The Congestion Impacts of Curfews and Externalities on Road Traffic Crashes*

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Abstract

Curfews are a popular tool for public safety, most recently used across the world with the aim of curbing the COVID-19 pandemic. Curfews change the cost of being on the road at different times of the day; the behavioral response this elicits from drivers could have important externalities for road safety. This paper studies this behavioral response using the example of a curfew implemented in Kenya during COVID-19. We find that the curfew leads to large reductions in crashes during the curfew hours, when cars are off the road, but that these reductions are fully offset by an increase in crashes in the hours before the curfew. We argue that this results from the inflexible nature of work trips, which shifts trips that would typically occur during the curfew to just before—as close as possible to the curfew (and their original departure time). This behavior leads to both increased density of vehicles on the road in the hours leading up to the curfew and increases in speed due to the urgency of reaching home before the start of the curfew. We use a change in the timing of the curfew that no longer interacts with work trips as well as a curfew policy implemented during a similar time but in the context of Paris, France where there was a mandatory work from home order to demonstrate that, under more flexible trip conditions, there is no longer a negative externality of the curfew.

JEL Codes: R41, R42, I18
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1 Introduction

Policies that change the relative cost of being on the road at different times are often used by governments to mitigate externalities that can arise from higher mobility and to achieve specific goals such as decreasing congestion or pollution in large cities, or supporting public health measures. Yet these policies in themselves could have externalities. One important externality relates to road traffic crashes. Increasing the cost of being on the road can have an ambiguous impact on road safety. On the one hand, these policies could improve road safety, with fewer vehicles on the road leading to a decrease in crashes due to the accident externality from each additional vehicle (Edlin and Karaca-Mandic, 2006). On the other hand, lower car density can enable driving at higher speeds; therefore, the policies could increase the probability of a crash if those remaining on the road drive at higher speeds. If the restrictions are limited to particular locations or times, they could also have spillover effects for the adjacent locations or time periods if people adjust their mobility patterns to compensate for the new policy. The size and sign of the impact will depend on the behavioral response to the restrictions.

In this paper, we focus on one type of policy that is frequently used across countries, the implementation of a curfew, to study how an extreme change in the price of being on the road affects road safety. This is one of the first studies to look at this question in a lower-middle-income country, despite the fact that 92% of fatalities occur in low- and middle-income countries (LMICs), which account for only 60% of the world's vehicles (WHO, 2023). We are able to focus on this important context due to our multiyear investment in data infrastructure that turned a data-poor into a relatively data-rich environment. In Kenya, a dusk-to-dawn curfew was implemented in March 2020 to prevent the spread of COVID-19. We use a double-difference strategy, harnessing detailed high-frequency data on road traffic crashes, to compare crashes before and after the curfew implementation and relative to the same period a year earlier. To assess the validity of the double-difference approach, we examine pre-trends and follow the sensitivity-check strategies for the parallel trends assumption proposed by Rambachan and Roth (2023). We focus on impacts during the curfew hours as well as the incidence of spillovers in the hours right before the curfew, including studying externalities in the form of changes in the crash rate. We look at changes in the density and speed of vehicles on the road, postulating inflexibility in evening departure times as a mechanism for the spillovers we find during the hours leading up to the curfew.

Our results show that the curfew leads to large reductions in crashes during the curfew hours, when cars are off the road. Nevertheless, the spillover effects are large and significant, with the reductions offset by an increase in crashes in the hours right before the curfew. Importantly, analyzing the change in crashes as compared to the change in vehicles on the road, the probability of a crash increases both during the curfew period and during the hours right before the curfew.

We argue that the spillovers during the pre-curfew hours are driven by the inflexibility in departure time during the

evening commute, the initial curfew being set during Nairobi's typical evening rush hour (19:00), and the high costs associated with violating the curfew. These factors caused trips typically taken during the curfew hours to be bunched in the hours right before the curfew, leading to higher density. Simultaneously, the close timing of these trips to the curfew start time causes urgency that leads to increased speeds, with the largest increase in speed between 18:00 and 19:00. We examine two cases where inflexible work trips are much less prevalent. In the first case, the curfew start time in Kenya is revised from 19:00 to 21:00 (after the evening rush hour). We find that the curfew reduced crashes in the night hours without generating offsetting increases in the hours prior to the curfew. There is also no longer an increase in the probability of a crash. Once the curfew is revised to start after the typical evening commute, there is no longer bunching of trips in the pre-curfew hours or the large increase in speed. The second case we look at is a similar curfew policy in Paris, France, from 18:00 until 6:00. The difference in the context is that in France there was a mandatory work from home order that led to huge increases in remote work and therefore fewer work trips occurring during this period. We find a decrease in severe crashes during the curfew period, though this seems to be proportional to the decrease in vehicles on the road as there is no significant change in the crash rate. We find no spillovers in the hours leading up to the curfew, which aligns with our findings that there are no increases in density or speed in the pre-curfew hours in Paris, unlike those present in Kenya during the first curfew.

Our contribution to the literature is threefold. First, we contribute to understanding externalities that can arise from road pricing policies. Green et al. (2016) and Tang and van Ommeren (2022) find a decrease in crashes in the area of London where congestion pricing was implemented, and positive spillovers in the form of fewer crashes in nearby areas (Green et al., 2016). In our context, we find that a high price (in the form of penalties for breaking the curfew) and associated large reductions in density lead to fewer crashes but a higher probability of being involved in a crash during the curfew hours. Moreover, the high price results in negative spillovers in the hours just before the price took effect (the start of the curfew), during which density, speeds, and crashes increase. Importantly, we extend the analysis of road safety beyond high-income contexts (Bünnings and Schiele, 2021; Edlin and Karaca-Mandic, 2006; Bauernschuster and Rekers, 2022; Van Benthem, 2015). As urbanization in LMICs continues to increase, congestion, a widespread problem already, will only worsen and policies to address this will be needed. Yet, while there is research on the impact of congestion pricing policies in high-income countries including the UK and US, the lessons learned may not translate to different settings. Road pricing policies that turn on at specific times could have different impacts in settings with more inflexible mobility—especially if pricing turns on during popular commuting times. Moreover, policies to reduce congestion could have different road safety impacts in settings with different infrastructure quality and effectiveness of speed enforcement.

Second, we contribute to the literature focused on curfews. Evidence looking at curfews used to curb night driving by inexperienced drivers finds a reduction in crashes (Williams and Preusser, 1997). Even when inexperienced drivers fully substitute night with day driving, crashes are reduced (Bolduc et al., 2013). Here we investigate what happens

when these restrictions are extended to all drivers. In this context, we find that curfews can create large negative unintended effects through spillovers on road safety by increasing the probability of a crash during non-curfew hours. This adds to the limited literature showing other negative externalities of curfews, such as on increases in gun violence (Carr and Doleac, 2018).

Third, we contribute to the literature looking at the impacts of disease control policies on behavior, and specifically the health externalities of these policies through the channel of road safety. Focusing on the U.S., Lin et al. (2021) find that lockdown policies led to an overall decrease in crashes, though they find heterogeneity based on demographic characteristics and geography. During the pandemic, curfews were found to have significant direct costs on freedom of movement, assembly and expression, especially when enforcement resorts to violence (Ravindran and Shah, 2023; Katana et al., 2021). They also appear to have had little impact on slowing the pandemic (de Haas et al., 2022; Huber and Langen, 2020) and may have even increased the spread of disease as individuals shifted activities to pre-curfew hours, increasing contact-density during these times (Sprengholz et al., 2021). Our results demonstrate important negative externalities of curfews for road safety, further raising into question whether this is a policy that should be implemented during a health crisis.

2 Background and Conceptual Framing

Road traffic crashes (RTCs) are the leading cause of death for children and young adults age 5-29; 20 million to 50 million people suffer non-fatal injuries each year (WHO, 2023). Kenya's rate of estimated fatalities per 100,000 is 28.2, higher than the already highest regional average of 19.4 fatalities per 100,000 for Africa (WHO, 2023). Policies that affect road safety, whether intentionally or unintentionally, can therefore have important consequences for human life and public health.

Policies that change the price of being on the road directly affect mobility and vehicles on the road and thus indirectly can affect road traffic crashes. Obvious policies that change the price of being on the road include congestion pricing and highway tolls. A policy that has not been studied is the implementation of a curfew. With the goal of reducing people (and vehicles) on the street and a cost equal to the penalty for breaking curfew if caught, this type of policy could be also seen as akin to other policies that directly change the price of being on the road. Curfews are widely used by governments for managing social unrest or containing specific groups of people, such as youth. During the COVID-19 pandemic, a large number of countries implemented a curfew as a measure to limit the spread of the disease.

We study the relationship between curfews and road safety using the curfew policies implemented in Kenya during COVID-19. On March 25th 2020, the government of Kenya announced that a dusk-to-dawn (19:00-5:00) curfew would take effect on March 27th (OSAC, 2020). The country simultaneously implemented additional mobility restricting

policies including closing schools, restricting travel and recommending work from home on March 15, 2020, and closing bars and restaurants (except for take-out) on March 22nd (Ministry of Health, 2020; Kagwe, 2020). On June 7th, the government eased some movement restrictions and revised the curfew hours to 21:00-4:00 (Kai, 2020). This curfew continued to remain in place until November 4, 2020, when curfew hours were reduced to 22:00-4:00. The penalty for failure to observe the curfew included either a fine of up to KSh10,000, imprisonment for up to three months, or both. The curfew was strictly enforced, with reports indicating that Kenyan Security forces detained those out after the curfew (Bearak and Ombuor, 2020). As with curfews in other contexts, exceptions were made to the curfew for certain categories of people, such as health professionals and utility works, among others (Government of Kenya, 2022).

