. Every individual has an *activity status*, that is, a type of economic activity from which she receives an income. The activity status is categorised into H^{act} economically active and H^{inact} economically inactive persons. Economically active persons are H^W workers and I investors. Workers are further divided in H_t^{E} employed and H_t^{U} unemployed persons. Each person also buys goods in the consumption market.

We also assume (i) a representative bank taking deposits from firms and households, extending loans to firms, and receiving advances from the central bank; (ii) a government consuming on the retail market (government consumption), levying taxes, and providing social contributions and benefits to households; (iii) a central bank setting the policy rate, providing liquidity to the banking system, holding reserves for the bank, and purchasing government bonds.

Finally, the foreign sector is modelled as an exogenous, aggregate entity fully calibrated on data, i.e. import prices, import supply and export demand are directly taken from data.

In the remainder of this section, we will provide further details only concerning firms' and households' behaviour, since these parts are essential to understand the results presented in section 4. The interested reader should refer to Poledna et al. (2023) and in particular its appendix, from which this section borrows extensively, for a more complete description of the model.

3.1 Firms

3.1.1 Production

Firm i produces a single good of type $g(i)$ using labour $\left(N_{i,t}\right)$, intermediate goods $\left(M_{i,t-1}\right)$, and physical capital $\left(K_{i,t-1}\right)$, which are combined in a Leontief production function:

$$Y_{i,t} = \min\Big(\tilde{Y}^*_{i,t}, \beta_{g(i)} M_{i,t-1}, \alpha_{i,t} N_{i,t}, \kappa_{g(i)} K_{i,t-1}\Big) \tag{15}$$

Where $\tilde{Y}^*_{i,t}$ is the desired production; $\beta_{g(i)}$ and $\kappa_{g(i)}$ are the productivities of intermediate goods and capital for any firms in sector $g(i)$; $\alpha_{i,t}$ is the *effective* labour productivity of firm i at time t.

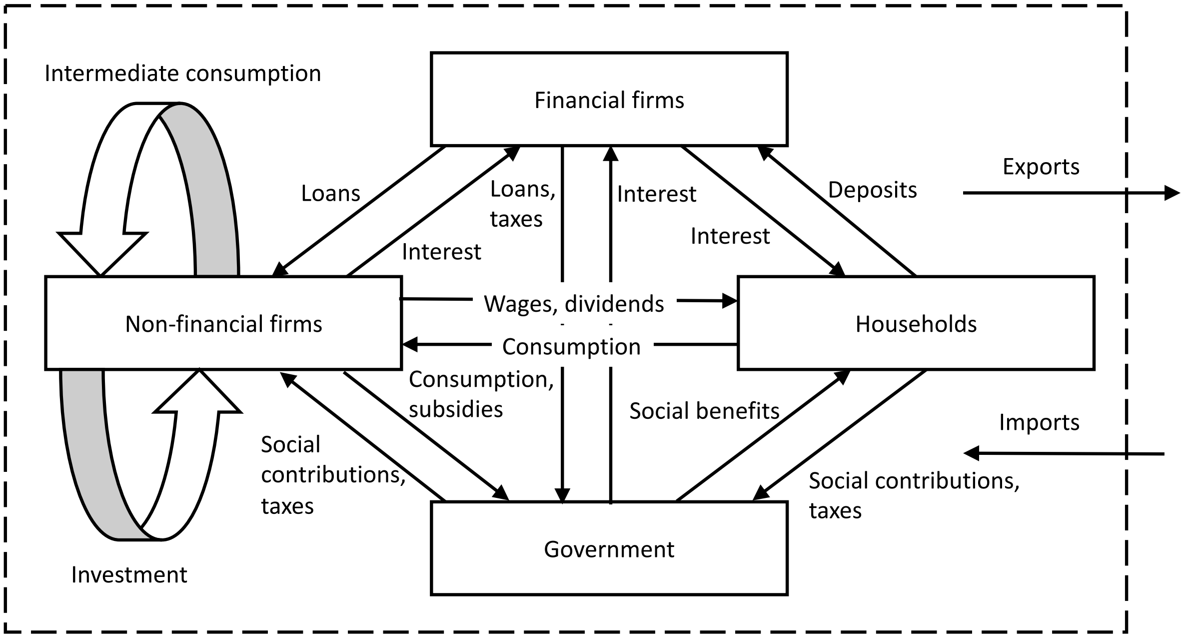

Figure 1: Model flow chart. Rectangles represent agent classes, arrows represent money flows, and the dashed frame contains the domestic economy.

We assume labour productivity $\left(\bar{\alpha}_{g(i)}\right)$ to be time-invariant and sector-specific. However, since $N_{i,t}$ denotes the number of workers employed by firm i at time t, and workers can work part-time or overtime, $N_{i,t}$ may differ from the effective amount of labour employed in production. Therefore, $\alpha_{i,t}$ adjusts in such a way to ensure that the effective amount of labour enters the production function correctly (see (19) below).

