



Research paper

Wealth, cost, and misperception: Empirical estimation of three interaction channels in a financial–macroeconomic agent-based model

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ABSTRACT

Financial–macroeconomic agent-based models offer a promising avenue for understanding complex economic interactions, but their empirical estimation is challenging, particularly when the relevant data are observed at different frequencies. We address this gap by developing a mixed-frequency adaptation of the simulated method of moments that evaluates macroeconomic and financial moment conditions at their native quarterly and daily frequencies within a single objective function. Applying it to a stylized integrated agent-based model on U.S. data from 1954 to 2025, we quantify three key interaction channels between the financial and real sectors. The stock market influences the real economy through the wealth effect on consumption and the cost effect on firms' financing. Conversely, the real economy influences the stock market through a price-misperception effect that shapes fundamental valuations. Our results provide the first model-based empirical evidence that all three channels are statistically significant, offering novel insights into macro-financial dynamics.

1. Introduction

The global financial crisis of 2007–2008 highlighted the limitations of traditional economic models in capturing the interconnectivity between the financial and real sectors (Battiston et al., 2016). In particular, it exposed the consequences of the financialization of the real economy and reinforced the importance of maintaining financial stability for sustained economic growth (Farmer and Foley, 2009; Delli Gatti et al., 2010a). Despite efforts to integrate financial dynamics into macroeconomics, as vigorously advocated by Krugman (2009), challenges persist in bridging the gap between theoretical models and empirical estimation, especially within the field of agent-based models (ABMs), where the coexistence of macroeconomic and financial data observed at fundamentally different frequencies poses an additional econometric obstacle that has received limited attention.

Traditionally, economic analysis has often treated the financial and real sectors in isolation. Neither early efforts to integrate financial dynamics into macroeconomics, such as those by Holmstrom and Tirole (1997) and Bernanke et al. (1999), nor the initial responses to the crisis, such as Gertler and Kiyotaki (2010) and Castelnovo and Nisticò (2010), were able to reverse the overall trend of separating finance and macroeconomic research.

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The progress in agent-based modeling of financial and economic systems followed a parallel trajectory. Despite the global financial crisis highlighting the need to integrate the financial and real sectors of the economy, these two branches remain rather isolated.¹ However, the need to incorporate financial realities into agent-based macroeconomics has become increasingly clear. While there have been notable modeling achievements — such as the outcomes of the EURACE project (Deissenberg et al., 2008; Cincotti et al., 2010) and, more recently, the CANVAS model developed by Hommes et al. (2025), a calibrated behavioral ABM operationally adopted by the Bank of Canada — the empirical estimation of financial–macroeconomic ABMs remains largely unexplored.

Our paper addresses this gap directly. Its primary contribution is methodological: we develop an estimation strategy that can reliably identify the interaction channels linking the macroeconomic and financial sectors of an integrated agent-based economy. The main innovation is a mixed-frequency adaptation of the simulated method of moments (SMM) that evaluates macroeconomic and financial moment conditions at their native quarterly and daily frequencies and combines them within a single objective function. To the best of our knowledge, this is the first SMM-based approach designed to accommodate the inherently mixed-frequency structure of macro-financial data within an ABM.

Enabled by this estimation strategy, our empirical contribution is to provide model-based estimates of the wealth, cost of capital, and price misperception channels linking the financial and real sectors within an integrated agent-based framework, showing that all three are statistically significant in U.S. data spanning 1954–2025. The integrated model, which combines a behavioral New Keynesian macroeconomy (De Grauwe and Ji, 2019; Kukacka and Sacht, 2023) with a heterogeneous-agent asset-pricing framework (Franke and Westerhoff, 2012; Zila and Kukacka, 2023), primarily draws on existing ABM components and serves as the structural framework for estimation. Specifically, we: (a) adapt SMM to handle mixed data frequencies within a single objective function; (b) construct a stylized integrated financial–macroeconomic model, based on existing ABM literature; (c) calibrate its well-established structural parameters using recent empirical evidence; and (d) estimate the three novel interaction parameters and assess their statistical significance.

Despite progress in the empirical validation of ABMs (Guerini and Moneta, 2017; Lamperti, 2018a,b; Fagiolo et al., 2019; Seri et al., 2021; Martinoli et al., 2024; Martinoli, 2025; Martinoli et al., 2025; Di Francesco and Hommes, 2025), quantifying empirical relationships remains the main challenge in the field. Traditional econometric techniques such as ordinary least squares (OLS) and maximum likelihood estimator (MLE) usually face fundamental limitations. The main issues stem from model complexity, characterized by strong nonlinearities arising from agent interactions and heuristic switching. Theoretical studies are often infeasible because there are no analytical solutions for the models, and the likelihood-based objective function cannot be expressed in closed form. These practical limitations make it much harder to test statistical hypotheses and choose between different models of the same economic reality. As a result, using ABMs to guide economic decisions and formulate real-world policies becomes significantly restricted. A further, and for our purposes central, obstacle is that macroeconomic models typically use quarterly or annual data, whereas financial models typically operate on a daily basis.

To overcome these challenges, we build on the SMM estimation approach. Its computational tractability, flexibility, and well-established track record in the ABM literature have made it a popular choice not only in empirical financial studies (Lux and Zwickels, 2018) but also, more recently, in the domain of macroeconomic ABMs (Franke et al., 2015; Jang and Sacht, 2016, 2021). Our methodological innovation is to modify this technique to accommodate the mixed-frequency structure of macro-financial data directly, by separately evaluating the moments of macroeconomic and financial time series at their native frequencies and then aggregating them within a single optimization objective function. This preserves the information content of both data sources and, to our knowledge, is the first such adaptation of SMM in the ABM literature.

In sum, our paper provides a methodological template for the mixed-frequency estimation of ABMs and illustrates its usefulness by showing that the interaction channels between the financial and real sectors can be empirically identified within an integrated agent-based framework. The substantive economic evidence — namely, the statistical significance of the wealth, cost, and price misperception channels in U.S. data spanning 1954–2025 — thus represents the first empirical payoff of the proposed estimation strategy.

The paper is structured as follows. The next Section 2 reviews the key methodological literature, and Section 3 presents the integrated financial–macroeconomic model and discusses its baseline parameterization. Details of the implementation of the SMM are described in Sections 4 and 5 presents the empirical datasets used for estimation. Following that, Section 6 summarizes the technical setup, and Section 7 reports and interprets the key empirical findings and provides implications for macro-financial policy. Finally, potential directions for future investigation, together with a concise conclusion, are summarized in Section 8. Additional details are provided in the Appendix.

2. Related literature

Integrating the financial and real sectors into economic modeling has been a major challenge in the past. Some early works, such as those by Holmstrom and Tirole (1997), Kiyotaki and Moore (1997), Bernanke et al. (1999) and Bernanke and Gertler (2000), attempted to incorporate financial frictions into macroeconomic models. These studies extended traditional frameworks by including elements such as transaction fees, credit restrictions, asset price misalignments, and even a basic credit market between companies and banks. However, these additions, which make sense in theory, usually increase the complexity of the original dynamic stochastic

¹ See excellent surveys on financial and macroeconomic ABMs by Franke and Westerhoff (2017), Dawid and Gatti (2018), Dieci and He (2018), Dilaver et al. (2018), Lux and Zwickels (2018), Hommes (2021) and Axtell and Farmer (2025).

general equilibrium (DSGE) models and make their econometric analysis and empirical validation more difficult (Christensen and Dib, 2008; Gallegati et al., 2019).

In response to the financial crisis, there was a renewed interest in understanding the interplay between financial markets and the real economy. Works by Gertler and Kiyotaki (2010), Castelnovo and Nisticò (2010), and Brunnermeier and Sannikov (2014) focused on how financial phenomena influence the real sector and vice versa. However, despite these efforts, the overall trend of separating finance and macroeconomics persisted.

A parallel strand of research examines macro-financial interactions within heterogeneous-agent general equilibrium frameworks. Heterogeneous agent New Keynesian (HANK) models, as developed by Kaplan et al. (2018) and recently surveyed by Auclert et al. (2025), incorporate household heterogeneity and distributional effects into the monetary transmission mechanism and can generate empirically relevant wealth effect channels. These models, however, maintain rational expectations and solve for a competitive equilibrium, which limits the endogenous instability observed in financial cycles. More broadly, Branch and McGough (2018) show that heterogeneous expectations within New Keynesian frameworks (HENK) can generate persistent fluctuations that standard rational expectations models cannot produce. Behavioral extensions that relax rational expectations within HANK frameworks, such as the cognitive-discounting model of Pfäuti and Seyrich (2022), bring the framework closer to the setting we consider while retaining a formal equilibrium solution concept. Our contribution differs along two dimensions. First, we allow for heuristic switching in both the real and financial sectors, following the heterogeneous expectations literature (De Grauwe, 2012a; De Grauwe and Ji, 2019; Hommes, 2021). Second, we enable endogenous financial dynamics driven by chartist–fundamentalist interactions outside equilibrium frameworks. The estimated interaction channels thus quantify macro-financial linkages in a setting that combines behavioral heterogeneity with endogenous market instability, features not jointly captured by HANK models or standard DSGE frameworks with financial frictions.

In the field of ABMs, the outcomes of the EURACE project stand out. It resulted in a large-scale agent-based model and simulator of the European economy that includes credit and financial markets (Deissenberg et al., 2008; Cincotti et al., 2010; Raberto et al., 2012; Dawid et al., 2014, 2016). Next, the work of Delli Gatti et al. (2010b) introduces a simple credit market between firms and banks in a macroeconomic ABM to study the financial accelerator phenomenon. This model is further extended by Riccetti et al. (2013, 2016), who allow for multiple credit links and debt structures spanning several periods and examine the impact of dividend distribution on the financial system. Proano (2011) analyzes the stability of a two-country macroeconomic system combined with an FX market populated by boundedly rational traders. An agent-based Keynesian model augmented with credit is constructed by Dosi et al. (2013) to model the banking sector and lending conditions, and the series of contributions by Russo et al. (2014), Riccetti et al. (2015) and Russo et al. (2016) develop a microfounded macroeconomic model consisting of heterogeneous individuals, households, firms, and banks interacting through decentralized matching mechanisms. Other ways to connect banks and businesses are suggested in Assenza et al. (2015) and Caiani et al. (2016). The first authors build on the macroeconomic agent-based framework of Delli Gatti et al. (2011) with capital and credit, while the other authors develop a fully decentralized agent-based stock-flow-consistent model that connects the real and financial economies. De Grauwe and Macchiarelli (2015) and Macchiarelli and Grauwe (2019) bring another modeling approach that is, to some extent, close to our contribution. It extends the behavioral macroeconomic model developed by De Grauwe (2012a) by including the banking industry and the real estate sector, which consists of financial intermediaries that gather deposits from customers and lend them to firms or provide secured housing loans. As the latest from our review, Reissl (2021) constructs a hybrid macroeconomic model that incorporates both the agent-based banking sector and stock-flow consistency.

The pioneers in integrating stylized financial and macroeconomic agent-based frameworks in a comprehensive microfounded manner are, nevertheless, Lengnick and Wohltmann (2013) and Lengnick and Wohltmann (2016), whose theoretical contribution we closely follow in our empirical study. These authors build on the work of Westerhoff (2012) and Naimzada and Pireddu (2014), who used an ABM to model the financial system and the standard Keynesian income–expenditure model for the real sector. This approach yields interconnected models that are simple and analytically tractable; however, they lack microfoundations for the real economy. Another source of inspiration, influenced by the agent-based financial literature, comes from Kontonikas and Ioannidis (2005), Kontonikas and Montagnoli (2006) and Bask (2012), where nonrational heterogeneous heuristics govern the dynamics of the financial side of the economy, while the expectation formation for the macroeconomic part of the model is derived from the rational expectations hypothesis. Nevertheless, to the best of our knowledge, no studies have shown how stylized heterogeneous ABMs interconnecting the financial and macroeconomic sectors can be empirically estimated using current econometric approaches. There are a few notable exceptions, such as strongly methodologically oriented working papers by Barde and van der Hoog (2017), Barde (2024). However, these papers focus on large-scale simulation-based object-oriented systems (Dawid et al., 2016; Caiani et al., 2016) rather than heterogeneous agent-based systems of differential equations.

While we rely on SMM as our approach, a growing set of estimation techniques has been applied to macroeconomic ABMs, which we briefly review for comparison. The most closely related classical simulation-based estimators are indirect inference (II; Gourieroux et al., 1993) and the efficient method of moments (EMM; Gallant and Tauchen, 1996), both of which rely on an auxiliary model to construct moment conditions or a binding function. Michaelides and Ng (2000) show in a Monte Carlo comparison that although II and EMM can achieve superior finite-sample precision and efficiency relative to SMM, this comes at a substantially higher computational burden, especially for complex nonlinear models. For ABMs in particular, where each model evaluation is costly, the simplicity and computational tractability of SMM make it usually the most practical choice.

