DISCUSSION PAPER

Clustered Into Control: Causal Impacts of Water Infrastructure Failure

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RESOURCES
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Clustered into control:
Causal impacts of water infrastructure failure[*]

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Abstract

The causal economic impacts of water infrastructure disruptions in OECD countries are largely unknown. Using details of water main break events in Washington, DC, and hourly traffic speeds for 2,182 road segments in a quasi-experimental difference-in-difference design, we estimate the causal effect of main failure on congestion. We use k-means clustering to match treated road segments to control segments. Although precisely estimated, the magnitude of our treatment effects is economically small even when accounting for temporal traffic heterogeneity. Our results suggest that traffic concerns alone are not a justification for policy makers to alter repair strategy for distributed water infrastructure.

Keywords: water main breaks, traffic congestion, water infrastructure, k-means clustering
JEL Codes: H41, H70, C10, L95, Q51, R42

1 Introduction

Infrastructure is widely acknowledged to be utilized beyond its useful life in the United States and many other Organisation for Economic Co-operation and Development (OECD) countries.[1] Water infrastructure in particular gets a lot of media attention. The 2014 Flint, Michigan, water crisis is resulting in criminal charges, a main break on the UCLA campus in 2014 received national media attention, and water main breaks routinely are reported by news outlets.[2]

Despite the widespread media attention, there is virtually no work in the economics literature that addresses the economic impacts of well-functioning water infrastructure in OECD countries. Most of the work addressing the causal impacts of water infrastructure is from field experiments in less developed countries (e.g., Galiani et al. (2005), Gamper-Rabindran et al. (2010), and Devoto et al. (2012)). Recent papers address the value of well-functioning infrastructure for electricity in India (Allcott et al., 2016), public transportation in the United States (Anderson, 2014), and interactions between infrastructure improvement subsidies and electric service reliability in Colombia (McRae, 2014), but there is little work on causal impacts of well-functioning and reliable water service. Some closer research focuses on estimating a dose-response function of water pollution on infant health (Currie et al., 2013) and bottled water purchases in response to water quality violations (Graff Zivin et al., 2011). The majority of the work on water infrastructure in OECD countries, however, uses computable general equilibrium (CGE) models with parameters taken from the literature (Rose and Liao, 2005). While a very valuable modeling technique, because the parameter values used are often not causal it is unclear how much policy makers should prioritize water infrastructure improvements based upon CGE output.

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[1] "Harvard Business Review" and "The Economist" routinely run stories on crumbling infrastructure. See https://hbr.org/2015/05/what-it-will-take-to-fix-americas-crumbling-infrastructure and http://www.economist.com/news/united-states/21605932-country-where-everyone-drives-america-has-shoddy-roads-bridging-gap.

[2] See https://www.washingtonpost.com/news/dr-gridlock/wp/2016/06/23/water-main-break-in-alexandria-likely-to-cause-traffic-delays/.

There are at least two main problems in developing policy to address optimal investment in improving water infrastructure. First, as discussed above, there are no causal estimates for how water supply disruptions impact any measure of economic welfare for OECD countries to our knowledge. Second, there are both centralized (e.g., water treatment facilities) and distributed (e.g., water mains under city surface streets) investments, which are to some extent mutually exclusive. Put another way, even if utilities were allocated a set amount of funds to invest in water infrastructure, it is unclear how to allocate those funds between distributed and centralized components of the water infrastructure system. Although the American Water Works Association notes, "The need to rebuild these pipe networks must come on top of other water investment needs, such as the need to replace water treatment plants and storage tanks, and investments needed to comply with standards for drinking water quality" (AWWA, 2012, 4), there is no clear causal evidence on the indirect economic outcomes of such an investment.

We address pieces of both of these problems by estimating the causal effect of water main breaks on traffic speeds. We choose water main breaks because they occur relatively frequently in an unpredictable fashion and they are an ideal example of distributed water infrastructure. When a water main breaks, it is typically repaired immediately by the local utility or another vendor. The repair job often shuts down streets and impacts traffic because construction crews have to cut through cement and asphalt to repair the broken water main. While there is a healthy literature examining the impacts of various market events and regulations on traffic and driving behavior, there has been no work on the traffic impacts of water main breaks (Burger and Kaffine, 2009; Anderson, 2014; Bento et al., 2014; Wolff, 2014a,b).

We study the universe of all water main breaks over a 12-month period in Washington, DC, during 2014 and 2015. Our data on water main breaks include location of the break, the severity of the break, and the times a break is reported and repairs are completed. We merge in high-frequency and spatially detailed traffic speed data for over 2,000 urban road

segments in DC. We use a difference-in-difference research design by comparing observed traffic speeds on "treated" road segments near a break to "control" road segments farther away from the break. As a result, we are able to identify causal effects of water infrastructure disruptions on indirect economic outcomes.

The first contribution of this paper is our methodology for selecting control road segments for treated road segments. We pre-process the data using a simple unsupervised machine learning algorithm called k-means clustering to classify similar road types based upon observed traffic speed levels, variance, changes, and directions of traffic on each segment for different hours of the day. Roads within the same cluster are most similar to one another and therefore serve as better controls. Our identifying assumption is that conditional on a break occurring, it occurs exogenously within a cluster. While k-means clustering has been used in the economics literature previously for classification (Crone, 2005), we are not aware that it has ever been used to create matched clusters for a treatment versus control causal analysis. This approach builds upon recent work using propensity-score matching to pre-process comparison group data for causal inference (Rosenbaum and Rubin, 1985; Ferraro and Miranda, 2014; Hamilton and Wichman, 2015). It is broadly applicable to other economic problems such as grouping subjects to stratify treatment across different populations in RCTs where treatment effects could be heterogeneous.

The second contribution of this paper is our main empirical finding: water main breaks cause a statistically significant decrease in traffic speeds—averaging between 1.1% and 1.9%—in most road segment clusters where they occurred. We also find that breaks are more likely to occur during lower traffic speed days (e.g., when it is colder and mains are more likely to break). As a result, finding the appropriate control group takes on added importance in our study. Clustering is also important: the difference between treatment and control groups is even more stark when controls are cluster-specific. The results are strongest for road segments where we observe the most breaks, which implies that failure to reject a null effect is possibly the result of low statistical power. These results are robust to a variety

of alternative specifications including changing the number of clusters, temporal and spatial controls, serial correlation of the standard errors, and falsification tests.

There is a very clear spatial and temporal pattern in the traffic impacts of water main breaks, which is consistent with recent findings in Anderson (2014). During the morning rush hour we find speed impacts over twice as large as in off-peak hours: -4.0% versus -1.8%. We also find that impacts decrease as distance from the break increases. These spillovers radiate to one-half mile from the location of a water main break. We take this as evidence, consistent with Anderson (2014), that accounting for temporal heterogeneity should be part of traffic studies.

While statistically significant and consistent across specifications, the magnitude of these effects is economically small. For the average water main break in our sample, a central estimate of the induced private congestion costs is approximately $1,350 per break. Total costs to DC drivers over the 12 months of our study were on the order of $695,275, or approximately $1 per resident of Washington, DC. To our knowledge, this is the first causal estimate of water infrastructure supply disruptions on any economic outcome in an OECD country.

Despite widespread media attention to water main breaks, our results imply that economic losses from traffic congestion due to water main breaks are not a reasonable justification for delaying large scale repair during, for example, low traffic periods at night. Rather, fixing breaks as they occur appears to be sensible policy when considering only traffic impacts. Put another way, this particular distributed water infrastructure supply disruption does not significantly impact welfare due to traffic congestion. Of course, this is only one of many potential impacts. There are other important attributes to consider in a full cost-benefit analysis, including indirect economic costs due to public, commercial, and residential buildings being without water; lost revenue from leaked water; health risks due to water quality degradation; and direct repair costs. To that end, our paper is a starting point rather than a decision point for policy makers considering water infrastructure investments.

The next section provides background on water infrastructure and water mains. We then detail the methodology, introducing the k-means clustering algorithm in our novel context. After presenting estimation results and robustness checks, we discuss policy implications.

2 Background

A water main is a pipe that supplies water to residential, commercial, and industrial buildings in a water supply system. When cities are constructed, water mains are often placed under city streets with smaller pipes leading into individual buildings. The water in a water main is pressurized to ensure access for utility customers.

Water main breaks occur due to the combination of pressurized water and pipe failure. Failure is related to pipe age, but also to sharp changes in temperature that cause the material making up the pipe to expand and contract. When a break occurs, "downstream" users may lose water and there is sometimes an "urban geyser" where the pressurized water breaks through the ground much like an opened fire hydrant. Much talk about crumbling infrastructure occurs due to increased likelihood of failure. Additional recent concerns also deal with securing infrastructure from human threats. In both cases, the infrastructure's age plays a critical role (AWWA, 2012).

In our study area, the distributed water infrastructure is indeed somewhat old. Table 1 shows the composition of mains by material and a coarse measure of main age for all water mains that had a break in the data we were provided by DC Water, the water utility for Washington, DC, through a Freedom of Information Act (FOIA) request. Almost all DC water mains are cast iron although 3% of breaks occurred in pipes of "unknown" material.[3]

More surprising is the age of mains that broke in our sample. We observe 515 breaks between July 1, 2014, and June 30, 2015; however, we focus on 278 breaks that occurred near a road in our data set. Of these, roughly 46% of breaks occurred in water mains that

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[3]Staff at DC Water noted that there is some incompleteness in the materials records. Rather than the material actually being unknown, these are likely instances of incomplete recording.

were over 100 years old, and the oldest break was from a main installed before the Civil War, in 1859. Unfortunately, we were not able to obtain the age distribution of the entire water main system with our FOIA request due to security concerns, so we cannot compare the age of broken mains relative to the entire water supply system. DC Water reports on its website, however, that the median age of all water pipes is 79 years, which is similar to the median age in our sample (90 years).[4] In the full set of 515 breaks, the median age is 81 years—only two years older than the population median.

