INSTITUTE
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Faculty of Social Sciences
Charles University

WEALTH, COST, AND MISPERCEPTION: EMPIRICAL ESTIMATION OF THREE INTERACTION CHANNELS IN A FINANCIAL-MACROECONOMIC AGENT-BASED MODEL

Jiri Kukacka
Eric Zila

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Institute of Economic Studies,
Faculty of Social Sciences,
Charles University in Prague

[UK FSV – IES]

Opletalova 26
CZ-110 00, Prague
E-mail : ies@fsv.cuni.cz
http://ies.fsv.cuni.cz

Institut ekonomických studií
Fakulta sociálních věd
Univerzita Karlova v Praze

Opletalova 26
110 00 Praha 1

E-mail : ies@fsv.cuni.cz
http://ies.fsv.cuni.cz

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Wealth, Cost, and Misperception: Empirical Estimation of Three Interaction Channels in a Financial-Macroeconomic Agent-Based Model

Jiri Kukacka[a,b]
Erik Zila[a,b]

[a]Czech Academy of Sciences, Institute of Information Theory and Automation, Czechia
[b]Charles University, Faculty of Social Sciences, Institute of Economic Studies
Corresponding author: jiri.kukacka@fsv.cuni.cz

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Abstract:
Financial-macroeconomic agent-based models offer a promising avenue for understanding complex economic interactions, but their use is hindered by challenging empirical estimation. Our paper addresses this gap by constructing a stylized integrated model and estimating its core parameters using US data from 1954 to 2022. To tackle econometric obstacles, including mixed data frequencies, we adapt the simulated method of moments. We then focus on three key interaction channels. The stock market influences the real sector through the wealth effect, which boosts current consumption, and the cost effect, which lowers financing costs for firms. Conversely, the real economy impacts the stock market via the price misperception effect, where economic conditions help approximate the fundamental value of stocks. Our results provide strong statistical support for all three channels, offering novel empirical insights into critical dynamics between the two sectors of the economy.

JEL: C13, C53, E12, G41, E71
Keywords: integrated agent-based model, behavioral finance and macroeconomics, bounded rationality, heuristic switching, simulated method of moments

1. Introduction

The aftermath of the 2007–2008 global financial crisis highlighted the limitations of traditional economic models in capturing the interconnectedness between the financial and real sectors (Battiston et al., 2016). The major lessons gained for the economic discipline emphasize the consequences of the financialization of the real economy and the significance of maintaining financial stability for broader economic progress (Farmer and Foley, 2009; Gatti et al., 2010). 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).

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 Castelnuovo and Nisticò (2010), were able to reverse the overall trend of separating finance and macroeconomic research.

The progress in agent-based modeling of financial and economic systems followed a parallel trajectory. Despite the global financial crisis highlighting the necessity of integrating 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 like the outcomes of the EURACE project (Deissenberg et al., 2008; Cincotti et al., 2010), the empirical estimation of financial-macroeconomic ABMs remains largely unexplored.

Our paper addresses this gap by focusing on the econometric issues inherent in estimating integrated ABMs. To be more specific, we seek to: a) construct a stylized integrated financial-macroeconomic model based on recent ABM frameworks; b) fine-tune its coefficients based on the latest empirical research; c) adapt the simulated method of moments (SMM) to deal with mixed data frequencies that the two integrated sectors typically operate at; and d) empirically identify the parameters representing interaction channels between the stock market and the real economy.

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., 2022), quantifying empirical relationships remains the main challenge in the field. Traditional econometric techniques such as ordinary least squares (OLS) or maximum likelihood estimator (MLE) usually face fundamental obstacles. The main issues stem from model complexity, which is characterized by strong nonlinearities due to agent interactions and heuristic switching. Theoretical studies are often infeasible because there are no analytical solutions for the models, and the objective function for likelihood-based estima-

[1] See recent excellent surveys on financial and macroeconomic ABMs by Franke and Westerhoff (2017); Dawid and Delli Gatti (2018); Dieci and He (2018); Dilaver et al. (2018); Lux and Zwinkels (2018); Hommes (2021); Axtell and Farmer (2022).

tion cannot be represented in a 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. Another issue in this particular study is that macroeconomic models typically use quarterly or annual data, while financial models usually operate on a daily basis.

To overcome these challenges, we employ the SMM estimation approach. Its straightforward implementation, flexibility, and lack of unrealistic theoretical assumptions have made it a popular choice not only in empirical financial studies (Lux and Zwinkels, 2018) but also, more recently, in the domain of macroeconomic ABMs (Franke et al., 2015; Jang and Sacht, 2016, 2021). Importantly, we modify this optimization technique to deal with different data frequencies. We do this by separately evaluating the moments of macroeconomic and financial time series and then ultimately aggregating them in the optimization objective function.

In a nutshell, while integrated ABMs hold promise for explaining complex economic phenomena, addressing related econometric issues is crucial for their effective utilization in guiding economic decisions. Our paper contributes to this endeavor by offering insights into their empirical estimation and providing a methodological foundation for future research in this area.

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 baseline parameterization. Details of the implementation of the SMM are described in Section 4, and the accompanying Section 5 presents empirical datasets used for estimation. Following that, Section 6 summarizes the technical setup, and Section 7 reports and interprets the key empirical findings. Finally, implications and potential directions for future investigation, together with a concise conclusion, are summarized in the Section 8. Additional details are provided in the Appendix.

2. Related literature

Integrating the financial and real sectors in economic modeling represented 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); Bernanke and Gertler (2000), attempted to incorporate financial frictions into macroeconomic models. These studies extended traditional frameworks by including elements like transaction fees, credit restrictions, asset price misalignments, or even a basic credit market between companies and banks. However, these additions that make sense in theory usually increased the complexity of the original dynamic stochastic general equilibrium (DSGE) models and made 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), Castelnuovo 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.

