

# A Complex Adaptive System Approach for Anticipating Technology Diffusion, Income Inequality and Economic Recovery

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**Abstract.** Technology progress challenges equilibrium structures of human, social, cultural and behavioral systems. These are seen in 'new normals' of discontinuous market changes and nonlinear trend dynamics underpinning new individual behavior and human connectivity. Here we instantiate an agent based model integrated in a CAS framework of micro individual socio-economic transactions games empowered by technology and played on different economic network structures and market sophistication for anticipating macroeconomic and social equality outcomes. We explore scenario comparisons across GDP shocks and their impact on inequality, market behavior and recovery patterns. Several different V, U, L and W-shaped macro recovery patterns are categorized specifically dependent on such CAS structures. More sophisticated markets with preferential connectivity tend to offer lower levels of inequality and are more economically robust than less developed, randomly connected, transactional markets. High resolution computational approaches such as this can offer policymakers deeper insights and more actionable policy levers to achieve desired socio-economic outcomes in times of crisis.

**Keywords:** Economic growth · Technology adoption · Economic recovery · Complex adaptive system · Co-evolution · Agent-based Modeling (ABM)

## 1 Introduction

Technology accessibility and adoption are a critical factor for economic growth and societal knowledge transfer [1] in a fourth industrial revolution. Technological progress both destroys and creates jobs. Job destruction reduces labor required to perform tasks, automation and altering of required employment tasks that eliminate some occupations. Job creation occurs where automation complements specific job tasks, creates new industries and products, increases productivity, lowers costs and ultimately results in higher growth and income, thus boosting aggregate demand for future growth [2].

While technology if often seen as a lifeline to survival, especially in a post pandemic world, the pace of adoption and development with its accompanying life-changing possibilities is also disruptive [3]. As innovation continue to enable economic growth, it also

© Springer Nature Switzerland AG 2021
O. Gervasi et al. (Eds.): ICCSA 2021, LNCS 12950, pp. 251–262, 2021.
https://doi.org/10.1007/978-3-030-86960-1_18

intensifies market competition and changes individuals' economic employment opportunities [4]. Wealth accumulation for individuals who are capable of accessing technology easier than others fuels societal inequalities often exacerbated across different societal levels [5]. These implications drive conversations on how we can embrace technology advantages and redirect it as part of the solution for inequality challenges coupled with evolving economic complexity and increased social connectivity.

Obviously technological progress challenges equilibrium structures of human, social, cultural and behavioral systems [4] to 'new normals' often through nonlinear, discontinuous change and emergent behavior. This forces us to scientifically embrace not just transdisciplinary approaches but also multiple scale frameworks for understanding emergent human dynamics. Here we provide an integrative micro-meso-macro perspective on technology, growth and inequality that leverages computational, agent based modelling in a complex adaptive systems (CAS) simulation framework. We begin with a simplified agent based, macro economy [5] to frame individuals' economic activities and their summed GDP growth trajectories over time. We then decompose these macroeconomic activities into the requisite various meso economic activity networks and individual level decision behaviors. Integrating an agent-based approach with the added details on individual behavior and information flows can shed light on many important questions on economic equality, stability, fragility and recovery from economic shocks [6]. Leveraging such, we uncover some future research avenues at the intersection of technology, growth and income inequality that can be further calibrated to implement effective policy responses.

## 2 Related Work

### 2.1 Micro and Macroeconomics

Beginning with traditional economic models through an agent-based approach, we decompose macroeconomic technology and growth into two respective subcomponents of cross-scale human behavior: individual's micro motivations behind the adoption of technology for competitive economic gains which coevolve into networked meso societal behaviors within a CAS framework. Individual's actions are incentivized by preferences and constrained by beliefs while path dependence and information shape their strategic decisions [4] in various spaces of possibilities. Previous macroeconomic models based on equilibrium theory formally show how macro deficits can lead to economic crashes, but result often lack cross-scale explanations of micro individual behavior and meso networked relationships. Integrating an agent-based approach with the added details on individual behavior and information flows can shed light on many important questions on stability, fragility and recovery from economic shocks [6] and its impact on income inequality.