Table 1: Age and material of DC water mains

	Count	Percentage
Total no. of water main breaks (July 1, 2014–June 30, 2015)	278	
Total no. main breaks with installation year recorded	268	100
Mean year	1921	
Median year	1926	
Before 1916	122	45.86
Before 1900	76	28.57
Before 1865	5	1.88
Total no. of water main breaks with material info	266	100
Cast iron	260	97.01
Ductile iron	5	1.87
PCCP-LCP	1	0.37
Steel	2	0.75

Notes: We analyze 278 water main breaks that are near roads for which we have traffic information, which is a subset of the total number of water main breaks that occurred in this time period. DC Water reported 515 total water main breaks for this time period.

While local utilities are responsible for upkeep of their distributed water infrastructure, such as water mains and sewage lines, they are also responsible for maintenance and expansion of centralized water infrastructure. Centralized water infrastructure takes the form of water intake pipes from water sources, water treatment facilities, and pump houses. In allocating public money for an optimal portfolio of infrastructure improvements, it is unclear how to allocate funds across centralized and decentralized projects. There is a separate question of the impact of disruptions on centralized water infrastructure. In this paper,

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[4]https://www.dcwater.com/about/rates/default.cfm.

we do not address centralized water infrastructure or any other type of infrastructure (e.g., transportation, electricity) that local and regional governments must address.

In the interests of tractability and precision, we focus on a single outcome that is affected by distributed water infrastructure—the effect of water main breaks on traffic. For a water main break there are other important outcomes that should be addressed in any complete cost-benefit analysis. For example, in many cities commercial buildings must be closed if they do not have access to drinking water. However, knowing precisely which buildings were impacted by a water main shutdown requires more detailed information than we have. Our research design and results, though, could be extended to this important economic impact in future work. As a result, we focus on estimating an accurate effect of water main breaks on traffic speeds as a first step in informing the larger policy question of optimal water infrastructure investment.

3   Methodology

To estimate the causal impacts of water main breaks on traffic congestion we combine unique data sets covering the Washington, DC, area. We then use a machine learning algorithm to cluster road segments into groups that are observationally similar. Finally, we use a flexible difference-in-difference design to test whether traffic is affected by main breaks and whether this effect diffuses over space. This section summarizes each of the steps in detail.

3.1   Data

We purchased traffic data from INRIX, a company that aggregates high frequency and fine granularity traffic speed data, for Washington, DC, covering July 1, 2014–June 30, 2015.[5] We have speed data in miles per hour (MPH) at one-minute intervals on each day in our study period, for 2,182 individual road segments in Washington, DC. Similar data are commonly

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[5]See http://inrix.com/.

used in the economics literature for a wide variety of traffic topics (Burger and Kaffine, 2009; Anderson, 2014; Bento et al., 2014; Wolff, 2014a,b; Hamilton and Wichman, 2015). Included in the set of road segment characteristics are the latitude and longitude points to identify road segment location, the direction of traffic flow, and the reference speed for the road. A road segment is typically around 0.25 miles in length and ranges from a small city street to an interstate highway; these segments, geographically indexed by their midpoint, serve as the unit of observation in our application. For tractability in our analysis, we use hourly averages of speed for each road segment and we drop observations on weekends and those outside of the 5AM–11PM time frame. As such, we have 8,956,589 individual hour-by-road-segment observations. Unlike Bento et al. (2013) and Anderson (2014), for example, who use traffic flow and delay data from the California Freeway Performance Measurement System (PeMS), we require data that is more finely disaggregated on a spatial scale to identify the impact of water main breaks within urban areas. The primary limitation of these data, however, is that the sole time-varying metric we have on traffic patterns is speed, which does not capture important characteristics such as the number of vehicles on the road.

DC Water provided us with a list of water main breaks in response to a FOIA request, providing us with the intersections or addresses of the breaks that occurred during the time period of our traffic data. These data include the date of reporting the water main break and the time of completion of work. We geo-referenced the locations (i.e., the street intersection or street address) of main breaks using Google Maps APIs.

We merge the two data sets—INRIX and DC Water—using latitude and longitude coordinates. The merged data are shown in Figure 1 with points representing water main breaks and lines representing streets with observed speed data. Because the geographic locations of water main breaks do not overlap perfectly with road segment midpoints, we assign a water main break to each road segment within a fixed distance from the break. We then let this distance vary by econometric specification as discussed below.

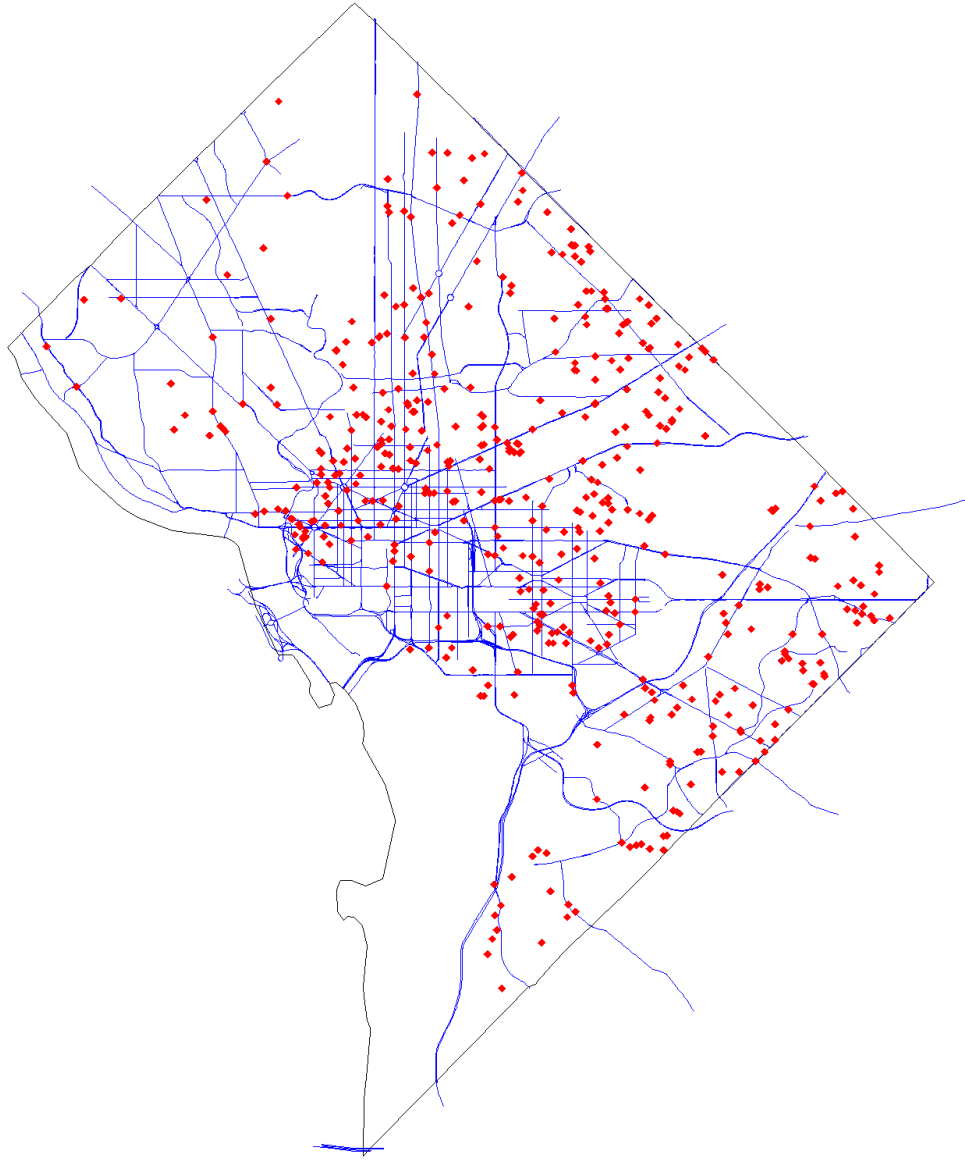The main limitation of our water main break data is that there is no information on

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Figure 1: Merged INRIX road segment and DC Water main break data from July 1, 2014, through June 30, 2015

when work actually began for each water main break. We observe when DC Water reports a repair completed and we observe when a problem is reported. If, however, there is a lapse in work during which there is no construction, that lapse will count as a "treated" period even though traffic could be flowing normally, leading to a lower bound for our estimated average treatment effects. We solve this errors-in-variables problem in several ways. First, we interpolate repair times for breaks that are implausibly long by replacing their repair times with the median repair times of breaks denoted as "most severe." This approach is motivated by severe breaks being prioritized so that their repairs garner the most immediate use of resources. Additionally, we include specifications that define a repair time as the lesser of (a) the difference between the time of a reported break and its completion and (b) one week from reported completion to provide a lower bound for traffic speed impacts.

3.2 k-means clustering

Our INRIX traffic data contain speeds for both surface streets and highways in DC. In our sample, there are several types of surface streets, including arteries and smaller residential streets that have commuter traffic and those without, and so forth. With 2,182 individual road segments, we adopt a method for classifying observationally similar streets together to provide the best possible counterfactual outcome for a road segment that is affected by a water main break.

In order to construct a measure of observationally similar streets from a time series of speed data for each road segment, there are two tasks. The first is to use the time series data to summarize the important characteristics of traffic patterns. The second is to use a method of classification based upon these summary statistics.

