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The Unintended Consequences of Curfews on Road Safety

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Abstract

During COVID-19, curfews spread like wildfire. Although their impact on curbing the spread of disease remains to be proven, curfews have the potential to bring about costs to society in multiple domains. This paper investigates the impact of curfews on road safety in an urban lower-middle-income setting. It shows that curfews lead to large reductions in crashes during the curfew hours when cars are off the road, but that these reductions can be fully offset by an increase in crashes during heavy traffic hours when people rush to get home before the curfew starts. These spillover effects result from a behavioral response to the curfew—increased driving speed—leading to higher crash rates. These findings forewarn that the use of curfews in future crises and pandemics should be carefully scrutinized and designed to minimize unintended negative effects.

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The Unintended Consequences of Curfews on Road Safety*

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1 Introduction

Historically, curfews have been used to manage social unrest and control crime, looting and violence. Often, they have been used to contain specific populations, especially young people. Their effectiveness in achieving public safety goals remains ambiguous, with some research finding decreases in crime, while others find curfews lead to increases in gun violence (Carr & Doleac, 2018; Kline, 2012). Curfews can have significant direct costs on freedom of movement, assembly and expression, especially when enforcement resorts to violence (Ravindran & Shah, 2023; Katana et al., 2021). Their indirect costs are even less well understood. The use of curfews must thus be carefully scrutinized and their effects, especially unintended ones, must be rigorously measured.

During COVID, more than 100 countries resorted to lockdowns and curfews to manage the spread of the virus. However, their justification did not have an empirical or theoretical underpinning. First, was the use of curfews during the onset of the pandemic justified? Did curfews reduce assembly or simply displace and concentrate assembly from night to daytime, potentially increasing transmission? Curfews appear to have had little impact on slowing the pandemic (de Haas et al., 2022; Huber & 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). Second, what were the effects of curfews on mobility and what was the effect of that change on other economic outcomes? For instance, did curfews reduce the volume of cars and road crashes, or did they lead to an increase in speeds and car crashes? Providing evidence on these questions is important for preventing the use of policy instruments in future pandemics and crises that are inherently costly as well as ineffective.

In this study, we shed some light on the question of whether curfews affect road safety. This is important because the cost of road safety is measured in people's lives just as is done in pandemics. The context we use is Nairobi, a capital in a low- and middle-income (LMIC) country with high rates of car crashes, and where we have made a multiyear investment in data infrastructure for urban management that turned a data-poor into a relatively data-rich environment.

A small pre-COVID literature looks at curfews used in various contexts to curb night driving by inexperienced drivers. This is effective in reducing crashes (Williams & 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. The question we ask is whether the reduction of cars on the road mechanically decreases the number of car crashes, or whether the curfew displaces driving, increases speeds and has a rebound effect on car crashes.

In our context, the dusk-to-dawn curfew was implemented in March 2020 purportedly to prevent the spread of COVID-19. We use a double-difference strategy, harnessing detailed high-frequency data on road traffic crashes, to look at crashes before and after the curfew implementation and relative to the same period a year earlier. In so doing, we study the impact of curfews on road traffic crashes. We also examine externalities during non-curfew hours and the incidence of spillovers in the hours right before the curfew.

From the literature we know that the probability of a crash depends on the density of cars on the road (Edlin & Karaca-Mandic, 2006). We also expect driver behavior, especially speed, to affect the likelihood of a crash (Bauernschuster & Rekers, 2022). Speed, in turn, is a function of car density and the cost of time for drivers. The higher the cost of time, the faster drivers will drive to reach their destination in a shorter amount of time. Therefore, crashes are a function of density, D, and speed, S, $Crash = f(D, S(D, C))$, where speed is a function of density and cost, C.

We expect curfews to impact both parameters D and C. During the hours of the curfew, we expect few cars and people on the road; therefore, D will approximate zero. Simultaneously, as density falls, lack of congestion induces increased speeds, which in turn can increase the likelihood of a crash and its severity. Therefore, the effect of the curfew on road safety during the curfew hours is ambiguous.

During the hours right before the curfew, density is expected to increase as people must complete their work, chores or other activities and get home before the curfew. The cost of time is also affected. Right before the curfew, time is scarce and more valuable. Speeds might increase as a result. As density and the cost of time rise, the effects of the curfew in the hours before the curfew are also ambiguous. Density will reduce speed but people will respond to the increased cost of time by weaving through traffic to get to their destinations on time.

Our results show that the curfew leads to large reductions in crashes during the curfew hours, when cars are off the road. The spillover effects are large and significant. These reductions are fully 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 look at a second round of curfews to understand whether these spillovers are inevitable. We find that the spillovers can be managed by delaying the onset of the curfew. When the government revised the curfew from 19:00 to 21:00, crashes were reduced 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. As curfew hours become less binding, spillovers and externalities are reduced.

Our contribution to the literature is twofold. First, the literature on congestion focuses on pricing policies (Green et al., 2016; Tang & van Ommeren, 2022). We add to the literature on the externalities of congestion on road safety by evaluating a policy that affects congestion indirectly. We also extend the analysis of road safety beyond high-income contexts (Bünnings & Schiele, 2021; Edlin & Karaca-Mandic, 2006; Bauernschuster & Rekers, 2022; Van Benthem, 2015). In those settings, good infrastructure and traffic enforcement may explain the decrease in crashes associated with congestion pricing or speeding policies. In low- and lower-middle-income countries, with uneven speed enforcement and poorer infrastructure, policies that reduce congestion, such as congestion pricing or curfews, could potentially increase crashes via the speed channel. Second, we demonstrate an additional important negative externality of curfew policies. Rigorous research in this space has been limited, with existing papers demonstrating curfews leading to increases in gun violence (Carr & Doleac, 2018) and negative mental health consequences (Altindag et al., 2022). We add to this literature on the externalities of curfews by showing that curfews that have shown to be ineffective in curbing COVID transmission, their intended objective, can create large negative unintended effects through spillovers on road safety by increasing the probability of a crash during non-curfew hours. The remainder of the paper is structured as follows. Section 2 describes the background on road safety and the policies implemented in Kenya. Section 3 describes the data and empirical strategy. In Section 4, we present our results and robustness checks. Conclusions are presented in Section 5.

