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Spatial and Time Spillovers of Driving Restrictions: Causal Evidence from Lima's *Pico y Placa* Policy*

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Abstract

Driving restrictions are popular interventions in rapidly urbanizing developing countries. Their relatively inexpensive implementation appeals to the pressing need to reduce traffic congestion and pollution. Their effectiveness however, remains contested. Using high frequency data from the community-based driving directions app Waze, we evaluate the causal effect on traffic congestion of Lima's *Pico y Placa* driving restriction policy introduced in 2019. We find small improvements in traffic congestion for the policy's directly targeted areas. However, those improvements are offset by time and spatial spillovers in the opposite direction in the aggregate. Speed improved by 2 percent during the early weeks of the intervention, but this effect disappeared 16 weeks after the start of the policy. Moreover, traffic conditions worsened in adjacent areas and in hours outside the time schedule of the policy. In the aggregate, accounting for time and spatial spillovers, a simulation exercise suggests that overall welfare declined by 2 percent, mostly driven by the extensive margin (more roads becoming congested) outside the direct areas and hours targeted by the policy. The policy seems not only to have failed to achieve its intended benefits in terms of congestion, but also probably caused increases in traffic-related pollution. These results highlight the need for policy makers to take into account the overall impacts of driving restrictions policies before implementing them.

Keywords: driving restrictions, congestion spillovers, welfare impacts
JEL codes: H41; Q58; R41; R48

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1 Introduction

With the acceleration of urbanization in developing countries, traffic congestion and its effect on pollution and economic activity remains a major concern. The United Nations (2018) estimates that by 2018, 55 percent of the world population lived in cities, and it forecasts that in the coming decades 90 percent of urban expansion will take place in developing countries. Latin America, in particular, finds itself vulnerable to the detrimental spillovers of unplanned urbanization (Yañez-Pagans et al., 2019). In this context, the city of Lima, Peru, provides a stark reminder of the consequences of uncontrolled urbanization for the quality of life of its inhabitants. Lima is ranked as the seventh most congested city in the world (TomTom, 2020). According to a 2018 survey by Lima Cómo Vamos (2019), the inhabitants of Lima consider problems with public transport as the second most pressing issue (46 percent) in the city, just after crime (82 percent). In addition, survey respondents cite pollution as the fifth most pressing problem (28 percent), and when asked about the causes of pollution, 72 percent of the respondents said vehicle pollution was the main factor.

Traffic congestion in Lima is typical of the congestion problem across major Latin American cities.[1] The policy responses have also been similar, with the imposition of driving restrictions being one of the preferred responses. Several cities have imposed such restrictions to combat traffic congestion and its associated ailments in the last 30 years (Blackman et al., 2018b).

Despite their popularity, however, the effectiveness of driving restrictions remains controversial. The literature has found mixed evidence on the impact of such restrictions, and in some cases there are signs of some perverse effects on pollution after drivers adjust to the specifics of the policy. While the existing literature has concentrated on the impacts of driving restriction on pollution, to our knowledge no prior studies have examined the impacts of these policies on traffic congestion. Therefore, this paper focuses on the traffic congestion margin — which can arguably be considered a *sine qua non* condition for observing any impacts on the pollution margin — and evaluate the causal effect on traffic congestion of Lima's *Pico y Placa* driving restriction policy introduced in 2019. Thanks to the detailed nature of our data, as will be explained below, we are able to examine novel within-city and across-hours impacts.

The earliest study in the driving restrictions literature is Eskeland and Feyzioglu (1997), who evaluated Mexico City's *Hoy No Circula*, a program introduced in 1989 that restricted vehicle circulation based on the last digit of license plates. The study found that, as a result of the policy, households bought an additional car to get additional driving privileges, which led to an increase in the number of cars in the city. In a subsequent evaluation of the same program, Davis (2008) showed that it did not improve air quality, while leading to more vehicles in circulation and more purchases of high-emission vehicles. De Grange and Troncoso (2011) evaluated the imposition of a restriction on vehicles without catalytic converters – a device to reduce pollutant gases – and found no effects on the use of private cars, except when the restriction was temporarily extended to all vehicles for certain hours of the day. When all vehicles faced a temporary restriction based on the last digit of the license plate, car usage dropped by 5.5 percent while ridership in the Metro system rose by 3 percent. Troncoso et al. (2012) evaluated the effect of the same temporary vehicle restriction on pollution and found reductions in carbon monoxide (CO) of between 7.6 and 9.4 percent.

Gallego et al. (2013a) modeled households' transport use decisions allowing for public and private modes. Studying the driving restrictions in Mexico City, the authors estimated that this

[1] According to TomTom (2020), five cities in Latin America are among the 20 most traffic congested cities in the world: Bogota (5th), Lima(7th), Mexico City (13th), Recife (15th), and Rio de Janeiro (20th).

type of policy had the unintended impact of increasing the number of circulating cars. In a similar study Gallego et al. (2013b) confirmed these results and found additional detrimental effects in terms of increased pollution. Other authors also find negative impacts. Ye (2017) found that driving restrictions in Lanzhou were ineffective in improving its air quality because drivers shifted their travel schedules, took detours, and acquired more cars. Bonilla (2019) found that Bogota's *Pico y Placa* generated a light increase in CO during the morning peak hours and higher vehicle ownership and gasoline consumption.

A small number of studies find positive impacts of driving restrictions policies, though some times paired with negative impacts on other outcomes. Viard and Fu (2015) estimated a 21 percent drop in air pollution during one-day-per-week restrictions in Beijing, together with a reduction in labor supply among workers with discretionary work time. Carrillo et al. (2016, 2018) found evidence of reductions in pollution levels resulting from Quito's driving restriction policy, but at the cost of higher crime rates following its implementation. In a study of a 1992 program in Santiago (Chile) that targeted old cars in an attempt to rid the city from high polluting vehicles, Barahona et al. (2020) found compelling evidence that vintage-specific driving restrictions incited fleet renewal towards cleaner cars.

Other studies suggest that incorporating all costs related to the restrictions, may diminish any benefits achieved by the policy. This become particularly relevant for policies with meager results . Blackman et al. (2018a,b) suggest that despite its growing popularity worldwide, license-plate–based driving restrictions do not always make good economic sense based on the availability of public transportation modes or a market for used cars.

While prior studies have been able to capture city-wide impacts, they could not identify impacts on smaller geographical areas within cities. In this paper, owing to highly refined data, we can explore in detail how the impact of driving restrictions propagates through the city. Thus, a major contribution of our analysis is the quantification of spatial and time spillovers of the policy. By using high-frequency and geocoded data on traffic jams we are able to disentangle these two types of spillovers associated with driving restrictions, which most of the prior literature speculated upon but was not able to estimate due to lack of adequate data.

The analysis relies on high-frequency data on traffic jams from the community-based driving directions app Waze. Through the use of a generalized propensity score, we select the streets and road segments that are comparable across different rings around the *Pico y Placa* intervention areas. Then, we estimate inverse probability weighting flexible difference-in-differences regressions, weighted by the inverse of the generalized propensity score, to obtain the causal impacts of the *Pico y Placa* policy. Methodologically, our paper is related to recent studies that use high-frequency data. Hanna et al. (2017) used traffic speed data from Android phones collected through Google Maps to investigate whether high-occupancy vehicle policies reduce traffic congestion. Kreindler (2016) used information collected through an app with precise GPS coordinates for over 100,000 commuter trips in Bangalore, India to examine the welfare effects of congestion pricing.

We find initial improvements in traffic congestion after the imposition of the *Pico y Placa* policy in Lima in the directly affected areas, with mostly non-significant negative spillovers on other areas or times, both during a transition period and in the first six weeks of full implementation of the policy. By week 16 of full policy implementation small positive impacts remain only for some areas directly affected by the policy and for certain times of day. However, these positive impacts are offset by time and spatial spillovers in the opposite direction in the aggregate. The number of minutes of a severe traffic jam on high-capacity roads increased by 117 percent in the morning in the area immediately adjacent to the intervened area. The probability of a severe traffic jam also increased by 5pp in nearby areas in the hours in between the morning and afternoon, which represents 71 percent of the pre-treatment average on high-capacity roads. Aggregate data on fines imposed on drivers suggest a sustained enforcement effort of driving restrictions throughout the analysis period, implying that observed changes are likely due to behavioral changes by drivers. A simulation exercise that accounts for all the effects suggests an overall welfare loss of about 2 percent in the final period of implementation of the policy. The welfare analysis, furthermore, suggests that the direct congestion benefits of the *Pico y Placa* policy during 2019 were at best small and localized, and that there were negative welfare impacts associated with time and spatial spillovers. A welfare decomposition suggests that most of those negative impacts were caused by the extensive margin (i.e. more roads becoming congested). The results highlight the need for policy makers to take into account the overall impacts of driving restrictions policies before implementing them.

The next section of this paper presents the context that motivated the *Pico y Placa* policy. Section 3 presents the data, while Section 4 describes the empirical methodology, including the study design, the selection of comparable streets, and the difference-in-differences approach used for estimation. Section 5 presents the results of the analysis, and Section 6 puts forth a welfare analysis to understand the overall impacts of the policy. Section 7 concludes.

2 Lima, Traffic Congestion, and *Pico y Placa*

The capital of Peru, Lima is a coastal city located by the shores of the Pacific Ocean. It is home to 10 million people, a third of the country's population. The city grew rapidly from a small cosmopolitan area in the early years of the 20th century to a robust economic center that has attracted large waves of migrants from the rest of the country since the 1950s. In 1991 the national government decreed that any resident with a motor vehicle could operate in the city as a provider of public transport services.[2] The rationale was to provide income-earning opportunities for the urban population, but the cost of the measure was a severe deterioration of the provision of public transit (Jauregui-Fung et al., 2019). The 21st century brought efforts to reorganize the public transit problem with the construction of an elevated light rail system (Linea 1) and a Bus Rapid Transit system (BRT), known as the *Metropolitano*, which were completed between 2010 and 2011.

However, traffic congestion in Lima remains a severe problem. Calatayud et al. (2021) estimate that the total cost of congestion in Lima in 2019 accounted for 0.7 percent of the city's per capita GDP. Calculations by TomTom (2020) for the same year suggest that the inhabitants of Lima lose 8.7 days a year stuck in traffic, below Bogotá where people lose 9.6 days a year, but above Santiago where people lose about 7.6 days a year, or Buenos Aires where the loss is about 5.5 days a year. Time lost in large metropolises from richer countries fall below Latin American standards: 6.2 days in London, 5.9 in New York, and 4.8 in Madrid.

In an influential annual opinion survey in 2018 only 37.5 percent of the respondents in Lima expressed satisfaction with their city (Lima Cómo Vamos, 2019). And, as previously mentioned, while 82.2 percent of respondents listed crime as the city's main problem, the second-most frequently cited problem was public transport (46.2 percent), with pollution cited by 28.5 percent of respondents.

In 2019, the Metropolitan Authority in Lima introduced a plan to restrict circulation in certain areas of the city in an effort to reduce air pollution and relieve traffic congestion, and as a way to ease the expected additional congestion associated with the 2019 Pan American and Parapan American Games to be held in the city in late July and August. The measure was piloted during the games, and based on initial results, the authorities decided to keep it after the conclusion of the Games.[3]

[2]Legislative Decree 651 of 1991.

[3]The Metropolitan Authority reported that in the week of 5 to 8 August 2019 speed increased by 11 percent in the

Figure 1 shows the area with the intervened roads in red, as well as six adjacent rings. The policy restricted circulation four days a week, from Monday to Thursday. Vehicles with an odd-numbered last digit on their license plate were restricted from circulation on Mondays and Wednesdays, while vehicles with an even-numbered last digit were restricted on Tuesdays and Thursdays. The municipality implemented two time schedules for the restriction. For the morning rush hour, circulation was restricted initially from 7:30 to 10 a.m., while for the afternoon rush hour circulation was restricted from 5 to 9 p.m. Later, the morning schedule was extended to start from 6:30 a.m. In the empirical estimations we consider morning schedules from 6 to 10 a.m. and afternoon schedules from 5 to 9 p.m.[4]

The restricted area included major thoroughfares within the red core depicted in Figure 1.[5] The figure shows a buffer of 250 meters around the restricted streets, roads, or highways in red. This red area is deemed "the direct intervention area," or *Pico y Placa* area. The figure also shows six adjacent rings of 250 to 500 meters each that define the areas of analysis in the empirical section, as explained below.

Figure 2 shows the evolution of Lima's traffic conditions throughout the day from January to June 2019, prior to the implementation of the restrictions. The figure shows three variables: speed, probability of a severe traffic jam and the number of minutes in a severe traffic jam. It also distinguishes by road type: local (panel a) and non-local (panel b) roads. Speed is measured in kilometers per hour, while the definition of a "severe" traffic jam is constructed based on the Waze classification. Waze considers a hierarchy of four types of traffic jams with categories from 1 to 4, where 4 is the most severe type. Our classification of "severe" corresponds to types 3 and 4; that is, when speed is less than 40 percent of a reference speed calculated by Waze as the non-traffic-jam speed.[6] As explained below, the unit of observation in this study is the road segment. We calculate speed for each segment, in every hour in the data, whether it is part of a severe traffic jam within that hour, and the number of minutes within that hour that the road segment has been reported as having a severe traffic jam.

Waze does not provide the reference speed used for traffic jam classification types. However, as explained below, we can use information provided by Waze to calculate a time-invariant free-flow speed (i.e. under non-traffic-jam conditions) for each road segment in the sample. While Section 3 provides more details, here we simply clarify that we define local roads as those road segments whose free-flow speed is less than 30 km per hour, and non-local roads are defined as road segments with free-flow speed of 30 km per hour or higher. With this definition we aim to proxy for road capacity: local roads are mainly small streets, while non-local roads could include highways or freeways. Based on this classification, we explore traffic conditions in Lima in the pre-*Pico y Placa* period in Figure 2.

Beyond the distinction between local and non-local roads, Figure 2 distinguishes by each distance ring depicted in Figure 1. Regardless of the road type, the *Pico y Placa* area under-performs all the other six adjacent areas, with the exception of speed on local roads (top left panel). Every

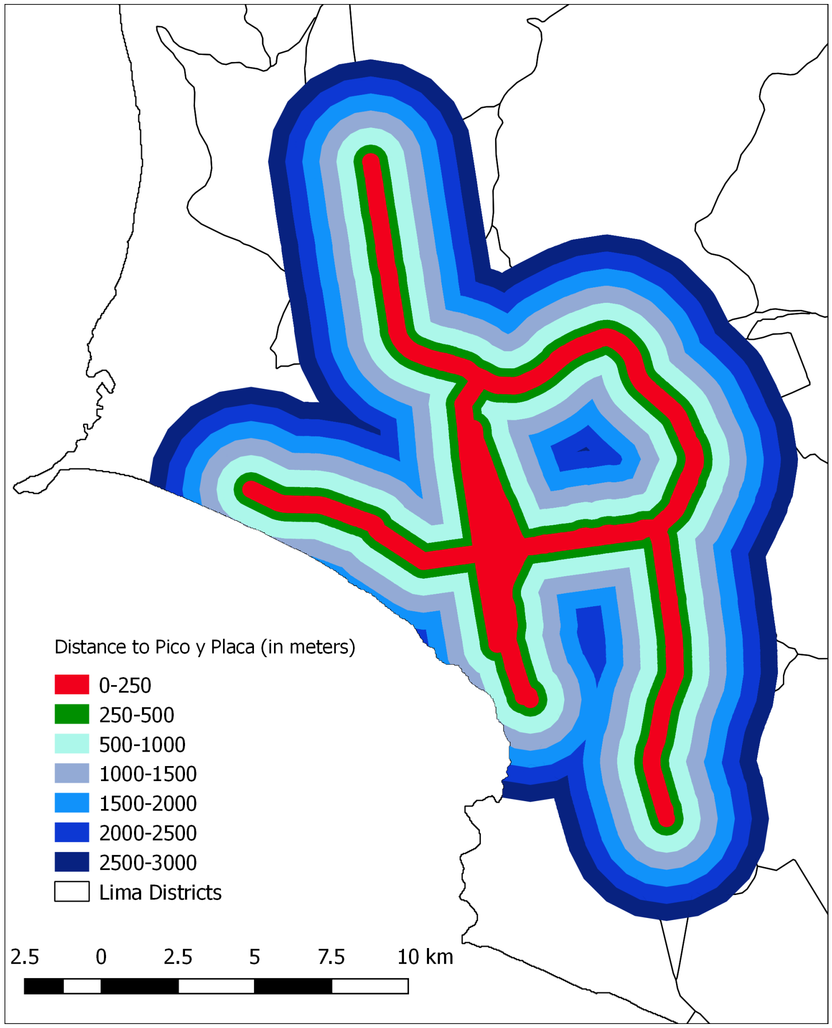
public transport blue and red corridors. It also reported increases of 19 percent in private transport speed in one of the main corridors, *Javier Prado*. See Municipalidad de Lima (undated).

[4] In both cases the ending hour of the restriction implies no restriction from that time; that is, the restriction from 6 to 10 a.m. indicates that the restriction is in place until 9:59, and as of 10:00 there is no restriction. Similar logic applies for the afternoon.

[5] These included *Panamericana Sur* and *Panamericana Norte*, from north to south in the east of the city; *Javier Prado* and *Avenida La Marina* from west to east; and two parallel key thoroughfares, *Via Expresa* and *Arequipa* corridors.

[6] To be classified as type 4, the reported speed must be less than 20 percent of the reference speed; for type 3, the reported speed must be less than 40 percent but higher than 20 percent of the reference speed; for type 2, the reported speed must be less than 60 percent but higher than 40 percent of the reference speed; and for type 1, the reported speed must be less than 80 percent but higher than 60 percent of the reference speed.

Figure 1. Area of Intervention and Distance Rings



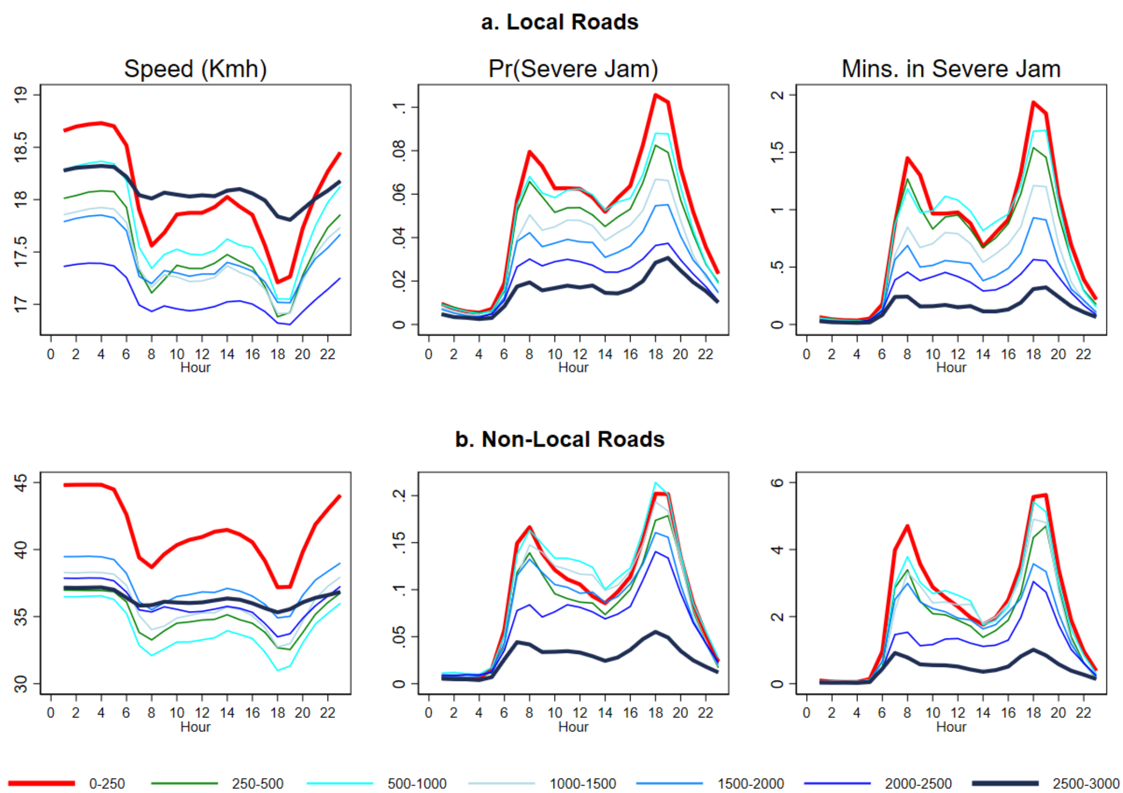
Source: Prepared by the authors. *Note*: For each ring, "distance" refers to distance in meters to the roads and streets intervened by the policy. The first ring includes the area intervened by *Pico y Placa* in a buffer of 250 meters. The adjacent ring includes road segments in the 250 to 500 meters buffer from the intervened area. The remaining distance rings are 500-meter buffers that are farther away.

distance ring on average performs better than the red ring affected by the driving restrictions.

For the three variables — speed, probability of a severe traffic jam, and minutes in a severe traffic jam — the largest traffic deterioration occurs in the afternoon. For instance, speed in the first ring (up to 250 meters away from *Pico y Placa*) drops from 18.4 km per hour at 1 a.m. to 17.2 km per hour at 8 a.m., and to 16.7 km per hour at 6 p.m. among the local road segments. For the group of non-local roads, the reduction is from 47.9 km per hour to 39.5 km per hour at 8 a.m. and to 36.7 km per hour at 6 p.m. As a percentage change, the morning drop in speed is 6.7 percent for local roads, and 17.5 percent for non-local roads, while for the afternoon, the drop in speed is 9.2 percent for local roads and 23 percent for non-local roads. Similarly, the increase in the probability of a severe traffic jam is higher in the afternoon: for local roads it increases from close to zero in the early morning to 0.10 pp at 8 a.m. and to 0.14 pp at 6 p.m. For non-local roads it also goes from close to zero in the early morning to 0.24 pp at 8 a.m. and 0.39 pp at 6 p.m. In terms of minutes in severe traffic jam, the increases are also stark: on average 1.5 minutes at

8 a.m. and 2.5 minutes at 6 p.m. for local roads, and 6 minutes at 8 a.m. and 8 minutes at 6 p.m. for non-local roads. While the changes in minutes may seem small, these are road segment-level changes; drivers end up driving through many road segments, implying cascading negative impacts on travel times.

