Dynamic Traffic Lights and Urban Mobility: An application of Waze data to the city of Medellín *

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Abstract

Traffic congestion has serious economic and environmental effects. We measure the impacts of dynamic traffic lighting (DTL) programs on traffic congestion and road safety. We look at the case of the city of Medellín, Colombia, that has made important investments in updating and adopting technological instruments to improve urban transport conditions. We exploit high frequency data provided by Waze on traffics jams and traffics events reported by app users. By dividing the city in equally-size polygons we estimate difference-in-differences models comparing changes in traffic conditions over time between treatment cells (polygons with at least one intersection under the new DTL) and control cells (polygons with not DTL systems). A test for parallel trends confirms the validity of our approach. Results show that DTL can be cost-effective tools to reduce congestion and increase speed. We find no statistically significant impacts on major accidents.

Keywords: roads, traffic, congestion, travel time.
JEL codes: L91, R41, C55.

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1 Introduction

Traffic congestion occurs whenever the demand for transport outpaces the infrastructure capacity. Congestion has serious impacts on the economy (in the form of productivity loss), on the road surface integrity (requiring more maintenance), and on the environment (through different kinds of contamination). Multiple alternatives are considered to improve urban mobility, such as building and encouraging the use of massive public transport, increasing the number of biking and walking lanes, and carpool initiatives, among others. In addition, the efficient operation of the traffic light network can play a fundamental role in the search for solutions to achieve an agile, comfortable, safe and sustainable mobility. These types of interventions can be seen as more short-term and potentially cost-effective alternatives. Yet, their impacts on urban traffic conditions has not been rigorously measured.

In this paper, we measure the impacts of dynamic traffic lighting (DTL) programs on traffic congestion and road safety. DTL programs are autonomous systems that dynamically optimize the timing of traffic lights in response to current traffic conditions. We look at the case of the city of Medellín, in Colombia, that has recently made important investments in updating and adopting technological instruments to improve urban transport conditions. For a long time, the traffic lights of Medellín have operated under classic programming models, mostly at fixed times in different time zones, and others in scheduled modes. More recently, and under an agreement with Waze, the city has developed an storage system for big data and has established a technological platform capable of receiving real-time traffic data and executing actions on the traffic light system when it identifies that there are events that generate traffic variations different from the normal conditions. So far, several intersections have benefited from these new systems, while others still remain under the traditional approach.

We exploit aggregated data provided by Waze and divide Medellín in equally-size polygons, which allows us a to distinguish between treatment (polygons with at least one intersection under the new DTL) and control areas (polygons with not DTL systems). We implement a difference-in-differences (DID) estimation and start by testing for parallel trends to validate our approach and show that treatment and control areas are as similar as possible. Our result show that in general traffic jams length reduces as a consequence of the implementation of the DTL. Also, the average speed increases along the traffic jam. That is, people can "leave" faster the traffic jam. Moreover, the average delay, the different with respect to a free flow traffic condition reduces. All these results, obtained with different sizes of grids and aggregates of time remain stable, and satisfy the parallel trend condition.

The evaluation of DTL programs presents multiple challenges, mostly related to data limitations, no clear definition of the unit of analysis, or the correct specification of a control group. Traditionally, the literature has implemented before and after comparisons in specific intersections using different sources of data. The types of data typically collected by transport authorities to inform these needs include: real-time traffic speeds and network travel times, real-time incident reports, site-specific traffic counts and origindestination (OD) travel matrices. The data collected for these purposes have historically been derived from household surveys, sensors traffic cameras, or road-side observers. In contrast, big data, such as the one facilitated by Waze, provides an affordable and easy resource for understanding travel behavior. The intensive use of smartphones and other mobile devices generates a significant amount of georeferenced information given that wherever people go, their trajectories can be recorded while using the application. Simultaneously, the interest in geographic data and geographic applications grows, because they enable users to locate themselves and to report important events, such as traffics accidents, road maintenance needs, among others (Quercia and Capra, 2009; Quercia et al., 2010). With a large number of Waze contributors, such applications is increasingly becoming an important source of information for cities around the world.

This paper thus presents a novel approach of evaluating the impact of the smart traffic management systems on traffic and road safety by using high frequency data collected from Waze. This paper is important for three reasons. First, there are still few causal evaluations looking at interventions that seek to reduce congestion, probably due to the complexities and costs of measuring congestion at a wider scale. To the best of our knowledge, this is the first study empirically measuring the causal impacts of DTL. The majority of studies on traffic lights available in the literature come from the transport field and as it will be summarized in the next section have been based on simulation models and using data collection in a relatively small number of intersections.

Second, this paper innovates by incorporating the use of big data to evaluate impacts on urban congestion and road safety. We collect traffic jams data (passively collected from Waze users) and events (actively reported by Waze users) from December 2017 until August 2018 in intervals of two minutes. Therefore, during this entire period of analysis, and for the municipality of Medellín, we obtain a total of 2,000,000 traffic jams recorded. By accumulating this information, we can construct profiles of traffic conditions during the period of analysis. Given the characteristics of the data, we can compute the delay, length, speed, and duration of the traffic jams.

Finally, this paper contributes to the our understanding of how transport interventions affect urban mobility in developing countries. Transport is an area that has been prioritized by many governments and development banks and that receives large investments. For instance, transportation is one of the main sectors of lending by the IDB, representing more than 20% of its net commitments as of 2019. Despite the importance of the transport sector, there are still few causal studies in this literature and the majority are still concentrated in developed countries (Yañez-Pagans et al., 2018).

The rest of this paper is organized as follows. Section 3 describes the most recent literature that analyzes... Section 4 examines the data set. Section 6 provides the empirical strategy. Section 7 offers the estimation results. Section 8 concludes.

2 Medellín Transport Conditions

Medellín, the second largest city in Colombia, has a total population of 2,223,078 inhabitants, and 3,312,165 people for the metropolitan area.[1] The public transportation system of the city is comprised of buses, a new Bus Rapid Transit (BRT) system, taxis and a Metro.[2] In 2004, traffic studies on strategic corridors showed that the average speed was about 13.7 miles per hour in the morning peak period and 10.6 miles per hour in the evening peak period. The average travel time in public transport was 35 minutes over an average distance of 5.4 miles. Speeds on the public transport network ranged between 3.1 and 16.2 miles per hour (Vélez, 2005). The lower speeds were observed in the downtown area (Central Business District) with values between 3.1 and 8.1 miles per hour; these low speeds are the result of traffic congestion and transit routing converging in the area (Gonzalez-Calderon and Ospina, 2004). Overall, there are high levels of congestion throughout the city, resulting from a saturated transportation network.