2 Background

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; therefore, any policies that affect road safety can have important health consequences (WHO, 2018). Kenya's rate of estimated fatalities per 100,000 is 27.8, higher than the already highest regional average of 26.6 fatalities per 100,000 for Africa (WHO, 2018).

Policies that affect road safety, whether intentionally or unintentionally, can therefore have important consequences for human life and public health. The lockdowns and other mobility policies widely implemented across the world to curb COVID-19 transmission have also significantly affected road traffic crashes. NSC (2021) published a report detailing the rise in fatal road crashes in the United States in 2021 after a year of lockdowns, and Lin et al. (2021) found road crashes decreased for all age groups, races, and genders in Los Angeles and New York City in 2021.

As with most other countries, Kenya implemented a number of measures to limit mobility. On March 15, 2020, two days after its first confirmed case, Kenya closed schools, restricted travel, and enacted work from home measures, among other policies (Ministry of Health, 2020). On March 22nd, the Kenyan government announced that bars would close and that restaurants would remain open only for take-out (Kagwe, 2020). Shortly after, on March 25th, the government announced that a dusk-to-dawn (19:00-5:00) curfew would take effect on March 27th (OSAC, 2020a). The curfew was strictly enforced, with reports indicating that Kenyan Security forces detained those out after the curfew (Bearak & Ombuor, n.d.). On June 7th, the government eased some movement restrictions and revised the curfew hours to 21:00-4:00 (OSAC, 2020b). This curfew continued to remain in place until November 4, 2020, when curfew hours were reduced to 22:00-4:00.

3 Empirical Framework

3.1 Data

There are three main types of data that we use in this paper. First, to study road traffic crashes (RTCs), we use data from the National Police Service that we digitized from paper situation reports. Police officers generate these reports for each crash that they record where there was an injury, fatality, or significant property damage. 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 study mobility and congestion including video-generated traffic counts, Waze, Uber and Google Maps.

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 5,075 crash reports from January 1, 2017-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.

We rely on four data sources to measure changes in vehicle density and speed. We use traffic jam information from the Waze Connected Cities Program (Waze, 2021). 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 from road sensors installed in six major intersections in Nairobi by the Kenya Urban Roads Authority. 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. We use the relationship between vehicles on the road and

[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.

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.[2] 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.[3] The predicted vehicle counts after the curfew is implemented across the different intersections demonstrates 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 how the curfew may have affected drivers' behaviors taking into account the overall decrease in mobility, we create a proxy of crash rates (crashes per car density) estimated as total road traffic crashes divided by the index of vehicle counts in 6 principal intersections in Nairobi described previously. This allows us to assess if there were changes in the probability of a crash due to the curfew in a context of lower mobility.

To measure speed, we query real-time travel times from Google Maps. We query travel times along 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 for the analysis. An overview of data sources and variable construction is shown in Table B.2.

For all the analyses, across all outcomes and indicators, we analyze 3 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 before 5:00 hours. While the curfew started at 19:00, we include the 19:00-20:00 hour interval in the pre-curfew time given the combination of: (1) the likely behavior with people rushing and getting in crashed around and beyond the curfew threshold at 19:00, and (2) 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 starting time.

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

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

[3] 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.

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.

3.2 Compliance with Curfew

The curfew plausibly affects road traffic crashes by changing the number of vehicles on the road. Additionally, driving speeds may change, either because the lower density of vehicles enables higher speeds or because the cost of being caught breaking the curfew leads people to drive faster in order to arrive at their destination before the curfew. If the curfew were not to have any impact on vehicle density or speeds, there would be no expected impact on road safety. Therefore, we first examine whether the curfew affected mobility and therefore vehicle density and speed.

There is a large decrease in the number of vehicles on the road based on the index for predicted vehicles on the road (Figure 1a). On average the drop in vehicles during the curfew hours is 88%, therefore, although imperfect, compliance with curfew was very high based on our measure of mobility.[4] During the daytime hours, the decrease is 31%. During the pre-curfew hours, the drop is smaller than the drop seen during the daytime hours—25%. As expected, the decrease in vehicles on the road allows drivers to increase the speed at which they drive, particularly during the daytime and early evening hours (Figure 1b). The increase is especially pronounced for weekdays when traffic is usually extremely heavy prior to the COVID-19 policies.

3.3 Identification and Estimation

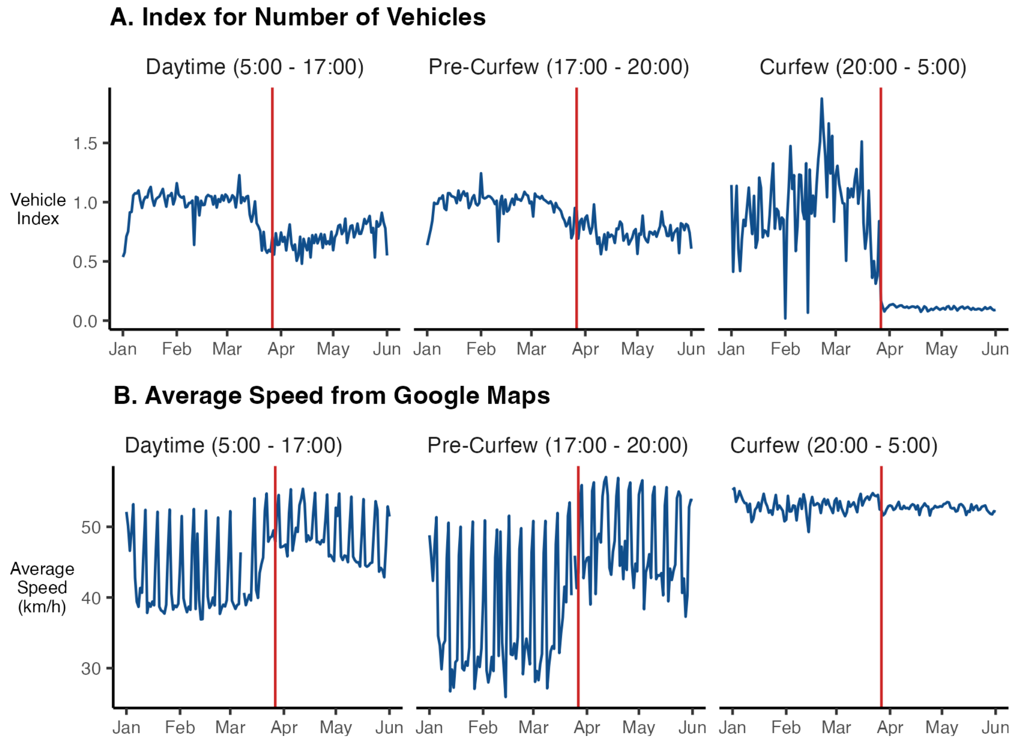
Our empirical strategy is a modified double-difference specification, comparing crashes in the period after the first curfew was implemented (March 27-June 6) to the period before any COVID-19 policies were implemented (January-March 15). We examine the difference between these two periods in 2020 and 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. We conduct a robustness check where we also include 2017 and 2018 as additional comparison years. Figure 2 shows the comparison of crashes between 2019 and 2020, before and after the curfew policy. Our main specification is:

