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Lack of Resilience in Transportation Networks: Economic Implications

Margaret Kurth[1], William Kozlowski[2], Alexander Ganin[1], Avi Mersky[1], Billy Leung[2], Maksim Kitsak[1], and Igor Linkov[1*]

[1]US Army Corps of Engineers, Engineer Research and Development Center, 696 Virginia Rd., Concord, MA 01742, USA   Igor.Linkov@usace.army.mil

Regional Economic Models Inc., 433 West St, Amherst, MA 01002, USA

Abstract

Disruptions to transportation networks are inevitable. When road networks are not resilient, i.e., they do not recover rapidly from disruptions, these unpredictable events can cause significant delays that may not be proportional to the extent of the disruption. Enhancing transportation system resilience can help mitigate the consequences of disruptions, however, required investments are difficult to justify given the low probability of event occurrence. This paper calculates economic implications of unmitigated random disruptions in urban road systems. We modeled delays in transportation network and demonstrated how resilience can be integrated with the microeconomic transportation planning model, REMI TranSight. The model was applied to 10 cities in the United States to calculate gross domestic product (GDP) and several other economic indicators. A baseline scenario was tested where economic impact was assumed to be proportional to the magnitude of disruptive events. Then, a test scenario was assessed, where the magnitude of disruption was used to calculate additional delays in transportation networks that were then integrated in REMI model. Results show that losses in GDP were far more pronounced in the case scenario as compared to the baseline. The economic output tends to rebound 1-2 years following disruptive event. We conclude that support for investment decisions on improvements in transportation networks should be based on a framework that utilizes resilience, quantified in terms that are compatible with standard practice, and scenarios to test the implications of topological attributes of transportation networks.

Introduction

Currently, most mandated development-related transportation planning is intended to prepare for frequently occurring and observable disruptions, while unpredictable events that have not yet occurred attract less attention. The current norm for improving transportation networks and remedying the economic impact of delays is undertaken through management for specific threats to reduce the travel time and improve efficiency. This emphasis on travel time and the monetary value of its duration allows prospective projects to enter the realm of cost-benefit analysis but carries the short-coming of representing only observable and predictable events. Recent experience clearly show that focus on resilience, defined as ability to recover from both predictable and unpredictable disruptions and adapt (NAS, 2012 Linkov and Trump, 2019) is necessary, but economic impact of lack of resilience in transportation networks has not been studied. This paper is the first to provide fusion of well-established Regional Economic Model (TranSight 4.2 User Guide, 2018) with the transportation network resilience model developed by Ganin et al (2017) and applied to multiple cities in the USA. This explicit integration of temporal resilience model linked with regional economic model allows comparative evaluation of multiple cities with respect to the impact of resilience rather than attempts to model just one city at a time.

Transportation system investments are principally motivated by the goal of reducing delay (Belenky, 2011) and, by nature of modeling norms and associated metrics, projects are designed to do so by targeting improvements in efficiency. Current practice is to evaluate road performance with Level of Service (LoS), or similar measure of efficiency, during the worst traffic of an average day and when the whole road network is running as expected (*Highway Capacity Manual, 5th Edition*, 2010).

The transportation field recognizes that variances in expected travel times have a cost, even when not incurred, as they need to be planned for by travelers. This is known as the Value of Reliability (U.S. Department of Transportation, 2016). While Value of Reliability is well researched and methodologies to estimate it do exist (Fosgerau and Karlström, 2010; Lam and Small, 2001), no standardized method has yet been adopted in the US (U.S. Department of Transportation, 2016). These costs may not be consistent across sectors and some workers may have more flexibility in where and when they work than others. These costs may also fluctuate with the amplitude of the delay, with small delays potentially being negligible, though more research is needed (Fosgerau et al., 2007; Mackie et al., 2003; U.S. Department of Transportation, 2016). A more standard metric used in planning is Value of Time (VOT), which is generally calculated on the assumption that variance in travel time from one scenario to another is certain and value is linearly calculated based on wage rates (U.S. Department of Transportation, 2016). Both of these methods fail to capture the costs of unpredictable delays, which cannot be accounted for in schedules and may have different costs than those associated with time passed in traffic.

The realm of possibilities between average traffic conditions and unpredictable disruptions, such as natural disasters, is comprised of events that can have non-trivial disruptions to mobility, and yet are outside the realm of planning and analysis. These events may be unpredictable in space and time and unknown in nature to the point of being random. Therefore, these unpredictable events should be the focus of resilience inquiries here and elsewhere (Ganin et al., 2019, 2017). Whereas mitigating risk of disruption (i.e., strengthening key nodes and links in transportation networks) is appropriate for specific hazards, events that are highly uncertain in space and time challenge our ability to characterize vulnerability to them and implement effective risk mitigation measures. Cost concerns ensure that completely minimizing physical risk at one location may inherently limit our ability to reduce risk elsewhere. Similarly, hardening a transportation system against the risk of new types of disruptions, such as cyber-attacks on Intelligent Transportation Systems (ITS), is difficult because the potential range of risk is too vast to be effectively predicted (Ganin et al., 2019). Network-wide management is therefore more appropriate than location-specific solutions, where the objective is to keep people and goods flowing through the network in spite of disrupted parts of the network. An apt measure of a network's performance with respect to that objective is resilience. Resilience in transportation is the ability to function despite disruption and/or to promptly recover after the disruption.

