Universidad de San Andrés

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TEMPORAL DISCONNECTION: IMPACT OF A MASSIVE INTERNET OUTAGE ON TRAFFIC INCIDENTS IN CIUDAD DE BUENOS AIRES

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Abstract

This study investigates the impact of a massive internet outage and mobile phone service disruption in Argentina on August 7, 2021, on road traffic accidents in the City of Buenos Aires. Using high-frequency data on injury records from road accidents between 2019 and 2021, the analysis reveals a significant increase in traffic accidents during the outage period from 4:00 PM to 7:00 PM. This finding persists across various study periods and is supported by robustness checks including placebo analyses and randomization techniques. Controlling for factors such as traffic flow and climatic variables, the study suggests that the internet outage remains a key factor influencing road safety in Buenos Aires. While the intrinsic mechanisms underlying this relationship require further exploration, the findings have crucial implications for road safety management and accident prevention policy. Future research integrating analysis of exogenous events with new technologies for detecting cell phone usage violations can provide deeper insights into the mechanisms linking network disruptions to driving behaviors, thereby informing more effective accident prevention strategies.

1 Introduction

The internet and the use of Information and Communication Technologies (ICT) have become integral elements in the daily lives of citizens around the world. According to data from the International Telecommunication Union (2023), provided by Statista, the number of mobile subscriptions worldwide increased from 740 million in 2000 to 8.891 billion in 2023. Additionally, the number of individuals using the internet worldwide was 2.730 billion in January 2014, and by January 2024, it had risen to 5.347 billion users. While these technological advances have revolutionized the way we communicate and perform daily tasks, they have also brought challenges related to attachment and dependence on these communication tools.

Indeed, according to Data Reportal (2023), the average time (in hours and minutes) that users aged 16 to 64 spend daily on social media increased from 1 hour and 37 minutes in the third quarter of 2023 to 2 hours and 31 minutes in the third quarter of 2022. This significant increase in time spent on social media implies a considerable proportion of the total time individuals spend using their mobile phones. One of the problems associated with the excessive use of mobile devices, particularly in the context of road safety, is its negative impact on individuals' attention in public spaces (Dirección de Investigación Accidentológica, 2022). In accordance with Sleight and Kempken (2023), citing data from the US National Highway Traffic Safety Administration (NHTSA), it is estimated that during the day, 354415 drivers use their phone while driving, and the number is even higher if we consider other actions they perform with the mobile device.

Despite evidence suggesting that cell phone use contributes to traffic accidents, it is not possible to precisely identify its causal effect on road accident records. In other words, we cannot conclusively determine whether cell phone use was the determining factor in a particular accident. Nevertheless, we have identified an exogenous event that we believe may be related to the use of these devices in the specific context of Argentina.

On August 7, 2021, according to reports from various media outlets in the country, a massive interruption in internet and mobile phone services occurred, affecting millions of users in Argentina. Considering this event and motivated by the analysis of mobile device usage in various aspects, the purpose of this study is to examine how variations in exposure to communication technologies, such as the internet and mobile phones, can influence the number of road accidents that occurred in the City of Buenos Aires during the 2019-2021 period.[1] However, it is crucial to clarify that this study does not aim to establish a causal relationship between the massive internet outage and the use of cell phones

[1] It is essential to note that preliminary results will be presented in subsequent sections, with the possibility of methodological adjustments in the future.

while driving, as the latter phenomenon is an unobservable factor in the available data. Nonetheless, it is considered that this unique event may have an influence on the use of mobile phones. In other words, this research will not directly address the question of how cell phone use affects road safety but will strive to explore factors related to these events and how they contribute to understanding road accidents.

It is important to underline that Argentina exemplifies, as do many regions worldwide, the pressing problem of mobile phone use as a significant distraction while driving. According to a report by the *Dirección de Investigación Accidentológica de la Agencia Nacional de Seguridad Vial* (ANSV) in 2022, the use of mobile phones while driving has significally escalated and become a growing concern in terms of road safety in the country. The report indicates that mobile device usage affects drivers' response capabilities, contributing to a high number of vehicle collisions and accidents involving pedestrians, both in urban and rural areas. Despite these findings, observational studies on people's behavior in public spaces conducted by ANSV in Argentina indicate an increase in the percentage of drivers of four-wheeled vehicles showing distraction factors, with mobile phones being the main source of distraction (increasing from 7.4% to 9.4%) between 2016 and 2018.

In this context, the analysis of possible causes contributing to traffic accidents is crucial in Argentina, as the average number of fatalities in the 2019-2022 period reached 3925.[2]

In relation to existing literature, epidemiological studies focused on randomly selected driver populations. A notable example is the work of Violanti and Marshall (1996), who, based on their findings, suggest that continuous use of mobile devices for more than 50 minutes per month while driving is associated with a 5.59 times higher risk of a traffic accident. However, it is important to note that this study was conducted in 1996, implying that, due to the evolution of communication technologies and the popularity of these devices in society, current users and their uses may differ significantly.