To help guide our analysis of the relationship between curfew policies and road traffic crashes, we use existing literature to outline an intuitive framing. The literature has looked at the role that car density plays in vehicle crashes holding speed constant (Edlin and Karaca-Mandic, 2006), as well as the impact of speed on road traffic crashes outside of the constraints of congestion (Bauernschuster and Rekers, 2022; Ashenfelter and Greenstone, 2004). To understand the impact of policies that change the cost of being on the road in an urban setting, density and speed need to be considered together.

Several papers layout a simple framework whereby most crashes occur between two or more vehicles, and therefore the probability of a crash depends on the number of vehicular encounters, and the number of accidents will increase as the square of the traffic flow, F (Newbery, 1988; Dickerson et al., 2000; Peirson et al., 1998). This suggests an accident externality from each additional driver on the road. In particular, Dickerson et al. (2000) proposes that the expected number of crashes, N, is given by $N = \frac{1}{2}\lambda F^2$, whereby λ represents road conditions, driving behavior, and road network characteristics. Higher levels of traffic reduce speed and make driving behavior safer, suggesting that λ is a function of F. How much the accident externality is internalized by road users depends on the functional form. At the same time driving behavior is also informed by the cost of being on the road. If the cost of being on the road goes up, drivers may increase speed in order to maintain their cost of travel time (Ashenfelter and Greenstone, 2004). Additionally, a high cost of being on the road could induce changes in behavior at the extensive margin if individuals choose to cancel trips or at the intensive margin if they shift trips to lower cost times (Kreindler, 2024).

A curfew policy leads to a large increase in the cost of being on the road during the curfew hours. This would decrease the number of vehicles on the road, which may lead to a decrease in crashes, with the size of the decline in crashes dependent on the decrease in vehicles and the size of the accident externality. At the same time, the lower number of vehicles could induce an increase in speed if vehicles were traveling below the speed limit due to traffic constraints, which could increase crashes. Additionally, for those individuals that were not exempted from the curfew, the higher cost of being on the road could lead to a further increase in speed in order to reach home more quickly and decrease the expected cost of travel time.

There could also be important spillovers in the hours outside of the curfew. The high cost of trips during the curfew may cause changes at the intensive margin with displacement of trips to non-curfew hours when the cost is lower. The more inflexible trips are in their departure timing, the more likely these displaced trips will be taken during the pre-curfew hours as close to the curfew time as possible. This could lead to significant increases in the number of vehicles in the pre-curfew hours, which would simultaneously reduce speed. At the same time, the closer the time is to the curfew, the higher the cost of travel, and in particular, the high cost imposed by the curfew could generate an urgency experienced by drivers aiming to arrive home before the curfew is in effect. This idea is in line with the preferences for urgency documented by Bento et al. (2020), which reflect discrete penalties that are faced by individuals for being late. This could affect driver behavior and induce higher speeds.

3 Data

There are three main types of data that we use in this paper. First, we use administrative data on road traffic crashes (RTCs) that come from paper records (situation reports) produced by the National Police Service. Second, we use data from Flare, the largest emergency response dispatch platform in Kenya with over 800 ambulances available on call, 200 of which are in Nairobi. Finally, we use several big data sources to analyze mobility and congestion including sensor-generated traffic counts, Waze, Uber and Google Maps. An overview of data sources and variable construction is shown in Table A.1.

3.1 Road Traffic Crash Data

Our main source of data on road traffic crashes comes from the Kenya National Police Service (NPS). We construct a unique, detailed dataset on the time and location of RTCs, which previously did not exist for Kenya, by working with NPS to digitize all the Situation Reports for the 14 traffic police stations in Nairobi. These are paper records that are produced for each crash that involves an injury or notable property damage. We use 9,760 crash reports from January 1, 2014-December 31, 2020 that we have manually digitized. While this data does not include minor crashes reported to the police or crashes that were not reported to the police, it is the most comprehensive set of data on the location, casualties and time of crashes for the city of Nairobi. We aggregate total crashes occurring per hour for Nairobi.

We cross-reference this dataset with data on road traffic crashes from Flare, an emergency response dispatch platform that aggregates emergency response fleets into a single platform and runs a 24/7 dispatch center much like 911. The majority of emergency calls made to Flare are for RTCs. Of the calls coming in, almost half come from good Samaritans who witness a situation requiring an ambulance. The other half of the calls are evenly split between calls coming from the police who show up on the scene of an emergency and calls coming from those who are part of

the membership service that Flare offers.[1] Similarly to the data from the police, we aggregate data on the number of RTCs recorded by Flare per hour for January 1, 2019 to December 31, 2020.

3.2 Data on Congestion and Speed

We rely on four data sources to measure changes in vehicle density and speed. We use traffic jam information from the Waze for Cities Program (Waze, 2025). Data has been collected by the team from November 2018-November 2022. Waze provides information on the location, speed, and delay time of traffic jams; data is updated at 2 minute intervals. We compute the total traffic delay time due to traffic jams in Nairobi hourly. We use this delay time of traffic jams as a proxy for congestion on the roads.

We use data on number of vehicles on the road measured from road sensors installed in six major intersections in Nairobi by the Kenya Urban Roads Authority. Data from each sensor cover a period of at least two months.[2] We use the relationship between vehicles on the road and congestion as measured by Waze to predict vehicles on the road during the months when we do not have data for some of the intersections.[3] In a context like Nairobi, where there is not a good measure of vehicles on the road or vehicle miles traveled, this high-frequency data provides one of the best measures for how the number of vehicles traveling throughout the day might be changing during this period.[4] Looking at the period after the curfew is implemented, we see that the predicted vehicle counts across the different intersections demonstrate very similar magnitudes of change. This makes us more confident that the changes we measure in these intersections are likely representative of vehicles on the road more broadly in the city. We generate an index for each intersection for vehicle counts using vehicle counts in the pre-curfew period of 2020 by day of week as the baseline. We use an average of this index across intersections as a proxy for the change in total vehicle counts for the city.

To measure speed, we query real-time travel times from Google Maps. We have collected data starting in February 2019. We query travel times along thirteen segments of major corridors in Nairobi, including Mombasa Road, Uhuru Highway and Waiyaki Way, that we selected due to their importance for travel within Nairobi. We obtain information on the time it takes to travel from the start to the end of the segment using a vehicle given current traffic conditions. The speed is calculated by dividing the distance of the segment by the estimated travel time. We query this information every 30 minutes. We verify these measures using speed information from Uber Movement data. Uber provides speed data aggregated from Uber trips at the road segment level across Nairobi. Average speed is available hourly, and data is made available through March 2020, after which time Uber stopped producing these statistics. Given data is not available beyond this time, the Uber data is only used for cross-validating speed data from Google and is not used

[1] Businesses can sign up through Flare's membership service, rescue.co, to have their employees or customers receive access to Flare services free of charge. This service has been especially popular with ride sharing companies.

[2] Data for four of the intersections is available for January and April 2020, for one of the intersections data is available for February and April in 2019 and 2020 and July 2020, and for one intersection data is available for January-April 2020.

[3] See Appendix B for a description of how these predictions were generated.

[4] For example, while there are data on vehicle registrations, data is not collected on vehicles that are no longer in commission, which hinders an accurate picture of the volume of active vehicles.

for the analysis. We find that during daytime hours, the two datasets align quite well (See Appendix Figure A.6 for comparison). At night after the curfew is implemented, we see the two datasets diverge in their speed values with the Google data showing lower values. Given the extremely low volume of vehicles during those hours, there may not be enough data to provide a valid signal on speed; therefore, we do not use the speed data during the night hours for analysis.

For all the analyses, across all outcomes and indicators, we analyze three time intervals: (1) Daytime, including 5:00 to 17:00 hours, (2) Pre-Curfew time, including 17:00 to 20:00 hours, and (3) Curfew time that covers 20:00 to 5:00. While the curfew started at 19:00, we include the 19:00-20:00 hour in the pre-curfew interval given the combination of: (1) the delay in the reporting of crashes by the police while they arrive to the crash scene, particularly at the time they are enforcing the curfew start time and (2) the behavior just after 19:00 is likely to be more closely associated with the behavior before the curfew rather than the behavior of those driving during the later curfew hours given that most likely people on the road just after 19:00 were aiming to get home before the 19:00 curfew and were delayed and still on the road after 19:00.

When working with data derived from smartphones, it is important to consider the potential for biased measures (Milusheva et al., 2021). The traffic and congestion data from Waze and Google Maps are likely to be minimally affected by bias arising from smartphone use because they collect measures of how quickly cars are able to travel based on the traffic on the road, which would be determined by both smartphone and non-smartphone owners on the road. Nevertheless, the data may have quality issues when few smartphone owners are on the road. By combining and comparing datasets, we can triangulate our measures to ensure consistency.

