

AGENT-BASED MODELING IN ECONOMICS AND FINANCE: A SIMPLE CRYPTOCURRENCY MARKET

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Abstract: *This paper discusses the methodological relevance of agent-based modeling and simulation (ABMS) in economics and finance and illustrates its analytical value through a simple cryptocurrency market model implemented in NetLogo. The paper first reviews the core principles of ABMS, emphasizing heterogeneous agents, bounded rationality, local interaction, endogenous dynamics and macro-level emergence. It then summarizes the role of ABMS in economic analysis, macroeconomic forecasting, financial market dynamics, systemic risk assessment and cryptocurrency research. In the empirical part, a regime-dependent agent-based model with fundamentalists and non-fundamentalists is used to simulate Bitcoin market dynamics under alternative specifications. The model is driven by macro-fundamental, crypto-fundamental and sentiment signals and validated against the historical Bitcoin price path and stylized facts of returns. The results show that the stabilized noBTC specification achieves the best compromise between price-path accuracy and regime stability, while the reproduction of stylized facts remains only partial. In particular, the simulations capture the lack of return autocorrelation fairly well, but volatility clustering, excess kurtosis and skewness remain weaker than in the benchmark study and in the empirical Bitcoin series. The findings support the view that ABMS is a useful complement to standard analytical and econometric models, especially when interactions, nonlinearities and institutional details are central to the problem under study.*

Key words: *agent-based modeling, heterogeneous agents, cryptocurrency market, herding, stylized facts, sentiment analysis*

JEL classification: *C63, G12, G17, G41*

1. INTRODUCTION

Agent-based modeling and simulation (ABMS) has become one of the most important computational approaches for the study of complex economic and financial systems. Instead of imposing aggregate outcomes from the top down, ABMS explains macro-level patterns from the bottom up, through the behavior and interaction of many heterogeneous agents embedded in an explicit environment. In this sense, ABMS complements standard mathematical and econometric approaches whenever realism, local interaction, institutional structure, and path dependence are more important than analytical tractability (Axtell and Farmer, 2022).

The growing relevance of ABMS is linked to several developments. First, the approach allows researchers to relax strong assumptions common in representative-agent frameworks, including perfect rationality, complete information, and instantaneous market clearing. These advantages are particularly salient in cryptocurrency markets, where speculative behavior, information asymmetry, and extreme volatility often deviate from traditional market efficiency. Second, it is particularly well suited to systems in which aggregate regularities are emergent outcomes

rather than direct implications of a closed-form equilibrium. Third, improvements in computing power and the availability of richer data have made it possible to move from simple theoretical models toward more empirically grounded simulations (Poledna et al., 2023).

The purpose of this paper is twofold. The first objective is to provide a concise, literature-based discussion of the methodological importance of ABMS in economics and finance. The second is to illustrate this importance through a simple cryptocurrency market model, implemented in the NetLogo environment, using a comprehensive dataset of daily observations spanning from 2018 to early 2025.

In this empirical illustration, heterogeneous agents interact under alternative bull and bear market regimes. The model is driven by a multi-channel signal structure, including macro-fundamental, crypto-fundamental, and non-fundamental sentiment signals derived from the Crypto Fear and Greed framework. To ensure a robust analysis, the paper compares three alternative specifications, OLD, NOBTC, and STABLE_NOBTC, with a focus on preserving a clean validation against the historical Bitcoin price path. The model's performance is evaluated based on its ability to replicate the historical price trajectory and key stylized facts of returns, such as the absence of autocorrelation, volatility clustering, and excess kurtosis. The application of artificial financial markets to study Bitcoin trading has proven effective in identifying the impact of trader heterogeneity on price formation (Cocco et al., 2019). This study builds upon such frameworks by introducing a dual-signal mechanism to test the robustness of these dynamics under different market regimes.

To provide a comprehensive analysis, this study first outlines the theoretical landscape of agent-based modeling in Section 2, followed by a detailed description of the model's architecture in Section 3. The empirical evaluation and discussion of results are presented in Section 4, while concluding remarks and future research directions are provided in the final section.