In more recent research, such as the study conducted by Asbridge, Brubacher, and Chan (2013), significant results have been obtained from traffic accident data collected by the police in British Columbia. These results indicate that cell phone use is related to a 70% increase in the likelihood of an at-fault accident. These findings were especially consistent in specific subgroups, such as male drivers, drivers aged 26 to 65, and drivers with a full license, among others.

Beyond the influence of cell phones, various lines of research have explored other factors that affect the probability of having an accident. Indeed, the determinants of vehicle collisions are complex and

[2]Data constructed from the historical series of Fatal Victims, prepared by the *Dirección de Estadística Vial* (DNOV – ANSV). See more at https://www.argentina.gob.ar/sites/default/files/2018/12/ansv_informe_siniestralidad_vial_fatal_2022_0.pdf.

closely linked to individual characteristics of drivers (Rolison et al., 2018). For example, lack of experience (McCartt et al., 2003), risky behaviors (Rolison et al., 2014), excessive speed (Gonzales et al., 2005; Lam, 2003), and drug and alcohol consumption (Bingham et al., 2008) have been associated with accidents involving young drivers. In contrast, the increase in the prevalence of visual and cognitive problems (Ball et al., 2010; Ball et al., 2006; Owsley et al., 1991; Owsley et al., 1998), as well as the use of psychoactive medications (Hemmelgarn et al., 1997; Meuleners et al., 2011; Ray et al., 1992), has been linked to collisions involving older drivers.

From another perspective, as mentioned earlier, road accident records do not report mobile phone use as one of the causes of the accidents. In fact, according to interviews with police officers in England, mobile phone use would be one of the main factors related to traffic accidents that are underreported in road accident records (Rolison et al., 2018). In this sense, the evidence investigating the risk of cell phone use on traffic accidents in natural environments, i.e., not controlled experiments, is limited (Ortega et. al, 2021). Again, while not aiming to conclusively demonstrate how mobile phone use affects the probability of a traffic accident, given the structural limitation of the study data, this work represents a new contribution, in the context of a natural event, to possible factors explaining the occurrence of a road accident.

In summary, this report will be structured in the following sections. Firstly, the subsequent section will provide a detailed account of the natural experiment triggered by the internet outage, along with the presentation of the data used in its analysis. Subsequently, the third section addresses the methodology used and presents the main results obtained using Ordinary Least Squares (OLS) in the research, accompanied by a detailed series of placebo tests. Finally, the report concludes with a section addressing the discussion of the results and presenting the conclusions derived from the findings presented.

2 The Internet Outage and Data

In this section, we will explore the massive internet outage on August 7, 2021, in Argentina and its impact on our research on traffic accidents in the City of Buenos Aires. This event, documented by various media outlets, is presented as unpredictable and exogenous, independent of factors such as traffic and weather. We will then detail the data used and the treatment given to it, describing the road accident database, traffic flow, and weather conditions.

2.1 Massive Internet Outage: Identification

On August 7, 2021, according to reports from various news media in Argentina, a massive disruption in internet and mobile phone services affected a large number of users. This interruption was due to technical issues caused by international providers Lumen, Internexa, and TIS, affecting the systems of cable, internet, and mobile phone companies. The disruptions began around 3:00 PM and became widespread by 4:00 PM. Most affected websites and platforms regained connectivity around 7:00 PM, and the service was fully restored after 8:00 PM. Among the affected services were Google, Netflix, Telecom, Cablevisión, Fibertel, Movistar, Zoom, Twitch, Telegram, WhatsApp, Telecentro, Personal, Claro, Instagram, and Facebook.[3]

The fact that the massive technical failure of phone and internet services is inherently unpredictable, reinforces the notion of its exogenous nature. This event, unpredictable for both communication providers and Argentine citizens, can be considered independent of traffic conditions, weather, and other factors that could influence the probability of a traffic accident.

The unpredictability not only underscores the exogenous nature of the incident but also acts as a key factor in minimizing correlations with confounding variables. Unpredictable events, by their nature, are less likely to be intertwined with other simultaneous factors that could distort the causal relationship. This characteristic strengthens the validity of the results presented in the following sections.

2.2 Data

In this section, we will address the methodology and data treatment used in the research to analyze the effects of the internet outage on traffic accidents in the City of Buenos Aires. The robustness of our conclusions depends largely on the quality and precision of the data used, so we will detail the sources and the collection process extensively.