We create a set of 52 summary statistics to characterize streets using the year's worth of data. These include mean speed by hour, standard deviation of speed by hour, difference between maximum observed hourly mean and mean speeds during commuting hours (to

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measure congestion), and categorical variables for traffic direction.[6]

Classifying road segments is a unique challenge for this paper. Our approach is similar, in spirit, to using propensity-score matching to construct a control group from observable characteristics (Rosenbaum and Rubin, 1985). Economists traditionally approach classification in this context by matching treatment and control units on the probability of being treated (Rosenbaum and Rubin, 1983). Our situation is fundamentally different because we do not have a constant treatment and control group throughout the study. That is, we need to construct a cluster of road segments that will "turn on" as controls when a road segment in that cluster is affected by a main break, and turn off when traffic is flowing normally within the cluster. Otherwise we could be comparing interstate speeds to surface street speeds, since both are present in our data. As a result, we require a tool to classify roads with no a priori information about the correct groups. Similar challenges exist for stores in classifying customer types to construct optimal price discrimination menus, for example.

Fortunately there is a set of tools used in machine learning for exactly this problem: unsupervised learning algorithms. Unsupervised learning is a term used in data science to put structure on data when there is no left-hand-side variable of interest. This is precisely our situation, since our goal is to identify similar roads to use as control roads for treated streets. We use a simple unsupervised learning algorithm—k-means clustering—which is a statistical method used to group a set of objects based on characteristic variables. This approach classifies N objects in an I-dimensional space into K clusters, choosing to minimize the Euclidean distance between an object's vector and a cluster center (the mean of all vectors in the group) (MacQueen, 1967). K, the number of clusters, and I, the set of clustering

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[6]Specifically, from our hour-by-segment level traffic speed data, we drop all observations that occurred before 5AM, after 10PM, or on Saturday or Sunday. We then aggregate the data to a segment level and generate variables giving the mean and standard deviation of speed over the entire year of data, with one variable for each hour of the day (i.e., annual mean and standard deviation of speed for the hour beginning at 5AM, 6AM, ..., 10PM). We also construct the difference in means for several peak hours relative to a baseline hour with minimal traffic (5AM–6AM). Lastly, using the road segment characteristics provided to us by INRIX, we create dummy variables for cardinal directions (NB, SB, EB, WB, clockwise, and counterclockwise) and highways (one variable indicating whether a road is an interstate, another for US routes). There are 52 total variables in the clustering matrix.

variables, are chosen by the researcher.

k-means clustering minimizes the within-cluster sum of squares, using the Euclidean distance within a cluster weighting each of the I dimensions equally,

$$\sum_{k \in K} \sum_{i \in I} ||x_i - \bar{x}_i^k||^2, \tag{1}$$

where x_i is a vector of the ith variable and $\bar{x}_i^k$ is the mean of the ith variable in cluster k. As with all machine learning classification algorithms, the precise form of the algorithm defines what k-means clustering is. The algorithm begins by assigning K group centers to random points.[7,8] Then, it iterates as follows:

1. Assignment step: Each data point is assigned to the nearest group center.

2. Update step: Group centers are adjusted to match the sample means (i.e., centroid) of the data points.

3. Repeat (1) and (2) until the assignments do not change.

Because simple Euclidean distance will overweight variables with larger nominal values, we standardize our clustering variables to weight each variable equally. We adopt the method recommended by Milligan and Cooper (1988), which is to create $\hat{x}_j = x_j/(\max(x_j) - \min(x_j))$ where x_j is the jth variable. The k-means algorithm will continue to run until each observa-

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[7]k-means clustering has several limitations. One is that the random assignment of starting points can lead to very different clusters based on where the initial placement is (i.e., multiple local maxima). One solution is to repeat the process many times and pick the result with the smallest squared error or, in the case of several with the same squared error, use some sort of average. Bernhardt and Robinson (2007) use multiple iterations and note the importance of doing this for clustering a large number of objects together. Another limitation is that k-means clustering does not consider the shape and distribution of the data. As a result, it is up to the researcher to provide the appropriate summary statistics to use for classification. A third limitation is the "hard" design of k-means clustering. Points are assigned to exactly one cluster, including border points that influence (and are influenced by) points in nearby clusters. This limitation spawned a second type of k-means algorithm known as "soft" or "fuzzy" clustering. This returns a membership degree for each cluster-object pair (Rezankova, 2014). While these aspects of clustering are largely beyond the scope of our application, our results are remarkably robust to various sensitivity tests in clustering.

[8]As a sensitivity test, we also apply k-median clustering to our data. k-median clustering is similar to k-means, but uses the 1-norm distance instead of Euclidean distance to assign objects to clusters (Anderson et al., 2006). Primary results for this approach are included in the Appendix Table A3

tion is located in a cluster with other observations that have similar elements to the clustering variables I.

Figure 2 shows the results of the k-means clustering procedure with $K = 10$. We choose 10 road clusters to allow for two (incoming and outflowing traffic) interstate roads, main surface streets, small surface streets, peripheral streets, and "other." In Figure 2, each road segment included in a panel is part of the cluster in that panel. The algorithm does well at matching similar road segments from visual inspection. $K = 10$ is our preferred number of clusters, but results are robust to other number of clusters. Primary results for $K = 8, 15$ are presented in Appendix Tables Appendix Table A4 and A5.

Table 2 shows summary statistics of clusters selected by the k-means algorithm. There are four clusters (5, 7, 8, and 10) containing many road segments and six smaller clusters. The larger clusters have lower average traffic speeds, suggesting that we have more observations on roads with more traffic. Additionally, the k-means clustering effectively groups streets by direction of traffic and along surface-highway delineations. Similarities in the variables within a row and differences across rows imply that the algorithm did an adequate job of clustering.

Table 2: Summary statistics for each cluster

Cluster ID	No. segments	Speed (Mean)	Speed (SD)	Max. diff. (MPH)	NB (Pr.)	SB (Pr.)	EB (Pr.)	WB (Pr.)	IS (Pr.)	US (Pr.)
1	121	22.823	6.392	4.913	0.975	0	0	0	0.008	0.008
2	41	41.358	8.534	7.311	0	0	1	0	0.073	0
3	121	42.501	9.639	10.127	0	0.678	0	0.298	0.025	0.033
4	38	29.237	13.261	13.916	0.079	0.737	0.079	0.105	0.053	0.026
5	442	17.77	5.57	4.382	0	1	0	0	0	0
6	90	41.816	10.205	11.313	1	0	0	0	0.044	0.011
7	484	18.252	6.301	3.796	0	0	0	1	0	0.004
8	355	15.829	4.117	3.049	1	0	0.003	0	0	0.006
9	130	23.54	6.297	5.49	0	0	1	0	0	0
10	358	16.049	4.442	3.769	0	0	1	0	0	0

Notes: NB = northbound, SB = southbound, EB = eastbound, WB = westbound, IS = interstate, and US = US highway. Max. diff. is the maximum difference in mean speeds during each hour of the day relative to speeds at 5AM within each cluster
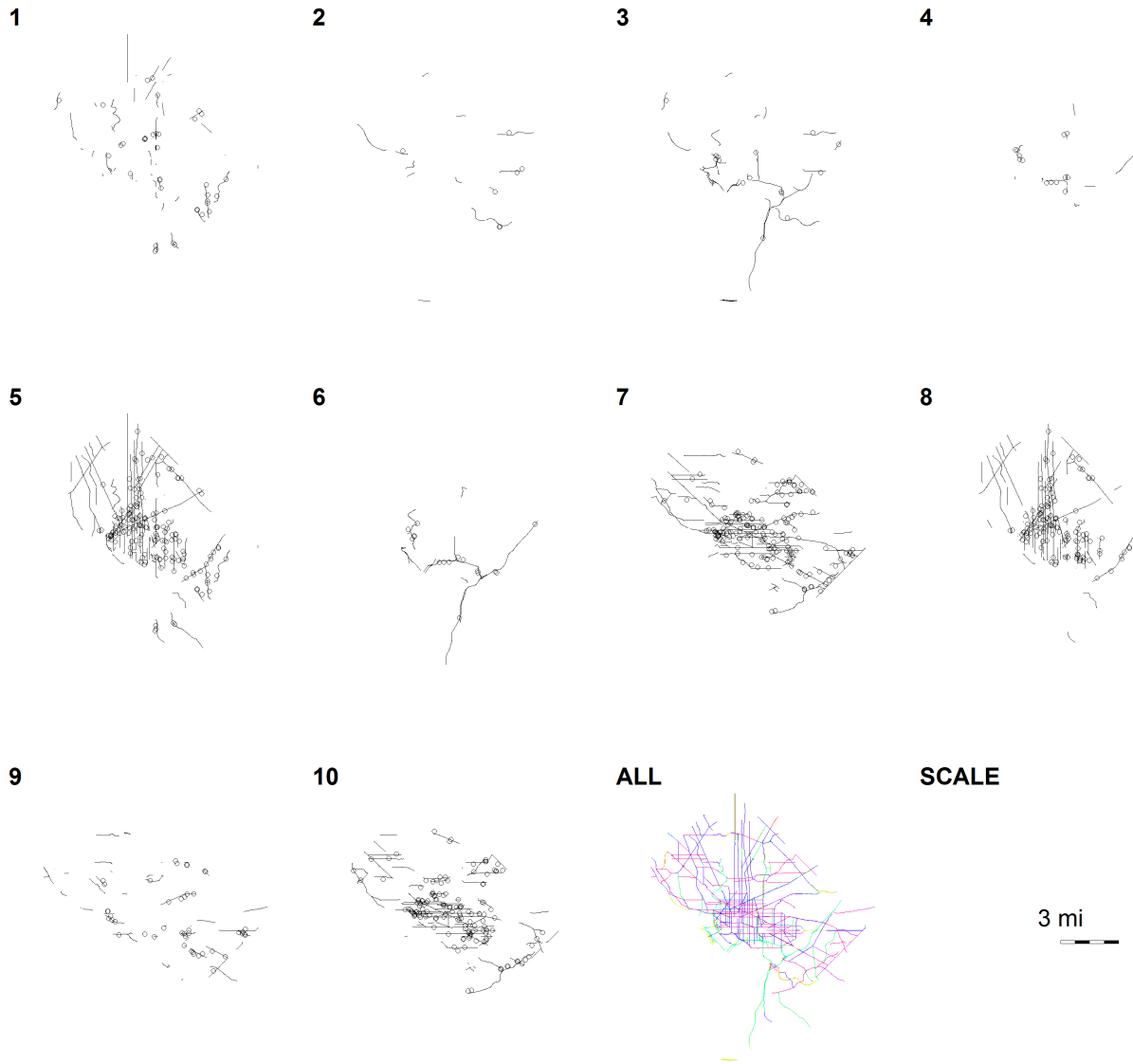
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Figure 2: Map of individual road segment clusters and water main breaks