Across various contexts, there is a growing recognition that lack of resilience can have grave socioeconomic consequences, especially in the context of damaged interconnected infrastructure (Florin and Linkov, 2016). Such is the finding of a recent World Bank report on infrastructure as a key enabler of economies and the macroeconomic impacts of not being resilient (Hallegatte et al., 2019). Presidential Policy Directive 21 - Critical Infrastructure Security and Resilience (Obama, 2013) formalized the call to enhance the nation's critical infrastructure functioning and resilience by recognizing the importance of operable critical infrastructure, including transportation systems. This resilience-related Policy Directive was focused one of 16 sectors that were considered vital to national economic security, public health, and safety ("Critical Infrastructure Sectors," 2019). The current state of practice in transportation planning lends itself to the conclusion that advances in resilience research need to be integrated into planning norms to help account for uncertain events and emerging risks. Quantitative resilience modeling results can be used in tandem with efficiency-driven modeling efforts to conduct tradeoffs among multiple objectives in transportation network investment.

This paper aims to demonstrate that joining resilience analysis with regional economic modeling can advance the methodological approach necessary for planning. The extent of socioeconomic impacts due to disrupted infrastructure is currently researched, yet the field is limited to forecasting or assessing impacts of specific disruptive events. For example, Ham et al. (2005) assessed the anticipated economic implications if an earthquake were to occur in the New Madrid Seismic Zone in the U.S. Midwest. Ham et al. (2005) concluded that the ensuing disruption to U.S. commodity flow could pose significant threat to economic stability and recovery at the regional, national, and international scale. Transportation network resilience, according to the Ham et al. (2005) context, refers the adaptability of commodity flow such that goods can be transported via multiple modes. Similarly, Tatano and Tsuchiya (2008) developed a spatial computable general equilibrium (CGE) model to estimate economic losses (e.g., changes in the cost of travel time) attributed to earthquake disruption of freight and passenger transportation flow. They used the 2004 Niigata-Chuetsu Japan earthquake as a case study, and regional economic losses were measured as a function of inter- and intraregional trade (Tatano and Tsuchiya, 2008). Pelling et al. (2002) discussed how the 1995 Kobe, Japan earthquake increased transportation costs in the region by over 50% and increased the cost of goods in the region by 10%. Internationally, the disablement of the Kobe Port halted the import and export of goods. Pelling et al. (2002) suggest that disasters possess an "inflationary potential" due to their capacity to affect the "production, distribution, marketing, and consumption" functions of markets. Cho et al. (2015) show how disruption to critical highway infrastructure, such as highway bridge and tunnel damage, can lead to economic losses in the U.S. on a state-by-state and industry basis. They conclude that the states and industries that can adapt to disruption suffer the least economic loss. Therefore, redundancy in transportation networks can mitigate the consequences of a disruptive event. This conclusion is mirrored by Worton (2012), who suggested that resilience engineering should focus less on efficiency than the capacity for preparedness, recovery, and adaptation (Mattsson and Jenelius, 2015). The shortcomings of existing studies on the economic implications of transportation disruptions are twofold: 1) resilience is often conflated with potential damages and 2) economic modeling is not underpinned by analysis of transportation network topology.

Resilience planning can integrate economic modeling that is based in transportation network analysis. This integration will allow for transportation costs to be associated with travel time delays, as delays are a primary contributor to economic impact. The current paper used REMI

TranSight (*TranSight 4.2 User Guide*, 2018), an established economic modeling process that uses input-output, computable general equilibrium, econometric and economic geography methods. Our application of REMI TranSight reinforced that the lack of resilient transportation networks can suffer from non-trivial economic consequences via the delays that they cause to travel. Disruption-induced delay results generated by Ganin et al. (2017) were translated to economic outcomes by formulating them as inputs to REMI TranSight. This expanded the use of travel delay information that is traditionally used in scenario and policy analysis. We introduced a process for quantifying the economic implications of resilience or lack thereof, which can be used to progress a planning approach that explicitly considers resilience. The method is demonstrated for ten U.S. cities. The methodology used in this study can be instrumental in the transition from current risk-based planning to true resilience planning, supported by economic analysis and subsequent selection of management alternatives.

Methods: Integration of Transportation Network Research and Economic Modeling

This paper joins two independently developed and documented models to assess economic impacts of resilience in transportation networks: 1) Ganin et al.'s (2017) urban traffic network simulation which estimates travel times given either a predictable disruption (e.g., peak commute hours) or andom disruptions and accidents (e.g., natural disasters and major accidents), and 2) TranSight (*TranSight 4.2 User Guide*, 2018), a regional economic forecasting model oriented specifically for simulating the outcomes of changes in transportation systems.

Network Model for Simulating Delays Associated with Disruptions

Effects of disruptions on an urban transportation infrastructure are quantified with the model proposed in Ganin et al. (2017). Specifically, the model assessed travel delays during peak-hours for private vehicle commuters in 40 urban areas in the continental U.S. Urban areas are densely developed and encompass residential, commercial, and other non-residential urban land uses (“2010 Census Urban and Rural Classification and Urban Area Criteria,” 2018). An example of the Houston, TX urban area is given in Figure 1.