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. (2010) 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 state of the financial system. Proaño (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); 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); Caiani et al. (2016). The first authors build on the Gatti et al. (2011) macroeconomic agent-based framework with capital and credit, while the other authors create a fully decentralized agent-based stock-flow-consistent model that connects the real and financial economies. Grauwe and Macchiarelli (2015); Macchiarelli and De 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, consisting of financial intermediaries gathering deposits from customers and lending them to firms or providing 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, 2016), whose theoretical contribution we closely follow in our empirical study. These authors build on the work of Westerhoff (2012); 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 inspiration influenced by the agent-based financial literature comes from Kontonikas and Ioannidis (2005); Kontonikas and Montagnoli (2006); Bask (2012), where nonrational heterogeneous heuristics governs the dynamics of the financial side of the economy, but the expectation formation for the macroeconomic part of the model is derived from the rational expectation hypothesis. Nevertheless, to the best of our knowledge, no studies indicate how stylized heterogeneous ABMs interconnecting the financial and macroeconomic sectors may 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 (2022). 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.

Finally, while alternative estimation techniques to the SMM exist, their application to ABMs remains limited. Most efforts have been made in the field of Bayesian inference (Grazzini et al., 2017; Deák et al., 2017; Delli Gatti and Grazzini, 2020; Özden, 2021; Barde, 2022; Dyer et al., 2022; Fischer, 2022; Lux, 2022; Platt, 2022), the sequential Monte Carlo (SMC) by Lux (2018); Zhang et al. (2023), the approximate Bayesian computation (ABC) by Lux (2023a), or the simulated maximum likelihood estimator (SMLE) by Kukacka and Barunik (2017) and Kukacka and Sacht (2023). These methods mostly depend on a numerical approximation of the likelihood function, which must be evaluated at every point in time with empirical data. This makes their use for mixed data sampling datasets complicated compared to a straightforward implementation of the SMM. Furthermore, the mixed data sampling (MIDAS) regression models, proposed by Ghysels et al. (2004, 2007), also address the problem of different data frequencies. Regrettably, this methodology was initially designed for linear models and not for complex ABMs. Although there have been proposals for nonlinear versions of the estimator (Andreou et al., 2010), we are not aware of any successful application of the MIDAS methodology in the field of the econometrics of ABMs.

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 the approach of behavioral heuristics switching macroeconomic modeling based on a three-equation New-Keynesian model (NKM), as proposed by De Grauwe (2010, 2011, 2012a); De Grauwe and Ji (2019, 2020). Various versions of the model setup have also been suggested, e.g., by Branch and McGough (2009, 2010); Massaro (2013); 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); Özden (2021); Jang and Sacht (2021); Kukacka and Sacht (2023); Zhang et al. (2023), 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 fundamental traders and speculators, who are also 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 carried out in Franke and Westerhoff (2016); Lux (2022); Platt (2022); 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); 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 exhibits a strong capability to fit real-world economic data and explain or predict macroeconomic phenomena. The model specification exactly follows Kukacka and Sacht (2023), while already being augmented by the interaction channels presented below in Subsection 3.1.1:

$$
\begin{aligned}
y_q &= \tilde{E}_{y,q} y_{q+1} - \tau(r_q - \tilde{E}_{\pi,q}\pi_{q+1}) + c_1 \tilde{E}_{\Delta s-\pi,q}(\Delta s_{q+1} - \pi_{q+1}) + \varepsilon_{y,q} && (1)\\
\pi_q &= \nu \tilde{E}_{\pi,q}\pi_{q+1} + \kappa y_q - c_2 s_q + \varepsilon_{\pi,q} && (2)\\
r_q &= \phi_y y_q + \phi_\pi \pi_q + \varepsilon_{r,q}, && (3)
\end{aligned}
$$

where $\tilde{E}_{\{y,\pi,\Delta s-\pi\},q}$ are the bounded rationality (BR) expectations operators and s_q represents the quarterly value of stock prices, both of which are also explicitly defined below in Subsection 3.1.2 and Subsection 3.1.1, respectively. For microfoundations of NKMs under BR expectations, see Branch and McGough (2009); Massaro (2013); Hommes et al. (2019).

The q subscript 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 equation (2) represents the supply side. It stands for the New Keynesian Phillips curve, which demonstrates how the (log) output gap (y_q) dynamics 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 $\sigma^2_{\{y,\pi,r\}}$, affect the external driving forces in the endogenous macroeconomic variables. The state-space representation of the forward-looking NKM is outlined in Appendix A. The forward-looking form of the model does not consider concepts such as habit formation, price indexation, and interest rate smoothing that lead to intrinsic persistence in the variables observed in real-world data. 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 Subsection 3.1.2 thus makes such simplification entirely acceptable.

3.1.1. Channels of interaction: the wealth and cost effects

The interaction channels between the financial and macroeconomic sectors of the economy adhere closely to the formalizations proposed by Lengnick and Wohltmann (2013, 2016). 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, FOCM 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):

$$s_q = \frac{1}{64} \sum_{t=64(q-1)+1}^{64q} p_t, \tag{4}$$

where p_t is the stock price value of the overall financial sector in day t, as defined below in (11). The quarterly value of stock prices is thus calculated by taking the average stock price value over an assumed period of 64 workdays leading up to the publication of macroeconomic statistics for the current quarter. Two interaction parameters, $c_1 \geq 0$ and $c_2 \geq$, 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 wealth effect is introduced via a new term, $\tilde{E}_{\Delta s-\pi,q}(\Delta s_{q+1} - \pi_{q+1})$, in the dynamic IS curve (1) based on the following rationale: when households expect future real stock prices to rise, future stock demand is anticipated to decrease. As a result, future consumption has a lower marginal utility than current consumption. To maintain a consistent level of marginal utility of consumption across subsequent quarters, there is an increase in contemporaneous consumption, contributing to an increased current output gap (Lengnick and Wohltmann, 2016). The cost effect is then introduced by simply adding the quarterly value of the stock price, s_q, to the New Keynesian Phillips curve (2). The reasoning beyond this extension follows this line of argumentation: increased prices of financial assets owned by companies as collateral enhance their ability to repay debts, providing them access to less expensive financing due to higher creditworthiness. Because the majority of firms rely heavily on credit, asset prices and firms' marginal real costs of production are inversely related (Lengnick and Wohltmann, 2013) as decreased production costs directly translate to consumer prices. We refer the interested reader to Lengnick and Wohltmann (2016) and Bernanke and Gertler (2000) for details on the microfoundations of the extended IS curve and the New Keynesian Phillips curve, respectively.