$$y_t = \beta_0 + \beta_1 I_{2020t} + \beta_2 Post_t + \gamma I_{2020t} \times Post_t + X_t' \boldsymbol{\delta} + \epsilon_t \quad (1)$$

[4] Curfew exemptions included essential service providers such as medical professionals, emergency response services, and other licensed providers for transport of goods, e-commerce, and home delivery for essential services.

[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.

Figure 1: Number of Vehicles and Speed in 2020



Notes. Red vertical lines correspond to the date the curfew policy was introduced.

where y_t is the outcome of interest on day t, either number of crashes or a proxy for rate of crashes. I_{2020t} is an indicator equal to one if the year is 2020 and zero otherwise, $Post_t$ is an indicator equal to one for the curfew period (March 27-June 6) and zero before the COVID-19 policies (January 1-March 15), X_t' includes weather variables and indicator variables for the day of week and week of the year (i.e., an indicator of the week within a calendar year, starting from week 1), and ϵ_t 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). The parameter γ is our parameter of interest. The analysis is conducted at the day level, using daily data on crashes.

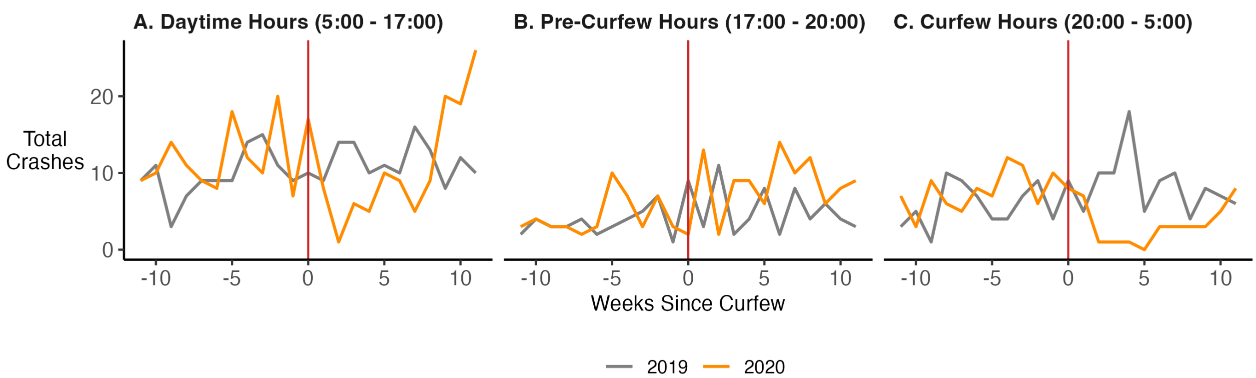
In the absence of the curfew, mobility and the number of cars on the road would still be lower due to the policies that closed down restaurants, bars and schools, and mandated work from home for government officials (Figure 1). In order to try to difference out the effect of lower mobility due to other 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 I_{2020t} and curfew period $Post_t$ with the hourly intervals i, where the two periods of interest are the curfew hours from 20:00-5:00 ($CurfewHours_t$) and the pre-curfew hours from 17:00-20:00 ($PreCurfewHours_t$), with the comparison being the daytime hours from 5:00-17:00. Therefore, γ_1 and γ_2 are our parameters of interest.

The analysis is conducted at the day and hour interval level, using daily data on crashes.

$$
\begin{aligned}
y_{it} = \alpha_0 + \alpha_1 I_{2020t} + \alpha_2 Post_t + \alpha_3 PreCurfewHours_i + \alpha_4 CurfewHours_i + \alpha_5 I_{2020t} \times Post_t \\
+ \alpha_6 I_{2020t} \times PreCurfewHours_i + \alpha_7 I_{2020t} \times CurfewHours_i + \alpha_8 Post_t \times PreCurfewHours_i \\
+ \alpha_9 Post_t \times CurfewHours_i + \gamma_1 I_{2020t} \times Post_t \times PreCurfewHours_i \\
+ \gamma_2 I_{2020t} \times Post_t \times CurfewHours_i + X_t' \lambda + \epsilon_{it} \quad (2)
\end{aligned}
$$

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.

Figure 2: Weekly Crashes in 2019 and 2020



To further estimate externalities of the curfew and the change in vehicle density, we examine whether the likelihood of a crash changed for those still using the road. Specifically, we examine whether the curfew caused a change in the crash rate. 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 for other users 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 & 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.

4 Results

We first look at the overall impact of the policies put in place to limit mobility on daily crashes (Table 1). During the initial curfew period, there is a significant overall decrease of 1.04 crashes with a fatality or injury per day (Column 1). This is over a mean of 3.27 crashes per day, which represents a 32% decrease. This effect includes the impact of the curfew but also other policies that limited mobility such as the closing of schools, bars and restaurants, and the work from home mandate for government workers and others.

