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DSGE and Agent-Based Models in Monetary Policy Analysis: A Comparative Perspective

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Abstract: This paper provides a systematic comparative assessment of New Keynesian Dynamic Stochastic General Equilibrium (NK-DSGE) models and Agent-Based Models (ABMs) as tools for macroeconomic and monetary policy analysis. It addresses three measurable research questions: (i) how the two frameworks differ in their theoretical foundations and behavioral assumptions; (ii) whether ABMs demonstrate empirical or forecasting advantages relative to DSGE models during crisis periods; and (iii) how central banks can integrate both approaches within a complementary modelling toolkit. The methodology combines a structured comparative review of post-2008 central bank applications with an illustrative quantitative simulation of a 100-basis-point monetary tightening shock using a calibrated three-equation NK-DSGE model and a stylized heterogeneous-agent ABM. The simulation results show that the ABM generates a recession nearly twice as deep (−4.8% versus −3.0%) and significantly more persistent than the DSGE counterpart, reflecting nonlinear amplification mechanisms absent in representative-agent structures. Surveyed empirical evidence further indicates competitive or superior forecasting performance of large-scale ABMs during major crises; for example, the Austrian model of Poledna et al. (2023) anticipated a six percent GDP contraction during the COVID-19 crisis and outperformed DSGE and VAR benchmarks in crisis forecasting. While NK-DSGE models retain advantages in normative and welfare-based policy evaluation due to analytical discipline and microfoundations, ABMs provide greater realism in modelling heterogeneity, financial frictions, and systemic instability. The findings support a dual-toolkit strategy in which reformed DSGE models and empirically grounded ABMs are used complementarily within modern central banking practice.

Keywords: Agent-Based Models, DSGE Models, macroeconomic policy, monetary policy, New Keynesian models.

JEL classification: C63, E17, E52

Introduction

The Global Financial Crisis of 2007–2009 triggered a fundamental reassessment of prevailing macroeconomic modeling paradigms. Prior to the crisis, New Keynesian Dynamic Stochastic General Equilibrium (NK-DSGE) models had become the dominant analytical framework in central banks and policy institutions, valued for their formal rigor, internal consistency, and strong microfoundations (Cincotti et al. 2022). However, the crisis exposed significant shortcomings. Standard DSGE models failed to anticipate the scale and nature of the downturn, and their reliance on restrictive assumptions—representative agents, rational expectations, market clearing, and linearization around a steady state—limited their capacity to account for crisis dynamics and guide policy under severe stress (Silva 2019, Fagiolo & Roventini 2017).

Despite these limitations, NK-DSGE models remain central to macroeconomic policy analysis, increasingly complemented by alternative empirical tools such as VAR and SVAR models for shock identification, forecasting, and robustness analysis. At the same time, the crisis underscored the need for frameworks capable of capturing economic complexity, nonlinearity, and heterogeneity. Agent-Based Models (ABMs) have consequently gained prominence. By modeling economies as evolving systems of interacting heterogeneous agents operating under bounded rationality and decentralized decision-making, ABMs enable the analysis of network contagion, endogenous crises, out-of-equilibrium dynamics, and nonlinear feedback mechanisms that are difficult to reconcile within the DSGE paradigm (Cincotti et al. 2022).

This paper contributes to the literature by providing a structured, policy-oriented comparison of DSGE and ABM frameworks grounded in recent central bank practice rather than purely theoretical critique. It addresses three central questions: (i) What are the key methodological and theoretical differences between NK-DSGE and ABM models in monetary policy analysis, particularly regarding microfoundations, behavior, equilibrium concepts, and transmission mechanisms; (ii) In which policy domains do ABMs demonstrate comparative advantages, especially in crisis forecasting, financial stability, and distributional and climate-related risk analysis; and (iii) How can central banks integrate both approaches into a complementary modelling toolkit that enhances robustness and policy relevance. Rather than framing the debate as a choice between paradigms, the paper advances a dual-framework perspective that leverages their respective strengths.

The remainder of the paper proceeds as follows. Section 1 outlines the structure and assumptions of the New Keynesian DSGE framework, followed by an introduction to agent-based macroeconomics. A systematic comparison then examines assumptions, equilibrium dynamics, shock propagation, policy transmission, and institutional realism (Table 1). To concretely illustrate these differences, the paper presents an illustrative simulation comparing impulse responses to a common monetary tightening shock. The conclusion discusses implications for central bank policy design and reinforces the complementarities between DSGE and ABM approaches.

1 Research Methodology

This paper adopts a systematic comparative review methodology to evaluate the relative strengths, limitations, and policy applications of New Keynesian Dynamic Stochastic General Equilibrium (NK-DSGE) models and Agent-Based Models (ABMs) in monetary policy analysis. The review is organized around a multi-dimensional analytical framework that contrasts the two modelling paradigms across key dimensions, including theoretical foundations, behavioral assumptions, equilibrium concepts, shock propagation mechanisms, policy transmission channels, and approaches to empirical validation. The analysis focuses on the post-2008 financial crisis period, when the limitations of standard DSGE models and the potential of alternative frameworks became central to academic and policy debates.