3.1.2 Investment

In each period firm i adjusts its real investment demand $\left(I^{\mathrm{d}}_{i,t}\right)$ to the expected wear and tear of the capital stock $\left(K_{i,t}\right)$, where we assume that only the capital actually employed in production depreciates at the sector-specific rate $\delta_{g(i)}$:

$$I^{\mathrm{d}}_{i,t} = \frac{\delta_{g(i)}}{\kappa_{g(i)}} \min\Big(\tilde{Y}^{*}_{i,t}, \kappa_{g(i)} K_{i,t-1}\Big) \tag{16}$$

The capital stock $K_{i,t}$ can be seen as a bundle of G goods where each g-good is associated with a weight b^{K}_{g}. These weights are assumed homogeneous across firms and sectors, therefore each firm demands a quantity of g-good $b^{\mathrm{K}}_{g} I^{\mathrm{d}}_{i,t}$ for the purpose of investment.

3.1.3 Intermediate goods demand

Each firm i holds a stock of input goods $M_{i,t}$. From this stock of intermediate input goods, firm i takes out materials for production as needed, and it keeps these goods in positive supply to avoid shortfalls impeding production. In each period, firm i has to decide on the desired amount of intermediate goods $\left(\Delta M^{\mathrm{d}}_{i,t}\right)$ that it intends to purchase to keep its stock in positive supply:

$$\Delta M^{\mathrm{d}}_{i,t} = \frac{\min\left(\tilde{Y}^{*}_{i,t}, \kappa_{g(i)} K_{i,t-1}\right)}{\beta_{g(i)}} \tag{17}$$

Firms thus try to keep their stock of material input goods within a certain relationship to $\tilde{Y}^{*}_{i,t}$ by accounting for planned material input use in this period. As for physical capital, the stock of intermediate goods $M_{i,t}$ can be seen as a bundle of G goods. In the case of intermediate goods, we assume the weights $b^{M}_{g(i),g}$ to be sector-specific, so that each firm demands a quantity of intermediate good g $\left(\Delta M^{\mathrm{d}}_{i,g,t}\right)$ equal to $b^{M}_{g(i),g} \Delta M^{\mathrm{d}}_{i,t}$.

3.1.4 Labour demand

The labour requirement of firm i $\left(N^{\mathrm{d}}_{i,t}\right)$ is defined in accordance to desired scale of production $(\tilde{Y}^*_{i,t})$ and the sector-specific labour productivity $(\bar{\alpha}_{g(i)})$:

$$N^{\mathrm{d}}_{i,t} = \max\left(1, \frac{\min\left(\tilde{Y}^*_{i,t}, \kappa_{g(i)} K_{i,t-1}\right)}{\bar{\alpha}_{g(i)}}\right) \tag{18}$$

As firms can be constrained on the labour, intermediate goods, and physical capital markets, they might need to adjust their effective labour input by requiring overtime work in case of labour shortages, or part-time work in case of intermediate inputs and physical capital shortages. We deal with this issue by adjusting the labour productivity of firm i $\left(\alpha_{i,t}\right)$ as follows:

$$\alpha_{i,t} = \bar{\alpha}_{g(i)} \min\left(1.5, \frac{\min\left(\tilde{Y}^*_{i,t}, \beta_{g(i)} M_{i,t-1}, \kappa_{g(i)} K_{i,t-1}\right)}{N_{i,t}\bar{\alpha}_{g(i)}}\right) \tag{19}$$

Where the maximum overtime allowed is 50% of a full-time position.

To remunerate part-time and overtime labour as compared to a full-time position, the average wage $\left(\bar{w}_i\right)$ paid by firm i is adapted accordingly:

$$w_{i,t} = \bar{w}_i \min\left(1.5, \frac{\min\left(\tilde{Y}^*_{i,t}, \beta_{g(i)} M_{i,t-1}, \kappa_{g(i)} K_{i,t-1}\right)}{N_{i,t}\bar{\alpha}_{g(i)}}\right)$$

Where $w_{i,t}$ is the real wage paid by firm i and nominal hourly wages are pegged to inflation expectations.

3.2 Households

3.2.1 Activity Status

An employed worker h of firm i in period t receives wage $w_{h,t} = w_{i,t}$. Unemployed workers supply labour to firms with open vacancies through a labour market modelled as a random *search-and-matching* process. All unemployed persons receive unemployment benefits, which are a fraction θ^{UB} of the wage received in the last period of employment.

We assume that each firm is owned by an investor, i.e. the number of investors matches the number of firms. Each investor receives income in the form of dividends whenever net profits are positive. We assume limited liability, i.e. in the case of bankruptcy, the associated losses are borne by the creditor and not the investor household.

An economically inactive person h receives social benefits sb^{inact}_t and does not look for a job. Additionally, each household receives additional social transfers sb^{other}_t from the government.

3.2.2 Consumption

Households consume a fraction of their expected disposable net income $\left(Y^{\mathrm{e}}_{h,t}\right)$. Expected disposable net income inclusive of social transfers is determined according to the household's activity status and the associated income from labour, expected profits or social benefits, as well as tax payments, the consumer price index of the last period, and inflation expectations $\left(\pi^{\mathrm{e}_t}\right)$. The consumption budget (net of VAT) of household h $\left(C^{\mathrm{d}}_{h,t}\right)$ is thus given by:

$$C^{\mathrm{d}}_{h,t} = \frac{\psi Y^{\mathrm{e}}_{h,t}}{1 + \tau^{\mathrm{VAT}}} \tag{20}$$

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

$$C^{\mathrm{d}}_{h,g,t} = b^{\mathrm{HH}}_g C^{\mathrm{d}}_{h,t} \tag{21}$$

Where b^{HH}_g is the homogeneous and time-invariant consumption coefficient for the good g.