According to the Valle de Aburrá's 2017 Origin-Destination (O-D) Survey,[3] the number of trips that takes place daily in the Aburrá valley has increased significantly since 2005. Of 4,875,000 trips in 2005, the city has had 6,131,727 trips, which represents a growth of 26%. The greater number of trips has been accompanied by an increase in the proportion of people traveling daily. The percentage of people who habitually travel in the Aburrá valley went from 65% to 69% between 2005 and 2012, and in 2017 it reached 74%. Also, the average travel time increased; between 2005 and 2012 it had gone from 25 minutes to 33, and in 2017 it reached 36 minutes on average.

The participation of the bus mode was reduced (nine percentage points, with respect to 2012) and the participation of the metro (three percentage points) and metroplús (three percentage points) modes was expanded. The car mode reduced its participation from 15% to 13%, while the motorcycle mode went from 11% to 12% between 2012 and 2017. The non-motorized modes increased their participation due to the increase of the trips on foot, which happened to be 26% in 2012 to 27% in 2017.

The average time of travel by metro is 62 minutes, and by bus and Metroplús, 47 minutes. With respect to private transport modes, the longest average displacement

[1] http://www.dane.gov.co/files/investigaciones/poblacion/proyepobla06_20/Municipal_area_1985-2020.xls.

[2] https://www.metrodemedellin.gov.co.

[3] Interactive interface available at https://www.metropol.gov.co/observatorio/Paginas/encuestaorigendestino.aspx. Microdata available at http://datosabiertos.metropol.gov.co/dataset/encuesta-origen-destino-2017-datos-por-hogares.

time is the car, with 35 minutes, followed by the motorcycle with 32 minutes. The increase in the number of trips, in the proportion of people who move in the city, and in the average times of displacement, accounts for increases in the demand for transportation, that is, a greater number of people demanding each time more trips within the city. As a consequence, the transportation infrastructure has been struggling to deal with this burden, making mobility one of the biggest challenges the city would face in the following years.

3 Related Literature

A traditional concept in the transportation literature is of hypercongestion. Figure A.3, extracted from the Transportation Research Board (2016), claims to show a supply curve for travel. With few vehicles on the road, travel is unconstrained, and average speeds are about 70 mph. Travel continues unconstrained at low demand levels, and then speeds modestly decrease when flow reaches a maximum capacity of about 2,000 vehicles per lane per hour. What is surprising, however, is that the curve then appears to bend backward. The manual explains that further increases in travel demand generate "flow breakdown", causing severe decreases in speed as well as decreases in freeway capacity, with flow rates falling well below the observed maximum. Transportation engineers are taught that this backward-bending supply curve is one of the "basic relationships" in traffic. The manual attributes these low-speed, low-flow observations to "oversatuated flow" arising from excess demand.

Hypercongestion has long been the primary rationale for freeway metering lights and other traffic interventions aimed at regulating demand (Diakaki et al., 2000; Smaragdis et al., 2004; Cassidy and Rudjanakanoknad, 2005). Multiple studies have been produced mostly in the transport engineering field to model the impacts of traffic light systems on traffic density and vehicle distribution. Studies in this area are mostly based on simulation models (Wang et al., 2016). Some of them combine simulations with field measurements that are used to calibrate and validate transport model. Given the costs of data collection, samples in almost all of these studies are restricted to a few intersections and this are purely before and after analyses(Al-Mudhaffar, 2010). Previous studies by economists have tended to take hypercongestion as given. For example, Walters (1961) takes a supply curve with hypercongestion from the transportation engineering literature and uses the parameters to derive efficient congestion prices. Similarly, Keeler and Small (1977) uses a supply curve with hypercongestion to develop a long-run model of highway pricing and investment. Most recently, Hall (2018) uses a hypercongestion model to show how highway pricing can generate a Pareto improvement when agents are homogeneous, even before redistributing toll revenues.

Regarding the economic literature looking at interventions seeking to reduce congestion, there is a strand of the literature looking at driving restrictions. These road rationing measures aim to directly reduce congestion and pollution and consist of barring drivers of private cars to access public roads only on certain days, usually based on the digits of their license plate or on special stickers. Such a policy was famously introduced in Mexico City in 1990 to reduce air pollution (Davis, 2008), and later implemented under various forms in Santiago de Chile, Bogota, Quito, and Beijing. There is a sizeable literature studying the aggregate impact of these policies, with mixed findings. The early near-consensus was that these policies are not effective at denting pollution and congestion (Eskeland and Feyzioglu, 1997; Davis, 2008; de Grange and Troncoso, 2011; Gallego et al., 2013). Two more recent paper find that restrictions are successful at reducing CO and PM10 in Quito and Beijing, respectively (Carrillo et al., 2016; Viard and Fu, 2015).

In a more general view, some recent studies have started to analyze the role of traffic congestion on urban mobility.Storeygard et al. (2018) develop a methodology to estimate city-level vehicular mobility indices, and apply it to 154 Indian cities. They use predicted travel data collected from Google Maps for 22 trips and show there is wide variation in mobility across cities. An exact decomposition of mobility highlights that variation is driven more by differences in uncongested mobility (free flow speed) than congestion. This implies that improvement in uncongested speed, for instance, more regular grid network and more primary roads creates much more mobility than optimal congestion pricing. Overall, their main argument is that more populated cities are slower, only in part because of congestion.

Kreindler (2018) quantifies the welfare consequences of pricing policies considering commuter preferences and of the road technology. The author looks at peak-hour traffic congestion equilibrium using travel behavior data collected through a smartphone app for over 100,000 commuter trips in Bangalore, India. To identify key preference parameters, such as the value of time spent driving and schedule flexibility, the study implemented a randomized experiment with two congestion charge policies showing that commuters exhibit moderate schedule flexibility and high value of time. In a separate of the road technology analysis the study shows a moderate and linear effect of traffic volume on travel time. Combining these two findings, the author conducts policy simulations of the equilibrium optimal congestion charge, which reveal notable travel time benefits, but limited welfare gains. Intuitively, the social value of the travel time saved by removing commuters from the peak-hour is not significantly larger than the costs to those commuters of traveling at different more inconvenient times.

There are relatively few studies that estimate commuter preferences using a revealed-preference approach. Small et al. (2005) analyze real-world driver decisions to use a faster tolled lane to estimate the value of time and of reliability, and Bento et al. (2017) estimate the value of urgency in a similar setting. Estimates of scheduling preferences are even rarer (Small, 1982). A separate group of papers analyzes reduced form impacts of road pricing experiments. Tillema et al. (2013) study a pilot offering rewards for avoiding peak hour driving.

Overall, we see that the topic of urban congestion has been increasingly important in the economics literature; however we still find a very limited set of causal empirical studies measuring the impacts of interventions that seek to reduce traffic congestion, mostly in the area if traffic restrictions. To the best of our knowledge, we have not identified studies looking at the causal impacts of dynamic traffics lights systems, which seem to offer a cost-effective alternative to alleviate urban congestion problems.