The literature selection follows three criteria. First, priority is given to studies applied or cited by central banks and international policy institutions, ensuring strong policy relevance. Second, foundational theoretical contributions that define the core assumptions and methodological innovations of each framework are included. Third, recent empirical applications demonstrating the operational feasibility of ABMs in real-world policy contexts—such as forecasting, financial stability analysis, central bank digital currencies, and climate-related risks—are incorporated. The comparison is operationalized through a structured taxonomy (Table 1) that systematically maps differences between DSGE and ABM approaches, enabling a transparent assessment of trade-offs and providing empirical grounding through recent central bank applications.

2 An Overview of New Keynesian DSGE Models: Structure and Assumptions

Silva (2019) characterizes New Keynesian DSGE (NK-DSGE) models as the modern “New Neoclassical Synthesis,” combining microfounded general equilibrium theory with Keynesian

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elements such as nominal rigidities. Building on a Real Business Cycle foundation, these models incorporate monopolistic competition, price and wage stickiness, and an explicit monetary policy rule, enabling analysis of short-run fluctuations alongside long-run equilibrium dynamics. The standard framework assumes an infinitely lived representative household and firm, relying on the representative agent (RA) assumption for aggregation, and presumes rational expectations, whereby forward-looking agents form model-consistent beliefs using all available information.

NK-DSGE models operate within a general equilibrium framework in which markets are assumed to be clear, at least under flexible price conditions. Their dynamics are commonly characterized by a small set of linearized equations around a deterministic steady state, implying the existence of a unique rational expectations equilibrium. This structure provides analytical tractability and facilitates policy analysis, but it also constrains the range of dynamic behaviors the model can generate.

The core structure of a standard NK-DSGE model is typically summarized by three equations. First, the dynamic IS equation, derived from the representative household's Euler condition, is given by equation (1):

$$x_t = E_t\left[x_{\{t+1\}}\right] - \left(\frac{1}{\sigma}\right)\left(i_t - E_t\left[\pi_{\{t+1\}}\right] - r_t^n\right) \tag{1}$$

It describes the evolution of the output gap x_t, defined as the deviation of actual output from its natural level. The equation links current economic activity to expected future output, $E_t\left[x_{\{t+1\}}\right]$, and to the real interest rate, given by the nominal interest rate i_t adjusted for expected inflation $E_t[\pi_{t+1}]$ and the natural rate of interest r_t^n. The parameter σ denotes the intertemporal elasticity of substitution and governs the sensitivity of households' consumption decisions to changes in real interest rates.

Equation (2) is the New Keynesian Phillips Curve (NKPC),

$$\pi_t = \beta E_t\left[\pi_{\{t+1\}}\right] + \kappa x_t \tag{2}$$

relates current inflation π_t to expected future inflation and the output gap. The parameter β represents the household discount factor, capturing the forward-looking nature of price setting, while κ measures the degree of price rigidity and reflects the responsiveness of inflation to real economic activity under staggered price adjustment.

In Equation (3), monetary policy is commonly represented by a Taylor-type interest rate rule,

$$i_t = \rho i_{\{t-1\}} + (1 - \rho)(\varphi_\pi \pi_t + \varphi_x x_t) + \varepsilon_t^i \tag{3}$$

which specifies how the central bank sets the nominal interest rate in response to deviations of inflation and output from their target levels. The parameter ρ captures interest rate smoothing, while φ_π and φ_x denote the policy response coefficients to inflation and the output gap, respectively. The term ε_t^i represents an exogenous monetary policy shock.

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The appeal of New Keynesian DSGE (NK-DSGE) models lies in their internal consistency, formal analytical structure, and strong microfoundations. Aggregate macroeconomic outcomes emerge from intertemporal optimization by forward-looking agents subject to clearly specified constraints, providing a coherent framework for normative policy analysis. Within this structure, policy experiments can be conducted in a controlled and transparent manner, allowing researchers and central banks to evaluate the transmission of monetary policy shocks to key macroeconomic variables such as output and inflation. Influential applications, such as Smets and Wouters (2007), illustrate how NK-DSGE models have been employed for forecasting and policy evaluation in central banking practice.

Estimation techniques commonly used in the DSGE literature are well established and contribute to the practical relevance of these models. These include calibration[1], Bayesian estimation[2], and moment-based approaches such as the Generalized Method of Moments (GMM)[3]. Together, these estimation strategies have enabled NK-DSGE models to be empirically implemented and systematically evaluated, reinforcing their prominence in applied macroeconomic and monetary policy analysis.

Despite these advantages, NK-DSGE models have been widely criticized for their simplifying assumptions. In particular, the representative agent framework abstracts from heterogeneity in income, preferences, and access to financial markets, while rational expectations imply near-perfect foresight and instantaneous coordination among agents. As a result, these assumptions limit the ability of NK-DSGE models to account for uncertainty, learning, bounded rationality, and distributional effects.

These limitations have been highlighted not only in academic critiques but also by policymakers. Blanchard (2018) argues that standard DSGE models rely on overly restrictive assumptions—particularly regarding rational expectations and inflation dynamics—and failed to adequately capture the financial frictions and nonlinearities revealed during the Global Financial Crisis. While not rejecting the DSGE framework, he advocates a more flexible and less insular approach in which DSGE models are complemented by alternative frameworks and reduced-form tools, such as IS-LM and policy models, capable of incorporating richer behavioral and institutional features without sacrificing analytical tractability. In this context, growing attention has shifted toward alternative approaches, most notably Agent-Based Models (ABMs), which allow for greater behavioral realism, structural heterogeneity, and non-equilibrium adjustment processes (Fagiolo & Roventini 2017).