4 How do different types of price-quantity rules affect economic dynamics?

To investigate differences across price-quantity rules, we conduct two sets of exercises: forecasting under business-as-usual scenarios and analyzing model reactions to predefined, exogenous shocks. For these exercises, we calibrate the framework using Eurostat data for the Austrian economy, following the calibration approach outlined in Poledna et al. (2023). Starting from a reference quarter, we run simulations with different price-quantity rules over a 12-quarter horizon, allowing for a systematic comparison under varying economic conditions.

Before presenting the results, it is important to clarify that they do not necessarily reflect the exact predictions of the models under consideration. To be precise, our results pertain to the rules discussed in Section 2.4 within the Poledna et al. (2023) framework. The difference may seem subtle and often reduces to nuances, but it is important to remember that these rules are applied somewhat outside their original context. As a result, the outcomes may differ from those produced within their original models. Whenever we identified such potential differences, we made an effort to alert the reader.

4.1 Forecasting

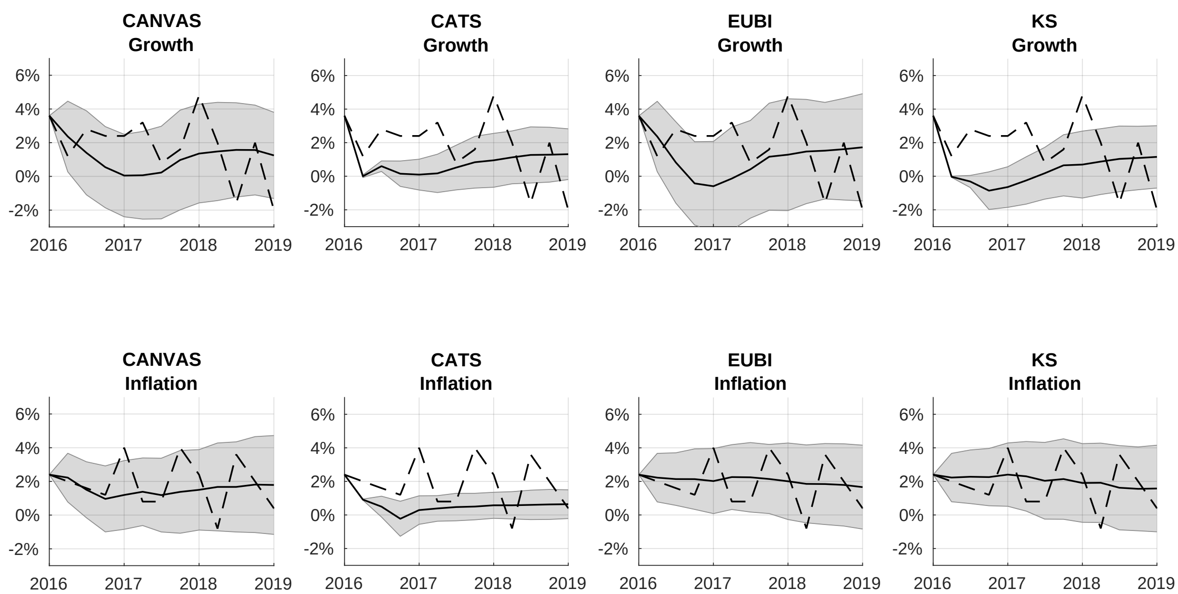

Figure 2: Out-of-sample forecasts with the different price-quantity rules. Forecasts for GDP growth and inflation measured by the CPI are 12 quarters ahead from Q1 2017 until Q4 2019 for the Austrian economy. The black lines show the respective forecasts with the different price-quantity rules and observed Eurostat data for Austria is shown with the dashed line. For each forecast, one standard deviation is plotted around the mean trajectory. Model results are obtained as an average of 500 Monte Carlo simulations.

To illustrate the differences among the respective price-quantity rules under a business-as-usual scenario, we present representative 12 quarters ahead out-of-sample forecasts in Figure 2. The figure displays GDP growth and inflation forecasts, measured by the Consumer Price Index (CPI), generated by the CANVAS, CATS, EUBI, and KS price-quantity rules, with observed Eurostat data for Austria provided as a benchmark. Overall, in the business-as-usual scenario, the price-quantity rules produce qualitatively similar forecasts for GDP growth and inflation. As seen in Figure 2, inflation forecasts are particularly consistent across the CANVAS, EUBI, and KS price-setting rules, with these rules generating closely aligned projections over the forecast horizon.

Similarly, the growth forecasts of the CANVAS and EUBI rules show a strong degree of comparability. Notable differences, however, are observed in the CATS and KS quantity choices. Both of these rules simplify by assuming naive demand expectations, where the expected demand is set equal to the demand of the previous period. This assumption results in somewhat lower forecast performance in the short run and introduces a bias in the projections, as these models are slower to adjust to changes in economic conditions. For the same reason, the CATS price-setting rule also shows a somewhat lower forecast performance and an overall bias in its projections.