4 Data

Our area of analysis corresponds to the municipality of Medellín. It comprises a total area of 380.64 km^2 (146.97 square miles). All our outcome variables are obtained from Waze, a free, community-based traffic and GPS-based navigation app that enlists users to report on traffic, road hazards, road conditions, and weather using their smartphone. Waze users type in their destination address and drive with the app open on their phone to passively contribute to traffic and other road data by allowing Waze to determine their speed and location. Users may also take a more active role by sharing road reports including accidents, hazards, and road closures to provide other users with this information. User volunteers are awarded points and levels based on their Waze experience and reporting history. Higher levels indicate more Waze experience and greater reliability, allowing users increased access to edit or update data. Waze also has an active community of online map editors that ensure data is as up-to-date as possible.

Access to Waze data was facilitated though the Waze Connected Citizens Program (CCP), which is a global initiative to facilitate a two-way traffic-related data exchange between Waze and its partners. These partners include government agencies and private road operators who are approved through the CCP. Waze partners share information such as road closure, constructions projects and incident data with Waze to help keep the app updated. Partners in exchange will receive real-time publicly-available closure and incident data including: accidents, traffic jams, and hazards reported by Waze drivers as well as estimated travel times. All information is aggregated geographically by Waze so the identity of the Waze user is never shared with partners.

Through the CCP we have a streaming of data, which we gather and store every 2 minutes with street-level granularity for the whole city. Our historical data goes from 01/01/2017 until 12/31/2018. Because of treatment took place between February and July of 2018, we construct a panel data set, at the grid level, from the period of December 2017 until August 2018. Each file recorded every two minutes includes the information related to the traffic jams (passively recorded by Waze from its users) and the events (actively recorded by Waze users). From the jams data we have information of the time when the jam was recorded for the first time, speed, delay, name and type of the street where the jam crosses,[4] level of the jam,[5] and start and end nodes. Speed refers to the current average speed on jammed segments in Km per hour. The delay variable reports in seconds the delay that is caused by a traffic jam by comparing the free flow speed versus the actual speed.

Table 3 shows the summary statistics where the jams are the unit of observations. We observe that traffic jams have an average duration between 13 and 17 minutes. That is that, for instance, a jam that last 20 minutes, which for instance started at 10:00 AM, will be included in the downloaded files of 10:00, 10:02 ..., 10:20. Our data set records a total of 26.3 millions jams in intervals of two minutes, which represent a total of 1.929.003 unique jams which vary in duration across the period of analysis.

The events data includes all traffic data reported by Waze users through the Waze mobile application. Each event has a Reliability and a Confidence score. A reliability score is based on other user's reactions ("Thumbs up", "Not there", etc.) and the level of the reporter (Wazers gain levels by contributing to the map, starting at level 1 and reaching up to level 6. The higher the level, the more experienced and trustworthy the Wazer is). An score in the dataset going from 0 to 10 indicates how reliable the report is. Each alert gets also a confidence score based on other user's reactions ("Thumbs up", "Not there"). This score ranges between 0 and 10. A higher score indicates more positive feedback from other Waze users.

In table 4 we observe the list of events reported by Wazers during our period of analysis. They vary in terms of characteristics and number of times they are reported. As we will discuss in the empirical section of this paper, some of the events will be used as outcome variables, while others will be used as controls. Overall, the Waze data we use for the analysis comprises data from 12/01/2017 to 08/31/2018, which we aggregate at 10 and 20 minute-intervals. Given that the impacts of traffics lights are mostly seen during days and hours of active road use, we eliminate all weekend data and also all data from 12:00 AM to 05:59 AM and from 21:00 PM to 11:59 PM each day.

Our measures of road network characteristics come from Open Street Map[6] (OSM), a collaborative worldwide mapping project. We downloaded OSM data within the city boundaries in December 2018. Table 1 shows the distribution of roads in the city, and figure A.4 shows the coverage of the road network in the city.

[4]Road type includes: Streets, Primary Street, Freeways, Ramps, Trails, Primary, Secondary, 4X4 Trails, Ferry crossing, Walkway, Pedestrian, Exit, Stairway, Private road, Railroads, Runway/Taxiway, Parking lot road, and Service road.

[5]Traffic congestion level (0 = free flow and 5 = blocked).

[6]https://www.openstreetmap.org/#map=13/6.2456/-75.5732

5 Empirical strategy

We implement a difference-in-differences estimation to estimate causal effects. In this section we describe carefully how we construct our main outcome variables, the unit of analysis, and the selection of the sample before explaining the regression models that are estimated.

Unit of observation

We divide the city in grids of equal size and work with a uniform unit of observation (i.e. grids). As part of our robustness checks, we present different analyses for different grid sizes considering grids of 150, 200, 250, and 500 square meters. Figures A.5 shows the representation of a typical unit of observation. We observe that inside each cell or grid, we can have different number of roads and length of segments, as well as different numbers of events reported by Wazers. Roads highlighted in the figure in red indicate that they have an active traffic jam and the length of the red shows where the traffic jam is located. Table 2, panel A, shows how the number of cells varies for the different grid sizes. For instance, if we divide the municipality of Medellín in grids of 500 square meters, we obtain a total of 1,650 cells (observations).

Sample selection

As we observe in figure A.4, it is not meaningful to analyze all the grids within the city. There are multiple cells where there are no roads (mostly mountainous areas), or where there are only residential roads and no traffic jams ever recorded. Plus, we want to have as much comparability as possible between our treatment and control areas. For those reasons, we apply a series of filters to select the sample of analysis before running estimations. Specifically, we drop from the sample all cells that include primary, secondary, tertiary, trunk or residential roads. This means we exclude cells reporting only unclassified roads or living streets that do not have traffic. Then we exclude all cells that are outside the area where all the traffic lights are located (see figure A.6). This means all of our cells will be located in areas where there are traffic lights reported by the transport authority in Medellín. Finally, we drop cells that are immediately adjacent to the treated cells given that there might be positive/negative spillover effects of the intervention and thus we seek to reduce any contamination to control cells.

Outcome variables

For each cell we compute different traffic measures extracted from Waze data and that are related to: (i) average delay, measured in seconds by comparing the free flow speed versus the actual speed; (ii) average speed in km per hour; and (iii) average length of the traffic jam measured in meters. For example, if a traffic jam covers 500 meters of a particular corridor and crosses 5 cells/grids, we will compute the speed, duration, delay of the traffic jam for each cell. Events reported by wazers, such as accidents, are aggregated at the cell level for each period of time considered (10 or 20 minutes). Given that cells might have different number of roads and length of roads, we normalize all variables considering the total length of roads in the cell. Therefore, our outcomes variables are constructed as follows:

- $y^1_{i,t} = \frac{average\ Queue\ length_{i,t}}{Length\ of\ roads_i}$,
- $y^2_{i,t} = \frac{average\ delay_{i,t}}{Length\ of\ roads_i}$,
- $y^3_{i,t} = \frac{average\ speed_{i,t}}{Length\ of\ roads_i}$,
- $y^{4,j}_{i,t} = number\ of\ events_{i,t}$,

where j includes different types of events, such as major accidents[7], stand still traffic, heavy traffic, moderate traffic. For instance, the outcome $y^1_{i,t}$ represents the total length of the traffic jams that occur at the cell i during the time aggregation t (which varies by cell and time), divided by the total length of the roads obtained from OSM that are inside the same cell (which is time invariant).