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. Exploiting straightforward behavioral rules is not considered irrational within this context; instead, it constitutes an optimal, boundedly rational approach for humans when addressing overly complex tasks under constraints such as limited information or time, alongside the existence of 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); 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:

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

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

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

The weighted combination of the prior actual value in x and agents' historical prediction, $\tilde{E}^{ADA}_{x,q-1} x_q$, 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 parametrized '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^{av}_{q-1}, 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 Žakelj (2014, 2018) for extensive lab-based evidence that supports the behavioral assumptions of simple forecasting heuristics and 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, $U^k_{x,q}$, $k \in \{ADA, TR, LAA\}$, is updated in each period while being standardly defined through squared forecast errors:

$$U^k_{x,q} \;\; = \;\; \rho U^k_{x,q-1} \; - \; (E^k_{q-2} x_{q-1} - x_{q-1})^2, \tag{8}$$

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 logistic 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:

$$\alpha^k_{x,q} \;\; = \;\; \frac{\exp(\gamma U^k_{x,q})}{\sum_{i=1}^{3} \exp(\gamma U^{k\{i\}}_{x,q})}, \tag{9}$$

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 $\alpha^k_{x,t}$ sum to one for each of the three heuristics.

The model is closed by updating the aggregated forecast for the economy. The aggregation of the agents' expectations about the future values of variables $x \in \{y, \pi, \Delta s - \pi\}$ is defined as a weighted average taking advantage of the output of (9), $k \in \{ADA, TR, LAA\}$:

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

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, engage in interactions and, similarly to macroeconomic agents, adapt to their dynamic environment by switching between the two groups. Finally, the financial part of the model has to run on a higher-frequency time scale; namely, it has a daily frequency 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 between consecutive periods by considering the excess demand for the asset. The adjustment is proportional to the excess demands of fundamentalists (d_t^f) and chartists (d_t^c), given by:

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

Here, n_t^f and $n_t^c = 1 - n_t^f$ represent the population shares of fundamentalists and chartists, respectively, and the parameter υ 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:

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

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

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. 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 index a_t, indicating the propensity to switch:

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

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

where δ_0 serves as a predisposition parameter, indicating a general inclination towards 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 for asset traders and governs the binomial logistic model (15) that determines the evolution of population shares of fundamentalists and chartists.

3.2.1. 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. This requirement excludes some agent-based approaches from the list of potential candidates. We strictly adhere to the Lengnick and Wohltmann (2013, 2016) interconnection principle and define:

$$p^* := p_t^* = hy_{q-1}, \qquad q = \text{floor}\frac{t-1}{64}, \tag{16}$$

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 updates quarterly based on the recent real economic progress. As such, it deviates from the assumption of the original model, where the fundamental value is set to zero for simplicity, while adhering to other financial ABMs, like those by Farmer and Joshi (2002); Alfarano et al. (2008), where the random walk process often approximates the time-varying fundament.

This impact from 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 the fact that determining the fundamental values of financial assets poses significant challenges in reality. 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 agents can afford higher consumption, leading to a higher output gap, the demand for stocks also increases.

Crucially, the three interaction channels mutually influence one another in a simultaneous fashion. 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 that connects the financial traders' stock demand to the 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, the implementation of this channel does not align with our accepted framework; thus, we are unable to incorporate it immediately into the examined model. 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 Subsection 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 empirically estimate the three new interaction parameters of the integrated financial-macroeconomic model. These are the fundamental price misperception effect parameter h in (16), the wealth effect parameters c_1 in (1), and the cost effect parameter c_2 in (2). For this purpose, the other coefficients of both model parts must be appropriately parametrized. We set the coefficient values according to the most recent empirical literature that estimates the same frameworks individually based on datasets of comparable spans as the one used in this study.

The complete set of parametrized coefficients is summarized in Table 1. The main parameters of the heuristics switching macroeconomic model are set according to Kukacka and Sacht (2023, Table 2, col. B) using 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 follows the recent empirical results of Zila and Kukacka (2023, Table 4, col. BSME eff.), 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); Platt (2022). Moreover, we later introduce robustness checks and sensitivity experiments

Table 1: Baseline model parameterization

Heuristics switching macroeconomic model												
τ	κ	ϕ_y	ϕ_π	η	ι	μ	γ	ν	ρ	σ_y	σ_π	σ_r
0.371	0.213	0.05	1.23	0.21	0.00	0.38	1.49	0.99	0	0.543	0.24	0.151

Financial agent-based model									
ψ	χ	σ_f	σ_c	δ_0	δ_h	δ_m	υ	β	p_1
0.02	2.01	0.835	4.02	-0.182	2.14	13.12	0.01	1	0

Note: Parameterization of the integrated model is based on Kukacka and Sacht (2023, Table 2, col. B), Jang and Sacht (2021, Table 2, col. EFB), Franke and Westerhoff (2012), and Platt (2022).

that alter some of the parametrized coefficients or the model structure. The specific modifications are described within 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). It obtains parameter estimates by conducting multiple model simulations over a wide range of parameter combinations. In the agent-based modeling literature, SMM often appears as a preferred estimation approach because of its desirable properties of asymptotic normality and consistency (Lee and Ingram, 1991; Duffie and Singleton, 1993) combined with practical features such as straightforward implementation, flexibility, and realistic assumptions. To leverage this method, all that is required is a simulation model generating time series corresponding to a specific set of parameter values. 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 arising from 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 $\boldsymbol{\theta}$ we want to estimate for an empirical time series $e = \{e_t\}_{t=1}^{T_{emp}}$. Furthermore, assume that we can draw a simulated sample $f(\boldsymbol{\theta}) = z^{\boldsymbol{\theta}} = \{z_t\}_{t=1}^{T_{sim}}$ of length $T_{sim} \geq T_{emp}$ from f for a given set of parameters $\boldsymbol{\theta}$. As a measure of closeness between the empirical and simulated time series, we can compute the distance between sample counterparts of D statistical moments of choice, called 'statistics', describing their distributions. For instance, the sample average is typically used as the sample counterpart for the expected value. To achieve our goal, we find $\boldsymbol{\theta}$ minimizing the overall distance between the D statistics calculated for the empirical and simulated time series.