Figure 2. Traffic Conditions in *Pico y Placa*'s Area of Influence throughout the Day, by Road Type and Distance Ring



Source: Prepared by the authors. *Note*: Averages are computed across all road segments from 7 January to 30 June 2019 using Monday through Thursday data. Local roads are defined as those road segments with free-flow speed below 30 km per hour, while non-local roads are the rest. Distance to *Pico y Placa* is expressed in meters. Averages use the 75,249 road segments that satisfy overlap (see Section 4) of the main text.

When the Metropolitan Authority of Lima introduced the *Pico y Placa* policy on 22 July 2019, the idea was to pilot the policy during the Pan American and Parapan American Games and then leave it in place if its effects were positive (Municipalidad de Lima, undated). Its design was similar to Quito's *Pico y Placa* policy (Carrillo et al., 2018), under which certain parts of the city were restricted during heavy traffic hours of the day. The circulation ban affected all vehicles, with a day schedule depending on the last digit of license plates as described above.[7]

A key element of a policy such as *Pico y Placa* is whether it is enforced, or at least perceived by drivers as being enforced. The authorities categorize traffic infractions in three groups: minor,

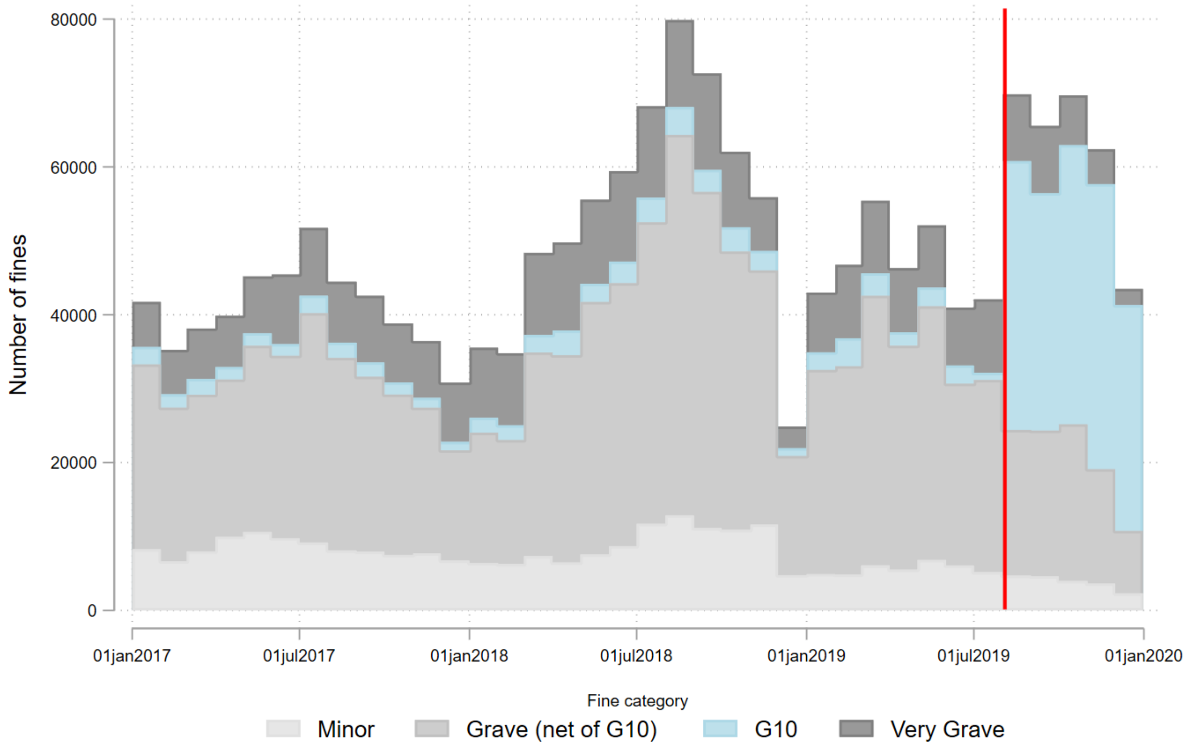
[7] Taxis and mini-vans (*combis*) were also affected by the policy. *Combis*, while largely informal, are very popular, used by 27 percent of the population according to Lima Cómo Vamos (2019)), due to the lack of proper public transport. Regulated public transport vehicles, large buses and the *Metropolitano* Bus Rapid Transit system, were exempted from the driving restrictions.

grave, and very grave. The violation of the *Pico y Placa* restrictions is considered a grave type of infraction, and is classified under the category $G10$ of the infraction code: "Failure to comply with the provisions on the use of rapid transit and/or restricted access roads." This type of infraction is costly, approximately US$ 106, although paying the fine early, within five days or between five and 15 days of issuance, could substantially reduce it to only around US$ 18 or US$ 35, respectively (SAT, undated).[8] As a reference, the full cost of the fine represented around 21 percent of average monthly earnings in the Lima metropolitan area in 2019 (INEI, 2020).

Figure 3 shows the evolution of the total number of fines related to traffic infractions issued per month from January 2017 to December 2019 in Lima. Numbers are cumulative, with minor infractions at the bottom (very light gray), followed by grave infractions net of $G10$ (light gray), $G10$ infractions (light blue) and very grave infractions (dark gray). The vertical red line indicates the first full month of *Pico y Placa*, August 2019. It is clear from the figure that there is a stark jump in the $G10$ category starting with the imposition of *Pico y Placa*. Even though the data do not identify fines related to *Pico y Placa* within the $G10$ category, there are no other policy changes at the same time that could explain this sharp increase. $G10$ fines go from an average of 2,500 per month from January 2017 to July 2019 to over 40,000 per month from August to December 2019. At the same time, the other categories of fines appear to remain relatively constant in the first few months, although non-$G10$ grave fines do show a decrease at the end of the period (which may suggest a reduction in the effort of enforcing non-$G10$ grave infractions). Overall, this evidence suggests that there was a concerted effort to enforce the *Pico y Placa* restrictions that remained relatively constant from August to December 2019.

[8] All dollar figures use an exchange rate of 3.32 soles per U.S. dollar, as of December 31, 2019 (U.S. Treasury, undated).

Figure 3. Lima: Number of Monthly Traffic Infractions by Type



Source: Municipality of Lima. *Note*: The vertical axis reports the cumulative number of fines. Infractions related to *Pico y Placa* fall under the $G10$ category of the infraction code: "Failure to comply with the provisions on the use of rapid transit and/or restricted access roads."

3 Data

We use high-frequency data on traffic jams produced by the community-based driving directions app Waze, to which we have access through the *Waze for Cities Program*.[9] A feed provides *aggregate* data on traffic jams and alerts every two minutes. In this paper we only use the traffic jams data. A traffic jam is defined by Waze as a traffic line of varying length and speed. The variability in traffic jam length depends on the time of observation: traffic lines tend to be longer during peak hours. Each traffic line (and thus its length) is constituted by a concatenation of time-invariant road segments. For this analysis we break traffic lines into their constituting time-invariant road segments, which we can thus follow through time in the form of a panel of segments. Hence, our unit of observation is the road segment. The average road segment is 60.3 meters long.

Waze reports the average speed of vehicles in the traffic jam, along with two speed-related statistics: the severity of the traffic jam and the delay in seconds.[10] While we read the feed in two-minute intervals, for purposes of the analysis we aggregate the data to the hourly level. We consider three variables in the analysis: speed, an indicator for a severe traffic jam, and the number of minutes in a severe traffic jam. Speed is measured in kilometers per hour and is the average speed for the segment in the hour. For each road segment appearance we also observe

[9] For more details see: https://www.waze.com/ccp/.

[10] See the discussion on traffic jam severity in footnote 6. Delay is defined against the time it would take for a vehicle to travel through the traffic jam line at free-flow speed; see footnote 11 for details on free-flow speed.

what type of traffic jam it is part of, and the duration of the jam. This allows for defining a dummy variable for each hour indicating if the segment has a severe traffic jam during that time period and the number of minutes within the hour in which the segment has the severe traffic jam.

Using information on the delay and speed associated with the traffic jam of which each road segment is part of, and averaging across appearances before the start of the policy, we calculate a time-invariant measure of free-flow speed, for each segment in the data.[11] Free-flow speed (FFS) allows us to classify each segment into two road types: (i) local roads for which FFS is less than 30 km/h, (ii) non-local roads for which FFS is 30 km/h or higher. Note that, in every two-minute interval in the feed, a segment is observed only when Waze reports a traffic jam. In that case, the reported traffic jam speed is used as a measure of the speed observed for the segment in that particular two-minute interval. If during a two-minute interval a segment is not reported in the feed as being part of a traffic jam, its associated FFS is used as the measure of speed for the interval. The speed for the segment in an hour is then obtained as the average of the speeds for all the two-minute intervals within the hour. In the same way, the number of minutes in an hour in which a segment is considered as having a severe traffic jam is determined as twice the number of two-minute intervals in which a segment pertains to a severe traffic jam in the feed, in that hour. Any segment for which the number of minutes in severe traffic jam in an hour is greater than zero is deemed as having a severe traffic jam during that hour. This strategy allows us to to assemble a balanced panel of segments.

We compute for each road segment the closest distance to any of the streets intervened by *Pico y Placa* and classify them into seven proximity groups or "rings": (i) less than 250 meters, (ii) between 250 and 500 meters, (iii) between 500 and 1000 meters, (iv) between 1000 and 1500 meters, (v) between 1500 and 2000 meters, (vi) between 2000 and 2500 meters, and (vii) between 2500 and 3000 meters. Figure 1 shows the rings used in our analysis. The red line is the directly intervened area (road segments less than 250 meters away from the closest *Pico y Placa* street), while the other rings represent road segments farther away. The dark blue ring is the farthest away, which in our estimation strategy, as discussed in Section 4, serves as the comparison group.

We assemble daily data for every hour of the day from 7 January 2019 to 22 December 2019. For the entire city of Lima we retrieve 259,501 segments, but only those within three kilometers of the *Pico y Placa* area of influence are used, which leaves us with 91,765 segments. From this initial pool of segments, 18 percent are dropped after imposing an overlap condition, explained in Section 4, leaving 75,249 comparable segments in the analysis data.

Table 1 presents summary statistics of some segment characteristics by distance ring. The direct area of influence of *Pico y Placa*, the first ring, is comprised of 11,625 of the 75,249 segments. This represents almost 15 percent of all segments, while 11 percent of the segments are located in the second distance ring, 21 percent in the 500-1000 meter ring, 19 percent in the 1000-1500 meter ring, 16 percent of the 1500-2000 meter ring, 11 percent in the 2000-2500 meter ring, and 7 percent in the farthest ring.

From column 3 onwards in Table 1, all figures are for the segments in column 2 (after overlap). Column 3 shows the total length distribution across rings. The design includes 4,535.5 km around the *Pico y Placa* areas. Column 4 indicates that on average 83 percent of the total length falls within the local road category, with little difference across rings, except for the *Pico y Placa* area itself, where 76.9 percent of the length corresponds to local roads. Columns 5 to 10 provide road segment averages for length and FFS distinguishing by road type. As expected, FFS on non-local

[11] Free-flow speed is usually defined as the speed at which traffic can flow without impediment. Our measure of free-flow speed is an approximation of the implicit speed associated with each segment by Waze, as represented by the delay variable. From conversations with Waze developers, we understand that this speed is obtained as the speed observed between 1 and 2 a.m.

roads is 120 percent higher than on local roads, but there is a relatively small difference in terms of average road segment length: 66 meters for non-local roads and 59.2 meters for local roads.[12]

Table 1. Summary Statistics of Road Segments by Distance Ring

Distance to *Pico y Placa* (meters):	Number of Road Segments Before Overlap	Number of Road Segments After Overlap	Total Road Segments Length (km)	Share of Local Roads in Total Segment Length (%)	Road Segment Averages					
					Length (meters)			*Free-Flow Speed (km/h)*		
					All	Local Roads	Non-Local Roads	All	Local Roads	Non-Local Roads
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
0-250	14,552	11,625	694.4	0.77	59.7	58.7	63.4	24.6	18.8	45.1
250-500	9,231	8,027	514.7	0.88	64.1	63.7	67.3	20.3	18.2	37.3
500-1000	17,690	15,593	943.7	0.86	60.5	59.8	65.1	20.9	18.5	37.0
1000-1500	15,965	14,256	846.6	0.84	59.4	58.6	63.7	21.1	18.0	38.7
1500-2000	13,874	11,817	700.8	0.81	59.3	57.3	69.4	21.5	17.9	39.8
2000-2500	11,288	8,251	473.0	0.82	57.3	55.8	65.5	20.7	17.5	38.4
2500-3000	9,065	5,680	362.2	0.79	63.8	62.1	71.4	21.9	18.4	37.4
All	91,765	75,249	4535.5	0.83	60.3	59.2	66.0	21.6	18.2	39.7

Source: Prepared by the authors. *Note*: Free-flow speed is speed at free circulation. Total length is the sum of all road segment lengths within the category. Figures in columns 3 to 10 refer to the segments in column 2 (after the imposition of overlap).

Table 2 presents, for the segments that satisfy overlap, the *pre-treatment* averages for the three dependent variables: speed, probability of a severe traffic jam, and number of minutes in a severe traffic jam. (From here on, we will refer to the severe traffic jam indicator outcome as the probability of a severe traffic jam, which is what the averages and estimated models capture.) The dependent variables averages are calculated separately by time of the day (morning, midday, afternoon). The general picture indicates that traffic worsens in the afternoon consistently across all distance rings. The total average number of minutes in a severe traffic jam in the 0-250 meter ring changes from 0.65 minutes (i.e., 39 seconds) in the morning to 2.2 minutes (i.e., 132 seconds) in the afternoon (column 7), which is a more than threefold increase. For the other distance rings the increase from morning to afternoon is of similar proportions or higher. Distinguishing by road type (local and non-local) yields similar increases from morning to afternoon. Similarly, the total average probability of a severe traffic jam in the 0-250 meter ring increases from 0.04 in the morning to 0.11 in the afternoon. Again, this worsening in traffic conditions is more or less homogeneous across distance rings and by road type. The table clearly suggests that the magnitude of the traffic problem is significantly higher in the afternoon time period.

[12] Appendix Table A1 presents evidence on how the imposition of overlap and inverse probability weighting (see Section 4 for details) improves the balancing of pre-treatment covariates across the different rings.

Table 2. Pre-treatment Summary Statistics of Dependent Variables by Schedule and Distance Ring

Distance to	Speed			Pr(Severe Traffic Jam)			Minutes in Severe Traffic Jam		
Pico y Placa (meters):	Total	Local Roads	Non-Local Roads	Total	Local Roads	Non-Local Roads	Total	Local Roads	Non-Local Roads
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel a. Morning									
0-250	23.67	18.32	42.76	0.04	0.03	0.06	0.65	0.45	1.40
250-500	19.77	17.75	35.78	0.03	0.03	0.05	0.44	0.38	0.93
500-1000	20.25	18.00	35.09	0.03	0.03	0.06	0.47	0.37	1.13
1000-1500	20.57	17.66	36.97	0.02	0.02	0.05	0.36	0.26	0.93
1500-2000	20.99	17.61	38.18	0.02	0.02	0.05	0.33	0.22	0.91
2000-2500	20.23	17.21	36.85	0.02	0.01	0.04	0.23	0.17	0.56
2500-3000	21.58	18.18	36.64	0.01	0.01	0.02	0.14	0.10	0.31
Panel b. Midday									
0-250	22.93	17.43	40.92	0.07	0.09	0.10	1.19	1.56	2.29
250-500	19.32	17.06	34.68	0.06	0.07	0.09	0.94	1.28	1.78
500-1000	19.62	17.22	33.42	0.07	0.08	0.12	1.16	1.42	2.37
1000-1500	19.98	17.05	35.27	0.06	0.06	0.11	0.93	0.99	2.25
1500-2000	20.52	17.13	36.76	0.05	0.05	0.10	0.73	0.75	1.97
2000-2500	19.83	16.87	35.50	0.03	0.03	0.08	0.50	0.49	1.23
2500-3000	21.39	17.89	36.14	0.02	0.03	0.03	0.20	0.27	0.47
Panel c. Afternoon									
0-250	22.02	17.43	38.39	0.11	0.09	0.17	2.20	1.56	4.50
250-500	18.87	17.06	33.20	0.08	0.07	0.15	1.54	1.28	3.59
500-1000	19.16	17.22	31.93	0.09	0.08	0.18	1.79	1.42	4.25
1000-1500	19.55	17.05	33.63	0.07	0.06	0.16	1.43	0.99	3.91
1500-2000	20.17	17.13	35.61	0.06	0.05	0.14	1.10	0.75	2.89
2000-2500	19.53	16.87	34.15	0.05	0.03	0.12	0.78	0.49	2.38
2500-3000	21.16	17.89	35.64	0.03	0.03	0.05	0.37	0.27	0.81

Source: Prepared by the authors. *Note*: Averages calculated using pre-treatment data on segments that satisfy overlap, from 7 January 2019 to 30 June 2019. Morning: 6:00 to 9:59 a.m., Midday: 10:00 to 4:59 p.m., Afternoon: 5:00 to 8:59 p.m.

4 Estimation

As the *Pico y Placa* policy was implemented to ease traffic congestion before and during the Pan American and Parapan American Games that were due to start 26 July and 23 August, respectively, the "full" effect of *Pico y Placa* is considered as starting as of the week of 2 September, right after the closure of the Parapan American Games. The difference-in-differences empirical strategy is based on using the road segments in the outermost ring (2500 to 3000 meters away from the restricted streets) as a comparison group while we the effect of the policy on the other rings around the intervened zone is evaluated. The estimating equation is:

$$\begin{aligned} y_{ith} &= \mu_i + \sum_{k=1}^{6} \beta_k T_{ki} \times PyP_t + \sum_{k=1}^{6} \theta_k T_{ki} \times PanG_t \\ &\quad + \tau_t + \gamma_h + f(t)_z + \varepsilon_{ith} \end{aligned} \tag{1}$$

where y_{ith} is the outcome variable for road segment i on day t at hour h. The three outcomes are (i) Ln(Speed), (ii) a dummy variable that activates when the road segment has a severe traffic jam during the hour, and (iii) the number of minutes within that hour that the road segment has a severe traffic jam. The coefficients of interest are as follows: each β_k is associated with a distance ring, T_{ki}; μ_i is a road segment fixed effect; PyP_t is a dummy variable for the period after the Parapan American Games; θ_k captures the effect of the Pan American and Parapan American Games that coincided with the first weeks of *Pico y Placa* (July 22 to September 1); τ_t is a day fixed effect to account for aggregate shocks in the city; γ_h is an hour of the day fixed effect; $f(t)_z$ is a set of linear trends by district z before and after the first day of the driving restrictions (July 22); and ε_{ith} is the error term. Standard errors are clustered by road segment. Clustering at the road segment level allows for arbitrary correlation across time within segments. To allow for both time and spatial correlation between segments we explored an alternative clustering strategy, based on allowing correlation between all segments within an enclosed area.[13] As discussed in Section 5, this alternative strategy does not change the statistical significance of most coefficients. However, it is quite costly in terms of computational time. Thus, we use the road segment level clustering for our main results.

A difference-in-differences strategy does not require that units in different treatment arms are equal in levels prior to treatment, only that they follow parallel trends pre-treatment. However, ensuring that units are similar in levels in the pre-treatment periods, and re-weighting units to ensure that the parallel trends assumption holds, lends robustness to the identifying assumptions (Ryan et al., 2019; Callaway and Sant' Anna, 2021). Thus, to ensure road segment comparability across different distance rings, we estimate a generalized propensity score (GPS), the probability of a road segment being in any of the rings (Imbens, 2000; Hirano and Imbens, 2004).[14] We follow the strategy proposed by Flores and Mitnik (2013) to identify *road segments* satisfying simultaneous overlap across distance rings.[15] Simultaneous overlap is attained by defining the overlap region for each distance ring: based on the probability of belonging to a particular ring $T = T_k$, only those road segments with probability above a certain quantile q threshold are deemed to be part of the overlap region for that distance ring. Simultaneous overlap deems as satisfying the overlap condition all the road segments that are part of the overlap region simultaneously for all distance rings. Intuitively, it implies that road segments are comparable in terms of covariates in *each* of the distance rings.

We estimate the GPS with a multinomial logit model using as covariates historical pre-intervention data and road segment characteristics. In particular, we model such probability based on average speed and minutes in severe traffic jam in morning and afternoon peak hours calculated for each of the 28 weeks preceding the intervention. We also use time invariant road segment characteristics such as free-flow speed (in logs), length, and number of appearances in the dataset before the start of the restrictions. Additionally, we include other time variant pre-intervention variables at the road segment level such as the average of the share of the segment length over the length of the traffic jam to which the segment belongs, in the morning and afternoon time periods. We also include variables from the 2017 population census calculated at the traffic-zone level:[16] proportion

[13]We define those areas by using resolution 10 hexagonal H3 cells (with a side length of around 66 meters and an area of approximately 11,300 square meters). H3 cells are a hexagonal hierarchical geospatial grid system originally developed by Uber to analyze sub-areas of the world at different grid sizes ("resolutions"). For more details on H3 cells, see `https://h3geo.org/`.

[14]The GPS is the probability of a particular treatment group conditional on covariates, $Pr(T = T_k|X = x)$, where $k = 1, ..., 7$ (the seven rings) and X refers to pre-treatment covariates.

[15]Following Flores and Mitnik (2013) simultaneous overlap is defined as $0 < \xi < Pr(T = T_k|X = x)$ for all T_k and $x \epsilon X$.

[16]We include these variables to attempt to control for any zone-level characteristics that may affect congestion patterns in each road segment. We rely on the 427 traffic zones defined in the 2004 and 2011 Origin-Destination surveys for the Lima metropolitan area (JICA, 2013). These traffic zones are constructed to capture homogeneous transport

of males, average age, proportion of individuals with primary, secondary, and tertiary education, proportion of permanent residents in the district, proportion of residents with more than five years in the district, share of Spanish speakers, share of individuals insured in the health system, proportion of people who study in a school outside their district of residence, and the proportion of working individuals whose job requires them to commute to another district. After estimating the GPS, we impose *simultaneous* overlap across all seven rings, following Flores and Mitnik (2013), as explained above, and using the value of $q = 1$ (i.e. percentile 1).[17] As mentioned in Section 3, we drop close to 18 percent of the road segments that do not satisfy the overlap condition. In all regressions we only use data associated with the road segments that satisfy this condition. Furthermore, to ensure good balancing between road segments across different distance rings, all regressions are estimated using inverse probability weighting (IPW) by the inverse of the GPS. In Appendix Table A1 we show how the imposition of simultaneous overlap plus weighting by the inverse of the GPS substantially improves balancing in time-invariant and pre-intervention time-variant covariates, across distance rings.[18]

5 Results

In this section we discuss different estimation results. First, we present an analysis to validate our empirical strategy. Second, we present the impacts of *Pico y Placa* for the intervention period (following the transition period during the 2019 Pan American and Parapan American Games), as well for subperiods of it. Third we present detailed impacts by hour of the day.