2.2.1 Traffic Accidents

To examine the impacts of the internet service interruption on traffic incidents, a high-frequency database was employed, with hourly records documenting injuries resulting from road accidents.[4] This database encompasses incidents that occurred in the City of Buenos Aires between 2019 and

[3] For more details, read the full article on Infobae (2021), retrieved on January 13, 2024, from https://www.infobae.com/tecno/2021/08/07/una-falla-masiva-de-internet-afecta-a-millones-de-usuarios-en-argentina/

[4] According to the definitions adopted by the *Observatorio de Seguridad Vial* (2023), a traffic incident is defined as "cualquier hecho de tránsito con la participación de al menos un vehículo en movimiento, que ocurra en una vía pública o en una vía privada con derecho de acceso para la población, y que resulte en al menos una persona herida o fallecida [any traffic event involving at least one moving vehicle that occurs on a public road or a private road with public access, resulting in at least one person injured or killed]" (p. 3).

2021, including detailed information such as date, location, type of involved transport, gender and age of victims, as well as the type of injury suffered.[5]

In the research framework, data treatment was divided into several crucial stages. First, the analysis and data collection were restricted to the period in which the massive internet outage significantly impacted most services, specifically from 4:00 PM to 7:00 PM. During this interval, injuries resulting from traffic accidents were recorded daily, generating one observation per day as in Gibbons and Rossi (2021).[6]

2.2.2 Traffic Flow

To broaden the scope of the analysis, traffic flow data were extracted from publicly available databases generated and disclosed by the Government of the City of Buenos Aires. Specifically, the time series addressing vehicular flow is constructed from information collected by *Autopistas Urbanas* (AUSA), which is broken down by hour and provides details on vehicle passage at specific locations equipped with radars on the city's highways. Additionally, the database includes detailed information on date, time, highway name, and radar location responsible for capturing vehicular flow in each instance.

It is important to add that, to address issues related to missing values, two approaches were employed, deemed most appropriate for each case. First, for the sample covering exclusively Saturdays from 2019 to 2021, missing data for each Saturday was completed using the total average of Saturdays in the respective month. However, in cases of traffic flow corresponding to February and December 2021, where no data was available, information was constructed by comparing February 2020 with February 2021, using the same multiplier reflecting the observed decrease between January 2020 and January 2021. These two approaches were applied similarly for the sample including all days.

2.2.3 Present Weather and Climate

Detailed data on meteorological conditions and climate variables in the City of Buenos Aires was requested on a customized basis, with the assistance of experts, from the *Servicio Meteorológico Nacional* (SMN), the specialized entity responsible for collecting this information. Specifically, in accordance with the Public Data Policy, the retrieved data includes accumulated precipitation every 6 hours and a series of variables broken down by hour, covering current weather conditions (a numeric indicator reflecting the type of observed climatic phenomenon), visibility in kilometers, wind direction in decagrades, wind speed in kilometers per hour, as well as the direction and speed of wind

[5] For more details, see https://data.buenosaires.gob.ar/dataset/victimas-siniestros-viales

[6] It is important to note that the official database does not record days without any reported traffic accidents. In order to mitigate this gap in the data, observations were manually generated by assigning a value of 0 to populate the database.

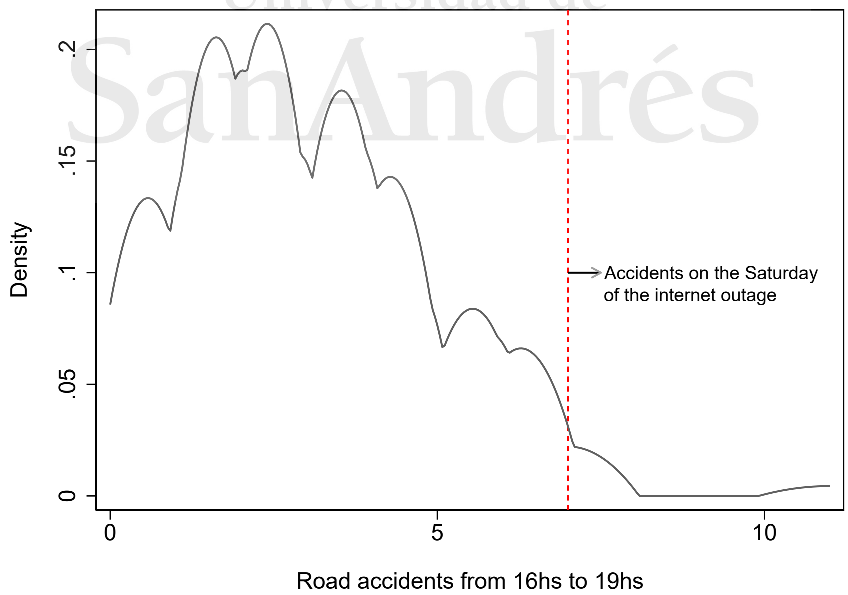
gusts. Based on the Present Weather Code provided by the SMN, it is established that missing data in the "Present Weather" category corresponds to code 0 (No cloud development was observed or could be observed).