Dynamic traffics lights interventions

Traffic lights networks are classified into: Fixed Time Control, Semi-acted, Actuated and Adaptive Control (Li et al., 2016). In general, in the Fixed Time Control, the parameters and times of the traffic signals are determined by using historical data about the vehicular flow at such point and they are invariably programmed during the control stage. This method, despite being easy to implement and with very low cost, can not respond to real traffic changes or adapt to the changing behavior of the environment. With the aim of improving this method, the management of Semi-Actuated and Acted traffic that directly involves providing intersections with sensors to determine the degree of congestion and which traffic light plan is appropriate. As an evolution we have the Adaptive traffic management system that optimizes the green times according to the measurements taken directly from the sensors installed in all the accesses and clearings of the road intersection.

The concept of Adaptive Traffic, which combines the use of different types of sensors, allows to measure the number of vehicles approaching and leaving the intersection to obtain real-time information on traffic conditions (Rachmadi et al., 2011). All this information is collected in a control panel, to make decisions and perform the corresponding actions to accelerate the flow of vehicles through the intersection by changing the times in which the traffic signal remains red, yellow or

[7]Wazers also report on minor accidents and we add then as a control with lagged values in our preferred specification

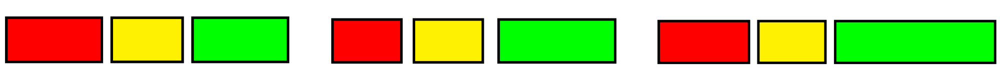
green. Given that the implementation of this method implies high economic costs and a complex installation in the road network, the concept of Collaborative Traffic arises making use of the large amount of information available thanks to the massification of cell phone services, internet mobile, social networks, cloud services, WiFi communications networks, Bluetooth, etc.

In Medellín, in order to face the challenge of improving mobility and dynamically controlling traffic signals using the information generated by the different sources of information, including historical data, traffic sensors and the information obtained from the different communities on the Internet, a multidisciplinary group made up of traffic engineers, data scientists, telecommunications engineers and technical support from suppliers.

To implement control strategies that depend on traffic conditions such as Actuated, Semi-Acted, or Adaptive, the traffic light systems require the implementation of a system for measuring traffic variables that is directly connected to the traffic light controllers. This information is the basis on which decisions are made at intersections, corridors or areas where the traffic management strategy is implemented. The systems for detecting traffic variables traditionally use electromagnetic loops or sensors,although they are the least cost-effective. Additionally the technological development has allowed to have different options such as Video Analytics, Radar Systems, Bluetooth Readers and Magnetometers mainly.

To overcome the barrier of high investment in the installation of thousands of sensors in the city, a global trend is being established to be able to use information external to traffic light systems to perform traffic management in what has been called " Collaborative model of traffic management". This model is based on the behavior of the different actors on the road, which are somehow generating information using current personal communication systems.

The municipality of Medellín has developed a technological platform that allows the dynamic allocation of traffic plans stored in the controllers according to the traffic conditions, and the information obtained from the collaborative models. The adaptive traffic light, under regular conditions, operates with traffic light cycle of 60 seconds (see figure 1a). In congested conditions (collection of planned cycles) there are two options: traffic light cycle of 90 seconds (figure 1b) and 120 seconds (figure 1c).



(a) 60 seconds (b) 90 seconds (c) 120 seconds

Figure 1: Traffic light cycles

The municipality of Medellín implemented the Adaptive traffic lights in particular corridors along the city. The treated corridors (and the corresponding cells of each grid size) are specified in table 5.

6 Model

The objective of this paper is to answer the following evaluation questions:

- Do the traffic conditions of the municipality of Medellín improve as a consequence of implementing the adaptive traffic lights system?
- Can the adaptative traffic light system become a model for other cities that until now could not measure in real time their traffic conditions?

6.1 Regressions

Given that the traffic light system covers a high proportion of the city of Medellín. Therefore, as we discussed in section 4, we divide the city in grids of different sizes. The unit of observation is a cell of an specific size, and for each cell, we compute the main characteristics of the traffic jam (if it exist) and events inside the cell. Moreover, from OSM, we also compute the analyze the roads that cross the cell. Then, a naive specification of our analysis tries to captures the effect on an outcome Y_i^j of the implementation of a new planned cycle in cell i, such that

$$Y_i^j = \alpha + \beta \times Treatment_i + \epsilon_i. \tag{1}$$

In order to be able to use an specification equivalent to the logarithm of the outcome of interest, and given the large number of zeros we have in our data, we apply the inverse hyperbolic sine transformation (IHS) to each variable.[8] Therefore, our outcome variable is defined as $Y_i = \log\left(y_i + \sqrt{y_i^2+1}\right)$.

Moreover, we use fixed effects models:

$$Y_{it}^j = \alpha + \beta \times Treatment_{it} + \epsilon_{it} \tag{2}$$

The full specification is given by,

$$Y_{it}^j = \alpha + \beta \times Treatment_{it} + \Phi_i + \Gamma \times X_{it} + \epsilon_{it}, \tag{3}$$

where X_{it} is a vector of cell characteristics such as: existence of road construction, lag of minor accidents, existence of lane closures, and severe weather. The vector Φ_i includes a set of fixed effect indicators, such as: month FE (Φ_i^m), day FE (Φ_i^d), hour FE (Φ_i^h), and hour of the day FE (Φ_i^{hd}).

[8] See Pence (2006).

7 Results

7.1 Parallel trend assumption

Before analyzing the effect of the DTL on the traffic of Medellín, we test if the parallel trend assumption holds. In order to do that, we run an specification where we replace $\beta \times Treatment_{it}$ with $\sum_{k=0}^{K} \delta_{-k} \times Treatment_{it-k}$ from equation 3, where now $Treatment_{it-k}$ is a dummy equal to one if the approval of the intervention occurred k periods in the past, and zero otherwise. Thus the coefficients δ_{-k} represent the treatment effect of interventions approved k periods ago. This allows us to understand whether there are differential impacts over time. This specification allows testing a key identifying assumption when estimating DID models, the parallel trends assumption (Angrist and Pischke, 2008). Under a DID model it should not be a concern if treated and not treated units present differences in pre-treatment levels of the dependent variable, as long as they do not differ in the pre-treatment trends in that variable. For example, a concern could be that roads that received an intervention are those located in areas where traffic jams are more likely to occur when compared to control roads. This would generate a selection bias that would invalidate our identification strategy.