3.3 Treatment effects over space and time

Now that we have grouped road segments into similar clusters, we can use this classification to inform our identification strategy. Let Y_{ijt} be the outcome variable of interest—traffic speed on road segment i in cluster j at time t. The unit of observation for speed is the road segment level, as defined by our INRIX data. Road segments are assigned to a cluster j based on our k-means algorithm.

We are interested in identifying the effect of a series of exogenous water main breaks on nearby traffic patterns. Since water main breaks vary over space and time throughout our sample, we assign treatment status, $T_{ijt} \in \{0,1\}$, to any road segment within $\omega_1 = 0.15$ mile of a water main break during the time period when our data indicate the presence of a water main break. Although this distance choice is admittedly arbitrary, we choose 0.15 mile as a distance that will capture the immediate effect of a water main break and also provide sufficient power to identify effects on congestion. We discuss robustness checks of varying this threshold below.[9] We also define a cluster indicator, $C_{ijt} \in \{0,1\}$, for road segments that are beyond $\omega_1 + \omega_2 = 0.5$ mile from the water main break, but are within the same cluster j as any treated road segment i. After grouping segments by k-means clustering, we contend that the control road segments are observationally similar to the treated road segments, conditional on segment (α_i) and time (τ_t) fixed effects. We can write this formally as the following conditional independence assumption,

$$E[Y_{ijt}^0|\alpha_i, \tau_t, C_{ijt} = 1, T_{ijt} = 1] = E[Y_{ijt}^0|\alpha_i, \tau_t, C_{ijt} = 1, T_{ijt} = 0], \qquad (2)$$

where Y_{ijt}^0 is the potential outcome in the absence of treatment. The previous equation asserts that the potential outcomes for observations *in the same cluster as a treated segment* ($C_{ijt} = 1$) provide a proper counterfactual for the unobserved term, $E[Y_{ijt}^0|\alpha_i, \tau_t, C_{ijt} = 1, T_{ijt} = 1]$.

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[9]Results are robust to varying this threshold, though estimated effects decrease in absolute value monotonically as this bandwidth increases, consistent with attenuation bias.

Using the clustered control group in a generalized difference-in-difference framework, we can then estimate the average treatment effect on the treated (ATT), defined as

$$\text{ATT} = E[Y_{ijt}^1 - Y_{ijt}^0 | \alpha_i, \tau_t, C_{ijt} = 1, T_{ijt} = 1]. \tag{3}$$

Since water main breaks are conditionally exogenous to our outcome variable, and thus our cluster indicator, we contend that the marginal effect of a water main break on affected road segments, relative to prevailing traffic patterns in the same cluster, is causal.

We also note that the stable unit treatment value assumption (SUTVA) plays an important role in our analysis. Given the natural spatial correlation of traffic patterns in a dense, urban road network, it is likely that the effect of a water main break at a given point may spill over into nearby road segments.

In Figure 3, we present a simplified diagram of our treatment assignment to highlight the spatial dimension of our analysis. If a water main break occurs at the point in the center of the diagram, we treat all road segments in the circle A (within ω_1 miles from the water main break) as treated. As shown, the markers # and + in A represent treated road segments (i.e., $C = 1, T = 1$). All other # and + segments in B and C represent potential control road segments that are in the same cluster as the treated segment (i.e., $C = 1, T = 0$). In the example shown, the marker $\star$ is not treated in A and hence none of its cluster-segments are considered treated (i.e., $C = 0, T = 0$).

Using Figure 3 as a reference point, we conduct three complementary econometric analyses to explore the potential bias arising from treatment spillovers. Specifically, SUTVA is violated if treatment in A affects the outcome in B. If the correlation between treatment in A and outcomes in B is positive, as is likely when considering traffic patterns, then the causal effect of the water main break is likely biased downward. To combat this, we explore this potential bias directly. First, we estimate a naive model using segments lying in A as treated ($C = 1, T = 1$), while clustered segments in B and C serve as "controls" ($C = 1, T = 0$).
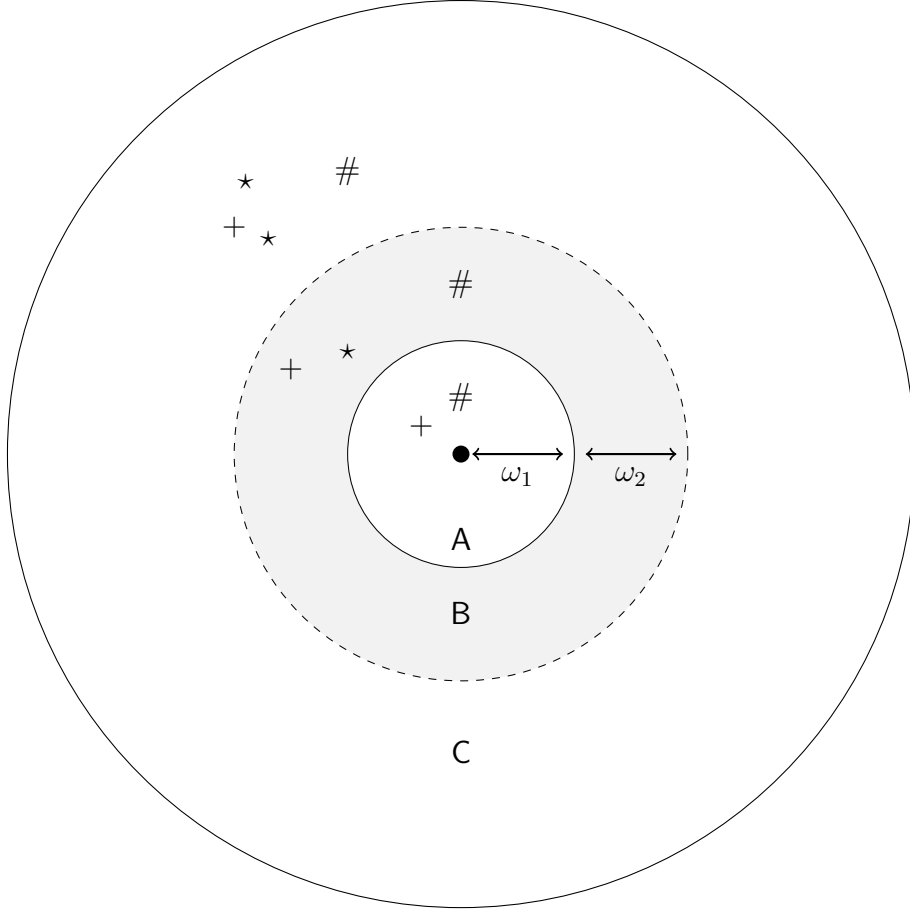
Figure 3: Simplified spatial treatment diagram

Second, we estimate a model using road segments in A as treated, and road segments in C (i.e., greater than $\omega_1 + \omega_2$ miles from the water main break) as controls. The treated clusters that lie in B are excluded from the set of controls ($C = 0, T = 0$). Last, we estimate the spillover effect directly by defining an indicator that corresponds to treated segments that lie in A and another that corresponds to spillover segments that lie in B, and all segments in C corresponding to a treated cluster are controls.

4 Empirical results and discussion

This section reports our main results. The simplest naive model has log of traffic speeds for a given road segment as the dependent variable and includes an indicator variable that

equals one if there is a water main break anywhere in Washington, DC,

$$\ln(speed_{ijt}) = \alpha_i + 1\{Any\ break_t\}\beta + \varepsilon_{ijt}. \tag{4}$$

In this specification we define $Any\ break_t = 1$ for each time period within the 12 hours before any break in the DC Water database is repaired, and zero otherwise. We choose 12 hours because it is the median repair time for the most severe type of the five types of breaks in the data. There were five types of breaks in the data, denoted as 1–5, with 1 being the least severe and 5 the most severe, as well as an "unreported" category. Summary statistics are presented in Table 3. As shown, the median repair time decreases with the severity of the break.[10] There are 515 total breaks in the data.