In previous work [7], we allow heterogeneous agents to play socio-economic transaction games to capture micro individual behaviors. Agents then interact under four different market typologies to simulate behavioral pattern changes driven by different societal networks of technology adoption and diffusion. For each typology, as technology proliferation increases economic connectivity and complexity, it also creates various structural changes across multiple scales of human behavior. Here we explore income

inequality and economic resiliency to exogenous shocks across different technologically enabled societies.

### 2.2 Economic Shocks and Recovery

Endogenous technological change warrants the potential to revolutionize industries creating highly competitive markets [8] often through continuous innovations which raise living standards. However, rapid technological change can also disrupt labor markets, with heterogenous sectoral impact, which subsequently can cause income gaps to widen both across and within groups. Several societies experience such increasing income disparity and technological unemployment despite surging macroeconomic growth [2]. For example, both labor income shares and labor productivity have significantly decreased in OECD countries over the last 20 years [9, 10]. Many economists discuss technology gap approaches [11–13] which emphasizes the crucial role of technology in economic growth processes. Given the prevalence of technology across multiple economic sectors, both economists and governments actively seek to understand the consequences of economic shock and recovery process. Many look to diagnose and anticipate associated recovery shapes and duration with empirical evidence into several types: whether exogenous economic shocks result in a quick V- shaped shock and recovery pattern, or U-shaped longer term recovery, W-shaped 'double dip' relapses, or a L-shaped prolonged crisis due to a stagnation trap [14].

## 3 Model Design

Enabled by connectivity, technology sources of innovation and disruption proliferate faster than we realize. As humans are strategic, dynamic and adaptive beings, behaviors by design often change and evolve in emergent, nonlinear and discontinuous fashions [15]. Thus, today we operate in many environments where novel individual micro actions can have a direct impact to other agents' decision-making process and consequently drive second and higher order changes and feedbacks at other scales of human behavior [16].

We explicitly model these cross-scale, integrated behaviors: micro evolutionary, heterogenous socio-economic transaction games, meso social and market networks where such micro games are conducted with the diffusion of technology in such contexts and finally the aggregate macro sum of all activities to understand the emergence of growth, technology and inequality. In our work, agents' behavior rules are designed bottom up to increase modeling fidelity, combining network analysis and information diffusion theory for socio-economic interactions. The resulting simulation provides insights on emergent properties that arise from agents' interaction, allowing us to potentially anticipate far from equilibrium macroeconomic behavior or new emergent system orders. Agent interactions are conducted on four unique socio-economic network typologies, i.e. random, preferential, dynamic-random, and dynamic-preferential, to capture aggregate economic outcomes as seen in Fig. 1. Furthermore, it also can offer insights into more actionable policy formulation and effectiveness.

We begin with Romer and others endogenous growth $Y$ functions [8] where firms are motivated by $L$ labor and $A$ technological change for the incentive of continuous $K$ capital accumulation:

$$Y_t = K_t^{\alpha}(A_t L_{Yt})^{1-\alpha}$$

Using these macroeconomic foundations as our departure point, our simulation space is designed to capture agents' socio-economic production functions, interactions and dynamic behavioral changes on different networks within this macroeconomic context. Starting at the micro level, each agent has its own unique cognitive process of choosing strategies, with or without technology, that they believe will provide maximum individual economic returns. Of course, this also depends on whether they or counterparties possess technological advantages in any transactional game as competitive or comparative advantages. Four different possible meso level interaction games result depending on player types possessing technology or not. The intuition here is that technology can enable synergistic gains and effects in cooperative interactions while conversely maximizing individual gains in non-cooperative, asymmetric technology interactions. Thus agent decision spaces of possibilities are explicitly shaped by technology. Such symmetric technology, cooperative games often produce higher relative economic gains than asymmetric, non-technology enabled games [7].

At each iteration, agents randomly select a socio-economic transaction partner by four designed groupings: both players have technology, $A_i$ has technology and $A_j$ does not, $A_i$ does not have technology and $A_j$ has, and finally both players do not have technology. $A_i$ strategies are adaptive over time, which affect $A_{ij}$ pairs locally.

