Effects of mobility-based dependency networks on economic resilience

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Introduction

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. Conventionally, survey data have been the primary source of information used to measure losses inflicted on businesses by negative shocks, however, 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 such losses, especially for businesses that rely on physical visits to stores, such as restaurants and cafes (Yabe et al., 2019). Such studies and analyses often quantify the losses in foot traffic based on individual points-of-interest (POIs), neglecting the interdependent relationships that may exist between businesses and other facilities. For example, university campus lockdowns imposed during the COVID-19 pandemic may severely impact foot traffic to student-dependent local businesses. Such dependent relationships between businesses 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).

Data and Methods

To identify such cascading effects, we build a "dependence demand network" of business using mobility data. We used large-scale anonymous, privacy-enhanced mobility data of more than 200K devices from the Metropolitan Boston Area collected in 2019 to 2021 (Moro et al., 2021). The dependency scores were computed based on the foot traffic patterns before the pandemic (September 2019 to January 2020). We compute the dependence of a target POI i on a source POI j by $dep(i,j) = |s_i \cap s_j|/|s_i|$, 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, $dep(i,j) \neq dep(j,i)$. This is a simple but intuitive measure that considers the asymmetric nature of dependencies between POIs. The set of users who visit each POI in a

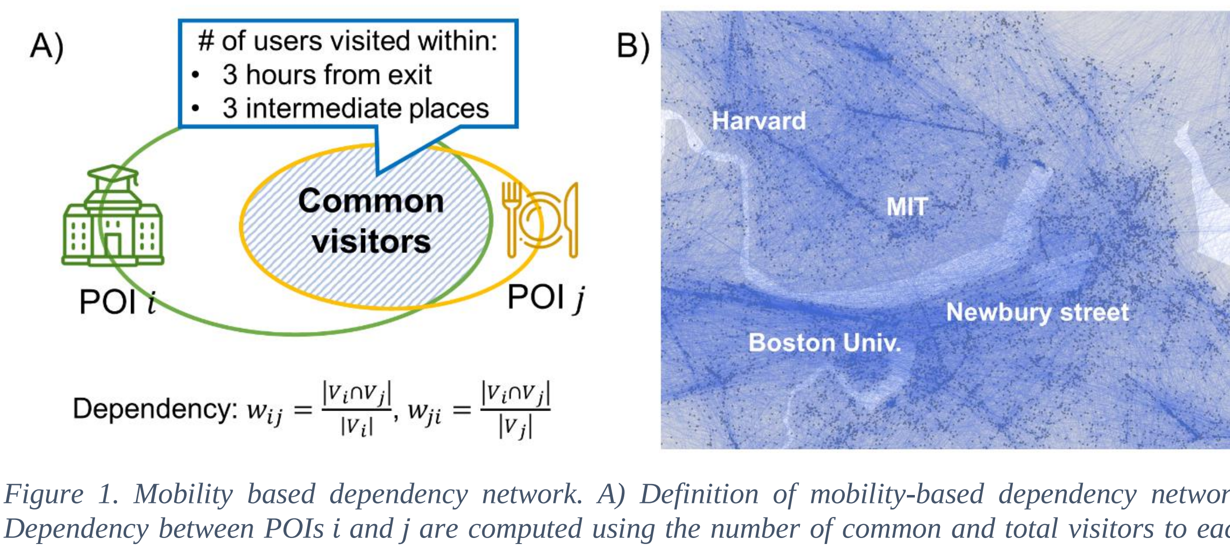
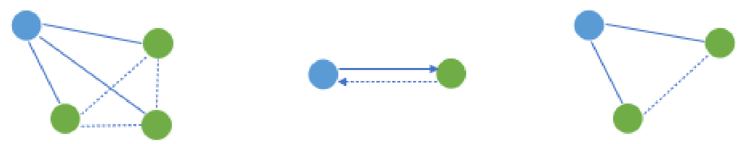


Figure 1. Mobility based dependency network. A) Definition of mobility-based dependency network. Dependency between POIs i and j are computed using the number of common and total visitors to each POI. B) Dependency network of POIs in Boston metropolitan area shows high clustering in local districts such as Harvard, MIT, Boston Universities and Newbury Street.

specific period is computed using mobility data collected from mobile phone devices. Figure 1A shows an overview of the methods on how the dependency between two POIs is computed. Figure 1B shows the dependency network in the Boston metropolitan area. Commercial and college districts, such as MIT, Harvard, and Boston University, as well as Newbury Street, can be seen in the network.

Network Characteristics

To quantitatively understand the characteristics of the dependency network, we constructed several null network models and compared various network statistics. For this analysis, edges with dependency weights greater than 0.05 were labeled as edges and the resulting unweighted directed network was analyzed. Null network models were created by randomly shuffling the links from the original (real) network in different ways. The most constrained random network controls the in- and out-degrees of each node and also keeps the distance distribution of the edges ('spatial configuration model'). As shown in Figure 2, network metrics such as the clustering coefficient, reciprocity, and transitivity are significantly and substantially higher in the real network compared to all null networks including the spatial configuration model, which indicates that POIs in the real network are more locally clustered and dependent on each other.