5.1 Validity of the Empirical Strategy

The validity of the difference-in-differences methodology depends on the "parallel trends" assumption (Angrist and Pischke, 2009) between the treatment and comparison groups before the start of the policy on July 22. The assumption is that unobservable characteristics associated with selection into treatment (defined by the proximity to the intervened area) remain constant and there are no observed differences in trends before the onset of the policy. To examine this, we estimate a variation of equation (1) that considers only the 28 weeks before the policy started, and divides it into two groups: the "pre-period" of 16 weeks prior to the implementation of *Pico y Placa* and the remaining 12 weeks as the excluded (base) period. The equation we estimate is:

$$y_{ith} = \mu_i + \sum_{k=1}^{6} \alpha_k T_{ki} \times Pre_t + \tau_t + \gamma_h + f(t)_z + \varepsilon_{ith} \tag{2}$$

where Pre_t is a dummy variable for the "pre-period" (the "placebo" treatment period). The validity of the strategy requires that the coefficients associated with α are not statistically significant. Table 3 shows the results of this test for all road segments in panel a, local road segments in panel b, and non-local segment roads in panel c. We group the results into three schedules: morning and

characteristics of the population within each zone.

[17] The results are robust to alternative values of q and are available upon request.

[18] Appendix Table A1 shows the raw means prior to imposing overlap and the IPW weighted means after imposing overlap, using the inverse of the GPS as the weight. In addition, for both types of means, it shows the p-value associated with the test of the joint hypothesis that the mean values for all distance rings are equal and the root mean square distance (RMSD) associated with each set of means. The RMSD is a normalized overall measure of distance among the estimated means (see Flores and Mitnik (2013) for details). Better balancing is captured by the RMSD values decreasing.

afternoon coinciding with *Pico y Placa* restriction hours, and the hours in between grouped under "midday". All regressions consider only road segments satisfying the overlap condition, and use the inverse of the GPS as weight.

Reassuringly, no coefficient is statistically significant, which validates the identification strategy. Appendix Figures B1 to B3 take a more flexible approach to test for parallel trends and report the results of a lead-and-lags exercise with biweekly coefficients, which confirms that trends in all variables before the start of the restrictions were parallel.[19]

[19]The estimated equation is $y_{ith} = \mu_i + \sum_{k=1}^{6} \alpha_k T_{ki} \times BW_t + \tau_t + \gamma_h + f(t)_z + \varepsilon_{ith},$, where BW_t is the set of biweekly dummies reported in the figures.

Table 3. Pre-treatment (Weeks -16 to -1) "Placebo" Impacts

Distance to *Pico y Placa* (meters):	Ln(Speed)			Pr(Severe Traffic Jam)			Minutes in Severe Traffic Jam		
	Morning	Midday	Afternoon	Morning	Midday	Afternoon	Morning	Midday	Afternoon
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Panel a. Overall					
0-250	-0.01	0.01	0.00	0.00	-0.01	-0.00	0.15	-0.19	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.20)	(0.21)	(0.20)
250-500	-0.00	0.01	0.00	0.00	-0.01	-0.00	0.11	-0.25	-0.05
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.20)	(0.21)	(0.20)
500-1000	-0.00	0.01	0.00	0.00	-0.01	-0.00	0.11	-0.14	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.20)	(0.21)	(0.19)
1000-1500	-0.00	0.00	0.00	0.00	-0.00	-0.00	0.13	-0.08	0.06
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.20)	(0.21)	(0.20)
1500-2000	-0.00	0.01	0.00	-0.00	-0.01	-0.00	0.09	-0.16	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.20)	(0.21)	(0.20)
2000-2500	0.00	0.01	0.00	-0.00	-0.01	-0.00	0.05	-0.20	-0.04
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.20)	(0.21)	(0.20)
				Panel b. Local Roads					
0-250	-0.00	0.01	0.01	0.00	-0.01	-0.00	0.07	-0.15	0.02
	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.23)	(0.26)	(0.24)
250-500	0.00	0.01	0.01	-0.00	-0.01	-0.01	0.02	-0.20	-0.02
	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.23)	(0.26)	(0.23)
500-1000	0.00	0.01	0.01	-0.00	-0.01	-0.00	0.02	-0.16	-0.02
	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.23)	(0.26)	(0.23)
1000-1500	0.00	0.01	0.01	-0.00	-0.01	-0.00	0.07	-0.11	0.01
	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.23)	(0.26)	(0.23)
1500-2000	0.00	0.01	0.01	-0.00	-0.01	-0.00	0.02	-0.12	0.04
	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.23)	(0.26)	(0.23)
2000-2500	0.01	0.01	0.01	-0.01	-0.01	-0.01	-0.06	-0.20	-0.12
	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.24)	(0.26)	(0.24)
				Panel c. Non-Local Roads					
0-250	-0.02	0.00	-0.00	-0.00	-0.01	0.00	0.38	-0.30	-0.12
	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.33)	(0.36)	(0.36)
250-500	-0.02	0.01	-0.00	0.01	-0.01	-0.00	0.38	-0.41	-0.24
	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.33)	(0.35)	(0.36)
500-1000	-0.02*	-0.01	-0.02	0.01	0.00	0.01	0.45	0.01	0.13
	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.33)	(0.36)	(0.36)
1000-1500	-0.02	-0.02	-0.02	0.00	0.01	0.01	0.30	0.15	0.36
	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.33)	(0.36)	(0.38)
1500-2000	-0.02*	-0.01	-0.02	0.01	-0.01	0.00	0.40	-0.25	-0.08
	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.33)	(0.37)	(0.37)
2000-2500	-0.02	-0.01	-0.03	0.01	0.01	0.02	0.42	-0.07	0.42
	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.34)	(0.36)	(0.40)

Source: Prepared by the authors. *Note*: Standard errors clustered at the road segment level. *, ** and *** denote statistical significance at the 10, 5 and 1 percent level, respectively. This table shows the coefficients associated with the Pre dummy in equation (2). The excluded category covers weeks -28 to -17. Morning: 6:00 to 9:59 a.m., Midday: 10:00 to 4:59 p.m., Afternoon: 5:00 to 8:59 p.m.

5.2 Overall and subperiods Impacts of *Pico y Placa*

Having established that the empirical strategy is credible, in Table 4 we report the baseline impacts of the *Pico y Placa* intervention, that is, the β_k coefficients from equation (1). Panel a presents the results for all roads pooled, while panels b and c report impacts for local and non-local roads respectively. We show results for all distance rings: the first 0-250 meter ring indicates the effect of the policy in the area of direct influence, while the remaining rings offer insights on the spatial spillovers.

The results indicate positive impacts on the *Pico y Placa* ring in the morning and for the local road segments, both in terms of speed and minutes in severe traffic jam. The impacts on speed are very small, just 3 log points. However, the impacts on minutes in a severe traffic jam are larger: the decrease of 0.45 minutes[20] is equivalent to an almost 70 percent decrease compared to the pre-treatment mean. There is some evidence of increases in the number of minutes in a severe traffic jam during the midday hour, but none of the coefficients are statistically significant at the 5 percent level.

Panel b, for local road segments, confirms the increase in speed in the 0-250 meter ring as well as the reduction in the number of minutes in a severe traffic jam. In this case, the 0.38 reduction in the number of minutes in severe traffic jam during the morning represents an 84 percent reduction of the pre-treatment mean. Interestingly, spatial spillovers are observed in the morning that reinforce the scope of the policy. In terms of speed, there is some evidence of improvements in speed of 2 log points in the morning, but the coefficient is not statistically significant. Also in the morning there is evidence of reductions in the number of minutes in a severe traffic jam for the second and third distance rings. With respect to pre-treatment averages, the reduction of 0.29 minutes in the second ring and 0.26 minutes in the third ring represent 76 percent and 70 percent of pre-treatment levels respectively.

Panel c shows that non-local road segments also improved their traffic congestion. Speed increased by 6 log points in the 0-250 meter ring both in the morning and afternoon. The number of minutes in a severe traffic jam also declined by 0.74 in the morning and 1.08 in the afternoon. These reductions represent 53 percent and 24 percent of pre-treatment averages, respectively. However, there is some evidence of increases in the number of minutes in a severe traffic jam during the mornings for the remaining five distance rings. The 0.87 minute increase for the second ring represents 93 percent of the pre-treatment average, while the increase of 0.8 minutes in the 1500-2000 meter ring represents 87 percent of the pre-treatment average.

To investigate further whether the impacts of the driving restrictions varied over time, in Table 5 we split the post-treatment period into two subperiods: (i) an early impact from September 2 to October 13 2019 and (ii) a late impact from October 14 to December 22 2019.

Though we do not observe drivers directly, this distinction between early and late impacts aims to understand possible changes in behavior in line with adaptations to the policy. As shown in Figure 3, the number of traffic infractions related to *Pico y Placa* remained high and fairly constant from August to December 2019, suggesting that there were no major changes in enforcement intensity of the policy in the analysis period. Thus, we believe the results in Table 5 capture drivers' behavioral changes.

In Table 5 we show results only for local and non-local roads in panels a and b. Each panel is subdivided into subpanels for these subperiods. This distinction helps to uncover important early impacts on traffic congestion on local roads that later disappear. Subpanel a.1 shows that morning speed improved across all distance rings. The probability of a severe traffic jam and the number

[20] That is, 27 seconds. As the unit of measure for this variable is minutes, values below one minute are proportions of a minute. For example, 0.5 minutes equals 30 seconds, and 2.5 minutes equals 150 seconds.

of minutes in a severe traffic jam also declined in the morning. For the afternoon, we only observe reductions in the number of minutes in severe traffic jam across all distance rings. Subpanel a.2 indicates that all these gains disappeared in the period from October 14 to December 22.

Regarding non-local roads, subpanel b.1 shows improvements in speed both in the morning and afternoon, and reductions in the probability of a severe traffic jam and in the number of minutes in a severe traffic jam both in the morning and afternoon. However in the following period (October 14 to December 22, subpanel b.2) these gains disappeared and in some cases we start to see a decline in the quality of traffic for some rings at different times of day. For instance, there is some evidence of a reduction in speed during midday, although only the reduction for the 2000-2500 meter ring of 0.07 log points is statistically significant at the 5 percent level. The number of minutes in a severe traffic jam increased in many distance rings away from the policy area during the three times of day, morning, midday and afternoon. We investigate this further in the next section.

Appendix Table A2 is similar to Table 5 but uses the alternative standard errors clustering approach to allow for both time and spatial correlation, as discussed in Section 4. While standard errors are generally larger, all statistically significant results remain significant.

Another issue of interest is whether there are heterogeneous impacts of *Pico y Placa* within the first treatment ring. In particular, this first ring includes road segments not directly affected by the policy in addition to the ones that are directly affected. In Appendix Table A3 we split the first ring in two: those road segments within a distance buffer of 20 meters around the centroids of the segments directly affected by the policy (58 percent of the ring segments), and the rest of road segments in the ring. Although the impacts in general appear as larger for the 0-20 meter ring, overall results appear as qualitatively the same.

Table 4. *Pico y Placa* Impacts

Distance to *Pico y Placa* (meters):	Ln(Speed)			Pr(Severe Traffic Jam)			Minutes in Severe Traffic Jam		
	Morning	Midday	Afternoon	Morning	Midday	Afternoon	Morning	Midday	Afternoon
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					Panel a. Overall				
0-250	0.03***	-0.02	0.01	-0.01*	0.02*	-0.00	-0.45***	0.29*	-0.13
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.13)	(0.16)	(0.13)
250-500	0.01	-0.02	-0.01	-0.00	0.02*	0.01	-0.11	0.31*	0.21
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.13)	(0.16)	(0.13)
500-1000	0.01	-0.02	-0.01	-0.00	0.02*	0.01	-0.09	0.27*	0.19
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.13)	(0.16)	(0.13)
1000-1500	0.01	-0.02	-0.01	0.00	0.02*	0.01	-0.04	0.28*	0.16
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.14)	(0.16)	(0.13)
1500-2000	0.01	-0.02	-0.00	0.00	0.02	0.00	-0.02	0.24	0.04
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.13)	(0.16)	(0.13)
200-2500	0.00	-0.01	-0.00	0.00	0.01	0.00	-0.04	0.26	0.10
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.14)	(0.16)	(0.13)
					Panel b. Local Roads				
0-250	0.02**	-0.01	-0.01	-0.01	0.01	0.00	-0.38***	0.22	0.07
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.12)	(0.16)	(0.09)
250-500	0.02*	-0.01	-0.01	-0.01	0.01	0.01	-0.29**	0.22	0.10
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.12)	(0.16)	(0.09)
500-1000	0.01	-0.01	-0.01	-0.01	0.01	0.01	-0.26**	0.14	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.12)	(0.16)	(0.09)
1000-1500	0.01	-0.01	-0.01	-0.00	0.01	0.01	-0.18	0.19	0.07
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.13)	(0.16)	(0.09)
1500-2000	0.01	-0.01	-0.00	-0.00	0.01	0.00	-0.18	0.19	-0.04
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.12)	(0.16)	(0.09)
200-2500	0.01	-0.01	0.00	-0.00	0.01	0.00	-0.13	0.13	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.12)	(0.16)	(0.09)
					Panel c. Non-Local Roads				
0-250	0.06**	-0.02	0.06**	-0.03	0.03	-0.04**	-0.74*	0.50	-1.08**
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.41)	(0.50)	(0.52)
250-500	-0.03	-0.04	-0.02	0.02	0.04	0.02	0.87**	0.68	0.80
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.42)	(0.50)	(0.53)
500-1000	-0.03	-0.04	-0.04*	0.03	0.04*	0.03*	0.76*	0.84*	1.08**
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.41)	(0.50)	(0.52)
1000-1500	-0.01	-0.03	-0.02	0.02	0.03	0.02	0.58	0.60	0.59
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.41)	(0.50)	(0.54)
1500-2000	-0.03	-0.03	-0.01	0.03	0.03	0.01	0.80**	0.45	0.61
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.40)	(0.50)	(0.52)
200-2500	-0.03	-0.03	-0.01	0.03*	0.03	0.02	0.34	0.67	0.57
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.46)	(0.50)	(0.53)

Source: Prepared by the authors. *Note*: Standard errors clustered at the road segment level. *, ** and *** denote statistical significance at the 10, 5 and 1 percent level, respectively. This table shows the coefficients associated with the PyP dummy in equation (1). Morning: 6:00 to 9:59 a.m., Midday: 10:00 to 4:59 p.m., Afternoon: 5:00 to 8:59 p.m.

Table 5. Early and Late *Pico y Placa* Impacts

Distance to	Ln(Speed)			Pr(Severe Traffic Jam)			Minutes in Severe Traffic Jam		
Pico y Placa	Morning	Midday	Afternoon	Morning	Midday	Afternoon	Morning	Midday	Afternoon
(meters):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel a. Local Roads									
Panel a.1 Early *Pico y Placa* (September 2 to October 13 2019)									
0-250	0.03***	-0.00	0.01**	-0.02***	0.00	-0.01**	-0.54***	0.06	-0.28**
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.09)	(0.10)	(0.13)
250-500	0.03***	-0.00	0.01	-0.01***	0.00	-0.00	-0.45***	0.06	-0.24*
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.09)	(0.11)	(0.13)
500-1000	0.02***	-0.00	0.01	-0.01***	0.00	-0.00	-0.39***	-0.01	-0.29**
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.09)	(0.10)	(0.13)
1000-1500	0.02***	-0.00	0.01	-0.01*	0.00	-0.00	-0.32***	0.03	-0.22*
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.10)	(0.10)	(0.14)
1500-2000	0.02***	-0.00	0.01**	-0.01**	0.00	-0.01*	-0.33***	0.04	-0.35***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.09)	(0.11)	(0.13)
200-2500	0.01***	0.00	0.01**	-0.01	0.00	-0.01*	-0.26***	0.04	-0.24*
	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.10)	(0.11)	(0.14)
Panel a.2 Late *Pico y Placa* (October 14 to December 22 2019)									
0-250	0.01	-0.03	-0.02	-0.00	0.02	0.02	-0.22	0.38*	0.44**
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.19)	(0.22)	(0.20)
250-500	0.01	-0.03	-0.02	-0.00	0.02	0.02	-0.14	0.38*	0.45**
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.19)	(0.23)	(0.20)
500-1000	0.00	-0.02	-0.02	-0.00	0.02	0.02	-0.11	0.30	0.33*
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.19)	(0.22)	(0.20)
1000-1500	0.00	-0.03	-0.02	0.00	0.02	0.02	-0.04	0.36	0.38*
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.20)	(0.23)	(0.20)
1500-2000	0.00	-0.02	-0.01	0.00	0.02	0.01	-0.03	0.34	0.28
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.19)	(0.23)	(0.20)
200-2500	-0.00	-0.02	-0.01	0.00	0.02	0.01	0.01	0.23	0.21
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.19)	(0.23)	(0.20)
Panel b. Non-Loca Roads									
Panel b.1 Early *Pico y Placa* (September 2 to October 13 2019)									
0-250	0.06**	-0.00	0.08***	-0.03*	0.01	-0.05***	-0.80**	0.27	-1.40***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.38)	(0.52)	(0.49)
250-500	-0.03	-0.01	-0.01	0.02	0.02	0.01	0.66*	0.32	0.28
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.39)	(0.52)	(0.49)
500-1000	-0.03	-0.02	-0.02	0.03	0.03	0.02	0.56	0.49	0.52
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.37)	(0.52)	(0.48)
1000-1500	-0.01	-0.01	-0.02	0.02	0.01	0.01	0.46	0.21	0.28
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.37)	(0.52)	(0.51)
1500-2000	-0.02	-0.01	-0.01	0.02	0.01	0.00	0.51	0.05	0.22
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.37)	(0.52)	(0.49)
200-2500	-0.03	0.01	0.01	0.03	0.00	0.00	0.37	0.15	-0.13
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.44)	(0.54)	(0.53)
Panel b.2 Late *Pico y Placa* (October 14 to December 22 2019)									
0-250	0.05*	-0.04	0.04	-0.03	0.04	-0.03	-0.67	0.73	-0.78
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.46)	(0.51)	(0.58)
250-500	-0.03	-0.06*	-0.04	0.03	0.05**	0.03	1.09**	1.03**	1.30**
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.47)	(0.51)	(0.59)
500-1000	-0.03	-0.06*	-0.06**	0.03	0.06**	0.05**	0.97**	1.19**	1.63***
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.45)	(0.51)	(0.57)
1000-1500	-0.01	-0.05	-0.03	0.01	0.04	0.02	0.72	0.99*	0.88
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.46)	(0.51)	(0.59)
1500-2000	-0.03	-0.05	-0.02	0.03	0.04	0.02	1.10**	0.86*	1.00*
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.45)	(0.52)	(0.58)
200-2500	-0.03	-0.07**	-0.03	0.04*	0.06**	0.03	0.30	1.20**	1.28**
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.51)	(0.56)	(0.63)

Source: Prepared by the authors. *Note*: Standard errors clustered at the road segment level. *, ** and *** denote statistical significance at the 10, 5 and 1 percent level, respectively. This table shows coefficients associated with a version of equation (1) where the PyP dummy is split into two subperiods (early and late). Morning: 6:00 to 9:59 a.m., Midday: 10:00 to 4:59 p.m., Afternoon: 5:00 to 8:59 p.m.

5.3 Hourly Impacts of *Pico y Placa*

To study in more detail the impacts of *Pico y Placa*, and to also analyze potential time spillover effects, we re-estimate equation (1) by each hour of the day and report in Figures 4 and 5 the associated β_k coefficients for both local and non-local roads and for the two post-treatment periods, as in Table 5. We discuss here the results for speed; those for the probability of severe traffic jam and minutes in severe traffic jam can be found in Appendix Figures B4 to B7.

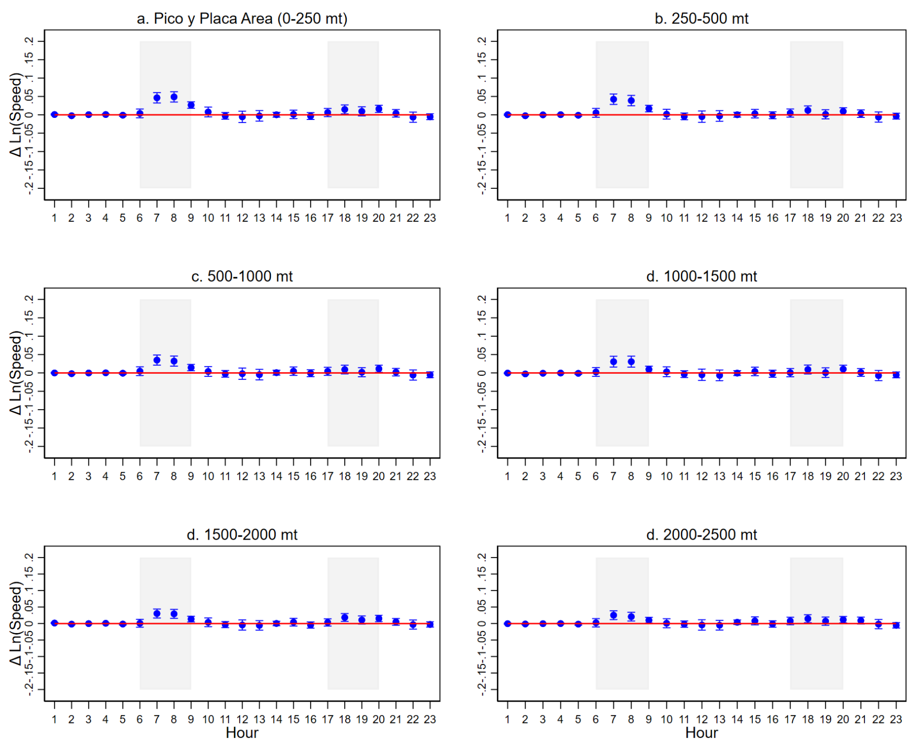
Figure 4 focuses on local roads. Panel a shows the early impacts while panel b shows late impacts. Results in panel a show improvements in speed in some hours of the morning peak times. These increases in log speed were not higher than 0.05 log points. Panel b indicates that those hourly gains are no longer statistically significant and close to zero in the later period. It also shows some evidence of reductions in speed at midday, though no coefficient is statistically significant.