The simulated maximum likelihood estimator (SMLE) by Kukacka and Barunik (2017) and Kukacka and Sacht (2023) approximates the likelihood function via kernel smoothing of simulated trajectories and shares the standard large-sample properties of maximum likelihood. More recent work has shifted toward Bayesian and machine-learning-based approaches. On the Bayesian side,

these include kernel density estimation (KDE)- and Markov chain Monte Carlo (MCMC)-based approaches such as [Grazzini et al. \(2017\)](#), [Deák et al. \(2017\)](#), [Delli Gatti and Grazzini \(2020\)](#), [Lux \(2022, 2024\)](#) and [Armenta and Milani \(2026\)](#); particle-filter and sequential Monte Carlo (SMC) methods ([Lux, 2018](#); [Fischer, 2022](#); [Zhang et al., 2023](#)), approximate Bayesian computation (ABC; [Lux, 2023](#)), and inference based on auxiliary/surrogate likelihood approximations ([Barde, 2024](#)). On the machine-learning side, recent contributions include neural posterior estimation (NPE; [Dyer et al., 2024](#)), simulation-based inference via normalizing flows ([Shiono, 2021](#)), and neural network likelihood approximation ([Platt, 2022](#)). The survey by [Axtell and Farmer \(2025\)](#) provides a comprehensive overview of these developments. All likelihood-based approaches must evaluate the likelihood, or its approximation, sequentially at each observation, which requires all variables to share a common time grid. Aligning quarterly macroeconomic series with daily financial observations on such a grid is non-trivial: it either requires treating one frequency as latent and imputing missing values through data augmentation, or reformulating the system as a state-space model. Both approaches add substantial complexity to already computationally demanding ABMs. By contrast, SMM matches population moments computed at each series' native frequency and aggregates deviations through a common objective function, making mixed-frequency sampling a practically feasible adaptation of the standard estimator rather than a fundamental complication.

Furthermore, mixed data sampling (MIDAS) regression models, proposed by [Ghysels et al. \(2004, 2007\)](#), also address the issue of mixed data frequencies. MIDAS is a reduced-form regression framework that uses parametric lag polynomials to incorporate high-frequency regressors into a low-frequency prediction equation ([Andreou et al., 2010](#)), estimating regression coefficients via nonlinear least squares (NLS). It is primarily designed for prediction in linear or moderately nonlinear settings. In this sense, it does not address the identification of structural behavioral parameters or the statistical properties of such estimates. Our approach differs fundamentally: we estimate structural ABM parameters by matching simulated and empirical moments, with the mixed-frequency adaptation consisting of the parallel evaluation of moment vectors at their native frequencies and their aggregation into a single objective function. While MIDAS addresses forecasting a low-frequency variable using mixed-frequency predictors, our framework identifies the structural parameters underlying the joint macro-financial data-generating process. The two approaches are therefore complementary rather than competing, and to the best of our knowledge, no successful application of MIDAS to structural ABM estimation exists, given the inherent nonlinearity of such models and the absence of a regression representation. For a formal treatment of MIDAS asymptotic properties in regression settings, see [Andreou et al. \(2010\)](#). We return to the econometric properties of our mixed-frequency SMM adaptation, including regularity conditions and parameter identification, in Section 4.6.

Abstracting from the need for empirical estimation, a particularly interesting approach to research on mixed-data sampling in ABMs is provided by simulation studies, such as [Kotb et al. \(2024\)](#) and [Proano and Kotb \(2026\)](#). These papers examine whether central banks should respond to high-frequency stock price information when macroeconomic variables are observed only with a delay, and show that stock prices may serve as a useful proxy for the contemporaneous state of the economy, with a moderate policy response improving stabilization.

In conclusion, while ABMs have achieved historical successes in explaining numerous complex economic phenomena, the limitations in their empirical estimation still hinder their effective utilization as artificial labs for policymakers and regulators.

3. Integrated model

The financial-macroeconomic integrated model is based on two prominent lines of agent-based economic literature. The macroeconomic framework follows a behavioral heuristics switching approach in macroeconomic modeling based on a three-equation New Keynesian model (NKM), as proposed by [De Grauwe \(2010, 2011, 2012a\)](#), [De Grauwe and Ji \(2019\)](#) and [De Grauwe and Ji \(2020\)](#). Various versions of the model setup have also been suggested, e.g., by [Branch and McGough \(2009, 2010\)](#), [Massaro \(2013\)](#) and [Di Bartolomeo et al. \(2016\)](#). It further incorporates microfounded decision-making heuristics derived from laboratory experiments conducted originally by [Anufriev and Hommes \(2012\)](#), introduced to behavioral macroeconomics by [Hommes et al. \(2019\)](#). Recently, researchers have conducted the first empirical examinations of these modeling frameworks, such as those done by [Jang and Sacht \(2016\)](#), [Deák et al. \(2017\)](#), [Jang and Sacht \(2021\)](#), [Kukacka and Sacht \(2023\)](#), [Zhang et al. \(2023\)](#) and [Ozden \(2025\)](#), some of which are used to parameterize our integrated model.

Second, the financial aspect of the economy is represented by the influential asset-pricing ABM developed by [Franke and Westerhoff \(2011, 2012\)](#), whose dynamics are based on repeated interactions between fundamentalists and chartists, both guided by an evolutionary heuristic switching mechanism. In recent years, the model has become a prominent reference for various empirical studies, as evidenced by investigations reported in [Franke and Westerhoff \(2016\)](#), [Lux \(2022\)](#), [Platt \(2022\)](#) and [Zila and Kukacka \(2023\)](#). Consequently, its characteristics are well-known within the research community. The establishment of reciprocal interaction channels between the two sectors of the economy is motivated by the recent theoretical contributions, as summarized in [Lengnick and Wohltmann \(2013, 2016\)](#), [Kotb et al. \(2024\)](#) and [Cho and Jang \(2019\)](#).

3.1. Heuristic switching macroeconomic model

The macroeconomic aspect of the economy is depicted using the three-equation, purely forward-looking form of the baseline NKM ([Galí, 2015](#)). This framework, while markedly simplified, is considered a realistic and influential model that has earned a reputation as the 'empirical workhorse' ([Blanchard and Galí, 2007](#)) of macroeconomic research and the prevailing paradigm in macroeconomics throughout recent decades. Renowned for its realistic assumptions and robust theoretical foundations rooted in individual optimization, this model possesses notable policy relevance. Furthermore, it demonstrates a strong ability to fit real-world economic data and to explain or predict macroeconomic phenomena. The model specification exactly follows [Kukacka and Sacht](#)

(2023), while already being extended by the first two of the three interaction terms: the ‘wealth effect’ channel is represented by the coefficient c_1 and the ‘cost effect’ by the coefficient c_2 as in [Lengnick and Wohltmann \(2013, 2016\)](#). For clarity, the rationale for incorporating these interaction terms into the original model is discussed separately in detail in Section 3.1.1.

$$y_q = \tilde{E}_{y,q} y_{q+1} - \tau(r_q - \tilde{E}_{\pi,q} \pi_{q+1}) + c_1 \tilde{E}_{\Delta s-\pi,q} (\Delta s_{q+1} - \pi_{q+1}) + \varepsilon_{y,q}, \quad (1)$$

$$\pi_q = \nu \tilde{E}_{\pi,q} \pi_{q+1} + \kappa y_q - c_2 s_q + \varepsilon_{\pi,q}, \quad (2)$$

$$r_q = \phi_y y_q + \phi_\pi \pi_q + \varepsilon_{r,q}, \quad (3)$$

where $\tilde{E}_{\{y,\pi,\Delta s-\pi\},q}$ denote the bounded rationality (BR) expectations operators defined in Section 3.1.2, and s_q represents the aggregated quarterly value of the nominal stock price, which generates the newly introduced interaction terms together with coefficients c_1 and c_2 , as explained in Section 3.1.1.

The q subscript, $q = \{1, \dots, Q\}$, indicates that the model has a quarterly frequency. The dynamic IS curve (1) represents the demand side of the economy. It is derived from the Euler equation, i.e., intertemporal utility maximization via optimization of consumption and savings to achieve consumption smoothing. The parameter $\tau \geq 0$ is the inverse intertemporal elasticity of substitution in consumer behavior. The Eq. (2) represents the supply side. It stands for the New Keynesian Phillips curve, which shows how the dynamics of the (log) output gap (y_q) affect the (log) inflation rate deviation from its target (π_q). This relationship arises from the assumptions of monopolistic competition and Calvo-type nominal price rigidity. The parameter ν denotes the discount factor, which must satisfy the condition $0 < \nu < 1$, and the parameter $\kappa \geq 0$ determines the slope of the New Keynesian Phillips curve, i.e., the impact of the output gap dynamics on the inflation rate fluctuation.

The monetary authority is assumed to respond immediately to current changes in output ($\phi_y \geq 0$) and inflation ($\phi_\pi \geq 0$) and sets the nominal (log) interest rate deviation from its target (r_q) based on a straightforward Taylor-type monetary policy rule (3). From a technical standpoint, the log-linearization process around the steady state implies that the targeted values for inflation and the nominal interest rate coincide with the zero solution of the NKM. The model further assumes that random shocks $\varepsilon_{\{y,\pi,r\},q}$, which are independently and identically distributed with an average of zero and variances $\sigma_{\{y,\pi,r\}}^2$, affect the external driving forces in the endogenous macroeconomic variables. The state-space representation of the integrated forward-looking NKM is outlined in [Appendix A](#), together with a brief explanation of the matrix formulation and of how the reduced-form expression is derived. The forward-looking form does not account for concepts such as habit formation, price indexation, and interest rate smoothing, which lead to intrinsic persistence in the variables observed in real-world data. Instead, because of BR expectations, the model variables’ inertia is guaranteed endogenously, even if there are no autocorrelated shocks. The application of backward-looking behavioral heuristics, explained in Section 3.1.2, thus makes such simplification entirely acceptable.

The original structural NKM model, comprising Eqs. (1) and (2), is strictly microfounded based on the Euler equation and firms’ profit maximization, as explained above, under both rational and behavioral expectations ([Galí, 2015; Hommes et al., 2019](#)). The behavioral expectations operators $\tilde{E}$ are likewise microfounded as optimal individual choices conditional on subjective heuristics ([Branch and McGough, 2009; Massaro, 2013](#)); additional details are provided in Section 3.1.2. Furthermore, the newly introduced interaction channels, which extend both the IS curve and the New Keynesian Phillips curve, are also microfounded. The wealth effect (c_1) is derived from the ‘Stock in Non-separable Utility’ approach, where stock holdings directly influence the marginal utility of consumption, while the cost effect (c_2) is based on credit-market frictions in which stocks serve as collateral that affects firms’ real marginal costs of production ([Bernanke and Gertler, 2000; Lengnick and Wohltmann, 2016](#)). In contrast, the Taylor-type monetary policy rule in Eq. (3) is not microfounded. Instead, it represents a behavioral reaction function describing how the central bank adjusts interest rates in response to observed economic deviations.

3.1.1. Channels of interaction: the wealth and cost effects

The interaction channels between the financial and macroeconomic sectors of the economy closely follow the formalizations proposed by [Lengnick and Wohltmann \(2013, 2016\)](#) and, most recently, by [Kotb et al. \(2024\)](#). As the models of the two sectors are typically designed to operate at different frequencies, namely daily and quarterly, their integration is not straightforward. The authors suggest maintaining the time scales of both modeling approaches while assuming that announcements from the real sector, such as GDP nowcasts, FOMC announcements, or macroeconomic experts’ forecasts, only have an aggregate impact on financial market agents once a quarter. Conversely, the impact of the financial system on the macroeconomy is represented by incorporating an aggregated quarterly value of the nominal stock price, denoted as s_q , to both the dynamic IS curve (1) and the New Keynesian Phillips curve (2):

$$s_q = \frac{1}{63} \sum_{t=63(q-1)+1}^{63q} p_t, \quad (4)$$

where p_t is the stock price value of the overall financial sector in day t , $t = \{1, \dots, T\}$, as defined below in (11). The quarterly value of stock prices is thus calculated by averaging the stock price over an assumed 63 workdays preceding the publication of macroeconomic statistics for the current quarter. Two interaction parameters, $c_1 \geq 0$ and $c_2 \geq 0$, represent the influence of the wealth effect ([Kontonikas and Montagnoli, 2006; Bask, 2012; Westerhoff, 2012; Naimzada and Pireddu, 2013](#)) and the cost effect ([Bernanke and Gertler, 2000; Lengnick and Wohltmann, 2013; Cho and Jang, 2019](#)) of stock prices, respectively.

The flat-averaging approach in (4) is taken directly from the integration framework of [Lengnick and Wohltmann \(2013, 2016\)](#) and matches the construction of the quarterly macroeconomic series on the left-hand side of the system, which are likewise measured as

within-period averages rather than end-of-period snapshots (Silvestrini and Veredas, 2008). A natural alternative would be a moving-average specification. However, this would overlap consecutive quarters and thus no longer align with the quarterly reporting calendar required by the macroeconomic block. From an econometric perspective, (4) may be interpreted as a restricted special case of MIDAS-type aggregation, in which equal weights are imposed by the structural specification rather than estimated from the data (cf. Section 2).

The wealth effect is introduced via a new term, $c_1 \tilde{E}_{\Delta s - \pi, q}(\Delta s_{q+1} - \pi_{q+1})$, in the dynamic IS curve (1) based on the following rationale: holding stocks creates utility similarly to consumption. When households expect future real stock prices to rise, holding stocks becomes relatively more attractive compared to consumption. As a result, households anticipate higher future wealth and adjust their intertemporal consumption decisions accordingly. This reduces the marginal utility of future consumption relative to current consumption. To restore the intertemporal balance implied by the Euler equation, households increase their contemporaneous consumption, thereby widening the current output gap (Lengnick and Wohltmann, 2016).

The cost effect is introduced into the New Keynesian Phillips curve (2) through the new term $-c_2 s_q$, where s_q denotes the aggregated quarterly value of the stock price. The reasoning behind this extension is as follows: higher prices of firms' financial assets used as collateral improve their borrowing conditions by increasing their creditworthiness. Because many firms rely heavily on credit financing, higher asset prices reduce firms' real marginal costs of production (Lengnick and Wohltmann, 2013). Lower production costs then translate into lower consumer prices.