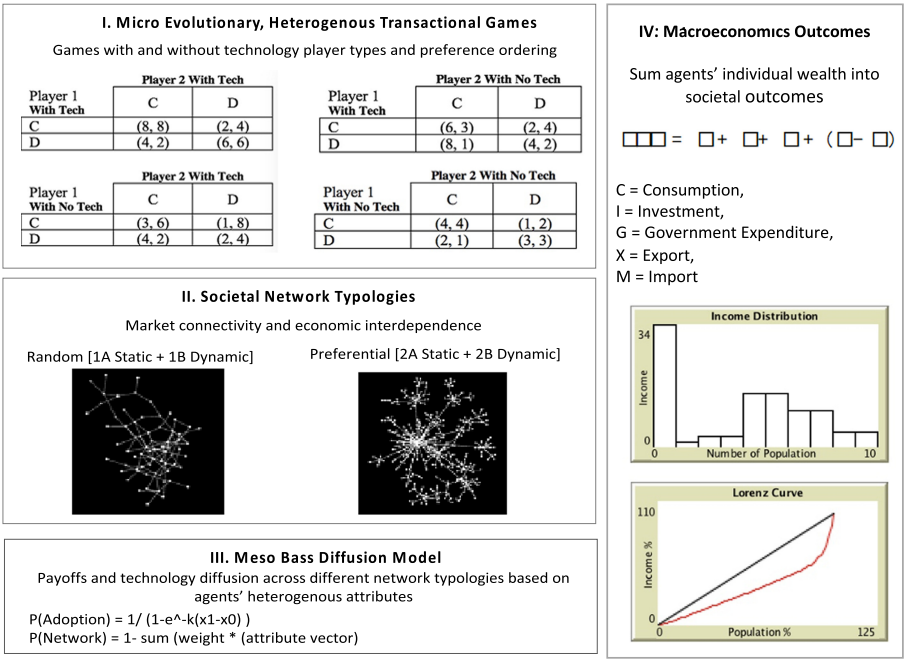


**Fig. 1.** CAS ABM processes

### 3.1 Network Typologies

In an adaptive evolving system, agents are capable of self-organizing to create or deactivate social ties which often can exhibit dynamic emergent behaviors [17]. Network formation is a complex process in which many individuals simultaneously attempt to maximize their own utility, under multiple, possibly conflicting, constraints with a tendency of homophily to avoid conflicting relationships with others [18, 19]. Our simulated economy is designed to increase interaction fidelity to capture agents' behavioral changes on different networks; creating local ties when they may be able to benefit from a cooperative relationship or dissolve social connections when they face increasing conflictual behaviors.

Agents are created with heterogeneous attributes including income, influence and perception towards technology; each agent has unique cognitive processes of choosing the strategy that best allow them to receive maximum return through socio-economic exchanges depending on whether counterparties possess technology or informational advantages. Individual's distinct cognitive characteristics and motivations contribute to creating social ties – different linkage and attachment rules, forming a collaborative social network. In this study, we include four different network typologies: static random (Erdős–Rényi) or static preferential (Barabási–Albert) network structures, as well as dynamic random and dynamic preferential networks that evolve over time. Learning and feedback loops occur as a result of personal interactions between individual and other agents and thus network formation can also dynamically evolve overtime.

Under random networks, the probability of node $i$ has exactly $k$ links following a binomial distribution:

$$p^k = (\frac{N-1}{k})p^k(1-p)^{N-1-k}$$

Such random networks can serve as proxies for undeveloped societies, low input factor production, opportunistic transactional markets and simpler economic structures.

Under preferential attachments, new nodes come in with $m$ edges that prefer to attach to well-connected nodes creating various centralized hubs following a power law distribution:

$$p(i) = m\frac{k_i}{\sum_j k_j}$$

Such preferential networks help instantiate more sophisticated markets, economic production functions and value chains based on requisite factors and inputs of production or services in knowledge economies.