Table 1: Impact of Mobility Reducing Policies on Daily Crashes

	All Hours			Only Curfew Hours
	OLS (1)	Poisson (2)	NegBi (3)	OLS (4)
Curfew Period (Post)	1.888 (1.340)	0.566* (0.335)	0.565* (0.336)	0.947* (0.519)
I_{2020} (2020)	1.397*** (0.484)	0.442*** (0.142)	0.445*** (0.142)	0.585*** (0.194)
Curfew Period (Post) x 2020	-1.041** (0.480)	-0.340** (0.141)	-0.348** (0.141)	-1.166*** (0.221)
Constant	-149.844*** (52.882)	-46.290*** (15.033)	-46.784*** (15.076)	-31.433 (25.185)
Observations	295	295	295	295
R^2	0.172	.	.	0.198

Notes. Robust standard errors are reported in parentheses. *** (**) (*) denotes significance at 1% (5%) (10%) level. Regressions include fixed effects for week and day of the week, and controls for weather (temperature, precipitation and two measures of wind).

Given the count nature of our outcome of interest, we also estimate both Poisson and negative binomial models of crashes (Columns 2 and 3). The results similarly show large and significant reductions in crashes of around 34%, which are comparable to the magnitude from the OLS estimate. We reject the null of no over-dispersion of the dependent variable (p=.057); therefore, the model is more correctly estimated using the negative binomial compared to the Poisson. Similar to Green et al. (2016), we compare the mean squared residuals for both the negative binomial and the linear specification to determine whether to continue with the negative binomial. We find the results are very similar, but slightly better for the OLS specification; therefore, we continue with the OLS specification for the rest of the paper.

We look specifically at the curfew hours interval, from 20:00 until 5:00. Crashes decrease by 1.17 crashes per day during the curfew (Table 1 Column 4), which is around a 100% reduction in crashes. This reduction aligns with the raw data in Figure 2, which shows weekly crashes going almost down to zero during the curfew period. With almost no cars on the road (Figure 1a), this large reduction in crashes is to be expected.

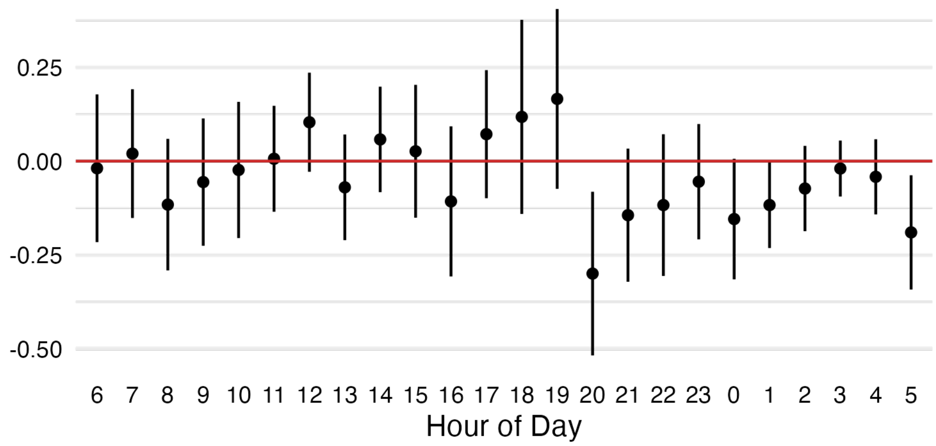
Overall, COVID policies led to a decrease in crashes, particularly during curfew hours; however, curfews can cause spillovers—affecting the number of crashes during non-curfew hours. To examine spillovers, we estimate the impacts of the curfew for each hour of the day. Figure 3 shows estimated coefficients from regressions following equation 1 at the hour level. Crashes increase in the hours right before and at the start of the curfew, while crashes decrease in the hours after the curfew starts and during the entire time of the curfew.

Given that hourly crash rates are noisy, we group the hours right before the curfew time, 17:00-20:00. Column 1 of Table 2 again shows the results for the curfew period. There is a significant positive increase in crashes during the three hours leading up to and at the beginning of the curfew (Column 2). 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 2, columns 1 and 2, result from both the curfew and other mobility restricting policies (e.g., work from home policies). 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 following equation 2. When analyzing only daytime hours, the estimated coefficient is negative at -0.465, though it is not significant (Table 2 Column 3). We use a triple-difference specification 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 -0.67 per day (Table 2 Column 4). On the other hand, the estimated coefficient on the pre-curfew hours is much larger, at 0.88 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.[6]

[6] As discussed in the methods section, it is possible the daytime mobility was also affected by the curfew in the form of more movement happening during the daytime hours than otherwise would have happened during the curfew hours in the absence of a curfew. If this were the case, then in the absence of a curfew but with all the other policies in place, there would have been even fewer vehicles on the road during the daytime, which would mean even fewer crashes would have happened during this time interval if there were no curfew. In that case, the current estimates are biased so that the spillovers are biased downward and the effect during the curfew period is biased upward.

Figure 3: Impact of Mobility Reducing Policies on Crashes per Hour of the Day



Notes. Vertical lines correspond to 95% confidence intervals. This figure is consistent with Equation 1 but at the hour level.

Table 2: Impact on Crashes by Time Intervals

	Curfew Hours (20:00-5:00) (1)	Pre-Curfew Hours (17:00-20:00) (2)	Daytime (5:00-17:00) (3)	All Intervals (4)
Curfew Period (Post)	0.947* (0.519)	-0.319 (0.456)	1.161 (1.085)	0.587 (0.491)
I_{2020} (2020)	0.585*** (0.194)	-0.040 (0.173)	0.447 (0.328)	0.309 (0.226)
Curfew Period (Post) x 2020	-1.166*** (0.221)	0.504** (0.221)	-0.465 (0.322)	-0.418 (0.315)
Curfew Hours				-0.471** (0.226)
Pre-Curfew Hours				-0.892*** (0.183)
Curfew Period (Post) x Curfew Hours				0.168 (0.282)
Curfew Period (Post) x Pre-Curfew Hours				-0.001 (0.248)
Curfew Hours x 2020				-0.073 (0.266)
Pre-Curfew Hours x 2020				-0.186 (0.248)
Curfew Period (Post) x Curfew Hours x 2020				-0.667* (0.391)
Curfew Period (Post) x Pre-Curfew Hours x 2020				0.876** (0.387)
Constant	-31.433 (25.185)	1.661 (12.905)	-38.352 (36.521)	-5.798 (11.186)
Observations	295	295	295	885
R^2	0.198	0.196	0.135	0.176

Notes. Robust standard errors are reported in parentheses. *** (**) (*) denotes significance at 1% (5%) (10%) level. Regressions include fixed effects for week and day of the week, and controls for weather (temperature, precipitation and two measures of wind). Columns 1 to 3 are double-difference estimates following Equation 1. Column 4 is a triple-difference specification following Equation 2.