2. AGENT-BASED MODELING AND SIMULATION IN ECONOMICS AND FINANCE

2.1. CORE PRINCIPLES OF ABMS

At its core, ABMS relies on three elements: agents, environment and interaction rules. Agents may represent households, firms, banks, miners, investors or regulators. They are explicitly heterogeneous and can differ in resources, expectations, decision heuristics, information sets,

learning capacity and network positions. The environment may consist of one or more markets, a spatial or network structure, institutions and exogenous processes. Interactions can be direct or indirect, centralized or decentralized, synchronous or asynchronous, and they are the main channel through which macro-dynamics emerge from micro-decisions (Turrell, 2016).

A crucial epistemological property of ABMS is emergence. Aggregate variables such as production, unemployment, volatility, price bubbles or systemic stress are not imposed *ex ante*. Instead, they arise from repeated interactions among agents and from feedback between agents and their environment. This property makes ABMS especially useful for the analysis of complex adaptive systems in which history matters, nonlinearity is pervasive, and small shocks may propagate into large macroeconomic consequences (Axtell and Farmer, 2022).

Another defining feature is bounded rationality. ABMS does not require every agent to solve an intertemporal optimization problem under fully rational expectations. Agents can use heuristics, local information, adaptive learning or imitation rules. This flexibility is important because it allows the modeler to represent empirically plausible behavior, specifically by distinguishing between agents who follow fundamental signals and those driven by market sentiment or trend-following heuristics, without sacrificing the possibility of studying market-level consequences. In finance, simple strategies such as trend following, liquidity provision, imitation and sentiment-driven trading can already generate important stylized facts of price dynamics (Wang et al., 2018). Furthermore, as digital asset markets lack traditional valuation anchors, the reliance on such behavioral heuristics and sentiment-driven signals, such as the Fear and Greed Index, becomes a defining driver of aggregate volatility. By incorporating dual fundamental signals, the model distinguishes between 'true' and 'spurious' herding, thereby isolating the effects of social imitation from synchronized agent responses to common informational shocks (Bokhari, 2025).

2.2. WHY ABMS MATTERS FOR ECONOMICS AND FINANCE

In economics, ABMS is important because it provides a natural way to model economies as systems of interacting, heterogeneous units. This matters in industrial organization, labor markets and macroeconomics, where the distribution of firm size, the propagation of shocks, or financial constraints depend on heterogeneity and interaction rather than on a single representative decision maker. Axtell and Farmer (2022)

emphasize that ABMS allows economists to move from idealized assumptions toward more realistic settings with many agents, distributed information, and path-dependent adjustment.

In finance, the relevance of ABMS is even more pronounced. Financial markets are archetypal complex systems: they contain heterogeneous traders, adaptive strategies, feedback loops and abrupt regime changes.

ABM studies have been particularly successful in explaining clustered volatility, fat-tailed return distributions, and systemic fragility, as well as in providing experimental environments—such as the NetLogo-based simulation developed in this paper—for the study of market design and behavioral interventions (Wang et al., 2018). For

central banking and regulation, this is valuable because it makes it possible to study how local disturbances propagate through networks instead of assuming instantaneous equilibrium (Turrell, 2016).

The established literature on agent-based modeling emphasizes that the generative power of ABMS lies in its ability to replicate regime-switching behavior and heavy-tailed distributions through the interplay of fundamentalist and non-fundamentalist agents (Hommes, 2006; Lee and Lee, 2015).

Building on these foundations, more recent studies focus on addressing structural instability to allow for a more robust empirical calibration (Baumann et al., 2023).