3.1.2. Behavioral heuristics

The BR expectations formation operators $\tilde{E}_{\{y, \pi, \Delta s - \pi\}, q}$ adopt the modeling approach suggested by Hommes et al. (2019) and examined using US macroeconomic data by Kukacka and Sacht (2023), whereas parameter homogeneity is assumed in line with the standard specification and utilization of New-Keynesian-types of models. The empirical microfoundation of behavioral 'rules-of-thumb' defined below in (5) to (7) is examined in detail in Anufriev and Hommes (2012, pp. 45–46) within an asset-pricing framework. These simple behavioral heuristics can be formally aggregated from individual decision rules into macroeconomic dynamics (Branch and McGough, 2009; Massaro, 2013). Exploiting straightforward behavioral principles is not considered irrational in this context; rather, it constitutes an optimal, boundedly rational approach for humans when addressing overly complex tasks under constraints such as limited information or time, alongside many parallel economic decisions. De Grauwe (2012b, pg. 29) and De Grauwe and Ji (2019, pg. 28) even 'redefine' economic agents' rationality following the concept of bounded rationality (Simon, 1955; Tversky and Kahneman, 1974) in the sense that "using heuristics is a rational response of agents who are aware of their limited capacity to understand the world" and that "agents in the model are rational, not in the sense of having rational expectations, [but because] they learn from their mistakes".

Hommes et al. (2019) and Assenza et al. (2021) further confirm these findings based on their own macroeconomic setup, where all three types of heuristics, as defined below by (5) to (7), are supported by experimental evidence:

$$\tilde{E}_{x,q}^{ADA} x_{q+1} = \eta x_{q-1} + (1 - \eta) \tilde{E}_{x,q}^{ADA} x_q, \quad (5)$$

$$\tilde{E}_{x,q}^{TR} x_{q+1} = x_{q-1} + \iota(x_{q-1} - x_{q-2}), \quad (6)$$

$$\tilde{E}_{x,q}^{LAA} x_{q+1} = \mu(x_{q-1}^{av} + x_{q-1}) + (x_{q-1} - x_{q-2}). \quad (7)$$

The weighted combination of the prior actual value in x and agents' historical prediction, $\tilde{E}_{x,q-1}^{ADA} x_q$, where $0 \leq \eta \leq 1$, determines the anticipation of a future outcome according to the adaptive (ADA) heuristic (5). When η equals 1, this expression represents a static/naïve method of forming expectations. For the trend-following (TR) heuristic (6), the past realization is taken into account, and the forecasting rule aligns with the direction of the most recent change in x indicated by the term $(x_{q-1} - x_{q-2})$. The parameter of extrapolation $\iota \geq 0$ captures the specific patterns in the dynamics of the variable. Next, in a parameterized 'learning anchoring and adjustment' (LAA) heuristic (7), the most recent change in x is extrapolated via an anchoring parameter, $\mu \geq 0$, from an anchor established through the summation of the average of all observations up to quarter $q-1$, x_{q-1}^{av} , and the latest available actual value. Finally, adhering to the established practice in behavioral macroeconomic modeling (De Grauwe and Ji, 2019; Hommes and Lustenhouwer, 2019; Jump and Levine, 2019; Hommes et al., 2019; De Grauwe and Ji, 2020), we use these heuristics with regard to the output gap, inflation rate, and real stock price increases expectations, i.e., $x \in \{y, \pi, \Delta s - \pi\}$. We direct the interested reader to Kukacka and Sacht (2023, Footnote 4) for an outline and discussion on the advantages and drawbacks of more sophisticated expectation formation concepts. Additionally, see Pfajfar and Zakelj (2014, 2018) for extensive lab-based evidence that supports the behavioral assumptions of simple forecasting heuristics, Anufriev et al. (2013) for the specification and experimental evidence regarding a 2-type heuristic switching model with the adaptive and trend-following heuristics only, Anufriev et al. (2019) for an overview of forecasting rules and models from the learning-to-forecast literature, and finally (Assenza et al., 2014) for a review of different types of macroeconomics experiments that involve gathering expectations or forecasts.

3.1.3. Heuristic switching

Consequently, for each of the three forecasted variables, $x \in \{y, \pi, \Delta s - \pi\}$, economic agents adaptively switch between the three groups following specific forecast heuristics (5) to (7). The economic utility of the forecast precision of each heuristic, $U_{x,q}^k$, $k \in \{ADA, TR, LAA\}$, is updated in each period while being standardly defined through squared forecast errors:

$$U_{x,q}^k = \rho U_{x,q-1}^k - (E_{q-2}^k x_{q-1} - x_{q-1})^2, \quad (8)$$

where the memory parameter, $0 \leq \rho \leq 1$, controls the speed of geometric dilution of the impact of past squared errors on the current utility of forecast precision.

The multinomial logit discrete-choice approach governs the switching process. In simpler terms, the heuristic that currently exhibits the highest precision, as indicated by the smallest squared forecast errors, attracts the largest share of agents. The adaptive switching mechanism defines those fractions using the output of (8) as:

$$\alpha_{x,q}^k = \frac{\exp(\gamma U_{x,q}^k)}{\sum_{i=1}^3 \exp(\gamma U_{x,q}^{k(i)})}, \quad (9)$$

where $\gamma \geq 0$ represents the intensity of choice (Brock and Hommes, 1997, 1998; Hommes, 2013) of macroeconomic forecasters. As γ increases, agents become more inclined to learn from their past forecast performance, leading to a greater willingness to switch to forecast heuristics with better precision. Naturally, fractions $\alpha_{x,t}^k$ sum to one for each of the three forecasted variables x .

The aggregated forecast for the economy is obtained by combining agents' expectations. Specifically, the aggregation of expectations about the future values of variables $x \in \{y, \pi, \Delta s - \pi\}$ is defined as a weighted average based on the fractions obtained from (9), $k \in \{ADA, TR, LAA\}$:

$$\tilde{E}_{x,q} x_{q+1} = \sum_{i=1}^3 (\alpha_{x,q}^{k(i)} \cdot \tilde{E}_{x,q}^{k(i)} x_{q+1}). \quad (10)$$

3.2. Financial agent-based model

The financial side of the economy, or simply the stock market, is represented by the asset-pricing ABM developed by Franke and Westerhoff (2011, 2012). Specifically, we use its empirically superior DCA-HPM version, where DCA stands for the discrete choice approach (Brock and Hommes, 1998), while HPM defines the drivers of the switching index, namely 'herding', 'predisposition', and price 'misalignment'; see (14) and (15) below. The main presumption is that distinct types of agents, other than those from the real sector, populate the financial market. Stock market trades follow different behavioral heuristics than macroeconomic forecasters, who, in turn, do not participate in stock trading. The model thus characterizes a market in which two segments of financial agents, namely fundamentalists and chartists, interact and, similarly to macroeconomic agents, adapt to their dynamic environment by switching between the two groups. Finally, the financial part of the integrated model must operate at a higher frequency, namely daily, as indicated by the t subscript.

The price of a market-traded asset is influenced by demand. In particular, a market maker adjusts the log price p_t from one period to the next based on the asset's excess demand. The adjustment is proportional to the excess demands of fundamentalists (d_t^f) and chartists (d_t^c), given by:

$$p_t = p_{t-1} + v(n_{t-1}^f d_{t-1}^f + n_{t-1}^c d_{t-1}^c). \quad (11)$$

Here, n_t^f and $n_t^c = 1 - n_t^f$ represent the population shares of fundamentalists and chartists, respectively, and the parameter v signifies the market maker's adjustment rate for the asset price. The trader's excess demand is determined by one of the following equations based on their current trading approach:

$$d_t^f = \psi(p^* - p_t) + \varepsilon_t^f, \quad \varepsilon_t^f \sim \mathcal{N}(0, \sigma_f^2), \quad (12)$$

$$d_t^c = \chi(p_t - p_{t-1}) + \varepsilon_t^c, \quad \varepsilon_t^c \sim \mathcal{N}(0, \sigma_c^2). \quad (13)$$

In this context, p^* stands for the log fundamental value of the asset, with ε_t^f and ε_t^c representing the noise terms for fundamentalists and chartists, respectively. The variances of these noise terms are determined by σ_f^2 and σ_c^2 , while ψ and χ act as the adjustment parameters for demands.

The governing principles for excess demands follow simple behavioral rules commonly found in the literature (Hommes, 2006, 2013; Dieci and He, 2018; Lux and Zwinkels, 2018). Specifically, the excess demand of fundamentalists responds to the deviation of the current asset price from its fundamental value. In contrast, the excess demand of chartists is driven by the asset's price change from the previous period to the current period. The adjustments in population shares of traders are influenced by the attractiveness index a_t , indicating the propensity to switch:

$$a_t = \delta_0 + \delta_h(n_t^f - n_t^c) + \delta_m(p_t - p^*)^2, \quad (14)$$

$$n_t^f = \frac{1}{1 + \exp(-\beta a_{t-1})}, \quad (15)$$

where δ_0 serves as a predisposition parameter, indicating a general inclination toward one of the trading rules. The parameter $\delta_h \geq 0$ reflects a herding effect, while $\delta_m \geq 0$ represents the impact of price misalignment resulting from deviations from the fundamental value. Similarly to the macroeconomic segment of the integrated model, $\beta \geq 0$ is the intensity of choice. It is now, however, specific to asset traders and governs the binomial logistic model (15), which determines the evolution of the population shares of fundamentalists and chartists.

Fundamental value and the misperception effect. The prerequisite for connecting the two parts of the economy is the existence of the concept of fundamental value in the financial model. Following the idea proposed by Westerhoff (2012) to make the fundamental value of the stock market proportional to national income, we adopt the interconnection framework by Lengnick and Wohltmann (2013, 2016) to connect the macroeconomic and financial parts of the model. Specifically, we define:

$$p^* := p_t^* = h y_{q-1}, \quad q = \text{floor} \frac{t-1}{63}, \quad (16)$$

where the perceived fundamental value of the asset, p^* from (12), is calculated as a factor of the macroeconomic output gap y_{q-1} released at the end of the previous quarter, and the floor operation rounds down to the nearest integer. The perceived fundamental value thus fluctuates around zero and is updated quarterly based on recent real economic progress. As such, it deviates from the original model's assumption that the fundamental value is set to zero for simplicity, while adhering to other financial ABMs, such as those by Farmer and Joshi (2002) and Alfaro et al. (2008), in which the random walk process often approximates the time-varying fundamental.

This impact of the real economy on the financial sector represents the third studied interaction channel, the so-called price 'misperception effect' (Kontonikas and Montagnoli, 2006; Westerhoff, 2012; De Grauwe and Kaltwasser, 2012; Naimzada and Pireddu, 2013). The intuition emphasizes that determining the fundamental values of financial assets poses significant challenges in practice. Fundamentalists are thus assumed not to be aware of the true value, but their view is skewed toward the most recent actual economic activity. They approximate the fundamental value by relying on information about recent economic conditions, as represented by the latest output gap, y_{q-1} . The nonnegativity of the interaction parameter $h \geq 0$ ensures that if output is above (below) its long-term trend, the fundamental price is assumed to be higher (lower) than its 'true' underlying value, and the fundamentalists' asset demand is adjusted accordingly. In simple terms, if economic agents can afford higher consumption, leading to a higher output gap, the fundamentalists' demand for stocks also increases.

Crucially, the three interaction channels mutually influence one another simultaneously. For instance, the expectation of a growing stock market positively influences output directly through the wealth effect in (1) and indirectly through the cost effect in (2) that propagates to the output equation through the contemporaneous nominal interest rate (3). In turn, growing output exerts a positive impact on the fundamental value approximation (16) that translates into traders' excess demand (12) increasing stock prices (11). Finally, note that Lengnick and Wohltmann (2013) only discuss the impacts of the cost and misperception effects, whereas Lengnick and Wohltmann (2016) expand the number of interaction channels to four. In addition to the wealth effect, they incorporate an additional channel linking financial traders' stock demand to average households' macroeconomic demand for stocks. This connection is a crucial component of their consumer utility maximization problem, which leads to the derivation of their log-linearized three-equation NKM. However, implementing this channel does not align with our accepted framework; therefore, we are unable to incorporate it into the examined model immediately. There are two aspects to the problem. Our stylized model does not include the households' stock demand function from the NKM microfoundation framework as defined by Lengnick and Wohltmann (2016, Eq. (4)). Expanding the model in this manner would result in inconsistency with our baseline model parameterization, as outlined in Section 3.3, and might have unpredictable effects on the estimation performance. In technical terms, it would necessitate the inclusion of three new estimated coefficients and an extra empirical time series. This might compromise the identification of the three parameters that are now being successfully estimated.

3.3. Baseline model parameterization

The purpose of this paper is to estimate the three novel interaction parameters of the integrated financial–macroeconomic model: the fundamental price misperception parameter h in (16), the wealth effect parameter c_1 in (1), and the cost effect parameter c_2 in (2). To make this possible, the remaining coefficients of both model blocks must be parameterized in advance. Their values are therefore taken from the most recent empirical literature estimating the same frameworks separately on datasets with time spans comparable to those used in the present study.

The complete set of parameterized coefficients is summarized in Table 1. The main parameters of the heuristics switching macroeconomic block are set according to Kukacka and Sacht (2023, Table 2, col. C) who use US quarterly data from 1954:Q3 to 2019:Q2. Other parameters are fixed in that study based on empirical results by Jang and Sacht (2021, Table 2, col. EFB). The financial ABM block follows the recent empirical results of Zila and Kukacka (2023, Table 4, col. FW9), who estimate the Franke and Westerhoff (2012) model using S&P 500 data from 1980-01-02 to 2022-09-08. Again, a few parameters are fixed in that study, following Franke and Westerhoff (2012) and Platt (2022). Moreover, we later introduce sensitivity experiments that modify selected parameters or the model structure, as detailed in Section 7.