Table 3: Difference between reported and completion time (in hours) by severity level

Severity Level	Count	1Q	Median	3Q	Mean
1	2	201.6	269.5	337.5	269.5
2	7	329.9	382.5	542.4	423.5
3	41	99.3	189.4	363.1	338.3
4	79	22.6	46.3	96.5	110.0
5	144	9.5	12.8	19.7	22.5
Unreported	5	7.6	18.9	50.4	45.6

Table 4 shows that when breaks occur traffic speeds are on average 0.15% faster. This is a function of the timing of reported audits: off-peak traffic hours are disproportionately represented in the data with noon to 3PM being the most common hours with reported breaks. To that end, when we include hour of day, day of week, and month fixed effects, speeds are on average 0.79% slower. This is likely due to the timing of breaks, which are most common in winter months when temperatures are colder and traffic speeds are, on average, slower because of snow and ice conditions in Washington, DC.

In our next specification, we restrict the definition of treatment and control segments

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[10]DC Water notes, "A simple water main repair can be completed in six to eight hours, but large or complicated repairs may take several days to a week" (source: `https://www.dcwater.com/wastewater/watermain_break.cfm`).

Table 4: The effect of a water main break on aggregate traffic speeds in Washington, DC

	(1) $\ln(speed_{ijt})$	(2) $\ln(speed_{ijt})$
Any break$_t$	0.00154**	-0.00794***
	(0.000710)	(0.000185)
Observations	8,956,589	8,956,589
R-squared	0.000	0.147
Number of segments	2,182	2,182
Fixed effects:		
Hour FE	NO	YES
Weekday FE	NO	YES
Month FE	NO	YES

Notes: Robust standard errors in parentheses clustered at the road segment level. *** p<0.01, ** p<0.05, * p<0.1

in line with the previous section. We define a treated segment, $Break_{ijt}$, as any segment within 0.15 mile of the address of a reported break. We define control segments, $Cluster_{ijt}$, as any segment that is in the same cluster as a treated segment and more than 0.5 mile from a break. In this sense, a segment can be treated and only segments in its same cluster can be controls. We also allow for segments in the same cluster between 0.15 and 0.5 mile from a break to be spillover segments, $Spillover_{ijt}$. We estimate a treatment effect of these segments to determine any possible diffusion of congestion radiating from a break. The precise specification we estimate is

$$\ln(speed_{ijt}) = \alpha_i + 1\{Break_{ijt}\}\beta + 1\{Cluster_{jt}\}\gamma_C + 1\{Spillover_{ijt}\}\gamma_S + \lambda_t + \varepsilon_{ijt} \quad (5)$$

In this specification, the coefficient of interest is β, which is the causal impact of a break on traffic speeds. In line with the definitions above, it is the marginal impact of a break on traffic speeds on a treated road segment. The coefficient γ_C describes the average difference in traffic speeds when a break occurs relative to baseline (i.e., it is similar to the 0.79% point estimate above). By assumption, this specification imposes that the average impact of a control period is assumed to be uniform across clusters. We relax this assumption in

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some specifications below. The coefficient γ_S is the spillover effect of traffic from a road segment where a break occurs. Our identifying assumption for causality is that a break occurs exogenously within a cluster, since γ_C controls for average speed differences during break hours. All regressions are estimated using Cochrane-Orcutt standard errors (Cochrane and Orcutt, 1949). To ensure this solves the serial correlation problem, we test for serial correlation in the error term using the Bhargava et al. (1982) modified Durbin-Watson error term and the Baltagi-Wu LBI statistic (Baltagi and Wu, 1999) in all models.

Table 5: Average treatment and cluster break effects

	(1) $\ln(speed_{ijt})$	(2) $\ln(speed_{ijt})$	(3) $\ln(speed_{ijt})$	(4) $\ln(speed_{ijt})$
$Break_{ijt}$	-0.0187***	-0.0174***	-0.0141***	-0.0142***
	(0.00350)	(0.00326)	(0.00327)	(0.00327)
$Cluster_{ijt}$			-0.00491***	-0.00489***
			(0.000311)	(0.000316)
$Spillover_{ijt}$				-0.00055
				(0.00138)
Observations	8,954,407	8,954,407	8,954,407	8,954,407
Number of segments	2,182	2,182	2,182	2,182
Fixed effects:				
Hour FE	NO	YES	YES	YES
Weekday FE	NO	YES	YES	YES
Month FE	NO	YES	YES	YES
Modified Bhargava et al. Durbin-Watson	0.6976	0.7823	0.7826	0.7826
Baltagi-Wu LBI	0.6997	0.7847	0.7849	0.7849

Notes: All models adjusted for autocorrelation. Robust standard errors in parentheses clustered at the road segment level. *** p<0.01, ** p<0.05, * p<0.1

The results from estimating equation (5) are shown in Table 5. Each column of the table adds more controls until column (4), which has the full model with controls in equation (5). There are three consistent results. First, the point estimate for the causal impact of water main breaks on traffic speeds is between 1.4% and 1.9%. Second, breaks occur when average traffic speeds are roughly 0.5% lower. This difference highlights the importance of having a valid control group. Third, there is no evidence of statistically significant spillover effects. Each of these point estimates is robust to varying the number of clusters, as shown in Appendix Tables A4 and A5.

We also can estimate the same specification but with cluster-specific treatment effects. Table 6 shows those results.[11] For clusters 1, 7, and 10 there are statistically significant treatment effects ranging from 1.3% to 3.6% in the final specification. Estimating different point estimates across segments highlights the value of using clustering to identify heterogeneous impacts. Recalling that clusters 5, 7, 8, and 10 are the largest clusters in the sample, the lack of significance in clusters other than 1 is plausibly attributable to power issues rather than a true zero effect. Clusters 5 and 8 have the expected sign and magnitudes, but are significant only in columns (1) and (2). In this specification we do not find evidence of nonzero spillover effects.

Clustering becomes more important in our study when we estimate the same regression with cluster-specific control indicators (due to their we report these results in Appendix Table A1). Compared to results in Table 6, the two statistically significant and largest in magnitude point estimates decrease with cluster specific controls. Further, in the full specification (column 4) the number of statistically significant road segments (at the 10% level) increases from two to six. This finding appears to be driven by statistically significant heterogeneity in cluster control variable. We take this as evidence of increased precision in treatment relative to control that is not present without the clustering algorithm.

4.1 Robustness checks

While our results are fairly consistent across specifications, in order to ensure that our estimates can be attributed to water main breaks we perform several robustness checks.

The first robustness check is a placebo test of randomly generated water main breaks. We generate 515 random water main breaks in our sample. We then construct treated and control segments using the exact same procedure as with reported breaks. Table 7 reports the results from estimating our main specification on the placebo data. We repeat the procedure several times, but report the results from only a single run. In no case do we find

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[11]Note: Table 6 includes only 2,180 road segments because 2 road segments in our sample have no identifying characteristics to be used in our clustering algorithm.

Table 6: Cluster-specific treatment effects

	(1) $\ln(speed_{ijt})$	(2) $\ln(speed_{ijt})$	(3) $\ln(speed_{ijt})$	(4) $\ln(speed_{ijt})$
$Break_{ijt} \times Cluster1$	-0.0504***	-0.0393***	-0.0359**	-0.0360**
	(0.0154)	(0.0143)	(0.0143)	(0.0143)
$Break_{ijt} \times Cluster2$	0.00721	0.0134	0.0176	0.0176
	(0.0402)	(0.0375)	(0.0375)	(0.0375)
$Break_{ijt} \times Cluster3$	0.00617	0.00818	0.0118	0.0118
	(0.0269)	(0.0251)	(0.0251)	(0.0251)
$Break_{ijt} \times Cluster4$	-0.0539**	-0.0370	-0.0340	-0.0340
	(0.0253)	(0.0236)	(0.0236)	(0.0236)
$Break_{ijt} \times Cluster5$	-0.0138*	-0.0125*	-0.00956	-0.00958
	(0.00730)	(0.00681)	(0.00681)	(0.00681)
$Break_{ijt} \times Cluster6$	0.0287	0.0353	0.0387	0.0387
	(0.0287)	(0.0269)	(0.0269)	(0.0269)
$Break_{ijt} \times Cluster7$	-0.0230***	-0.0250***	-0.0219***	-0.0219***
	(0.00729)	(0.00678)	(0.00678)	(0.00678)
$Break_{ijt} \times Cluster8$	-0.0181**	-0.0138*	-0.0106	-0.0106
	(0.00811)	(0.00756)	(0.00757)	(0.00757)
$Break_{ijt} \times Cluster9$	-0.0311*	-0.0220	-0.0184	-0.0184
	(0.0172)	(0.0161)	(0.0161)	(0.0161)
$Break_{ijt} \times Cluster10$	-0.0122	-0.0161**	-0.0125*	-0.0126*
	(0.00784)	(0.00728)	(0.00729)	(0.00729)
$Cluster_{ijt}$			-0.00491***	-0.00489***
			(0.000311)	(0.000316)
$Spillover_{ijt}$				-0.00055
				(0.00138)
Observations	8,952,305	8,952,305	8,952,305	8,952,305
Number of segments	2,180	2,180	2,180	2,180
Fixed effects:				
Hour FE	NO	YES	YES	YES
Wkday FE	NO	YES	YES	YES
Month FE	NO	YES	YES	YES
Modified Bhargava et al. Durbin-Watson	0.6976	0.7823	0.7826	0.7826
Baltagi-Wu LBI	0.6997	0.7847	0.7849	0.7849

Notes: All models adjusted for autocorrelation. Robust standard errors in parentheses clustered at the road segment level. *** p<0.01, ** p<0.05, * p<0.1

a statistically significant impact of breaks on traffic speeds.