4 Empirical Framework

Our main empirical strategy is a modified double-difference specification modeled after Tarduno (2021). We compare crashes in the period after the first curfew was implemented (March 27-June 6) to the period before any COVID-19 policies were implemented (January 1-March 15). We examine the difference between these two periods in 2020 and 2019.[5] We use 2019 as the comparison year, as it is closest to our year of interest and therefore most comparable in terms of road infrastructure and policies. To check for pre-trends, we also examine the difference between these periods from 2014 to 2018 against 2019. Our main specification is:

$$C_{it} = \alpha + \sum_{y \neq 2019} \beta_y \cdot \mathbf{I}\{\text{Year} = y\} \times \text{Post}_{it} + X'_{it}\boldsymbol{\delta} + \lambda_{\text{dow}(t)} + \lambda_{\text{week}(t)} + \lambda_{\text{year}(t)} + \varepsilon_{it} \tag{1}$$

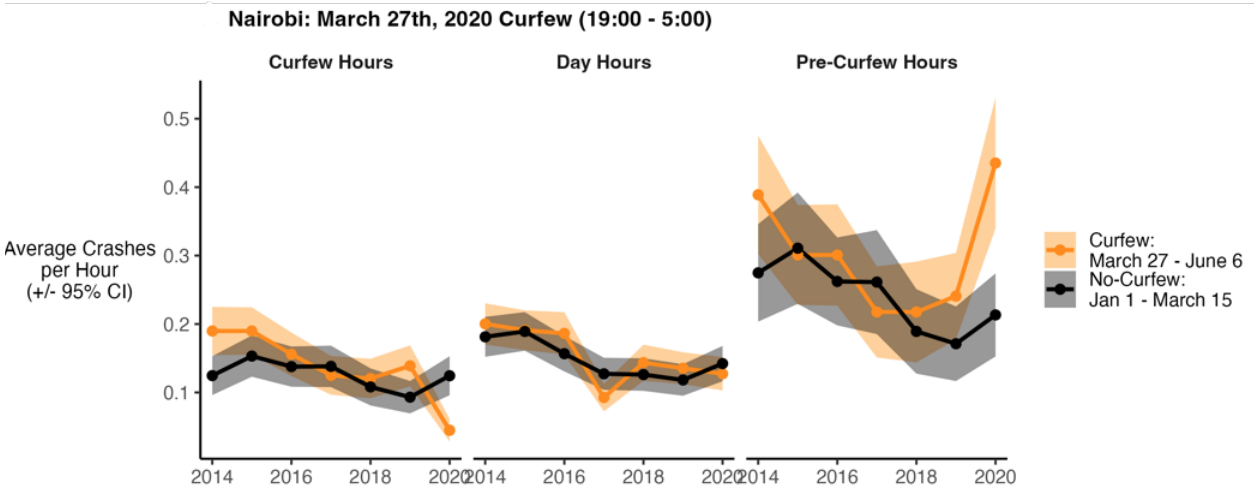
where C_{it} is the outcome of interest on day i of year t, either number of crashes or a proxy for rate of crashes. β_y

[5] We do not include the days from March 16-March 26 in the analysis because some policies had been implemented to limit mobility but the curfew was not yet implemented.

captures the difference in the outcome for year y relative to the baseline year 2019 in the post-curfew period. X_{it} is a vector of weather controls (precipitation, temperature, and wind speed). $\lambda_{\text{dow}(t)}$, $\lambda_{\text{week}(t)}$, and $\lambda_{\text{year}(t)}$ are day-of-week, week-of-year, and year fixed effects, respectively. ε_{it} is the error term. We estimate this equation for three time intervals focused on crashes during curfew hours (20:00-5:00) as well as during the pre-curfew hours (17:00-20:00) to test for spillovers, and daytime hours (5:00-17:00) as a comparison. The analysis is conducted at the daily level. Our main coefficient of interest is β_{2020}, which captures the impact of COVID-19 policies on our outcomes.

The main assumption required in order for us to interpret β_{2020} as a causal impact relies on parallel trends in previous years between the two time periods that we are calling treatment and control. We look at the raw data, comparing the treatment period when the curfew was implemented (March 27-June 6) to the control period when there were no COVID-19 policies in place (January 1 - March 15) across years from 2014 until 2020 (Figure 1). We analyze the three time intervals separately. Overall the two time periods move in parallel, with a steady decrease in crashes across the years from 2014 to 2019. We capture this explicitly in our specification by including the pre-trends, which are captured by β_{2014} - β_{2018}. We also apply the robust inference method of Rambachan and Roth (2023) which allows for bounded deviations from pre-treatment trends to conduct valid inference under plausible violations of the parallel-trends assumption. We test the degree to which the slope of the pre-trend could change to still maintain valid inference.

Figure 1: Trends in crashes



In the absence of the curfew, mobility and the number of cars on the road would still be lower due to the other mobility policies, including the closure of restaurants, bars and schools. In order to try to difference out the effect of lower mobility due to other policies, we estimate a triple-difference specification as in Equation 2, integrating all hour intervals into the same regression. We interact the indicators for the curfew year $\mathbf{I}\{2020 = y\}$ and curfew period $Post_t$ with the curfew hour intervals c, where the two periods of interest are the curfew hours from 20:00-5:00 and

the pre-curfew hours from 17:00-20:00, with the comparison being the daytime hours from 5:00-17:00. Therefore, $\delta_{2020,c=curfew}$ and $\delta_{2020,c=precurfew}$ are our coefficients of interest. As with the double-difference, we estimate the equation using data from 2014 to 2020 and also estimate triple difference parameters for years 2014 through 2018 to help test for pre-trends and conduct sensitivity analysis following Rambachan and Roth (2023). The analysis is conducted at the daily level. The daytime interval may have been affected by the curfew as well if individuals shift trips they would have performed in the evening to the daytime, but this would bias us towards finding smaller spillover effects during the pre-curfew hours.

$$C_{it} = \alpha + \sum_{y \neq 2019} \beta_y \, \mathbf{I}\{\text{Year} = y\} + \theta \, \text{Post}_t + \sum_{c \neq \text{daytime}} \phi_c \, \mathbf{I}\{\text{CurfewHours} = c\} + \sum_{y \neq 2019} \sum_{c \neq \text{daytime}} \delta_{yc} \, \mathbf{I}\{\text{Year} = y\} \times \text{Post}_t \times \mathbf{I}\{\text{CurfewHours} = c\} + X_{it}'\boldsymbol{\gamma} + \lambda_{\text{dow}(t)} + \lambda_{\text{year}(t)} + \lambda_{\text{week}(t)} + \varepsilon_{it} \quad (2)$$

We estimate two outcomes. The first is the number of crashes. The second outcome is the crash rate, which is a measure of the probability of being in a crash. Changes in crash rates have been observed in response to other policies that impact mobility, where some researchers have found a U-shaped association between traffic and crash rates—with the highest crash rates occurring at the lowest and highest levels of congestion (Green et al., 2016). Changes in the rate of crashes are an important indication of the additional externality of vehicle density and driver behaviors as an additional car on the road or more aggressive behavior could lead to an increase in the likelihood of a crash that goes beyond the proportional increase (Edlin and Karaca-Mandic, 2006). We use the index for vehicles on the road during each time interval as a proxy for changes in total vehicles on the road in Nairobi. We divide crashes by the index to measure the proportional change in crashes. We use bootstrap standard errors given the estimated nature of the outcome variable.

5 Results

5.1 Crashes during the curfew and spillovers

We first examine the impact of the curfew on road traffic crashes during the curfew hours interval, from 20:00 until 5:00. Crashes decrease by 1.12 crashes per day during the curfew (Table 1 Column 1). The results suggest that during the curfew hours, the decrease in vehicle miles traveled was so large that it dominated the impact on road traffic crashes, leading to large decreases in crashes even if the lower density may have led to increases in speeds for those vehicles remaining on the road.

There is an important question of whether the curfew policy had spillover effects on the other hours in the day, in particular if trips that would typically be taken during the curfew hours are shifted to earlier. We study these potential spillovers by focusing on the hours right before the curfew time, 17:00-20:00. There is a significant positive increase in crashes during the three hours leading up to and at the beginning of the curfew (Column 2).[6] This result indicates negative spillover effects of the curfew in the form of more crashes occurring right before the curfew hours.

The estimated effects measured in Table 1, columns 1 and 2, result from both the curfew and other mobility restricting policies (e.g., closure of schools and bars). To isolate the impact of the curfew—irrespective of other mobility restricting policies—we compare our results to changes in crashes that occurred during the daytime hours of 5:00-17:00. When analyzing only daytime hours, the estimated coefficient is negative at -0.332, though it is not significant (Table 1 Column 3). We use a triple-difference specification following equation 2 to compare crashes in the pre-curfew hours and during the curfew hours to crashes during the daytime (again comparing 2019 to 2020 and comparing the period before the curfew was implemented and after the curfew was implemented). The estimated coefficient on the curfew hours is still negative and significant, but it is now smaller at -0.754 per day (Table 1 Column 4). On the other hand, the estimated coefficient on the pre-curfew hours is much larger, at 0.826 per day. Thus, controlling for the other policies that also affected mobility throughout the day, the negative spillovers during the pre-curfew hours fully offset any positive gains for road safety during the curfew hours.

A key assumption that is required for us to interpret these results as causal is that parallel trends exist when comparing the March 27-June 6 period with the January 1-March 15 period prior to 2020. The raw data presented in Figure 1 provides initial support for this assumption. Furthermore, we do not estimate any statistically significant differences between the two time periods prior to 2020 (see Appendix Figure A.1 for a visual representation of these findings). Nevertheless, there are limitations in using pre-treatment differences to evaluate the parallel trends assumption (Roth, 2022; Rambachan and Roth, 2023). To account for this, we also conduct sensitivity analysis following Rambachan and Roth (2023). Rather than imposing that the parallel trends assumption holds exactly, we instead bound the post-treatment violation to say that it cannot deviate too much from a linear extrapolation of the pre-trend. This is measured by M, which indicates the largest allowable deviation in pre-trend slopes that still permits valid inference for the reported coefficients before they "break down". Focusing on the double difference, the breakdown value M for a significant effect for the curfew analysis is greater than 0.05 and for the pre-curfew regression coefficient it is $M = 0.03$ (see Appendix Figure A.2). For the triple difference, the coefficient on the curfew does not pass the sensitivity analysis, but for the pre-curfew coefficient the breakdown value is $M = .04$. This analysis shows that the deviation from the estimated linear time trend needs to be huge to have a null effect of the impact of the curfew. For example, focusing on the spillover effect in the pre-curfew interval using the double difference specification, we can

[6] If crashes occurring during the hour 19:00-20:00 are removed from the analysis, the results still hold, with a significant positive increase in crashes from 17:00-19:00. See the robustness section for results.