4. Implementation of the simulated method of moments

To empirically identify parameters h , c_1 , and c_2 representing the interaction channels, we employ the SMM pioneered by McFadden (1989) and Pakes and Pollard (1989). In the agent-based modeling literature, SMM is a well-established estimator with known asymptotic properties: consistency and asymptotic normality under standard regularity conditions (Lee and Ingram, 1991; Duffie and Singleton, 1993). While alternative simulation-based estimators, including II, EMM, or pseudo-maximum likelihood estimator (PMLE), can achieve superior finite-sample precision and efficiency in specific settings (Michaelides and Ng, 2000), SMM's straightforward implementation, flexibility, computational tractability, and its wide use in the ABM econometrics literature make it a natural choice for complex models, where each model evaluation is costly. SMM estimates parameters by running multiple model

Table 1

Baseline model parameterization.

Heuristics switching macroeconomic block												
τ	κ	ϕ_y	ϕ_π	η	ι	μ	γ	ν	ρ	σ_y	σ_π	σ_r
0.20	0.05	0.04	1.27	0.20	0.00	0.44	1.39	0.99	0	0.543	0.240	0.151
Financial agent-based block												
		ψ	χ	σ_f	σ_c	δ_0	δ_h	δ_m	ν	β	p_1	
		0.010	0.767	0.870	4.21	0.022	1.74	24.32	0.01	1	0	

Note: Parameterization of the integrated model is based on Kukacka and Sacht (2023, Table 2, col. C), Jang and Sacht (2021, Table 2, col. EFB), and Zila and Kukacka (2023, Table 4, col. FW9).

simulations over a wide range of parameter combinations. Empirical estimates are then derived by minimizing the discrepancy between a chosen set of moments from simulated data that approximate the population values and the sample moments observed from real-world data, such as the sample mean, variance, or correlations between variables. This makes the approach broadly applicable across a spectrum of potential econometric scenarios. Importantly, the SMM also plays a crucial role in addressing the challenge posed by the different frequencies between the two components of the model, as explained in the subsequent detailed discussion.

4.1. Formal definition

Assume that we have a stochastic model f whose parameters θ we want to estimate for an empirical time series $e = \{e_t\}_{t=1}^{T_{emp}}$. Furthermore, assume that we can draw a simulated time series $f(\theta) = z^\theta = \{z_t^\theta\}_{t=1}^{T_{sim}}$ of length $T_{sim} \geq T_{emp}$ from f for a given set of parameters θ . As a measure of closeness between the empirical and simulated time series, we can compute the distance between the sample counterparts of D statistical moments of choice, called ‘statistics’, that describe the distributions of the time series. For instance, the sample average is typically used as the sample counterpart for the expected value. To achieve our goal, we find θ that minimizes the overall distance between the D statistics calculated from the empirical and simulated time series.

Each of the D statistics can be represented as a function m_d , $d \in \{1, \dots, D\}$, which takes a time series as an input and returns the statistic’s value. For simulated time series, variability of the calculated statistics can be reduced by independently generating S simulated time series z_s^θ , $s \in \{1, \dots, S\}$, and taking the average over the statistics as $\frac{1}{S} \sum_{s=1}^S m_d(z_s^\theta)$.² Then, we can organize the D statistics computed in this manner into a couple of vectors $\mathbf{m}^{emp} = [m_1(e), \dots, m_D(e)]$ and $\mathbf{m}^{sim}(\theta) = [\frac{1}{S} \sum_{s=1}^S m_1(z_s^\theta), \dots, \frac{1}{S} \sum_{s=1}^S m_D(z_s^\theta)]$. Finally, we can define an objective function J computing the distance between the two vectors as follows:

$$J(\theta) = \mathbf{h}(\theta)^T \mathbf{W} \mathbf{h}(\theta), \quad (17)$$

where $\mathbf{h}(\theta) = \mathbf{m}^{emp} - \mathbf{m}^{sim}(\theta)$ and $\mathbf{W} \in \mathbb{R}^{D \times D}$ is a positive definite weighting matrix. The SMM estimator $\hat{\theta}$ is found by minimizing the objective function:

$$\hat{\theta} = \arg \min_{\theta} J(\theta), \quad (18)$$

where $\theta \in \Theta$, Θ is the parameter space of the search.

4.2. Weighting matrix

The weighting matrix $\mathbf{W}$ can be calculated using several approaches. The general rule, however, is to assign greater importance to moments that remain stable across independent realizations of the true multivariate time series process. Ideally, the weights should also reflect correlations between moments to account for as many distinct characteristics of the time series as possible and avoid excessive focus on potentially overlapping information. Consequently, the appropriate and most common choice is to use Σ , the covariance matrix of moments, and set $\mathbf{W} = \Sigma^{-1}$.

To estimate the covariance matrix Σ , we employ a block bootstrap approach introduced by Franke and Westerhoff (2012) and refined by Zila and Kukacka (2023) by allowing block overlaps to address small sample bias issues of the original procedure. Specifically, we split the empirical time series into $T_{sim} - B_L + 1$ overlapping blocks of B_L observations each. Then, we randomly sample B_N of these blocks and concatenate them to create a new bootstrapped time series $b = \{b_t\}_{t=1}^{T_{bs}}$, where $T_{bs} = B_N \times B_L$. We

² The asymptotic variance of the SMM estimator takes the general form $\text{Var}_{\text{SMM}} = (1 + \text{IF}) \text{Var}_{\text{GMM}}$, where Var_{GMM} denotes the variance of the infeasible generalized method of moments (GMM) estimator based on known population moments and IF is a simulation-noise inflation factor (Duffie and Singleton, 1993; McFadden, 1989). With a single long simulation ($S = 1$, $T_{sim} = k \times T_{emp}$), $\text{IF} = 1/k$, so $\text{IF} \rightarrow 0$ as $k \rightarrow \infty$. With S parallel simulations of length $T_{sim} = T_{emp}$, $\text{IF} = 1/S$. The two designs are asymptotically equivalent, but the latter is preferred in the ABM literature because it is parallelizable, numerically more stable for highly nonlinear models, and ensures that the simulated moments inherit the same finite-sample properties as their empirical counterparts.

repeat this process a total of B_B times to produce a stack of bootstrapped time series b_i , $i \in \{1, \dots, B_B\}$, that can be used to generate moment vectors $\mathbf{m}_i^{bs} = [m_1(b_i), \dots, m_D(b_i)]$. Then, we estimate Σ as follows:

$$\hat{\Sigma} = \frac{1}{B_B} \sum_{i=1}^{B_B} (\mathbf{m}_i^{bs} - \bar{\mathbf{m}})(\mathbf{m}_i^{bs} - \bar{\mathbf{m}})^\top, \quad (19)$$

where $\bar{\mathbf{m}} = \frac{1}{B_B} \sum_{i=1}^{B_B} \mathbf{m}_i^{bs}$. Finally, we take the inverse of $\hat{\Sigma}$ and use it as the weighting matrix $\mathbf{W}$ in the objective function J (17).

4.3. Moment conditions

The integrated financial–macroeconomic model generates a total of four time series, including the output gap, $y = \{y_q\}_{q=1}^Q$, inflation rate, $\pi = \{\pi_q\}_{q=1}^Q$, nominal interest rate, $r = \{r_q\}_{q=1}^Q$, and the price, $p = \{p_t\}_{t=1}^T$ from which we calculate log returns that enter the SMM estimation routine. Crucially, the use of the SMM in this multivariate context, with time series of varying lengths, introduces no additional complexity to the optimization problem. This is because the moments of financial and macroeconomic time series can be evaluated separately and ultimately aggregated in the optimization objective function. The sole additional requirement is that prior to the method's application, it is necessary to decide which of the m_d functions will be applied to which of the time series. Additionally, some of the compared statistics may now accept multiple different time series as input, for example, to calculate the sample counterpart of the covariance of two series.

In total, we use $D = 87$ moment conditions in our application of the SMM. The conditions used cover 78 and 9 moments for macroeconomic and financial data, respectively. For macroeconomic data, we follow [Franke et al. \(2015\)](#) and [Jang and Sacht \(2016, 2021\)](#) and utilize lagged auto- and cross-covariances whose sample counterparts are calculated as follows:

$$m(l, X, Y) = \frac{1}{Q} \sum_{q=l+1}^Q (X_q - \bar{X})(Y_{q-l} - \bar{Y}), \quad (20)$$

where l is the lag of choice, X and Y are random variables, and $\bar{X}$ and $\bar{Y}$ are their sample averages. Importantly, the statistic is order-dependent for cross-covariances whenever $l \neq 0$. We consider auto-covariances with lags $l \in \{0, 1, \dots, 8\}$ for the three macroeconomic time series y , π , and r , adding up to $3 \times 9 = 27$ moment conditions. For cross-covariances, we consider all six permutations under the same lags, adding up to the remaining $3 \times 9 + 3 \times 8 = 51$ macroeconomic moment conditions (since, for example, $m(0, r, \pi) = m(0, \pi, r)$).

For financial data, we follow [Franke and Westerhoff \(2011, 2012, 2016\)](#) and use the set of 9 moments proposed for their original model, including autocorrelation at lag 1 of raw returns, the unconditional first moment of absolute returns, the Hill estimator of the tail index of absolute returns using 5% of extreme observations, and autocorrelations at lags $l \in \{1, 5, 10, 25, 50, 100\}$ of absolute returns.

4.4. Block bootstrap approach for mixed-frequency data sampling

When generating bootstrapped time series in order to estimate the covariance matrix Σ , we draw B_N random integers from $\langle B_L, Q \rangle$. This represents a random sampling of B_N quarterly observations from the macroeconomic data. For each random draw R , we take the corresponding blocks $y_{(R-B_L+1):R}$, $\pi_{(R-B_L+1):R}$, and $r_{(R-B_L+1):R}$ from our empirical macroeconomic time series and concatenate the drawn blocks to form bootstrapped time series. For the financial time series, we take the corresponding blocks of observations by considering the subset of data starting from the date of the quarterly observation at $R - B_L$ and ending on the last day before the quarterly observation at R . This way, the bootstrapped macroeconomic time series always have the same length, while the length of the bootstrapped financial time series can vary depending on the actual number of work days in the B_L quarters prior to the drawn quarterly observation. We employ this bootstrap method, validated by [Zila and Kukacka \(2023\)](#) against alternative schemes such as the non-overlapping block bootstrap ([Franke and Westerhoff, 2012](#)) or the history sampling bootstrap ([Franke and Westerhoff, 2016](#)), with the primary benefit of limiting the impact of small-sample bias by significantly increasing randomness.

Having generated bootstrapped time series, we split the covariance matrix estimation problem into two subtasks, one for macroeconomic moment conditions (78×78 matrix $\hat{\Sigma}_M^{-1}$) and the other for financial moment conditions (9×9 matrix $\hat{\Sigma}_F^{-1}$). Due to the large size of the macroeconomic covariance matrix, we follow [Franke et al. \(2015\)](#) and [Jang and Sacht \(2021\)](#), and, in particular, the comprehensive discussion in [Jang and Sacht \(2016\)](#), and estimate only its diagonal elements, i.e., the variances of the macroeconomic moment conditions, using the block bootstrap approach described above. At the same time, we estimate the full covariance matrix for financial moment conditions. Subsequently, we concatenate the two estimated matrices to form a full 87×87 $\hat{\Sigma}$ matrix.

This block-diagonal structure is well-behaved. The diagonal macro block avoids the ill-conditioning, that is, the numerical sensitivity to small errors in noisy cross-moment estimates that could be strongly amplified by inversion, as well as the singularity problems that arise when large, dense covariance matrices with highly dependent auto- and cross-covariances are inverted ([Franke et al., 2015](#)). Full inversion is therefore required only for the 9×9 financial block. More fundamentally, omitting the off-diagonal cross-sector blocks from $\hat{\Sigma}$ is a deliberate design choice rather than an implicit independence assumption. Estimating cross-frequency covariances would also require *ad hoc* temporal alignment rules, thereby introducing additional researcher discretion into the weighting matrix. The within-sector design, therefore, trades some potential efficiency for parsimony. This, however, does not imply full independence between macroeconomic and financial moments: the optimizer minimizes deviations across both sectors

jointly, and the three interaction parameters (h, c_1, c_2) drive both data-generating blocks. Changes in these parameters are therefore reflected in moments in both parts of $\hat{\Sigma}$, so the moment set contains sufficient information for their identification. This is analogous to multi-equation GMM, where moment conditions are specified equation by equation while parameters are estimated jointly.

Concerning the dimensionality of the moment set relative to the three estimated parameters, overidentification in GMM and SMM is generally desirable: with an accurately estimated weighting matrix, additional valid moment conditions weakly improve asymptotic efficiency (Hansen, 1982). At the same time, our choice of $D = 87$ moments fully aligns with the financial and macro ABM estimation literature, which specifies which stylized facts each block is expected to match (Franke and Westerhoff, 2011, 2012; Franke et al., 2015). Moreover, a multiple excess of moments relative to the number of estimated parameters is in line with established macro ABM-SMM practice (Jang and Sacht, 2016, 2021), which has also been recently studied and numerically supported by Zila and Kukacka (2023) for financial ABM-SMM applications. The usual ill-conditioning problem and the ‘curse of dimensionality’ associated with large moment sets are avoided by the block-diagonal structure as discussed above. The $D - K = 84$ overidentifying restrictions would, in principle, support a Hansen-type J -test. We do not rely on it, however, given its well-known size and power distortions in misspecified, highly nonlinear structural settings (Dridi et al., 2007). Taken together, the strong overidentification is itself evidence against overfitting concerns rather than in support of them.