Network	Clustering coefficient	Reciprocity (% edges returned)	Transitivity (% triangles closed)
Real Network	**0.054**	**0.131**	**0.030**
Erdos-Renyi	< 0.001	< 0.001	< 0.001
Spatial E-R	0.011	0.020	0.021
Configuration	< 0.001	< 0.001	< 0.001
Spatial configuration (null model)	**0.003**	**0.004**	**0.002**

Figure 2. Network statistics of the real dependency network compared with multiple null network models, including the spatial configuration model which controls for the in- and out-degrees of each node and also the overall distance distribution of the edges. Analysis shows that metric related to local clustering, such as the clustering coefficient, reciprocity, and transitivity are all significantly greater in the real network compared to the null models.

Economic Impacts of Dependency Networks

To measure how such dependency relationships may affect the resilience of businesses to external shocks, we analyze how dependency on visits from office POIs and university/college POIs affects the magnitude of disruption that restaurant and café POIs experienced during the COVID-19 pandemic. The dependency weights were computed based on the foot traffic patterns before the pandemic, and as the objective variable, the percentage drop in the number of foot traffic to POIs were used. The reduction in foot traffic to restaurant and café POIs were calculated relative to the foot traffic in January to February 2020. First, the intuitive relationship between dependency on colleges of restaurants were investigated. Figure 3A shows the relationship between the dependency on visits from/to offices and university/college POIs (x-axis, between 0 and 1) and the foot traffic levels compared to pre-pandemic levels (y-axis, in %). The relationships are shown for two periods (April 2020 and April 2021). We observe a negative trend between

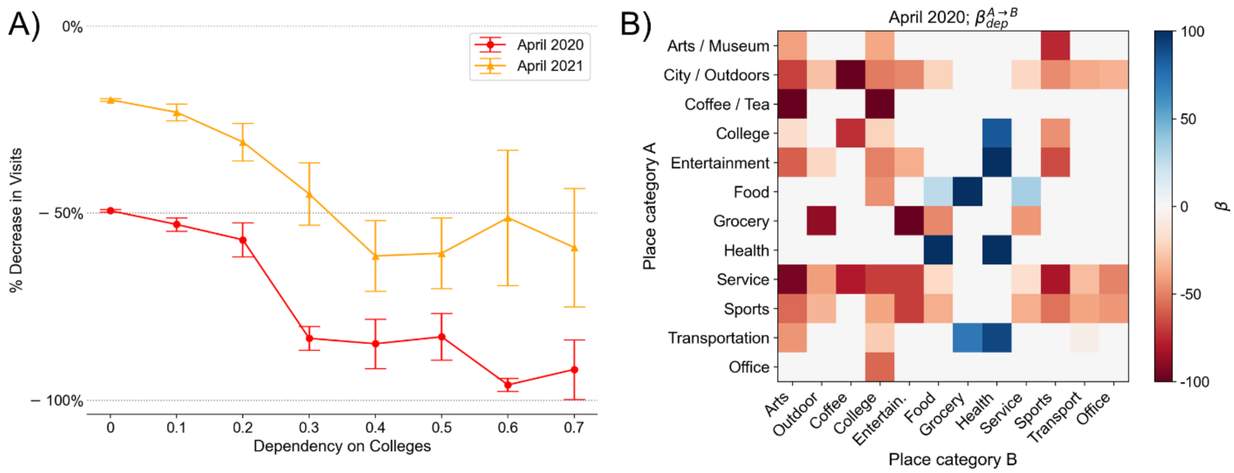


Figure 3. Economic impacts of dependency networks. A) Food and coffee places that were more dependent on colleges suffered larger losses in foot traffic during the pandemic. B) POIs that were dependent more on many of the POI categories suffered more, however, food and health places that were dependent more on grocery and health facilities performed better than other POIs.

dependency and foot traffic for both periods, indicating that restaurants and cafés that were more dependent on offices and universities experienced more substantial negative impacts of the non-pharmaceutical intervention policies during COVID-19. Similarly, Figure 3B shows the regression coefficients of dependency between all POI category pairs. A negative coefficient β indicates that the higher the dependency on place category B, POIs in place category A performed worse during the pandemic. On the other hand, relationships in blue color indicate that POIs that were dependent on grocery and health places performed better than those which did not. This methodology enables us to further investigate the effects of mobility-based dependency networks, and its impacts on the local economy with various hypothetical urban shocks, including not just pandemics but also natural disasters (Sadri et al., 2018), public transport disruptions, and also positive interventions such as festivals and public events.

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