Table 1. Key contributions of ABMS in economics and finance

Domain	Representative contribution	Main insight	Implication
Micro and industrial economics	Axtell and Farmer (2022)	ABMS captures heterogeneous firms, local adjustment and institutional detail.	Useful when aggregate outcomes depend on decentralized interaction rather than representative agents.
Macroeconomics and forecasting	Poledna et al. (2023)	A large-scale ABM can compete with VAR and DSGE benchmarks in out-of-sample forecasting.	ABMS can be relevant not only for explanation but also for quantitative policy analysis.
Financial market dynamics	Wang et al. (2018)	ABMs link investor heterogeneity and interaction to volatility, bubbles and crashes.	Suitable for studying stylized facts and market instability.
Bitcoin and crypto-economics	Cocco and Marchesi (2016)	An ABM can jointly model mining, transactions and price dynamics.	ABMS integrates technical, economic and market mechanisms in one framework.
Crypto herding and regimes	Bokhari (2025)	ABM helps distinguish true from spurious herding across bull and bear regimes.	The framework is well suited for behavioral and sentiment-driven markets.

Source: Prepared by the author based on Axtell and Farmer (2022), Poledna et al. (2023), Wang et al. (2018), Cocco and Marchesi (2016) and Bokhari (2025).

The recent literature also suggests that ABMS is increasingly relevant in new financial environments such as cryptocurrency markets. These markets combine speculative behavior, retail participation, and strong sentiment effects.

As a result, they are difficult to study with conventional valuation-based frameworks alone. Agent-based models can integrate these features explicitly and are therefore especially useful for understanding asymmetric behavior across market regimes, mining incentives, and the complex relation between sentiment signals and price dynamics (Cocco and Marchesi, 2016; Bokhari, 2025).

A significant challenge in this domain is the validation of simulated price paths against historical data while distinguishing between 'true herding' (imitation) and 'spurious herding' (common response to exogenous signals).

By integrating sentiment analysis into agent-based frameworks, researchers can now achieve higher correlation with actual price trajectories (Poledna et al., 2023), providing a more reliable environment for studying market design and behavioral interventions in the cryptocurrency space.

3. A SIMPLE CRYPTOCURRENCY MARKET MODEL

3.1. MODEL STRUCTURE

To illustrate the analytical value of ABMS, this paper uses a simple regime-dependent cryptocurrency market model implemented in NetLogo. The model simulates the dynamics of one crypto-asset in discrete daily time within an environment of 200 agents. Following the established taxonomy of financial market participants (Schmitt et al., 2022), the agent architecture in this study distinguishes between fundamentalists and trend-followers to explain the endogenous dynamics and volatility shifts observed in the simulated environment. Non-fundamentalists update their opinions using social interaction, a private signal, and a non-fundamental sentiment index. Fundamentalists rely on social interaction, a private signal, and two distinct fundamental information signals. In both cases, the active market regime (bull or bear) determines which behavioral coefficients and sensitivities are prioritized.

The economic meaning of the model becomes clearer if the three exogenous channels are separated conceptually. The variable If_1 is a macro-fundamental signal that summarizes broad economic and financial conditions outside the crypto market and therefore plays the role of a slow-moving valuation anchor. The variable If_2 is a crypto-fundamental signal intended to capture information that is common to the wider digital-asset environment but not mechanically identical to the historical Bitcoin series. By contrast, Inf is a non-fundamental sentiment indicator derived from the Crypto Fear and Greed framework and should be interpreted as a proxy for market mood,

speculative appetite and willingness to imitate, rather than as a direct measure of intrinsic value. Regime switching is therefore not an additional signal of the same kind, but a state variable that changes the behavioral weights assigned to social influence, private information and external signals. In economic terms, bull and bear regimes determine how strongly traders react to the same information set.

The core idea is that trading intentions are formed at the micro-agent level and subsequently aggregated into excess demand (D). The model therefore treats prices as emergent outcomes of decentralized interaction rather than as exogenously imposed equilibrium objects. Social influence is captured through ordered weighted averages of group opinions, while private signals are based on the local trend of the simulated log-price. A market-maker mechanism translates the aggregated net demand into price changes using a liquidity parameter (λ). This parameter represents market depth, determining the sensitivity of price adjustments to imbalances in demand. This market-maker architecture, consistent with the framework proposed by Hommes (2006), ensures greater numerical stability during long-term simulations (covering over seven years of daily data) and reduces the computational noise often found in high-frequency order-book benchmarks (Baumann et al., 2023). Furthermore, a regime-dependent volatility process introduces stochastic disturbances and occasional jump effects to reflect the high-risk nature of crypto markets.