In order to study travel delays in each of the urban areas under both normally functioning and disruption scenarios, Ganin et al. (2017) first built transportation graphs comprised of intersections connected by roadways and then generated trips based on population assigned to each intersection. The population assignment was done with Voronoi tessellation and data from the U.S. Census Bureau. Trip distribution was accomplished with a modified gravity model and only privately-owned vehicle (POV) mode of travel was studied. Route assignment was done assuming free-flow speeds on all roadways. Next, based on traffic volumes on each roadway, the authors proposed a model that estimated the effective traffic speed. Using those congestion-based speeds, the authors evaluated the ensuing total annualized travel time. The model was subsequently calibrated to match measured data on annualized delay per a peak-hours auto commuter as given by the Urban Mobility Scorecard (Schrank et al., 2015). Modeled delays were calculated as the difference between travel times under congestion and travel times with free-flow speeds. The details of each step of the model development can be found in Ganin et al., (2017).

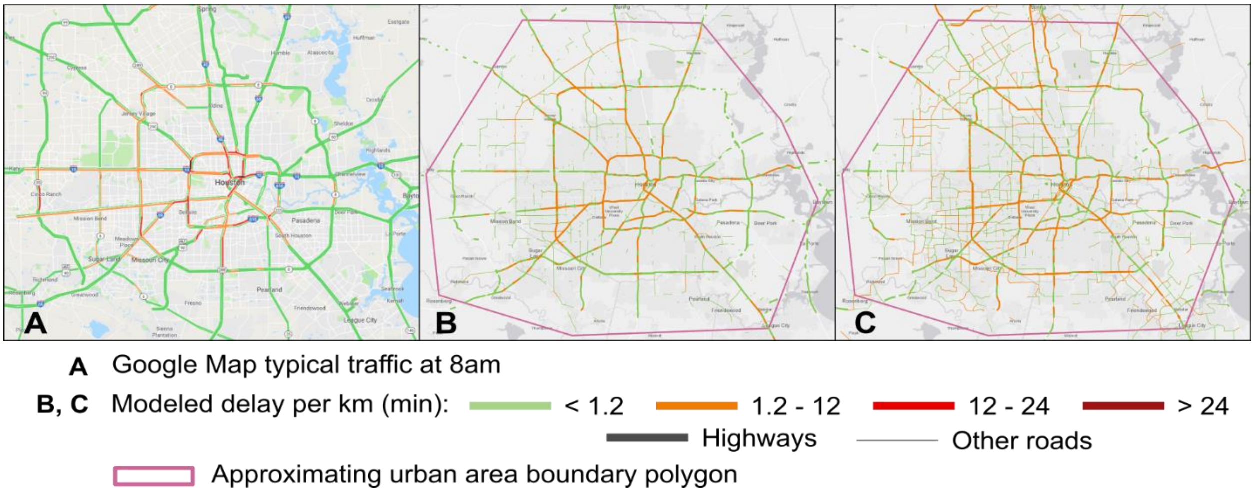

Figure 1. Roadway networks of Houston, TX: (A) Congestion patterns at 8 am per Google Maps, (B) Modeled delays per kilometer of travel in normal conditions (B) and under 5% disruption (C). Purple line shows an approximation of the urban area boundary in panels (B) and (C).

To characterize the resilience of modeled cities, Ganin et al. (2017) generated disruptive events on the transportation networks by disabling links. Resilience was quantified as the additional delay resulting from these disruptions. More specifically, Ganin et al. (2017) randomly selected a fixed fraction ρ of network links that was made non-functional by reducing their free-flow speeds to 1 km/h. Links were selected at random, with probabilities proportional to their lengths to account for the fact that longer roads are more likely to be affected by adverse events. Then, traffic was redistributed per the updated link free-flow travel times assuming the same origin-destination demand matrix. Additional delays that resulted from those events were evaluated as the difference between annualized travel time with and without a disruption.

Economic Modeling for Insight into Impacts of Transportation Network Changes

TranSight (*TranSight 4.2 User Guide*, 2018) is designed to be used with transportation forecasting models to translate the outcomes of improvement measures into regional economic implications. In this case, instead of forecasting models, the transportation resilience model by Ganin et al. (2017) was used to generate additional travel time (delay) that resulted from transportation system disruptions. For transportation studies, cost-savings, capital investment, and other financial and economic concerns associated with prospective infrastructure projects are related to the regional economy via changes to economic variables, which are called "policy variables" in the model. These policy variables represent the effect of travel time on individual spending on fuel and subsequently their disposable income and consumer spending. Additionally, costs to industries were estimated via the extent to which labor demand is met and composite price of goods they send to market. All of the linkages between travel times and associated costs to the policy variables that are used in regional economic models are detailed in (*Model Equations*, 2017; *TranSight 4.2 User Guide*, 2018). TranSight can also account for the economic effects of changes to emissions, safety, and time saved as a result of transportation projects. These effects enter the economy as a change in the non-pecuniary amenity policy variable, which accounts for the desirability of an area as a place to live, independent from financial concerns such as wage levels.

Regional Economic Models Inc., the developer of TranSight and related products, maintains regional economic models for a wide variety of U.S. regions and states in order to support research. For a particular city or region, economic effects of transportation projects are forecasted in economic terms that include gross domestic product (GDP), employment, delivered price, commodity access, labor access, and relative cost of production. These are the outputs of PI+ Engine, a model that mixes techniques from Input-Output (I-O) and Computable General Equilibrium (CGE) modeling, as well as economic geography and econometric techniques (Model Equations, 2017). The transportation-economic modeling sequences (TranSight with PI+ Engine) typically supports the evaluation of alternative transportation projects and policies.