Each of the D statistics can be represented as a function m_d, $d \in \{1, \ldots, D\}$, 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 $z_s^{\boldsymbol{\theta}}$, $s \in \{1, \ldots, S\}$, and taking the average over the statistics as $\frac{1}{S}\sum_{s=1}^{S} m_d(z_s^{\boldsymbol{\theta}})$. Then, we can organize the D statistics computed in this manner into a couple of vectors $\mathbf{m}^{emp} = [m_1(e), \ldots, m_D(e)]$ and $\mathbf{m}^{sim}(\boldsymbol{\theta}) = [\frac{1}{S}\sum_{s=1}^{S} m_1(z_s^{\boldsymbol{\theta}}), \ldots, \frac{1}{S}\sum_{s=1}^{S} m_D(z_s^{\boldsymbol{\theta}})]$. Finally, we can define an objective function J computing the distance between the two vectors as follows:

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

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

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

where $\boldsymbol{\theta} \in \boldsymbol{\Theta}$, $\boldsymbol{\Theta}$ is the parameter space of the search.

4.2. Weighting matrix

The weighting matrix $\mathbf{W}$ can be calculated using a number of different approaches. The general rule, however, is to assign more 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 take into account as many distinct characteristics of the time series as possible and avoid placing excessive focus on potentially overlapping information. Consequently, the appropriate and most common choice is to use $\boldsymbol{\Sigma}$, the covariance matrix of moments, and set $\mathbf{W} = \boldsymbol{\Sigma}^{-1}$.

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

$$\widehat{\boldsymbol{\Sigma}} = \frac{1}{B_B} \sum_{i=1}^{B_B} (\mathbf{m}_i^{bs} - \overline{\mathbf{m}})(\mathbf{m}_i^{bs} - \overline{\mathbf{m}})^\top, \tag{19}$$

where $\overline{\mathbf{m}} = \frac{1}{B_B}\sum_{i=1}^{B_B} \mathbf{m}_i^{bs}$. Finally, we take the inverse of $\widehat{\boldsymbol{\Sigma}}$ 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 utilization of the SMM in this multivariate context, featuring time series of inconsistent 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 $D = 100$ moment conditions in our application of the SMM. The conditions used cover 78 and 22 moments for macroeconomic and financial data, respectively. For macroeconomic data, we follow Franke et al. (2015); Jang and Sacht (2016, 2021) and utilize lagged auto- and cross-covariances whose sample counterparts are calculated as follows:

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

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 $l \in \{0, 1, \ldots, 8\}$ 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 $\big($since, for example, $m(0, r, \pi) = m(0, \pi, r)\big)$.

For financial data, we follow Zila and Kukacka (2023) and use the unconditional second and fourth moments of raw returns, autocorrelations at lags $l \in \{1, 2, 3\}$ of raw returns, the unconditional first moment of absolute returns, the Hill estimator of the tail index of absolute raw returns using 2.5% and 5% of extreme observations, autocorrelations at lags $l \in \{1, 5, 10, 15, 20, 25, 50, 100\}$ of absolute returns, and autocorrelations at lags $l \in \{1, 5, 10, 15, 20, 25\}$ of squared returns. According to Zila and Kukacka (2023), even a small number of carefully chosen moments can result in superior SMM estimation performance. However, they also conclude that the accuracy of the method does not markedly deteriorate as the number of moments increases, as long as the weights in matrix $\mathbf{W}$ are accurately estimated. This allows for a cautious approach of adopting an entire set of 22 moments instead of the specific sets proposed for the original model, taking into account that incorporating the Franke and Westerhoff (2012) model into our financial-macroeconomic framework can markedly affect its dynamics.

4.4. Block bootstrap approach for mixed data sampling

When generating bootstrapped time series in order to estimate the covariance matrix $\mathbf{\Sigma}$, 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 corresponding to the quarterly observation at $R - B_L$ until the last day right 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.

Having generated bootstrapped time series, we split the covariance matrix estimation problem into two subtasks, one for macroeconomic moment conditions (78×78 matrix $\widehat{\mathbf{\Sigma}}_M^{-1}$) and the other for financial moment conditions (22×22 matrix $\widehat{\mathbf{\Sigma}}_F^{-1}$). Due to the large size of the macroeconomic covariance matrix, we follow Franke et al. (2015); Jang and Sacht (2021) and especially a comprehensive discussion in Jang and Sacht (2016) and estimate only its diagonal elements, i.e., variances of the macroeconomic moment conditions, using the block bootstrap approach described above. At the same time, we estimate the full matrix for financial moment conditions. Subsequently, we concatenate the two estimated matrices in order to form a full 100×100 $\widehat{\mathbf{\Sigma}}$ matrix.