3 Agent-Based Macroeconomic Models: Foundations and Comparison with DSGE

Agent-Based Models (ABMs) offer a bottom-up, process-driven alternative to the equilibrium-centric structure of DSGE models. Rather than assuming convergence to a rational expectations equilibrium, ABMs represent the economy as an evolving system of heterogeneous, boundedly rational agents—such as households, firms, banks, and governments—who interact using simple heuristics and limited information. Rooted in behavioral and evolutionary economics,

[1] Calibration fixes structural parameters using external empirical evidence or steady-state targets and evaluates the model's quantitative implications. For a recent central-bank-style application of calibrated DSGE models, see Hlédik et al. (2024).
[2] Bayesian estimation combines the likelihood implied by the DSGE model with prior information on parameters to obtain posterior distributions and perform model comparison. A standard reference is Herbst and Schorfheide (2016), Bayesian Estimation of DSGE Models (Princeton University Press).
[3] GMM estimation matches theoretical moments generated by the DSGE model to empirical moments computed from the data and is particularly useful when full-information likelihood methods are difficult to implement. See Ruge-Murcia (2013).

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this framework emphasizes adaptation, learning, path dependence, and rule-based decision-making instead of intertemporal optimization, allowing macroeconomic outcomes to emerge endogenously from decentralized interactions rather than being imposed by equilibrium conditions.

A central strength of ABMs lies in their ability to capture disequilibrium dynamics, structural change, and nonlinear feedback mechanisms, as shocks—such as firm bankruptcies or bank failures—can propagate through production, credit, or financial networks, generating contagion effects and system-wide disruptions. Importantly, large macroeconomic fluctuations may arise endogenously within this framework, without the need for large or repeated exogenous shocks. From a computational perspective, ABMs rely on simulation-based methods to generate distributions of possible economic trajectories, and model validation therefore emphasizes the replication of key stylized empirical facts—such as firm size distributions, unemployment dynamics, income inequality, and output volatility—rather than likelihood-based estimation or equilibrium fit, which remain central to DSGE models (Cincotti et al. 2022, Napoletano 2018).

A key distinction between ABMs and DSGE models concerns the treatment of agent behavior, as DSGE frameworks assume fully rational, forward-looking agents with complete model knowledge, whereas ABMs adopt bounded rationality and adaptive learning (Levine et al. 2013), with agents following empirically motivated rules that generate aggregate regularities as emergent properties of decentralized interaction rather than as outcomes of explicit intertemporal optimization. As a consequence, ABMs are inherently nonlinear and capable of producing endogenous macroeconomic fluctuations, including herd behavior, boom–bust cycles, and systemic risk, while DSGE models typically rely on linearization around a steady state and analyze responses to exogenous disturbances, a feature that can constrain their ability to represent crisis dynamics, amplification effects, and regime shifts.

These differences extend to the modeling of economic policy, as in DSGE frameworks monetary and fiscal policies are typically specified as forward-looking rules that agents internalize and respond to optimally, whereas in ABMs policy interventions modify the environment in which agents operate, and responses depend on local heuristics and institutional constraints, thereby enabling the analysis of uneven policy transmission, credit rationing, targeted interventions, and macroprudential regulation. Overall, DSGE models offer analytical clarity, internal consistency, and well-established estimation techniques, making them particularly valuable for normative policy analysis, while ABMs provide greater flexibility in capturing heterogeneity, structural complexity, and systemic instability; for these reasons, ABMs are increasingly viewed as a complementary framework capable of enriching macroeconomic policy analysis alongside traditional DSGE models (Cincotti et al. 2022).

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Table 1: Key Methodological Differences between DSGE and AB Models

Dimension	DSGE Models	AB Models
Microfoundations	Built on utility/profit maximization under rational expectations.	Based on empirical behavior and bounded rationality with heuristic rules.
Expectations	Rational expectations—agents forecast perfectly within the model.	Adaptive or rule-based expectations; agents may imitate or learn over time.
Equilibrium	Assumes market-clearing equilibrium; deviations are temporary.	Allows disequilibrium states, including persistent unemployment or gluts.
Shocks and Dynamics	Exogenous shocks drive deviations from the steady state; dynamics are often linearized.	Endogenous dynamics; complex behavior emerges from agent interaction.
Policy Modeling	Policies embedded via fixed rules (e.g., Taylor rule); agents respond optimally.	Policies affect the environment; agents respond heterogeneously and often sub-optimally.
Solution Method	Solved analytically or numerically via equilibrium paths.	Solved through simulations and Monte Carlo experiments.
Validation Focus	Emphasis on internal consistency, analytical clarity, and fit to macro aggregates.	Focus on replicating stylized facts at both macro and micro levels.
Strengths	Normative policy analysis, clarity, and tractability.	Realism, heterogeneity, and suitability for complex/crisis scenarios.
Weaknesses	Unrealistic assumptions; limited crisis modeling.	Harder to calibrate and interpret; computationally intensive.