In detail, the request obtained and ensured data corresponding to observations from the meteorological station at Jorge Newbery Aeroparque (code 87582) and the Observatory of Buenos Aires (code 87585), covering the period from January 1, 2019, to December 31, 2021.

3 Methodology and Results

Approaching the issue from a practical perspective, we build upon empirical strategies employed in previous research, such as those conducted by Gibbons and Rossi (2021), who analyzed the impact of a YouTube service interruption on the number of violations in the United States. In our case, the study primarily focuses on comparing Saturday, August 7, 2021, the day of the internet outage, with the rest of the Saturdays in the complete sample (156 observations). Consistent with this approach, Figure 1 depicts the Kernel density distribution of the number of traffic accidents for each Saturday. The data singular that only 3.57% of Saturdays have an equal or higher number of accidents than those recorded on August 7, 2021.[7] In fact, only one Saturday shows a higher number.

Figure 1: Kernel Density Distribution of Traffic Accidents per Saturday, Period 2019–2021.

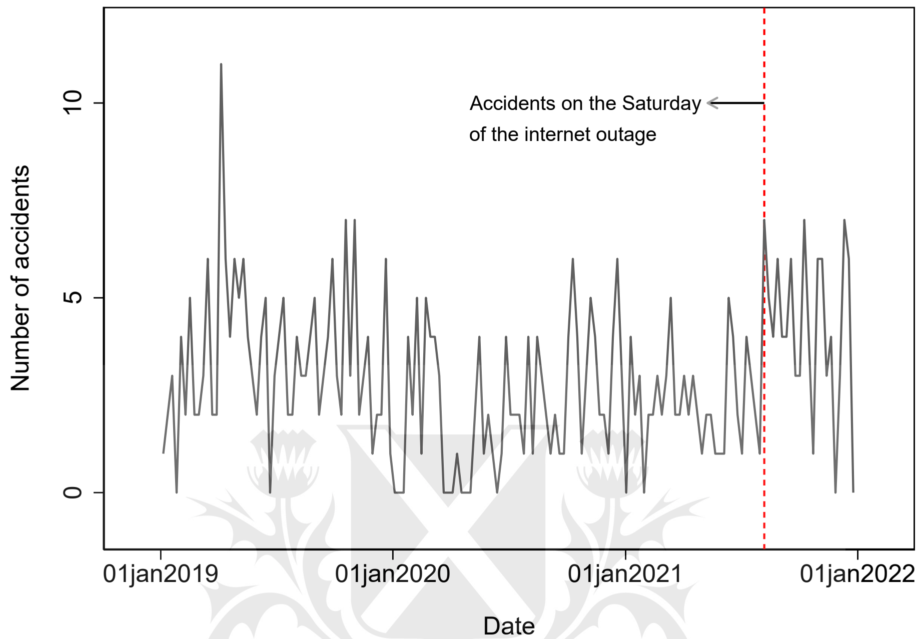


Source: Own elaboration based on data from the Government of the City of Buenos Aires. *Notes*: 3.57% of Saturdays have an equal or higher number of accidents than those recorded on August 7, 2021.

[7] Four Saturdays (October 19, 2019; November 2, 2019; October 9, 2021; and December 11, 2021) exhibit 7 accidents in the specified time slot, equal to that recorded on August 7, 2021, with only one Saturday surpassing this number with 11 accidents, on June 4, 2019.

Similarly, Figure 2 illustrates the evolution of traffic accidents over time. The red dashed line marks the day of the internet outage, with a total of 7 accidents recorded during the 4:00 PM to 7:00 PM period.

Figure 2: Trend in the Number of Traffic Accidents per Saturday, Period 2019–2021.



Source: Own elaboration based on data from the Government of the City of Buenos Aires. *Notes*: The day of the internet outage (red dashed line) saw a total of 7 accidents during the 4:00 PM to 7:00 PM period.

Using a simple regression employing Ordinary Least Squares (OLS), we explored the impact of the internet outage on the number of Injuries from Traffic Accidents. Initially, we considered four different time periods, taking into account significant events such as the pandemic and mandatory lockdown: (1) the complete period from 2019 to 2021; (2) from 2020 to 2021, excluding 2019, as this year may differ in certain factors such as traffic flow and urban mobility; (3) excluding the year 2020; (4) excluding observations from March to September 2020. However, it is important to note that in the rest of the report, the additional estimates we work with will correspond to the sample covering the complete period, using this specification as the baseline. Formally, the model we have estimated can be represented as follows:

$$\textit{Injuries from Traffic Accidents}_s = \beta \; \textit{Internet Outage}_s + \delta \; X_s + \epsilon_s \tag{1}$$

Equation (1) denotes the dependent variable, *Injuries from Traffic Accidents*, representing the number of traffic accidents recorded in the Autonomous City of Buenos Aires (CABA) between 4:00 PM and 7:00 PM on Saturday s, in relation to our variable of interest, *Internet Outage*, and a set of controls. *Internet Outage* is a dummy variable taking the value 1 if it corresponds to Saturday, August 7, 2021, and 0 for any other Saturday s. Then, X is a set of controls for Saturday s, including the number of vehicles in circulation captured by AUSA radars between 4:00 PM and 7:00 PM, average temperature, total precipitation accumulated on the day, as well as other weather variables recording the day's average s between 4:00 PM and 7:00 PM with respect to wind speed in km/h and visibility in km. Finally, ϵ_s is the error term.