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 2022-09-23]. The dataset encompasses the period from 1954:Q3 to 2022:Q2, i.e., a total of 272 quarterly observations. Output is derived from seasonally adjusted real GDP based on billions of chained 2012 USD, while inflation is quantified using the seasonally adjusted CPI. The one-sided Hodrick-Prescott filter with a standard smoothing parameter of $\lambda = 1,600$ is used to estimate the trend for the output time series data to obtain the gap format, as shown in Stock and Watson (1999). We also add robustness checks later using output gap data calculated with much higher smoothing parameters, as suggested by Franke et al. (2023). The two utilized smoothing values are $\lambda_{DT;ST} = \{18736; 12016\}$ and the results are presented in Subsection 7.1. Finally, the short-term nominal interest rate is represented by the effective federal funds rate. The inflation and interest rate data are essentially demeaned to match the theoretical log-linearized specification of the NKM model. This is similar to the Hodrick-Prescott detrending of the output data.

Regarding financial data, we follow the standard practice and utilize the log returns of the S&P 500 stock market index. Our dataset spans from 1954-07-01 to 2022-06-30, i.e., a total of 17119 daily observations [database accessed on 2022-11-24]. The specific starting and ending points of the data span are due to the adjustment of the period to fit along with the macroeconomic data, according to (16). For downloading the dataset, interested readers are directed to the GitHub repository.

6. Estimation setup

6.1. Monte Carlo and computational complexity

All computations reported in this paper are implemented in `Julia 1.6.1` (Bezanson et al., 2017) and utilize 300 independent Monte Carlo re-estimations 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 single 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 of the experiments on a server with a 48-core Intel Xeon Gold 6126 @ 2.60GHz processor and 400 GB of RAM. Under this configuration, each estimation procedure with 300 independent runs amounts to approximately 59 compute hours.

6.2. Technical implementation details

We use a warm-up period of 50 quarterly and 3000 daily observations to mitigate any potential biases introduced by the model's initialization. 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 272 quarterly observations. When generating financial data, we follow Lengnick and Wohltmann (2016) in using the assumption that each quarterly observation should correspond to 64 daily observations, i.e., we generate time series with $272 \times 64 = 17408$ 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 1024 daily) observations. Simulated moments in the objective function (17) of the SMM are calculated as averages over $S = 100$ independent realizations. To optimize the function, we employ the recommended optimizer `:adaptive_de_rand_1_bin_radiuslimited` from the `BlackBoxOptim.jl` package with 4000 functional evaluations. We restrict the search space explored by the optimizer to $\widehat{h} \in \langle 0, 1.5 \rangle$, $\widehat{c}_1 \in \langle -1, 4 \rangle$, and $\widehat{c}_2 \in \langle 0, 30 \rangle$. The only exception is experiment F, which dictates expanded bounds for one of the parameters, namely $\widehat{c}_1 \in \langle -1, 9 \rangle$.

Table 2: Numerical results of the empirical study

Par./Exp.	A	B	C
$\widehat{h}$	0.586	0.586	0.589
$\langle 0, 1.5\rangle$	(0.492, 0.675)	(0.494, 0.677)	(0.497, 0.684)
$\widehat{c}_1$	0.309	0.321	0.326
$\langle -1, 4\rangle$	(0.087, 0.578)	(0.080, 0.662)	(0.083, 0.652)
$\widehat{c}_2$	16.3	16.4	16.3
$\langle 0, 30\rangle$	(14.6, 18.2)	(14.8, 18.7)	(14.8, 18.4)

Note: The constraints for optimization search are given in $\langle\rangle$ brackets. The sample means based on 300 random 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.

7. Empirical analysis

This section showcases the primary findings of our estimation study. Initially, we present and analyze the empirical estimates of the three model interaction parameters, accompanied by two further robustness checks. Subsequently, we examine the sensitivity of the estimation outcomes when certain model coefficients are re-parametrized, or the model structure is slightly modified. In addition to numerical findings, we depict the estimation output visually.

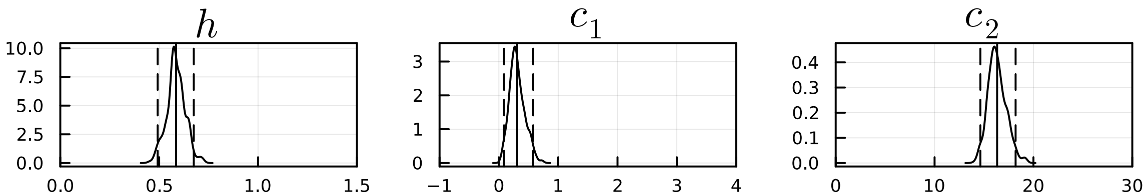
7.1. Main findings and robustness checks

The estimation results are summarized in Table 2. To the best of our knowledge, our study provides the first empirical estimates for the three interaction channels in the agent-based modeling literature. Column A reports the main set of empirical estimates. In Columns B and C, robustness experiments are shown using output gap data that was calculated with much higher smoothing parameters, as suggested by Franke et al. (2023), with $\lambda_{DT;ST} = \{18736; 12016\}$. The related graphical depiction is provided in Figure 1.

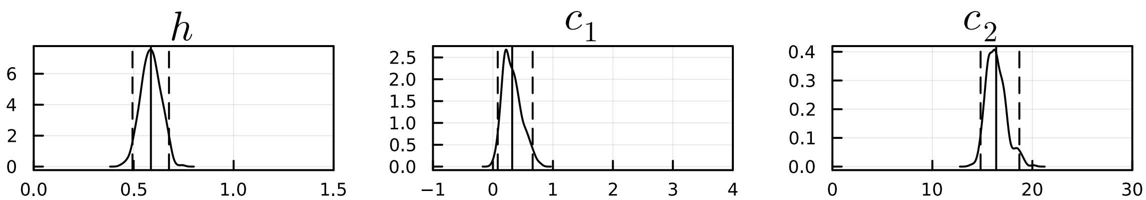
The crucial observation is that all three interaction parameters estimated in Table 2, Column A, are statistically significant at the 95% confidence level. The empirical findings, therefore, provide strong statistical support in favor of all three interaction channels in our financial-macroeconomic integrated ABM of the US economy. Furthermore, as observed in Figure 1, Panel (a), the parameter estimators have narrow densities with generally symmetrical shapes close to a normal distribution with only modest skewness and slight excess kurtosis ($skew_{\widehat{h}}$ based on 300 random runs is 0.059 and $ex.\ kurt_{\widehat{h}} = 0.249$; $skew_{\widehat{c}_1} = 0.537$, $ex.\ kurt_{\widehat{c}_1} = 0.097$; $skew_{\widehat{c}_2} = 0.466$, $ex.\ kurt_{\widehat{c}_2} = 0.249$). This observation further supports the utilization of the 95% confidence intervals of the sample estimates as confidence intervals for single parameters as noted in Section 6.