Figure 5 indicates that early impacts on non-local roads are higher in magnitude. For the 0-250 meter ring, increases in morning speed are close to 0.10 log points for 7, 8 and 9 a.m. A similar pattern emerges for the afternoon with important increases in speed for 6 and 7 p.m. (hours 18 and 19, respectively, as shown in the figure). For the rest of the distance rings the effects are not statistically significant. In terms of late impacts, panel b shows that some of the morning and afternoon increases in speed for the 0-250 meter ring remain, but for the remaining rings there is evidence of reductions at different hours of the day.

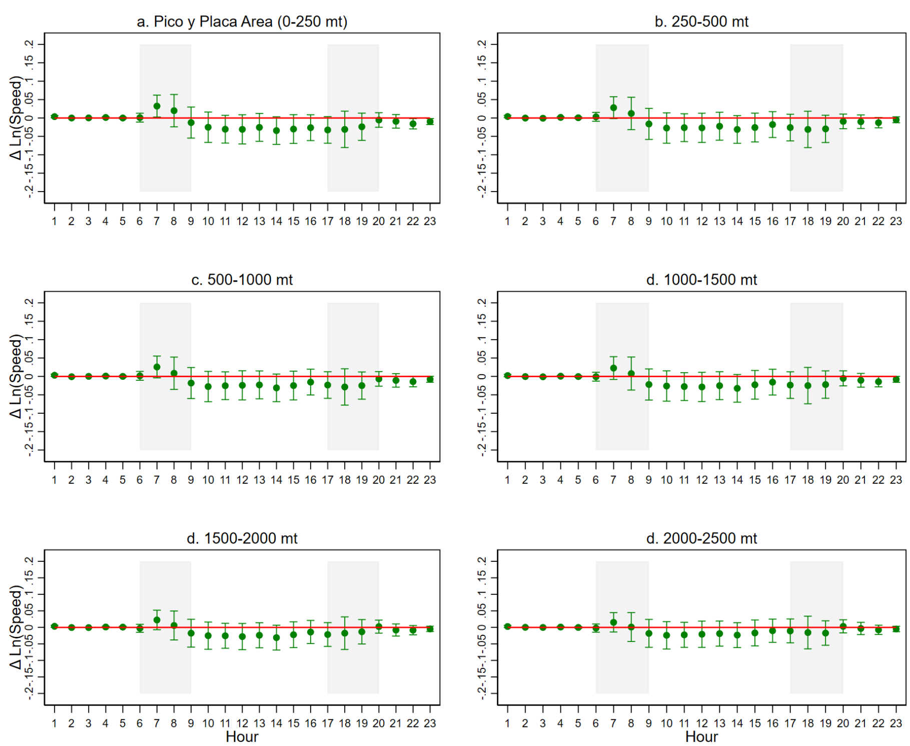
Taken together, the results imply that an account of the full impact of the driving restrictions intervention requires properly considering both types of spillovers (spatial and time), while also considering the heterogeneous impact by type of road. We attempt such analysis in the next section.

Figure 4. Hourly Impacts of *Pico y Placa* on Speed - Local Roads

Panel a. Early Impact (September 2 to October 13 2019)



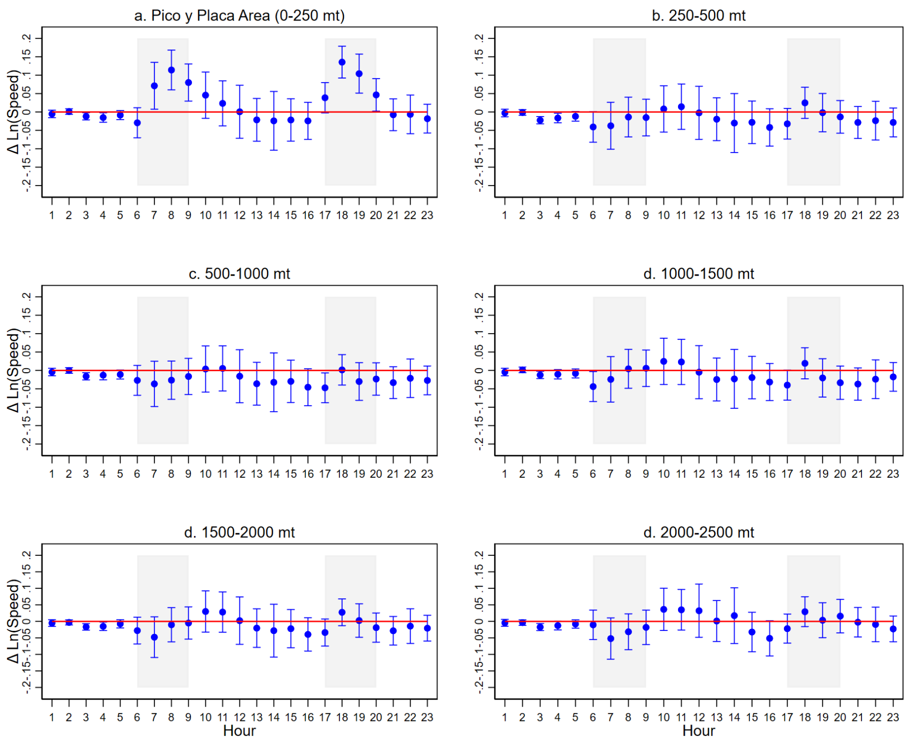
Panel b. Late Impact (October 14 to December 22 2019)



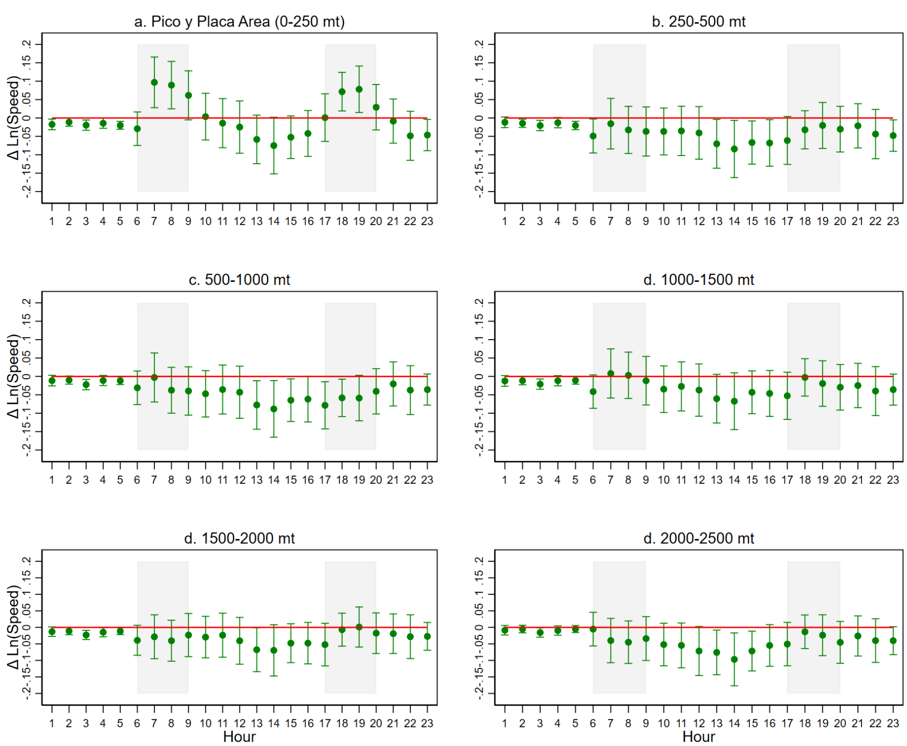
Source: Prepared by the authors. *Note*: The horizontal axis is the hour of the day. Morning and afternoon *Pico y Placa* hours are represented by the shaded areas. The panels show the coefficients associated with the PyP dummy, when estimating equation (1) at each hour of the day, with standard errors clustered at the road segment level. The vertical lines represent 95 percent confidence intervals.

Figure 5. Hourly Impacts of *Pico y Placa* on Speed - Non-Local roads

Panel a. Early Impact (September 2 to October 13 2019)



Panel b. Late Impact (October 14 to December 22 2019)



Source: Prepared by the authors. *Note*: The horizontal axis is the hour of the day. Morning and afternoon *Pico y Placa* hours are represented by the shaded areas. The figures show the coefficients associated with the PyP dummy, when estimating equation (1) at each hour of the day, with standard errors clustered at the road segment level. The vertical lines represent 95 percent confidence intervals.

6 Welfare Analysis

Given the heterogeneous impacts and spillovers of the driving restrictions intervention outlined above, in this section we propose a strategy to calculate the aggregate welfare impacts of the policy, and decompose those impacts by the contributing source (intensive and extensive margins). In addition, we present evidence on the welfare impacts of the time and spatial spillovers of the driving restrictions policy identified in the prior section.

6.1 Welfare Analysis Setup and Decomposition

The impact of the driving restrictions on welfare ultimately depends on how much the policy changes the travel time for different groups of the population. An ideal estimation of the welfare net benefits would link the amount of saved travel time with the associated value of time, and discount any cost incurred by the policy. Recent literature (Hall, 2021a,b) shows that the welfare change of policies that impose tolls depends on the characteristics (and preferences) of the drivers affected by the policy. Drivers might be unresponsive to policy changes if their preferences for routes and time schedules are strong. These preferences may be associated with their socioeconomic status. For instance, well-off drivers may be willing to pay the toll in order to stick to their route and time schedule, which is now less congested because poor drivers divert to toll-free routes and time schedules. This yields a policy that would disproportionately affects drivers from disadvantaged situations.

Unfortunately, in the present setting, while we can estimate the change in travel time at every road segment before and after the policy, we cannot observe individual drivers. Thus, the welfare analysis needs to be based purely on changes in travel time in the road segments. This simplified welfare analysis can still to properly account for spatial and time spillovers, but it cannot speak to the distributional consequences of the *Pico y Placa* intervention.

However, we do attempt to quantify welfare changes associated with the *characteristics* of the road segments, weighting more higher capacity and higher usage roads. In addition, to better understand *some* distributional impacts, we conduct a couple of welfare analyses that rely on broad characterizations of commuter routes. In the first one, we restrict the analysis to parts of the city that, we argue, disproportionately benefit public transport users (which tend to be, on average, less well off than individual drivers). In the second one, we compare welfare changes across broad areas (traffic zones), that we characterize by the socioeconomic status of the majority of commuters to those areas.

Hall (2021b) emphasizes not only the role of travel time (key in all congestion models) but also the role of travelers' trade-off between longer or shorter travel times in exchange for arriving too early or too late compared to the preferred arrival time. Given the nature of our data, we can only focus on road segment travel time, but the spatial and time spillovers discussed above are probably capturing some of the same trade-offs. In this sense, our welfare analysis, while only using travel time, can very broadly capture the observed *aggregate* trade-off decisions made by road users.

Thus, the key variable for our welfare analysis is travel time. Using road segment's length L_i and average speed S_i, we can define travel time associated with road segment i as $\tau_i = \frac{L_i}{S_i}$. The impact of the driving restrictions policy on travel time then is:

$$\Delta\tau_i = \tau_i^1 - \tau_i^0 = \frac{L_i}{S_i^1} - \frac{L_i}{S_i^0} \tag{3}$$

where τ_i^0 and τ_i^1 are travel time averages for road segment i before (0) and after (1) the policy. As L_i is fixed, the policy changes travel time by changing average speed from S_i^0 (before) to S_i^1 (after).

The percentage change in travel time η_{τ_i} can be defined in terms of the percentage change of circulation speed η_{S_i}:

$$\eta_{\tau_i} = \frac{-\eta_{S_i}}{(1+\eta_{S_i})} \tag{4}$$

where $\eta_{\tau_i} = \frac{\Delta\tau_i}{\tau_i^0}$ and $\eta_{S_i} = \frac{\Delta S_i}{S_i^0}$.

On the other hand, circulation speed S_i can be defined as the expectation between average speed when the road segment is in a traffic jam, $\tilde{S}_i$, and free-flow speed when there is no traffic jam, F_i:

$$S_i = p_i\tilde{S}_i + (1-p_i)F_i \tag{5}$$

where p_i is the probability of a traffic jam in road segment i in the period of observation.

Then, the driving restrictions policy affects S_i by changing either p_i, $\tilde{S}_i$, or both. The change in average speed from period 0, without the policy, to period 1, with the policy, is $\Delta S_i = S_i^1 - S_i^0$. Substituting equation (5) in the last expression, and substituting $\tilde{S}_i^1$ for $\Delta\tilde{S}_i + \tilde{S}_i^0$, and p_i^1 for $\Delta p_i + p_i^0$, we arrive to an expression that links the change in circulation speed to the changes in the probability of a traffic jam, the change in traffic jam speed, and the initial conditions:

$$\Delta S_i = (\Delta p_i + p_i^0)\Delta\tilde{S}_i + \Delta p_i(\tilde{S}_i^0 - F_i). \tag{6}$$

Dividing equation (6) by the pre-policy speed average S_i^0; denoting the percentage changes induced by the policy in circulation speed, traffic jam speed, and probability of traffic jam as $\eta_{S_i} = \Delta S_i/S_i^0$, $\eta_{\tilde{S}_i} = \Delta\tilde{S}_i/\tilde{S}_i^0$, and $\eta_{p_i} = \Delta p_i/p_i^0$, respectively; and noticing that from equation (5) we can re-express $\tilde{S}_i^0/S_i^0$ as

$$\frac{S_i^0 - (1-p_i^0)F_i}{p_i^0 S_i^0};$$

we can arrive to the following expression:

$$\eta_{S_i} = (1+\eta_{p_i})\eta_{\tilde{S}_i}\left[1-(1-p_i^0)\frac{F_i}{S_i^0}\right] + \eta_{p_i}(1-\frac{F_i}{S_i^0}). \tag{7}$$

Equation (7) shows how the percentage change in circulation speed, η_{S_i}, is related to the percentage change in the probability of a traffic jam (i.e. extensive margin), η_{p_i}, and to the percentage change in traffic jam speed (i.e. intensive margin), $\eta_{\tilde{S}_i}$. If we estimate η_{S_i} and η_{p_i}, then $\eta_{\tilde{S}_i}$ can be recovered without estimation.[21]

From equation (7) we can see that when the extensive margin is zero (i.e., the policy does not affect the probability of a traffic jam: $\eta_{p_i} = 0$), circulation speed changes only through changes in the intensive margin:

[21] Note that in equation (5) and onward, p_i refers to the probability of any traffic jam. However, the results in Section 5 refer to the probability of a severe traffic jam. Hence, for the welfare calculations in this section we have also estimated the impacts of the *Pico y Placa* policy on the probability of any traffic jam (available upon request) and used these impacts in the welfare calculations.

$$\eta_{S_i} \mid_{\eta_{p_i=0}} = \eta_{\tilde{S}_i} \left[1 - (1 - p_i^0) \frac{F_i}{S_i^0} \right]. \tag{8}$$

Similarly, when the intensive margin is zero (i.e., the policy does not affect the traffic jam speed: $\eta_{\tilde{S}_i} = 0$), circulation speed changes only through changes in the extensive margin:

$$\eta_{S_i} \mid_{\eta_{\tilde{S}_i=0}} = \eta_{p_i} (1 - \frac{F_i}{S_i^0}). \tag{9}$$

We can use equations (8) and (9) to *decompose* the changes in travel time caused by the policy into the changes due to impacts on the extensive and intensive margins, plus a residual change θ_i:

$$\eta_{\tau_i} = \eta_{\tau_i}(\eta_{S_i} \mid_{\eta_{p_i=0}}) + \eta_{\tau_i}(\eta_{S_i} \mid_{\eta_{\tilde{S}_i=0}}) + \theta_i. \tag{10}$$

The quantification of welfare impacts depends, then, on the average η_τ across all road segments and can be decomposed into extensive and intensive margins, and a residual component.

Note that the average travel time for a group of road segments at any hour h can be obtained as $E[\eta_{\tau_i}] = \hat{\eta}_\tau = f(\hat{\eta}_S, \hat{\eta}_p)$. That is, we can use the average impacts estimated for speed and probability of a traffic jam to obtain the estimated impacts on travel time. Indeed, we can estimate as many η_τ as hours and road segment aggregations we define. Following the empirical results presented in the prior section, we could estimate 288 travel time semi-elasticities: 6 distance rings x 24 hours x 2 road segment types (local/non-local). In addition, we could estimate these 288 semi-elasticities for the three periods analyzed: (i) transition, (ii) early impact, and (iii) late impact.[22]

Any welfare estimation requires aggregation across these different groups. With this in mind, we associate changes in estimated welfare with changes in travel time and aggregate using weights that take into account the relative importance of different road segment types and rings at different hours. The welfare function is defined as:

$$W = -E[\eta_\tau \kappa_{rhl}], \tag{11}$$

with weights $\kappa_{rhl} = M_{rl} \times (\overline{F}_{rhl} / \overline{S}^0_{rhl})$ re-scaled to sum to one. The first term of the weight κ, M_{rl}, is the total number of road kilometers in ring r and road type l (local/non-local). It attempts to capture the size disparities (in kilometers) of the ring/road type combinations. To properly account for the differential road capacity implicitly associated with variations in free-flow speed across road segments, when we calculate M_{rl} we weight segment length by FFS (i.e. a road segment with a FFS of 40 km/h is assumed to be able to handle double the traffic of a road segment with a FFS of 20 km/h). The second term in κ captures the *average* pre-treatment gap between free-flow speed and circulation speed by distance ring r, hour of the day h, and road type l. This term attempts to capture the disparities in pre-treatment congestion levels of each ring/road type combination at each hour h, giving a higher weight to those ring/road type/hours more congested, that is, where pre-treatment average circulation speed is farthest away from FFS.

In sum, the welfare function in equation (11) makes clear that improvements in speed are reflected as reductions in travel time, and thus in welfare gains. These welfare gains, furthermore, are aggregated giving higher importance to bigger and more congested (in the pre-treatment period) ring/road type/hours combinations. Any welfare changes associated with the implementation

[22]While for the sake of space we have not shown results for the transition period, they are available upon request.

of the driving restriction policy, in turn, can be decomposed into the portions explained by the extensive and intensive margins and a residual.

6.2 Overall and Time and Spatial Spillovers Welfare Impacts

In this subsection we estimate the welfare impacts of the *Pico y Placa* driving restrictions policy, analyzing changes in welfare impacts over time as well as the welfare impacts of the time and spatial spillovers described in Section 5.

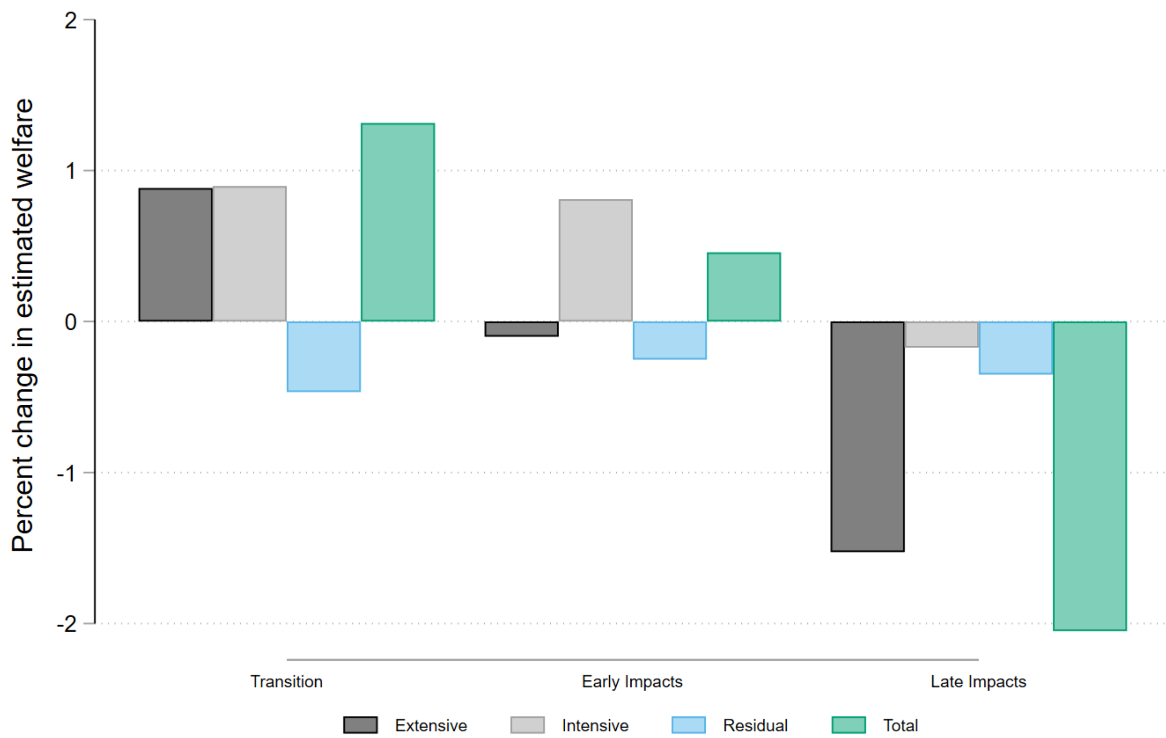
Figure 6 plots the overall change in travel time for the three post-restriction subperiods. Estimated total welfare increased by 1.3 percent during the transition subperiod, with an increase of 0.88 percent explained by the extensive margin and 0.89 percent by the intensive margin, and a reduction of 0.47 percent explained by the residual. By the early impacts subperiod, after the end of the Parapan American Games, the results start to reverse. While total estimated welfare is still up by 0.45 percent, this is driven by improvements in welfare due to the intensive margin of 0.8 percent. By then one can already see welfare losses associated with the extensive margin and the residual component by 0.1 and 0.25 percent, respectively. In the late-impact subperiod (from October 14 to December 22), we observe there is a total welfare loss of 2.05 percent, of which the extensive margin is responsible for 73 percent (1.5 percent). The rest is divided between the intensive margin and the residual.

Overall, the results suggest that while the driving restrictions initially improved both margins, the extensive margin worsened significantly over time, leading to an overall welfare loss higher than the initial welfare gain. This means that most of the negative effects, by the late-impact subperiod, come from segments that had not had severe traffic jams prior to the intervention, and that started having traffic jams post-intervention. A smaller portion of the negative impacts comes from reduced speeds in the segments that already had traffic jams prior to the intervention.

