Why a Causal Graph Based Propagation Perspective is Needed in Digital and AI Economies

Karthika Mohan
School of Electrical Engineering and Computer Science
Oregon State University

Digital technologies and AI systems have increased the scale and complexity of economic interactions, from digitally coordinated supply chains and marketplaces to algorithmic decision rules in platforms, logistics networks and financial markets. These settings generate disturbances that propagate across sectors and over time, and standard empirical tools often identify correlations or equilibrium co-movements without specifying the mechanisms through which shocks travel or how alternative decisions would change outcomes. Causal graphical models that capture inter- and intratemporal connections provide a structured way to make these mechanisms explicit (Pearl, 2009).

This need is especially acute in digital and AI-intensive environments, which rely on coordination mechanisms, platform-mediated interactions, algorithmic rules and real-time data flows that create dense interdependencies. Research in the economics of digitization documents how platforms and search technologies generate such linkages (Goldfarb and Tucker, 2019), and work in the AI economy shows how algorithmic choices, automation and compute constraints influence responses across these systems (Brynjolfsson et al., 2025; Aral, 2021). Production-network and supply-chain research demonstrates how shocks propagate through tightly connected systems (Acemoglu et al., 2012; Carvalho, 2014; Tang, 2006). Because these environments involve many interacting actors connected through platform rules, data flows and algorithmic coordination, they can be viewed as large dynamic causal graphs that depict the evolution of the system over time. In such dynamic causal graphs, each time step contains a vast number of variables linked by intratemporal causal connections, while intertemporal causal links represent how these variables transition and influence one another across time.

The suitability of causal graphical models for representing complex systems and serving as a general language for describing their structure is well established. They separate correlation from causation, represent pathways of influence, and formalize how agents combine data with causal assumptions when forming beliefs. This perspective has been developed extensively in the causal

inference literature (Pearl, 2009; Pearl and Mackenzie, 2018) and adapted for economic analysis in works such as Spiegler (2020), which shows how these graphs can represent subjective causal models, capture misattribution or mistaken reasoning, and clarify the behavioral and equilibrium implications of such beliefs. A further advantage of graphical models is that they directly connect representation to identification which is a central concern in empirical work broadly and in economics in particular. Graphical representations make it possible to leverage established graph-based algorithms that determine whether a causal query is identifiable (Shpitser and Pearl, 2006). Graph-based algorithms can also be used for efficient computation (estimation) of the query once identification is established.

Thus a causal propagation perspective using graphs provides a systematic way to analyze how shocks move through networks and over time, consistent with insights from propagation-based and production-network analyses (Acemoglu et al., 2012; Carvalho, 2014). More specifically, in digital and AI economies, such graphs can encode platform rules, algorithmic decision processes, data flows and user interactions, making it possible to trace how algorithmic updates or policy changes propagate through these systems. First, explicit pathways clarify mechanisms and reduce reliance on ad hoc assumptions. Second, causal representations support interventional and counterfactual analysis of platform rules, supply-chain configurations or compute bottlenecks. Third, dynamic causal approaches can incorporate heterogeneity, adaptation and nonlinear responses common in algorithmic environments, themes increasingly emphasized in digital and AI-driven research (Brynjolfsson et al., 2025). Fourth, they enable new forms of measurement by using real-time digital and operational data to estimate pathway-specific effects, attribute propagation to particular interactions and evaluate interventions (Goldfarb and Tucker, 2019). Fifth, they offer a unified way to analyze phenomena central to digitization and the AI economy, including bullwhip dynamics, bottlenecks, contagion and cross-sector spillovers, long examined in supply-chain and operational research (Simchi-Levi et al., 1999; Pettit et al, 2010; Tang, 2006). Taken together, these elements show why a causal graph-based propagation perspective is indispensable for studying digitally mediated and AI-intensive systems in a coherent and operational way.

Disclosure. The authors received no external research support for this work and have no financial relationships or other potential conflicts of interest to disclose.

References

Acemoglu, D., Carvalho, V. M., Ozdaglar, A., and Tahbaz-Salehi, A. (2012). The network origins of aggregate fluctuations. *Econometrica*, 80(5):1977–2016.

Aral, S. (2021). The hype machine: How social media disrupts our elections, our economy, and our health–and how we must adapt. . Crown Currency.

Baqaee, D. and Farhi, E. (2019). The macroeconomic impact of microeconomic shocks: Beyond Hulten's theorem. *Econometrica*, 87(4):1155–1203.

Brynjolfsson, E, Li, D., and Raymond, L. (2025) Generative AI at Work. *The Quarterly Journal of Economics*, 140.2: 889-942.

Carvalho, V. M. (2014). From micro to macro via production networks. *Journal of Economic Perspectives*, 28(4):23–48.

Goldfarb, A. and Tucker, C. (2019). Digital economics. *Journal of Economic Literature*, 57(1):3–43.

Pearl, J. (2009). *Causality*. Cambridge University Press.

Pearl, J. and Mackenzie, D. (2018). The Book of Why: The New Science of Cause and Effect. *Basic Books*.

Pettit, T. J., Fiksel, J. and Croxton, L.K..(2010). Ensuring Supply Chain Resilience: Development of a Conceptual Framework. *Journal of Business Logistics*, 31(1):1–21

Shpitser, I. and Pearl, J. (2006). Identification of conditional interventional distributions. *Proceedings of the Twenty-Second Conference on Uncertainty in Artificial Intelligence (UAI'06)*, pp. 437–444. AUAI Press, Arlington, VA.

Simchi-Levi, D., Kaminsky, P. and Simchi-Levi, E. (1999). Designing and Managing the Supply Chain: Concepts, Strategies, and Cases. McGraw-Hill, New York.

Spiegler, R. (2020). Behavioral Implications of Causal Misperceptions. *Annual Review of Economics*, 12(1):81–106.

Tang, C. (2006). Perspectives in supply chain risk management. *International Journal of Production Economics*, 103(2):451–488.