Subsequently, Table 1 presents the results of the OLS regression of equation (1) for the four periods considered in the sample subdivision, excluding the analysis and inclusion of other control variables. As evident, the initial results are statistically significant and suggest a positive effect of the internet outage on traffic accidents in each of the study periods.

Table 1: *Regressions under Different Time Windows*

	Dependent variable: *Traffic Accident Injuries*			
Variables	Model 1	Model 1B	Model 1C	Model 1D
Internet Outage	4.097**	4.408**	3.748*	3.866**
	(1.953)	(1.848)	(1.963)	(1.930)
Observations	156	104	104	135
R^2	0.028	0.053	0.034	0.029

Notes: Model 1 considers all Saturdays available in the sample, from 2019 to 2021. Model 1B excludes Saturdays recorded in 2019, while Model 1C removes observations from 2020. Lastly, Model 1D excludes the period between March and September 2020 from the analysis. Standard errors in parentheses.
* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1% level

Given the potential influence of climatic factors on driving quality and, consequently, on the probability of traffic accidents, it is essential to consider variables such as precipitation, temperature, visibility in kilometers, and wind speed. In this context, it is logically posited that the level of daily precipitation may impact the number of traffic accidents by affecting pavement conditions (whether wet asphalt or soil) and visibility, in addition to causing discomfort during driving (Federal Highway Administration, 2023; Zou, Zhang, and Cheng, K., 2021). Likewise, temperature could have significant effects on vehicles and drivers (Pińskwar, Choryński, and Graczyk, 2024). In the case of vehicles exposed to strong winds, such as motorcycles, the speed of these weather phenomena is a relevant factor in determining their impact on accidents of this kind. Furthermore, large trucks facing strong winds may pose a hazardous condition on roads. Finally, average driving visibility stands as a determining factor in the probability of accidents, by restricting the driver's field of vision and maneuvers (Federal Highway Administration, 2023).

Table 2 presents the OLS estimates of equation (1), disaggregating the results through the inclusion of each of the controls. Additionally, since the number of observations is relatively small, we conduct a random inference analysis using permutations (over time) based on Monte Carlo simulations. To this end, we report the p-values obtained from using the ritest command in Stata (Heß, 2017), a novel tool in its development. Indeed, we perform 500, 1000, 5000, and up to 10000 permutations of the coefficient of interest, obtaining a 5% significance level in all cases.

Table 2: *Regressions with Controls*

	Dependent variable: *Traffic Accident Injuries*					
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Internet Outage	4.097**	3.868**	3.760*	4.010**	3.979**	3.971**
	(1.953)	(1.923)	(1.920)	(1.941)	(1.938)	(1.941)
Permutation analysis						
500 replications	[0.028]	[0.018]	[0.026]	[0.012]	[0.012]	[0.012]
1000 replications	[0.034]	[0.027]	[0.035]	[0.018]	[0.018]	[0.018]
5000 replications	[0.041]	[0.032]	[0.039]	[0.019]	[0.019]	[0.019]
10000 replications	[0.041]	[0.033]	[0.041]	[0.020]	[0.020]	[0.020]
Observations	156	156	156	156	156	156
R^2	0.028	0.066	0.076	0.081	0.091	0.093
Traffic Flow	No	Yes	Yes	Yes	Yes	Yes
Average Temperature	No	No	Yes	Yes	Yes	Yes
Wind Speed	No	No	No	Yes	Yes	Yes
Total Precipitation	No	No	No	No	Yes	Yes
Average Visibility	No	No	No	No	No	Yes

Notes: In all cases, the sample corresponds to Saturdays available from 2019 to 2021. Average temperature is calculated as the mean of 24 hours of the day, while the average wind speed (in km/h) and visibility (in km) are based on values observed between 4:00 PM and 7:00 PM, coinciding with the internet service interruption. Total precipitation represents the accumulation of levels in mm throughout the day. Standard errors are indicated in parentheses. P-values (two-tailed), obtained from randomized inference using the *ritest* command in Stata, are within brackets.
* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1%

It is noteworthy that the results presented in Table 2 remain consistent when varying the data source on the climatic variables used. In other words, the results of re-estimating models 1-6 with data from the Buenos Aires Observatory respect both the magnitude and significance of our parameter of interest (see Appendix).