Table 1: Impact of Mobility Reducing Policies on All Crashes in Nairobi, Kenya

	N Crashes				Crash Rate	
	Curfew Hours	Pre-Curfew Hours	Day Hours	All Hours	Curfew Hours	Pre-Curfew Hours
Panel A: March 27th Curfew						
2020 X Curfew Period	−1.133***	0.434**	−0.356		1.212*	0.821***
	(0.233)	(0.216)	(0.325)		(0.686)	(0.230)
2020 X Curfew Period X Curfew Hours				−0.751*		
				(0.396)		
2020 X Curfew Period X Pre-Curfew Hours				0.837**		
				(0.390)		
Num.Obs.	1017	1017	1017	3051	291	291
R2	0.171	0.083	0.099	0.180	0.139	0.223
R2 Adj.	0.135	0.045	0.061	0.161	0.032	0.130
Analysis Years	2014-2020	2014-2020	2014-2020	2014-2020	2019-2020	2019-2020
Panel B: June 6th Curfew						
2020 X Curfew Period	−0.217	0.067	0.026		0.115	0.105
	(0.153)	(0.189)	(0.317)		(0.214)	(0.195)
2020 X Curfew Period X Curfew Hours				−0.313		
				(0.348)		
2020 X Curfew Period X Pre-Curfew Hours				−0.006		
				(0.363)		
Num.Obs.	1584	1584	1584	4752	453	453
R2	0.103	0.074	0.098	0.318	0.114	0.185
R2 Adj.	0.071	0.041	0.066	0.306	0.019	0.097
Analysis Years	2014-2020	2014-2020	2014-2020	2014-2020	2019-2020	2019-2020

Notes. For regressions estimating crashes, robust standard errors are reported in parentheses; for regressions estimating crash rates, bootstrap standard errors are reported in parentheses and are estimated after performing 200 replications. *** (**) (*) denotes significance at 1% (5%) (10%) level. Regressions include fixed effects for year, week, and day of the week, and controls for weather (temperature, precipitation and wind). Only regression coefficients for 2020 are shown. See Appendix Figure A.1 for coefficients for 2014-2018. Crash data comes from the National Police Service and was digitized by the research team.

reject a null effect unless we are willing to allow for the linear extrapolation in the post-period to be off by more than ±55% from the linear trend estimated in the pre-period (see Table A.2 for the pre-trend slopes.).

The large decrease in crashes during the curfew and increase in crashes during the pre-curfew hours could potentially be explained just by the change in number of vehicles on the road. To analyze whether there may also be behavioral changes in how people drive or externalities from fewer/more vehicles on the road as seen in Green et al. (2016), we look at the crash rate in addition to the number of crashes. Focusing on the probability of a crash during curfew hours, we find that the curfew led to a significant increase in the crash rate despite the decrease in crash numbers (Table 1 Column 5). This suggests that while only a fraction of vehicles remained on the road during the curfew, the cost of being on the road at that time may have led to more unsafe driving behaviors such as an increase in speed that increased the probability of a crash. We also find a large and significant increase in the probability of a crash during pre-curfew hours (Table 1 Column 6). This could arise from two channels. If density increased during parts of this period because trips typically during the curfew period were displaced to these pre-curfew hours, it could lead to an increase in the crash rate due to the crash externality imposed by an additional vehicle on the road (Green et al., 2016; Edlin and Karaca-Mandic, 2006). If individuals increased their speed due to the urgency of getting home before the curfew, this could also lead to an increase in the likelihood of a crash. There is no change in the crash rate during the daytime hours.

5.2 Spillover Mechanisms

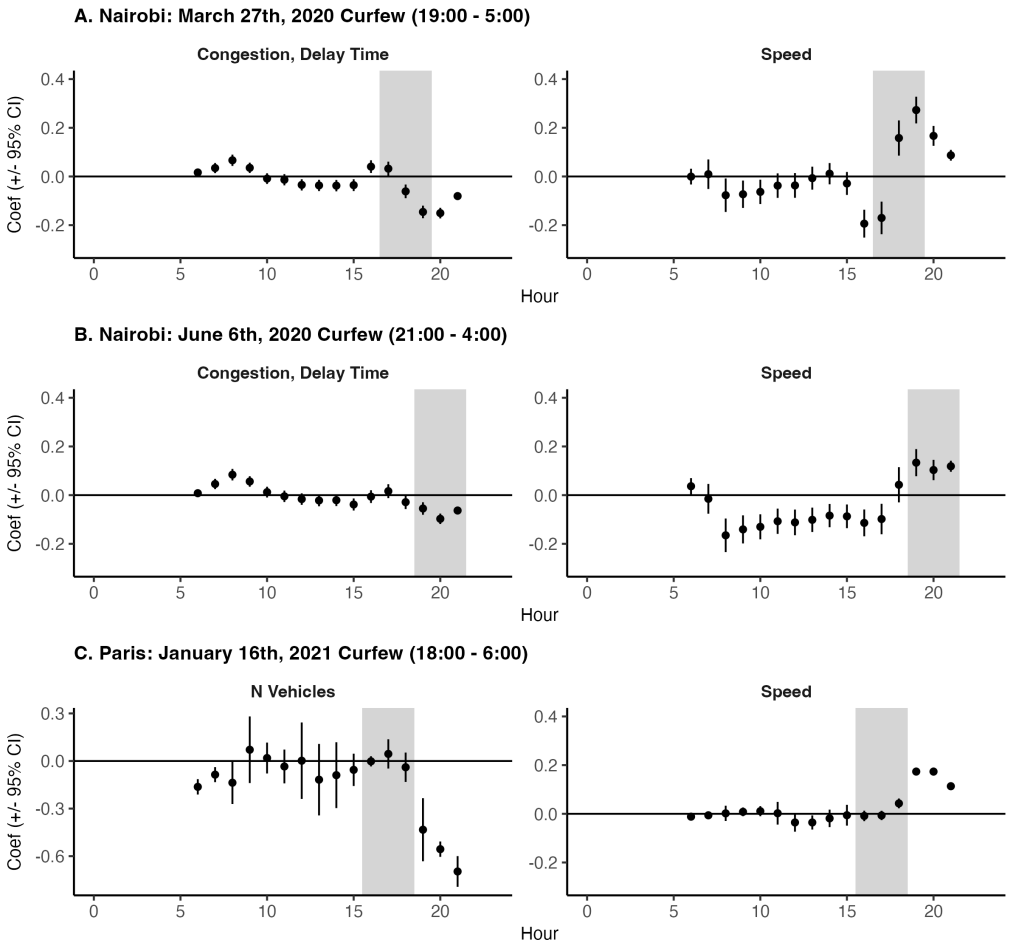
The intuitive framing provided earlier suggests two mechanisms that could lead to the spillover effects measured during the pre-curfew hours. First, if people shift trips that they would typically make during the curfew hours (which are now high cost) to non-curfew hours (which are lower cost), there could be an increase in vehicle density, which could increase crashes. Second, the high penalty for being late and driving past curfew leads to a significant increase in the cost of being on the road, especially the closer in time to the start of the curfew, which could induce increases in speed that could increase the road traffic crashes.

We use high frequency data on congestion and travel time from Waze and Google maps as proxies for density and speed. Unlike road traffic crashes, which are rare events, studying these outcomes using high frequency data makes it possible for us to focus on a shorter period and be able to compare the days after the first set of policies were implemented to the days after the curfew was implemented in order to isolate the impacts from just the curfew, as compared to the other mobility policies. Focusing on congestion across hours of the day, coefficients from hourly regressions demonstrate relatively little change from 6am until 15:00. There is then a significant increase in congestion 16:00-17:00, followed by a decrease in congestion at 18:00 and a larger decrease at 19:00 (Figure 2). In contrast, when looking at the changes in congestion during the days after the first set of COVID-19 policies were implemented and before the curfew, there is a significant decrease in congestion across all daytime hours from 6:00 until 18:00 (Appendix Figure A.5). This suggests that after the curfew is implemented, during the pre-curfew hours both effects may be present, whereby during part of the period there is an increase in density as trips that typically may happen during the curfew shift to those earlier hours followed by a large decrease in density during the second half of the pre-curfew period as vehicles start to get off the road in order to comply with the curfew. It is important to note that the average one way commute in Nairobi is close to one hour, which means a large number of trips are much longer, which would explain an increase in the density during the early pre-curfew hours, which allows time for individuals to make it home before the curfew starts.

Turning to speed, during the early daytime hours there is almost no change as compared to the days after COVID-19 policies were first put in place but before the curfew. At 16:00 and 17:00 there is a significant decrease in speed, which aligns with the increase in congestion. With higher congestion, vehicles are not able to drive as fast. At 18:00 and 19:00 there is a very large increase in speed (Figure 2). This supports the hypothesis that density decreasing leads to an increase in speed. Yet, the increase in speed is much larger than the comparable decrease in congestion suggesting that there is a behavioral shift of individuals changing their behavior in those hours right before the curfew to drive even faster. This supports the mechanism of urgency leading to more unsafe behavior.

The increase in density we see followed by the large increase in speed right before the curfew hours suggests that a large number of trips occurring during the curfew are inflexible ones that are shifted to just before the curfew and

Figure 2: Hourly difference-in-difference regressions for congestion, speed, and vehicles



lead to the spillover in crashes. We postulate that these inflexible trips are mainly people commuting home from work. We explore this hypothesis by studying two cases where the number of commuting trips affected by a curfew would be more limited in order to test if we measure the same changes in behavior that lead to spillovers in crashes. The first is looking at the same context of Nairobi, Kenya but analyzing what happens when the start of the curfew is shifted to later after the typical commute for most people. The second is looking at a different context, Paris, France, where a curfew was also implemented during the time of the typical commute. The difference in Paris, though, was that there was a mandatory work from home order that was strictly enforced, which would limit the number of commuters with inflexible trips.