These observations from Figure 2 are further corroborated by the quantitative evaluation of forecast performance along the lines of Poledna et al. (2023) shown in Appendix B. Table 2 in this appendix provides detailed out-of-sample forecast performance, showing root mean square error (RMSE) statistics for different forecast horizons. The results indicate that the CANVAS and EUBI price-quantity rules tend to outperform the CATS and KS rules over short forecast horizons, where the latter models show a tendency for increased forecast errors. Table 3 in Appendix B further highlights the mean biases of the models across different forecast horizons, showing that the CATS and KS models tend to produce more biased forecasts for short forecast horizons.

4.2 Shocks

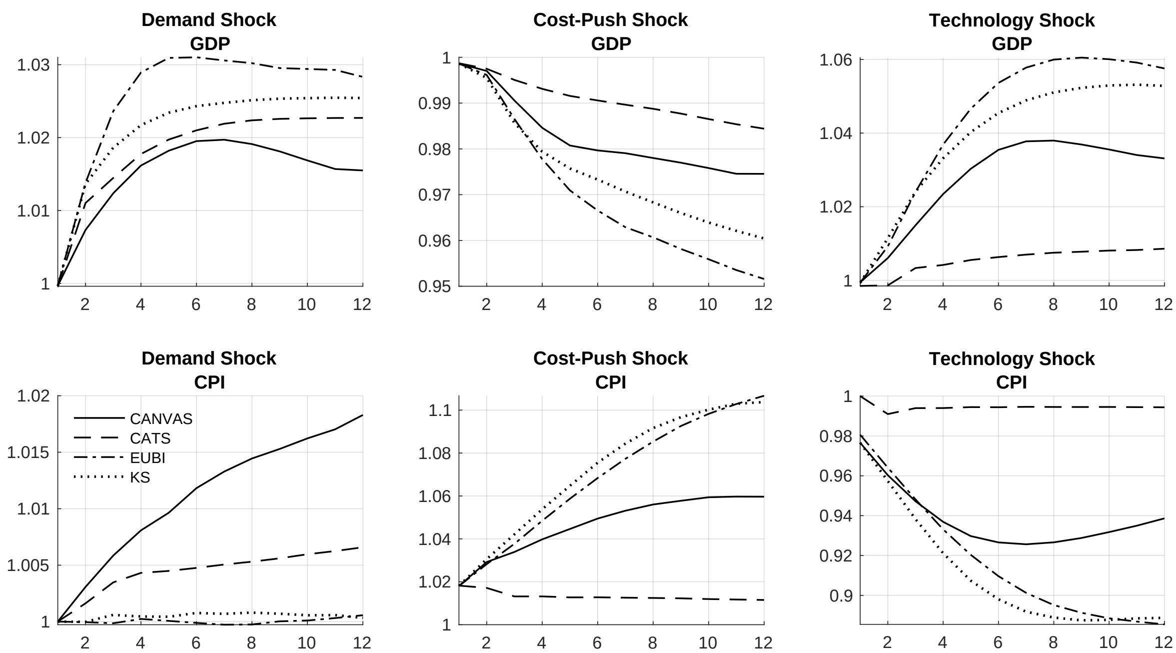

Figure 3: Responses of GDP and the Consumer Price Index (CPI) to three types of exogenous shocks—demand shock, cost-push shock, and technology shock—across four different price-quantity rules: CANVAS, CATS, EUBI, and KS. The simulations are run over a 12-quarter horizon, starting from a reference quarter calibrated with Eurostat data for the Austrian economy. The top panels show the relative changes in GDP, while the bottom panels display the corresponding effects on CPI.

We experiment with three different shocks: a demand shock, a cost-push shock, and a non-idiosyncratic technological shock. Each shock is imposed in isolation and involves a permanent 10% increase in one of the following variables: government spending (public consumption), import prices, or labour productivity. Figure 3 summarizes adjustments to shocks across different rules, focusing on GDP and CPI expressed as deviations from their baseline values.

The *demand shock* triggers inflation only in the CANVAS and CATS rules, while the CPI remains unaffected in EUBI and KS.[11] This difference is due to the absence of the demand-pull channel in the price equations of EUBI and KS, where the entire demand shock is passed into quantities. When demand-pull is not passed onto prices, the real effects of demand shocks are more pronounced, resulting in larger multipliers for EUBI and KS compared to CANVAS and CATS. Moreover, we observe a

[11] It is important to emphasize once again that our results do not necessarily or perfectly reflect the predictions of the models under consideration. Indeed, although the implemented price and quantity rules closely align with those of the models, they are applied somewhat outside their original context. For instance, in EUBI and KS, nominal wages grow when the labour market is tight. It follows that in the original EUBI and KS frameworks, a positive demand shock would likely lower unemployment and therefore trigger wage inflation, which would then be passed on to prices, resulting in some level of positive inflation.