Figure A.7 shows the evolution of the main outcomes analyzed, where we observe that, before treatment, the trend of these variables behave in the same fashion for both the treated and the control cells. We test this assumption in tables 11, 12, and 13, for the aggregation time of twenty minutes and for different grid sizes. We analyze the trend of the outcome variables during the previous two, four, and more than 5 weeks before the first intervention (02/02/2018). In general, we observe that the main effects still hold for the main outcome analyzed, and also the pre-treatment coefficients are not significant.

7.2 Main results

This section shows the estimation results of the model presented in equation 3.

First, table 6 shows the results of the impact of the adaptative traffic light system on the average delay at the cell level. Given the huge amount of data, we combine the information obtained very two minutes in aggregates of 10 and 20 minutes. Also, we analyze the variability of the results for different grid sizes. We observe in column 1 the results of the naive OLS estimate (eq. 1). Column 2 represents the application of a fixed effect model, without any control variable. In column 3 we include month FE, while columns 4, 5 and 6 add day, hour and day $\times$ hour FE, respectively, to the previous specification. Finally, the full specification is represented in column 7, where we add the control variables (existence of road construction, lag of minor accidents, existence of lane closures, and severe weather). For the different time and grid sizes aggregates, we observe that the implementation of the adaptative traffic light system reduces the average length of the traffic jam, even though the results are not significant.

Table 7 shows the results for average speed. In this case, results are significant but at the 5 and 1 percent, depending the grid size.

Another interesting result is presented in table 8, which shows the estimates for delay. Remember that this variable represents the time, in seconds, of delay with respect to a free flow traffic in the same section of the road. As we can see, for different time aggregations and grid sizes, the obtained results are in the expected direction: the elasticity of the delay is negative as we implement the treatment in the selected corridor.

Table 9 shows the results for heavy traffic jam, while table 10 shows the results for stand still traffic jam. In both cases, even though the results are with the expected sign, they are not significant.

8 Conclusion

Over the past forty years, the share of urban population in Latin America and the Caribbean (LAC) has increased from 50% of the population in 1970 to 80% by 2013 (United Nations and Social Affairs, 2012), being the most urbanized region in the world. This unprecedented growth of cities has brought important opportunities and challenges. One the one hand, the concentration of the population around urban areas facilitates the provision of basic, and more sophisticated, services to the population. On the other hand, increased population density is associated with increased problems of transportation capacity, urban sprawl that comes with informal housing development, and reduced citizen security, among others.

In order to overcome the problem generated by the increasing demand of transportation and the consequent effect on traffic, traffic control agencies are implementing new technologies. The cost of the different technologies of traffic lights systems has lead to the agencies to be creative in the implementation of the different solutions. The Big data represents a novel solution to control the traffic of a city because it availability, accuracy, velocity and veracity. The municipality of Medellís a pioneer in the application of this technology in the traffic control of the city.

At the same time, the Big Data also represents an opportunity to evaluate, because it gives us the chance the analyze problems that in the past were to costly to collect the data or were not available. Developing countries have a great opportunity to explore this new source of data, as they do not need to spend a big amount of money in data collection. Also, years ago it was impossible for these economies to show impact of traffic lights systems across the whole city and not only in an intersection.

In our analyzes we observe important results of the application of the adaptative traffic light system. Moving from a cycle of 60 seconds to a cycle of 90 or 120 seconds have effects on the traffic, but it is only thanks to our big data approach that we are able to capture the impacts. In general, we observe robust results that confirm that the average length of the traffic jams reduces, or the speed of the jam increases, that is, people can “leave” the traffic jam faster. Also, the delay (a concept created by the Waze application, and not available in other source of data) reduces as the implementation of the intervention.

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Appendix

A Figures

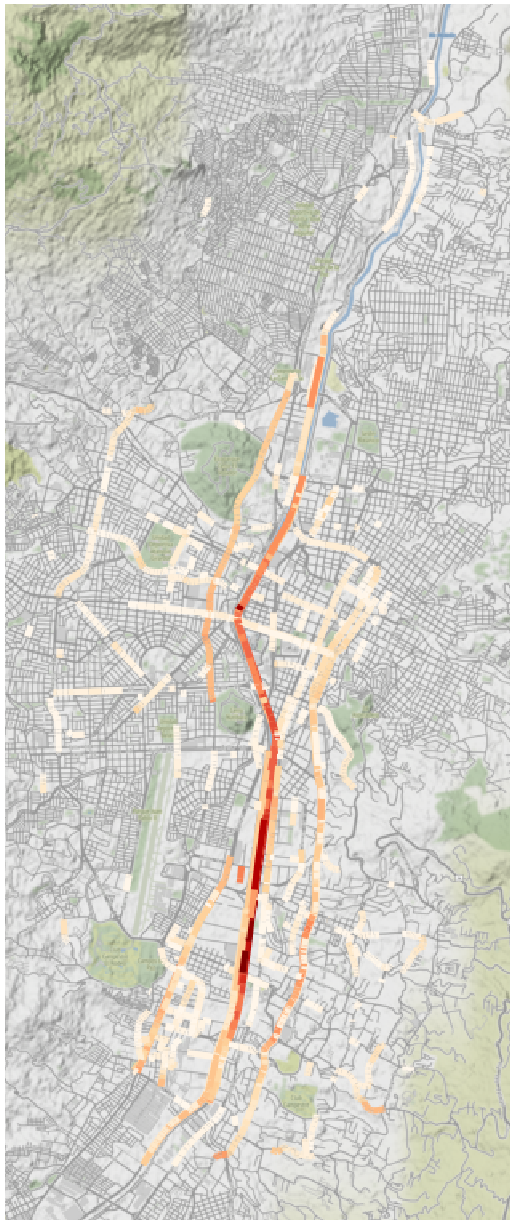
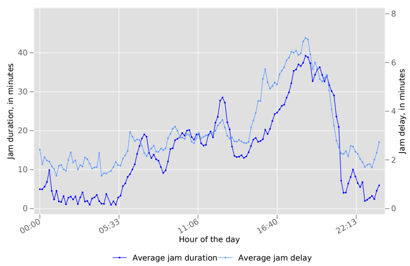
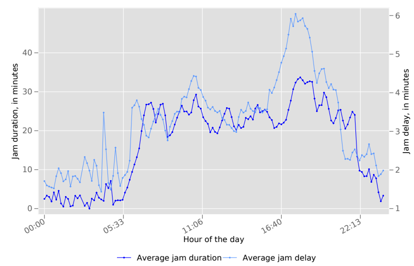


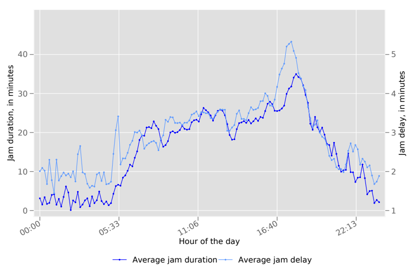
Figure A.1: Jams over 5 minutes delay at peak hour inside study area