4.5. Partial estimation and the role of calibrated parameters

Our estimation strategy focuses on three interaction parameters, h , c_1 , and c_2 , while the remaining coefficients of the integrated model are fixed at values drawn from prior empirical work (see Section 3.3 and Table 1 for details). This is because they are the novel parameters introduced by integrating the behavioral New Keynesian model with the heterogeneous-agent asset-pricing model, and therefore are the only ones without pre-existing empirical estimates. The remaining coefficients have already been estimated in their original single-sector settings, using recent empirical data and moments tailored to each block, and therefore provide the best available priors.

This setup can be viewed as partial indirect inference in the sense of Dridi et al. (2007). Let the parameter vector be decomposed as $\theta_{1\&2} = (\theta_1, \theta_2)$. Their main results show that matching a selected subvector of moments yields a consistent estimator of θ_1 , provided the moment conditions used for estimation are informative about θ_1 and are not distorted by the calibrated values of θ_2 , a requirement referred to as the ‘partial encompassing’ condition. This result holds even when ‘full encompassing’ fails, which is generally unrealistic for any serious structural model because every such model is, to some extent, misspecified.

In our application, $\theta_1 = \theta = (h, c_1, c_2)$ and θ_2 collects the remaining calibrated parameters in Table 1. The partial encompassing condition appears plausible here for three reasons. First, h , c_1 , and c_2 govern the interaction between the two blocks and therefore affect the dynamics of both. By contrast, the calibrated parameters mainly shape the within-block dynamics for which they were originally estimated. Second, because moments are evaluated at their native frequencies, macro moments are driven mainly by the macro block, and financial moments by the financial block, limiting spillovers between blocks. Third, our Monte Carlo exercise in Section 7.5 shows stable recovery of (h, c_1, c_2) across $R = 256$ replications, and the sensitivity experiments in Section 7 mostly leave the three estimates within reasonable ranges. This provides an empirical counterpart to the robustness emphasized by Dridi et al. (2007).

We acknowledge that, for a model of this complexity, the partial encompassing condition cannot be established analytically. It therefore remains an assumption supported by numerical and sensitivity evidence, a limitation shared more broadly across the ABM estimation literature. Given this caveat, the partial indirect inference framework best explains our design: it allows consistent estimation of the parameters of genuine economic interest without requiring correct model specification, and avoids the prohibitive identification problems of jointly estimating all model parameters.

Whether these parameters suffice to represent the interaction channels is a question of model design rather than estimation. The three channels cover the main transmission mechanisms emphasized in the macro-finance literature, linking macroeconomic conditions to perceived financial fundamentals and transmitting asset price movements to aggregate demand and costs of capital. In this specification, each channel is captured by a single coefficient, so the three parameters correspond directly to the three interaction channels. Other mechanisms, such as credit frictions, collateral constraints, or an explicit banking sector, are omitted from this stylized framework to keep the model tractable (Lengnick and Wohltmann, 2013, 2016).

4.6. Econometric properties of the mixed-frequency SMM estimator

The adaptation of SMM to mixed-frequency data raises several broad econometric questions. Since these concern the general design of the estimation framework rather than a single technical step, we address them separately in the dedicated paragraphs below. In particular, we discuss the assumptions on the data-generating process, model misspecification, regularity conditions, and parameter identification.

Data-generating process and moments. We treat the observed macro-financial time series as a realization of an unknown joint stochastic data-generating process and impose only mild regularity conditions: it is assumed to be stationary and ergodic, with finite population moments. Under these conditions, the empirical moments $\mathbf{m}^{emp}$ are consistent and asymptotically unbiased estimators of their population counterparts by the ergodic theorem, which is the standard justification for using sample averages, and, more generally, sample moments, in SMM (Lee and Ingram, 1991; Duffie and Singleton, 1993). The same argument applies to simulated moments: conditional on θ and after discarding the warm-up period, the model-generated time series is stationary and ergodic by construction, i.e., the simulated sample averages/moments consistently estimate the corresponding model-implied population moments.

Model misspecification. The structural model is viewed as a stylized approximation, or even a crude idealization, of the true data-generating process introduced above rather than as the data-generating process itself. We therefore do not assume correct model specification. Under inevitable, and likely severe, misspecification, the SMM estimator converges to pseudo-true parameter values that minimize a loss function with a clear economic interpretation rather than a purely formal statistical fit. Within this partial indirect inference framework, the estimated parameters representing the three interaction channels retain a well-defined economic interpretation as the parameter values that help to match the main stylized facts of the data, without being overly affected by other poorly identified parts of the model (see Section 4.5, [Dridi et al., 2007](#)).

Regularity conditions. The asymptotic properties of the SMM estimator, namely consistency and asymptotic normality, rest on a set of well-known regularity conditions ([Lee and Ingram, 1991](#); [Duffie and Singleton, 1993](#)) that can be broadly summarized as: (i) compactness of the parameter space Θ ; (ii) geometric ergodicity of the simulated process; (iii) unique identification of the true parameter vector θ through the moment conditions; (iv) existence of the relevant finite population moments; and (v) sufficient smoothness of the moment functions with respect to the parameters. In our application, condition (i) is satisfied by construction, as the search ranges for h , c_1 , and c_2 used by the optimization algorithm define a compact parameter space (see Section 6.2). Condition (iv) is assumed to characterize the data-generating process, as discussed above, but it is also supported empirically, since all moments entering the objective function remain finite across the parameter configurations explored during estimation and throughout the $R = 256$ Monte Carlo replications. In general, conditions (ii), (iii), and (v) can hardly be verified analytically for nonlinear ABMs because of strong nonlinearities induced, e.g., by the discrete switching structure of the heuristic rules, and the absence of a closed-form likelihood. This limitation is shared within the broader ABM-SMM literature. We therefore follow the approach advocated by [Grazzini and Richiardi \(2015\)](#), who essentially establish SMM consistency for ergodic ABMs and argue that numerical verification via Monte Carlo experiments represents the standard practical substitute for analytical proofs. More specifically, for *ergodicity*, a sufficient warm-up period is discarded prior to moment computation, and starting the optimization from diverse initial values, 256 random Monte Carlo replications recover all three parameters with narrow confidence intervals, which is in line with the stationary ergodic behavior of the simulated process. For *identification*, the same Monte Carlo evidence provides numerical support for at least local identification, in the sense that the moment function exhibits a well-defined minimum in the neighborhood of the estimated values. Finally, for *smoothness*, although moment functions are not guaranteed to be smooth in the classical sense because of discrete switching rules, averaging over $S = 100$ independent simulation runs in the SMM objective function (see Section 6.2) provides a supporting smoothing effect that helps to mitigate potential discontinuities ([Grazzini and Richiardi, 2015](#)); nevertheless, this condition remains a maintained assumption, in line with standard practice in the literature ([Franke and Westerhoff, 2012](#); [Jang and Sacht, 2021](#); [Kukacka and Sacht, 2023](#)). We do not claim formal proofs of these regularity conditions. Instead, following standard practice in the applied ABM estimation literature, we use numerical diagnostics and Monte Carlo validation to support the assumptions underlying the estimator's large-sample properties (cf. [Lux, 2023](#)), while acknowledging that their formal verification remains an open problem for the field ([Fagiolo et al., 2019](#)).

Parameter identification. Formal global identification is generally intractable for complex nonlinear ABMs because of their non-analytic structure ([Fagiolo et al., 2019](#); [Lux, 2023](#)). However, the mixed-frequency structure of our estimation design provides a natural source of information in the data that helps identify the values of the interaction parameters. Because parameters h , c_1 , and c_2 govern the cross-sector linkages, they influence both quarterly macroeconomic moments and daily financial moments. A candidate parameter vector must therefore match the data at both frequencies, which imposes stronger restrictions than using either frequency alone. The mixed-frequency design thus strengthens rather than complicates identification of the interaction channels, as each parameter is reflected differently in the macroeconomic and financial moment sets.

We further assess *local* identification numerically through the Monte Carlo validation exercise described in Section 7.5. Specifically, the three interaction parameters h , c_1 , and c_2 are recovered with low bias, small variance, and reasonably narrow 95% confidence intervals across 256 independent replications. Building on the ergodicity assumption, this provides numerical evidence for local identification ([Grazzini and Richiardi, 2015](#)): small changes in parameter values yield different simulated moments, indicating that the selected moment conditions are locally informative about estimated parameters in a neighborhood of the true values. At the same time, the high degree of overidentification in our setup suggests that identification does not rely on any single moment condition, which provides additional robustness to the estimation design.

5. Data

Quarterly macroeconomic data for the United States are collected from the Federal Reserve Bank of St. Louis website: fred.stlouisfed.org [database accessed on 2026-02-21]. The dataset spans the period from 1954:Q3 to 2025:Q3 and comprises 285 quarterly observations. Output is derived from the seasonally adjusted annual rate of real GDP in billions of chained 2017 USD (GDPC1). The one-sided Hodrick–Prescott filter with a standard smoothing parameter of $\lambda = 1600$ is used to estimate the trend for the output time series, yielding the gap format, as shown in [Stock and Watson \(1999\)](#). Inflation is measured by the seasonally adjusted annualized CPI (CPIAUCSL), and the short-term nominal interest rate is represented by the annualized effective federal funds rate (FEDFUNDS). Quarterly values are obtained as the geometric mean of monthly observations to account for compounding. The inflation and interest rate series are then demeaned to align with the theoretical log-linearized specification of the NKM model, similarly to the Hodrick–Prescott detrending applied to the output data.

Regarding financial data, we follow standard practice and use the log returns of the S&P 500 stock market index, collected from [LSEG Workspace](#). The daily dataset spans from 1954-07-01 to 2025-09-30, i.e., a total of 17857 daily observations [database

Table 2
Numerical results of the empirical study.

Par./Col.	A	B	C	D
$\hat{h}$	0.435	0.375	0.438	0.405
$\langle 0, 2 \rangle$	(0.360, 0.503)	(0.312, 0.457)	(0.370, 0.518)	(0.345, 0.498)
$\hat{c}_1$	0.258	0.364	0.258	0.257
$\langle 0, 1 \rangle$	(0.155, 0.396)	(0.262, 0.491)	(0.147, 0.386)	(0.156, 0.390)
$\hat{c}_2$	3.17	3.36	3.29	3.27
$\langle 0, 10 \rangle$	(2.72, 3.49)	(2.91, 3.70)	(2.81, 3.66)	(2.83, 3.64)

Note: The constraints for optimization search are given in $\langle \rangle$ brackets. The sample medians based on 256 independent runs are reported as parameter estimates. The 95% confidence intervals of the sample estimates are reported in $()$ parentheses. The figures are rounded to three valid digits.

accessed on 2026-02-26]. The specific starting and ending points of the data span are due to the adjustment of the period to align with the macroeconomic data, as in (16). The empirical datasets are available in a public [GitHub repository](#) [files US.jld and SP500.jld].

Moreover, we later introduce a series of robustness checks and sensitivity experiments using alternative datasets and shorter sample periods. The specific modifications are described in Section 7.

6. Estimation setup

6.1. Monte Carlo and computational complexity

All computations reported in this paper are implemented in Julia 1.10.5 (Bezanson et al., 2017) and utilize 256 independent Monte Carlo replications to obtain sample densities of parameter estimates. The Monte Carlo approach should not only eliminate the impact of randomness represented by sequences of random shocks $\varepsilon_{\{y,\pi,r\},q}$ and noise terms $\varepsilon_{\{f,c\},t}$ but also directly provide us with confidence intervals for individual parameters as approximated by confidence intervals of the sample estimates as discussed in Franke and Westerhoff (2011, pg. 74) and Franke and Westerhoff (2016, pg. 24). We execute most experiments on a server with a 2×24 -core Intel Xeon Gold 6542Y processor and 1024 GB of RAM. Under this configuration, each estimation procedure with 256 independent runs amounts to approximately 75 compute hours.

6.2. Technical implementation details

We use a warm-up period of 50 quarters and 3150 daily observations to mitigate any potential influence from the model's initialization and reach the stationary distribution.³ The observations corresponding to the warm-up period are discarded whenever a new time series is generated by the simulation model. When simulating macroeconomic time series, we follow the length of our macroeconomic data, i.e., we generate a time series with 285 quarterly observations. When generating financial data, we follow Lengnick and Wohltmann (2016) in assuming that each quarterly observation corresponds to 63 daily observations, i.e., we generate time series with $285 \times 63 = 17955$ daily observations. Since the SMM calculates and compares statistics over empirical and simulated data, any differences in lengths between the two should have no impact. Nevertheless, when faced with relatively small amounts of empirical data, simulated data can be scaled by a factor to reduce the variability of the simulated series, as done by Franke and Westerhoff (2016) and Chen and Lux (2018).

The weighting matrix is implemented using the block bootstrap approach as described in Section 4 with $B_B = 5000$ bootstrap size. Each bootstrapped time series consists of $B_N = 40$ overlapping blocks of $B_L = 16$ quarterly (and 1008 daily) observations.⁴ Simulated moments in the objective function (17) of the SMM are calculated as averages over $S = 100$ independent realizations. We use the recommended optimizer :adaptive_de_rand_1_bin_radiuslimited from the BlackBoxOptim.jl package with 4000 functional evaluations, and we restrict the explored search space to $\hat{h} \in \langle 0, 2 \rangle$, $\hat{c}_1 \in \langle 0, 1 \rangle$, and $\hat{c}_2 \in \langle 0, 10 \rangle$.