The inputs for TranSight include: (a) the change in Vehicle Miles Traveled (*VMT),* (b) Vehicle Hours Traveled (*VHT),* and (c) vehicle trips attributable to improvement measures. Improvement measures include changes to transportation metrics such as average travel velocity (measured by divided VMT by VHT) and the average delivery trips to be made in a given amount of time (measured by the number of trips divided by VHT). In TranSight, changes in velocity from the baseline scenario to the improvement (test) scenario is formulated as proportional to effect on *transportation cost* and changes in trips that can be made is formulated as proportional effect on *accessibility cost.* Transportation projects were presumed to effect various economic variables via changes in "effective distance", which functions to change travel time, or commuting time and expenses. Cost-savings due to reduced travel times accrue to industry firms in the model from reduced commuting and transportation costs, and increased access to markets.

Connecting Transportation Network Resilience and Regional Economic Modeling

For the specified road network disruption severity ρ, quantifying the fraction of affected roadways, the network model (Ganin et al., 2017) calculates the resulting average annualized travel time $T(\rho)$ per a peak-hours commuter. The topological attributes that yield higher or lower $T(\rho)$ values are not called into question in this research.

We assumed a linear relation between the transportation costs and the travel time, estimating the corresponding percent increase in transportation costs $c(\rho)$ as

$$c(\rho) = {}^{\Delta T(\rho)}\!\big/_{T(0)} \tag{1}$$

where $\Delta T(\rho) = T(\rho) - T(0)$.

For the purposes of this demonstration, we relied on changes in Gross Domestic Product (GDP) as an indication of economic impact for individual cities assessed. We did not probe the specific mechanisms of the economies of each city. To quantify the effects of transportation cost increase on GDP we utilized the TranSight model, and then generated the relative change in GDP as function of disruption severity for the 10 cities of interest. Two scenarios are modelled:

1) *Baseline scenario.* Assumes that transportation cost increases are directly proportional to road disruption severity ρ:

$$c^0(\rho) \equiv \rho, \tag{2}$$

2) *Test scenario.* Assumes that transportation cost increases are proportional to the additional travel time induced by disruption, not to the fraction of roads affected (see Equation 1).

Results

Table 1 displays the percent increase in transportation cost computed for different cities at specific values of road network disruption severity ρ and serves as the base for subsequent analysis of economic implications

Table 1. Transportation cost $c(\rho)$ increases by city that result from road network disruptions of severities varying from 1 to 5 percent. Shown in red are the transportation cost increase values exceeding 25%.

		Fraction of Affected Roadways (Network Links), ρ				
		1%	**2%**	**3%**	**4%**	**5%**
Transportation Cost Increase, $c(\rho)$	**Atlanta**	4%	10%	16%	23%	**33%**
	Detroit	3%	6%	9%	14%	19%
	Houston	5%	11%	16%	24%	**32%**
	Jacksonville	7%	13%	22%	**33%**	**44%**
	Los Angeles	1%	3%	5%	7%	9%
	Miami	4%	9%	13%	18%	23%
	Orlando	4%	9%	14%	20%	**26%**
	San Francisco	9%	20%	**34%**	**43%**	**51%**
	Seattle	3%	6%	9%	13%	17%
	Tampa	6%	12%	20%	**26%**	**37%**

We observed that the same disruption results in different cost increases across multiple cities. The cost escalated quickly – even at 3% disruption San Francisco exhibits cost increase of 34%. Economic impacts of transportation disruption were most pronounced in San Francisco, where 5% disruption resulted in a 51% increase in transportation costs. Similar disruption in Los Angeles resulted in only 9% increase in transportation costs. Jacksonville is the second most sensitive city considered, with 44% increase in transportation costs.

Figure 2 shows the temporal impact of a 5% increase in transportation costs on the GDPs for the baseline and test case scenarios. All simulated cities showed significant impact on GDP in the year in which disruption occurs (2019) and the residual effect of that shock over the five subsequent years was relatively small. All of the cities recover to within 0.2% of their expected GDP (simulated GDP in the absence of a shock) by 2020 and have exceeded it by 2023. For example, this corresponded to a loss of $250,000 in Atlanta in the year following the shock. The profile of the initial impact and recovery was very similar for the test case, yet the magnitude was substantially greater, with disruption roughly an order of magnitude worse than the baseline case. Notice the difference in the y-axis of the Figure 2 graphs.