Source: Author generated

4 Recent Applications of ABMs in Monetary Policy

Macroeconomic models serve multiple purposes, among which monetary policy analysis and financial stability assessment are particularly central to central banking. In recent years, central banks have increasingly incorporated Agent-Based Models (ABMs) into their analytical toolkits as complementary frameworks to equilibrium-based models, particularly following the Global Financial Crisis (Borsos et al. 2025, Fagiolo & Roventini 2017). This shift reflects the recognition that ABMs are well suited to capturing heterogeneity, network interconnections, and nonlinear feedback mechanisms that are difficult to represent within representative-agent DSGE structures (Tesfatsion 2006, Fagiolo & Roventini 2017).

4.1 Central Bank Adoption and Institutional Integration

Several central banks have integrated ABMs into financial stability and macroprudential analysis. The Bank of England developed an agent-based housing market model to evaluate loan-to-value and loan-to-income regulations (Baptista et al. 2016), while network-based and stock-flow consistent ABMs have been used to study financial contagion and balance-sheet interdependencies following the crisis (Caiani et al. 2016, Haldane & May 2011). These applications highlight the capacity of ABMs to simulate interconnected balance sheets, leverage cycles, and shock propagation across financial and real sectors.

More broadly, ABMs model economies as systems of interacting heterogeneous agents operating across interconnected markets (Tesfatsion 2006, LeBaron & Tesfatsion 2008), making them well suited to capturing nonlinear feedback, sudden shocks, and contagion dynamics (Geanakoplos et al. 2012, Haldane & May 2011) that are difficult to represent within equilibrium-based frameworks (Fagiolo & Roventini 2017). Central banks have applied these models to analyze flash crashes, leverage cycles, investor behavior, and the systemic transmission of shocks (Bookstaber 2017, Caccioli et al. 2014), as well as to test

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macroprudential tools such as circuit breakers, capital requirements, and risk limits (Bardoscia et al. 2024, Borsos et al. 2025).

Despite substantial data and computational demands, advances in computing power, granular data, and modeling techniques have improved scalability and feasibility (Dosi et al. 2019, Poledna et al. 2023), expanding the range of policy applications (Borsos et al. 2025, Axtell & Farmer 2025). As documented by Borsos et al. (2025), ABMs have become integral to central banks since the 2007–2009 crisis, evolving from interbank network models to frameworks incorporating multilayer financial exposures, including interbank lending, foreign exchange positions, and portfolio investments.

Applications extend to housing markets and real-sector spillovers (Baptista et al. 2016), with country-specific models for Brazil, Hungary, and Uruguay assessing household and firm distress (Borsos et al. 2025), and housing market ABMs developed at the Bank of England and later adapted in Denmark, Italy, and Hungary evaluating loan-to-value and loan-to-income limits and their macroeconomic implications (Bardoscia et al. 2024, Mérő et al. 2023). Beyond these areas, ABMs increasingly address emerging policy challenges such as climate-related risks and central bank digital currencies (CBDCs), with institutions including the International Monetary Fund using simulation-based frameworks to assess systemic vulnerabilities under alternative monetary and regulatory scenarios (Gross & Letizia 2023, Borsos et al. 2025). Their flexibility allows the integration of heterogeneous balance sheets, institutional detail, and adaptive behavior, making them particularly suitable for complex and evolving policy environments (Fagiolo & Roventini 2017).

4.2 ABMs in Macroeconomic Forecasting and Crisis Analysis

Empirical evidence indicates that large-scale ABMs can generate competitive macroeconomic forecasts relative to econometric and DSGE models. Poledna et al. (2023) develop a detailed ABM calibrated to Austrian and euro area data and show that it matches or outperforms VAR, VECM, and DSGE benchmarks in long-horizon GDP and inflation forecasting, particularly during instability. During the COVID-19 crisis, the model anticipated a six percent GDP contraction and identified sectoral vulnerabilities. Similarly, Hommes and Poledna (2023) demonstrate that incorporating adaptive learning and financial frictions improves forecasting performance during the Global Financial Crisis and the COVID-19 recession, with superior results for GDP, inflation, and interest rates. These findings suggest that micro-level interactions and nonlinear propagation mechanisms can generate empirically realistic macroeconomic dynamics.

Beyond forecasting, ABMs have been applied to inflation dynamics, monetary–fiscal interactions, and systemic disruptions such as the COVID-19 shock (Dosi et al. 2020, Caiani et al. 2016). Their explicit treatment of balance sheets, networks, and adaptive behavior makes them particularly suitable for analyzing macrofinancial linkages and crisis dynamics (Schasfoort et al. 2021, Assenza et al. 2021). While early macroeconomic ABMs lacked explicit central bank representation (Caiani et al. 2016), recent models incorporate rule-based monetary policy and unconventional instruments. Assenza et al. (2021) introduce a central bank operating under a Taylor rule with quantitative easing activated when unemployment exceeds a threshold, finding that proactive QE reduces the frequency and severity of crises relative to reliance on conventional rate rules alone. Schasfoort et al. (2021) extend the stock-flow consistent framework of Caiani et al. (2016) to model interest rate transmission through bank lending, investment, and consumption, showing that monetary effects are modest, nonlinear, and strongly shaped by heterogeneity and sectoral feedback.