7. Empirical analysis

This section showcases the primary findings of our estimation study. Initially, we present and analyze empirical estimates of the three model interaction parameters, along with three robustness checks based on minor adjustments to the setup. Subsequently, we examine the sensitivity of the estimation outcomes through a series of additional experiments. The estimation output is always presented both numerically and visually.

³ See Zila and Kukacka (2023, pg. 375), who address the warm-up period issue explicitly for the Franke and Westerhoff (2012) model using Welch's diagnostic method (Welch, 1983), recently revisited in Vandin et al. (2022).

⁴ B_L is set by a rule of thumb to at least double the maximum lag lengths evaluated in our moment conditions (8 quarters for macroeconomic covariances and 100 days for financial autocorrelations). This ensures that the relevant temporal dependency structures are consistently captured within each block, thereby mitigating the join-point problem that arises when connecting randomly drawn blocks.

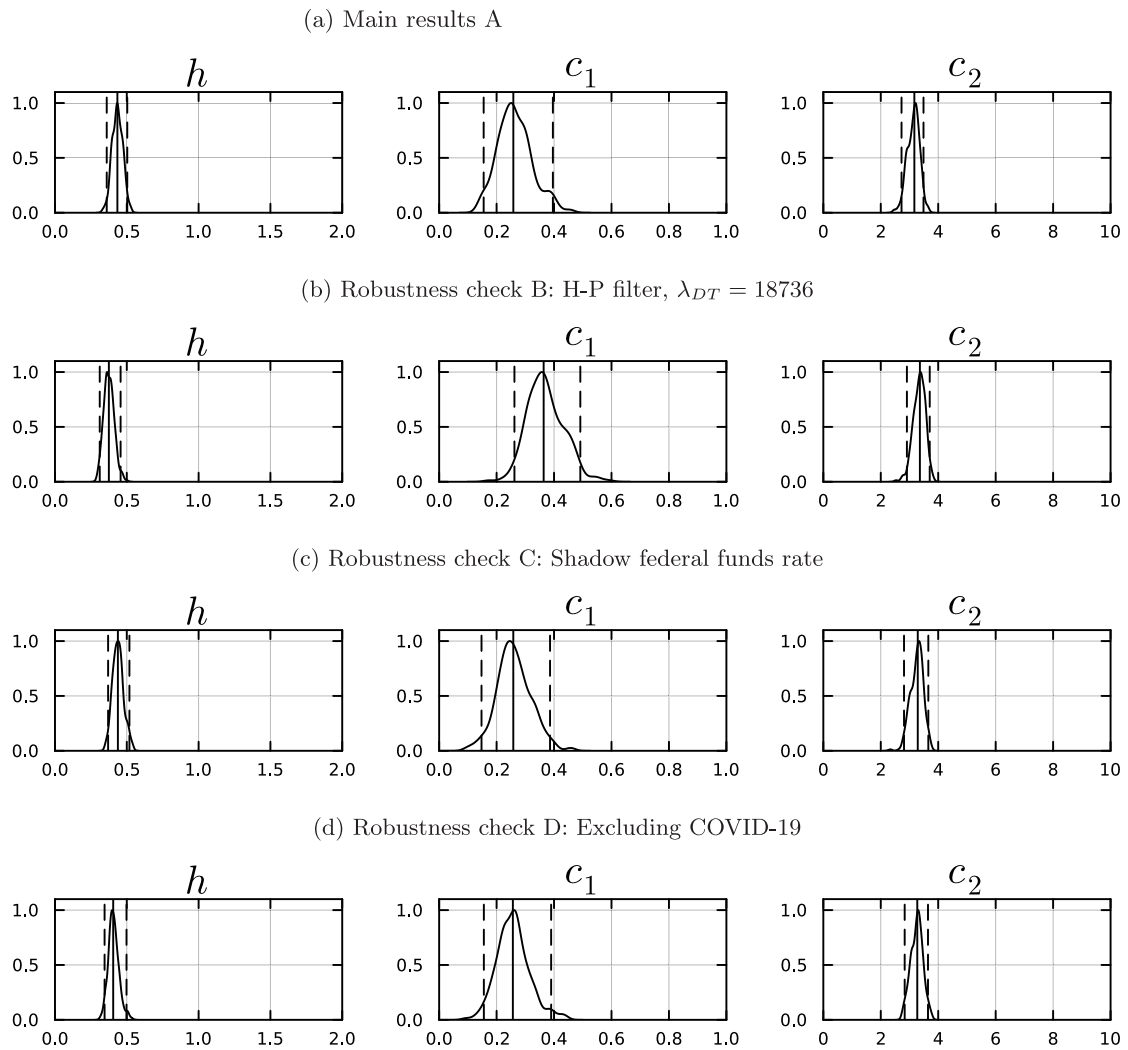


Fig. 1. Densities of the estimated interaction parameters. *Note:* The curves depict the normalized kernel density estimates of the sample densities based on 256 independent replications; vertical markers indicate their medians (full) and 95% confidence intervals (dashed) of the sample estimates.

7.1. Main results

To the best of our knowledge, our study provides the first empirical estimates for the three interaction channels in the agent-based modeling literature, as summarized in [Table 2](#). Column A reports the main empirical findings, highlighted in bold. The key observation is that all three interaction parameters are statistically significant at the 95% confidence level. Our estimation results, therefore, provide strong statistical support for all three interaction channels in our financial–macroeconomic integrated ABM of the US economy.

Furthermore, the corresponding visualization is provided in [Fig. 1](#), Panel (a). The parameter estimators are shown to have narrow densities with only minor deviations from normality, with $|\text{skewness}|$ remaining below 0.5 and excess kurtosis close to zero (based on 256 independent replications, $\text{skew}_{\hat{h}} = -0.024$ and $\text{ex. kurt}_{\hat{h}} = -0.205$; $\text{skew}_{\hat{c}_1} = 0.490$ and $\text{ex. kurt}_{\hat{c}_1} = 0.255$; $\text{skew}_{\hat{c}_2} = -0.322$ and $\text{ex. kurt}_{\hat{c}_2} = 0.015$). This observation further supports the utilization of the 95% confidence intervals of the sample estimates as confidence intervals for individual parameters as noted in [Section 6](#).

In the financial ABM, the fundamental price misperception effect parameter in [\(16\)](#) is estimated to be $\hat{h} = 0.435$. We can hardly compare its numerical value to the existing empirical literature, while its interpretation is straightforward: stock market participants following fundamental trading strategies approximate the stock market's fundamental value at roughly 44% of the most recently observed output gap. On the macroeconomic side of the integrated model, the wealth effect parameter c_1 in the extended dynamic IS curve [\(1\)](#) is estimated to be $\hat{c}_1 = 0.258$. While interpreting the numerical values of estimated parameters is generally difficult in

Table 3
Sensitivity analysis experiments.

Par./Exp.	E	F	G	H
$\hat{h}$	0.606	1.02	0.452	0.331
$\langle 0, 2 \rangle$	(0.490, 0.695)	(0.834, 1.26)	(0.384, 0.532)	(0.270, 0.408)
$\hat{c}_1$	0.033	0.060	0.212	0.214
$\langle 0, 1 \rangle$	(0.000, 0.193)	(0.000, 0.276)	(0.130, 0.339)	(0.050, 0.358)
$\hat{c}_2$	2.93	3.65	3.28	2.53
$\langle 0, 10 \rangle$	(2.36, 3.41)	(2.77, 4.32)	(2.84, 3.64)	(2.10, 2.87)

Note: The constraints for optimization search are given in $\langle \rangle$ brackets. The sample medians based on 256 independent runs are reported as parameter estimates. The 95% confidence intervals of the sample estimates are reported in $()$ parentheses. The figures are rounded to three valid digits.

such a complex, nonlinear system of simultaneous equations, as an initial idea, we might follow a markedly simplified *ceteris paribus* approach to assess effects known from linear models. The estimated parameter suggests that the current consumption contributing to the output gap indeed reacts positively (negatively) to the expected increase (decrease) in real stock prices, but these optimistic (pessimistic) expectations translate into an actual output gap of circa 26%. In other words, a 10% rise in real stock price is associated with an approximately 2.6% increase in the output gap.

Next, the cost effect parameter c_2 in (2) is estimated to be $\hat{c}_2 = 3.17$, suggesting that the current inflation rate indeed reacts negatively to the current value of stock prices, i.e., that cheaper credit genuinely decreases costs of production, which directly translates to consumer prices. While, at first glance, the numerical value of the cost effect estimate appears relatively large, its actual impact is strongly mitigated by the negative feedback loop in the system of simultaneous Eqs. (1) to (3). Concretely, the impact in period q propagates from the inflation rate Eq. (2) gradually through the monetary policy rule (3) to the output Eq. (1), where r_q is multiplied by $-\tau$, which is clearly negative. Thus, when it finally loops back from (1) to (2) through y_q , it has the opposite direction, effectively alleviating the actual impact of a large $\hat{c}_2$ from the beginning of this contemporaneous feedback loop. Nonetheless, following the simplified elasticity interpretation logic of the log-linearized NKM, a large estimated value of c_2 generally suggests that even a slight decrease in the aggregated quarterly value of stock prices results in strong inflationary pressures via the cost channel.

7.2. Robustness checks

A first robustness check is shown in Column B of Table 2 and the corresponding Panel (b) of Fig. 1, using output gap data calculated with a much higher smoothing parameter, as suggested by Franke et al. (2026), namely $\lambda_{DT} = 18736$ [file US_DT.jld]. We further report in Column C/Panel (c) results of a robustness check using the Wu and Xai (2016) model-based shadow rate in place of the effective federal funds rate, motivated by the recent ‘zero-lower-bound episodes’ of 2008:Q4 to 2015:Q4 and 2020:Q1 to 2022:Q1, collected from the Federal Reserve Bank of Atlanta: [fred.atlantafed.org](https://fred.frbatlantafed.org) [database accessed on 2026-02-21, file US_SR.jld]. The final robustness experiment in Column D/Panel (d) excludes the turbulent COVID-19 episode, effectively ending the quarterly dataset by 2019:Q3, thus reducing the corresponding macroeconomic sample by 24 observations. All alternative empirical datasets are also available in the [GitHub repository](#).

The overall finding is that the estimation results are robust to these changes to the setup. In particular, the estimated parameters and the corresponding sampling distributions closely resemble those reported for the Main results A, with one minor exception: in the robustness experiment B employing a substantially higher smoothing parameter in the Hodrick–Prescott filter, we observe a higher estimate of the wealth effect c_1 and a slightly lower estimate of the price misperception effect h .

7.3. Sensitivity analysis experiments

We next examine sensitivity to more substantial changes in the model setup: an alternative output gap filter (Baxter–King, experiment E), reparameterization of the macroeconomic block (experiment F), an expectation-based Taylor rule (experiment G), and an alternative stock market index (NASDAQ, experiment H). Since the parameters of any model do not exist *per se*, i.e., inherently on their own, but rather depend on the model structure or the configuration of other coefficients, it is realistic to anticipate variations in some estimated values. The emphasis will not be placed on the numerical values but rather on the qualitative distinctions concerning the main results in Column A/Panel (a). Additional empirical datasets are available in the [GitHub repository](#).

Baxter–King filter. As a first sensitivity experiment E, we re-estimate the model using the output gap computed via the symmetric band-pass Baxter–King filter (Baxter and King, 1999), with a cycle band of 6 to 32 quarters and a lag length of 12 periods, corresponding to the standard quarterly parameterization. The filter is implemented as a fixed-length moving average, implying the loss of 12 observations at both ends of the sample. Consequently, the respective quarterly dataset ends in 2022:Q2, while the starting point remains unchanged at 1954:Q3, as additional pre-sample observations for output are available to extend the time series prior to filtering [file US_BK.jld].

The one-sided Hodrick–Prescott filter is used to estimate a smooth, time-varying trend, while the residual is interpreted as an output gap that may also contain short-run noise. In contrast, the Baxter–King approach is designed to isolate fluctuations at business-cycle frequencies, yielding the cyclical component as a finite-sample approximation to an ideal band-pass filter. However, it suffers

from an endpoint problem: as a symmetric two-sided filter, it requires both past and future observations. In our BR NKM setup, this makes the one-sided Hodrick–Prescott filter a preferable baseline, as it can be implemented recursively using only information available at each point in time. We therefore employ the alternative detrending procedure to examine the sensitivity of our results, presented in Table 3, Column E, and visualized in Fig. 2, Panel (e).

This experiment reveals a notable shift relative to the Main results A. The substantial change concerns $\hat{c}_1$, which declines from 0.258 to 0.033, making the wealth effect parameter effectively negligible and statistically insignificant. The corresponding density in Panel (e) is visibly skewed toward zero. A plausible interpretation is that isolating business-cycle frequencies and removing both high-frequency noise and low-frequency trend components produces an output gap with a different dependence structure with stock prices, potentially less relevant for identifying c_1 in (1).

In contrast, $\hat{c}_2$ remains close to the main results, while $\hat{h}$ increases to 0.606, suggesting that the band-pass filtered output gap provides a cyclical signal to which fundamentalists assign greater weight when approximating the stock market's fundamental value in (16). Overall, experiment E primarily highlights the sensitivity of the wealth effect estimation to the detrending procedure, further supporting the use of the one-sided Hodrick–Prescott filter as the baseline.

Macroeconomic block reparameterization. Next, we reparameterize the macroeconomic coefficients in experiment F. These were also varied in Kukacka and Sacht (2023), where the authors face difficulties in estimating the inverse elasticity of substitution τ in (1) and the slope of the New Keynesian Phillips curve κ in (2). We set the four structural parameters according to Jang and Sacht (2021, Table 2, col. EFB): $\tau = 0.371$, $\kappa = 0.213$, $\phi_y = 0.709$, and $\phi_\pi = 1.914$, implying a substantially stronger monetary policy response to output gap and inflation fluctuations under the Taylor rule. The behavioral parameters follow the corresponding estimates from Kukacka and Sacht (2023, Table 2, col. B): $\eta = 0.21$, $\iota = 0.00$, $\mu = 0.38$, and $\gamma = 1.49$. The results are reported in Column F/Panel (f).