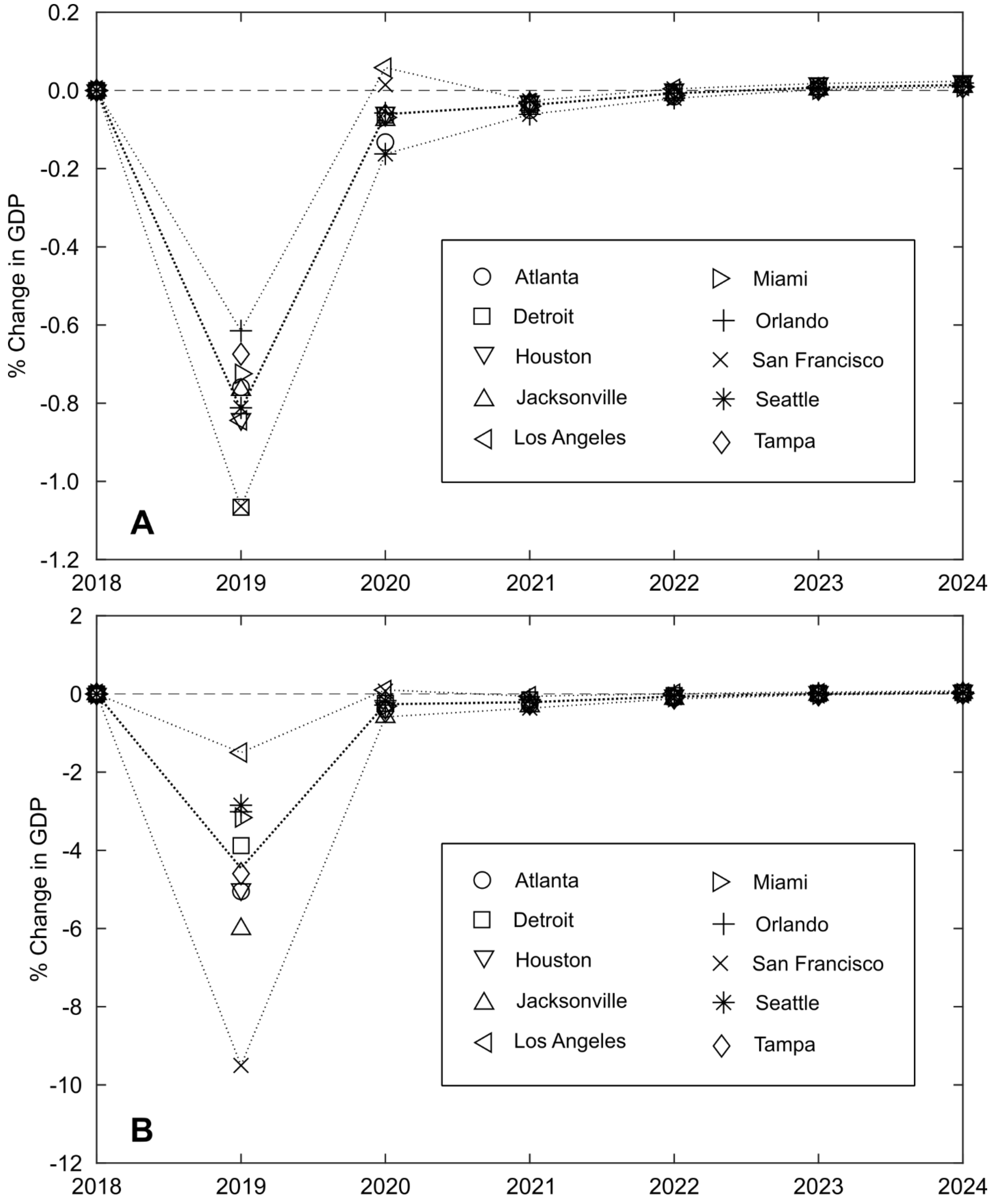

Figure 2. Temporal performance of regional economies (as measured by GDP) in response to a 5% increase in travel costs that lasted one year (A) and to a 5% transportation network disruption (B). Dotted lines show to the lowest, mean, and highest values for each year. Dashed line corresponds to zero change in GDP from expected GDP in the absence of disruption.