stronger GDP response in EUBI as compared to KS. The reason is that in EUBI, individual quantity decisions are also linked to expected aggregate demand growth, which in the case of demand shocks, boils down to an additional, coordinated pull factor. Finally, the inflationary effect is stronger under the CANVAS rule compared to CATS. This difference stems from how nominal wages feed back into the price equation via the cost channel. In CATS, wage increases are fully absorbed in the markup, unlike under CANVAS, where we have full pass-through. Therefore, nominal wages being pegged to the CPI, demand-pull inflation leads to nominal wage growth, which further drives prices under rules assuming positive pass-through.[12]

The *cost-push shock* impacts only models featuring cost channel in the price equation, specifically CANVAS, EUBI, and KS.[13] However, responses are heterogeneous across rules, with CANVAS exhibiting moderate inflation as compared to EUBI and KS. This difference stems from the demand-pull channel in the CANVAS price rule. Cost-push shocks typically lead to stagflation, where the recessionary aspect of the shock causes individual firms to experience lower-than-expected demand. In CANVAS, this prompts firms to reduce prices, counteracting the inflationary pressures from the cost-push shock. We also observe a slight difference in CPI under the EUBI and KS rules, with the latter featuring more inflation. This is due to the different recursions adopted by the two models in the markup rule (9), implying perfect pass-through (i.e., more inflation) for KS and only partial pass-through (i.e., less inflation) for EUBI. Finally, the magnitude of the recession is tightly linked to the extent of the pass-through, with EUBI and KS showing the strongest GDP loss, CANVAS showing moderate GDP loss, and CATS being only slightly impacted.

The *non-idiosyncratic technological shock* is symmetric to the cost-push shock. While CANVAS, EUBI, and KS see reductions in inflation, the magnitude differs. CANVAS shows a moderate deflationary effect due to its demand-pull channel, which diminishes the price effect of productivity growth. In contrast, EUBI and KS show stronger deflationary effects, with KS exhibiting the most significant price reduction due to its perfect pass-through mechanism. The productivity shock also leads to an increase in GDP across all models, with the strongest growth observed in EUBI and KS, and a moderate increase in CANVAS. CATS, as expected, is only slightly affected.

5 Conclusions

The design of behavioral rules is a key ingredient of agent-based macroeconomic models and an important determinant of differences between these models. In this paper we make two main contributions to foster a systematic analysis of the impact of the design of behavioral rules on model output. First, focusing on a particular set of firm decisions, namely price and quantity choice, we derive a general representation of rules, that allows to systematically categorize rules according to which channels are active in determining the action under the rule. We exploit this approach by considering price and quantity rules in four families of agent-based macroeconomic models, but the approach is much more generally applicable as a tool to describe and compare different rules systematically.

Second, we embed the different rules in an identical macroeconomic framework, which allows us to isolate their effect on the economic dynamics emerging in the model. Our forecasting exercise reveals only minor differences across rules, indicating that in a business-as-usual scenario, the choice of a specific rule has little impact on the results. However, we find that the model's response to macroeconomic shocks differs significantly across the rules, both quantitatively and qualitatively. This variability underscores the need for a careful analysis of these rules to understand which ones perform best under specific conditions. In particular, using data for time windows including severe disruptions, such as supply respectively demand shocks triggered by COVID-19, or cost push shocks due to energy price hikes, performance of the models in terms of matching empirical observations could be examined. Such an analysis is beyond the current chapter and left for future work.

The results presented here should be seen only as a first step. The analysis should be extended to other important classes of decision rules and a broader spectrum of agent-based macroeconomic models. Work along these lines will improve our understanding of the drivers of differences in behaviour across

[12]It should be noted that in this particular case, the cost channel constitutes a second order effect and therefore it is not sufficient to generate inflation. Since nominal wages are tied to inflation (but not to labour market tightness), the cost channel only activates if the shock initially triggers inflation through demand-pull, which is not the case for EUBI and KS.

[13]The slight increase in CPI observed for CATS is a mechanical effect seen across all models, as import prices are included in the CPI calculation.

different models and play an important role in interpreting results, such as insights about policy effects, that have been obtained in different model frameworks. Finally, this type of analysis might also provide guidance concerning which types of behavioral rules perform best in terms of short- and medium-term forecasting.

References

Ashraf, Q., Gershman, B., Howitt, P., 2017. Banks, market organization, and macroeconomic performance: An agent-based computational analysis. Journal of Economic Behavior and Organization 135, 143–180.

Assenza, T., Gatti, D.D., Grazzini, J., 2015. Emergent dynamics of a macroeconomic agent based model with capital and credit. Journal of Economic Dynamics and Control 50, 5–28.

Axtell, R.L., Farmer, J.D., 2024. Agent-based modeling in economics and finance: Past, present, and future. Journal of Economic Literature (forthcoming) .

Basurto, A., Dawid, H., Harting, P., Hepp, J., Kohlweyer, D., 2023. How to design virus containment policies? A joint analysis of economic and epidemic dynamics under the COVID-19 pandemic. Journal of Economic Interaction and Coordination 18, 311–370.

Borsos, A., Carro, A., Glielmo, A., Hinterschweiger, M., Kaszowska-Mojsa, J., Uluc, A., 2024. Agent-based modeling at central banks: Recent developments and new challenges, in: This Book.

Ciola, E., Turco, E., Gurgone, A., Bazzana, D., Vergalli, S., Menoncin, F., 2023. Enter the matrix model: a multi-agent model for transition risks with application to energy shocks. Journal of Economic Dynamics and Control 146, 104589.