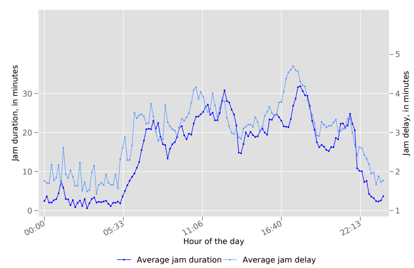
(a) Monday



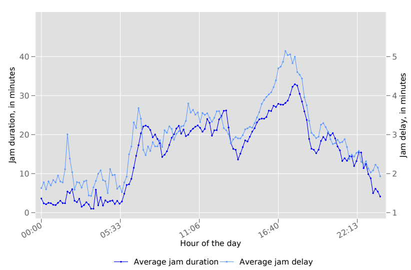
(b) Tuesday



(c) Wednesday



(d) Thursday



(e) Friday

Figure A.2: Average jam characteristics for March 2018

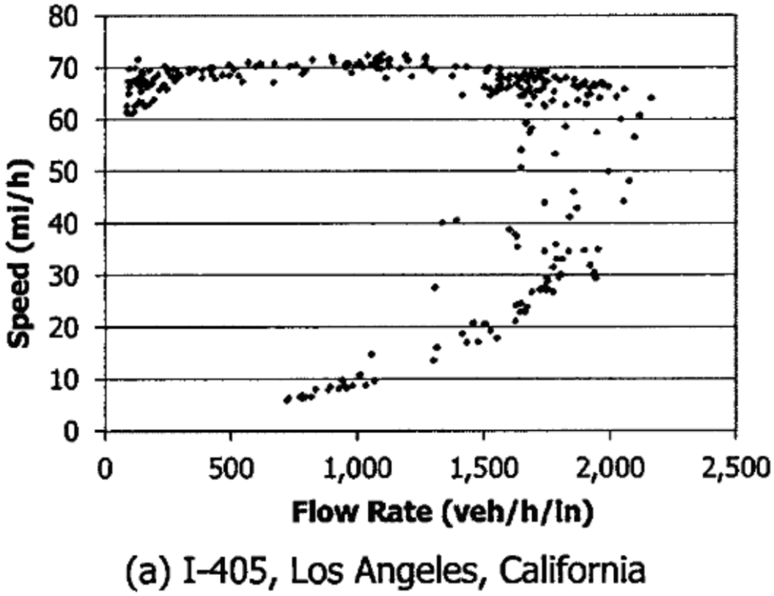


Figure A.3: Hypercongestions

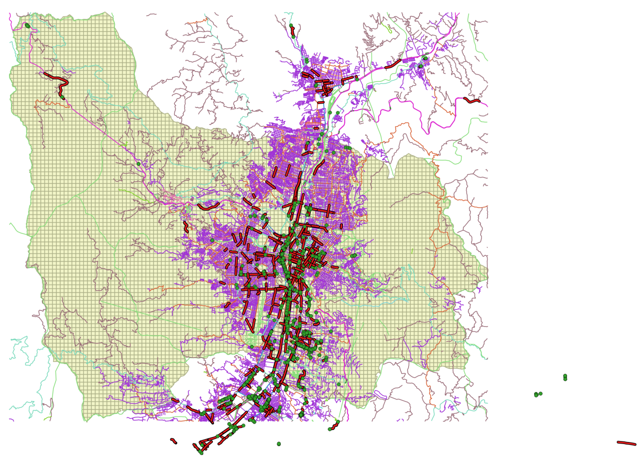


Figure A.4: Medellin

B Tables

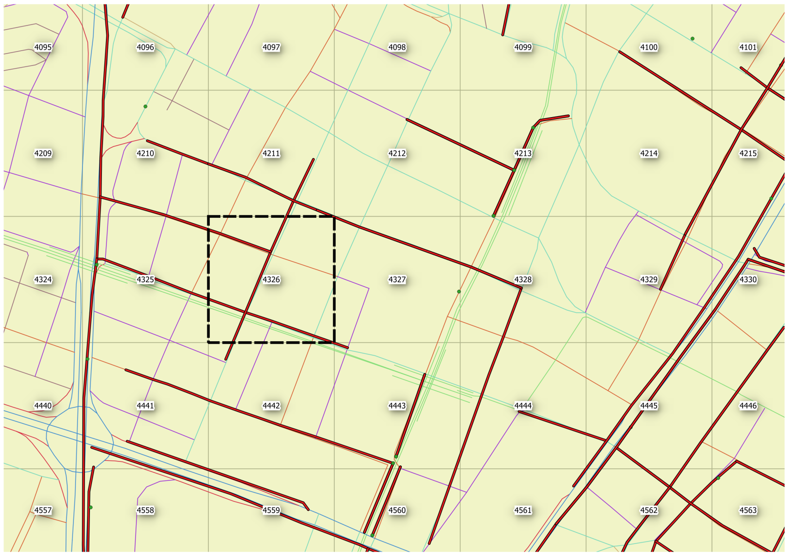


Figure A.5: Unit of observation

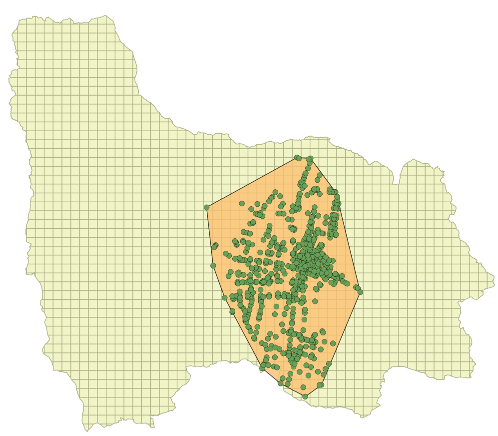
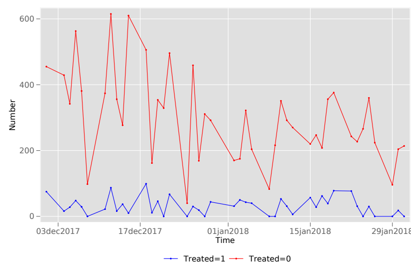
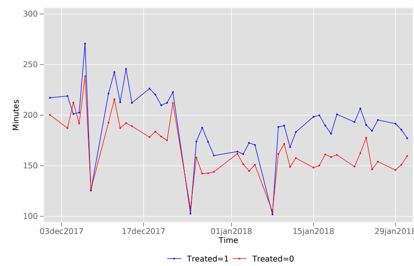