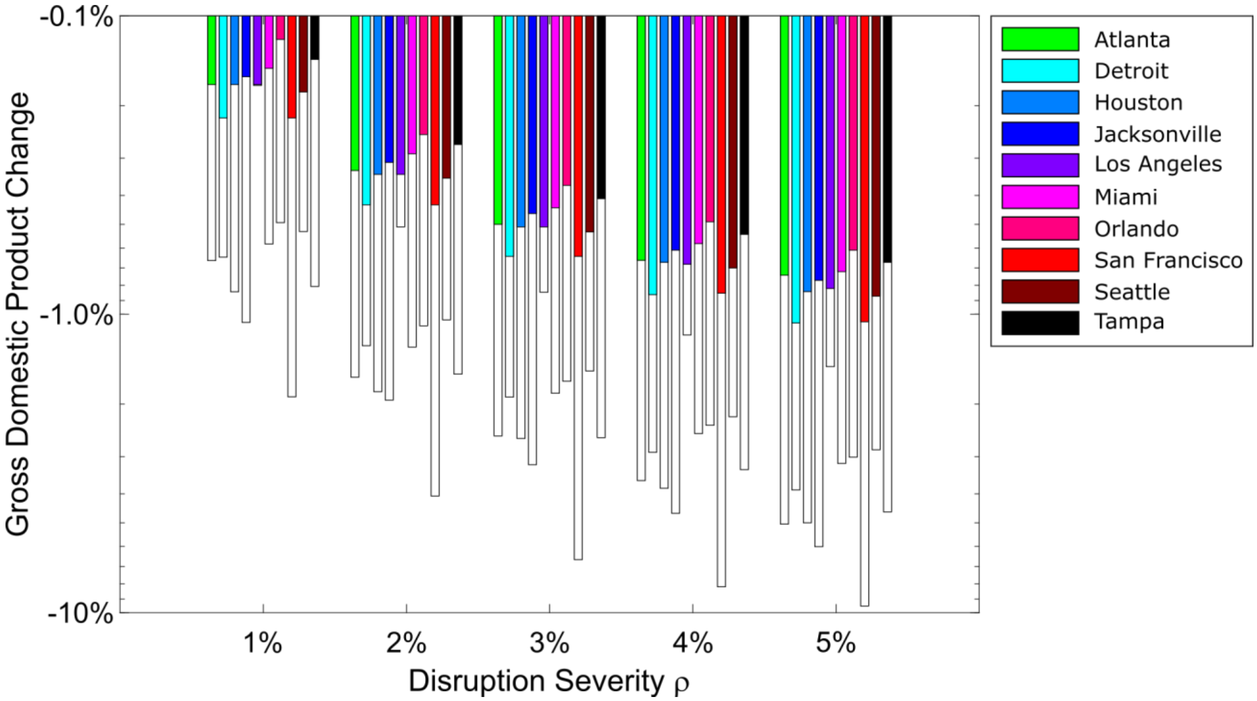

Figure 3. Impact of disruption on GDP (vertical axis scale is logarithmic). The colored bars correspond to the baseline scenario with transportation cost increase being proportional to the disruption severity ρ while the transparent bars present the case when transportation costs change per travel time increase in response to a disruption.

In Figure 3, GDP changes for the baseline scenario are displayed by the colored bars and those for the test scenario are shown with the transparent bars. For both scenarios, GDP progressively declined as a function of disruption severity ρ. At the same time, we note that changes in GDP due to travel time delays were significantly more consequential than their baseline counterparts. In this demonstration, for example, a random disruption of $\rho = 3\%$ of road segments in the San Francisco urban area results in $c(\rho) = 34\%$ transportation cost increase, which translates to 6.64% GDP decrease, significantly more than the baseline result of 0.64%. Not all cities show such disparate results between the two scenarios. For example, for Los Angeles (the 5th bar), a 1% roadway disruption increases the travel time by approximately 1% and therefore the GDP effects are the same (the transparent and the colored bars completely overlap).

To find how regional economies of different sizes are sensitive to unpredictable road disruption events we compared the percent changes in GDP, Δg_i, due to the random disruptions of $\rho = 5\%$ of road segments with the average GDP per capita values G_i for each of the cities $i = 1, .., 10$ (Figure 4). For convenience, we show the mean values of $\langle G \rangle = \$73{,}422$ and $\langle \Delta g \rangle = -4.46\%$ on each of the axes with dashed lines. The worst response to disruption and a GDP decrease of 9.5% is found in San Francisco while the lowest GDP decrease of 1.5% is found in Los Angeles consistently with cost increases per Table 1. This showed that the GDP changes under road disruptions did not correlate with the GDP per capita values under the baseline (no disruption) conditions.