In the financial ABM, the fundamental price misperception effect parameter in (16) is estimated to be $\widehat{h} = 0.586$. We can hardly compare its numerical value to any existing empirical literature, while its interpretation is straightforward: the stock market participants following the fundamental trading strategies approximate the fundamental value of the stock market as roughly

(a) Main results A



(b) Robustness check B: $\lambda_{DT} = 18736$



(c) Robustness check C: $\lambda_{ST} = 12016$

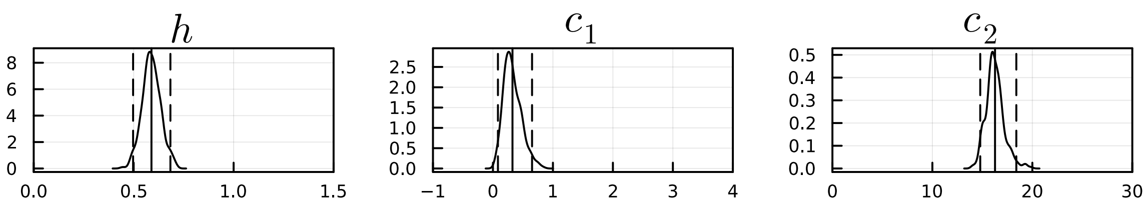


Figure 1: Densities of the parameter estimates. *Note:* The black curves depict the kernel density estimates of the sample densities, while the full and dashed vertical lines represent their means and the 95% confidence intervals of the sample estimates, respectively. Based on 300 random runs.

59% 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 $\widehat{c}_1 = 0.309$. As the interpretation of the numerical values might be difficult in such a complex nonlinear system of equations, we follow a simplified *ceteris paribus* way of assessing the 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) of real stock prices, but these optimistic (pessimistic) expectations only translate to the value of the actual output gap by circa 31%. In other words, a 10% rise in real stock price is associated with an approximately 3% increase in the output gap. Next, the cost effect parameter c_2 in (2) is estimated to be $\widehat{c}_2 = 16.3$, 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. To some extent, this interaction channel seems to balance the positive impact of the actual output gap on the inflation rate. Following the elasticity interpretation logic of the log-linearized NKM, a large estimated value of c_2 suggests that even a slight decrease in the aggregated quarterly value of stock prices results in strong inflationary pressures via the cost channel.

Table 3: Sensitivity analysis experiments

Par./Exp.	D	E	F	G
$\widehat{h}$	0.616	0.375	0.400	0.496
$\langle 0, 1.5\rangle$	(0.442, 0.893)	(0.299, 0.433)	(0.345, 0.464)	(0.418, 0.580)
$\widehat{c}_1$	2.08	0.979	5.18	0.149
$\langle -1, 4\ (9)\rangle$	(0.320, 3.48)	(0.630, 1.29)	(4.40, 5.95)	(0.100, 0.216)
$\widehat{c}_2$	14.7	6.30	20.5	21.7
$\langle 0, 30\rangle$	(11.7, 18.4)	(5.58, 7.16)	(18.7, 22.1)	(19.4, 24.0)

Note: The constraints for optimization search are given in ⟨⟩ brackets. The sample means based on 300 random 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.

Finally, two experiments with different smoothing parameters for the output gap calculation are presented in Table 2, columns B and C, accompanied by a visual depiction in Figure 1, panels (b) and (c). The overall finding is that the estimation results are robust when using different output gap calculation settings. Literally, the estimated parameters and the estimated densities of the parameter estimators closely resemble the main result based on the commonly used smoothing parameter $\lambda = 1,600$, and all distributions remain reasonably close to normality based on sample skewness and kurtosis.

7.2. Sensitivity analysis experiments

We now examine the sensitivity of the estimation outcomes when some model coefficients are re-parameterized, or when the model structure is slightly modified. The non-estimated coefficients of the model are parameterized based on the latest empirical literature that estimates those frameworks separately. Some simplifications were necessary in those papers to make empirical estimation possible. We incorporate these simplifications also in our integrated model to ensure its parameterization is as consistent with empirical findings as possible. Nevertheless, given that we no longer estimate these coefficients in our study, we may loosen some of these simplifications and evaluate the effect on estimating the interaction parameters of the main interest.

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 of these modifications but rather on the qualitative distinctions concerning the major estimation results in Table 2, Column A, and Figure 1, Panel (a).

7.2.1. Coefficient re-parameterization

We first re-parameterize the structural coefficients of the macroeconomic part of the model in experiment D. 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). These two parameters are thus set according to Jang and Sacht (2021, Table 2, col. EFB) in our baseline model parameterization, and we now also set