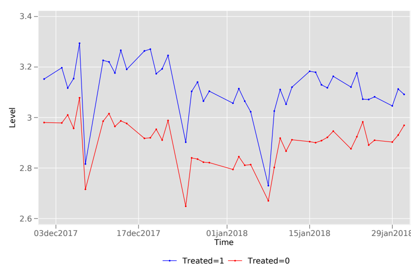
Figure A.6: Are with traffic lights



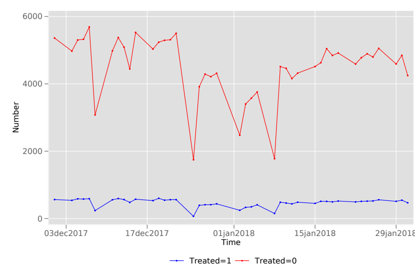
(a) IHS of number of major accidents



(b) IHS of average jam delay



(c) IHS of average jam level



(d) IHS of # traffic jam

Figure A.7: Parallel trend test

Table 1: Types of roads according to OSM

Road type	total length (in kms)
living_street	19.98
primary	60.53
residential	1160.03
secondary	184.92
tertiary	222.85
trunk	41.71
trunk_link	0.27
unclassified	42.43
Total	1732.72

Table 2: Number of observations for different grid sizes

	150	**200**	**250**
Panel A:			
Grid, cells	17,294	9,804	6,325
Panel B:			
- Filters:			
Roads type	(12,440)	(6,839)	(4,292)
	4,845	2,965	2,033
- Area outside traffic light zone	(1,782)	(1,140)	(814)
	3,072	1,825	1,219
- Cells next to treated areas	(139)	(122)	(111)
Number of cells	2,933	1,703	1,108

Table 3: Summary statistics of traffic jams (full sample)

Year	Month	Duration				Delay				Speed				Length			
		Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
2017	December	17.56	13.89	0	72.66	2.99	1.29	1	10.99	10.37	3.71	2.16	45.21	226.17	38.54	71.8	437.88
2018	January	14.24	11.57	0	82.96	2.64	0.96	1	8.62	10.2	3.96	1.3	44.67	221.91	39.32	51.39	484.58
	February	17.29	13.07	0	77.88	3.06	1.41	0.73	10	2.94	1.08	0.33	13.27	228.11	38.38	36.15	491.39
	March	14.84	11.64	0	55.53	2.92	1.31	1	10.64	2.98	1.08	0.66	12.27	228.01	39.03	15.56	525.74
	April	16.17	11.92	0	63.05	2.96	1.25	1	9.88	3.02	1.15	0.41	13.45	229.32	39	51.39	518.73
	May	16.52	12.49	0	54.28	3.05	1.29	1	19.99	3.18	1.3	0.42	12.89	232.48	41.37	36.15	519.81
	June	13.33	10.07	0	136.16	2.85	1.22	0.84	35.85	3.33	1.29	0.62	13.38	233.59	41.43	4.08	484.58
	July	14.3	10.81	0	52.56	2.8	1.11	1.02	19.05	3.14	1.14	0.24	12.06	228.26	40.01	49.49	453.59
	August	16.49	12.1	0	115.74	2.89	1.18	1	16.23	3.02	1.02	0.19	13.11	227.38	36.21	27.24	461.32

Table 4: Summary statistics of events reported

Type of event	Freq.	
Outcome variables:		
ACCIDENT MAJOR	19,120	0.43
JAM HEAVY TRAFFIC	498,458	11.32
JAM MODERATE TRAFFIC	129,767	2.95
JAM STAND STILL TRAFFIC	369,298	8.38
Control variables:		
ACCIDENT MINOR	60,568	1.37
HAZARD ON ROAD CONSTRUCTION	390,570	8.87
HAZARD WEATHER	109	0.00
ROAD CLOSED CONSTRUCTION	4,658	0.11
ROAD CLOSED EVENT	2,724,948	61.86
Total	4,404,948	

Table 5: Treated corridors and cells

Treated corridor	**Implementation**	**150**	**200**	**250**	**500**
Av. San Juan (West and East)	02/02/2018	17	13	12	5
Av. Del Ferrocaril (North)	04/03/2018	6	4	3	2
Av. Colombia (West)	06/29/2018	5	4	4	2
Calle 4 (South)	07/05/2018	2	2	2	1
Av. Poblado (North)	07/11/2018	7	5	4	2
Av. 80 (South)	07/13/2018	8	6	5	3
Total treated cells in 2018		45	34	30	15

Table 6: IHS of the mean of traffic jam length

	(1) OLS	(2) FE	(3) + Month FE	(4) + day FE	(5) + hour FE	(6) + day#hour FE	(7) + controls
Aggregation time: 10 minutes							
Treatment (150)	-0.032*	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
N=8,903,218	(0.013)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Treatment (200)	-0.017	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003
N=6,306,642	(0.015)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Treatment (250)	-0.007	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
N=4,616,601	(0.013)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Aggregation time: 20 minutes							
Treatment (150)	-0.035**	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
N=5,451,107	(0.013)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Treatment (200)	-0.020	-0.003	-0.004	-0.004	-0.003	-0.003	-0.004
N=3,829,138	(0.014)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Treatment (250)	-0.011	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
N=2,793,131	(0.012)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Column (1) presents the estimated coefficient β of equation 1 for the effect of the intervention on the outcome of interest for each grid size and aggregation of time. Column (2) implements a fix effects specification according to equation 2. Columns (3) to (7) add to the previous specification month FE, day FE, hour FE, day$\times$hour FE, and a set of control variables according to equation 3.

Table 7: IHS of the mean of traffic jam speed

	(1) OLS	(2) FE	(3) + Month FE	(4) + day FE	(5) + hour FE	(6) + day#hour FE	(7) + controls
Aggregation time: 10 minutes							
Treatment (150)	-0.002	0.001	0.003*	0.003*	0.003*	0.003*	0.003*
N=8,903,218	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Treatment (200)	-0.002	0.001	0.002**	0.002**	0.002**	0.002**	0.002**
N=6,306,642	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Treatment (250)	-0.001	0.001	0.002**	0.002**	0.002**	0.002**	0.002**
N=4,616,601	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Aggregation time: 20 minutes							
Treatment (150)	-0.002	0.001	0.004*	0.004*	0.004*	0.004*	0.004*
N=5,451,107	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Treatment (200)	-0.002	0.001	0.002**	0.002**	0.002**	0.002**	0.002**
N=3,829,138	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Treatment (250)	-0.001	0.001	0.002**	0.002**	0.002**	0.002**	0.002**
N=2,793,131	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Column (1) presents the estimated coefficient β of equation 1 for the effect of the intervention on the outcome of interest for each grid size and aggregation of time. Column (2) implements a fix effects specification according to equation 2. Columns (3) to (7) add to the previous specification month FE, day FE, hour FE, day$\times$hour FE, and a set of control variables according to equation 3.