We first look at the revision of the curfew in Nairobi to two hours later on June 6, 2020.[7] There is a significant but smaller drop in the number of crashes during the revised curfew period (Table 1 Panel B Column 1). Importantly, there is no longer a spillover effect of more crashes occurring during the pre-curfew hours from 19:00 to 22:00 (Column 2). Studying additional externalities by using the proxy for rate of crashes, there is no significant impact on the probability of a crash either during the curfew hours or the pre-curfew hours (Columns 3 and 4).

These findings suggest that the exact timing of the curfew can have important implications for road safety. When setting the curfew at a time when there are typically many inflexible trips, these trips are pushed to the times right before the curfew, leading to large increases in density. Additionally, the high number of people on the road right before the curfew also face a high penalty if they are late getting home, and this urgency leads to higher speeds. In contrast, when the timing of the curfew is at a later hour when there are already fewer people on the road, then any shifts in the timing of those few trips does not lead to large changes in density at one point in time right before the curfew. Additionally, those later trips may be more flexible since they are less likely to be tied to work, and therefore, individuals may be more able to either avoid the trips altogether or shift them in a way that does not lead to the same level of urgency to get home before the curfew. In a context with a large number of inflexible trips at certain times, the timing of the curfew can be very important and setting it outside of those times can help with minimizing negative externalities. Depending on the purpose of the curfew, there may be less flexibility with the specific hours. If the main goal, though, is having people stay home during the night hours, a curfew start time at 21:00 seems to be a better alternative for minimizing the externalities on road safety.

We further explore the role of flexibility in trips using a different context, Paris, France, which, similarly to Kenya implemented a curfew policy from 18:00 to 6:00 starting on January 16, 2021. An important difference from the Kenyan context is that France had a mandatory work from home requirement which led to a large percent of workers working remotely full or part time.[8] This would potentially lead to a decrease in the number of people on the road

[7] We focus on the first two months after the curfew is revised in order to match the length of time for which we observe the first curfew. The new curfew started at 21:00 hours but we again take 22:00 as the start of the curfew time to allow for the delays in the police registration of the crashes.

[8] There was over a 50% increase in full time work from home between the first quarter of 2021 and the first quarter of 2020 (Cahuc, 2022). This was similar to other high income countries, where overall the number of workers working from home nearly tripled. In contrast, in low and

overall, but also importantly would decrease trips that are inflexible. The large difference in people working from home can be seen from the google mobility reports that show the percent change in workplace activity from the pre-COVID period, with a much larger and sustained drop in Paris as compared to Nairobi (Appendix Figure A.3).

We conduct a parallel analysis to the one we do for Kenya. We use a similar difference in differences strategy, comparing the curfew period (January 16, 2021 - March 31, 2021) to a period when there were no mobility restriction policies that year (June 20, 2021 - December 11, 2021), and also comparing to these two periods in 2019, prior to the COVID-19 pandemic.[9] Data on road traffic crashes and vehicle counts (to determine a proxy for the crash rate) come from the French government's open data platform Direction Interministérielle du Numérique (DINUM) (2025). For our main analysis, we focus on fatal and severe crashes to ensure comparability with Kenya—where crash data primarily includes crashes of a similar severity. We split the day into the same three intervals: curfew hours (19:00-6:00), pre-curfew hours (16:00-19:00), and daytime (6:00-16:00).[10]

There is a large decline in fatal and severe crashes during the curfew hours, with no change during the daytime or pre-curfew hours (Table 2). Using the triple difference specification, in comparison to the daytime period, there is a significant decrease in crashes during the curfew period and no change in crashes during the pre-curfew period (Table 2 Column 4). This suggests there is no negative spillover of the curfew during the pre-curfew period and instead the restriction on mobility during the curfew has a positive externality for road safety with a decline in severe and fatal crashes. Our proxy for the severe crash rate shows no change during the curfew or pre-curfew hours (Table 2).

Looking at the mechanisms in Paris, there is no change in the number of vehicles on the road in the hours leading up to the curfew (Figure 2 Panel C). In particular, there is no increase in vehicles that would indicate people shifting trips from the curfew period to the time right before the curfew. There is a large decrease in vehicles during the curfew hours of around 60%, and we see that this large decline in vehicle density leads to an increase in speed on the road, though the percent increase in speed is only around one third of the percent decrease in vehicles (Figure 2 Panel C). Importantly, we do not see large increases in speed during the pre-curfew hours as we see in Kenya.

5.3 Robustness Checks

We conduct a number of different robustness checks (Table 3). First, there is the possibility that the likelihood of a crash being recorded by the police may have been affected by the curfew policy if it changed the likelihood of reporting a crash to the police or if the curfew led to increased police presence that increased reporting. In order to check if this may be driving the results, we use a different source of data on crashes coming from Flare to analyze the impacts of the curfew on crashes. We see very similar results for the curfew hours and pre-curfew hours as with the police

lower-middle income countries like Kenya, there was only a 4% increase.

[9] Full lockdown policies had been implemented prior to January 16, 2021 as well as after March 31, 2021; therefore, we focus on the period when the curfew policy was the main mobility restricting policy and there was no lockdown in place.

[10] Similarly to Kenya, we include the first hour of the curfew as part of the "pre-curfew" period given the potential delay in the timing of reporting of crashes relative to the occurrence of the crash.

Table 2: Impact of Mobility Reducing Policies on Severe/Fatal Crashes in Paris, France

	N Crashes				Crash Rate	
	Curfew Hours	Pre-Curfew Hours	Day Hours	All Hours	Curfew Hours	Pre-Curfew Hours
2021 X Curfew Period	−1.069***	0.155	0.005		0.001	0.002
	(0.254)	(0.205)	(0.316)		(0.003)	(0.005)
2021 X Curfew Period X Curfew Hours				−1.052**		
				(0.414)		
2021 X Curfew Period X Pre-Curfew Hours				0.160		
				(0.384)		
Num.Obs.	1751	1751	1751	5253	1738	1745
R2	0.544	0.442	0.593	0.546	0.514	0.369
R2 Adj.	0.528	0.422	0.579	0.538	0.498	0.347

Notes. For regressions estimating crashes, robust standard errors are reported in parentheses; for regressions estimating crash rates, bootstrap standard errors are reported in parentheses and are estimated after performing 200 replications. *** (**) (*) denotes significance at 1% (5%) (10%) level. Regressions include fixed effects for year, week, and day of the week, and controls for weather (temperature, precipitation and wind). Crashes include all crashes recorded by official sources. Data from 2014 - 2019 and 2021 used.

data (Panel A of Table 3). The coefficient for the decrease in crashes during the curfew hours is smaller; therefore, in the triple difference, we do not see a significant drop in crashes during the curfew period hours in comparison to the daytime hours. We see a very large and significant increase during the pre-curfew hours.

Given some extreme outliers in the number of crashes in a given daily time interval, we also test removing the top 1% of time intervals with the most crashes (out of all time intervals with at least one crash). This means we remove all time intervals that have 5 crashes or more, and we see that the results remain stable and are not driven by these extreme outliers (Table 3 Panel B).

As discussed, we include the hour from 19:00 to 20:00 in the "pre-curfew" hours interval despite the fact that the curfew began at 19:00, first because there may be delays in reporting of crashes and second because especially in the early part of that hour the behaviors may be more closely aligned to pre-curfew behaviors as individuals rushing home to beat the curfew start time find themselves on the road when the curfew initially starts. We test removing this hour from the pre-curfew interval and only focusing on 17:00-19:00. We find that results remain significant and comparable for the pre-curfew period, though the size of the coefficient is smaller (Table 3 Panel C).[11] This suggests that the results are not driven just by the 19:00-20:00 hour.

For the main analysis, the crash data is aggregated daily for each time period, but we also explore running the analysis at the individual hourly level and also aggregating further at the weekly level. In both cases, we find the results to remain consistent and significant (Table 3 Panel D and Panel E).

[11] The smaller coefficient may be mechanical since we now only include crashes happening in a two hour span as compared to a three hour span before.

Table 3: Impact of Mobility Reducing Policies on All Crashes in Nairobi, Kenya: Robustness Tests

	Curfew Hours	Pre-Curfew Hours	Day Hours	All Hours
Panel A: *Crashes Measured Using Data from Flare*				
2020 X Curfew Period	−0.723***	0.473**	−0.530*	
	(0.146)	(0.210)	(0.296)	
2020 X Curfew Period X Curfew Hours				−0.207
				(0.333)
2020 X Curfew Period X Pre-Curfew Hours				1.000***
				(0.367)
Num.Obs.	1017	1017	1017	3051
R2	0.319	0.318	0.381	0.351
R2 Adj.	0.289	0.288	0.354	0.336
Panel B: *Outlier Observations (5 or more crashes) Removed*				
2020 X Curfew Period	−1.149***	0.446**	−0.381	
	(0.213)	(0.216)	(0.298)	
2020 X Curfew Period X Curfew Hours				−0.723**
				(0.363)
2020 X Curfew Period X Pre-Curfew Hours				0.871**
				(0.368)
Num.Obs.	1009	1017	995	3021
R2	0.170	0.086	0.107	0.173
R2 Adj.	0.133	0.047	0.066	0.153
Panel C: *Crashes Occurring from 19:00 - 20:00 Removed*				
2020 X Curfew Period	−1.149***	0.286*	−0.347	
	(0.234)	(0.170)	(0.326)	
2020 X Curfew Period X Curfew Hours				−0.749*
				(0.395)
2020 X Curfew Period X Pre-Curfew Hours				0.691*
				(0.367)
Num.Obs.	1017	1017	1017	3051
R2	0.174	0.060	0.100	0.246
R2 Adj.	0.138	0.019	0.060	0.228
Panel D: *Analysis at Hourly Level*				
2020 X Curfew Period	−0.127***	0.148**	−0.031	
	(0.025)	(0.071)	(0.025)	
2020 X Curfew Period X Curfew Hours				−0.093***
				(0.036)
2020 X Curfew Period X Pre-Curfew Hours				0.179**
				(0.076)
Num.Obs.	9153	3051	12 204	24 408
R2	0.059	0.038	0.013	0.025
R2 Adj.	0.054	0.024	0.009	0.022
Panel E: *Analysis at Weekly Level*				
2020 X Curfew Period	−4.883***	4.566***	−1.469	
	(1.039)	(1.059)	(2.814)	
2020 X Curfew Period X Curfew Hours				−5.100
				(3.568)
2020 X Curfew Period X Pre-Curfew Hours				4.938
				(3.500)
Num.Obs.	157	157	157	471
R2	0.302	0.203	0.249	0.490
R2 Adj.	0.222	0.119	0.163	0.436

Notes. Robust standard errors are reported in parentheses. *** (**) (*) denotes significance at 1% (5%) (10%) level. Regressions include fixed effects for year, week, and day of the week, and controls for weather (temperature, precipitation and wind). Only regressions coefficients for 2020 are shown; coefficients for 2014-2018 are excluded. Crashes include all crashes recorded by official sources.