4.1 Crash Rate

The estimates in the previous two sections demonstrate a decrease in the number of crashes during the curfew hours, but the decrease is offset by spillovers during the hours right before the curfew begins. Especially for the curfew period, these results still do not speak to the externality of congestion since the decreases seen may be proportional to the decreases in vehicles. 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 3). We also find a large and significant increase in the probability of a crash during pre-curfew hours. This result is not surprising as the pre-curfew hours experienced a decrease in congestion (indicating a decrease in cars on the road), and an increase in crashes. Therefore, the curfew not only led to a spillover of crashes to pre-curfew hours, but the curfew also led to an additional externality of an increase in the probability of being in a crash during both curfew hours and the hours right before the curfew. There is no change in the crash rate during the daytime hours (Column 3).

Table 3: Impact of Mobility Reducing Policies on Crash Rates

	Curfew Hours (20:00-5:00) (1)	Pre-Curfew Hours (17:00-20:00) (2)	Daytime (5:00-17:00) (3)
Curfew Period (Post)	5.630	-0.770	0.388
	(3.734)	(0.676)	(1.193)
I_{2020} (2020)	-0.242	-0.172	0.133
	(0.584)	(0.201)	(0.386)
Curfew Period (Post) x 2020	1.787**	0.962***	0.203
	(0.798)	(0.306)	(0.389)
Constant	27.947	4.884	-42.219
	(89.915)	(15.592)	(47.028)
Observations	293	293	293
R^2	0.224	0.246	0.140

Notes. 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 week and day of the week, and controls for weather (temperature, precipitation and two measures of wind).

4.2 Spillover Mechanisms

The increase in crashes in the pre-curfew hours suggests that there could be a few things happening. First, as the number of vehicles on the road decreases and congestion decreases, there is an opportunity for vehicles to driver faster, which may increase the likelihood of a crash. During the pre-curfew hours, people may also drive even faster and more aggressively than they typically would under the same density circumstances because the time cost is higher because of the risk of punishment for being caught on the street past curfew. We explore this by looking at how speed changes in relation to the curfew during different times of day (see Appendix Figure A.2 for a comparison of speed versus congestion before and after the curfew for each hour of the day).

There are increases in speed both during the daytime hours and during the pre-curfew hours, though the increase is twice as large during pre-curfew hours (Table 4).[7] This demonstrates that the combined effect of changes in density and behavior is an increase in the speed that individuals drive. Additionally, given that we see no effect on crashes during the daytime hours (if anything the coefficient is negative, indicating a decrease in crashes), it seems that the increase in speed from the drop in congestion does not lead to increases in crashes. This is in line with the findings from Green et al. (2016).

When we control for vehicle density using the congestion delay data from Waze, "relative" speed decreases during the daytime hours the COVID-19 policies are implemented. During the pre-curfew hours there is still a significant increase in "relative" speed. This demonstrates that beyond the increase in speed that can occur when the number of vehicles decreases, individuals are driving at even higher speeds during the pre-curfew hours. We also look at this in a triple-difference framework, comparing the increases in speed between the pre-curfew hours and the daytime hours, before and after the curfew period in 2019 and in 2020, controlling for the level of congestion. We see a large positive increase in speed during the pre-curfew period as compared to the other daytime hours. This increase in speed that goes beyond the mechanical change in speed that occurs when congestion decreases could help to explain the increase in the probability of a crash during the pre-curfew time interval.

[7]Note that during the curfew hours, there seems to be a decrease in speed as measured by Google Maps (Figure 1b). The number of vehicles on the road at this time drops to close to 0; therefore, the measured decrease in speed may be a function of how Google calculates driving time in the absence of vehicles. To confirm the data, we compare the percent change in speeds from Google with the percent change in speeds from Uber. While the Uber and Google data are fully aligned for the daytime hours and the hours right before the curfew, there is a deviation in the percent change between Uber and the Google speed data for the curfew hours for the period where Uber is still reporting this statistic. Since we do not have data from Uber after March 2020, we do not consider the curfew hours when conducting any analysis related to speed (Appendix Figure A.1).

Table 4: Impact of Mobility Reducing Policies on Hourly Speed
(Daytime and Pre-Curfew Hours)

	Panel A. No Controls			Panel B. Congestion Controls		
	Daytime (5:00-17:00) (1)	Pre-Curfew Hours (17:00-20:00) (2)	Daytime and Pre-Curfew Hours (3)	Daytime (5:00-17:00) (4)	Pre-Curfew Hours (17:00-20:00) (5)	Daytime and Pre-Curfew Hours (6)
Curfew Period (Post)	1.395***	1.557***	1.514***	0.574***	1.013**	0.682***
	(0.226)	(0.593)	(0.226)	(0.190)	(0.403)	(0.196)
I_{2020} (2020)	0.114	0.379	0.240	1.416***	3.662***	1.931***
	(0.228)	(0.614)	(0.226)	(0.194)	(0.435)	(0.198)
Curfew Period (Post) x 2020	4.492***	10.201***	4.457***	-1.128***	1.464**	-1.641***
	(0.271)	(0.763)	(0.271)	(0.235)	(0.646)	(0.241)
Pre-Curfew Hours			-4.651***			1.614**
			(0.975)			(0.786)
Curfew Period (Post) x Pre-Curfew Hours			-0.683			-0.228
			(0.455)			(0.360)
Pre-Curfew Hours x 2020			-0.455			0.178
			(0.429)			(0.356)
Curfew Period (Post) x Pre-Curfew Hours x 2020			5.959***			4.993***
			(0.731)			(0.527)
Waze Delay (hr)				-7.157***	-5.985***	-6.502***
				(0.217)	(0.393)	(0.174)
Waze Delay (hr)^2				1.045***	0.519***	0.797***
				(0.059)	(0.081)	(0.041)
Waze Delay (hr)^3				-0.051***	-0.015***	-0.034***
				(0.005)	(0.005)	(0.003)
Constant	13.698	-25.808	7.475	54.842***	19.236	46.879***
	(13.278)	(38.932)	(13.085)	(8.078)	(20.416)	(7.799)
Observations	2981	744	3725	2981	744	3725
R^2	0.771	0.755	0.776	0.907	0.898	0.905

Notes. Robust standard errors are reported in parentheses. *** (**) (*) denotes significance at 1% (5%) (10%) level. Regressions include fixed effects for week and day of the week, and controls for weather (temperature, precipitation and two measures of wind). Google speed data is missing for some hours.

