Behavior-based dependency networks improve predictability of economic resilience

Keywords: resilience, human mobility, economic networks, cities, network dependence

Extended Abstract

Quantifying the economic costs of businesses caused by extreme shocks, such as the COVID-19 pandemic and natural disasters, is crucial for developing preparation, mitigation, and recovery plans (Kousky, 2014). Drops in foot traffic quantified using large scale human mobility data (e.g., mobile phone GPS) have recently been used as low-cost and scalable proxies for losses of businesses that rely on physical visits to stores, such as restaurants and cafes (Yabe et al, 2020). However, studies have so far neglected the interdependent relationships that may exist between businesses and other facilities. For example, university campus lockdowns during the pandemic may severely impact foot traffic to student-dependent local businesses. Such dependency networks could cause secondary and tertiary cascading impacts of shocks and policies, posing a significant threat to the economic resilience of business networks (Zhai and Yue, 2021).

To model such network cascading effects, we construct, analyze, and simulate dependency networks of business using mobility data of millions of co-visits to different point-of-interest (POI) in five US urban areas (New York, Boston, Los Angeles, Seattle, Dallas) (Moro et al., 2021). We compute the dependence of a POI i on another POI j, $w_{ij} = |s_i \cap s_j|/|s_i|$, where s_i and s_j denote the sets of users who visit POIs i and j respectively. Because the denominator is based on the number of users who visit the target POI i, $w_{ij} \neq w_{ji}$. This simple but intuitive measure considers the asymmetric nature of dependencies between POIs. The set of users who visit each POI in a specific period is computed using mobility data collected from mobile phone devices. We obtain the weighted directed dependency network with adjacency matrix W.

The empirical mobility-based dependency network reveals substantial variability in the inweights and out-weights of nodes. Moreover, the average dependency $\overline{w_{ij}}$ of all POIs i and j decays with the Euclidean distance δ_{ij} with a power law trend. However, does inter-POI distance fully explain dependency weights w_{ij} ? Using simple regression models, we find that the Euclidean distance δ_{ij} explains around 20% of the variance of w_{ij} . To better understand the characteristics of the dependency network, we construct several null networks (e.g., weighted spatial configuration model) that control for the in and out degrees and the distribution of Euclidean distance of the edges, as shown in Figure 1A, and compare characteristics between the null and actual networks. Results show that the real network has substantially and significantly higher clustering properties measured by the clustering coefficient and transitivity (Figure 1B). We further find significant excess dependency between specific POI categories, such as food and college compared to the null networks (Figure 1C).

Can the dependency network improve the predictability of the resilience of businesses during shocks? To answer this question, we test whether pre-pandemic dependency relationships could improve the predictability of loss of visits to POIs during the pandemic, using a regression framework. For each pair of categories A and B, we obtain a regression coefficient β^{AB} that characterizes the marginal effects of dependency on category B on loss of visits to

9th International Conference on Computational Social Science IC²S² July 17-20, 2023 – Copenhagen, Denmark

POIs in category A. Even when compared to the coefficients obtained when using the weighted spatial configuration model, we obtain substantial and significant predictive power for the dependency network. For example, results indicate that POIs that had high dependency on arts and museums, coffee and tea places, and colleges experienced substantial decrease in visits, while places that had high dependency on grocery stores and shopping stores performed better during the pandemic. Moreover, such statistically significant relationships between dependency and resilience were consistent for individual brands such as Starbucks Coffee, McDonald's, Burger King, and Subway.

Finally, we predict the propagation of changes in visits to POIs ΔV under hypothetical external shock scenarios f^* via the Leontief (input-output) model using the dependency network W. An example of the simulation is shown in Figure 2, where we simulate the spatial cascades of the impact of 50% reduction of visits to colleges on nearby POIs, which has substantial negative effect on POIs with high dependency on colleges, even in areas far away from college campuses such as Massachusetts Avenue and Back Bay. Future applications of this method include applications to assessing the cascading impacts of various urban shocks including disasters (Sadri et al., 2018) and urban policies including rewiring of the transportation network and addition and removal of nodes (e.g., parks, transit hubs) to and from the urban network via public investments.

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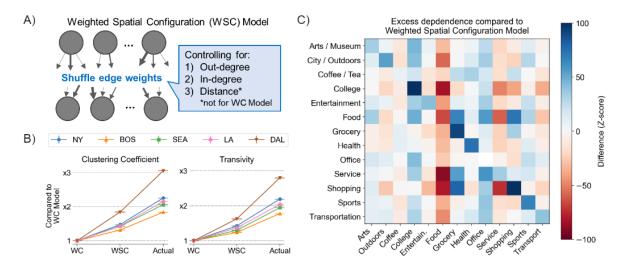


Figure 1. Understanding the characteristics of dependency networks. A) To test the extent to which the dependency network can be characterized by co-location between POIs, null networks were simulated using the weighted spatial configuration model. B) The observed dependency networks have denser connectivity compared to the null network models in all cities, with 2 – 3 times larger clustering coefficients and transitivity compared to the null model. C) Matrix shows the significantly more (e.g., food on college) or less (e.g., college on food) dependence between specific POI categories compared to the null model.

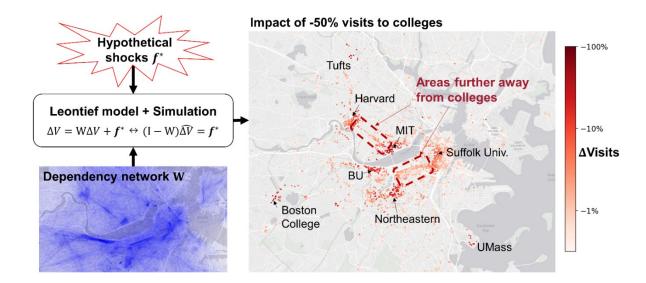


Figure 2. Using the dependency network and input-output type models, we can simulate the spatial cascades of various urban shocks. The left map shows the impact of 50% reduction in visits to colleges on nearby POIs. Exogeneous shocks to colleges in Boston could have a substantial negative effect on POIs with high dependency on colleges, even in areas with larger physical distance from college campuses as highlighted in the figure.