Further advancements include Peters et al. (2022), who introduce Mak(h)r0, a macroeconomic ABM developed within the ML3 continuous-time framework. The model comprises households, firms, banks, central banks, and government agents governed by heuristic rules, featuring endogenous money creation, reserve requirements, Basel III capital constraints, macroprudential regulation, and a Taylor-rule-based interest rate corridor. Calibration relies on sensitivity analysis and Plackett–Burman design, with validation against OECD U.S. business cycle data. Simulated over 600 quarterly periods with multiple replications, Mak(h)r0 provides high-resolution insights into monetary transmission and macrofinancial stability.

The Austrian ABM of Poledna et al. (2023) incorporates heterogeneous households and firms across more than sixty industries, banks, government, a central bank, and a foreign sector interacting through decentralized markets. Expectations follow adaptive AR(1) learning, yielding a Behavioral Learning Equilibrium. Goods markets operate via search-and-match mechanisms, credit markets through risk-based lending and Basel-type constraints, and monetary policy follows a Taylor rule alongside fiscal transfers. Calibrated with Eurostat micro- and macro-data and simulated at 1:1 scale over 500 quarters, the model captures nonlinear feedback from bankruptcies to employment and credit availability and outperforms standard forecasting benchmarks.

Hommes and Poledna (2023) develop a stock-flow consistent euro area ABM integrating heterogeneous agents, financial frictions, and adaptive learning. The model includes a financial accelerator, VARX (1)-based learning, borrowing constraints tied to balance sheets, and a Taylor rule augmented by learning dynamics. It generates endogenous crises and persistent downturns without large exogenous shocks and outperforms DSGE and VAR models during major crises, capturing slow recoveries and sector-specific vulnerabilities.

4.3 ABM Applications for Emerging Policy Challenges

ABMs are increasingly used to evaluate the macrofinancial implications of central bank digital currencies (CBDCs) (Gross & Letizia 2023, Infante & Saez 2023). Policy-oriented studies by institutions such as the International Monetary Fund, De Nederlandsche Bank, and the Bank of Italy demonstrate how agent-based frameworks assess payment behavior, financial intermediation, and distributional effects under alternative digital currency designs (Gross & Letizia 2023, Barucci et al. 2025).

Recent methodological advances have further expanded the scope of ABMs in monetary policy (Borsos et al. 2025). Hungary's development of a large-scale 1:1 agent-based model based on granular microdata reflects increasing empirical resolution and institutional realism (Mérő et al. 2023), while machine learning techniques have been introduced to improve calibration and behavioral modeling, including applications at the Bank of Italy (Delli Gatti & Grazzini 2020). In parallel, central banks—including the IMF, the Bank of Italy, and the Bank of England—are integrating artificial intelligence methods, particularly reinforcement learning, to model adaptive behavior and policy learning (Catullo et al. 2017, Borsos et al. 2025), enhancing scalability and realism.

Beyond traditional objectives such as price and financial stability, ABMs address emerging policy challenges including CBDC design (Gross & Letizia 2023), non-bank financial intermediation, distributional inequality (Caiani et al. 2016), climate-related risks (Lamperti et al. 2019), adaptive macrofinancial dynamics (Catullo et al. 2017, Borsos et al. 2025), and geopolitical uncertainty (Borsos et al. 2025, Axtell & Farmer 2025). Their flexibility allows the

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integration of institutional detail and heterogeneous sectoral responses (Fagiolo & Roventini 2017).

5 Discussion

A critical reflection on models such as EURACE and EURACE@Unibi highlights a fundamental trade-off in contemporary macroeconomic modeling (Lengnick 2013, Dawid et al. 2012). These agent-based frameworks offer substantial flexibility in representing complex system dynamics, heterogeneous behavior, and decentralized interactions, as their open-ended architecture allows macroeconomic outcomes to emerge endogenously from micro-level interactions, making them particularly well-suited for studying feedback mechanisms and structural change. However, this flexibility comes at a cost, since the outcomes generated by ABMs are often highly sensitive to assumptions regarding agent behavior, market structure, and institutional design. While such sensitivity enables the generation of rich and nonlinear dynamics, it can also introduce model-specific biases and limit the generalizability of results across economic contexts. As a consequence, the behavioral rules embedded in ABMs are frequently subject to scrutiny, especially when they lack strong empirical grounding or clear theoretical discipline.

In contrast, New Keynesian DSGE (NK-DSGE) models adopt a more rigid, theory-driven structure rooted in rational expectations and intertemporal optimization, a framework that enhances internal consistency and facilitates transparent welfare-based policy evaluation. Over time, NK-DSGE models have evolved to address some of their earlier empirical limitations, as recent studies incorporate Markov-switching regimes to capture changes in fiscal or monetary policy stances (Jin & Xiong 2021, Alstadheim et al. 2013), thereby allowing for nonlinear responses to structural shifts. Moreover, DSGE frameworks have expanded to include richer interactions between monetary and fiscal policy. Omotosho (2019) presents a model for oil-exporting economies with Ricardian and non-Ricardian households, examining how monetary policy interacts with fiscal instruments such as debt, fuel subsidies, and oil revenue management. These mechanisms influence exchange rates, inflation, and overall macroeconomic stability, and provide a more institutionally grounded perspective than many early DSGE or ABM formulations.