Table 7: Placebo clusters and breaks

	(1) ln($speed_{ijt}$)	(2) ln($speed_{ijt}$)	(3) ln($speed_{ijt}$)	(4) ln($speed_{ijt}$)
$Break_{ijt}$	0.00177	2.05e-06	-7.51e-05	-7.30e-05
	(0.00654)	(0.00617)	(0.00619)	(0.00619)
$Cluster_{ijt}$			9.97e-05	9.70e-05
			(0.000550)	(0.000555)
$Spillover_{ijt}$				0.000133
				(0.00369)
Observations	8,954,407	8,954,407	8,954,407	8,954,407
Number of segments	2,182	2,182	2,182	2,182
Fixed effects:				
Hour FE	NO	YES	YES	YES
Weekday FE	NO	YES	YES	YES
Month FE	NO	YES	YES	YES
Modified Bhargava et al. Durbin-Watson	0.6976	0.7823	0.7824	0.7824
Baltagi-Wu LBI	0.6997	0.7846	0.7847	0.7847

Notes: All models adjusted for autocorrelation. Robust standard errors in parentheses clustered at the road segment level. *** p<0.01, ** p<0.05, * p<0.1

One challenge of this study is possible measurement error in the treatment effect. For severe breaks, which receive the highest priority, the median time between when a break is reported and when it is repaired is 12 hours (rounded down; see Table 3). However, the least severe breaks have median repair times of over 200 hours. This is likely due to lower-resourced and less timely repair schedules for less "important" breaks. This concern initially led us to define treatment as the 12 hours before a repair is completed in order to mitigate the errors-in-variables problem.

As a robustness check, we also estimate our main specification using the lesser of (a) the difference between the time of a reported break and its completion and (b) one week from reported completion as the treatment window. Results are in Table 8. The alternate treatment window finds estimated results of -1.9%, relative to that of our primary treatment definition of -1.4% in the analogous specification above. These estimates, however, are not statistically different. Given the robustness of our primary result to this alternative treatment definition, we view this as evidence that our preferred specification is likely to provide an

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accurate point estimate.

We estimated the same regression as in equation 5 with severity-level treatment effects, rather than pooled, to account for the prioritization of DC Water directly. We present this table in the Appendix (Table A2) and we find significant point estimates between -1.0% and -4.8% for severity level 1, 2, 3, and 5 breaks. Notably, the treatment effect for severity 5 breaks is statistically similar to our preferred treatment estimate and does not suffer from small sample problems. Further, it is these breaks that are prioritized to be fixed immediately, so this result suggests that our preferred estimates are robust to congestion mitigation efforts by the constructions crews (such as waiting until nighttime, when there is less traffic, to repair the main).

Table 8: Average treatment and cluster break effects: reported time = start time (maximum 1 week)

	(1) $\ln(speed_{ijt})$	(2) $\ln(speed_{ijt})$	(3) $\ln(speed_{ijt})$	(4) $\ln(speed_{ijt})$
$Break_{ijt}$	-0.0119***	-0.0170***	-0.0195***	-0.0199***
	(0.00226)	(0.00202)	(0.00202)	(0.00202)
$Cluster_{ijt}$			0.00781***	0.00807***
			(0.000311)	(0.000315)
$Spillover_{ijt}$				-0.00462***
				(0.00081)
Observations	8,954,407	8,954,407	8,954,407	8,954,407
Number of segments	2,182	2,182	2,182	2,182
Fixed effects:				
Hour FE	NO	YES	YES	YES
Weekday FE	NO	YES	YES	YES
Month FE	NO	YES	YES	YES
Modified Bhargava et al. Durbin-Watson	0.6976	0.7824	0.7826	0.7826
Baltagi-Wu LBI	0.6997	0.7847	0.7849	0.7849

Notes: All models adjusted for autocorrelation. Robust standard errors in parentheses clustered at the road segment level. *** p<0.01, ** p<0.05, * p<0.1

4.2 Heterogeneous impacts by time of day

Anderson (2014) shows that the impacts of transit infrastructure disruptions vary by time of day. Intuitively, a disruption is more problematic during high traffic volume periods when

Table 9: Average treatment and cluster break effects: by time of day

	(1) $\ln(speed_{ijt})$	(2) $\ln(speed_{ijt})$	(3) $\ln(speed_{ijt})$	(4) $\ln(speed_{ijt})$	(5) $\ln(speed_{ijt})$
$Break_{ijt}$	-0.0397***	-0.0182***	-0.0180**	0.0130	-0.0126*
	(0.00863)	(0.00703)	(0.00727)	(0.00799)	(0.00695)
$Cluster_{ijt}$	-0.00828***	-0.0141***	-0.0321***	-0.0310***	-0.0340***
	(0.000783)	(0.000668)	(0.000706)	(0.000781)	(0.000692)
$Spillover_{ijt}$	-0.0190***	-0.00482	-0.00829***	0.00458	-0.0194***
	(0.00385)	(0.00301)	(0.00304)	(0.00329)	(0.00287)
Observations	1,680,016	1,680,019	1,673,519	1,677,910	1,673,462
Number of segments	2,182	2,182	2,182	2,182	2,182
Hours	7AM-10AM	10AM-1PM	1PM-4PM	4PM-7PM	7PM-10PM
Fixed effects:					
Hour FE	YES	YES	YES	YES	YES
Weekday FE	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES
Modified Bhargava et al.					
Durbin-Watson	0.9390	0.9013	0.8963	0.8548	0.9037
Baltagi-Wu LBI	1.2807	1.2330	1.2734	1.2021	1.2063

Notes: All models adjusted for autocorrelation. Robust standard errors in parentheses clustered at the road segment level. *** p<0.01, ** p<0.05, * p<0.1

the marginal impact of another commuter is more problematic. As a result, we estimate both aggregated and cluster-specific versions of the econometric model restricting the sample to time-of-day bins. Specifically, we break the day into five parts: 7AM–10AM, 10AM–1PM, 1PM–4PM, 4PM–7PM, and 7PM–10PM.

Table 9 shows results for our time-of-day regressions. We find several important patterns in the data that are robust to alternative specifications. First, the causal impact of breaks varies throughout the day. Largest impacts are during the morning commute (-3.97%) and the magnitude of these impacts weaken throughout the day. This is consistent with repairs having a higher probability of being fixed by later in the day. To that end we find a positive and insignificant impact of treatment on speeds during the afternoon rush hour.

Second, spillovers are much more pronounced when breaking out results by time of day. In all but one case, the spillover effect is smaller in magnitude than the direct treatment impact. During the time period when the spillover effect is larger than the treatment effect (7PM–10PM) the two estimated coefficients are not significantly different. This finding is

consistent with a spatial diffusion of delays with strongest impacts at the point of the water main break.

Third, having the appropriate control group takes on extra importance in the time-of-day results. Table A6 in the Appendix shows results including cluster-specific controls. As before the coefficients on *Break* and *Spillover* are defined as marginal impacts on top of speeds in the control streets in the same cluster. The table shows statistically significant heterogeneity in the control cluster speeds by time of day. These results reveal increases in precision and magnitude of treatment effects by hour of day. We note that spillover impacts remain unchanged relative to the specification where the average impact of a control period is assumed to be uniform across clusters.

5   Policy implications and conclusions

We find small but statistically significant impacts of water main breaks on traffic speeds. The average impacts are on the order of a 1.4% decrease in traffic speeds in road segments proximate to the break. This average impact masks heterogeneity apparent due to the k-means clustering technique. In general, we find that breaks are most likely to occur during hours when speeds are slightly lower than average, consistent with beliefs that breaks occur during winter months when temperatures are colder. These results are robust to a variety of specifications and classification criteria. Our falsification tests show the estimated effects are driven by main breaks.

The direction of our results is not surprising but the magnitudes are somewhat surprising for two reasons. First, water main breaks are frequently reported by local and national media outlets. Second, there is a growing acknowledgment that water and other public infrastructure is deteriorating. Our evidence is consistent with these stylized facts. In our study, however, we find that the costs of a single type of public infrastructure break is not large for the single outcome we examine. Changing water infrastructure investment strategies
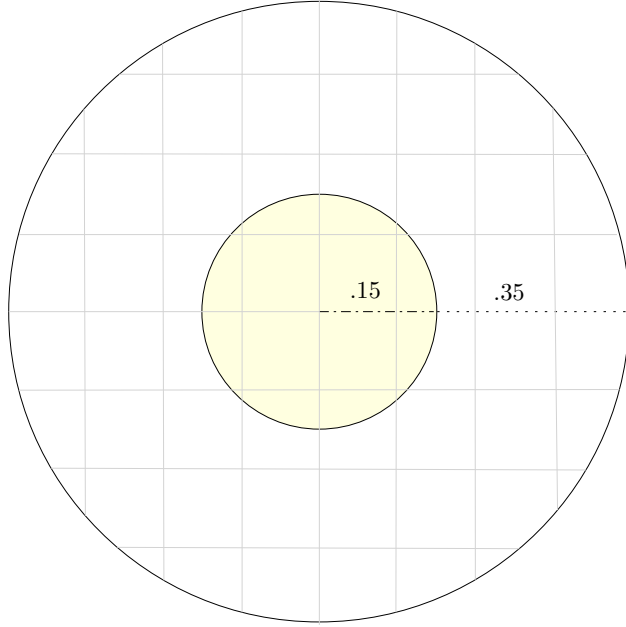
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Figure 4: Schematic of assumed street layout

because of concerns about the effects of water main breaks on indirect economic outcomes (e.g., traffic delays) seems not to be justified.