Figure 7 splits the welfare calculations by times of day. The larger welfare loss in the late-impact subperiod takes place in the midday hours, when the driving restrictions are not active. In the afternoon, a similar pattern (with smaller losses) emerges. So, while there is still a small welfare gain in the morning of about 0.08 percent, the welfare losses are about 3.4 percent in the midday hours and 1.78 percent in the afternoon. Welfare losses in both time schedules are led by reductions in welfare in the extensive margin; 75 percent of the reduction in total welfare in the afternoon is explained by losses in the extensive margin, while 70 percent of the total welfare loss in midday is explained by the extensive margin. The negative impacts on the extensive margin (more roads becoming congested) make clear the costs imposed by the policy on travelers outside the restriction hours, and to a lesser extent in the afternoon restriction hours.

Another important dimension is that of the spatial split of welfare changes. In Figure 8 we present welfare changes by distance ring. By the late-impact subperiod, welfare declines in all distance rings in the three margins. It is interesting to note that only in the 0-250 meter ring, under the direct area of influence of the policy, there still is a small welfare gain in the intensive margin. On the other hand, the welfare losses observed in the other distance rings are led by losses in the extensive margin. Again, the story is clear: the policy seems to have caused more roads to become congested, not only in the hours outside the policy hours, but also in the areas outside the areas directly influenced by the policy. Interestingly, the size of those negative impacts does not seem to change much with distance, except for the much-smaller negative impacts in the first ring, suggesting that the policy caused welfare losses that are spread spatially in a relative equal way.

Figure 6. Overall Welfare Effects

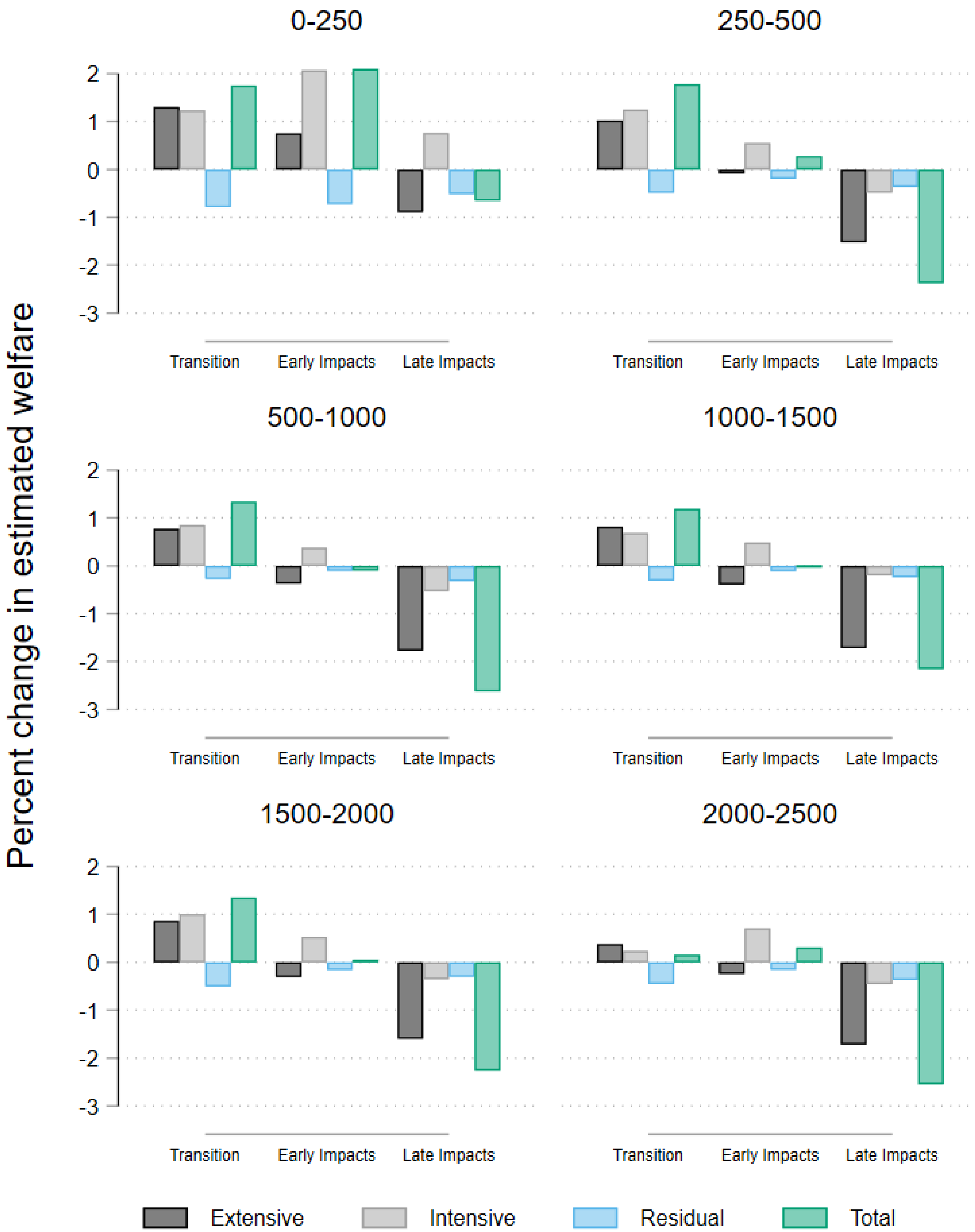


Source: Prepared by the authors. *Note*: For each subperiod the welfare change is estimated as a weighted average of η_τ. Weights are the interaction of the initial ratio of average free-flow speed over average circulation speed by hour, distance ring and road type; and total kilometers by distance ring and road type. The aggregation of kilometers weights by free-flow speed to consider differences in road capacity.

Figure 7. Welfare Effects by Time of Day Schedule

Source: Prepared by the authors. *Note*: For each period the welfare change is estimated as a weighted average of η_τ. Weights are the interaction of the initial ratio of average free-flow speed over average circulation speed by hour, distance ring and road type; and total kilometers by distance ring and road type. The aggregation of kilometers weights by free-flow speed to consider differences in road capacity.

Figure 8. Welfare Effects by Distance Ring



Source: Prepared by the authors. *Note*: For each period the welfare change is estimated as a weighted average of η_τ. Weights are the interaction of the initial ratio of average free-flow speed over average circulation speed by hour, distance ring and road type; and total kilometers by distance ring and road type. The aggregation of kilometers weights by free-flow speed to consider differences in road capacity.

6.3 Distributional Welfare Impacts Based on Commuter Routes

As mentioned above, we can only very imperfectly try to approximate the distributional welfare impacts of the driving restriction policy, by relying on broad characterizations of commuter routes.

An argument could be made that welfare losses for individual vehicle riders could be offset by welfare gains for public transport users, who represent around 71 percent of all commuters (Lima Cómo Vamos, 2019). While we cannot observe public transport users directly, we can attempt to approximate the welfare impacts of the policy on public transport users by evaluating changes in travel time along city roads that are heavily used by public transport.

Lima's public transport system is heavily informal, making it hard to pinpoint exact routes. However, we can focus on the route covered by one of the few formal modes available in the city, the *Metropolitano* Bus Rapid Transit (BRT) system. There is evidence linking the opening and operation of this BRT system to higher usage of public transport, specially among women (Martinez et al., 2020).

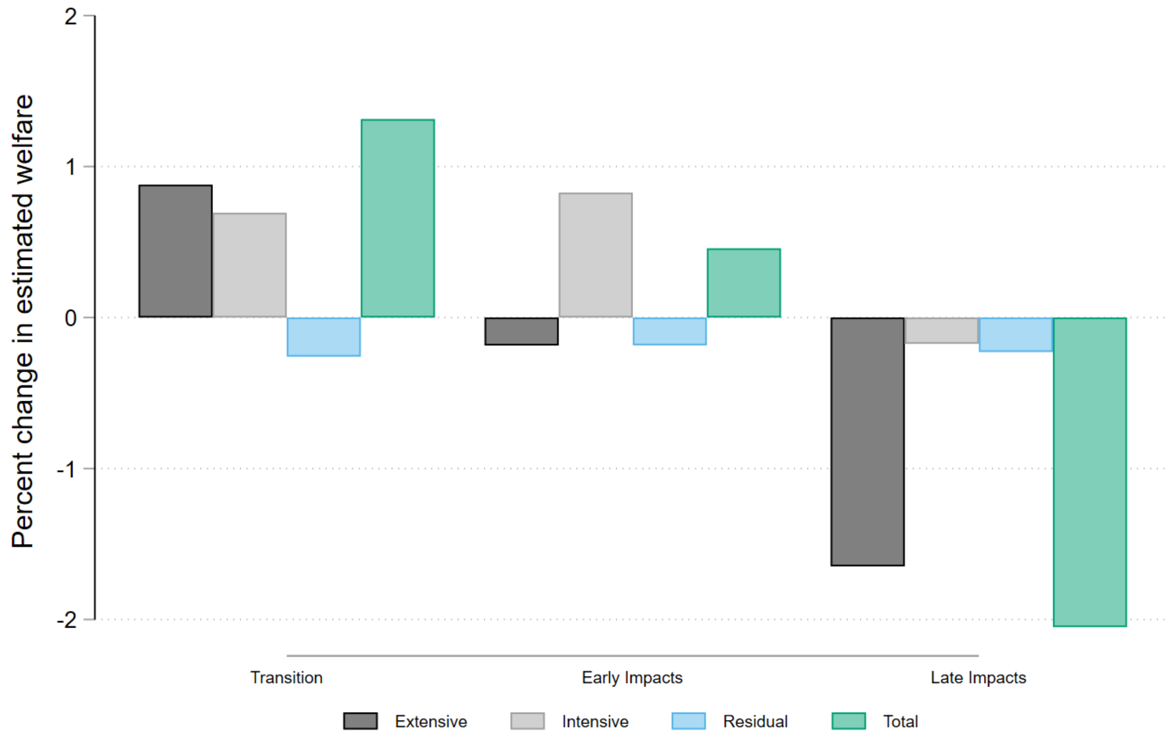
We use all the road segments that fall within the BRT route and its feeder buses to estimate changes in welfare for the late-impact subperiod (from October 14 to December 22 2019), only for those road segments. The results for this reduced group of road segments, shown in Figure 9, are quite similar to those for all the road segments. The total change in estimated welfare is essentially the same, a 2.05 percent loss. However, the welfare loss associated with the extensive margin is slightly larger at 1.65 percent, representing over 80 percent of the total loss, compared to 73 percent explained using all the segments. The evidence therefore suggests that the negative impacts of the policy are not different for those roads used by the BRT system when compared to the overall negative impacts, and that the extensive margin appears to be even more important in explaining those negative welfare impacts, for BRT system-related roads.

An alternative attempt to quantifying distributional impacts is to compare welfare changes across all commuters, not only public transit users, classified by socioeconomic status (SES). For this, we classify different areas of the city according to the SES of the majority of commuters they attract, using data from Lima's 2012 Origin-Destination survey (JICA, 2013). The survey has five SES categories ranging from A (rich) to E (very poor). We reclassify these five categories into three where categories A and B are classified as upper SES, C as middle SES, and D and E as low SES. A traffic zone is classified by SES using a “majority rule” based on the category with the highest share across the three categories. Using this approach, 17 percent of the traffic zones are classified as upper SES, 39 percent as middle SES, and the remaining 44 percent as low SES.

Appendix Figure B8 presents the total welfare change for each of the SES categories and overall. Compared to the total overall welfare impacts, we observe only marginal differences across the three SES categories; qualitatively there are no substantive differences. The decomposition into the extensive and intensive margins (not presented) shows similar results.

Based on these two analyses we conclude that there is no evidence that the *Pico y Placa* policy had any differential welfare impacts by commuter-characteristics, at least based on the limited characterization conducted in this subsection.

Figure 9. Total Welfare Effects for BRT-System-Related Road Segments



Source: Prepared by the authors. *Note*: For each period the welfare change is estimated as a weighted average of η_τ. Weights are the interaction of the initial ratio of average free-flow speed over average circulation speed by hour, distance ring and road type; and total kilometers by distance ring and road type. The aggregation of kilometers weights by free-flow speed to consider differences in road capacity.

7 Conclusion

This paper has evaluated the effects of Lima's driving restriction policy known as *Pico y Placa*. The policy restricted vehicle circulation on several important roads with the aim of reducing traffic congestion and pollution.

The analysis exploited high-frequency road-segment-level congestion data from the community-based driving directions app Waze. We restricted the analysis to road segments within three kilometers of the area of influence of the restrictions and imposed a generalized propensity score-based overlap condition, to guarantee comparability of segments across seven distance rings from roads directly affected by the policy.

We estimated difference-in-differences models using the segments that satisfy the overlap condition and weighting by the inverse of the generalized propensity score. The outcomes of interest were circulation speed, probability of a severe traffic jam and the number of minutes in a severe traffic jam.

Our results suggest small gains in the intervened area combined with small losses in nearby areas and at hours outside the time schedule of the policy. Although the direct area of influence improved speed by 2 percent, further analysis that distinguishes by road types and timing of the policy suggests that these gains disappeared weeks after the start of the policy.

The highly detailed data allowed for quantifying impacts by hour, road type and distance to the intervened area, which ultimately helped to quantify spatial and time spillovers that appear negative in areas and hours not directly affected by the policy.

We conducted a welfare analysis and estimated welfare impacts in a transition period and in two (early and late) impact subperiods. While during the transition and early-impact subperiods there were small welfare gains, by the late-impact subperiod we estimate an overall welfare loss from the policy of 2 percent. Most of those losses, 73 percent, are explained by the extensive margin, that is, more roads becoming severely congested. Most of the welfare loss took place in the midday hours outside the target hours of the policy. While the area directly targeted showed a net small welfare gain, all other areas showed clear welfare losses. Both, the time and spatial spillover-driven welfare losses seem to be mostly explained by the extensive margin. Finally, welfare changes in areas with heavy public transport use, or with a majority of commuters with different socioeconomic status seem to be very similar to the overall welfare changes; that is, they suffered very similar welfare losses.

Our results indicate that while the very localized direct effects of the *Pico y Placa* policy may appear to have been slightly positive, the overall impact was clearly negative. Overall, congestion increased in the areas analyzed, which goes against one of the stated objectives of the policy (to reduce traffic congestion).

Furthermore, if cars are taking longer to drive the same routes (or are taking less-optimal routes to avoid the driving restrictions), both gasoline consumption and pollution associated with driven miles and idling time increases. That is, the policy appears to have failed in its second stated objective (to reduce pollution), while increasing other environmental costs through increased gasoline consumption.

These results highlight the need for policy makers to take into account the overall impacts of driving restrictions policies before implementing them. Indeed, the analysis in this paper suggests that these types of policies can only be justified if the authorities put a very high weight on the very localized areas that unambiguously benefit from the policy. Otherwise, these policies seem difficult to justify, at least in the setting studied.

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Online Appendix - Not for publication

A Appendix Tables

Table A1. Balancing

	Raw Means							IPW Means After Imposing Overlap							p-value		RMSD	
	T=0	T=1	T=2	T=3	T=4	T=5	T=6	T=0	T=1	T=2	T=3	T=4	T=5	T=6	Raw	Ovlp + IPW	Raw	Ovlp + IPW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Panel a. Morning Variables																		
Speed (By-week -1)	3.65	3.61	3.52	3.55	3.57	3.60	3.61	3.61	3.59	3.61	3.58	3.58	3.58	3.56	0.00	0.00	0.01	0.00
Speed (By-week -2)	3.64	3.60	3.51	3.53	3.56	3.59	3.60	3.60	3.58	3.60	3.58	3.57	3.57	3.56	0.00	0.00	0.01	0.00
Speed (By-week -3)	3.64	3.60	3.51	3.54	3.57	3.59	3.60	3.61	3.58	3.61	3.58	3.57	3.58	3.56	0.00	0.00	0.01	0.00
Speed (By-week -4)	3.64	3.60	3.51	3.53	3.56	3.59	3.60	3.61	3.58	3.60	3.57	3.57	3.57	3.55	0.00	0.00	0.01	0.01
Speed (By-week -5)	3.65	3.61	3.53	3.55	3.58	3.60	3.60	3.61	3.59	3.62	3.59	3.58	3.58	3.57	0.00	0.00	0.01	0.00
Speed (By-week -6)	3.65	3.62	3.52	3.55	3.57	3.60	3.60	3.61	3.59	3.61	3.59	3.58	3.58	3.57	0.00	0.00	0.01	0.00
Speed (By-week -7)	3.65	3.60	3.51	3.54	3.57	3.59	3.60	3.60	3.58	3.61	3.58	3.57	3.57	3.56	0.00	0.00	0.01	0.00
Speed (By-week -8)	3.65	3.57	3.49	3.52	3.55	3.58	3.59	3.59	3.57	3.59	3.57	3.56	3.56	3.54	0.00	0.00	0.01	0.00
Speed (By-week -9)	3.64	3.59	3.50	3.52	3.55	3.58	3.59	3.60	3.57	3.59	3.57	3.56	3.56	3.54	0.00	0.00	0.01	0.01
Speed (By-week -10)	3.65	3.61	3.52	3.54	3.57	3.58	3.60	3.62	3.58	3.60	3.58	3.57	3.57	3.56	0.00	0.00	0.01	0.01
Speed (By-week -11)	3.66	3.64	3.55	3.58	3.60	3.62	3.61	3.64	3.61	3.63	3.61	3.60	3.60	3.59	0.00	0.00	0.01	0.00
Speed (By-week -12)	3.66	3.64	3.55	3.58	3.60	3.62	3.61	3.65	3.61	3.64	3.61	3.60	3.61	3.59	0.00	0.00	0.01	0.01
Speed (By-week -13)	3.66	3.67	3.56	3.59	3.61	3.63	3.62	3.65	3.62	3.64	3.62	3.61	3.61	3.60	0.00	0.00	0.01	0.00
Speed (By-week -14)	3.66	3.66	3.55	3.58	3.60	3.62	3.62	3.65	3.62	3.64	3.61	3.61	3.61	3.59	0.00	0.00	0.01	0.01
Pr(Severe Traffic Jam = 1) (By-week -1)	0.02	0.15	0.09	0.10	0.07	0.05	0.03	0.08	0.06	0.06	0.07	0.07	0.07	0.08	0.00	0.08	0.54	0.11
Pr(Severe Traffic Jam = 1) (By-week -2)	0.02	0.15	0.10	0.11	0.08	0.06	0.04	0.08	0.07	0.07	0.07	0.07	0.07	0.08	0.00	0.48	0.51	0.07
Pr(Severe Traffic Jam = 1) (By-week -3)	0.02	0.15	0.10	0.10	0.07	0.06	0.04	0.08	0.07	0.07	0.07	0.07	0.07	0.08	0.00	0.26	0.53	0.08
Pr(Severe Traffic Jam = 1) (By-week -4)	0.02	0.16	0.10	0.11	0.08	0.06	0.04	0.08	0.07	0.07	0.07	0.07	0.08	0.09	0.00	0.36	0.52	0.07
Pr(Severe Traffic Jam = 1) (By-week -5)	0.02	0.15	0.09	0.09	0.07	0.06	0.03	0.08	0.06	0.06	0.06	0.06	0.07	0.08	0.00	0.15	0.54	0.11
Pr(Severe Traffic Jam = 1) (By-week -6)	0.02	0.14	0.09	0.10	0.07	0.06	0.04	0.09	0.07	0.06	0.06	0.07	0.07	0.07	0.00	0.08	0.52	0.11
Pr(Severe Traffic Jam = 1) (By-week -7)	0.02	0.15	0.10	0.10	0.07	0.06	0.04	0.09	0.07	0.07	0.07	0.07	0.07	0.08	0.00	0.29	0.51	0.10
Pr(Severe Traffic Jam = 1) (By-week -8)	0.02	0.17	0.11	0.11	0.09	0.07	0.04	0.10	0.08	0.08	0.08	0.08	0.08	0.09	0.00	0.09	0.53	0.10
Pr(Severe Traffic Jam = 1) (By-week -9)	0.02	0.16	0.11	0.11	0.09	0.07	0.04	0.09	0.08	0.07	0.08	0.08	0.08	0.09	0.00	0.21	0.50	0.09
Pr(Severe Traffic Jam = 1) (By-week -10)	0.02	0.15	0.09	0.10	0.08	0.06	0.04	0.07	0.07	0.07	0.07	0.07	0.07	0.08	0.00	0.09	0.50	0.07
Pr(Severe Traffic Jam = 1) (By-week -11)	0.01	0.12	0.07	0.08	0.05	0.04	0.03	0.06	0.05	0.05	0.05	0.05	0.05	0.06	0.00	0.36	0.59	0.12
Pr(Severe Traffic Jam = 1) (By-week -12)	0.01	0.13	0.07	0.08	0.05	0.04	0.03	0.06	0.05	0.05	0.05	0.05	0.05	0.06	0.00	0.32	0.59	0.10
Pr(Severe Traffic Jam = 1) (By-week -13)	0.01	0.11	0.06	0.07	0.05	0.03	0.02	0.05	0.04	0.04	0.04	0.04	0.04	0.05	0.00	0.47	0.57	0.10
Pr(Severe Traffic Jam = 1) (By-week -14)	0.01	0.12	0.07	0.07	0.05	0.04	0.02	0.05	0.04	0.04	0.05	0.05	0.05	0.06	0.00	0.20	0.58	0.10
Mins. in Severe Traffic Jam (By-week -1)	0.31	3.32	1.78	1.91	1.34	0.94	0.54	1.69	1.10	1.20	1.14	1.19	1.19	1.69	0.00	0.27	0.65	0.18
Mins. in Severe Traffic Jam (By-week -2)	0.35	3.46	1.96	2.08	1.46	1.06	0.60	1.61	1.29	1.33	1.27	1.33	1.34	1.75	0.00	0.68	0.62	0.12
Mins. in Severe Traffic Jam (By-week -3)	0.33	2.90	1.64	1.72	1.20	0.89	0.49	1.22	1.15	1.07	1.03	1.14	1.10	1.42	0.00	0.13	0.62	0.10
Mins. in Severe Traffic Jam (By-week -4)	0.37	3.43	1.95	2.02	1.39	1.04	0.55	1.17	1.29	1.26	1.22	1.30	1.33	1.69	0.00	0.45	0.63	0.12
Mins. in Severe Traffic Jam (By-week -5)	0.29	3.34	1.72	1.74	1.27	0.97	0.55	1.25	1.13	1.14	1.09	1.15	1.21	1.52	0.00	0.50	0.66	0.11
Mins. in Severe Traffic Jam (By-week -6)	0.30	3.33	1.82	1.87	1.39	1.00	0.62	1.37	1.25	1.17	1.12	1.24	1.24	1.55	0.00	0.13	0.63	0.10
Mins. in Severe Traffic Jam (By-week -7)	0.34	3.71	2.11	2.15	1.52	1.13	0.72	1.49	1.37	1.35	1.25	1.35	1.40	1.75	0.00	0.18	0.62	0.11
Mins. in Severe Traffic Jam (By-week -8)	0.39	4.36	2.46	2.43	1.78	1.28	0.74	1.65	1.59	1.55	1.43	1.59	1.59	2.01	0.00	0.07	0.64	0.10
Mins. in Severe Traffic Jam (By-week -9)	0.45	4.03	2.31	2.42	1.84	1.37	0.81	1.58	1.62	1.60	1.47	1.61	1.63	2.00	0.00	0.14	0.58	0.09
Mins. in Severe Traffic Jam (By-week -10)	0.36	3.61	1.98	2.12	1.59	1.28	0.69	1.34	1.52	1.41	1.30	1.43	1.46	1.96	0.00	0.02	0.60	0.14
Mins. in Severe Traffic Jam (By-week -11)	0.23	2.90	1.44	1.50	0.90	0.73	0.47	0.98	0.89	0.96	0.87	0.88	0.97	1.26	0.00	0.43	0.71	0.13
Mins. in Severe Traffic Jam (By-week -12)	0.21	2.81	1.45	1.46	0.91	0.71	0.49	0.86	0.82	0.85	0.85	0.87	0.89	1.15	0.00	0.67	0.70	0.12
Mins. in Severe Traffic Jam (By-week -13)	0.17	2.29	1.21	1.22	0.80	0.62	0.40	0.86	0.71	0.76	0.73	0.72	0.78	1.08	0.00	0.48	0.68	0.15
Mins. in Severe Traffic Jam (By-week -14)	0.19	2.65	1.35	1.32	0.96	0.68	0.38	0.76	0.74	0.80	0.81	0.77	0.84	1.29	0.00	0.32	0.71	0.21

...cont.