These various societal network typologies determine how technology diffusion and adaptation occur through the well-known Bass diffusion [20] model: with $F(t)$ as the installed base fraction of technology, $f(t)$ the change in the installed base fraction with $p$ innovation and $q$ imitation. The 1-$F(t)$ denominator constraint creates decreasing technology diffusion at higher technology levels and over time across different network typologies.

$$\frac{f(t)}{1-F(t)} = p + qF(t)$$

### 3.2 Nonlinear Micro Behaviors to Simulated Macroeconomics Outcomes

At each iteration $t$, agents interact and perform socio-economic transaction games given differences in technology advantages which later form further connections based on various network typologies. Knowledge spreads through the network work and the rate of information diffusion varies by network type leading to the adoption of technology. As a result, agents update their income which allows us to observe change in society outcomes including inequality measured by the Gini index and Gross Domestic Product (GDP) below, where $p(c_i)$ is the probability of class $c$ in node $i$.

$$Gini = 1 - \sum_{i=1}^{n} p^2(c_i)$$

Agents are adaptive, capable of learning to make strategic decisions to improve socio-economic transaction results. First, information flows and technology accessibility are designed at rates correspond to agents' income level to accurately capture inequality challenges. Based on socio-economic transactional game results, individuals can randomly choose whether to adopt technology or not depending on their ability and preference. Obviously, this has direct, second order effects across coupled meso and macro scales of behavior, including income growth, inequality, decision sets and strategy.

## 4 Results

Given the CAS framework described above, we instantiate several scenarios calibrated with real data for total population, export, import, investment and expenditure to our designed experiment space to capture aggregate macro changes in GDP. Simulated results allow us to explore changes in individual level games, technology diffusion and the resulting macroeconomic inequality to reveal possible recovery patterns following economic shocks. Below we explore scenario comparisons from baseline, mild and severe recessions to investigate the amplitude of economic shocks to GDP and identify underlying recovery patterns. To better understand the influence of these shocks, we leverage key control parameters of percentage of shock loss at t = 30 and 60 to systemically investigate strength of shocks and resulting system recovery patterns. For mild shock, percentage of income loss is set at 30% and for recession it is set at 80%. These values are meant to instantiate income losses, such as the 35% GDP decline in Q2 2020 due to COVID-19 pandemic, but also any other mild and severe employment shocks across heterogenous societal income groups (Table 1).

### 4.1 Income and Recessions

First we setup our model to instantiate various shock scenarios under heterogenous network typologies. By controlling for shock depth at $t = 30, 60$ with different socio-economic networks, we hope to offer new insights on the effects of individual ties, economic networks, market structures and social interactions. In Fig. 2, the income y-axis in each shock scenario follows different scales to allow visible variations for

**Table 1.** Baseline parameters

| Parameters | Description | Base value |
|---|---|---|
| Population | Total number of agents | 100 |
| Initial percentage of using technology | Percentage of population already using technology | 10% |
| Probability of using technology | Probability of individual have chance using technology | 10% |
| Probability of informed | Probability of individual could receive using technology information | 20% |
| Probability of T | Probability of individual could use technology | 10% |
| Max Tolerance | Tolerance would impact individual preference to switch use technology | 5 |
| Nodes | Number of nodes | 30 |
| Degree | Average of nodes degree | 15 |
| Probability of rich using technology | Probability of high-income class people using technology | 40% |
| Probability of middle using technology | Probability of middle-income class people using technology | 20% |
| Probability of poor using technology | Probability of low-income class people using technology | 10% |
| Probability of shock | Probability of economic shock | 0% |
| Shock loss | Percentage of income loss from economic shock | 0% |

average income under different network typologies and recovery scenarios. All scenarios correctly show growth recovery, however comparisons across recovery patterns yield interesting insights. In the static random shock scenarios, recovery happens quickly regardless of shock depth due to the resiliency of randomized transactions. Conversely, in the preferential static shock scenarios, recovery to previous levels is much slower and lower due to the destruction of sophisticated preferential market linkages. Both dynamic random and dynamic preferential network shock scenarios exhibit better income recovery response levels and rates as efficient interaction patterns can reform under more agile economic structures.