6 Conclusion

Rigorous evidence on the use of curfew policies for public safety in urban settings is close to non-existent, yet, curfews were enacted ubiquitously during the COVID-19 pandemic, in the hope of curbing the spread of the disease.[12] The limited evidence that surfaced suggests that curfews have had limited effectiveness in reducing the burden of infectious disease and could have even increased the spread of it.

Curfews resonate of war and conflict, crowd management and public safety, and the question of whether curfews are an effective tool to protect public safety is important, especially because curfews can impinge directly on personal freedom. Here we have studied rigorously one aspect of public safety: safety on the road. Given that curfews in effect set a very high price of being on the road at certain times, the behavioral response they elicit and their impacts can be informed by the literature studying congestion, speed and road traffic crashes. Indeed, this policy instrument has important externalities for road safety that might directly juxtapose the goal of improving public safety. In the context of a developing country metropolis, with high mortality on the road, and leveraging high-frequency data from multiple sources, we study the impact of curfews on road safety.

We find that there is a direct decrease in crashes during the curfew hours when a dusk-to-dawn curfew is implemented, and a concomitant increase in the number of crashes during the hours before the curfew. The spillover effect is large enough to cancel out the post curfew reduction in crashes, and it occurs even though the number of vehicles on the road is lower, signifying an increase in the probability of a crash per car.

We measure an increase in density during the pre-curfew hours that suggests a shift in trips from the curfew hours to the pre-curfew hours. We also measure large increases in speed right before the curfew, which align with the high penalty for being late causing a sense of urgency that leads to higher speeds the closer to the start of curfew. When we examine a shift in the curfew to later hours when there are fewer trips being taken and likely more flexibility in those trips, there is no longer an increase in density or speed right before the curfew start. Along with this, we still see decreases in crashes during the curfew hours but no spillovers in the pre-curfew hours. Also looking at a high-income context with a similarly timed curfew but where there was also a mandatory work from home order that led to large increases in people working from home, we also do not see changes in behavior in the pre-curfew hours. Similarly to the late curfew in Kenya, there is a significant decrease in crashes during the curfew hours and no effect in the pre-curfew hours. We pose that this is suggestive evidence of the interaction between the timing of the curfew and the level of flexibility of trips that are typically taken during the time of the curfew, which will determine the level of spillovers that may be experienced. Policymakers can use this information to try to optimize the timing of curfews to achieve the intended goal of the curfew while minimizing potential negative externalities for road traffic crashes.

[12] Curfews were still being implemented as late as end of 2021 due to the omicron variant.

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Appendix A Additional Figures and Tables

Figure A.1: Pre-Trend Coefficients Looking at the Impact of Mobility Reducing Policies on Crashes in Nairobi, Kenya (March 27 Curfew)

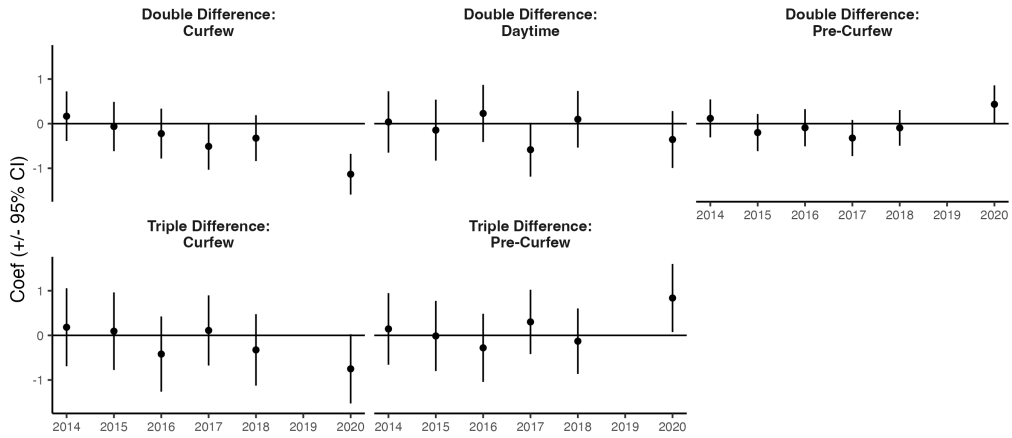


Figure A.2: Sensitivity analysis on $2020 \times CurfewPeriod$ coefficient for examining the impact of mobility reducing policies on all crashes in Nairobi, Kenya (March 27 curfew). Sensitivity analysis based on smoothness restriction of pre-trend deviations; M reflects allowable slope change between periods.

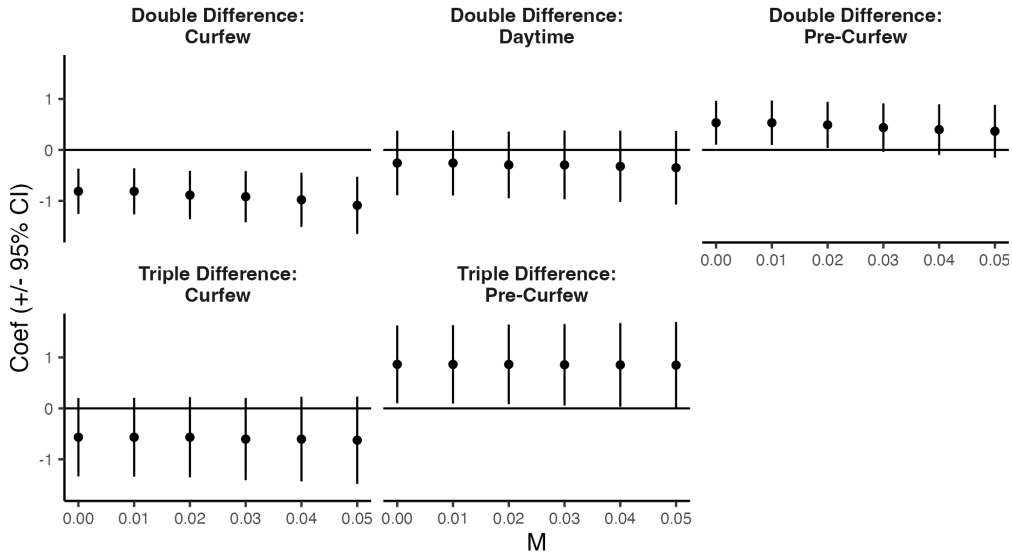


Figure A.3: Percent change in workplace activity from pre-COVID period. Data from Google COVID-19 Community Mobility Reports