Table 8: IHS of average delay

	(1) OLS	(2) FE	(3) + Month FE	(4) + day FE	(5) + hour FE	(6) + day#hour FE	(7) + controls
Aggregation time: 10 minutes							
Treatment (150)	-0.080*	-0.020***	-0.030***	-0.030***	-0.028***	-0.027***	-0.028***
N=8,903,218	(0.034)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Treatment (200)	-0.054*	-0.008*	-0.014***	-0.014***	-0.013**	-0.013**	-0.013**
N=6,306,642	(0.024)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Treatment (250)	-0.015	-0.004	-0.008***	-0.008***	-0.007**	-0.007**	-0.007**
N=4,616,601	(0.021)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Aggregation time: 20 minutes							
Treatment (150)	-0.074*	-0.016**	-0.026***	-0.026***	-0.024***	-0.024***	-0.024***
N=5,451,107	(0.033)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Treatment (200)	-0.049*	-0.006	-0.013**	-0.013**	-0.011**	-0.011**	-0.011**
N=3,829,138	(0.023)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Treatment (250)	-0.014	-0.002	-0.007**	-0.007**	-0.006**	-0.006**	-0.006**
N=2,793,131	(0.020)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Column (1) presents the estimated coefficient β of equation 1 for the effect of the intervention on the outcome of interest for each grid size and aggregation of time. Column (2) implements a fix effects specification according to equation 2. Columns (3) to (7) add to the previous specification month FE, day FE, hour FE, day$\times$hour FE, and a set of control variables according to equation 3.

Table 9: IHS of accident major

	(1) OLS	(2) FE	(3) + Month FE	(4) + day FE	(5) + hour FE	(6) + day#hour FE	(7) + controls
Aggregation time: 10 minutes							
Treatment (150)	0.010**	0.001	-0.000	-0.000	-0.000	-0.000	-0.001
N=2,497,207	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Treatment (200)	0.005	-0.002	-0.004	-0.004	-0.004	-0.004	-0.004
N=2,142,714	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Treatment (250)	0.005	-0.000	-0.003	-0.002	-0.002	-0.002	-0.002
N=1,746,893	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)
Aggregation time: 20 minutes							
Treatment (150)	0.011**	0.001	0.000	0.000	0.000	0.000	-0.000
N=1,408,125	(0.004)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)
Treatment (200)	0.004	-0.003	-0.004	-0.004	-0.004	-0.004	-0.005
N=1,199,908	(0.004)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Treatment (250)	0.004	-0.001	-0.003	-0.003	-0.003	-0.003	-0.003
N=976,622	(0.004)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Column (1) presents the estimated coefficient β of equation 1 for the effect of the intervention on the outcome of interest for each grid size and aggregation of time. Column (2) implements a fix effects specification according to equation 2. Columns (3) to (7) add to the previous specification month FE, day FE, hour FE, day$\times$hour FE, and a set of control variables according to equation 3.

Table 10: IHS of stand still traffic jam

	(1) OLS	(2) FE	(3) + Month FE	(4) + day FE	(5) + hour FE	(6) + day#hour FE	(7) + controls
Aggregation time: 10 minutes							
Treatment (150)	0.113***	-0.032	-0.042	-0.042	-0.042	-0.042	-0.052
N=2,497,207	(0.034)	(0.030)	(0.030)	(0.030)	(0.029)	(0.029)	(0.031)
Treatment (200)	0.136***	-0.029	-0.035	-0.035	-0.035	-0.035	-0.039
N=2,142,714	(0.032)	(0.032)	(0.032)	(0.032)	(0.031)	(0.031)	(0.032)
Treatment (250)	0.126**	-0.056	-0.053	-0.052	-0.050	-0.049	-0.053
N=1,746,893	(0.039)	(0.038)	(0.034)	(0.034)	(0.032)	(0.032)	(0.034)
Aggregation time: 20 minutes							
Treatment (150)	0.115**	-0.039	-0.052	-0.053	-0.053	-0.053	-0.061
N=1,408,125	(0.036)	(0.034)	(0.035)	(0.035)	(0.034)	(0.034)	(0.035)
Treatment (200)	0.142***	-0.033	-0.042	-0.042	-0.042	-0.042	-0.043
N=1,199,908	(0.035)	(0.037)	(0.037)	(0.036)	(0.036)	(0.036)	(0.037)
Treatment (250)	0.132**	-0.061	-0.062	-0.061	-0.059	-0.058	-0.059
N=976,622	(0.044)	(0.042)	(0.038)	(0.038)	(0.036)	(0.036)	(0.038)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Column (1) presents the estimated coefficient β of equation 1 for the effect of the intervention on the outcome of interest for each grid size and aggregation of time. Column (2) implements a fix effects specification according to equation 2. Columns (3) to (7) add to the previous specification month FE, day FE, hour FE, day$\times$hour FE, and a set of control variables according to equation 3.

B.1 Parallel test

Table 11: Parallel trend test, agg: 20, size: 150

	(1) Mean of length (st)	(2) Mean speed (st)	(3) Average delay	(4) Accident major
Treatment (150)	-0.002	0.005*	-0.035***	0.000
	(0.002)	(0.002)	(0.007)	(0.006)
Weeks -1 and -2	-0.001	0.003	-0.008	-0.006
	(0.002)	(0.006)	(0.008)	(0.008)
Weeks -3 and -4	-0.002	0.003	-0.012	0.028
	(0.004)	(0.006)	(0.009)	(0.017)
Weeks -5+	-0.001	0.003	-0.008	0.013
	(0.003)	(0.006)	(0.010)	(0.009)
Observations	5,451,107	5,451,107	5,451,107	1,408,125

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Parallel trend test, agg: 20, size: 200

	(1) Mean of length (st)	(2) Mean speed (st)	(3) Average delay	(4) Accident major
Treatment (200)	-0.004	0.003**	-0.018***	-0.006
	(0.003)	(0.001)	(0.004)	(0.006)
Weeks -1 and -2	0.001	0.001	-0.007	-0.012
	(0.005)	(0.002)	(0.007)	(0.008)
Weeks -3 and -4	-0.001	0.000	-0.012	0.035
	(0.003)	(0.002)	(0.008)	(0.019)
Weeks -5+	-0.002	0.001	-0.005	0.012
	(0.004)	(0.003)	(0.009)	(0.010)
Observations	3,829,138	3,829,138	3,829,138	1,199,908

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: Parallel trend test, agg: 20, size: 250

	(1) Mean of length (st)	(2) Mean speed (st)	(3) Average delay	(4) Accident major
Treatment (250)	-0.002	0.002**	-0.010**	0.001
	(0.003)	(0.001)	(0.003)	(0.008)
Weeks -1 and -2	0.001	0.002	-0.007	-0.007
	(0.002)	(0.002)	(0.006)	(0.009)
Weeks -3 and -4	0.003	0.002	-0.013*	0.042**
	(0.004)	(0.002)	(0.005)	(0.016)
Weeks -5+	0.001	0.002	-0.009	0.008
	(0.003)	(0.002)	(0.006)	(0.008)
Observations	2,793,131	2,793,131	2,793,131	976,622

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$