	Raw Means							IPW Means After Imposing Overlap							p-value		RMSD	
	T=0	T=1	T=2	T=3	T=4	T=5	T=6	T=0	T=1	T=2	T=3	T=4	T=5	T=6	Raw	Ovlp + IPW	Raw	Ovlp + IPW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Panel b. Afternoon Variables																		
Speed (By-week -1)	3.63	3.52	3.46	3.49	3.53	3.57	3.58	3.58	3.57	3.59	3.54	3.54	3.54	3.52	0.00	0.00	0.02	0.01
Speed (By-week -2)	3.64	3.51	3.46	3.49	3.53	3.57	3.58	3.58	3.57	3.59	3.54	3.54	3.54	3.53	0.00	0.00	0.02	0.01
Speed (By-week -3)	3.64	3.52	3.47	3.50	3.54	3.58	3.59	3.60	3.58	3.60	3.55	3.55	3.55	3.53	0.00	0.00	0.02	0.01
Speed (By-week -4)	3.64	3.50	3.45	3.48	3.53	3.57	3.58	3.59	3.56	3.59	3.54	3.54	3.54	3.53	0.00	0.00	0.02	0.01
Speed (By-week -5)	3.64	3.52	3.46	3.50	3.53	3.58	3.59	3.59	3.57	3.59	3.55	3.55	3.55	3.54	0.00	0.00	0.02	0.01
Speed (By-week -6)	3.64	3.52	3.47	3.50	3.54	3.58	3.59	3.60	3.57	3.59	3.56	3.55	3.55	3.54	0.00	0.00	0.02	0.01
Speed (By-week -7)	3.64	3.51	3.46	3.49	3.53	3.58	3.59	3.59	3.57	3.59	3.55	3.55	3.55	3.54	0.00	0.00	0.02	0.01
Speed (By-week -8)	3.64	3.51	3.45	3.49	3.53	3.58	3.59	3.59	3.57	3.59	3.55	3.55	3.55	3.54	0.00	0.00	0.02	0.01
Speed (By-week -9)	3.64	3.53	3.46	3.49	3.52	3.57	3.59	3.59	3.57	3.58	3.55	3.54	3.54	3.53	0.00	0.00	0.02	0.01
Speed (By-week -10)	3.64	3.54	3.47	3.50	3.54	3.58	3.59	3.61	3.58	3.60	3.56	3.56	3.55	3.54	0.00	0.00	0.02	0.01
Speed (By-week -11)	3.64	3.55	3.48	3.51	3.54	3.59	3.59	3.61	3.58	3.60	3.56	3.56	3.56	3.54	0.00	0.00	0.01	0.01
Speed (By-week -12)	3.64	3.53	3.47	3.51	3.54	3.59	3.59	3.62	3.58	3.60	3.56	3.56	3.55	3.54	0.00	0.00	0.02	0.01
Speed (By-week -13)	3.65	3.59	3.51	3.54	3.56	3.60	3.60	3.63	3.60	3.62	3.58	3.58	3.58	3.57	0.00	0.00	0.01	0.01
Speed (By-week -14)	3.64	3.55	3.49	3.52	3.54	3.59	3.59	3.62	3.58	3.60	3.57	3.57	3.56	3.55	0.00	0.00	0.01	0.01
Pr(Severe Traffic Jam = 1) (By-week -1)	0.03	0.22	0.14	0.15	0.11	0.08	0.03	0.11	0.08	0.09	0.10	0.10	0.10	0.11	0.00	0.00	0.54	0.10
Pr(Severe Traffic Jam = 1) (By-week -2)	0.03	0.23	0.15	0.14	0.11	0.08	0.04	0.10	0.09	0.09	0.10	0.10	0.10	0.11	0.00	0.00	0.55	0.09
Pr(Severe Traffic Jam = 1) (By-week -3)	0.03	0.22	0.14	0.13	0.10	0.07	0.04	0.09	0.08	0.08	0.09	0.09	0.09	0.11	0.00	0.00	0.57	0.10
Pr(Severe Traffic Jam = 1) (By-week -4)	0.03	0.23	0.15	0.15	0.11	0.08	0.04	0.10	0.09	0.09	0.10	0.10	0.10	0.11	0.00	0.00	0.56	0.08
Pr(Severe Traffic Jam = 1) (By-week -5)	0.03	0.22	0.14	0.14	0.10	0.07	0.03	0.10	0.08	0.08	0.09	0.09	0.10	0.10	0.00	0.00	0.57	0.08
Pr(Severe Traffic Jam = 1) (By-week -6)	0.03	0.21	0.14	0.13	0.10	0.07	0.04	0.10	0.08	0.08	0.09	0.09	0.09	0.10	0.00	0.00	0.57	0.07
Pr(Severe Traffic Jam = 1) (By-week -7)	0.03	0.22	0.14	0.14	0.10	0.07	0.04	0.10	0.08	0.08	0.09	0.09	0.10	0.10	0.00	0.00	0.57	0.08
Pr(Severe Traffic Jam = 1) (By-week -8)	0.03	0.23	0.15	0.14	0.11	0.07	0.04	0.10	0.08	0.09	0.09	0.10	0.10	0.11	0.00	0.00	0.58	0.08
Pr(Severe Traffic Jam = 1) (By-week -9)	0.03	0.21	0.14	0.14	0.11	0.08	0.04	0.10	0.09	0.09	0.10	0.10	0.10	0.11	0.00	0.00	0.55	0.08
Pr(Severe Traffic Jam = 1) (By-week -10)	0.03	0.21	0.14	0.14	0.10	0.07	0.04	0.09	0.08	0.08	0.09	0.09	0.09	0.10	0.00	0.00	0.55	0.07
Pr(Severe Traffic Jam = 1) (By-week -11)	0.03	0.20	0.13	0.13	0.10	0.07	0.03	0.09	0.08	0.08	0.09	0.09	0.09	0.10	0.00	0.00	0.55	0.08
Pr(Severe Traffic Jam = 1) (By-week -12)	0.03	0.22	0.14	0.13	0.10	0.06	0.03	0.08	0.08	0.08	0.09	0.09	0.09	0.10	0.00	0.00	0.58	0.09
Pr(Severe Traffic Jam = 1) (By-week -13)	0.02	0.17	0.11	0.11	0.08	0.05	0.02	0.07	0.06	0.06	0.07	0.07	0.08	0.08	0.00	0.00	0.56	0.09
Pr(Severe Traffic Jam = 1) (By-week -14)	0.03	0.20	0.13	0.12	0.10	0.06	0.02	0.07	0.07	0.07	0.08	0.08	0.09	0.10	0.00	0.00	0.57	0.11
Mins. in Severe Traffic Jam (By-week -1)	0.50	5.92	3.44	3.44	2.41	1.51	0.93	1.96	2.42	1.93	1.47	0.98	2.04	1.64	0.00	0.00	0.67	0.11
Mins. in Severe Traffic Jam (By-week -2)	0.46	6.02	3.52	3.43	2.42	1.59	0.96	2.09	2.45	1.93	1.56	1.04	2.00	1.66	0.00	0.00	0.67	0.10
Mins. in Severe Traffic Jam (By-week -3)	0.38	5.68	3.31	3.15	2.13	1.32	0.76	1.82	2.16	1.65	1.30	0.82	1.53	1.48	0.00	0.00	0.71	0.12
Mins. in Severe Traffic Jam (By-week -4)	0.45	6.24	3.76	3.53	2.45	1.48	0.90	2.06	2.44	1.91	1.48	0.97	1.80	1.71	0.00	0.00	0.69	0.10
Mins. in Severe Traffic Jam (By-week -5)	0.38	5.73	3.42	3.20	2.25	1.38	0.87	1.85	2.20	1.72	1.38	0.93	1.53	1.55	0.00	0.00	0.69	0.12
Mins. in Severe Traffic Jam (By-week -6)	0.38	5.70	3.37	3.14	2.26	1.31	0.81	1.86	2.10	1.70	1.28	0.86	1.56	1.52	0.00	0.00	0.70	0.09
Mins. in Severe Traffic Jam (By-week -7)	0.43	6.04	3.67	3.49	2.38	1.50	0.92	2.16	2.39	1.85	1.50	0.97	1.75	1.72	0.00	0.00	0.68	0.08
Mins. in Severe Traffic Jam (By-week -8)	0.37	6.24	3.78	3.51	2.45	1.48	0.83	2.14	2.37	1.90	1.46	0.89	1.68	1.63	0.00	0.00	0.71	0.09
Mins. in Severe Traffic Jam (By-week -9)	0.42	5.78	3.58	3.45	2.61	1.59	0.90	2.10	2.40	2.04	1.55	0.93	1.76	1.67	0.00	0.00	0.65	0.09
Mins. in Severe Traffic Jam (By-week -10)	0.44	5.39	3.31	3.22	2.32	1.32	0.86	1.84	2.17	1.78	1.28	0.86	1.47	1.50	0.00	0.00	0.66	0.09
Mins. in Severe Traffic Jam (By-week -11)	0.43	5.29	3.17	3.10	2.14	1.29	0.93	1.70	2.15	1.62	1.25	0.97	1.40	1.47	0.00	0.00	0.66	0.11
Mins. in Severe Traffic Jam (By-week -12)	0.42	5.81	3.34	3.16	2.21	1.21	0.89	1.72	2.14	1.68	1.16	0.91	1.27	1.43	0.00	0.00	0.71	0.15
Mins. in Severe Traffic Jam (By-week -13)	0.37	4.23	2.56	2.38	1.77	0.93	0.67	1.34	1.64	1.30	0.90	0.70	1.10	1.04	0.00	0.00	0.68	0.12
Mins. in Severe Traffic Jam (By-week -14)	0.40	5.16	3.08	2.81	2.19	1.15	0.77	1.60	1.95	1.64	1.09	0.81	1.15	1.29	0.00	0.00	0.69	0.16

...cont.

	Raw Means							IPW Means After Imposing Overlap							p-value		RMSD	
	T=0	T=1	T=2	T=3	T=4	T=5	T=6	T=0	T=1	T=2	T=3	T=4	T=5	T=6	Raw	Ovlp + IPW	Raw	Ovlp + IPW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Panel c. Share of road segment length over jam length																		
Share length morning (By-week -1)	0.00	0.02	0.02	0.02	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.40	0.47	0.11
Share length morning (By-week -2)	0.01	0.02	0.02	0.02	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.02	0.00	0.66	0.46	0.10
Share length morning (By-week -3)	0.00	0.02	0.02	0.02	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.72	0.48	0.11
Share length morning (By-week -4)	0.01	0.02	0.02	0.02	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.02	0.00	0.66	0.46	0.09
Share length morning (By-week -5)	0.00	0.02	0.02	0.02	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.24	0.47	0.15
Share length morning (By-week -6)	0.00	0.02	0.02	0.02	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.49	0.47	0.15
Share length morning (By-week -7)	0.00	0.02	0.02	0.02	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.48	0.46	0.13
Share length morning (By-week -8)	0.00	0.03	0.02	0.02	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.02	0.00	0.48	0.48	0.13
Share length morning (By-week -9)	0.00	0.03	0.02	0.02	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.02	0.00	0.32	0.45	0.12
Share length morning (By-week -10)	0.00	0.02	0.02	0.02	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.02	0.00	0.28	0.46	0.07
Share length morning (By-week -11)	0.00	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.12	0.52	0.13
Share length morning (By-week -12)	0.00	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.28	0.52	0.09
Share length morning (By-week -13)	0.00	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.19	0.51	0.09
Share length morning (By-week -14)	0.00	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.07	0.52	0.10
Share length afternoon (By-week -1)	0.01	0.03	0.02	0.02	0.02	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.00	0.00	0.48	0.12
Share length afternoon (By-week -2)	0.01	0.03	0.03	0.02	0.02	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.00	0.00	0.49	0.09
Share length afternoon (By-week -3)	0.01	0.03	0.02	0.02	0.02	0.01	0.01	0.02	0.01	0.01	0.02	0.02	0.02	0.02	0.00	0.00	0.50	0.11
Share length afternoon (By-week -4)	0.01	0.03	0.03	0.02	0.02	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.00	0.00	0.50	0.10
Share length afternoon (By-week -5)	0.01	0.03	0.02	0.02	0.02	0.01	0.01	0.02	0.01	0.02	0.02	0.02	0.02	0.02	0.00	0.00	0.50	0.11
Share length afternoon (By-week -6)	0.01	0.03	0.02	0.02	0.02	0.01	0.01	0.02	0.01	0.02	0.02	0.02	0.02	0.02	0.00	0.01	0.51	0.10
Share length afternoon (By-week -7)	0.01	0.03	0.03	0.02	0.02	0.01	0.01	0.02	0.01	0.02	0.02	0.02	0.02	0.02	0.00	0.00	0.51	0.10
Share length afternoon (By-week -8)	0.01	0.03	0.03	0.02	0.02	0.01	0.01	0.02	0.01	0.02	0.02	0.02	0.02	0.02	0.00	0.00	0.52	0.10
Share length afternoon (By-week -9)	0.01	0.03	0.03	0.02	0.02	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.00	0.00	0.49	0.10
Share length afternoon (By-week -10)	0.01	0.03	0.02	0.02	0.02	0.01	0.01	0.02	0.01	0.02	0.02	0.02	0.02	0.02	0.00	0.01	0.50	0.08
Share length afternoon (By-week -11)	0.01	0.03	0.02	0.02	0.02	0.01	0.01	0.02	0.01	0.02	0.02	0.02	0.02	0.02	0.00	0.04	0.49	0.08
Share length afternoon (By-week -12)	0.01	0.03	0.02	0.02	0.02	0.01	0.01	0.02	0.01	0.02	0.02	0.02	0.02	0.02	0.00	0.00	0.51	0.08
Share length afternoon (By-week -13)	0.00	0.03	0.02	0.02	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.50	0.10
Share length afternoon (By-week -14)	0.01	0.03	0.02	0.02	0.02	0.01	0.01	0.02	0.01	0.01	0.02	0.02	0.02	0.02	0.00	0.01	0.51	0.08

...cont.

	Raw Means							IPW Means After Imposing Overlap							p-value		RMSD	
	T=0	T=1	T=2	T=3	T=4	T=5	T=6	T=0	T=1	T=2	T=3	T=4	T=5	T=6	Raw	Ovlp + IPW	Raw	Ovlp + IPW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Panel d. Travel Zone Characteristics																		
Share of male inhabitants	0.49	0.47	0.47	0.48	0.48	0.48	0.49	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.00	0.00	0.01	0.00
Age in years	33.07	37.61	37.61	37.18	36.44	35.41	33.74	36.46	36.21	36.38	36.52	36.43	36.58	36.88	0.00	0.00	0.05	0.01
Share of 5-year residents	0.97	0.95	0.95	0.95	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.00	0.00	0.01	0.00
Share of birth-residents	0.83	0.77	0.78	0.79	0.80	0.81	0.83	0.82	0.79	0.80	0.80	0.80	0.80	0.79	0.00	0.00	0.03	0.01
Share of uninsured	0.28	0.22	0.22	0.22	0.23	0.25	0.27	0.23	0.23	0.23	0.23	0.23	0.23	0.23	0.00	0.03	0.10	0.01
Share of Spanish speakers	0.87	0.91	0.91	0.91	0.91	0.90	0.88	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.00	0.00	0.02	0.00
Share of primary educated	0.24	0.17	0.17	0.18	0.19	0.20	0.23	0.19	0.19	0.19	0.19	0.19	0.19	0.18	0.00	0.00	0.13	0.02
Share of secondary educated	0.53	0.44	0.44	0.45	0.46	0.48	0.52	0.47	0.46	0.46	0.46	0.46	0.46	0.45	0.00	0.00	0.07	0.01
Share of tertiary educated	0.09	0.10	0.10	0.10	0.10	0.10	0.09	0.10	0.10	0.10	0.10	0.10	0.10	0.11	0.00	0.00	0.04	0.02
Share of students studying in other districts	0.38	0.54	0.52	0.50	0.48	0.44	0.40	0.44	0.49	0.48	0.48	0.48	0.49	0.52	0.00	0.00	0.12	0.04
Share of employed	0.46	0.49	0.48	0.48	0.48	0.47	0.46	0.47	0.48	0.48	0.48	0.48	0.48	0.48	0.00	0.00	0.02	0.01
Share of workers working in other districts	0.55	0.59	0.59	0.59	0.58	0.57	0.55	0.58	0.59	0.58	0.58	0.58	0.59	0.61	0.00	0.00	0.03	0.02
Share of local roads	0.80	0.75	0.88	0.85	0.83	0.82	0.81	0.80	0.83	0.81	0.84	0.85	0.84	0.82	0.00	0.00	0.05	0.02
Ln(Free-flow speed)	2.99	3.12	2.95	2.98	2.98	2.98	2.96	3.03	2.99	3.01	2.98	2.98	2.98	2.98	0.00	0.00	0.02	0.01
Ln(Road segment length)	3.79	3.73	3.84	3.76	3.73	3.73	3.68	3.79	3.76	3.72	3.74	3.77	3.75	3.76	0.00	0.01	0.01	0.01
Ln(Road segment appearances)	3.99	6.67	5.76	5.81	5.34	4.85	4.41	5.37	5.29	5.19	5.30	5.34	5.28	5.37	0.00	0.04	0.16	0.01

Source: Prepared by the authors. *Note*: Free-Flow Speed is speed at free circulation. Total length is the sum of all road segment lengths within category. Raw Means are calculated before imposing overlap, while IPW refers to the weighted (after imposing overlap) variable using the inverse of the GPS as the weight. RMSD refers to root mean square distance, an overall measure of distance among the estimated means (see Flores and Mitnik (2013)). The p-value is for the test of the joint hypothesis that the means across *all* distance rings are equals. $T = 0$ corresponds to the outermost rings (2500-3000 meters, while $T = 1, ..., 6$ refer to the six rings starting in order from 0-250 meters, 250-500 meters, etc.

Table A2. Early and late *Pico y Placa* impacts: Alternative specification with standard errors clustered at the resolution 10 H3 cell level

Distance to	Ln(Speed)			Pr(Severe Traffic Jam)			Minutes in Severe Traffic Jam		
Pico y Placa	Morning	Midday	Afternoon	Morning	Midday	Afternoon	Morning	Midday	Afternoon
(meters):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel a. Local Roads									
Panel a.1 Early *Pico y Placa* (September 2 to October 13 2019)									
0-250	0.03***	-0.00	0.01*	-0.02***	0.00	-0.01	-0.54***	0.06	-0.28*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.12)	(0.12)	(0.16)
250-500	0.03***	-0.00	0.01	-0.01***	0.00	-0.00	-0.45***	0.06	-0.24
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.12)	(0.12)	(0.16)
500-1000	0.02***	-0.00	0.01	-0.01**	0.00	-0.00	-0.39***	-0.01	-0.29*
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.12)	(0.12)	(0.16)
1000-1500	0.02***	-0.00	0.01	-0.01	0.00	-0.00	-0.32**	0.03	-0.22
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.12)	(0.12)	(0.16)
1500-2000	0.02***	-0.00	0.01*	-0.01*	0.00	-0.01	-0.33***	0.04	-0.35**
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.12)	(0.12)	(0.16)
200-2500	0.01**	0.00	0.01*	-0.01	0.00	-0.01	-0.26**	0.04	-0.24
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.12)	(0.12)	(0.16)
Panel a.2 Late *Pico y Placa* (October 14 to December 22 2019)									
0-250	0.01	-0.03	-0.02	-0.00	0.02	0.02	-0.22	0.38	0.44**
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.21)	(0.23)	(0.22)
250-500	0.01	-0.03	-0.02	-0.00	0.02	0.02	-0.14	0.38	0.45**
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.21)	(0.24)	(0.22)
500-1000	0.00	-0.02	-0.02	-0.00	0.02	0.02	-0.11	0.30	0.33
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.21)	(0.23)	(0.22)
1000-1500	0.00	-0.03	-0.02	0.00	0.02	0.02	-0.04	0.36	0.38*
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.22)	(0.24)	(0.22)
1500-2000	0.00	-0.02	-0.01	0.00	0.02	0.01	-0.03	0.34	0.28
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.21)	(0.23)	(0.22)
200-2500	-0.00	-0.02	-0.01	0.00	0.02	0.01	0.01	0.23	0.21
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.21)	(0.24)	(0.22)
Panel b. Non-Loca Roads									
Panel b.1 Early *Pico y Placa* (September 2 to October 13 2019)									
0-250	0.06	-0.00	0.08***	-0.03	0.01	-0.05**	-0.80	0.27	-1.40*
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.02)	(0.61)	(0.73)	(0.78)
250-500	-0.03	-0.01	-0.01	0.02	0.02	0.01	0.66	0.32	0.28
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.02)	(0.61)	(0.73)	(0.78)
500-1000	-0.03	-0.02	-0.02	0.03	0.03	0.02	0.56	0.49	0.52
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.02)	(0.59)	(0.73)	(0.77)
1000-1500	-0.01	-0.01	-0.02	0.02	0.01	0.01	0.46	0.21	0.28
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.02)	(0.59)	(0.73)	(0.78)
1500-2000	-0.02	-0.01	-0.01	0.02	0.01	0.00	0.51	0.05	0.22
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.02)	(0.58)	(0.73)	(0.77)
200-2500	-0.03	0.01	0.01	0.03	0.00	0.00	0.37	0.15	-0.13
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.02)	(0.66)	(0.76)	(0.83)
Panel b.2 Late *Pico y Placa* (October 14 to December 22 2019)									
0-250	0.05	-0.04	0.04	-0.03	0.04	-0.03	-0.67	0.73	-0.78
	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.74)	(0.77)	(0.95)
250-500	-0.03	-0.06	-0.04	0.03	0.05	0.03	1.09	1.03	1.30
	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.75)	(0.79)	(0.96)
500-1000	-0.03	-0.06	-0.06	0.03	0.06	0.05	0.97	1.19	1.63*
	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.72)	(0.78)	(0.94)
1000-1500	-0.01	-0.05	-0.03	0.01	0.04	0.02	0.72	0.99	0.88
	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.72)	(0.78)	(0.95)
1500-2000	-0.03	-0.05	-0.02	0.03	0.04	0.02	1.10	0.86	1.00
	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.71)	(0.78)	(0.94)
200-2500	-0.03	-0.07	-0.03	0.04	0.06	0.03	0.30	1.20	1.28
	(0.04)	(0.05)	(0.04)	(0.03)	(0.04)	(0.03)	(0.78)	(0.84)	(0.99)

Source: Prepared by the authors. *Note*: Standard errors clustered at the resolution 10 H3 cell level. *, ** and *** denote statistical significance at the 10, 5 and 1 percent level, respectively. This Table shows coefficients associated with a version of equation (1) where the PyP dummy is split in two subperiods (early and late). Morning: 6:00 a.m. to 9:59 a.m., Midday: 10:00 a.m. to 4:59 p.m., Afternoon: 5:00 p.m. to 8:59 p.m.