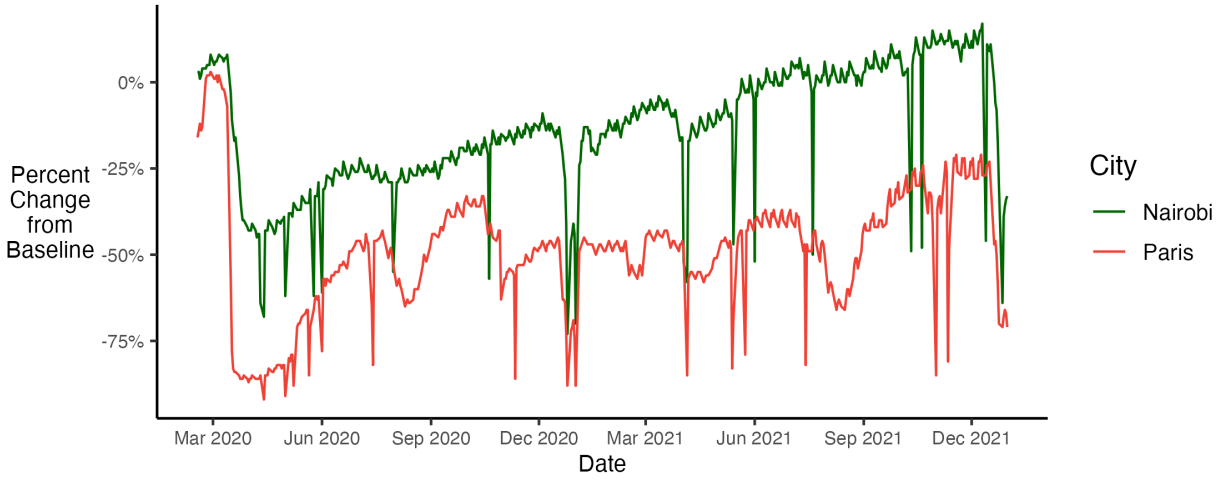


Figure A.4: Hourly speed across different time periods

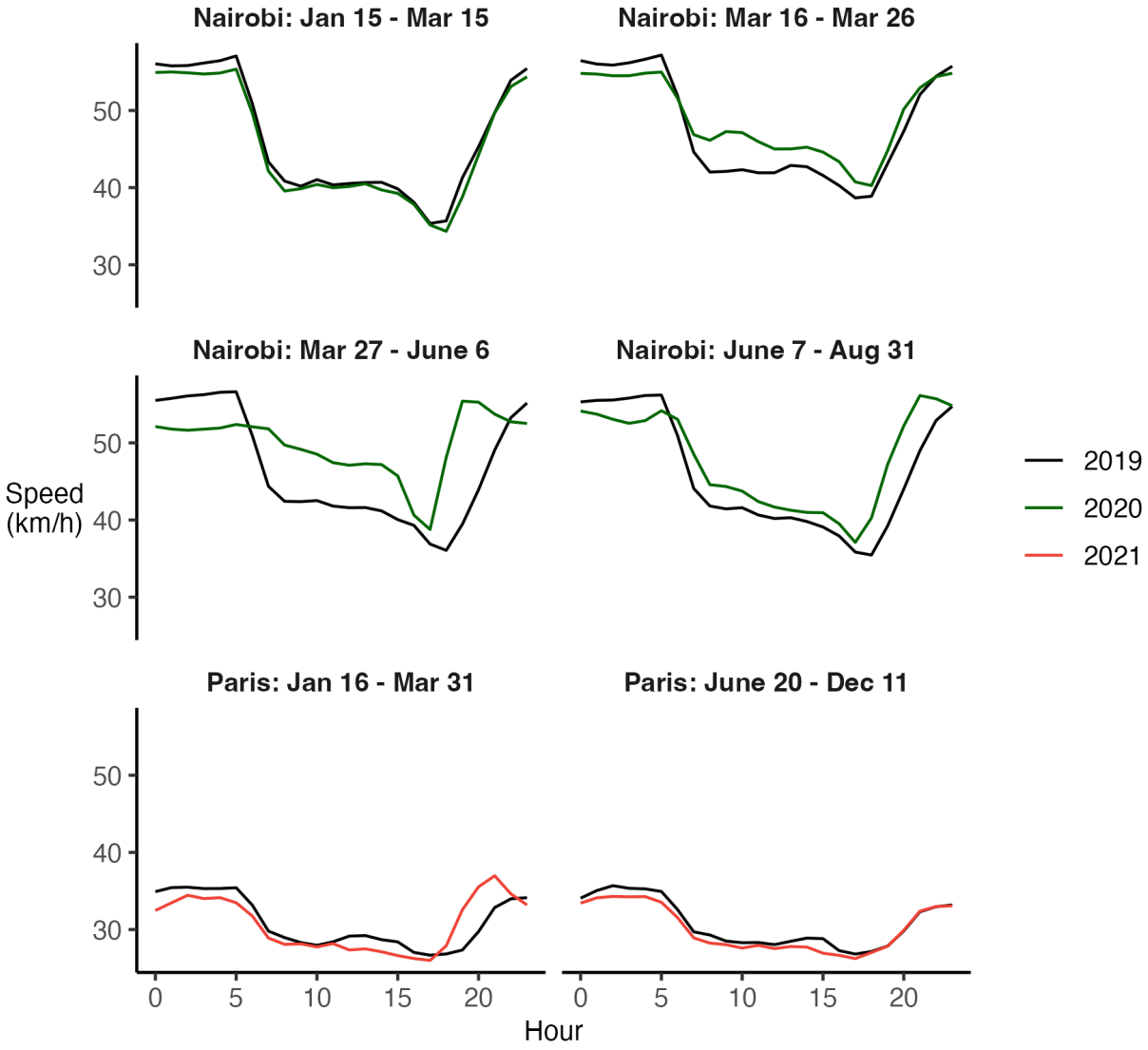


Figure A.5: Hourly congestion across different time periods. The total delay time is computed by taking the total delay time across all segments within an hour; the value report is the average value across hours in the time period

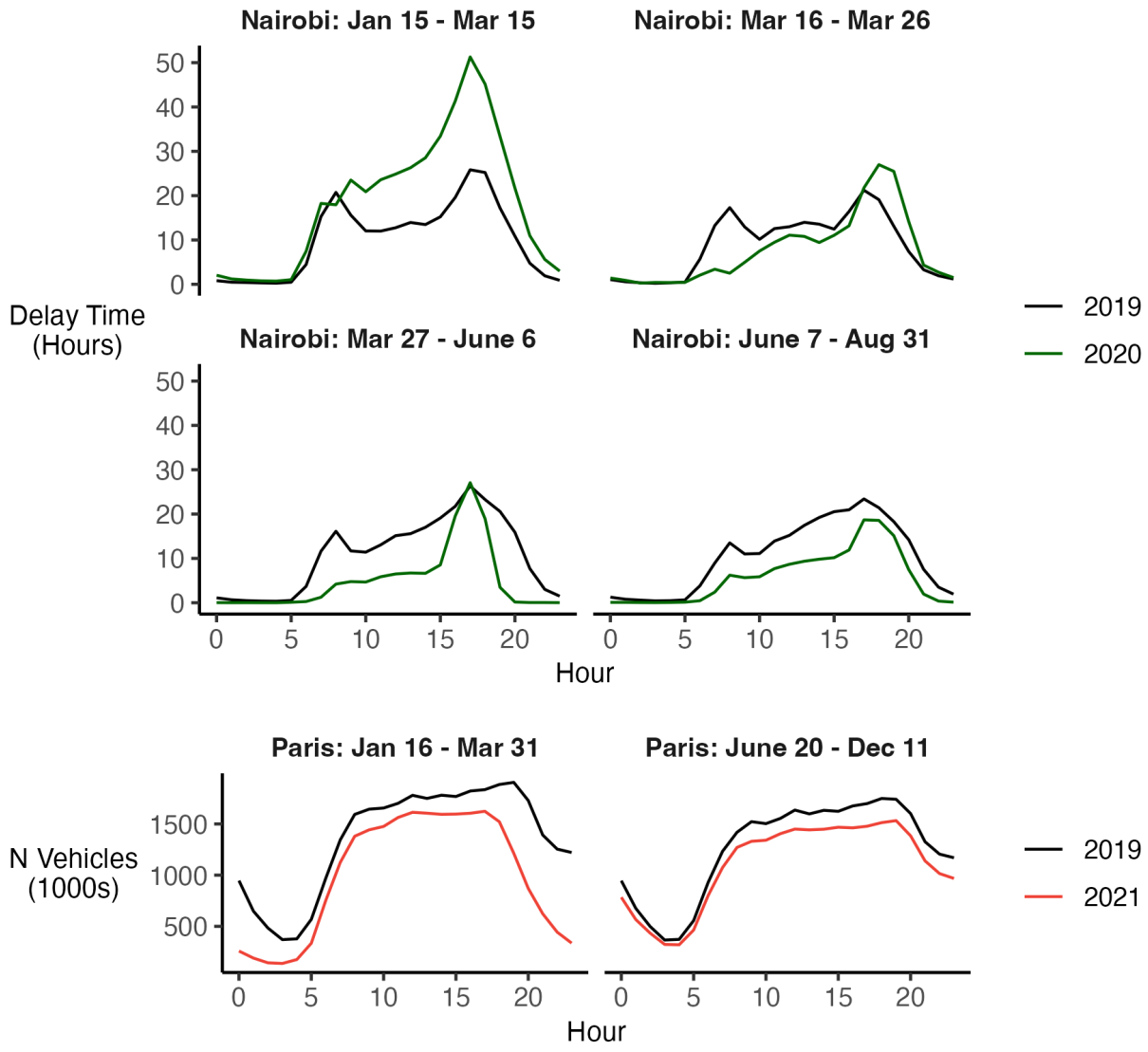


Figure A.6: Percent Change in Speed based on Google Data and Uber Data

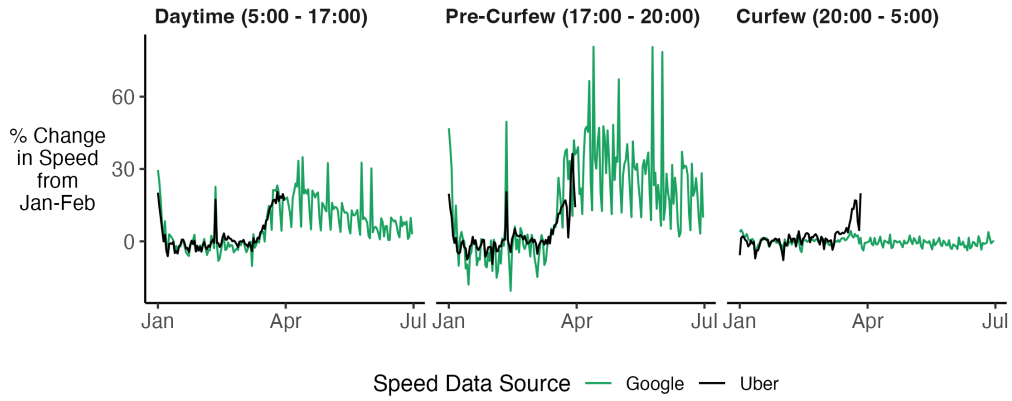


Figure A.7: Speed versus Congestion Hourly, Before and After the Curfew Policy in 2020