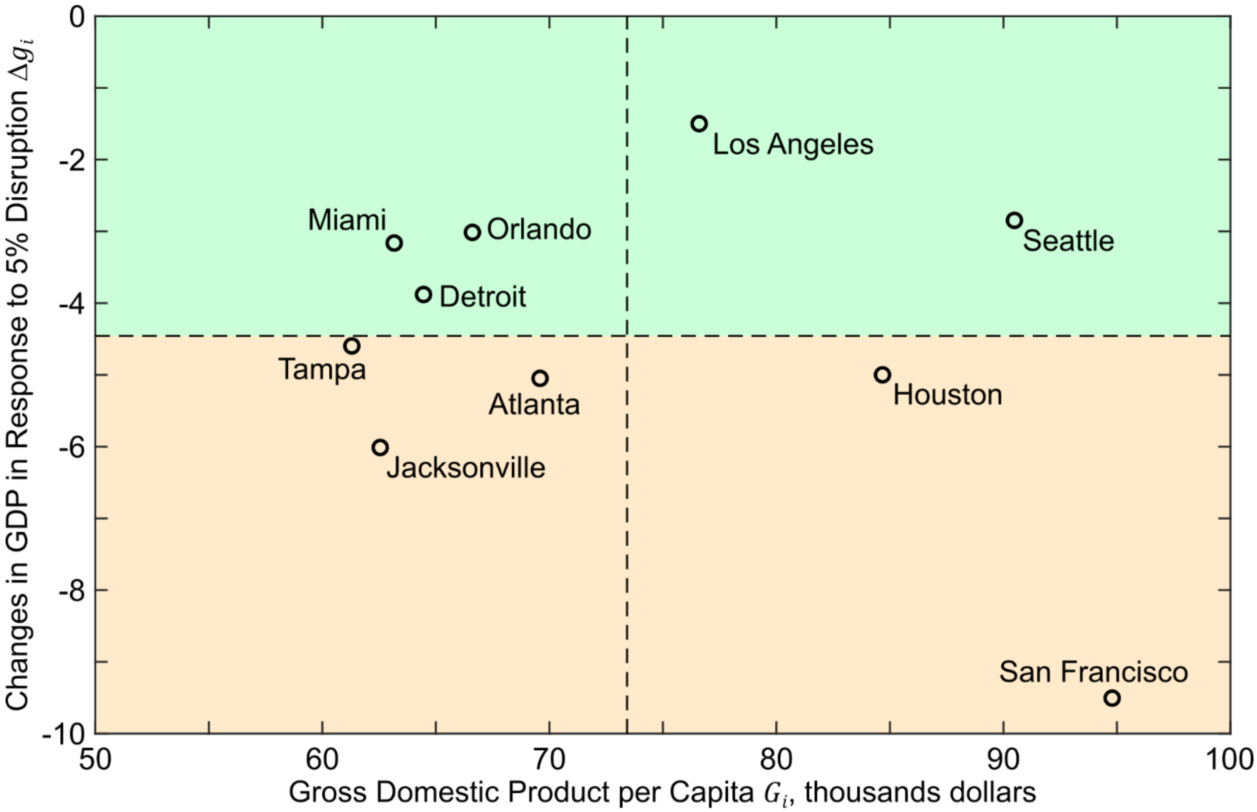

Figure 4. Scatter plot of GDP per capita and change in GDP per capita in response to a 5% increase in transportation costs. The dashed lines indicate the means of the plotted values.

Discussion and Conclusions

Improving the ability of infrastructure systems to maintain functioning in the face of unexpected disruptions (i.e., resilience) is emerging as a high priority in infrastructure planning and an objective that has to be balanced against other system performance objectives, including efficiency and of transportation networks. Ganin et al. (2017) demonstrated that efficiency and resilience are not correlated in the case of 40 U.S. cities. Yet, Ganin et al. (2017) did not assess the economic implications of network efficiency and resilience. It is intuitive that the implications of disruptive events are not isolated to the infrastructure that is directly impacted and yet, the extent that impacts can propagate through regional economies need to be quantified to motivate remedial action and inform priorities. Standard practices for how to incorporate resilience thinking into planning and management are broadly lacking but, as this research demonstrates, there are existing methods can serve to create and process metrics of resilience. Here, the network model produces additional delay, which is designated as a metric of resilience and is compatible as an input to TranSight.

This research demonstrates that, in developing the workflow that can support resilience analysis and decision making, economic models must be paired with network analysis in order to best reflect the impact of disruption on economically important processes, such as commuters accessing their workplaces and firms moving their commodities to market. This work dispels the viability of the assumption that degree of disruption (i.e., percent of roadways disrupted) should be set as proportional to transportation cost increase. As such, one important conclusion of this work is that losses associated with network disruptions may be an order of magnitude higher than the size of disruption itself, as evidenced in Figure 3. The model is limited however in that the calculated transportation cost increase was applied for a period of an entire year; a finer temporal resolution would be preferable. On the other hand, in reality, unexpected delays, can be expected to result in disproportionally higher cost increases as compared to expected delays. For example, traffic congestion does not disrupt businesses on a day to day basis because it can be planned for whereas unforeseen delay cannot be planned around and may cause disruptions that hurt businesses. Because Value of Reliability is not taken into account in the economic model used here, the economic impacts of transportation disruption were conservative.

The finding that economic effects of road disruptions do not scale with the size of city economies (in terms of GDP per capita) and that not all of the regional economies in the study are equally affected by the adverse events merits future research as to what makes some cities more sensitive than others. A naïve expectation is that the larger the economy, the more sensitive it will be to transportation infrastructure disruption however, the results of this study point to the likelihood that more complex processes are at work. Similarly, cities recover from increased transportation costs differently, as shown in Figure 24, which is further evidence of their differing sensitivity to disruptions. We can speculate that sensitivity of an economy is dependent on the reaction of the transportation network to disruption as well as the dependence of the economy on its transportation network. The implication is that both region-specific economic and transportation models are necessary for resilience planning. Future work should explore the driving factors of uneven outcomes across cities, namely the reasons for transportation network sensitivities to disruption as well as local economy sensitivities to transportation failures and ability to recover. Additionally, future work can advance areas in which this study was limited and move the method toward practical application in transportation planning. For example, the topological attributes of road networks that yield more or less delay are not called into question in this research. Similarly, the mechanisms by which network disruptions cause economic impact in the results are not investigated. Efforts to enhance the resilience of road networks to disruption and/or the regional economy to lack of road network resilience will need to study the outcomes of the models in detail. Rose (2017) gives a comprehensive overview of the challenges faced in accounting for the economic impacts of disruption including that of translating damaged public infrastructure into broader economic loses. Other limitations include that the network models that underpin delays do not currently incorporate public transportation options, a significant mode in some cities, most notably New York City. Similarly, the traffic model is intentionally abstract and simple and only uses publicly available data sets and economic variables have a time step of one year.

Additionally, the current model does not differentiate between the expected travel times, variance of everyday traffic and unpredictable delays. Future work should investigate how to integrate potential methods of measuring the Value of Reliability, separate from expected travel times, as well as how unexpected delays may best have their costs modeled and integrated.

A key motivation of this research is to highlight that efficiency, risk reduction and resilience are different objectives. Pairing process models with economic simulation should stimulate greater attention to the differences between these objectives. Although the outcome of disruptive events is delay, and sometimes much more pronounced delay than routine congestion, they cannot be prevented solely by efficiency improvement or risk reduction; planning for resilience is functionally different than planning for efficiency (Ganin et al., 2017). Risk reduction can have limited success for uncertain events. For example, in flow networks, such as transportation systems, efficiency may be achieved by having sufficient roadway capacity, while resilience can result from the availability of, potentially not very efficient, alternative routes, which would ensure graceful performance degradation under disruption as opposed to a complete collapse. As this paper demonstrates, the consequence of neglecting to plan for disruptive events from a resilience perspective is disproportionate impact to both the primary system and the connected, dependent economy.