Dawid, H., Delli Gatti, D., 2018. Agent-based macroeconomics. Handbook of computational economics 4, 63–156.

Dawid, H., Harting, P., 2012. Capturing firm behavior in agent-based models of industry evolution and macroeconomic dynamics. Applied Evolutionary Economics, Behavior and Organizations, ed. by G. Bünsdorf, Edward-Elgar , 103–130.

Dawid, H., Harting, P., Van der Hoog, S., Neugart, M., 2019. Macroeconomics with heterogeneous agent models: fostering transparency, reproducibility and replication. Journal of Evolutionary Economics 29, 467–538.

Dawid, H., Harting, P., Neugart, M., 2018. Cohesion policy and inequality dynamics: Insights from a heterogeneous agents macroeconomic model. Journal of Economic Behavior & Organization 150, 220–255.

Delli Gatti, D., Desiderio, S., Gaffeo, E., Cirillo, P., Gallegati, M., 2011. Macroeconomics from the Bottom-up. volume 1. Springer Science & Business Media.

Delli Gatti, D., Reissl, S., 2022. Agent-Based Covid economics (ABC): Assessing non-pharmaceutical interventions and macro-stabilization policies. Industrial and Corporate Change 31, 410–447.

Dosi, G., Fagiolo, G., Napoletano, M., Roventini, A., Treibich, T., 2015. Fiscal and monetary policies in complex evolving economies. Journal of Economic Dynamics and Control 52, 166–189.

Dosi, G., Fagiolo, G., Roventini, A., 2010. Schumpeter meeting keynes: A policy-friendly model of endogenous growth and business cycles. Journal of Economic Dynamics and Control 34, 1748–1767.

Dosi, G., Roventini, A., 2019. More is different... and complex! the case for agent-based macroeconomics. Journal of Evolutionary Economics 29, 1–37.

Eliasson, G., 2023. Bringing markets back into economics: On economy wide self - coordination by boundedly rational market agents. Journal of Economic Behavior & Organization 216, 686–710.

Filatova, T., Akkerman, J., 2024. Complexity economics view on physical climate change risk and adaptation, in: This Book.

Harvey, D., Leybourne, S., Newbold, P., 1997. Testing the equality of prediction mean squared errors. International Journal of Forecasting 13, 281–291.

Hommes, C., He, M., Poledna, S., Siqueira, M., Zhang, Y., 2024a. CANVAS: A Canadian behavioral agent-based model for monetary policy. Journal of Economic Dynamics and Control (forthcoming) .

Hommes, C., Kozicki, S., Poledna, S., Zhang, Y., 2024b. How an agent-based model can support monetary policy in a complex evolving economy, in: This Book.

Hötte, K., 2020. How to accelerate green technology diffusion? directed technological change in the presence of coevolving absorptive capacity. Energy Economics 85, 104565.

Lamperti, F., Dosi, G., Napoletano, M., Roventini, A., Sapio, A., 2020. Climate change and green transitions in an agent-based integrated assessment model. Technological Forecasting and Social Change 153, 119806.

Lamperti, F., Dosi, G., Roventini, A., 2024. Complex systems perspectives on the economics of climate change, in: This Book.

Lengnick, M., 2013. Agent-based macroeconomics: A baseline model. Journal of Economic Behavior and Organization 86, 102–120.

Mincer, J.A., Zarnowitz, V., 1969. The evaluation of economic forecasts, in: Economic forecasts and expectations: Analysis of forecasting behavior and performance. NBER, pp. 3–46.

Pichler, A., Pangallo, M., del Rio-Chanona, M., Lafond, F., Farmer, D., 2022. Forecasting the propagation of pandemic shocks with a dynamic input-output model. Journal of Economic Dynamics and Control 144, 104527.

Poledna, S., Miess, M.G., Hommes, C., Rabitsch, K., 2023. Economic forecasting with an agent-based model. European Economic Review 151, 104306.

Riccetti, L., Russo, A., Gallegati, M., 2013. Leveraged network-based financial accelerator. Journal of Economic Dynamics and Control 37, 1626–1640.

Salle, I., Seppecher, P., 2018. Stabilizing an unstable complex economy on the limitations of simple rules. Journal of Economic Dynamics and Control 91, 289–317.

Savin, I., Creutzig, F., Filatova, T., Foramitti, J., Konc, T., Niamir, L., Safarzynska, K., van den Bergh, J., 2023. Agent-based modeling to integrate elements from different disciplines for ambitious climate policy. Wiley Interdisciplinary Reviews: Climate Change 14, e811.

Turco, E., Bazzana, D., Rizzati, M., Ciola, E., Vergalli, S., 2023. Energy price shocks and stabilization policies in the matrix model. Energy Policy 177, 113567.