Table A3. Early and late *Pico y Placa* impacts: Heterogeneity within 0-250 meters ring

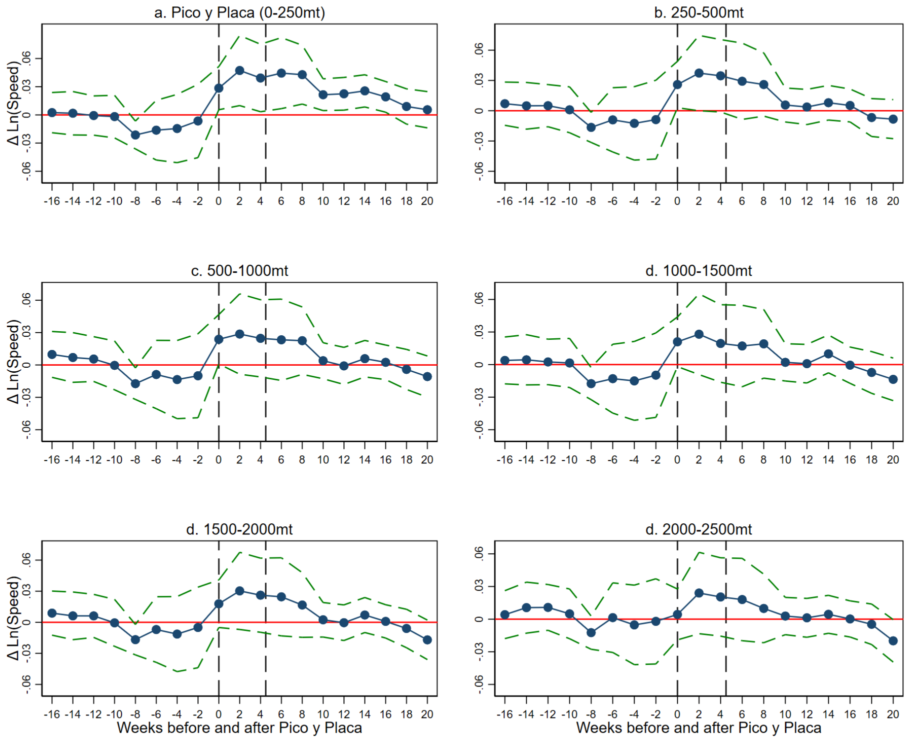
Distance to *Pico y Placa* (meters):	Ln(Speed)			Pr(Severe Traffic Jam)			Minutes in Severe Traffic Jam		
	Morning (1)	Midday (2)	Afternoon (3)	Morning (4)	Midday (5)	Afternoon (6)	Morning (7)	Midday (8)	Afternoon (9)
Panel a. Local Roads									
Panel a.1 Early *Pico y Placa* (September 2 to October 13 2019)									
0-20	0.05***	0.00	0.05***	-0.04***	-0.00	-0.04***	-0.97***	-0.08	-1.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.12)	(0.11)	(0.16)
20-250	0.03***	-0.00	0.01	-0.01***	0.00	-0.00	-0.48***	0.08	-0.19
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.09)	(0.10)	(0.13)
250-500	0.03***	-0.00	0.01	-0.01***	0.00	-0.00	-0.45***	0.06	-0.24*
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.09)	(0.11)	(0.13)
500-1000	0.02***	-0.00	0.01	-0.01***	0.00	-0.00	-0.39***	-0.01	-0.29**
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.09)	(0.10)	(0.13)
1000-1500	0.02***	-0.00	0.01	-0.01*	0.00	-0.00	-0.31***	0.04	-0.22
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.10)	(0.10)	(0.14)
1500-2000	0.02***	-0.00	0.01**	-0.01**	0.00	-0.01*	-0.33***	0.04	-0.35***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.09)	(0.11)	(0.13)
2000-2500	0.01***	0.00	0.01**	-0.01	0.00	-0.01*	-0.26***	0.04	-0.24*
	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.10)	(0.11)	(0.14)
Panel a.2 Late *Pico y Placa* (October 14 to December 22 2019)									
0-20	0.03*	-0.03*	0.01	-0.02**	0.03	-0.01	-0.67***	0.38	-0.01
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.20)	(0.23)	(0.22)
20-250	0.01	-0.03	-0.03	-0.00	0.02	0.02	-0.17	0.39*	0.50**
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.19)	(0.22)	(0.20)
250-500	0.01	-0.03	-0.02	-0.00	0.02	0.02	-0.14	0.38*	0.45**
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.19)	(0.23)	(0.20)
500-1000	0.00	-0.02	-0.02	-0.00	0.02	0.02	-0.12	0.30	0.33*
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.19)	(0.22)	(0.20)
1000-1500	0.00	-0.03	-0.02	0.00	0.02	0.02	-0.04	0.36	0.38*
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.20)	(0.23)	(0.20)
1500-2000	0.00	-0.02	-0.01	0.00	0.02	0.01	-0.03	0.34	0.28
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.19)	(0.23)	(0.20)
2000-2500	-0.00	-0.02	-0.01	0.00	0.02	0.01	0.01	0.23	0.21
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.19)	(0.23)	(0.20)
Panel b. Non-Loca Roads									
Panel b.1 Early *Pico y Placa* (September 2 to October 13 2019)									
0-20	0.12***	-0.01	0.15***	-0.07***	0.02	-0.10***	-2.00***	0.43	-3.37***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.40)	(0.53)	(0.52)
20-250	0.03	-0.00	0.05**	-0.01	0.01	-0.02	-0.18	0.19	-0.37
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.38)	(0.52)	(0.49)
250-500	-0.03	-0.01	-0.00	0.02	0.02	0.01	0.64*	0.33	0.25
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.38)	(0.52)	(0.49)
500-1000	-0.03	-0.02	-0.02	0.02	0.03	0.02	0.53	0.50	0.48
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.37)	(0.52)	(0.48)
1000-1500	-0.01	-0.01	-0.02	0.02	0.01	0.01	0.44	0.22	0.25
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.37)	(0.52)	(0.51)
1500-2000	-0.02	-0.01	-0.00	0.02	0.01	0.00	0.49	0.05	0.19
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.37)	(0.52)	(0.49)
2000-2500	-0.03	0.01	0.01	0.03	0.00	0.00	0.36	0.15	-0.15
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.44)	(0.54)	(0.53)
Panel b.2 Late *Pico y Placa* (October 14 to December 22 2019)									
0-20	0.11***	-0.05	0.12***	-0.07***	0.04	-0.09***	-1.81***	0.96*	-2.99***
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.48)	(0.52)	(0.62)
20-250	0.03	-0.03	0.01	-0.01	0.04	-0.00	-0.08	0.62	0.37
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.46)	(0.51)	(0.58)
250-500	-0.03	-0.06*	-0.03	0.03	0.05**	0.03	1.07**	1.04**	1.26**
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.47)	(0.51)	(0.59)
500-1000	-0.03	-0.06*	-0.06*	0.03	0.06**	0.05**	0.94**	1.20**	1.57***
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.45)	(0.51)	(0.57)
1000-1500	-0.01	-0.05	-0.02	0.01	0.04	0.02	0.70	1.00*	0.84
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.46)	(0.51)	(0.59)
1500-2000	-0.03	-0.05	-0.02	0.03	0.04	0.02	1.08**	0.87*	0.96*
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.45)	(0.52)	(0.58)
2000-2500	-0.03	-0.07**	-0.03	0.04*	0.06**	0.03	0.29	1.20**	1.26**
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.51)	(0.56)	(0.63)

Source: Prepared by the authors. *Note*: Standard errors clustered at the road segment level. *, ** and *** denote statistical significance at the 10, 5 and 1 percent level, respectively. This Table shows coefficients associated with a version of equation (1) where the PyP dummy is split in two subperiods (early and late). Morning: 6:00 a.m. to 9:59 a.m., Midday: 10:00 a.m. to 4:59 p.m., Afternoon: 5:00 p.m. to 8:59 p.m.

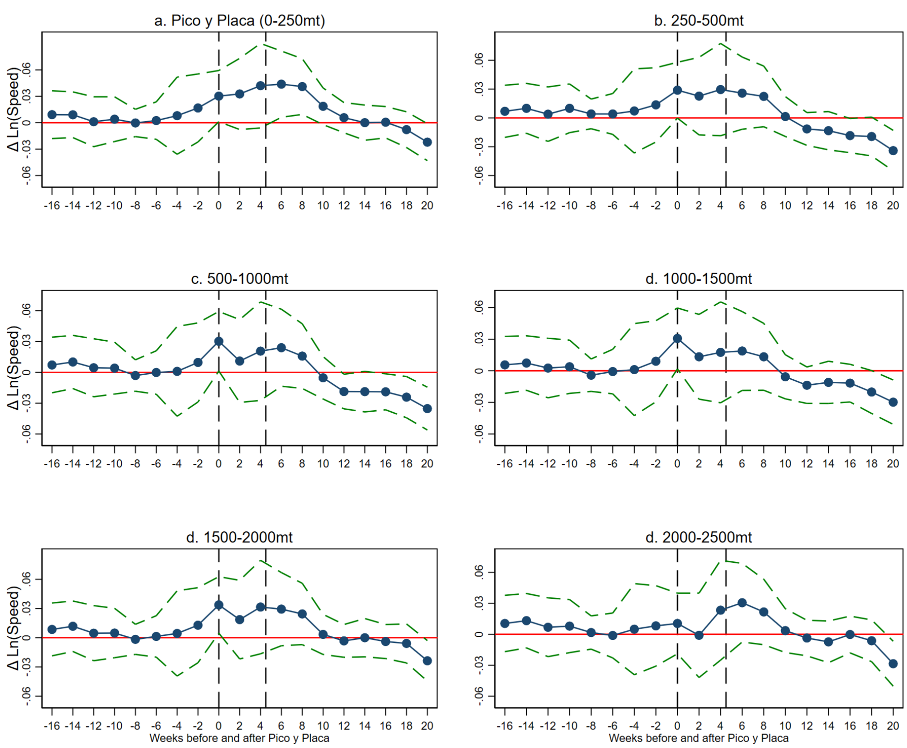
B Appendix Figures

Figure B1. Leads and lags: Ln(Speed)

Panel a. Morning



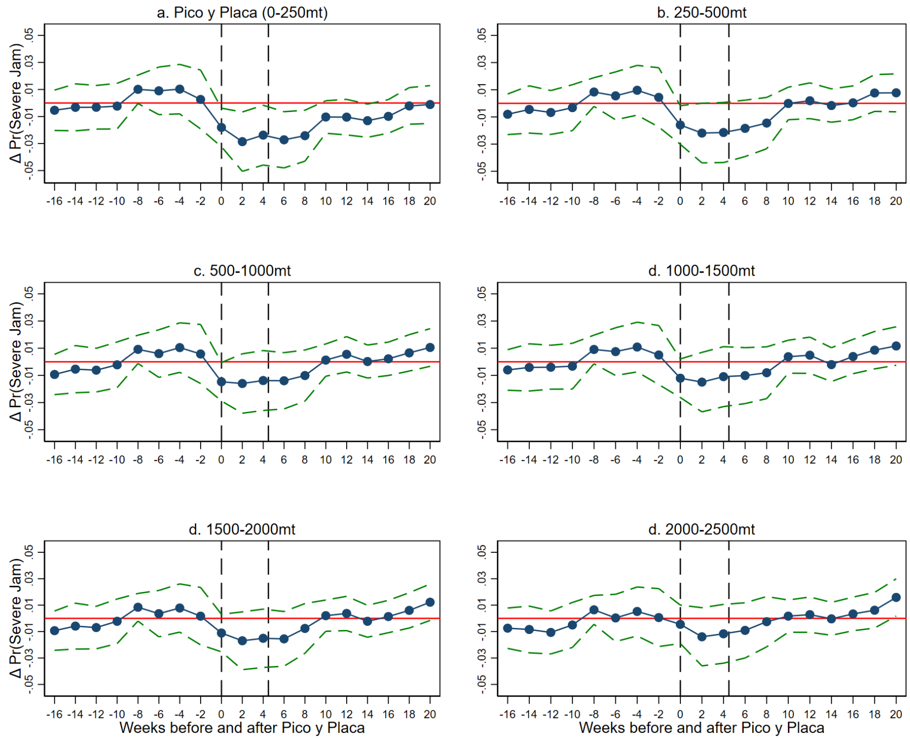
Panel b. Afternoon



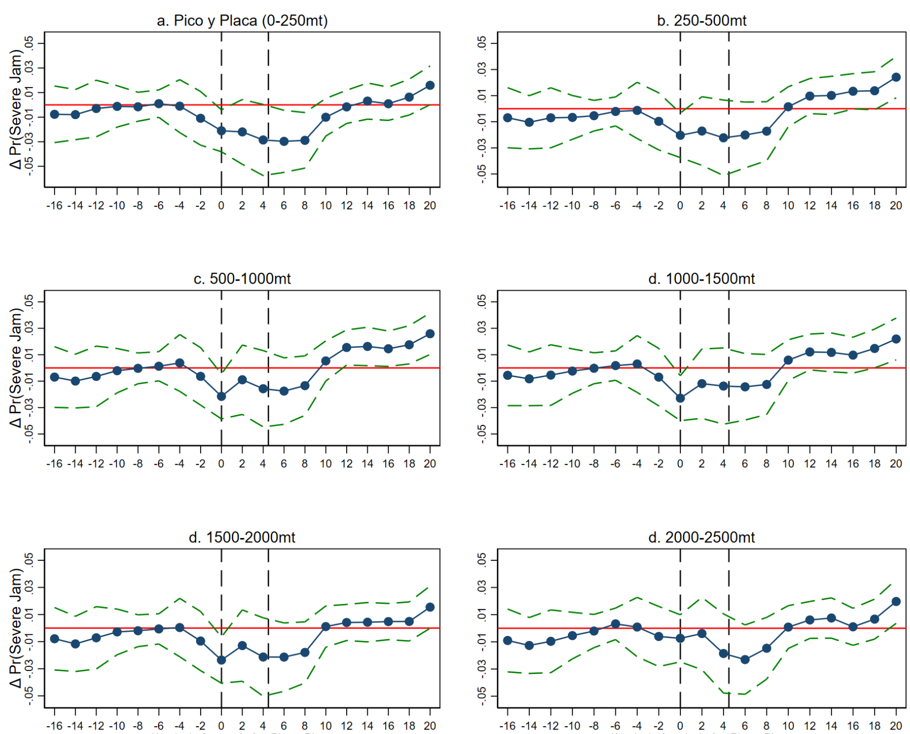
Source: Prepared by the authors. *Note*: Horizontal axis represents two-weeks perods. Period 0 are the two weeks when *Pico y Placa* sarted. Period 1 is the two-weeks following, and so on. The two dashed vertical lines mark the start and end of the transition period that coincided with the Panamerican and Parapanamerican Games. The reference period includes weeks -28 to -21 before the start of the restrictions. All figures show 95 percent CI.

Figure B2. Leads and lags: Probability of severe traffic jam

Panel a. Morning



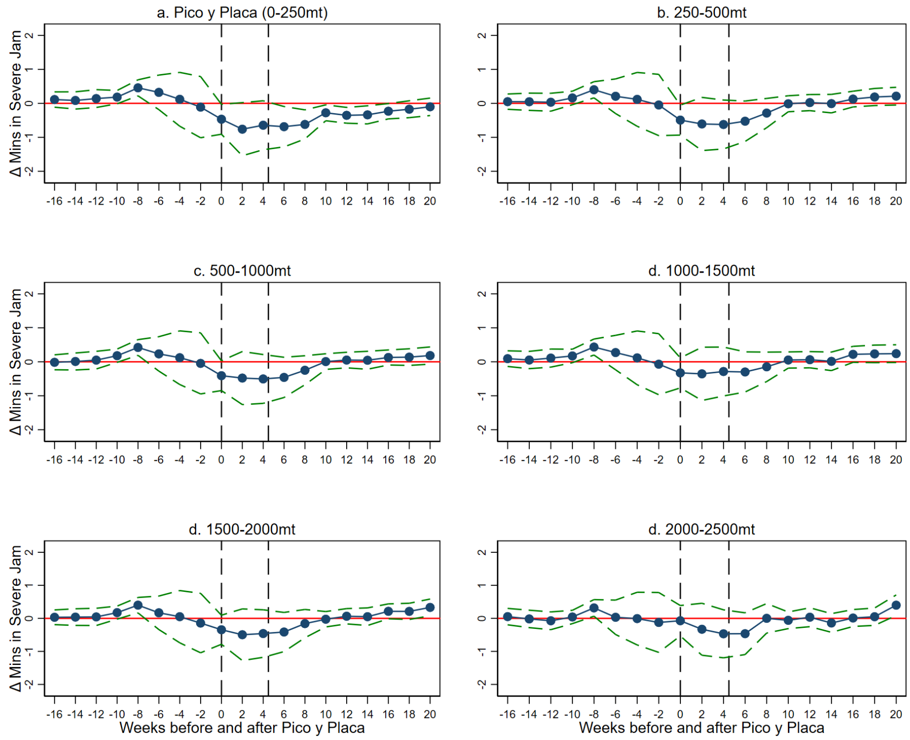
Panel b. Afternoon



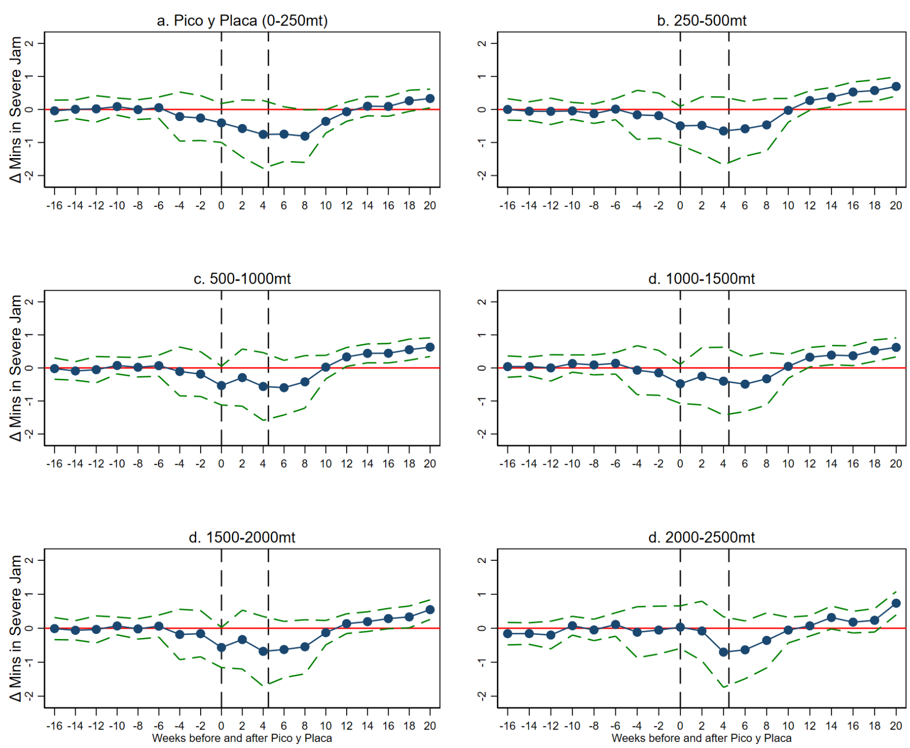
Source: Prepared by the authors. *Note*: Horizontal axis represents two-weeks periods. Period 0 are the two weeks when *Pico y Placa* sarted. Period 1 is the two-weeks following, and so on. The two dashed vertical lines mark the start and end of the transition period that coincided with the Panamerican and Parapanamerican Games. The reference period includes weeks -28 to -21 before the start of the restrictions. All figures show 95 percent CI.