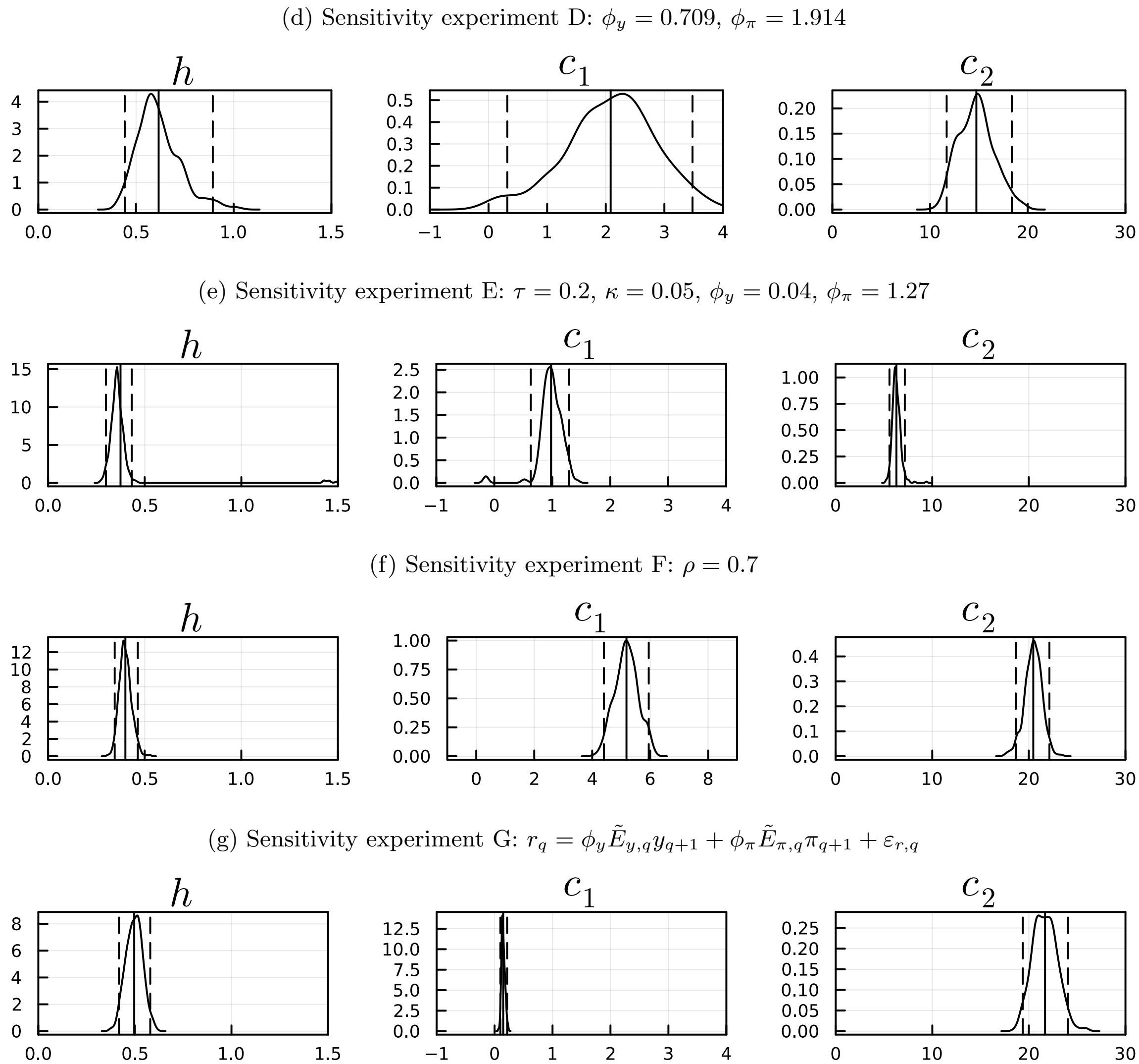


Figure 2: Densities of the parameter estimates. *Note:* The black curves depict the kernel density estimates of the sample densities, while the full and dashed vertical lines represent their means and the 95% confidence intervals of the sample estimates, respectively. Based on 300 random runs.

the Taylor-type monetary policy rule coefficients according to the same paper: $\phi_y = 0.709$, $\phi_\pi = 1.914$. Second, in experiment E, we set all four structural parameters of the macroeconomic model according to Kukacka and Sacht (2023, Table 2, col. C), in which τ and κ follow a 'plain vanilla' parameterization by De Grauwe and Ji (2020, pg. 8) while ϕ_y and ϕ_π are estimated (however, very similarly to the baseline model parameterization): $\tau = 0.2$, $\kappa = 0.05$, $\phi_y = 0.04$, $\phi_\pi = 1.27$. The results are presented in Table 3, Columns D and E, and visualized in Figure 2, Panels (d) and (e), respectively.

The key finding regarding the statistical significance of the interaction parameters remains unchanged, whereas, as expected, one can observe numerical shifts and qualitative changes in the estimation performance under given re-parameterizations. In experiment D, the interaction parameters h and c_2 are estimated comparably to our main results; only the variance of the SMM estimator increases as demonstrated by wider confidence intervals. Although finding a causal way of reasoning why modified $\phi_y = 0.709$, $\phi_\pi = 1.914$ make it so is tricky in such a nonlinearly interconnected system, a possible line of explanation might be that stronger dynamics of the Taylor rule equation (3) under numerically larger monetary policy coefficients can overshadow the model dynamics necessary for determining interaction channels. Moreover, the wealth effect interaction parameter is estimated by order of magnitude larger, $\widehat{c}_1 = 2.08$, suggesting that the impact of stronger dynamics of the nominal interest rate r_q, which is plugged into the dynamic IS curve (1) with the negative $-\tau$ coefficient, must be much strongly compensated by the wealth effect that influences the current output gap positively.

Conversely, experiment E reveals slightly narrower confidence intervals for h and c_2 while both interaction parameters are estimated to be smaller compared to our main results: $\widehat{h} = 0.375$ and $\widehat{c}_2 = 6.30$. On the other hand, the wealth effect interaction parameter is again estimated to be considerably larger: $\widehat{c}_1 = 0.979$. A potential causal way of reasoning is the following: a markedly smaller structural coefficient $\tau = 0.2$ and a larger c_1 are both likely to positively influence the output gap (1). Therefore, a smaller fundamental value misperception effect parameter h for the stocks' fundamental value approximation in (16) is necessary to capture the dynamics of data. Additionally, with a smaller structural coefficient $\kappa = 0.2$, a smaller cost effect parameter c_2 is necessary to compensate for the impact of the current output gap in (2). Nonetheless, why the estimated wealth effect interaction parameter $\widehat{c}_1$ remains large is not straightforward to explain due to the structure of the baseline NKM in which all three current observables together with structural coefficients are interconnected in a complex manner.