This experiment reveals broadly similar patterns to those observed in E, but with more considerable shifts relative to the Main results A: $\hat{c}_1$ declines substantially to 0.060, becomes statistically insignificant, and exhibits a visibly wider density in Panel (f). A plausible interpretation parallels that of experiment E: the reparameterized Taylor rule, with strong response coefficients ϕ_y and ϕ_π , amplifies the effect of interest rate dynamics on the output gap through the $-\tau$ term in (1), thereby overshadowing the identifiable contribution of the wealth effect channel c_1 .

Similarly, $\hat{c}_2$ remains comparatively stable but increases slightly to 3.65, while $\hat{h}$ increases markedly to 1.02. This suggests that with a larger structural coefficient $\kappa = 0.213$, a higher cost effect parameter c_2 is required to offset the impact of the current output gap in (2), and that stronger monetary policy dynamics amplify the feedback from the real sector to the financial block. Overall, experiment F highlights the sensitivity of $\hat{c}_1$ and $\hat{h}$ to changes in model calibration, as well as their inverse relationship, implied by (1) via the price misperception effect, which is already weakly observable in robustness check B. The cost channel remains the most robust across both experiments. Moreover, the variance of the SMM estimator generally increases, as reflected in wider confidence intervals.

Expectation-based Taylor rule. Next, we examine the impact of altering the macroeconomic component of the integrated model. In particular, we alter the Taylor-type monetary policy rule (3) such that it is no longer based on contemporaneous realizations of the output gap and inflation rate, but instead on BR expectations of their future values. This modification aligns the policy rule with the forward-looking nature of the remaining equations in the baseline NKM:

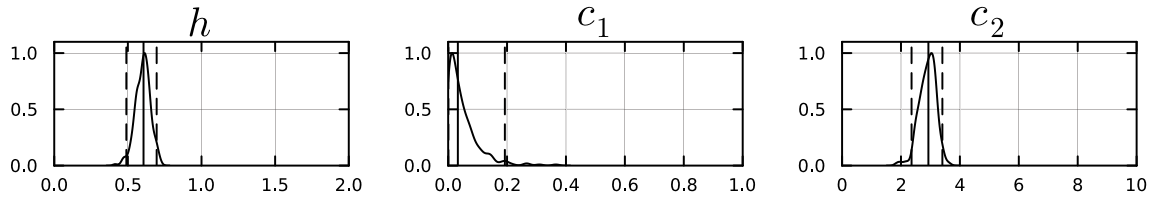
$$r_q = \phi_y \tilde{E}_{y,q} y_{q+1} + \phi_\pi \tilde{E}_{\pi,q} \pi_{q+1} + \varepsilon_{r,q}. \quad (21)$$

The concept of an expectation-based Taylor rule aligns with the behavioral NKM frameworks proposed by authors such as Branch and McGough (2009, 2010) and Lengnick and Wohltmann (2013, 2016) and, most recently, De Grauwe and Ji (2023) and Lux (2024). While De Grauwe and Ji (2023) conclude that the forward-looking Taylor rule can increase volatility, so central banks should respond to current inflation and output, Lux (2024) convincingly argues that this approach significantly simplifies the system of differential equations that represent the NKM model. In particular, it eliminates the simultaneous dependence of the nominal interest rate on the current output gap and inflation rate. Instead, the construction of expectations through the BR heuristics relies on their past values, which ultimately supports the identification of key model parameters. The results are reported in Column G/Panel (g).

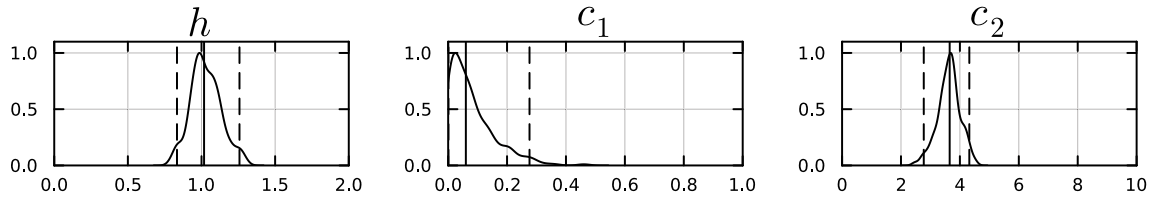
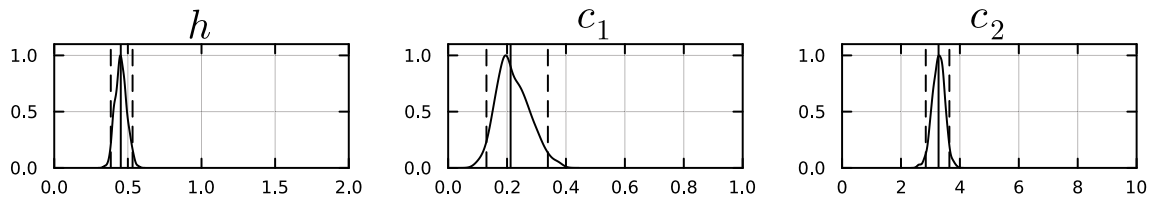
Experiment G yields the most stable results across all sensitivity experiments. All three interaction parameters remain statistically significant, with estimates and confidence intervals closely resembling those of the Main results A. In contrast to sensitivity experiments E and F, where $\hat{c}_1$ declines toward zero, the forward-looking Taylor rule leaves all three interaction channels largely unaffected. This stability suggests that replacing contemporaneous output and inflation with their BR expectations in (3) does not materially affect the estimation outcomes, while potentially improving identification by removing the simultaneous dependence among current endogenous variables (Lux, 2024).

NASDAQ index. The final sensitivity experiment, reported in Column H/Panel (h), substitutes the S&P 500 with an alternative U.S. stock market index, namely the NASDAQ Composite. As the NASDAQ has a shorter available history, the quarterly dataset in this specification begins in 1980:Q1 [file NASDAQ.jld]. This modification leads to only modest numerical shifts: the misperception parameter declines to $\hat{h} = 0.331$, with slightly wider confidence intervals. Although the markedly different sample period makes direct comparison non-trivial, a plausible interpretation is consistent with the NASDAQ's greater concentration in high-growth technology firms, whose valuations are less closely tied to contemporaneous output gap dynamics. The wealth effect, $\hat{c}_1 = 0.214$, and the cost effect, $\hat{c}_2 = 2.53$, remain close to the Main results A, confirming that the main qualitative conclusions remain robust to the choice of stock market index.

(e) Sensitivity experiment E: Baxter-King filter



(f) Sensitivity experiment F: Macroeconomic block reparameterization

(g) Sensitivity experiment G: $r_q = \phi_y \tilde{E}_{y,q} y_{q+1} + \phi_\pi \tilde{E}_{\pi,q} \pi_{q+1} + \varepsilon_{r,q}$ 

(h) Sensitivity experiment H: NASDAQ Composite index

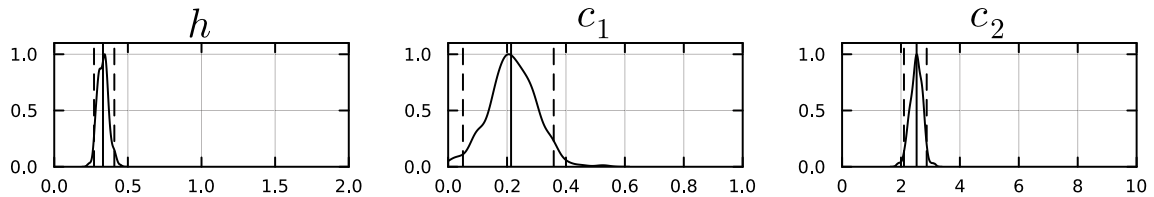


Fig. 2. Densities of the parameter estimates for sensitivity analysis experiments. *Note:* The black curves depict the normalized kernel density estimates of the sample densities, while the full and dashed vertical lines represent their medians and the 95% confidence intervals of the sample estimates, respectively. Based on 256 independent runs.

7.4. Illustrative simulated time series

To complement the moment-based estimation, we also report illustrative simulated paths for all estimated models. To ensure comparability across simulations, the random seed is kept fixed, since each realization depends on the specific sequence of random shocks and may therefore appear somewhat arbitrary. Moreover, the length of each simulated time series corresponds to that of the empirical dataset, i.e., approximately 68 years of observations. Because the integrated model has a mixed-frequency structure, the stock market is simulated at daily frequency, whereas the macroeconomic variables evolve at quarterly frequency. Simulation results for all estimated specifications are reported in [Appendix B](#). Since the qualitative dynamics are broadly similar across the estimated models, we focus the discussion on the simulated paths based on the Main results A and the robustness checks depicted in [Fig. B.4](#), while briefly commenting on notable pattern differences observed for sensitivity analysis experiments in [Fig. B.5](#) for reasons of space.

The simulated returns display the familiar stylized facts of financial markets: periods of moderate fluctuations are interrupted by bursts of volatility and occasional large jumps in both directions, consistent with fat tails, volatility clustering, and boom–bust episodes in the underlying price process. The output gap is clearly serially correlated and exhibits cyclical fluctuations around zero, with amplitudes comparable to those reported in standard behavioral macro simulations, such as [De Grauwe and Ji \(2019\)](#), their Figure 2.1) and [Jang and Sacht \(2016\)](#), their Figure 1). Inflation deviations also fluctuate within a broadly comparable range, but

Table 4
Validation exercise I.

Parameter	True value	Recovered value	Bias	RMSE
h	0.435	0.545 (0.297, 1.74)	0.110	0.413
c_1	0.258	0.217 (0.072, 0.432)	−0.041	0.100
c_2	3.17	3.18 (2.08, 4.70)	0.010	0.671

Note: The constraints for optimization search are given in $\langle \rangle$ brackets. Recovered values are reported as medians from 256 independent estimations for pseudo-empirical time series generated using the true parameter values in bold. The 95% confidence intervals of the values are reported in $()$ parentheses. The bias is computed as the difference between the recovered and true values. The root mean square error (RMSE) is calculated over the sample of recovered values. The figures are rounded to three valid digits.

(i) Validation exercise I

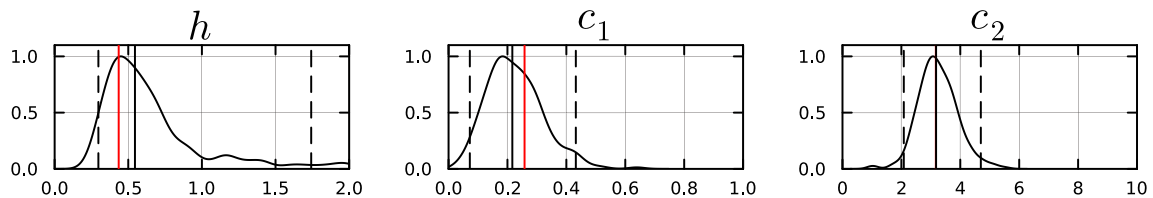


Fig. 3. Densities of the parameter estimates from the Monte Carlo validation exercise. Note: The black curves depict the normalized kernel density estimates of the recovered values, while the full and dashed vertical lines represent their medians and the 95% confidence intervals, respectively. The full red vertical lines represent true parameter values. Based on 256 independent runs.

exhibit a more erratic oscillatory pattern. A plausible interpretation is that the relatively strong estimated cost effect channel ($\hat{c}_2$) transmits stock price fluctuations directly into inflation dynamics through the New Keynesian Phillips curve. Finally, the interest rate deviations closely mirror the inflation path. This can be viewed as a natural trade-off arising from the highly parsimonious Taylor rule specification (3), in which the central bank reacts only to contemporaneous output and inflation, with no autoregressive smoothing term included. Given the implemented parameterization presented in Table 1, inflation stabilization (ϕ_π) clearly plays the dominant role in the policy response, whereas the contribution of the output gap (ϕ_y) to the central bank's reaction remains very limited. Two pattern differences can be observed in the sensitivity analysis experiments. First, experiment F, with macroeconomic block reparameterization, appears to lead to generally lower fluctuations across most simulated trajectories. Second, experiment G, with an expectation-based Taylor rule, appears to slightly reduce the erratic oscillatory tendency in inflation and interest rates.

7.5. Monte Carlo validation exercise

To assess the statistical properties of our estimator and evaluate the robustness of our empirical findings, we conduct an additional Monte Carlo validation exercise. Specifically, we test the ability of the estimator to recover parameters estimated as part of our primary empirical exercise presented in Section 7.1, namely $h = 0.435$, $c_1 = 0.258$, and $c_2 = 3.17$, while keeping all the other parameters constant. Under this configuration, we independently generate 256 time series using the simulation model. We then apply our SMM estimation methodology to each of these pseudo-empirical time series and assess its ability to estimate the known, underlying parameters used to generate them.

The results of the validation exercise are reported in Table 4 and visualized in Fig. 3. The estimator recovers the cost effect parameter c_2 with negligible bias (0.01) and low RMSE (0.671), with overall density closely centered around the true value. The wealth effect parameter c_1 is recovered with a small negative bias (−0.041) and a slightly larger RMSE (0.100). The fundamental price misperception parameter h is recovered with a larger bias (0.110) and a relatively large RMSE (0.413) resulting from a small number of heavily positively biased estimates. Even though the recovered value remains statistically significant and close to the true parameter value, the distribution of estimates across the pseudo-empirical samples is wider than in the empirical exercises. These results suggest that the estimator recovers the model parameters reasonably well overall, while indicating that inference on h should be interpreted with greater caution.