Finally, it is crucial to clarify a central point in these estimations: the specified standard errors are not robust. Unlike what could be considered the conservative convention in the use of robust standard errors (or Huber–White's robust standard errors), aimed at avoiding additional assumptions about homoscedasticity, employing these errors in the context of the estimations presented in tables 1 and 2 biases the inference regarding the coefficient of our variable of interest, "Internet Outage". Specifically, due to the nature of Huber–White's robust standard errors and the peculiarities of the model presented here, this strategy induces a variance of the estimator very close to zero. This results in an exponential increase in the t-statistics, which in turn implies that the observed levels of significance are extremely low, as the t-statistic deviates considerably from the 95% confidence intervals. Even when conducting placebo tests, it is possible to demonstrate that regardless of the fictitious day the event is moved to, with robust standard errors, the estimated coefficient will be statistically significant with confidence at the 1% level. However, this novel result is evident in the model that includes only the regressor of interest (and also few regressors), as incorporating a relatively large number of explanatory variables increases the variance of the estimator regarding our dependent variable of interest, the residual of the estimation for the day of the event stops being exactly 0, and the use of Huber–White's robust standard errors makes sense. Thus, this discussion clarifies the difference between the present and the subsequent section, as it will be observed that the standard errors of the model using the sample of all days expose both White-Huber robust standard errors and Newey and West (1994) standard errors in their estimations. The mathematical proof of this phenomenon can be found in the Appendix.

3.1 Exploring the Entire Sample

In order to broaden our analysis and bolster the robustness of previously obtained results, this section delves into the effects of internet outage on the number of traffic accidents recorded over the 1096 days spanning from 2019 to 2021. Formally, the detailed estimation in this section is expressed by the following equation:

$$\textit{Injuries from Traffic Accidents}_t = \beta \; \textit{Internet Outage}_t + \delta \; Z_t + \epsilon_t \tag{2}$$

Analogous to the preceding section, equation (2) models the variable *Injuries from Traffic Accidents* for day t, with respect to our variable of interest, *Internet Outage*, and a new set of controls. Specifically, Z encompasses controls for day t, including dummies for day of the week, month, and day of the month, a quadratic daily time trend, the count of vehicles in circulation captured by AUSA radars between 4:00 PM and 7:00 PM, and the set of climatic control variables previously employed (average temperature, total precipitation, wind speed, and visibility).

In this vein, Table 3 presents the Ordinary Least Squares (OLS) estimates of regressing equation (1) for the 1096 days of the entire sample. As observed once again, the results are disaggregated based on the controls considered in each specification, with the only difference being that climatic controls are consolidated in one instance (Model 12). In summary, the findings indicate a positive and significant effect of internet outage on traffic accidents, both with and without controls. Furthermore, the results of Model 12 remain consistent when utilizing alternative data sources for climatic variables from the Buenos Aires Observatory (see Model 12A in the Appendix). Thus, it becomes evident that these new regressions enhance the robustness of the findings discussed in Table 2.

Table 3: *Estimates with all days recorded between 2019-2021*

	The dependent variable is *Traffic Accident Injuries*						
Variables	Model 1	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Internet Outage	2.440	4.097	3.835	3.390	3.872	3.741	3.960
	(0.093)***	(0.156)***	(0.300)***	(1.298)***	(1.229)***	(1.066)***	(0.971)***
	[0.138]***	[0.156]***	[0.401]***	[1.299]***	[1.233]***	[1.081]***	[1.022]***
Observations	1,096	1,096	1,096	1,096	1,096	1,096	1,096
R^2	0.001	0.180	0.213	0.426	0.432	0.442	0.448
Day of the Week	No	Yes	Yes	Yes	Yes	Yes	Yes
Month	No	No	Yes	Yes	Yes	Yes	Yes
Day of the Month	No	No	No	Yes	Yes	Yes	Yes
Temporal Trend	No	No	No	No	Yes	Yes	Yes
Traffic Flow	No	No	No	No	No	Yes	Yes
Climate Controls	No	No	No	No	No	No	Yes

Notes: The sample includes 1096 days between 2019-2021. Climate Controls encompass average temperature (24-hour mean), average wind speed (in km/h), and visibility (in km), observed from 4:00 PM to 7:00 PM during the internet service outage. Total precipitation reflects daily accumulation in mm. Robust standard errors are indicated in parentheses. Newey and West's (1994) standard errors consistent with heteroskedasticity and autocorrelation are shown in brackets.
*Significant at the 10% level
**Significant at the 5% level
***Significant at the 1% level

It is important to emphasize that our estimations report both robust White-Huber standard errors and Newey and West's (1994) standard errors consistent with heteroskedasticity and autocorrelation. [8]

[8]For each estimation, the optimal number of lags is determined using the first step of Newey and West's (1994) inclusion procedure, which sets the number of lags as the integer floor of $[4(T/100)^{2/9}]$, where T represents the number of observations. In our case, the corresponding number of lags is equal to 6.