4.3 Timing of the Curfew

When the curfew is revised on June 6, 2020 to start two hours later, we can look at how the timing of the curfew can affect the externality on road safety.[8] There is a significant but smaller drop in the number of crashes during the revised curfew period (Table 5 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. Setting the start time of the curfew after the evening rush hour can minimize negative externalities of increased crashes due to people speeding to get home before the curfew. 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.

[8] 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.

Table 5: Impact of Curfew Revision after June 6th on Crashes and Crash Rate

	Crashes		Crash Rate	
	Curfew Hours (22:00-4:00) (1)	Pre-Curfew Hours (19:00-22:00) (2)	Curfew Hours (22:00-4:00) (3)	Pre-Curfew Hours (19:00-22:00) (4)
Curfew Period (Post)	0.764	1.176	1.647	0.994
	(0.492)	(0.767)	(2.060)	(0.775)
I_{2020} (2020)	0.241	0.413**	-0.047	0.410
	(0.177)	(0.170)	(0.344)	(0.207)
Curfew Period (Post) x 2020	-0.657***	-0.058	-0.071	0.185
	(0.208)	(0.264)	(0.543)	(0.356)
Constant	-24.674	2.403	11.028	8.483
	(22.705)	(17.486)	(67.791)	(21.619)
Observations	259	259	258	258
R^2	0.229	0.178	0.273	0.216

Notes. Robust standard errors are reported in parentheses for columns (1) and (2) and bootstrap standard errors are reported in parentheses for columns (4) and (5). *** (**) (*) denotes significance at 1% (5%) (10%) level. Regressions include fixed effects for week and day of the week, and controls for weather (temperature, precipitation and two measures of wind).

4.4 Robustness Checks

We conduct a number of different robustness checks (Table 6). 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 data (Panel A of Table 6). 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.

Since we have data on road traffic crashes from the police, we go further back in time to 2017 and use data from 2017, 2018 and 2019 as a comparison to 2020 and comparing the pre-COVID-19 policies period of Jan 1-March 15 with the post-curfew implementation period of March 27-June 6 for each year. When adding in the historical data, the results remain consistent and significant (Table 6 Panel B).

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 6 Panel C and Panel D).

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 6 Panel E).

Finally, we conduct placebo tests where we compare 2018 and 2019, using 2019 as the treatment year and similarly we compare 2017 and 2018, where we treat 2018 as the treatment year. We do not find any significant effects when comparing the pre and post periods in each of the pairs (Table 7).

5 Conclusion

Rigorous evidence on the use of curfew policies for public safety 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.[9] 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. 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. Controlling for congestion on the road, we observe that speed increases during the hours right before the curfew, as people rush to reach their final destination just before the curfew. This is especially true when the curfew begins during rush hour. When it begins after rush hour, spillovers are mitigated. We conclude that the evidence is at best too thin to justify the enactment of curfews, especially to manage pandemics, and that governments should exercise caution and consider other instruments in their toolbox.

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

Table 6: Impact of Mobility Reducing Policies on Crashes: Robustness Tests

	Double Difference			Triple Difference
	Curfew Hours (20:00-5:00) (1)	Pre-Curfew Hours (17:00-20:00) (2)	Daytime (5:00-17:00) (3)	All Intervals (4)
Panel A: *Crashes Measured Using Data from Flare*				
Curfew Period (Post) x 2020	-0.783*** (0.158)	0.424** (0.203)	-0.423 (0.293)	
Curfew Period (Post) x Curfew Hours x 2020				-0.226 (0.332)
Curfew Period (Post) x Pre-Curfew Hours x 2020				0.910*** (0.352)
Observations	295	295	295	885
R^2	0.301	0.281	0.253	0.254
Panel B: *Crashes from 2017-2019 Used as Controls*				
Curfew Period (Post) x 2020	-0.897*** (0.181)	0.603*** (0.195)	-0.298 (0.268)	
Curfew Period (Post) x Curfew Hours x 2020				-0.595* (0.321)
Curfew Period (Post) x Pre-Curfew Hours x 2020				0.818** (0.332)
Observations	589	589	589	1767
R^2	0.157	0.119	0.080	0.135
Panel C: *Analysis at Hourly Level*				
Curfew Period (Post) x 2020	-0.127*** (0.026)	0.191*** (0.071)	-0.030 (0.025)	
Curfew Period (Post) x Curfew Hours x 2020				-0.091** (0.036)
Curfew Period (Post) x Pre-Curfew Hours x 2020				0.191** (0.075)
Observations	2655	885	3540	7080
R^2	0.046	0.079	0.014	0.036
Panel D: *Analysis at Weekly Level*				
Curfew Period (Post) x 2020	-7.814*** (1.469)	3.251** (1.555)	-3.221 (2.717)	
Curfew Period (Post) x Curfew Hours x 2020				-4.190 (3.053)
Curfew Period (Post) x Pre-Curfew Hours x 2020				6.508** (3.020)
Observations	46	46	46	138
R^2	0.520	0.442	0.305	0.500
Panel E: *Outlier Observations (5 or more crashes) Removed*				
Curfew Period (Post) x 2020	-1.217*** (0.210)	0.449** (0.215)	-0.521* (0.290)	
Curfew Period (Post) x Curfew Hours x 2020				-0.532 (0.348)
Curfew Period (Post) x Pre-Curfew Hours x 2020				0.966*** (0.352)
Observations	293	294	285	872
R^2	0.216	0.173	0.113	0.166

Notes. Robust standard errors are reported in parentheses. *** (**) (*) denotes significance at 1% (5%) (10%) level. Regressions include fixed effects for week and day of the week, and controls for weather (temperature, precipitation and two measures of wind) Columns 1 to 3 are double-difference estimates following Equation 1. Column 4 is a triple-difference specification following Equation 2.