### 4.2 Gini Index

Figure 3 displays a panel of Gini index trajectories across sampled shock scenario space considering technology adoption under various network typologies. The Gini index measures the inequality among values of a frequency distribution with a value of zero expressing perfect equality while a value of one indicates maximal inequality. In general,

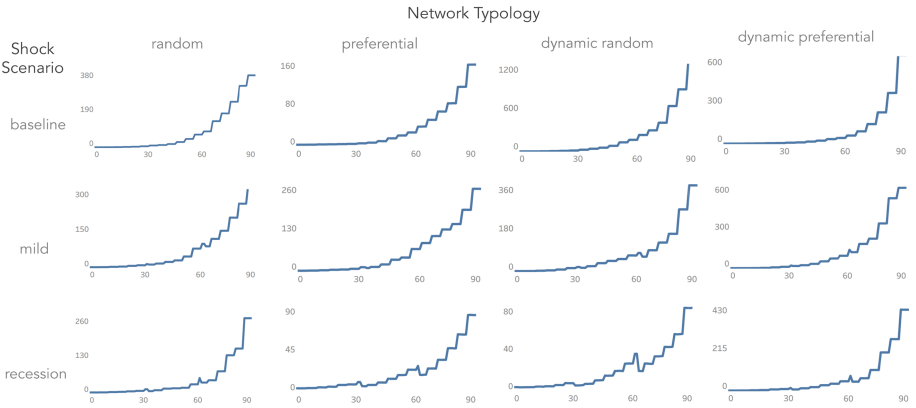


**Fig. 2.** Average income response across shocks and network typology

we observe an immediate inequality decrease follow by a sharp increase in income inequality, with more notable changes under preferential networks but at lower levels of inequality. This result suggests that while shocks and recession can reduce agents' income, temporarily minimizing income gaps among groups, these gaps can widen again during economic recovery. Overall, sophisticated economic structures and markets with preferential connectivity tend to offer lower mean levels of inequality than random, transactional markets and economic structures.

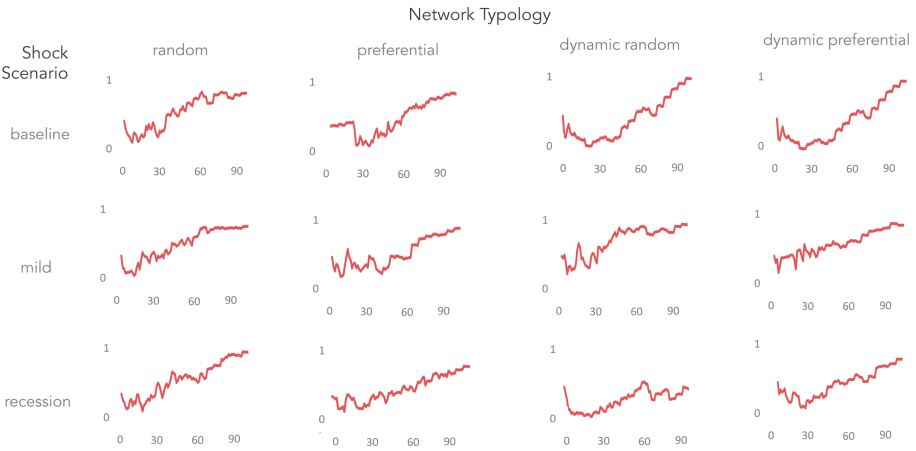


**Fig. 3.** Gini index response across shocks and network typology

### 4.3 Socio-economic Transaction Games

Figure 4 shows how agents' strategies simultaneously co-evolve over time across shock and economic network typology scenarios, driving changes with feedback processes

through $t + k$ iterations. The vertical axis depicts the percentage of agent population adopting the corresponding strategy type. As $t$ progresses and the depth of shock increases, defect strategies become dominant in all typologies, suggesting that agents will adopt different strategies that benefits themselves depending on external macro environmental influences which further impact localized path dependency of micro decision-making processes over time. However, strategy covariance is more tightly coupled in randomized network typologies given our symmetric and asymmetric technology transactional game setup. This is consistent with many other evolutionary game theory insights, experiments and findings [21–23].