The opinion dynamics for non-fundamentalists and fundamentalists are governed by a continuous-time adjustment logic discretized for daily simulations. The update rules are defined as follows:

For non-fundamentalists:

$$x_{i,t+1} = clip \left\{ x_{i,t} + \frac{[-x_{i,t} + \beta_0 \tanh(OWA_{nf,t} + OWA_{f,t}) + \beta_1 b_{i,t} + \beta_2 Inf_t]}{\tau_x} \right\}$$

For fundamentalists:

$$x_{j,t+1} = clip \left\{ x_{j,t} + \frac{[-x_{j,t} + \beta_3 \tanh(OWA_{f,t} + OWA_{nf,t}) + \beta_4 b_{j,t} + \beta_5 If_{1,t} + \beta_6 If_{2,t}]}{\tau_x} \right\}$$

The price formation mechanism is governed by a market-maker who translates the aggregate net demand, defined as $D_t = \sum x_{i,t} + \sum x_{j,t}$, into price changes according to the following log-price equation:

$$\log P_t = \log P_{t-1} + \frac{D_t}{\lambda} + jump_t + \varepsilon_t,$$

$$\varepsilon_t \sim N(0, \sigma_t)$$

In the notation above, x denotes agent opinion, b the private signal, If_1 and If_2 the macro-fundamental and crypto-fundamental signals and Inf the sentiment indicator, while τ_x represents the time constant of opinion adjustment, governing the speed at which agents react to these incoming

signals, social influence, and the stochastic noise component ε .

While the structure follows the general logic of Bokhari (2025), the implementation used here introduces a stabilized noBTC specification for the crypto-fundamental signal (If_2). Such an adjustment ensures that the model's ability to track the Bitcoin price path is a result of underlying fundamental and sentiment drivers rather than a direct correlation with the target variable. Consequently, this approach preserves a cleaner validation and guarantees that the model's performance is not a result of endogenous dependency on the target variable.

3.2. DATA AND INPUT SIGNALS

The empirical configuration of the model utilizes a comprehensive dataset of daily observations spanning from 1 February 2018 to 23 January 2025. The simulation is driven by a structured input file that integrates four primary variables: a macro-fundamental composite signal (If_1), a crypto-fundamental signal (If_2), a non-fundamental sentiment indicator (Inf), and a market regime switch. The If_1 signal serves as a proxy for broader economic conditions, while the Inf component is derived from the Crypto Fear and Greed framework to quantify market psychology. A critical methodological refinement in the final specification is the implementation of a noBTC version of the If_2 signal. By stripping this crypto-fundamental component of direct Bitcoin price data, the model ensures a more rigorous and independent validation process. This approach is designed to prevent endogeneity and prove that the simulated price trajectory emerges from underlying fundamental and sentiment drivers rather than a trivial correlation with the target variable itself.

Three alternative specifications are compared. The OLD specification corresponds to the earlier benchmark model. NOBTC redefines the crypto-fundamental component without direct Bitcoin input, while STABLE_NOBTC adds two stabilization devices. The first is a smoother regime structure with persistence, implemented so that short-lived reversals do not trigger immediate changes between bull and bear states. The second is a conservative volatility-memory mechanism, which allows past price stress to affect current volatility only gradually and within bounded limits. Compared with NOBTC, this lowers the risk of regime chattering and reduces self-reinforcing feedback between optimistic sentiment, rising opinions and explosive price paths. Economically, the stabilized specification does not eliminate endogenous instability; instead, it filters

out very short transient episodes and yields more interpretable market phases.