Table 7: Changes in Crashes Using a Placebo Test with 2017/2018 and 2018/2019

	A. 2018 to 2017 Comparison		B. 2019 to 2018 Comparison	
	Curfew Hours (20:00-5:00)	Pre-Curfew Hours (17:00-20:00)	Curfew Hours (20:00-5:00)	Pre-Curfew Hours (17:00-20:00)
	(1)	(2)	(3)	(4)
Curfew Period (Post)	-0.610	-0.377	-0.344	-0.182
	(0.645)	(0.382)	(0.515)	(0.451)
$I_{Placebo}$ (2018/2019)	-0.354*	-0.210	-0.165	-0.046
	(0.186)	(0.163)	(0.174)	(0.136)
Curfew Period (Post) x $I_{Placebo}$	0.116	0.276	0.104	0.083
	(0.275)	(0.218)	(0.271)	(0.215)
Constant	13.950	-2.765	-39.654	-4.962
	(29.707)	(13.325)	(26.007)	(11.627)
Observations	294	294	294	294
R^2	0.208	0.152	0.191	0.087

Notes. Robust standard errors are reported in parentheses. *** (**) (*) denotes significance at 1% (5%) (10%) level. Regressions include fixed effects for week and day of the week, and controls for weather (temperature, precipitation and two measures of wind). For the placebo test, we compare 2017 and 2018, using 2018 as the treatment year (Panel A) and similarly we compare 2018 and 2019, where we treat 2019 as the treatment year (Panel B).

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Appendix A Additional Figures

Figure A.1: Percent Change in Speed based on Google Data and Uber Data

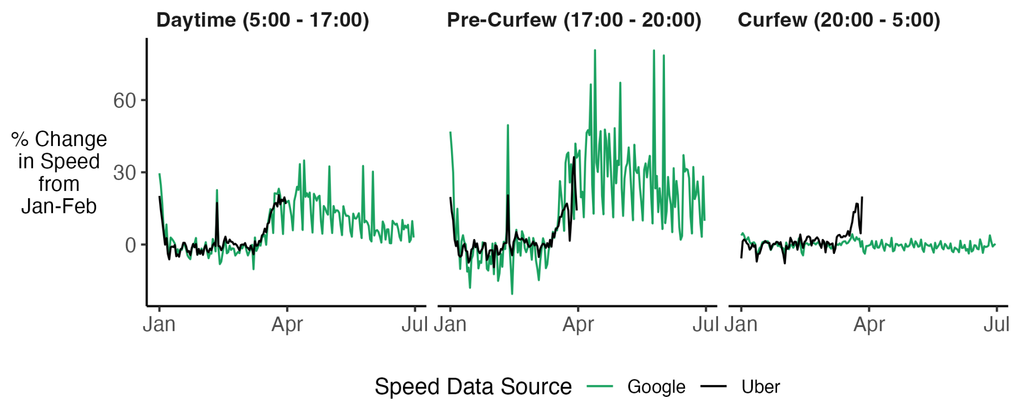
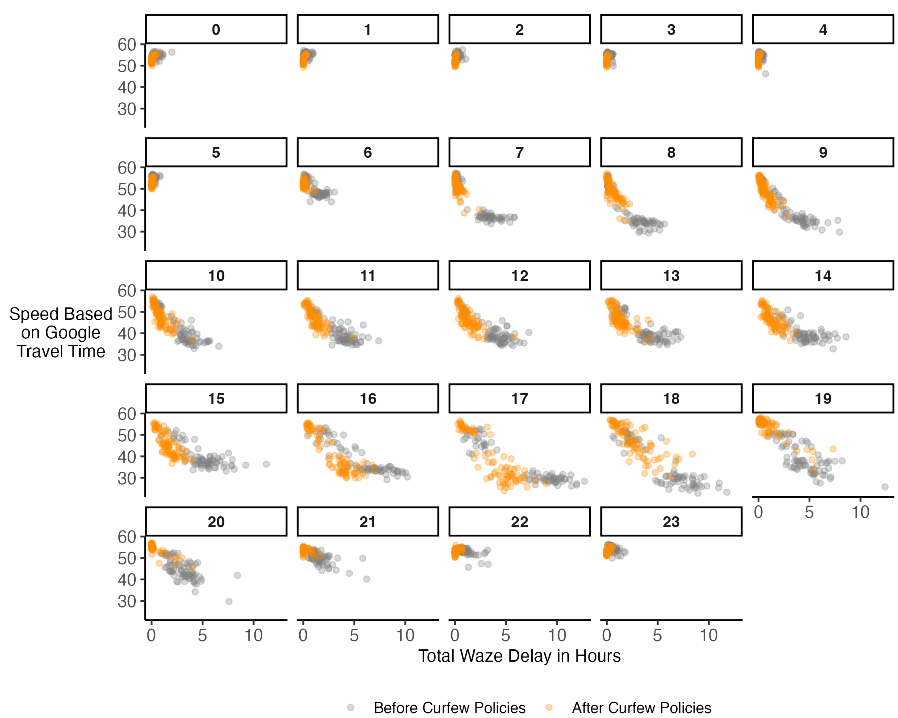