A practical illustration of this evolution is provided by the Czech National Bank’s modeling framework, which progressed from the model in Andrle et al. (2009) to the updated G3+ model (Bruzda et al. 2023). The latter introduces a structural foreign economy block to better capture external shocks, incorporates oil as a production input, and distinguishes between heterogeneous households—savers and non-savers—with habit formation in consumption. Investment dynamics are linked to foreign demand, and a formal convergence mechanism models long-run alignment with the euro area.

Forecasting performance is further enhanced by relaxing the assumption of full information, allowing agents to operate under informational constraints. These developments improve both realism and policy relevance, underscoring that contemporary DSGE models differ substantially from the simplified structures often criticized in earlier literature. Accordingly, assessments of DSGE performance should account for this methodological progress.

Despite these advances, NK-DSGE models continue to abstract from certain dimensions of economic behavior, including bounded rationality, financial instability, and sectoral contagion—areas in which ABMs have clear comparative advantages. The core trade-off thus lies between the analytical clarity, discipline, and interpretability of DSGE models and the flexible realism and adaptability of ABMs.

It is also important to acknowledge that although ABMs were under development prior to the 2008 financial crisis, they did not anticipate the crisis, raising concerns about their empirical maturity and institutional readiness at the time. This limitation, however, was not unique to ABMs. NK-DSGE models of that period also lacked adequate representations of financial sector dynamics and systemic risk, limiting their usefulness for real-time policy surveillance.

In the aftermath of the crisis, ABMs have gained prominence not only because of their capacity to model heterogeneity, financial frictions, and adaptive learning, but also due to a broader recognition of the need for frameworks capable of capturing nonlinear, evolving system-wide interactions. Advances in data availability, computational power, and institutional engagement have further supported their development.

This paper contributes to the ongoing methodological debate by offering a structured comparison between DSGE and ABM frameworks, moving beyond abstract theoretical critiques to examine their operational logic, foundational assumptions, and implications for monetary policy. Rather than advocating for the replacement of one approach with another, the analysis emphasizes their complementary roles in policy practice. By situating both modeling traditions within real-world central banking applications, the study clarifies how different tools can be deployed to address contemporary macroeconomic challenges involving heterogeneity, systemic risk, and nonlinear dynamics.

6 Illustrative Simulation: Monetary Tightening Shock

To provide a practical illustration of the theoretical differences discussed, this section presents a simple simulation contrasting the responses of a standard NK-DSGE model and a stylized ABM to a common monetary tightening shock[4]. The simulation is not intended for empirical validation but to highlight the qualitative and quantitative differences in shock propagation that arise from the models' distinct structural assumptions, directly addressing the reviewer's suggestion to enhance the paper's novelty.

6.1 Model Setup

New Keynesian Model: A standard three-equation New Keynesian framework (Section 1, Equations 1–3) calibrated using benchmark values from the literature: $\sigma = 1$, $\beta = 0.99$, $\kappa = 0.10$, and Taylor rule coefficients $\varphi_\pi = 1.5$ and $\varphi_x = 0.5$ (Clarida et al. 1999, Galí 2015). The monetary policy shock persistence is set to $\rho_\varepsilon = 0.60$ (Smets & Wouters 2007). Unemployment dynamics are derived using a stylized Okun's Law coefficient of 0.5 (Ball et al. 2017).

Agent-Based Model: A stylized ABM incorporating heterogeneous agents, bounded rationality, and financial frictions (Assenza et al. 2021, Caiani et al. 2016). Median impulse responses are calibrated to be qualitatively and quantitatively consistent with large-scale ABMs that explicitly model monetary transmission channels (Poledna et al. 2023, Schasfoort et al. 2021), with output and unemployment amplification factors set to 1.85× and 2.20×, respectively. Uncertainty bands (16th–84th percentiles) are computed from 300 Monte Carlo replications of a simplified heterogeneous-agent simulation (Lengnick 2013, Caiani et al. 2016).

[4] The full Python replication code for the simulation, including calibration parameters, Monte Carlo replications (300 runs), and figure generation routines, is publicly available at: https://gist.github.com/NourSafar2024/617fbfc5d25588ffe18a8086fa6498d9