3.3. EXPERIMENTAL DESIGN AND VALIDATION CRITERIA

To evaluate the impact of structural refinements on simulation accuracy, the research framework compares three alternative specifications. The OLD specification serves as the initial benchmark, representing the model's earlier iteration. The NOBTC version builds upon this by redefining the crypto-fundamental component to eliminate direct dependency on Bitcoin's price history. Finally, the STABLE_NOBTC specification introduces a stabilized regime structure and a conservative volatility-memory mechanism to enhance long-term simulation stability. The performance of these models is validated through a dual-track approach. First, price-path validation assesses the model's ability to replicate the historical log-price of Bitcoin over the seven-year period. Second, the model is tested against the stylized facts of financial returns, ensuring that the simulated data demonstrates an absence of return autocorrelation, significant volatility clustering, and the characteristic excess kurtosis and skewness associated with "fat-tailed" cryptocurrency return distributions.

4. RESULTS AND DISCUSSION

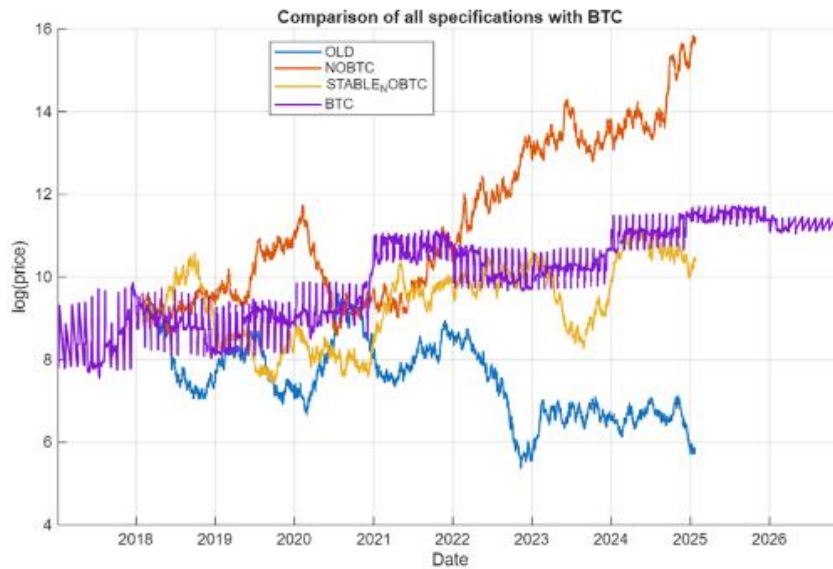
To ensure the reliability of the ABMS, the model's output is evaluated against empirical stylized facts, a standard procedure for the validation of agent-based financial models (Lux and Zwickels, 2018). By replicating the statistical properties of real-world returns, the model demonstrates its capacity to capture the underlying complexity of the cryptocurrency market. The comparison of the three model specifications indicates that the main empirical trade-off lies between reproducing the historical Bitcoin price path and reproducing the stylized facts of financial returns. The OLD version is the least satisfactory from the standpoint of price-path validation because its correlation with the historical Bitcoin log-price is negative. By contrast, NOBTC and STABLE_NOBTC both generate a positive correlation of approximately 0.62 with Bitcoin, which is close to the benchmark reported in Bokhari (2025). However, the NOBTC specification achieves this at the cost of an unrealistically unstable regime process and an excessively high terminal price level. STABLE_NOBTC delivers the best overall compromise by preserving the positive correlation with Bitcoin while substantially reducing the root mean squared error (RMSE) of the simulated log-price and lowering the number of regime switches. In this sense, the stabilized noBTC version is the most convincing specification from the viewpoint

of overall model plausibility. It neither collapses like the OLD version nor explodes like NOBTC, and it tracks the broad cyclical pattern of Bitcoin more faithfully than the other two variants as illustrated in Figure 1. The numerical results of this comparison are summarized in Table 2. The performance of the STABLE_NOBTC specification ($r = 0.624$) aligns with the findings of Bokhari (2025) and Poledna et al. (2023), who argue that the predictive and explanatory power of ABMs increases significantly when agents are allowed to switch behaviors based on market regimes. While the standard NOBTC version exhibits terminal price explosions, these nonlinear spikes resemble the market fragility often induced

by 'whale' investors and extreme capital concentration (Shen & Shi, 2025), which the stabilized version effectively mitigates