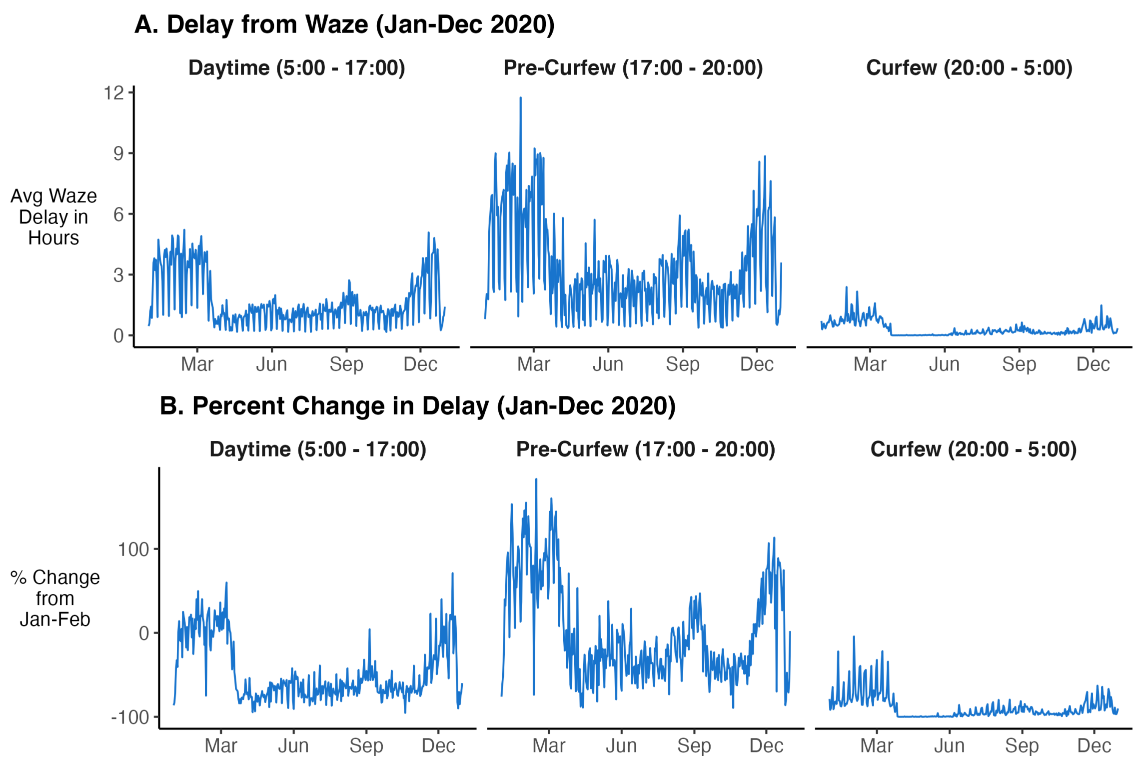
Figure A.2: Speed versus Congestion Hourly, Before and After the Curfew Policy in 2020



Appendix B Predicting Vehicles on the Road

We predict the vehicles on the road for six major intersections with available data.[10] The main predictor is congestion measured using Waze data (Figure B.1), and we include both linear and quadratic terms for this. We also control for the year and for indicators of weather (temperature, precipitation and two measures of wind). We estimate regressions separately for the different time intervals of the day and predict vehicle counts for each interval separately based on each regression. Table B.1 predicts vehicle counts 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.

Figure B.1: Trends in Waze Data



[10] 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.

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

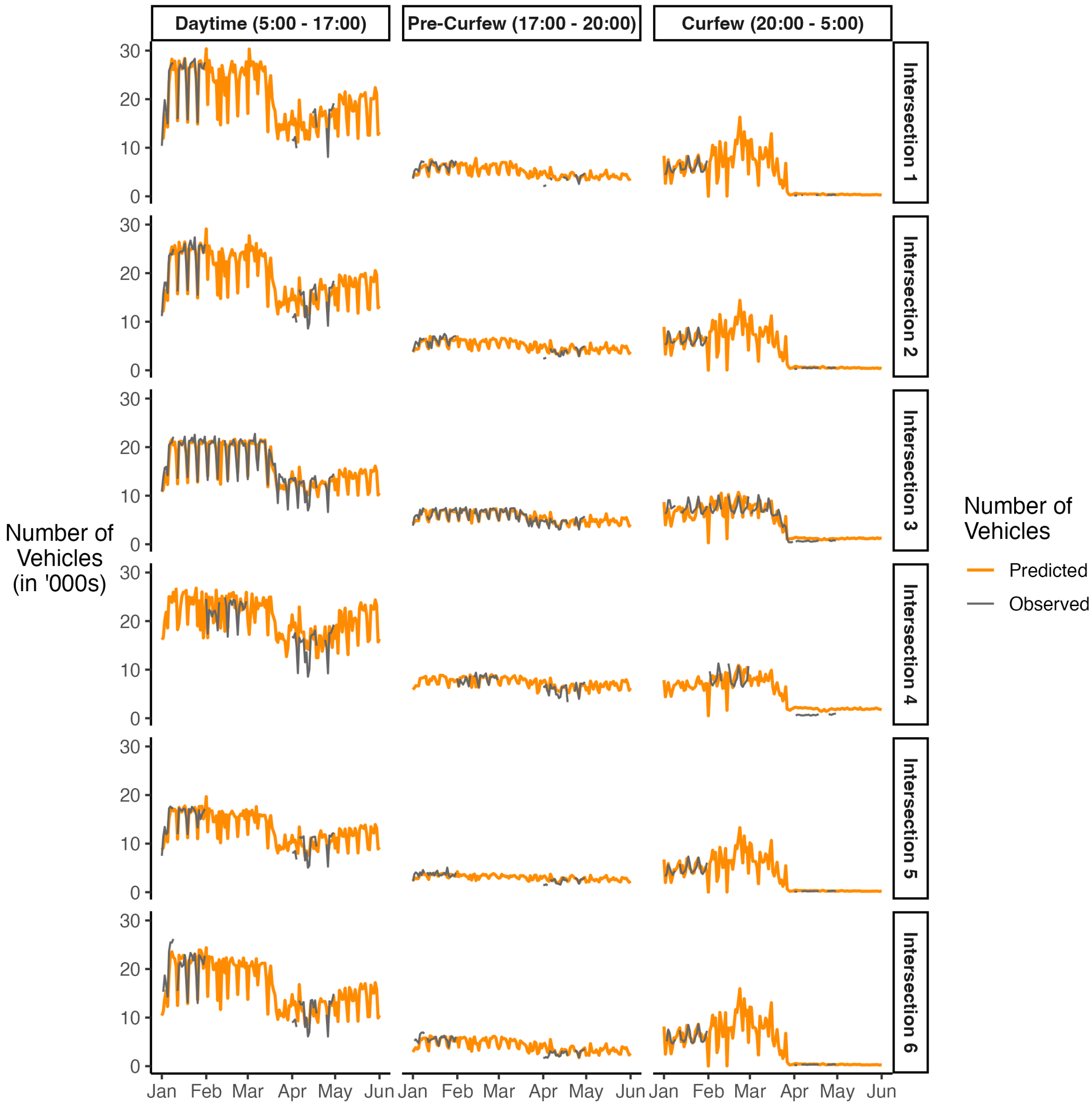


Table B.2: Data and Variable Construction

Indicator	Description	Source
Road traffic crashes	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
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	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)
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