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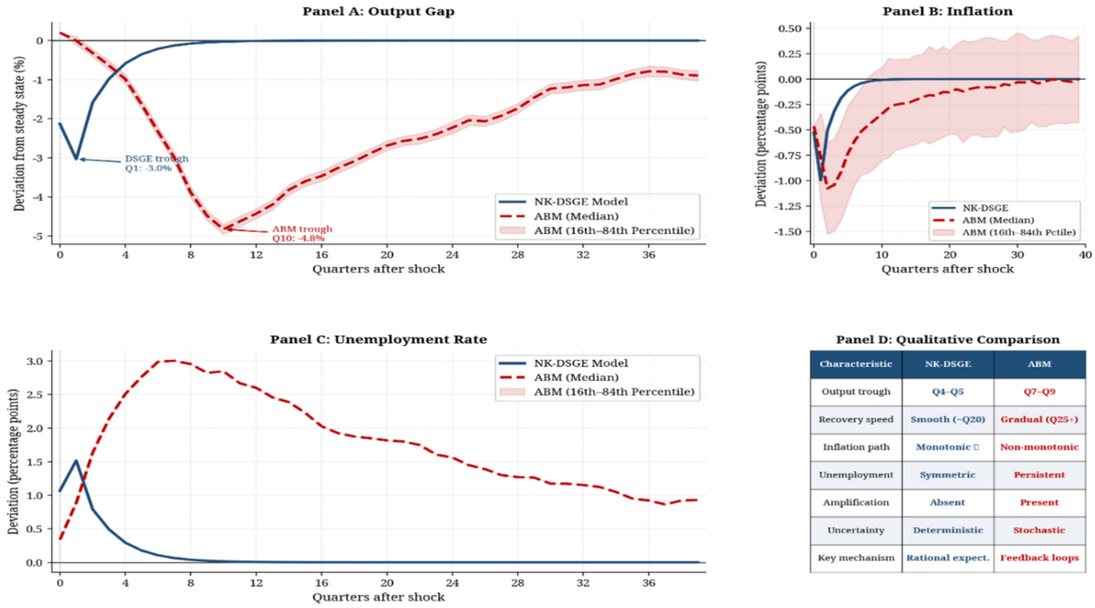
6.2 Simulation Results and Interpretation

Both models are subjected to an unexpected 100-basis-point (1%) contractionary monetary policy shock. The resulting impulse response functions (IRFs) for the output gap, inflation, and unemployment are presented in Figure 1.

Figure 1: Impulse Response Functions to a 100-Basis-Point Monetary Tightening Shock New Keynesian DSGE Model vs. Agent-Based Macroeconomic Model



Characteristic	NK-DSGE	ABM
Output trough	Q4–Q5	Q7–Q9
Recovery speed	Smooth (~Q20)	Gradual (Q25+)
Inflation path	Monotonic □	Non-monotonic
Unemployment	Symmetric	Persistent
Amplification	Absent	Present
Uncertainty	Deterministic	Stochastic
Key mechanism	Rational expect.	Feedback loops

Notes: DSGE model: three-equation New Keynesian framework (Galí, 2015; Clarida et al., 1999) with $\sigma = 1$, $\kappa = 0.1$, $\beta = 0.99$, $\varphi\_\pi = 1.5$, $\varphi\_x = 0.5$, $\rho = 0.75$, $\rho\_\varepsilon = 0.60$. Unemployment derived via Okun's Law (coefficient = 0.5; (Ball et al., 2017). ABM median calibrated to findings in Schasfoort et al. (2021), Poledna et al. (2023), and Assenza et al. (2021). Uncertainty bands from 300 replications of a simplified heterogeneous agent model (Lengnick 2013, Caiani et al. 2016).

As shown in Panel A, the two frameworks produce markedly different output responses. The NK-DSGE model generates a smooth, hump-shaped response, with the output gap reaching a trough of -3.0% in the first quarter before rapidly returning toward the steady state. This behavior is driven by the efficient, forward-looking adjustments of the representative agent. In contrast, the ABM exhibits a deeper and more persistent downturn. The output trough is nearly twice as deep (4.8%) and occurs much later (at quarter 10). The recovery is also significantly slower, with the output gap remaining substantially negative even after 20 quarters. This amplification and persistence are hallmarks of the ABM, arising from feedback loops between firm bankruptcies, credit constraints, and falling household income.

These differences are also reflected in the inflation and unemployment dynamics. In the DSGE model, inflation (Panel B) declines monotonically, and unemployment (Panel C) rises symmetrically with the output gap, peaking at 1.5 percentage points. The ABM, however, produces a non-monotonic inflation path and a much larger and more persistent increase in unemployment, which peaks at 3.0 percentage points. The shaded area around the ABM median response highlights the model's inherent uncertainty, a feature absent in the deterministic DSGE framework.

The underlying drivers of these divergent responses are illustrated in Figure 2, which contrasts the monetary policy transmission mechanisms in each model.

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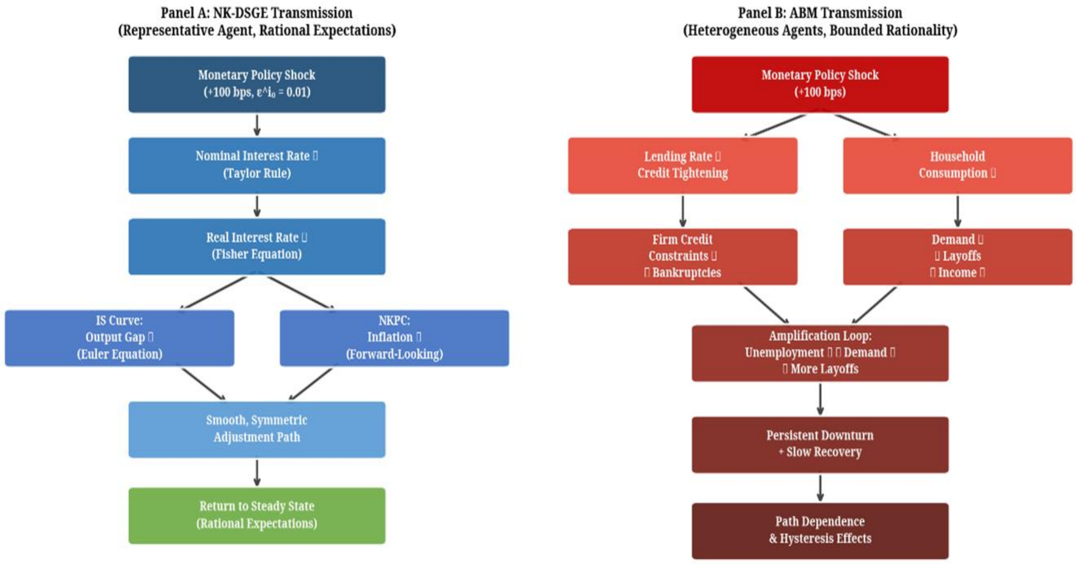
Figure 2: Monetary Policy Transmission Mechanisms: NK-DSGE vs. ABM