7.2.2. Structural changes

Next, we examine the impact of two slight modifications to the structure of the macroeconomic component of the integrated model. Our baseline parameterization in Table 1 is based on setting the memory parameter $\rho = 0$ in (8) so that the economic utility of the forecast precision is solely based on the most recent squared forecast error. This simplification allows Kukacka and Sacht (2023) to identify the intensity of choice of macroeconomic forecasters γ in (9). Since the memory parameter is now fixed in our study, we can experiment with setting it to $\rho = 0.7$ according to calibration in Hommes et al. (2019). Exponentially declining weights of all previous squared forecast errors then determine the forecast precision. Lastly, we change the Taylor-type monetary policy rule (3) so that it is no longer based on the current output gap and inflation rate but on BR expectations of their future realizations. This is consistent with the other two equations in our forward-looking baseline NKM:

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

The concept of an expectation-based Taylor rule aligns with the behavioral NKM frameworks proposed by authors such as Branch and McGough (2009, 2010); Lengnick and Wohltmann (2013, 2016) and, most recently, Lux (2023b). Lux (2023b) convincingly argues that this approach significantly simplifies the system of differential equations that represent the NKM model, as 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 presented in Table 3, columns F and G, and visualized in Figure 2, panels (f) and (g), respectively.

Again, the statistical significance of the interaction parameters is not endangered by these structural changes, while some estimation results are affected markedly. Introducing memory into the evaluation process of the precision of macroeconomic forecast heuristics in experiment F slightly decreases the estimate of the fundamental value misperception parameter $\widehat{h} = 0.400$ and increases the estimated cost effect parameter $\widehat{c}_2 = 20.5$. All this while maintaining a comparable estimation uncertainty, as can be seen from the confidence intervals. But it primarily surges up the wealth effect parameter $\widehat{c}_1 = 5.18$. The expected change of real stock prices thus no longer contributes partially to the development of the output gap, but its impact is amplified approximately five times. Therefore, the assumption about how much macroeconomic forecasters look into the past when evaluating the attractiveness of forecasting rules seems critical for a correct estimation of the wealth effect.

Intriguingly, under the restructured expectation-based Taylor rule in experiment G, one observes a similar impact for $\widehat{h} = 0.496$ $\widehat{c}_2 = 21.7$, while the estimated cost effect parameter $\widehat{c}_1 = 0.149$ is reduced to approximately half, yet still statistically significant at the 95% confidence level. This experiment, therefore, similarly calls for a correctly specified form of the monetary policy rule within the NKM framework for the correct estimation of the wealth effect, while the other two effects are only slightly influenced.

8. Conclusion

This study pioneers the empirical estimation of a stylized integrated financial-macroeconomic ABM, addressing the econometric challenges posed by the interconnection of the two sectors of the economy. Our focus on three interaction channels—the wealth effect, cost effect, and price misperception—reveals statistically significant and economically meaningful parameters, demonstrating the interconnections between the US stock market and the real economy over the last seven decades. Overcoming the limitations of traditional econometric techniques and mixed data sampling, we employ the simulated method of moments, showcasing its effectiveness in estimating complex agent-based models even under different data frequencies.

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 supplementary robustness checks and sensitivity experiments reinforce the integrated model's credibility while emphasizing the importance of a proper model specification. Exploring alternative parameterizations and structural adjustments, the estimated model maintains relative stability, mainly regarding price misperception and cost channels, and adaptability in reparameterization. Despite nuanced shifts, all interaction parameters always retain statistical significance and economic importance.

The practical implications of the identified interaction channels highlight the substantial mutual impacts between stock market dynamics and key macroeconomic variables. Understanding the relationship between the financial and real sectors becomes crucial for policymakers when formulating effective economic strategies. The estimated parameters provide insights into the responsiveness of consumption, inflation, and investment to stock market fluctuations, as well as how the behavior of stock market participants relates to current economic conditions and macroeconomic expectations. Regulators in both sectors can leverage this understanding to design more targeted policy interventions, considering the mutually reinforcing effects across sectors. Overall, these practical implications highlight the significance of integrating financial and macroeconomic dynamics for informed policy decision-making.

Addressing future research directions, we propose two avenues. First, extending the model's estimation to encompass the entire framework, not just the interaction channels, would offer a comprehensive understanding of the integrated system. Nevertheless, we are slightly skeptical regarding the capability of the SMM to accomplish this objective. It is possible that a more sophisticated simulation-based estimation method needs to be implemented. Second, incorporating additional possible interaction channels would introduce an additional layer of complexity, contributing to a more nuanced understanding of the interplay between financial and macroeconomic dynamics.

In conclusion, this research advances the empirical exploration of integrated economic ABMs, offering valuable insights into the dynamic interactions between financial and macroeconomic 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.

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Declarations

Declaration of competing interest: The authors declare that they have no conflict of interest.

Availability of data: The empirical dataset analyzed during the current study is available in the GitHub repository: github.com/jirikukacka/Kukacka_Zila_Integrated_ABM [created 2024-01-23].

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

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

$$\mathbf{B} = \begin{bmatrix} 1 & \tau & c_1 \\ 0 & \nu & 0 \\ 0 & 0 & 0 \end{bmatrix} \tag{A.2}$$

$$\mathbf{C} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & -c_2 & 0 \\ 0 & 0 & 0 \end{bmatrix} \tag{A.3}$$

$$\mathbf{D} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{A.4}$$

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

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

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Univerzita Karlova v Praze, Fakulta sociálních věd
Institut ekonomických studií [UK FSV – IES] Praha 1, Opletalova 26
E-mail : ies@fsv.cuni.cz http://ies.fsv.cuni.cz