7.6. Implications for macro-financial policy

Since the model is deliberately stylized, abstracts from important features such as an explicit banking sector, fiscal policy, and open-economy dimensions, and leaves the remaining parameters calibrated rather than jointly estimated, this subsection focuses on broader qualitative interpretations rather than quantitative policy recommendations. We therefore restrict the discussion to policy implications supported by the econometric evidence on the statistically significant interaction channels.

Wealth effect. The significant parameter c_1 indicates that stock market fluctuations are transmitted to aggregate demand through household consumption. This provides agent-based evidence consistent with the recent HANK literature (Kaplan et al., 2018; Auclert et al., 2025), in which asset holdings shape intertemporal consumption decisions and, thereby, the monetary transmission mechanism. The quantitative relevance of this channel supports accounting for asset price information when analyzing consumption dynamics, particularly during periods of elevated market volatility.

Cost effect. The significant parameter c_2 supports the logic of the financial accelerator (Bernanke et al., 1999; Bernanke and Gertler, 2000): asset prices affect firms' external financing conditions and, through marginal costs of capital, the inflation dynamics. This finding contributes directly to the macroprudential policy debate, as it implies that financial market conditions feed back into the real economy not only through demand, but also through supply-side channels. This therefore supports the view that monetary and macroprudential policy should be closely coordinated and jointly designed (Brunnermeier and Sannikov, 2014).

Price misperception effect. The significant parameter h provides empirical evidence that fundamentalists' perceptions of the fair value of stocks are shaped by recent macroeconomic conditions, in line with the behavioral finance literature, which suggests that market participants do not fully process information about fundamentals (Daniel et al., 1998; Barberis and Thaler, 2003). This channel matters for monitoring whether asset prices move away from fundamentals, because broader economic conditions and macroeconomic expectations can change how investors perceive the value of stocks, even if the underlying fundamentals do not.

8. Conclusion

This study pioneers a mixed-frequency estimation for integrated financial–macroeconomic ABMs and applies it to a stylized model of the interconnection between the two sectors of the economy. The core methodological contribution is an adaptation of the simulated method of moments that evaluates macroeconomic and financial moment conditions at their native quarterly and daily frequencies within a single objective function, thereby overcoming the mixed-frequency obstacle that has so far limited the empirical estimation of macro-financial ABMs. Our focus on three interaction channels — the wealth effect, cost effect, and price misperception — then yields the first model-based empirical evidence of statistically significant and economically meaningful interaction parameters, demonstrating the interconnections between the US stock market and the real economy over the last seven decades.

Our empirical findings contribute novel insights into the complicated relationships between the financial and real sectors. Notably, the wealth effect parameter highlights the sensitivity of current consumption to real stock prices, while the cost effect parameter emphasizes the influence of stock prices on inflation dynamics. The fundamental price misperception effect parameter sheds light on how financial market participants approximate the true value of stocks based on real economic conditions.

The robustness checks and sensitivity experiments support the credibility of the integrated model. While the cost and misperception channels remain stable across virtually all considered specifications, the wealth effect exhibits greater sensitivity to the choice of detrending procedure and model parameterization, highlighting the importance of careful specification. Despite these variations, all three interaction parameters remain statistically significant and economically relevant across the majority of estimated variants.

The fact that all three channels are both significant and economically meaningful highlights the close connection between the financial and real sectors. Stock market movements affect consumption, inflation, and investment, while macroeconomic conditions feed back into asset prices, so that shocks arising in either sector can spread through the entire system. Our estimates thus provide evidence that financial markets shape key macroeconomic outcomes and that financial traders are influenced by real economic conditions. For policymakers and regulators, this suggests that interventions should not be designed in isolation, since actions targeting one sector inevitably affect the other. This strengthens the case for integrated monetary–macroprudential frameworks that explicitly account for cross-sectoral feedback effects.

Addressing future research directions, we propose two avenues. First, extending the estimation to encompass the entire parameter set, rather than just the interaction channels, would provide a comprehensive understanding of the integrated system. Nevertheless, we are slightly skeptical of the SMM's ability to achieve this objective, and it may be necessary to develop more sophisticated simulation- or machine-learning-based estimation methods. Second, incorporating additional interaction channels would introduce additional complexity, contributing to a deeper understanding of the interplay between financial and macroeconomic dynamics.

In conclusion, this research advances the empirical exploration of integrated economic ABMs by providing both a methodological template for mixed-frequency estimation and the first empirical evidence on the wealth, cost, and price misperception channels linking the financial and real sectors. The established methodology provides a robust foundation for further empirical estimation studies, contributing to the ongoing methodological discussion on the empirical validation of ABMs.

CRedit authorship contribution statement

Jiri Kukacka: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Data curation, Resources, Writing – original draft, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Eric Zila:** Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used the paraphrasing tool [QuillBot](#) and the generative AI systems [ChatGPT-3.5 to 5.4](#) and [Claude 4.5 to 4.7](#) in order to improve readability and language of the article, especially in the introductory, model, and concluding sections. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. State-space representation of the integrated forward-looking NKM

For analytical convenience, the financial–macroeconomic forward-looking NKM can be written in a compact state-space representation that collects the three endogenous macroeconomic variables, namely the output gap (y_q), inflation rate deviation (π_q), and the nominal interest rate deviation (r_q), into a single vector.

The first matrix Eq. (A.5) is an equivalent representation of the structural system in (1)–(3). In particular, matrix **A** summarizes the contemporaneous relations among the endogenous variables implied by the dynamic IS curve, the New Keynesian Phillips curve, and the Taylor rule, while matrix **B** collects the coefficients on the forward-looking expectations, including the additional wealth effect expectations channel. Matrix **C** captures the direct effect of the contemporaneous stock price (s_q) on inflation through the cost effect channel, and matrix **D** accounts for the random shocks into the system.

The second Eq. (A.6) then rewrites the same model in reduced form by premultiplying the system by $\mathbf{A}^{-1}$. In this formulation, the current macroeconomic state is jointly determined by all three components: expectations about future macroeconomic and financial developments, the contemporaneous stock price (s_q), and exogenous shocks. In this way, the state-space representation provides a compact summary of how the integrated forward-looking NKM can be solved and analyzed as a system of interdependent linear equations.

$$\mathbf{A} = \begin{bmatrix} 1 & 0 & \tau \\ -\kappa & 1 & 0 \\ -\phi_y & -\phi_\pi & 1 \end{bmatrix} \quad (\text{A.1})$$

$$\mathbf{B} = \begin{bmatrix} 1 & \tau & c_1 \\ 0 & \nu & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad (\text{A.2})$$

$$\mathbf{C} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & -c_2 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad (\text{A.3})$$

$$\mathbf{D} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (\text{A.4})$$

$$\mathbf{A} \begin{bmatrix} y_q \\ \pi_q \\ r_q \end{bmatrix} = \mathbf{B} \begin{bmatrix} \tilde{E}_{y,q}^j y_{q+1} \\ \tilde{E}_{\pi,q}^j \pi_{q+1} \\ \tilde{E}_{\Delta s - \pi, q} (\Delta s_{q+1} - \pi_{q+1}) \end{bmatrix} + \mathbf{C} \begin{bmatrix} s_q \\ s_q \\ s_q \end{bmatrix} + \mathbf{D} \begin{bmatrix} \varepsilon_{y,q} \\ \varepsilon_{\pi,q} \\ \varepsilon_{r,q} \end{bmatrix} \quad (\text{A.5})$$

$$\begin{bmatrix} y_q \\ \pi_q \\ r_q \end{bmatrix} = \mathbf{A}^{-1} \left(\mathbf{B} \begin{bmatrix} \tilde{E}_{y,q}^j y_{q+1} \\ \tilde{E}_{\pi,q}^j \pi_{q+1} \\ \tilde{E}_{\Delta s - \pi, q} (\Delta s_{q+1} - \pi_{q+1}) \end{bmatrix} + \mathbf{C} \begin{bmatrix} s_q \\ s_q \\ s_q \end{bmatrix} + \mathbf{D} \begin{bmatrix} \varepsilon_{y,q} \\ \varepsilon_{\pi,q} \\ \varepsilon_{r,q} \end{bmatrix} \right) \quad (\text{A.6})$$

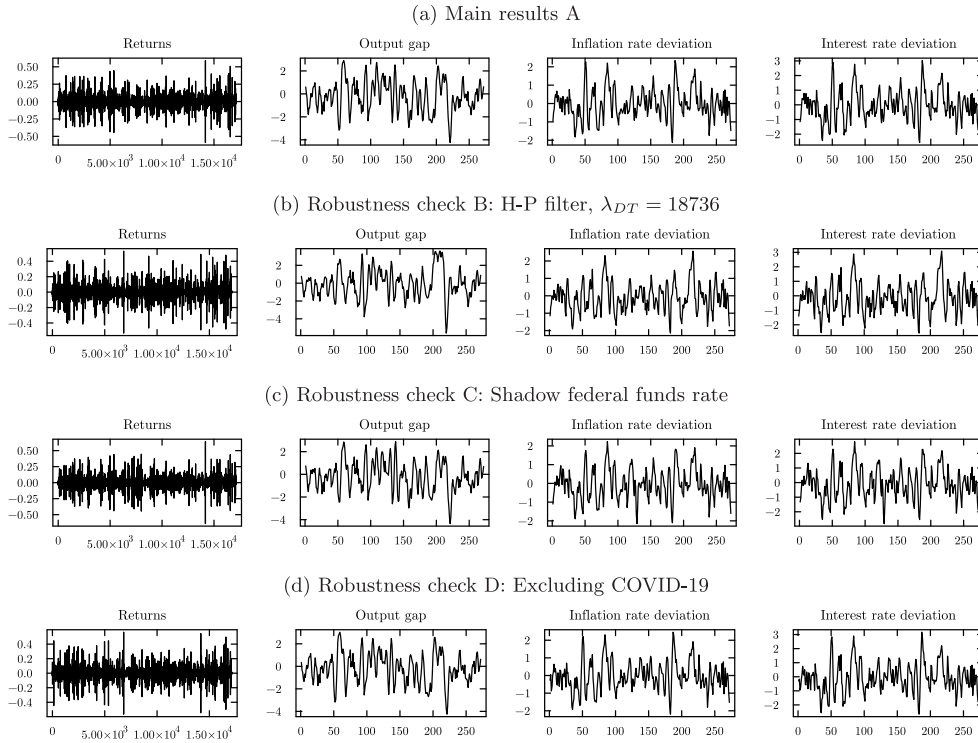


Fig. B.4. Time series simulations of the estimated models. *Note:* The length of the simulated time series corresponds to the length of the empirical dataset. The random seed is kept fixed across all simulations.

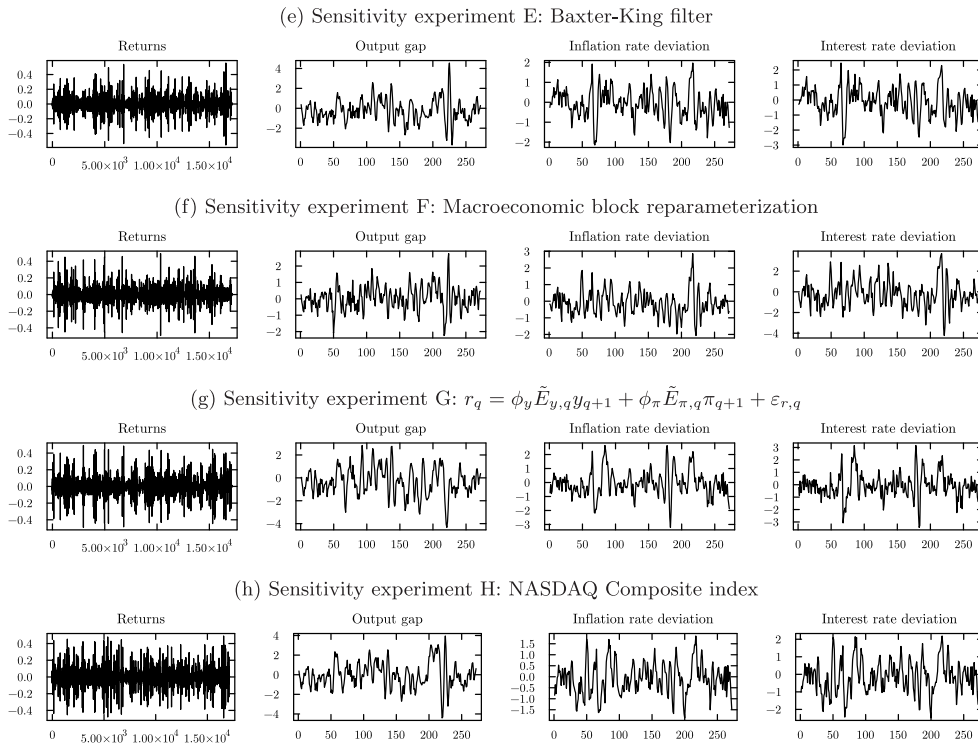


Fig. B.5. Time series simulations of the estimated models for sensitivity analysis experiments. *Note:* The length of the simulated time series corresponds to the length of the empirical dataset. The random seed is kept fixed across all simulations.

Appendix B. Illustrative simulated time series

See Figs. B.4 and B.5.

Data availability

The empirical dataset collected and used in this study, together with a complete Julia replication archive, are publicly available in the GitHub repository: github.com/jirikukacka/Kukacka_Zila_Integrated_ABM [updated 2026-04-11].

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