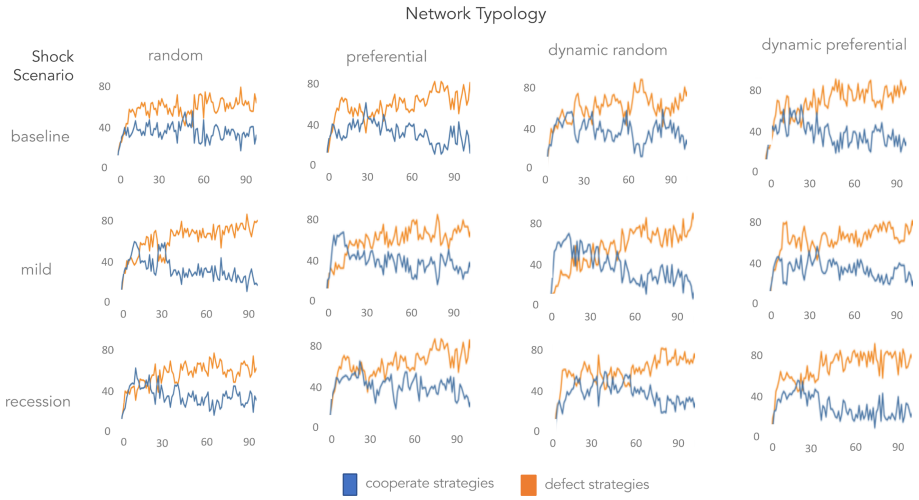


**Fig. 4.** Strategic game responses across shocks and network typology

### 4.4 Recovery

A large amount of both theoretical and empirical research discusses the relevancy between recovery path and GDP over time to identify possible recession duration and the nature of recovery to help provide evidentiary support in determining effective policy measurements under extreme uncertainties [24]. Given a particular exogenous shock, an anticipated V-shape recovery will suggest the economy may experience a sharp decline but an almost-immediate return to original growth dynamics. A U-shaped pattern indicates a relatively slower rebound compare to a V-shape paths. Next a W-shape recovery or "double-dip recession" often occurs where there may be an imbalance between fiscal and monetary policies after the first chock which further pushes the economy into a second wave of recession. Lastly, we have L-shaped recoveries which often result in structural breaks between supply and demand mechanism and are the lengthiest recession period.

In Fig. 5, we observe distinct shock and recovery geometries under different scenarios by comparing anticipated GDP trajectories from previous years mean performance. In the static random and dynamic preferential scenarios, our simulated results show a W-shaped

pattern, indicating oscillatory recoveries as macroeconomic environments coupled with micro decision making and market networks are recalibrated. In the preferential network scenario, GDP recovery trends exemplifies U-shaped patterns consistent with our earlier network findings where economies with destroyed value chains take longer to recover. Finally, we detect L-shaped patterns in dynamic random markets, where sophisticated, economic value creation activities do not occur and structural breaks often persist well after an exogenous shock.