Appendix

A Microfoundations for the demand model

In this section of the appendix we demonstrate that the simple linear demand function (5) used by the firms can be derived from simple interaction structures with heterogeneous consumers. An example of a market structure giving rise to this form of expected demand is a market setup in which each consumer c intending to buy the product in t visits two producers and chooses between these producers based on a utility function $u^c_{i,t} = \bar{u} - \tilde{\zeta}_t \frac{P_{i,t}}{\bar{P}_t}$ and a (stochastic) idiosyncratic preference between the producers. The fact that the dis-utility of paying $P_{i,t}$ is normalized by $\bar{P}_t$ captures that prices are evaluated in terms of purchasing power and pure inflationary effects are neutralized. More precisely, consumer visiting firms i_1 and i_2 purchases from producer i_1 if and only if

$$u^c_{i_1,t} - u^c_{i_2,t} \geq \epsilon^c_{i_1,i_2},$$

where $\epsilon^c_{i_1,i_2}$ captures the idiosyncratic preference of consumer c between the producers and is assumed to be uniformly distributed in $[-k, k]$ and iid across consumers and firm pairs. Assuming that k is sufficiently large such that $\tilde{\zeta}_t \frac{P_{i_1,t} - P_{i_2,t}}{\bar{P}_t} \in [-k, k]$, then the probability that consumer c buys from firm i_1 is given by

$$\begin{aligned} q_{i_1}(i_2) &= \mathbb{P}(\epsilon^c_{i_1,i_2} \leq u^c_{i_1,t} - u^c_{i_2,t}) = \mathbb{P}\left(\epsilon^c_{i_1,i_2} \leq \tilde{\zeta}_t \frac{P_{i_2,t} - P_{i_1,t}}{\bar{P}^e_t}\right) \\ &= \frac{1}{2k}\left(\tilde{\zeta}_t \frac{P_{i_2,t} - P_{i_1,t}}{\bar{P}_t} - (-k)\right) = \frac{1}{2} - \frac{\tilde{\zeta}_t}{2k} \frac{P_{i_1,t} - P_{i_2,t}}{\bar{P}_t}. \end{aligned}$$

Based on this, the probability that an arbitrary consumer c buys from firm i can be calculated as

$$\begin{aligned} &\mathbb{P}(c \text{ buys from } i) \\ &\quad = \mathbb{P}(c \text{ visits } i \text{ in } t) \sum_{\tilde{i} \neq i} \mathbb{P}(c \text{ visits } \tilde{i} \text{ in } t | c\text{visits } i \text{ in } t) q_i(\tilde{i}) \\ &\quad = \frac{2}{F_C} \frac{1}{F_C - 1} \sum_{\tilde{i} \neq i} \left(\frac{1}{2} - \frac{\tilde{\zeta}_t}{2k} \frac{P_{i,t} - P_{\tilde{i},t}}{\bar{P}_t}\right) \\ &\quad = \frac{1}{F_C} - \frac{\tilde{\zeta}_t}{k} \sum_{\tilde{i}=1}^{F_C} \frac{P_{i,t} - P_{\tilde{i},t}}{F_C \bar{P}_t} \\ &\quad = \frac{1}{F_C} - \frac{\tilde{\zeta}_t}{k} \left(\frac{P_{i,t}}{\bar{P}_t} - 1\right) \\ &\quad = \frac{1}{F_C} - \zeta_t \left(\frac{P_{i,t}}{\bar{P}_t} - 1\right), \end{aligned}$$

with $\zeta_t = \frac{\tilde{\zeta}_t}{k}$. The corresponding expectation of firm i at time t about this parameter is denoted by $\zeta^e_{i,t}$. This yields an expected market share of firm i given by (5).

B Forecast performance

Table 2: Out-of-sample forecast performance

	GDP	Inflation	Household consumption	Investment
AR(1)	*RMSE-statistic for different forecast horizons*			
1q	0.48	0.36	0.76	1.42
2q	0.69	0.37	0.92	1.98
4q	1.17	0.37	1.24	3.16
8q	2.01	0.37	2.1	4.49
12q	2.8	0.37	2.87	6.09
CANVAS	*Percentage improvements (+) or losses (-) relative to AR(1) model*			
1q	0.2 (0.83)	-11.7 (0.04**)	-3.1 (0.79)	3.9 (0.14)
2q	0.1 (0.93)	-29.8 (0.04**)	-23.2 (0.30)	6.9 (0.06*)
4q	-0.4 (0.95)	-8.6 (0.61)	-8.2 (0.80)	8.9 (0.11)
8q	7.9 (0.72)	-18.3 (0.00***)	30.1 (0.45)	12.8 (0.04**)
12q	25.4 (0.49)	-30.7 (0.23)	38.7 (0.45)	14.1 (0.00***)
CATS	*Percentage improvements (+) or losses (-) relative to AR(1) model*			
1q	-24.1 (0.08*)	-50.6 (0.00***)	-13.4 (0.39)	-8.4 (0.04**)
2q	-22.1 (0.25)	-50 (0.00***)	-30.8 (0.23)	-13 (0.04**)
4q	-2 (0.93)	-38.9 (0.00***)	-28.5 (0.49)	-10.4 (0.06*)
8q	17.1 (0.69)	-16 (0.03**)	2.3 (0.96)	-4.5 (0.66)
12q	21.1 (0.65)	-7.1 (0.08*)	23.1 (0.74)	3.5 (0.59)
EUBI	*Percentage improvements (+) or losses (-) relative to AR(1) model*			
1q	0.2 (0.83)	-11.7 (0.04**)	-3.1 (0.79)	3.9 (0.14)
2q	-1.1 (0.54)	-15.5 (0.08*)	-26.2 (0.27)	4.6 (0.20)
4q	-9.6 (0.44)	-6.3 (0.56)	-17.1 (0.64)	5.4 (0.25)
8q	-7.7 (0.77)	-11.2 (0.28)	27.1 (0.50)	12.2 (0.05*)
12q	11.8 (0.66)	5.1 (0.00***)	39.7 (0.51)	19.1 (0.01***)
KS	*Percentage improvements (+) or losses (-) relative to AR(1) model*			
1q	-24.4 (0.08*)	-11.7 (0.04**)	-14.3 (0.37)	-8.2 (0.04**)
2q	-40.9 (0.08*)	-17 (0.09*)	-42.3 (0.14)	-17.9 (0.02**)
4q	-29 (0.36)	-8.6 (0.43)	-42.4 (0.35)	-19.7 (0.01**)
8q	8.6 (0.87)	-12.4 (0.29)	6.2 (0.90)	-12.3 (0.33)
12q	26.1 (0.68)	6.4 (0.17)	27.1 (0.70)	-0.8 (0.86)