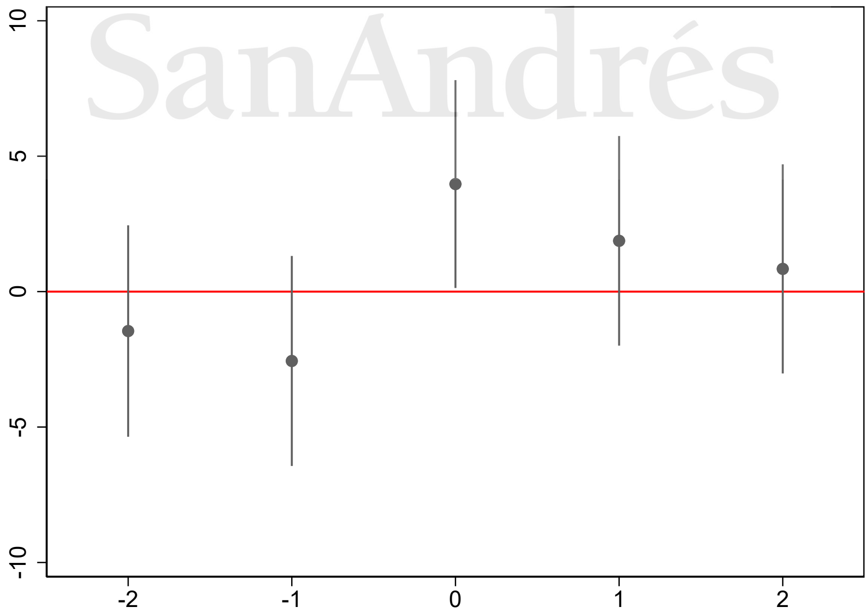
Finally, when using traditional standard errors, the p-values for the estimations of Models 7 to 12 (without controlling for *Day of the Month)* range between 0.126 (Model 12, without the *Day of the Month* control) and 0.169 (Model 8). Additionally, conducting a permutation analysis (500 replications), we obtain a p-value of 0.116 for the "modified" Model 12. However, when controlling for Day of the Month, Model 12 yields a p-value of 0.260.

3.2 Placebo Tests

This final segment of the section aims to reinforce the robustness of previously obtained results, thereby lending validity and bolstering the causal interpretation of the research. The placebo tests conducted in this study address result consistency through exploration of various testing approaches, ranging from variations in treatment date to an adaptation of Fisher's randomization test (1935).

In this context, the initial exercise of these tests involves generating placebos by fictitiously manipulating the treatment window, i.e., arbitrarily shifting the day when the internet service interruption occurred. Initially, 4 placebos were created from the Saturdays around the event day, August 7, 2021. This involved shifting the treatment period 1 and 2 weeks backward and forward in time, with the aim of comparing the coefficients of these placebo tests with our original estimation. Figure 3 visually presents the coefficient values obtained when estimating, in all cases, Model 6 of Table 2.

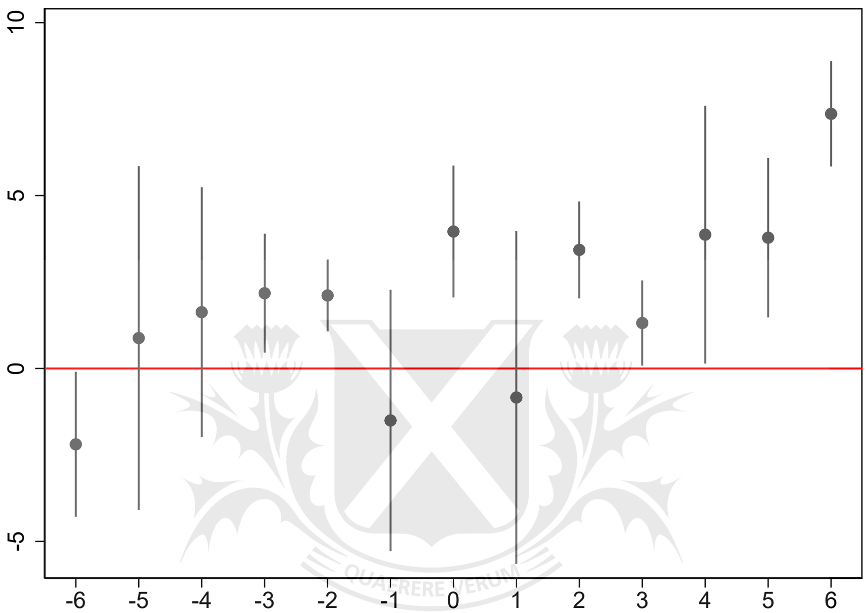
Figure 3: *Placebo Analysis: 2 Weeks Before and 2 Weeks After*



Source: Own elaboration. *Notes*: This figure displays the estimated coefficients for our parameter of interest, derived from 4 placebos generated from Saturdays near August 7, 2021. In all cases, the estimation of Model 6 of Table 2 was conducted. On the horizontal axis, point 0 corresponds to the estimation of the internet interruption day, while -1, -2, 1, and 2 represent the placebo treatments obtained by artificially shifting the treatment one and two weeks backward and forward in time.