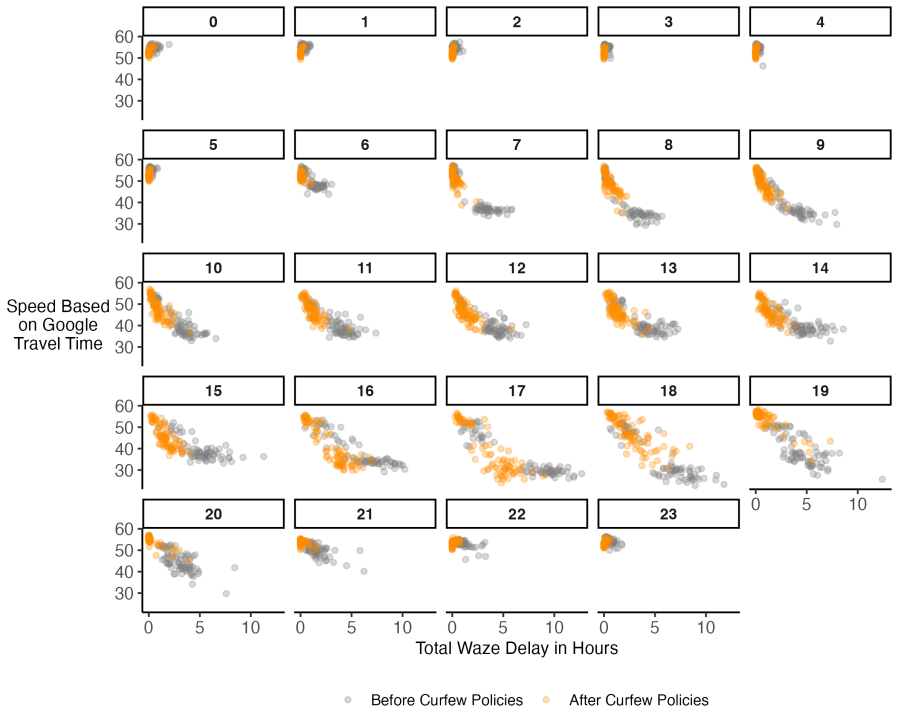


Table A.1: Data and Variable Construction

Indicator	Description	Source
Road traffic crashes (Nairobi)	Crashes with an injury/ fatality/ major property damage in police situation reports.	Kenya National Police Service (NPS)
	Crashes reported to the largest emergency response platform in Kenya (24/7) – 200 ambulances in Nairobi.	Flare
Road traffic crashes (Paris)	Crashes involving bodily injury recorded by law enforcement unit that responded to the crash	The French Road Safety Observatory (ONISR)
Vehicle speed	Average speed (km/hr) = distance road segment / estimated travel time from Google maps for select road segments.	Google maps
	Average speed (km/hr) aggregated from Uber trips at the road segment level across Nairobi per hour, available prior to March 2020.	Uber
Congestion proxy	Traffic delay (in hours) due to traffic jams in Nairobi for select roads.	Waze
Vehicle count (Nairobi)	Count of vehicles on the road from sensor strips installed in six major intersections in Nairobi available for Jan-Jul 2020.	Kenya Urban Roads Authority (KURA)
Vehicle count (Paris)	Count of vehicles on the road from sensor strips installed across Paris.	Ville de Paris
Crash rate proxy	Proxy of crash rate (crashes per car density) estimated as total road traffic crashes divided by an index of vehicle counts in 6 principal intersections in Nairobi.	Authors' estimates based on KURA, NPS and Google data
Predicted number of vehicles	Estimated from a regression of vehicle counts at 6 principal intersections on congestion (Waze), weather and time indicators.	Authors' estimates based on KURA, NPS and Google data
Index of number of vehicles	Index of number of vehicles based on data from 6 principal intersections. Number of vehicles/number of vehicles before curfew (Jan 1, 2020 – March 15, 2020) for each day of week and hour interval (daytime, pre-curfew hours, and curfew hours).	Authors' estimates based on KURA, NPS and Google data
Weather indicators	Temperature (measured in Kelvins, K), Precipitation (meters), Eastward Wind (meters/second) and Northward Wind (meters/second).	Google Earth Engine

Table A.2: Pre-Trend Slopes

Time Period	Specification	Slope
Curfew	Double Difference	-0.1428
Pre-Curfew	Double Difference	-0.0549
Daytime	Double Difference	-0.0318
Curfew	Triple Difference	-0.0999
Pre-Curfew	Triple Difference	-0.0235

Appendix B Predicting Vehicles on the Road

We predict the vehicles on the road for six major intersections with available data.[13] The main predictor is congestion measured using Waze data (Figure B.1). This congestion is measured as the total amount of delay time due to traffic jams across the city. To capture heterogeneity in the relationship between delays measured by Waze and vehicle counts across time of day, we conduct this comparison within each time interval (daytime, pre-curfew, or curfew).[14]

$$y_t = \beta_0 + \beta_1 waze_t + \beta_2 waze^2{}_t + X_t' \boldsymbol{\delta} + \epsilon_t \tag{3}$$

Our outcome of interest, y_t, is number of vehicles crossing the intersection. We use a poisson regression given the count nature of this outcome variable. We include both linear and quadratic terms for the main predictor, congestion measured using Waze data (Figure B.1). We also control for indicators of weather (temperature, precipitation and two measures of wind), X_t'. We predict vehicle counts for each interval and intersection separately. Table B.1 shows regressions for a single intersection as an illustration and Figure B.2 presents actual and predicted values for the six intersections. The correlations between the actual vehicle counts and the predicted counts are .97, .966, .974, .973, .97, and 0.961, respectively, for each intersection.

[13] Data for four of the intersections is available for January and April 2020, for one of the intersections data is available for February and April in 2019 and 2020, and for one intersection data is available for January, February, March and April 2020.

[14] Equivalently, we can interact each right-hand side term with the time interval dummy.

Figure B.1: Trends in Waze Data

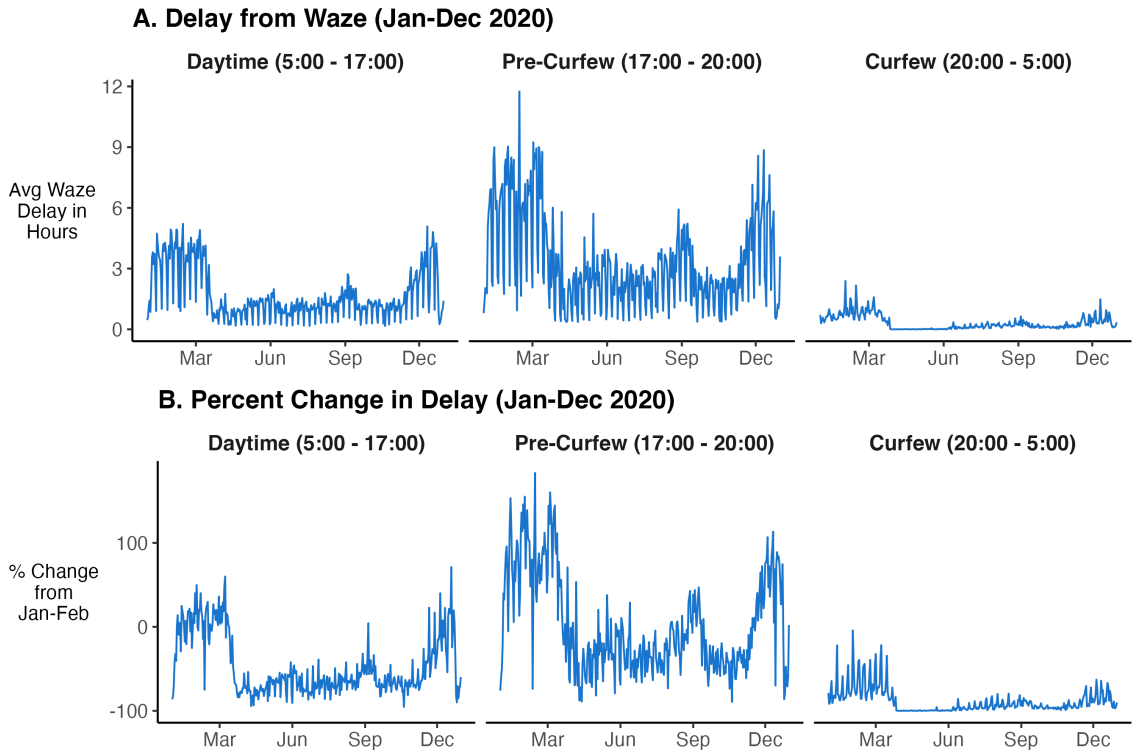


Table B.1: Regression Estimates of Vehicle Counts on Waze Congestion Data

	Curfew Hours (20:00-5:00) (1)	Pre-Curfew Hours (17:00-20:00) (2)	Daytime (5:00-17:00) (3)
Waze Delay (hr)	0.251***	0.043***	0.032***
	(0.001)	(0.001)	(0.000)
Waze Delay (hr)^2	-0.008***	-0.001***	-0.000***
	(0.000)	(0.000)	(0.000)
Year	-0.600***	-0.031***	-0.120***
	(0.004)	(0.003)	(0.002)
Precipitation (m)	-365.048***	-6.875***	54.321***
	(11.167)	(1.980)	(5.266)
Temperature (K)	0.061***	0.020***	0.016***
	(0.002)	(0.001)	(0.001)
Eastward Wind (m/s)	0.081***	-0.003*	-0.015***
	(0.003)	(0.002)	(0.001)
Northward Wind (m/s)	-0.238***	-0.046***	-0.033***
	(0.003)	(0.003)	(0.002)
Constant	1200.971***	65.707***	246.420***
	(9.135)	(6.752)	(4.867)
Observations	112	110	112

Notes. Robust standard errors are reported in parentheses. *** (**) (*) denotes significance at 1% (5%) (10%) level. Temperature is measured in Kelvins (K), precipitation is measured in meters (m), and wind is measured in meters/second (m/s).

Figure B.2: Total Vehicle Counts Compared to Vehicle Counts Predicted Based on Congestion Data from Waze