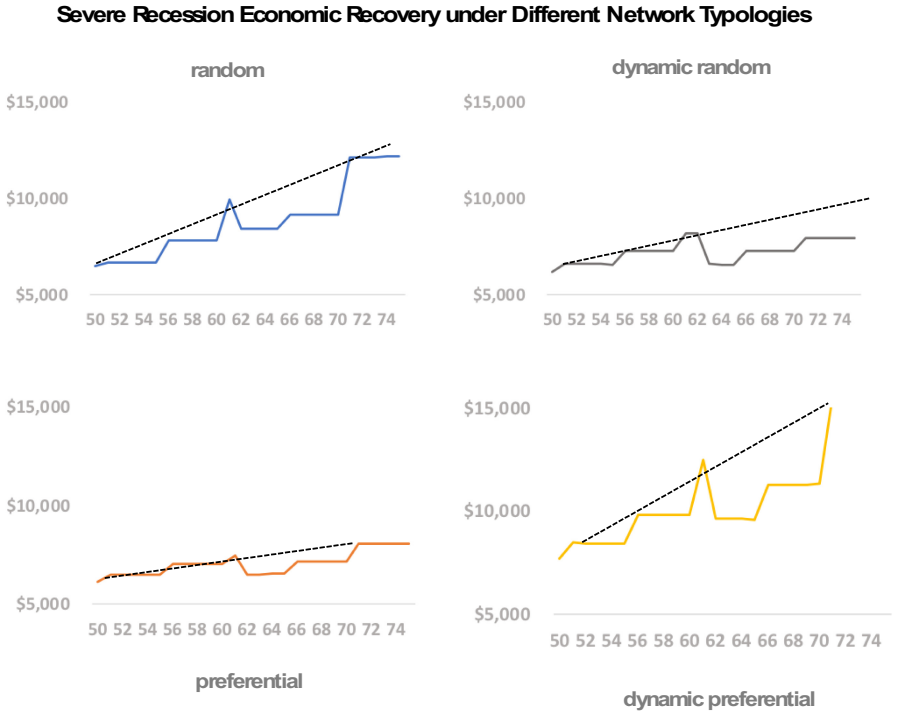


**Fig. 5.** GDP recovery patterns at second shock ($t = 60$).

## 5 Conclusions

Our initial implications include how individual strategic choices, based on localized limited resources, access to technology and incentive structures, can drive very different macro social and economic behaviors. Those macro structural outcomes feedback and shape individual agent choices and spaces of decision possibilities. This begs for us to dive deeper into understanding the nuances of technology as an enabler across multiple scales of human activity. Especially in light of shock and recovery scenarios, our approach helps illuminate the potential robustness, resiliency and adaptiveness of different economic structures, markets and societies. These have very different consequences

for recovery patterns and income inequality effects enabled by technology. While not detailed here, technology asymmetries in transactional games can also drive unique emergent behaviors, new market orders with significant social and economic equality consequences.

Decomposing macroeconomic growth, technology and income equality models into their behavioral subcomponents and then re-integrating in a CAS cross-scale framework offers several scientific and policy advantages. First, modeling complex, scale variant human behavior increases not only explanatory fidelity but offers insights for bridging seemingly disparate theory from different fields via computational methods. Second, nonlinear macroeconomic outcomes and discontinuities in far from equilibrium conditions can hopefully be better anticipated and accounted for as we still continue to understand the intended and unintended second and higher order effects of quantitative easing policies for example. Third, while our approach here is just an initial foray and not fully empirically calibrated yet, it does provide policy making promise through increased descriptive, predictive and prescriptive insights in complex, dynamic human systems.

A key advantage of agent based, CAS and other cross scale modeling approaches is creating more actionable policy levers. For example, a macroeconomic model might suggest a policy option of increasing labor productivity by a certain amount to achieve desired growth targets, but does offer any suggestions on how exactly to increase such labor productivity levels. With an agent or CAS approach, one can explicitly test a priori policy 'how, who and where' answers to potential micro incentive changes as well as meso transactional network effectiveness. One general but weak critique of such approaches is modeling complexity for the sake of complexity, not specific for explanation, prediction or control. However, we know from the scientific law of requisite variety that the number of controllers or levers in a system has to be equal or greater than the number of sources of variance in the system [25] as practiced in many fields demanding systems engineering and dynamic optimization.

While simple, elegant explanatory models might help build cognitively digestible theory, policy actionability requires more detailed modeling, simulation and engineering prowess. Cross-scale modeling efforts such as the one presented here decompose complex human systems into their various subcomponents of which there is often increasing fidelity and policy lever actionability to help achieve desired socio-economic outcomes, especially in times of crisis. This seems particularly necessary in light of increasing complexity and connectivity of human activities intertwined by technology, growth and income inequality. Thus expanding scientific, empirical and policy insights into comprehensive, cross-scale human behavioral approaches is key to understanding, anticipating and hopefully shaping better societal outcomes equitably.