Source: own

The DSGE transmission mechanism (Panel A) is linear and primarily driven by intertemporal substitutions. The policy rate increase raises the real interest rate, inducing the rational representative agent to postpone consumption, which smoothly opens a negative output gap and lowers inflation. The ABM transmission (Panel B) is far more complex and nonlinear. The initial shock is amplified through multiple channels, including credit tightening, which leads to firm bankruptcies and layoffs. This, in turn, reduces household income and aggregate demand, creating a powerful feedback loop that deepens and prolongs the downturn. These mechanisms—absent in the standard DSGE framework—are crucial for explaining the deeper recession, persistent unemployment, and slower recovery observed in the ABM simulation.

In summary, this illustrative exercise demonstrates how the foundational assumptions of each framework lead to fundamentally different conclusions about the macroeconomic impact of monetary policy, reinforcing the argument that DSGE and ABM approaches offer complementary, rather than competing, insights for policy analysis.

Conclusion

This paper has provided a structured and policy-oriented comparison of New Keynesian Dynamic Stochastic General Equilibrium (NK-DSGE) models and Agent-Based Models (ABMs), demonstrating that they operate as complementary rather than competing tools in modern macroeconomic policy analysis. Drawing on a systematic review of their theoretical foundations, methodological assumptions, and recent empirical applications, and supported by an illustrative monetary policy simulation, the study clarifies how each framework contributes differently to understanding monetary transmission, crisis dynamics, and policy effectiveness. Rather than framing the debate as a methodological rivalry, the analysis shows that model choice depends fundamentally on the nature of the policy question, the institutional context, and the degree of systemic complexity under consideration.

Three central findings emerge. First, ABMs demonstrate a measurable forecasting and crisis-analysis advantage during periods of instability, particularly when nonlinear interactions, financial frictions, and heterogeneous balance sheets play a decisive role. Empirical evidence indicates that large-scale agent-based models can match or outperform traditional econometric and DSGE benchmarks in long-horizon forecasting during major disruptions. The Austrian model of Poledna et al. (2023) anticipated a six percent GDP contraction during the COVID-19 crisis, while Hommes and Poledna (2023) report superior performance relative to DSGE and VAR models in forecasting GDP and inflation during both the Global Financial Crisis and the COVID-19 recession. Second, DSGE models remain indispensable for normative and welfare-based policy evaluation due to their internal consistency, optimization-based discipline, and transparent equilibrium structure.

However, their reliance on representative agents and equilibrium assumptions creates blind spots in distributional analysis and crisis amplification. This limitation is illustrated in the simulation exercise, where the ABM generates a recession nearly twice as deep (−4.8% versus −3.0%) and significantly more persistent than the DSGE counterpart, reflecting amplification mechanisms absent in standard NK-DSGE specifications. Third, methodological progress within DSGE modeling—incorporating financial frictions, regime-switching mechanisms, and richer institutional detail—confirms that reform, rather than abandonment, remains the appropriate response. This conclusion echoes Blanchard's (2018) critique that DSGE models rely on restrictive assumptions—particularly rational expectations and insufficient inflation dynamics—but should be reformed to incorporate greater behavioral and institutional realism rather than rejected outright.

These results support a dual-toolkit strategy in which DSGE models are employed for baseline projections, rule evaluation, welfare analysis, and structured counterfactual exercises, while ABMs are deployed for stress-testing financial stability, modeling non-equilibrium dynamics, analyzing heterogeneous transmission channels, and capturing crisis amplification mechanisms. For central banks such as the Czech National Bank, integrating a complementary medium-scale ABM alongside existing DSGE infrastructures would strengthen analysis of housing markets, household heterogeneity, and macrofinancial linkages. For international institutions such as the International Monetary Fund, investment in scalable cross-country ABM frameworks would enhance systemic risk monitoring and the evaluation of emerging challenges, including financial contagion, climate transition risks, and digital currency adoption.

Although this study remains a qualitative comparative assessment rather than a formal meta-analysis or direct empirical horse race, it underscores the need for standardized validation protocols and hybrid DSGE–ABM frameworks that integrate micro-founded discipline with heterogeneous-agent realism. Recent crises have demonstrated that no single modeling paradigm can fully capture the evolving complexity of modern economies. A pluralistic methodological strategy—combining the analytical rigor of reformed DSGE models with the nonlinear and systemic realism of ABMs—offers a more robust and institutionally resilient foundation for macroeconomic policy analysis.

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