Note: The forecast period is 2010:Q2 to 2019:Q4. Models 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 models 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.

Table 3: Mean biases of models

	GDP	Inflation	Household consumption	Investment
AR(1)	*Mean biases for different forecast horizons*			
1q	0.0004 (0.34)	-0.0007 (0.23)	0.0019 (0.26)	-0.0035 (0.20)
2q	0.0011 (0.39)	-0.0008 (0.17)	0.0032 (0.07*)	-0.0084 (0.02**)
4q	0.0031 (0.27)	-0.0009 (0.26)	0.0065 (0.00***)	-0.0183 (0.00***)
8q	0.0085 (0.02**)	-0.001 (0.18)	0.0133 (0.00***)	-0.0322 (0.00***)
12q	0.0149 (0.00***)	-0.0007 (0.47)	0.0202 (0.00***)	-0.0469 (0.00***)
CANVAS	*Mean biases for different forecast horizons*			
1q	0.0003 (0.29)	-0.0007 (0.00***)	-0.0017 (0.14)	-0.0034 (0.23)
2q	0.001 (0.35)	-0.0019 (0.00***)	-0.004 (0.01***)	-0.0075 (0.03**)
4q	0.0031 (0.28)	-0.0016 (0.00***)	-0.0062 (0.00***)	-0.015 (0.00***)
8q	0.0077 (0.03**)	0.0013 (0.00***)	-0.0044 (0.25)	-0.0229 (0.00***)
12q	0.0064 (0.03**)	0.0034 (0.00***)	-0.0004 (0.62)	-0.0361 (0.00***)
CATS	*Mean biases for different forecast horizons*			
1q	-0.0039 (0.00***)	-0.0038 (0.00***)	-0.0033 (0.02**)	-0.0076 (0.00***)
2q	-0.0049 (0.00***)	-0.004 (0.00***)	-0.0066 (0.00***)	-0.0138 (0.00***)
4q	-0.005 (0.04**)	-0.0038 (0.00***)	-0.0109 (0.00***)	-0.0245 (0.00***)
8q	-0.0012 (0.22)	-0.0025 (0.00***)	-0.015 (0.00***)	-0.0348 (0.00***)
12q	0.0025 (0.05**)	-0.0019 (0.03**)	-0.0155 (0.00***)	-0.0444 (0.00***)
EUBI	*Mean biases for different forecast horizons*			
1q	0.0003 (0.29)	-0.0007 (0.00***)	-0.0017 (0.14)	-0.0034 (0.23)
2q	0.0004 (0.48)	-0.0009 (0.00***)	-0.0049 (0.00***)	-0.0082 (0.02**)
4q	0.002 (0.61)	-0.0011 (0.02**)	-0.0077 (0.00***)	-0.0164 (0.00***)
8q	0.0106 (0.02**)	-0.0009 (0.01**)	-0.0057 (0.09*)	-0.0208 (0.00***)
12q	0.0131 (0.01***)	-0.0005 (0.60)	-0.0051 (0.23)	-0.0313 (0.00***)
KS	*Mean biases for different forecast horizons*			
1q	-0.004 (0.00***)	-0.0007 (0.00***)	-0.0036 (0.01**)	-0.0075 (0.01***)
2q	-0.0067 (0.00***)	-0.0009 (0.00***)	-0.0079 (0.00***)	-0.0151 (0.00***)
4q	-0.0092 (0.00***)	-0.0009 (0.01**)	-0.0126 (0.00***)	-0.0281 (0.00***)
8q	-0.0055 (0.22)	-0.0011 (0.01***)	-0.0139 (0.00***)	-0.0386 (0.00***)
12q	-0.0023 (0.49)	-0.0009 (0.44)	-0.0137 (0.00***)	-0.0488 (0.00***)

Note: The forecast period is 2010:Q2 to 2019:Q4. Models 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 Mincer and Zarnowitz (1969) tests, where we test whether the bias is significant. *, **, and *** denotes significance at the 10 per cent, 5 per cent, and 1 per cent levels, respectively.