The simulated trajectories in Figure 1 represent the average log-price paths for each specification, where it is evident that the STABLE_NOBTC variant (yellow line) most closely aligns with the historical Bitcoin price (purple line), successfully capturing its cyclical dynamics without the terminal price explosion seen in the NOBTC version or the structural collapse of the OLD benchmark

Figure 1. Comparison of the three specifications with the historical Bitcoin log-price



Source: Author's calculation based on the simulation results

Table 2. Comparative diagnostics of the three specifications

Specification	corr(log price, BTC)	RMSE log-price	Regime switches	LBQ p-value returns	LBQ p-value squared returns	Excess kurtosis
OLD	-0.369	2.887	26	0.618	0.000	0.077
NOBTC	0.618	2.103	126	0.419	0.294	0.097
STABLE_NOBTC	0.624	0.982	47	0.472	0.069	-0.104

Source: Prepared by the author from simulation outputs and comparative validation files

From the perspective of stylized facts, the results are more nuanced, highlighting a trade-off between price-path accuracy and the replication of higher-order statistical moments. As shown in Table 2, all three specifications reproduce the first stylized fact—the absence of strong linear autocorrelation in daily returns—reasonably well. The Ljung–Box p-values for raw returns are well above the 0.05 threshold in every case, suggesting that the simulated series do not display economically

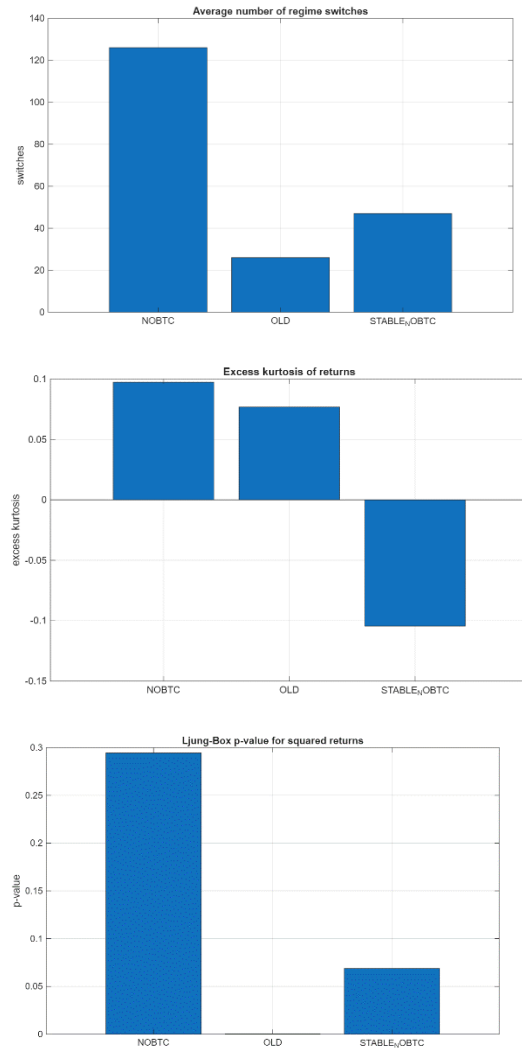
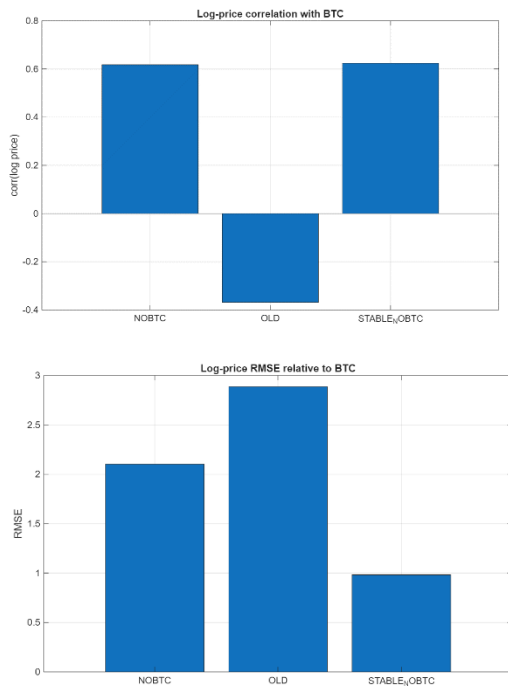
meaningful short-run return predictability. This result is consistent with the weak-form unpredictability characteristic of high-frequency financial returns, indicating that the model family performs satisfactorily in this dimension. The results regarding the absence of return autocorrelation confirm that the model satisfies the weak-form market efficiency, aligning with the early findings of Cocco and Marchesi (2016). Although the model exhibits lower excess kurtosis