References

1. 2010 Census Urban and Rural Classification and Urban Area Criteria [WWW Document], 2018. U.S. Census Bureau. URL https://www.census.gov/programs-surveys/geography/guidance/geo-areas/urban-rural/2010-urban-rural.html (accessed 5.31.19).
2. Belenky, P., 2011. The Value of Travel Time Savings: Departmental Guidance for Conducting Economic Evaluations, Revision 2. U.S. Department of Transportation, Washington DC.
3. Cho, J., Gordon, P., Moore II, J.E., Pan, Q., Park, J., Richardson, H.W., 2015. TransNIEMO: economic impact analysis using a model of consistent inter-regional economic and network equilibria. Transportation Planning and Technology 38, 483–502. https://doi.org/10.1080/03081060.2015.1039230
4. Critical Infrastructure Sectors [WWW Document], 2019. . U.S. Department of Homeland Security. URL https://www.dhs.gov/cisa/critical-infrastructure-sectors (accessed 8.5.19).
5. Florin, M.-V., Linkov, I. (Eds.), 2016. IRGC resource guide on resilience. EPFL International Risk Governance Center (IRGC), Lausanne, Switzerland.
6. Fosgerau, M., Hjorth, K., Lyk-Jensen, S.V., 2007. The Danish Value of Time Study (No. 5). The Danish Transport Research Institute, Copenhagen, Denmark.
7. Fosgerau, M., Karlström, A., 2010. The value of reliability. Transportation Research Part B: Methodological 44, 38–49. https://doi.org/10.1016/j.trb.2009.05.002
8. Ganin, A.A., Kitsak, M., Marchese, D., Keisler, J.M., Seager, T., Linkov, I., 2017. Resilience and efficiency in transportation networks. Science Advances 3, e1701079. https://doi.org/10.1126/sciadv.1701079
9. Ganin, A.A., Mersky, A.C., Jin, A.S., Kitsak, M., Keisler, J.M., Linkov, I., 2019. Resilience in Intelligent Transportation Systems (ITS). Transportation Research Part C: Emerging Technologies 100, 318–329. https://doi.org/10.1016/j.trc.2019.01.014
10. Hallegatte, S., Rentschler, J., Rozenberg, J., 2019. Lifelines: the resilient infrastructure opportunity, Sustainable infrastructure series. World Bank Group, Washington.
11. Ham, H., Kim, T.J., Boyce, D., 2005. Assessment of economic impacts from unexpected events with an interregional commodity flow and multimodal transportation network model. Transportation Research Part A: Policy and Practice 39, 849–860. https://doi.org/10.1016/j.tra.2005.02.006
12. Highway Capacity Manual, 5th Edition, 2010. Transportation Research Board, Washington, D.C.
13. Lam, T.C., Small, K.A., 2001. The value of time and reliability: measurement from a value pricing experiment. Transportation Research Part E: Logistics and Transportation Review 37, 231–251. https://doi.org/10.1016/S1366-5545(00)00016-8

14. Mackie, P.J., Wardman, M., Fowkes, A.S., Whelan, G., Nellthorp, J., Bates, J., 2003. Values of Travel Time Savings UK (No. 567). The University of Leeds, Leeds, UK.
15. Mattsson, L.-G., Jenelius, E., 2015. Vulnerability and resilience of transport systems – A discussion of recent research. Transportation Research Part A: Policy and Practice 81, 16–34. https://doi.org/10.1016/j.tra.2015.06.002
16. Model Equations, 2017. . Regional Economic Models Inc., Amherst, MA.
17. Obama, B., 2013. Presidential Policy Directive 21 - Critical Infrastructure Security and Resilience. U.S. Office of the Press Secretary.
18. Pelling, M., Özerdem, A., Barakat, S., 2002. The macro-economic impact of disasters. Progress in Development Studies 2, 283–305. https://doi.org/10.1191/1464993402ps042ra
19. Rose, A.Z., 2017. Defining and measuring economic resilience from a societal, environmental and security perspective, Integrated disaster risk management. Springer, Singapore.
20. Schrank, D., Eisele, B., Lomax, T., Bak, J., 2015. 2015 Urban Mobility Scorecard. Texas A&M Transportation Institute and INRIX, College Station, TX.
21. Tatano, H., Tsuchiya, S., 2008. A framework for economic loss estimation due to seismic transportation network disruption: a spatial computable general equilibrium approach. Nat Hazards 44, 253–265. https://doi.org/10.1007/s11069-007-9151-0
22. TranSight 4.2 User Guide, 2018. . Regional Economic Models Inc., Amherst, MA.
23. U.S. Department of Transportation, 2016. The Value of Travel Time Savings: Departmental Guidance for Conducting Economic Evaluations Revision 2 (2016 Update). U.S. Department of Transportation, Washington, DC.
24. Worton, K.E., 2012. Using Socio-Technical and Resilience Frameworks to Anticipate Threat, in: 2012 Workshop on Socio-Technical Aspects in Security and Trust. Presented at the 2012 Workshop on Socio-Technical Aspects in Security and Trust (STAST), IEEE, Cambridge, MA, USA, pp. 19–26. https://doi.org/10.1109/STAST.2012.16