To put our estimated treatment effects in context, we size welfare impacts of traffic disruptions attributable to water main breaks using both average impacts over the entire sample and the heterogeneous time-of-day impacts in the spirit of Anderson (2014). To do so we download daily traffic count data from Washington, DC. The average city street has roughly 12,500 unique cars travel on it per day.[12] Consistent with the Department of Transportation guidelines, we use half the hourly wage rate in the Washington, DC, metropolitan statistical area (MSA) as reported by the Bureau of Economic Analysis website to value time: $18.80/hour. Table A7 in the Appendix shows mean speed by hour of day over all city streets.[13] By using average speed by hour of day, we construct the number of minutes to travel one mile. We can compare average speeds and expected speeds during

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[12]See `http://rtdc.mwcog.opendata.arcgis.com/datasets/fd3a40a7e317420faff13864c7b82bc7_0?uiTab=table`.

[13]This table also includes mean and standard deviation of the INRIX "score" for the speed data. Score measures the data quality averaged over an hour. 30 is an actual reading and perfect data, 10 is an interpolated speed reading. The overall average data quality according to this metric is 26 and data quality is roughly consistent across our sample.

treated hours to infer the time cost attributable to water main breaks.

We make two simplifying assumptions to make the welfare calculation tractable. First, we have to determine the total number of miles of street that are subject to the treatment effect and the spillover effect. To do so, we assume there is a unique street every 0.1 mile since city blocks are commonly 0.1 mile. We also ignore diagonal arterial streets in DC. This is shown in Figure 4. Shaded area is considered the treated area and the unshaded counted as spillover. Each gray line is a single street. In the welfare calculations, we assume the total length of all streets in the shaded circle of radius 0.15 mile is the length of all treated streets during a "treated" period. The total street length in the doughnut surrounding the shaded region is the length of spillover streets. We calculated street lengths using the Pythagorean Theorem since streets are assumed to be spaced at exactly 0.1 miles and circles are symmetric.

Second, we have to determine how many cars travel on each road segment over a day and, in the time-of-day calculation, each time period of the day. To do so, we assume each street has a total of 12,500 cars traveling on it each day. We both assume cars are uniformly distributed throughout the day and that volumes more than double during rush hours in different specifications. Because we have no data on volumes by road segment type, we focus exclusively on temporal heterogeneity since temporal traffic patterns are more well known than spatial patterns. We take parameter estimates from Tables 5, 8, and 9 to perform the time costs. The magnitude of the time costs is similar to that using other parameter estimates. An Excel spreadsheet with precise calculations is available from the authors upon request.

Table 10 shows the results of the time costs attributable to water main breaks that occurred over the 12 months we study. Accounting for temporal heterogeneity rather than simple average impacts, we find time costs increase by roughly 400%. This result is consistent with Anderson (2014) who finds the impacts of transit infrastructure disruptions vary by time of day in a similar way.

Table 10: Annual traffic time costs of Washington, DC, water main breaks

Method	Coefficients table	Rush hour car volume	Normal car volume	Total cost
Average (without spillover)	5	n/a	n/a	$125,988
Average (with spillover)	5	n/a	n/a	$159,222
Average (with spillover)	8	n/a	n/a	$444,490
Time of day	9	2,500	2,500	$648,279
Time of day	9	4,000	1,500	$695,275

Notes: Assume 12,500 total volume per road/day and value of time of $18.80/hour. A total of water main breaks occurred between July 1, 2014, and June 30, 2015. For the time-of-day, non-uniform calculation, we find the time cost per break is roughly $1,350.

Our preferred cost calculation is the bottom one in which we use our estimated time-of-day effects and assume more traffic occurs during rush hours. In doing so we estimate a time cost per water main break of roughly $1,350. This works out to roughly $700,000 over the entire year. While half or twice this number is possible, we are reasonably confident this is the correct order of magnitude. Given that the total population of Washington, DC, is roughly 700,000, this works out to roughly $1 per person. In this case $1 per person is almost surely an overestimate: the time-weighted population of Washington, DC, is much larger than 700,000, as many people commute into the city from more suburban areas. We do not view this as a large cost.

The use of these estimates for other urban areas is somewhat plausible, but they probably do not transfer to less urban areas. Washington is a dense urban area with various alternative transport options. The metropolitan DC area consistently ranks as one of the most congested cities, ranking first in annual hours of delay per commuter (Schrank et al., 2015). As a result, the effect of a water main break on traffic patterns in DC may be small relative to a city with fewer alternative commuting options, whether those are alternative routes or different modes of transport. This logic would imply that our results are externally valid for dense road networks in urban cities and likely a lower bound when fewer substitutes are present. Despite this, urban areas on average tend to contain older infrastructure that is of critical policy importance.

Our results, however, do not suggest that infrastructure investment is not important. In fact, the number of water main breaks, and the corresponding age of the mains, for a single urban area within our year-long study period is alarming. Rather, we provide evidence that a single indirect economic cost (increased congestion) from distributed water infrastructure failure is small. Other direct and indirect effects could be large. That said, if other indirect costs of failure were small, then centralized water infrastructure improvements could provide more value than improvements to distributed infrastructure. Further, it could be that observed failures are not the right measure in this space; water infrastructure investment might be best framed in terms of forgoing the worst possible outcome, much as electric utilities plan to mitigate the probability of blackouts. In that case, though, we are not aware of a good economic framework for estimating the impacts of those large, and in some cases never observed, events.[14]

More generally, our paper is a starting point rather than a decision point for policy makers in this space. There is a gap in the literature in identifying causal impacts of water infrastructure failure on economic outcomes. While there is a larger literature on dose-response functions that could be used to perform back-of-the-envelope calculations on the costs of deterioration, there is a need to inform policy makers so that they can plan their infrastructure investments efficiently.

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[14]One example is trying to identifying the causal impact of a never before observed human threat to water supplies.

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Appendix A − Additional results

Table A1: Cluster-specific treatment effects with cluster-specific controls

	(1) $\ln(speed_{ijt})$	(2) $\ln(speed_{ijt})$
$Break_{ijt} \times Cluster1$	-0.0302**	-0.0302**
	(0.0144)	(0.0144)
$Break_{ijt} \times Cluster2$	-0.00160	-0.00165
	(0.0380)	(0.0380)
$Break_{ijt} \times Cluster3$	0.00881	0.00878
	(0.0252)	(0.0252)
$Break_{ijt} \times Cluster4$	-0.0434*	-0.0434*
	(0.0241)	(0.0241)
$Break_{ijt} \times Cluster5$	-0.00673	-0.00677
	(0.00682)	(0.00682)
$Break_{ijt} \times Cluster6$	0.0298	0.0297
	(0.0270)	(0.0270)
$Break_{ijt} \times Cluster7$	-0.0206***	-0.0207***
	(0.00679)	(0.00679)
$Break_{ijt} \times Cluster8$	-0.0153**	-0.0154**
	(0.00758)	(0.00758)
$Break_{ijt} \times Cluster9$	-0.0268*	-0.0269*
	(0.0162)	(0.0162)
$Break_{ijt} \times Cluster10$	-0.0136*	-0.0136*
	(0.00730)	(0.00730)
$Break_{ijt} \times Cluster\ Control1$	-0.0128***	-0.0127***
	(0.00184)	(0.00184)
$Break_{ijt} \times Cluster\ Control2$	0.0164**	0.0164**
	(0.00676)	(0.00676)
$Break_{ijt} \times Cluster\ Control3$	-0.00108	-0.00104
	(0.00296)	(0.00296)
$Break_{ijt} \times Cluster\ Control4$	0.00869	0.00880
	(0.00698)	(0.00698)
$Break_{ijt} \times Cluster\ Control5$	-0.00933***	-0.00930***
	(0.000611)	(0.000613)
$Break_{ijt} \times Cluster\ Control6$	0.00732*	0.00738*
	(0.00379)	(0.00379)
$Break_{ijt} \times Cluster\ Control7$	-0.00686***	-0.00683***
	(0.000559)	(0.000561)
$Break_{ijt} \times Cluster\ Control8$	0.00197***	0.00202***
	(0.000750)	(0.000753)
$Break_{ijt} \times Cluster\ Control9$	0.00607***	0.00610***
	(0.00184)	(0.00184)
$Break_{ijt} \times Cluster\ Control10$	-0.00352***	-0.00348***
	(0.000680)	(0.000682)
$Spillover_{ijt}$		-0.00100
		(0.00138)
Observations	8,952,305	8,952,305
Number of segments	2,180	2,180
Fixed effects:		
Hour FE	YES	YES
Weekday FE	YES	YES
Month FE	YES	YES
Modified Bhargava et al. Durbin-Watson	0.7827	0.7827
Baltagi-Wu LBI	0.7850	0.7850

Notes: All models adjusted for autocorrelation. Robust standard errors in parentheses clustered at the road segment level. *** p<0.01, ** p<0.05, * p<0.1

Table A2: Average treatment and cluster break effects by break severity

	(1)	(2)	(3)	(4)
	$\ln(speed_{ijt})$	$\ln(speed_{ijt})$	$\ln(speed_{ijt})$	$\ln(speed_{ijt})$
$Break_{ijt} \times Severity1$	-0.159***	-0.103***	-0.101***	-0.101***
	(0.0289)	(0.0267)	(0.0267)	(0.0267)
$Break_{ijt} \times Severity2$	-0.0686***	-0.0683***	-0.0644***	-0.0644***
	(0.0262)	(0.0244)	(0.0244)	(0.0244)
$Break_{ijt} \times Severity3$	-0.0541***	-0.0519***	-0.0488***	-0.0488***
	(0.00830)	(0.00773)	(0.00774)	(0.00774)
$Break_{ijt} \times Severity4$	0.00485	0.00210	0.00531	0.00528
	(0.00621)	(0.00575)	(0.00575)	(0.00575)
$Break_{ijt} \times Severity5$	-0.0162***	-0.0147***	-0.0114**	-0.0114**
	(0.00514)	(0.00481)	(0.00482)	(0.00482)
$Break_{ijt} \times Severity\ Unreported$	0.0607	0.0815**	0.0855**	0.0855**
	(0.0381)	(0.0355)	(0.0355)	(0.0355)
$Cluster_{ijt}$			(0.000311)	(0.000316)
			(0.000314)	(0.000319)
$Spillover_{ijt}$				-0.000561
				(0.00138)
Observations	8,954,407	8,954,407	8,954,407	8,954,407
Number of segments	2,182	2,182	2,182	2,182
Fixed effects:				
Hour FE	NO	YES	YES	YES
Weekday FE	NO	YES	YES	YES
Month FE	NO	YES	YES	YES
Modified Bhargava et al. Durbin-Watson	0.6976	0.7823	0.7826	0.7826
Baltagi-Wu LBI	0.6998	0.7847	0.7849	0.7849