than observed in actual Bitcoin data, this remains a common challenge in the calibration of behavioral agent-based models (Axtell & Farmer, 2022).

The second stylized fact, volatility clustering, is only partially reproduced. While the OLD model shows the strongest evidence of persistence in squared returns, the NOBTC specification almost entirely loses this heteroskedastic structure. The STABLE_NOBTC version restores part of this missing structure; however, its performance remains weak compared to empirical benchmarks. In practical terms, while the stabilized specification improves upon the NOBTC variant, it does not generate sufficiently strong or persistent volatility bursts. This suggests that while the incorporated volatility-memory mechanism is a functional addition, it remains too conservative to fully match the empirical Bitcoin series.

The third and fourth stylized facts represent the primary limitations of the current implementation. Excess kurtosis remains close to zero across all specifications, implying that the simulated return distributions are too close to a Gaussian benchmark and fail to generate the "fat tails" typical of crypto-asset markets. Similarly, skewness values are near zero, whereas empirical cryptocurrency returns usually exhibit visible asymmetry. Consequently, the model is more effective at capturing the direction and broad cyclical shape of the price path than the higher moments of the return distribution.

Figure 2 Joint diagnostics of price-path fit, regime stability and stylized facts



Source: Author's calculation based on the simulation results.

Taken together, the evidence suggests that STABLE_NOBTC is the preferred specification as demonstrated by the joint diagnostics in Figure 2. It is the only variant that simultaneously preserves a strong correlation with the historical Bitcoin path, yields the lowest RMSE, and maintains regime dynamics within a plausible range. Nevertheless, the validation against stylized facts remains incomplete. While the model successfully replicates weak autocorrelation, it underrepresents volatility clustering, fat tails, and asymmetry. Therefore, the current framework should be viewed as a robust intermediate empirical representation—highly useful for studying regime-dependent behavior and price-path dynamics, but requiring further refinement to achieve a fully realized statistical match with the Bitcoin market.

CONCLUSION

This paper has argued that agent-based modeling and simulation (ABMS) represents a methodologically vital tool for both economics and

finance, as it enables researchers to move beyond the limitations of representative-agent abstractions. By focusing on systems of heterogeneous, interacting, and adaptively learning agents, ABMS provides a more nuanced understanding of market dynamics. As evidenced by the literature, this approach is particularly valuable when aggregate outcomes are emergent, institutions are significant, and market behavior is shaped by nonlinear interactions rather than a single equilibrium condition. In this context, the proposed model demonstrates that the complexities of modern digital asset markets can be effectively deconstructed through a decentralized behavioral framework.

The cryptocurrency market model presented here illustrates these methodological advantages in practice. By linking social interaction, private signals, market regimes, and sentiment indicators—specifically the Fear and Greed Index—to aggregate price dynamics, the study provides a transparent and flexible simulation environment for testing market hypotheses. Methodologically, the model distinguishes between true and spurious herding through the use of dual fundamental signals, thereby isolating the effects of internal social imitation from synchronized responses to external informational shocks. The empirical comparison of the three specifications reveals that the STABLE_NOBTC version is the most robust compromise. It successfully reproduces the broad historical Bitcoin price path while maintaining a plausible regime structure, thereby avoiding the instability inherent in simpler model variants. However, the model still falls short of fully capturing the higher-order stylized facts of cryptocurrency returns, such as significant excess kurtosis and strong volatility clustering.