Figure B3. Leads and lags: Number of minutes in severe traffic jam

Panel a. Morning



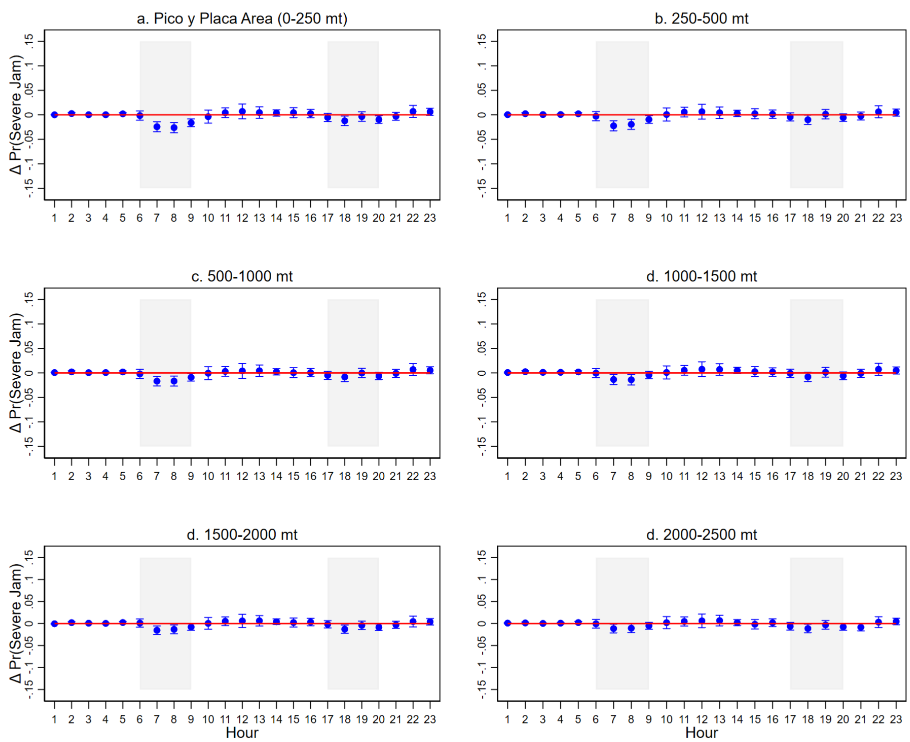
Panel b. Afternoon



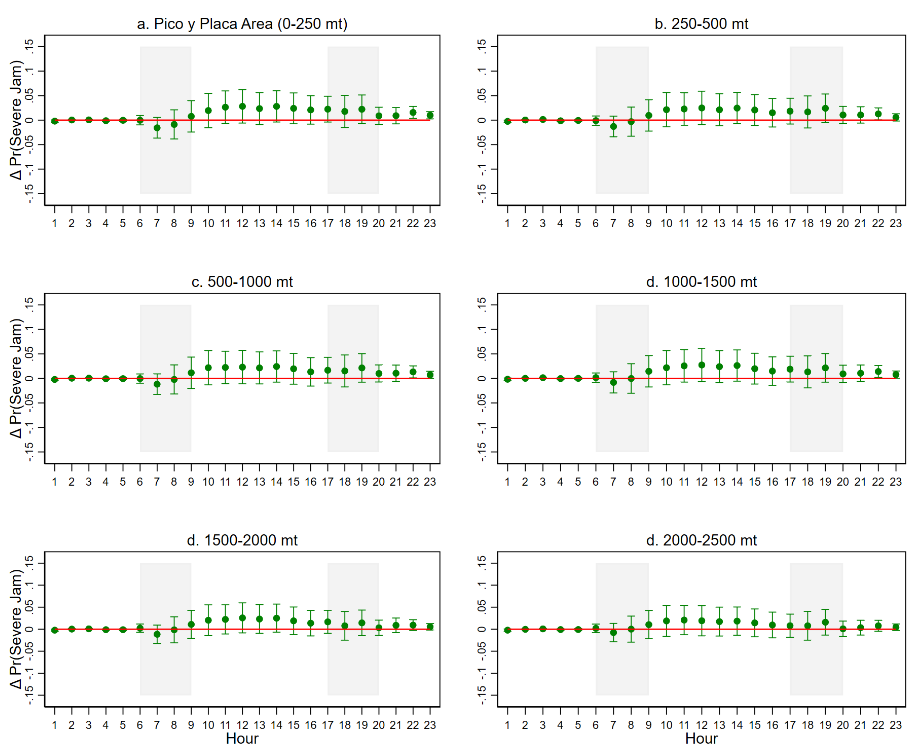
Source: Prepared by the authors. *Note*: Horizontal axis represents two-weeks periods. Period 0 are the two weeks when *Pico y Placa* sarted. Period 1 is the two-weeks following, and so on. The two dashed vertical lines mark the start and end of the transition period that coincided with the Panamerican and Parapanamerican Games. The reference period includes weeks -28 to -21 before the start of the restrictions. All figures show 95 percent CI.

Figure B4. Hourly impacts of *Pico y Placa* on Pr(severe traffic jam) - Local roads

Panel a. Early Impact (September 2 to October 13 2019)



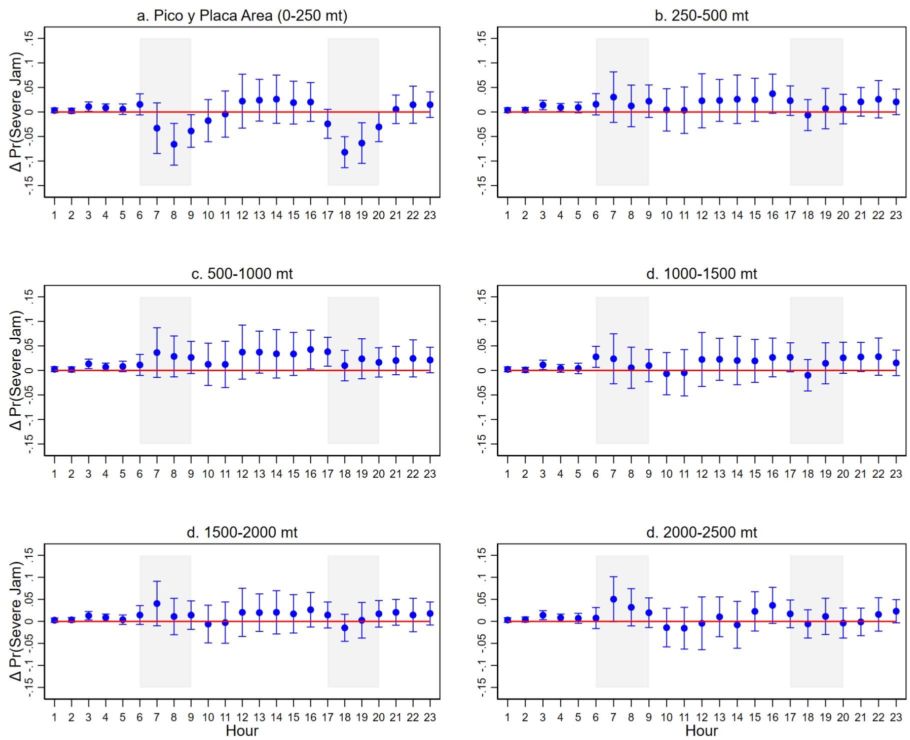
Panel b. Late Impact (October 14 to December 22 2019)



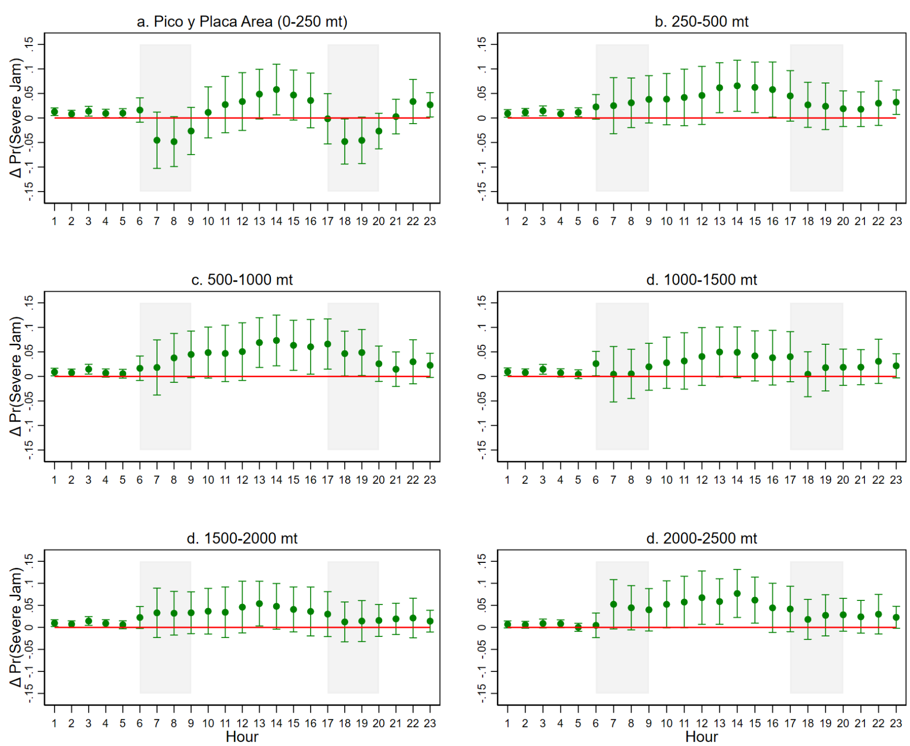
Source: Prepared by the authors. *Note*: The horizontal axis is the hour of the day. Morning and afternoon *Pico y Placa* hours are represented by the shaded areas. The vertical lines represent 95 percent confidence intervals.

Figure B5. Hourly impacts of *Pico y Placa* on Pr(severe traffic jam) - Non-local roads

Panel a. Early Impact (September 2 to October 13 2019)



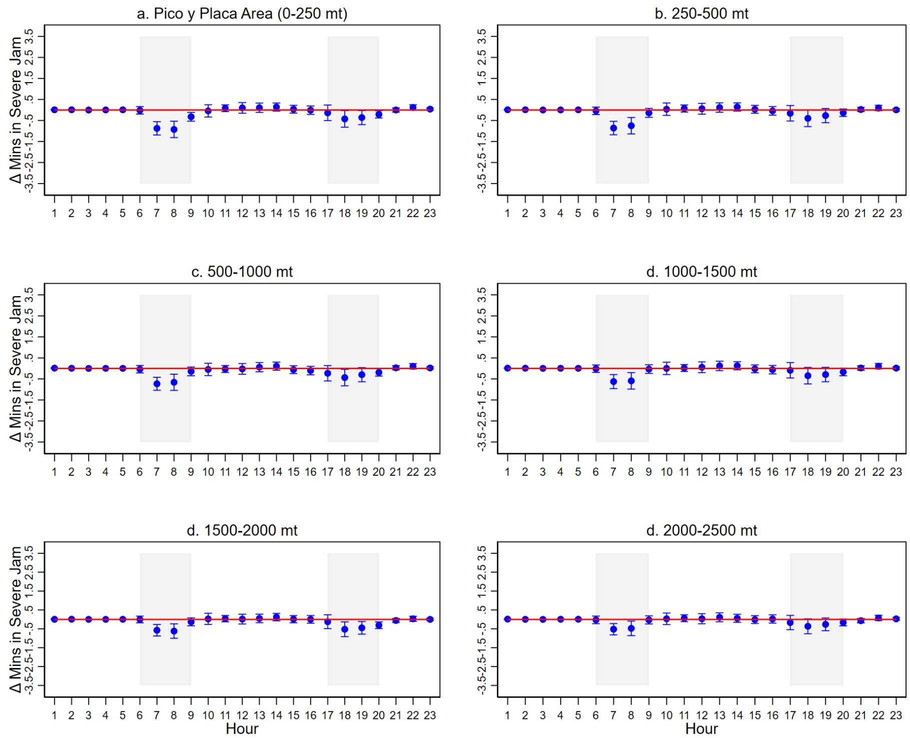
Panel b. Late Impact (October 14 to December 22 2019)



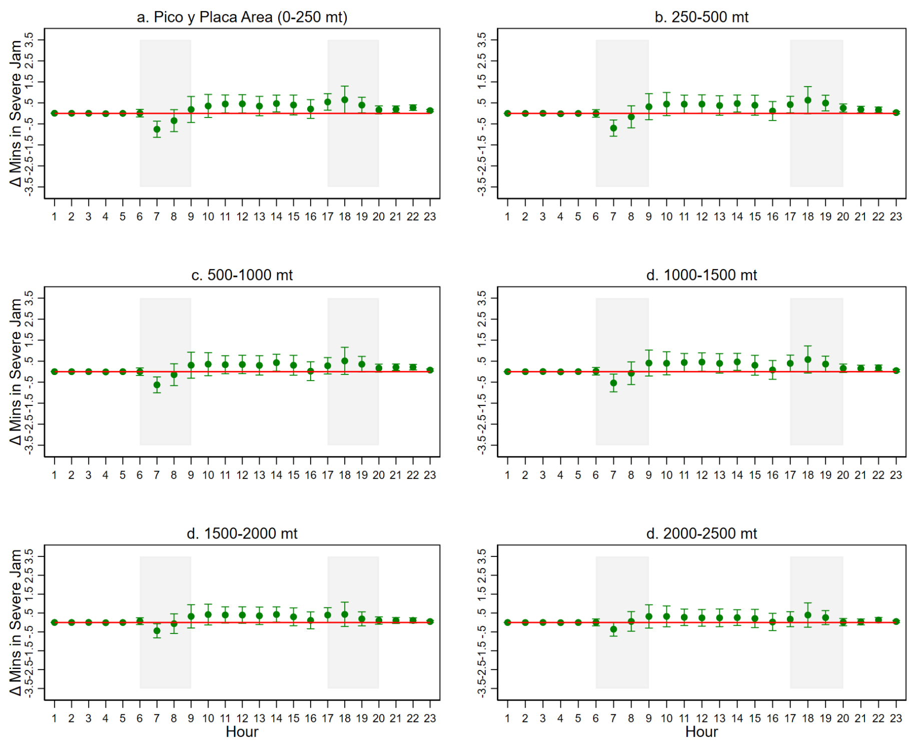
Source: Prepared by the authors. *Note*: The horizontal axis is the hour of the day. Morning and afternoon *Pico y Placa* hours are represented by the shaded areas. The vertical lines represent 95 percent confidence intervals.

Figure B6. Hourly impacts of *Pico y Placa* on minutes in severe traffic jam - Local roads

Panel a. Early Impact (September 2 to October 13 2019)



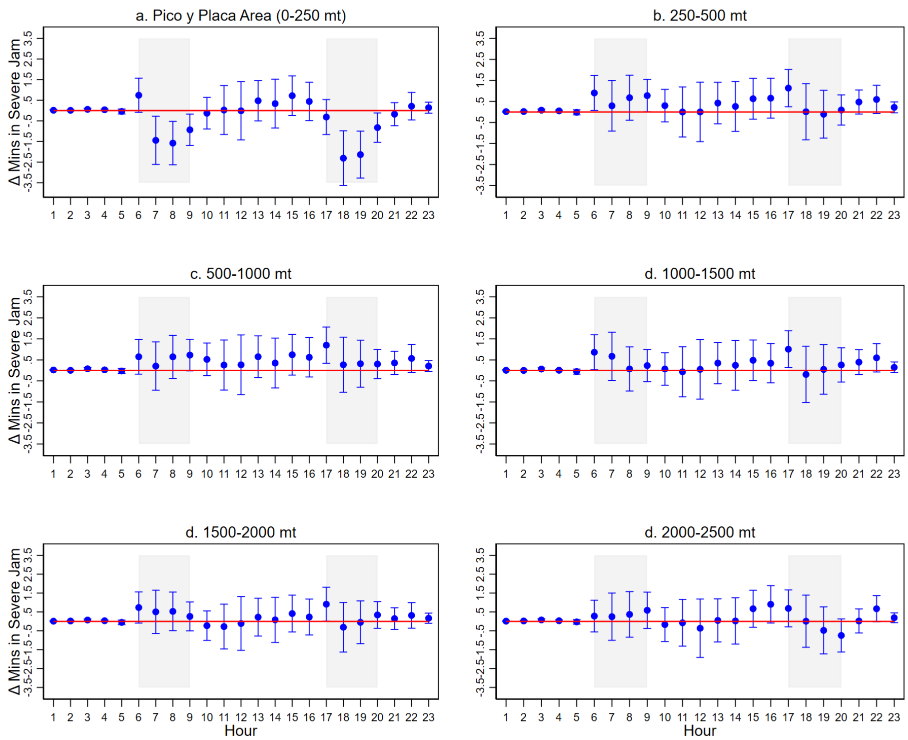
Panel b. Late Impact (October 14 to December 22 2019)



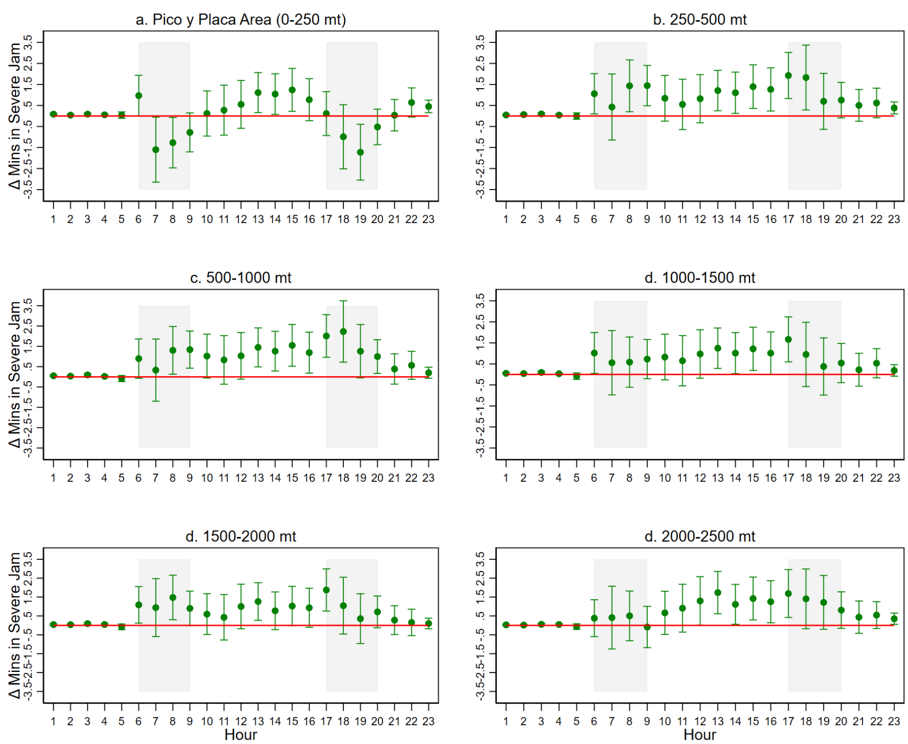
Source: Prepared by the authors. *Note*: The horizontal axis is the hour of the day. Morning and afternoon *Pico y Placa* hours are represented by the shaded areas. The vertical lines represent 95 percent confidence intervals.

Figure B7. Hourly impacts of *Pico y Placa* on minutes in severe traffic jam - Non-local roads

Panel a. Early Impact (September 2 to October 13 2019)

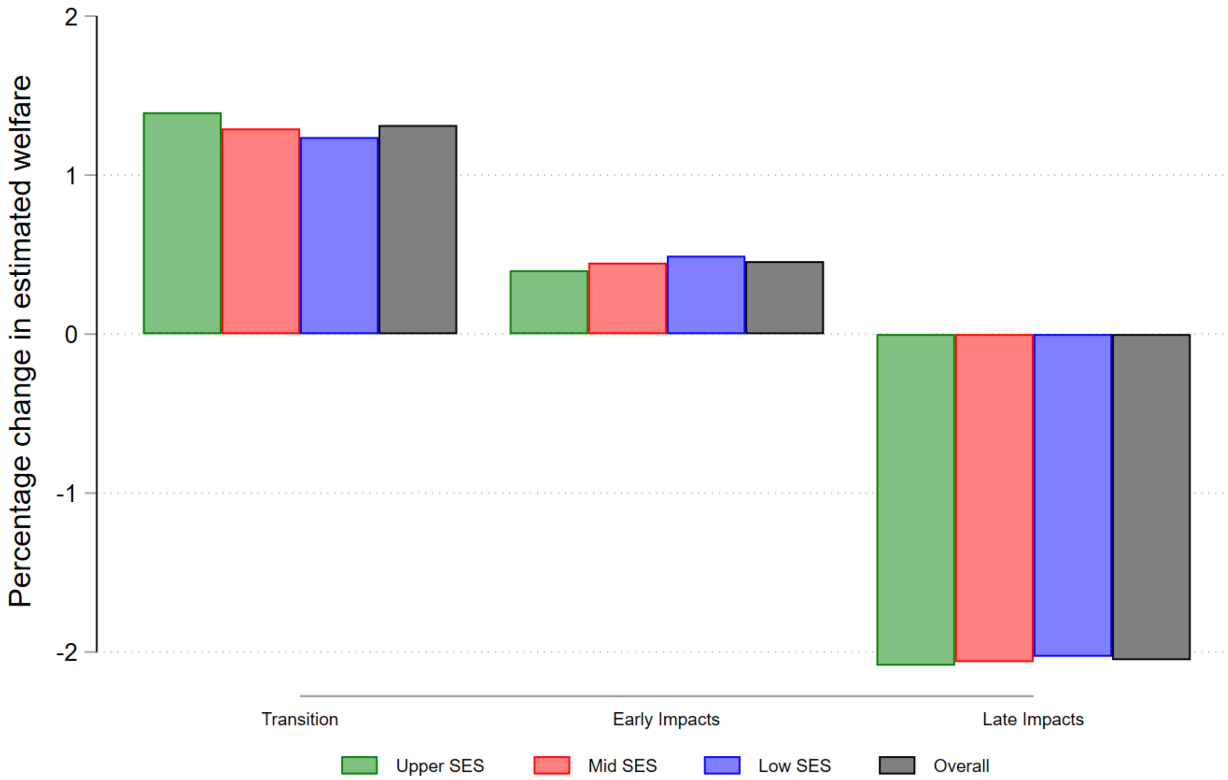


Panel b. Late Impact (October 14 to December 22 2019)



Source: Prepared by the authors. *Note*: The horizontal axis is the hour of the day. Morning and afternoon *Pico y Placa* hours are represented by the shaded areas. The vertical lines represent 95 percent confidence intervals.

Figure B8. Total Welfare Effects by Socioeconomic Status



Source: Prepared by the authors. *Note*: For each period the estimated welfare change is estimated as a weighted average of η_τ. Weights are the interaction of the initial ratio of average free-flow speed over average circulation speed by hour, distance ring and road type; and total kilometers by distance ring and road type. The aggregation of kilometers weights by free-flow speed to consider differences in road capacity. Weights are computed for the group of segments that fall within the corresponding SES boundaries defined by the traffic zone. The SES classification of the traffic zones was based on the majority SES category in the traffic zone according to Lima's 2012 Origin-Destination survey (JICA, 2013)