## References

1. Schwab, K.: The fourth industrial revolution. Currency (2017)
2. Bruckner, M., LaFleur, M., Pitterle, I.: The impact of the technological revolution on labour markets and income distribution. Front. Issues 1–49 (2017)
3. Schelling, T.C.: Micromotives and Macrobehavior. WW Norton & Company, New York (2006)

4. Arthur, W.B.: Is the information revolution dead. Business **2**, 65–72 (2002)
5. Wilensky, U., Rand, W.: NetLogo Random Network model (2008). http://ccl.northwestern.edu/netlogo/models/RandomNetwork. Center for Connected Learning and Computer-Based Modeling, Northwestern Institute on Complex Systems, Northwestern University, Evanston, IL
6. Graham, C.: America's crisis of despair: A federal task force for economic recovery and societal well-being. Brookings, 23 March 2021. https://www.brookings.edu/research/americas-crisis-of-despair-a-federal-task-force-for-economic-recovery-and-societal-well-being/
7. Abdollahian, M., Chang, Y., Lee, Y.-Y.: Technology, growth and inequality: an agent-based model of micro transactional behaviors and meso technology networks for macroeconomic growth. In: Nunes, I.L. (ed.) AHFE 2021. LNNS, vol. 265, pp. 39–48. Springer, Cham (2021). https://doi.org/10.1007/978-3-030-79816-1_5
8. Romer, P.M.: Endogenous technological change. J. Polit. Econ. **98**(5, Part 2), S71–S102 (1990)
9. The Sustainable Development Goals Report 2019. United Nations, New York (2019)
10. "Decoupling of Wages From Productivity: What Implications For Public Policies?" OECD Economic Outlook, Volume 2018, Issue 2
11. Posner, M.V.: International trade and technical change. Oxford Econ. Pap. **13**(3), 323–341 (1961)
12. Gomulka, S.: Inventive activity, diffusion, and the stages of economic growth, vol. 24. Aarhus University, Institute of Economics, Aarhus (1971)
13. Singer, H.W., Reynolds, L.: Technological backwardness and productivity growth. Econ. J. **85**(340), 873–876 (1975)
14. Carlsson-Szlezak, P., Reeves, M., Swartz, P.: Understanding the economic shock of coronavirus. Harv. Bus. Rev. (2021). https://hbr.org/2020/03/understanding-the-economic-shock-of-coronavirus
15. Abdollahian, M.: Surfing the conflux: technology, information environments and great power competition convergence. In: Farhadi, A., Masys, A.J. (eds.) The Great Power Competition Volume 1, pp. 1–29. Springer, Cham (2021). https://doi.org/10.1007/978-3-030-64473-4_1
16. Camagni, R.: Technological change, uncertainty and innovation networks: towards a dynamic theory of economic space. In: Capello, R. (ed.) Seminal Studies in Regional and Urban Economics, pp. 65–92. Springer, Cham (2017). https://doi.org/10.1007/978-3-319-57807-1_4
17. Holland, J.H.: Complex adaptive systems. Daedalus **121**(1), 17–30 (1992)
18. Knoke, D., Yang, S.: Social Network Analysis. Sage Publications, Thousand Oaks (2019)
19. Voinea, C.F.: Political Attitudes: Computational and Simulation Modelling. Wiley, Hoboken (2016)
20. Bass, F.M.: The bass model. Manag. Sci. **50**(12 Supplement), 1833–1840 (2004)
21. Axelrod, R.: An evolutionary approach to norms. Am. Polit. Sci. Rev. **80**, 1095–1111 (1986)
22. Colander, D., Holt, R.P., Barkley, J.: The Changing Face of Economics: Conversations with Cutting Edge Economists. University of Michigan Press, Ann Arbor (2004)
23. Nowak, M.A.: Five rules for the evolution of cooperation. Science **314**(5805), 1560–1563 (2006)
24. Ghosh, I.: Shapes of Recovery: When Will the Global Economy Bounce Back? Visual Capitalist, 16 September 2020. https://www.visualcapitalist.com/shapes-of-recovery-when-will-the-global-economy-bounce-back/
25. Ashby, W.R.: An Introduction to Cybernetics. Chapman & Hall Ltd., London (1961)