Notes: All models adjusted for autocorrelation. Robust standard errors in parentheses clustered at the road segment level. *** p<0.01, ** p<0.05, * p<0.1

Table A3: k-medians clustering

	(1) $\ln(speed_{ijt})$	(2) $\ln(speed_{ijt})$
$Break_{ijt}$	-0.0130***	-0.0130***
	(0.00327)	(0.00327)
$Cluster_{ijt}$	-0.00644***	-0.00644***
	(0.000339)	(0.000345)
$Spillover_{ijt}$		-0.000136
		(0.00146)
Observations	8,954,407	8,954,407
Number of segments	2,182	2,182
Fixed effects:		
Hour FE	YES	YES
Weekday FE	YES	YES
Month FE	YES	YES
Modified Bhargava et al. Durbin-Watson	0.7826	0.7826
Baltagi-Wu LBI	0.7849	0.7849

Notes: All models adjusted for autocorrelation. Robust standard errors in parentheses clustered at the road segment level. *** p<0.01, ** p<0.05, * p<0.1

Table A4: Average treatment and cluster break effects, $k=8$

	(1) $\ln(speed_{ijt})$	(2) $\ln(speed_{ijt})$
$Break_{ijt}$	-0.0141***	-0.0141***
	(0.00327)	(0.00327)
$Cluster_{ijt}$	-0.00515***	-0.00515***
	(0.000301)	(0.000305)
$Spillover_{ijt}$		-1.40e-05
		(0.00135)
Observations	8,954,407	8,954,407
Number of segments	2,182	2,182
Fixed effects:		
Hour FE	YES	YES
Weekday FE	YES	YES
Month FE	YES	YES
Modified Bhargava et al. Durbin-Watson	0.7826	0.7826
Baltagi-Wu LBI	0.7849	0.7849

Notes: All models adjusted for autocorrelation. Robust standard errors in parentheses clustered at the road segment level. *** p<0.01, ** p<0.05, * p<0.1

Table A5: Average treatment and cluster break effects, k=15

	(1)	(2)
	$\ln(speed_{ijt})$	$\ln(speed_{ijt})$
$Break_{ijt}$	-0.0143***	-0.0144***
	(0.00327)	(0.00327)
$Cluster_{ijt}$	-0.00443***	-0.00442***
	(0.000339)	(0.000344)
$Spillover_{ijt}$		-0.0024
		(0.00144)
Observations	8,954,407	8,954,407
Number of segments	2,182	2,182
Fixed effects:		
Hour FE	YES	YES
Weekday FE	YES	YES
Month FE	YES	YES
Modified Bhargava et al. Durbin-Watson	0.7825	0.7825
Baltagi-Wu LBI	0.7848	0.7848

Notes: All models adjusted for autocorrelation. Robust standard errors in parentheses clustered at the road segment level. *** p<0.01, ** p<0.05, * p<0.1

Table A6: Cluster-specific treatment effects with cluster-specific controls by time

	(1) $\ln(speed_{ijt})$	(2) $\ln(speed_{ijt})$	(3) $\ln(speed_{ijt})$	(4) $\ln(speed_{ijt})$	(5) $\ln(speed_{ijt})$
$Break_{ijt} \times Cluster1$	-0.0488	-0.00579	-0.0508	0.0249	-0.0684**
	(0.0405)	(0.0290)	(0.0323)	(0.0312)	(0.0298)
$Break_{ijt} \times Cluster2$	-0.0230	-0.0344	-0.00681	-0.0740	0.0716
	(0.121)	(0.0710)	(0.0864)	(0.0896)	(0.0802)
$Break_{ijt} \times Cluster3$	0.126*	0.0589	0.0112	-0.0110	-0.0485
	(0.0647)	(0.0525)	(0.0552)	(0.0595)	(0.0586)
$Break_{ijt} \times Cluster4$	-0.0987	-0.0793	-0.108**	0.0251	-0.122***
	(0.0722)	(0.0617)	(0.0538)	(0.0469)	(0.0453)
$Break_{ijt} \times Cluster5$	-0.0312*	-0.0305**	-0.0214	0.0164	-0.0158
	(0.0178)	(0.0148)	(0.0152)	(0.0166)	(0.0143)
$Break_{ijt} \times Cluster6$	-0.0149	0.0709	0.00300	0.111*	0.0680
	(0.0706)	(0.0580)	(0.0690)	(0.0655)	(0.0611)
$Break_{ijt} \times Cluster7$	-0.0532***	0.00501	-0.0376**	-0.0181	-0.0273*
	(0.0181)	(0.0145)	(0.0150)	(0.0170)	(0.0147)
$Break_{ijt} \times Cluster8$	-0.0485**	-0.0454***	-0.00767	0.0173	-0.000380
	(0.0202)	(0.0167)	(0.0168)	(0.0186)	(0.0158)
$Break_{ijt} \times Cluster9$	-0.0452	-0.00224	-0.00626	-0.0590	-0.0646**
	(0.0395)	(0.0348)	(0.0365)	(0.0406)	(0.0322)
$Break_{ijt} \times Cluster10$	-0.0467**	-0.0283*	-0.0193	0.0237	0.00594
	(0.0189)	(0.0155)	(0.0160)	(0.0185)	(0.0161)
$Break_{ijt} \times Cluster\ Control1$	0.00404	0.000199	0.0191***	0.00617	-0.00197
	(0.00459)	(0.00398)	(0.00433)	(0.00416)	(0.00405)
$Break_{ijt} \times Cluster\ Control2$	0.200***	-0.0204*	0.175***	0.0844***	0.0391***
	(0.0188)	(0.0124)	(0.0148)	(0.0178)	(0.0150)
$Break_{ijt} \times Cluster\ Control3$	0.0176**	0.0336***	0.0865***	0.138***	0.142***
	(0.00848)	(0.00567)	(0.00577)	(0.00698)	(0.00741)
$Break_{ijt} \times Cluster\ Control4$	-0.152***	-0.0538***	0.100***	0.00870	0.0927***
	(0.0227)	(0.0180)	(0.0155)	(0.0135)	(0.0135)
$Break_{ijt} \times Cluster\ Control5$	-0.00419***	-0.0193***	-0.0366***	-0.0371***	-0.0397***
	(0.00148)	(0.00131)	(0.00134)	(0.00141)	(0.00127)
$Break_{ijt} \times Cluster\ Control6$	0.129***	0.0915***	0.170***	0.0458***	0.0164*
	(0.00857)	(0.00784)	(0.0101)	(0.00927)	(0.00875)
$Break_{ijt} \times Cluster\ Control7$	-0.0131***	-0.00991***	-0.0290***	-0.0284***	-0.0335***
	(0.00139)	(0.00116)	(0.00123)	(0.00140)	(0.00122)
$Break_{ijt} \times Cluster\ Control8$	-0.00327*	-0.0237***	-0.0473***	-0.0366***	-0.0416***
	(0.00189)	(0.00161)	(0.00160)	(0.00177)	(0.00151)
$Break_{ijt} \times Cluster\ Control9$	0.0302***	0.0259***	0.0392***	0.0355***	0.0340***
	(0.00464)	(0.00365)	(0.00436)	(0.00460)	(0.00414)
$Break_{ijt} \times Cluster\ Control10$	-0.0247***	-0.0212***	-0.0467***	-0.0497***	-0.0425***
	(0.00171)	(0.00147)	(0.00148)	(0.00171)	(0.00152)
$Spillover_{ijt}$	-0.0194***	-0.00472	-0.00917***	0.00415	-0.0188***
	(0.00385)	(0.00301)	(0.00304)	(0.00329)	(0.00287)
Observations	1,679,622	1,679,625	1,673,125	1,677,518	1,673,074
Number of segments	2,180	2,180	2,180	2,180	2,180
Hours	7AM-10AM	10AM-1PM	1PM-4PM	4PM-7PM	7PM-10PM
Fixed effects:					
Hour FE	YES	YES	YES	YES	YES
Weekday FE	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES
Modified Bhargava et al. Durbin-Watson	0.9392	0.9014	0.8965	0.8552	0.9040
Baltagi-Wu LBI	1.2808	1.2331	1.2736	1.2024	1.2066

Notes: All models adjusted for autocorrelation. Robust standard errors in parentheses clustered at the road segment level. *** p<0.01, ** p<0.05, * p<0.1

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Table A7: Mean speed and data quality score by time of day

Time	Mean speed	SD speed	Mean score	SD score	Observations
7A-10A	20.51	9.93	26.17	4.14	1,682,760
10A-1P	21.2	10.6	26.21	4	1,682,760
1P-4P	20.79	10.3	26.14	4	1,676,262
4P-7P	19.36	9.47	25.73	4.09	1,680,658
7P-10P	21.61	10.22	24.17	4.18	1,676,496
All	20.7	10.14	25.69	4.16	8,398,936