Consequently, while the current research achieves its primary goal of price-path validation and regime stability, it highlights clear directions for further refinement. Future work should focus on the enhancement of volatility-memory mechanisms and the incorporation of "rare jump" stochastic components. Such improvements could better replicate the extreme tail behavior of the Bitcoin market without sacrificing the gains already achieved in price-path accuracy and structural stability. Ultimately, this research contributes to the growing body of literature that seeks to bridge the gap between behavioral agent-based modeling and empirical financial market analysis.

REFERENCES

- [1] Axtell, R.L. and Farmer, J.D. (2022) Agent-Based Modeling in Economics and Finance: Past, Present, and Future. INET Oxford

- Working Paper No. 2022-10. <https://oms-inet.files.svcdn.com/staging/files/JEL-v2.0.pdf>
- [2] Baumann, M. H., Baumann, M., Grüne, L. and Hafele, S. (2023). Market structure and instability artifacts in heterogeneous agent models: Lessons from implicit discretizations of stiff equations. *Computational Economics*, 62(2), 855–890. <https://doi.org/10.1007/s10614-022-10285-z>
- [3] Bokhari, A. (2025). Unpacking Herding in Crypto Markets: An Agent-Based Study of True and Spurious Herding Dynamics. *Procedia Computer Science*, 274, 463–476. <https://doi.org/10.1016/j.procs.2025.12.046>.
- [4] Cocco, L. and Marchesi, M. (2016). Modeling and Simulation of the Economics of Mining in the Bitcoin Market. *PLoS ONE*, 11(10), e0164603. <https://doi.org/10.1371/journal.pone.0164603>
- [5] Cocco, L., Tonelli, R., and Marchesi, M. (2019). An agent-based artificial market model for studying the Bitcoin trading. *IEEE Access*, 7, 42908–42920. <https://doi.org/10.1109/ACCESS.2019.2907880>
- [6] Hommes, C. (2006). Heterogeneous Agent Models in Economics and Finance. In: *Handbook of Computational Economics II: Agent-Based Computational Economics*, edited by Leigh Tesfatsion and Ken Judd, Elsevier, Amsterdam 2006, 1109–1186. [https://doi.org/10.1016/S1574-0021\(05\)02023-X](https://doi.org/10.1016/S1574-0021(05)02023-X)
- [7] Lee, S., and Lee, K. (2015). Heterogeneous expectations leading to bubbles and crashes in asset markets: Tipping point, herding behavior and group effect in an agent-based model. *Journal of Open Innovation: Technology, Market, and Complexity*, 1(1), 1–13. <https://doi.org/10.1186/s40852-015-0014-8>
- [8] Lux, T., and Zwinkels, R. C. (2018). Empirical validation of agent-based models. In C. Hommes & B. LeBaron (Eds.), *Handbook of Computational Economics*, 4, 437–488. <https://doi.org/10.1016/bs.hescm.2018.02.003>
- [9] Poledna, S., Miess, M.G., Hommes, C. and Rabitsch, K. (2023). Economic forecasting with an agent-based model. *European Economic Review*, 151, 104306. <https://doi.org/10.1016/j.euroecorev.2022.104306>

- [10] Schmitt, N., Schwartz, I., and Westerhoff, F. (2022). Heterogeneous speculators and stock market dynamics: a simple agent-based computational model. *The European Journal of Finance*, 28 (13–15), 1263–1282. <https://doi.org/10.1080/1351847X.2020.1832553>
- [11] Shen, D., & Shi, G. (2025). The role of whale investors in the bitcoin market. *Research in International Business and Finance*, 78, 103008. <https://doi.org/10.1016/j.ribaf.2025.103008>
- [12] Turrell, A. (2016). Agent-based models: understanding the economy from the bottom up', *Bank of England Quarterly Bulletin*, Q4, 173–188.
- [13] Wang, L., Ahn, K., Kim, C. and Ha, C. (2018). Agent-based models in financial market studies. *Journal of Physics: Conference Series*, 1039, 012022. <https://doi.org/10.1088/1742-6596/1039/1/012022>



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