Secondly, we proceeded similarly to the previous case, but varying the event date 6 days backward and forward in time, around August 7, 2021. In this regard, we generated 12 additional placebos to the original estimation, which can be compared and observed in Figure 4. Each of these coefficients was obtained by regressing Model 12 of Table 3, with the treatment period being the only difference between the estimations.

Figure 4: Placebo Analysis: 6 Days Before and 6 Days After



Source: Own elaboration. *Notes*: This figure presents the estimates of Model 12 of Table 3, but using the 12 days around August 7, 2021, as placebos. On the horizontal axis, point 0 corresponds to August 7, 2021, while -1 to -6 and 1 to 6 represent the placebo treatments obtained by artificially shifting the treatment from 1 to 6 days backward and forward in time.

Observing Figures 3 and 4, it is evident that in all cases, except for August 13, 2021 (6 days after the Internet service interruption), the estimated coefficient for August 7, 2021, is larger in magnitude. However, it is essential to acknowledge that the confidence intervals (CIs) of the coefficients, computed based on a Student's t-distribution, for August 7 and the following Friday, partially overlap. Specifically, the CI for August 7 falls within the range $[2.054, 5.856]$, while the CI for the Friday proximal to the event spans $[5.840, 8.887]$.

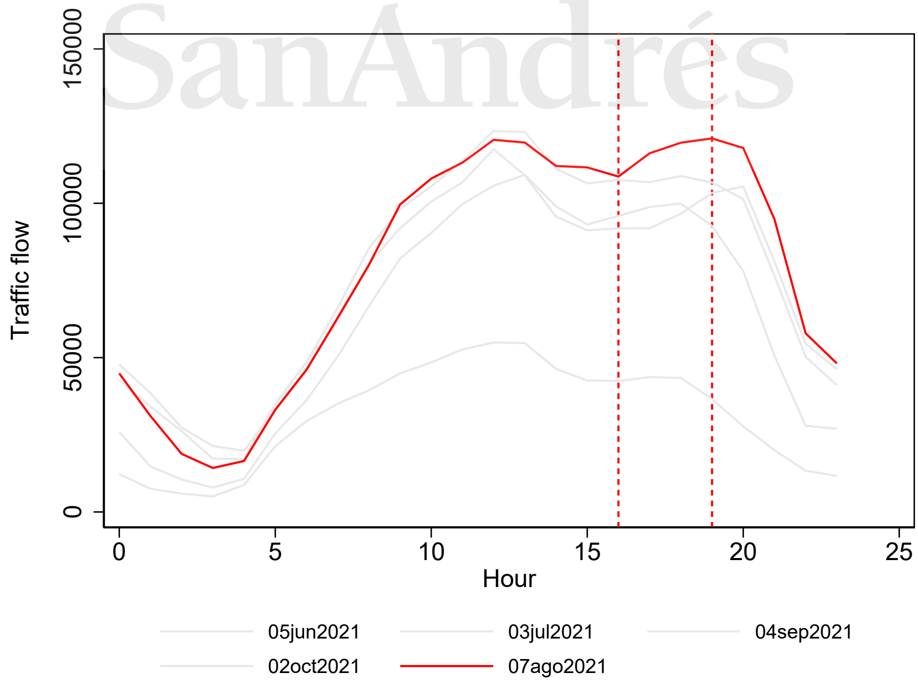
Finally, inference in studies of this nature with time series data often raises concerns. In order to address potential deviations from standard assumptions of homogeneity, we implemented a variant of Fisher's randomization test (1935) (see Buchmueller, DiNardo, and Valletta, 2011). This test involves comparing our original estimate with 1095 placebos generated from additional estimations for each day other than August 7, 2021. In other words, akin to previous placebo experiments, we artificially shifted the treatment period for each day between 2019 and 2021, rendering these placebo estimates representative of the sampling distribution for the parameter of interest. Thus, the significance of the coefficient is determined by the rank occupied by the August 7, 2021, estimate in the distribution of placebo estimates. Specifically, when conducting this exercise for Model 12 of Table 3, August 7, 2021, occupies the 958th position out of 1096, implying that 12.59% of placebo estimates are above the estimate for the day of the internet service interruption.

3.3 Potential Mechanisms

The aim of this subsection was to explore and shed light on the discussion of potential mechanisms that could explain how the internet outage, according to the results obtained, might lead to an increase in traffic accident injuries in CABA. Although this evidence is preliminary, it prompts reflection on possible future lines of research that could better explain the mechanisms behind the observed effects.

As observed in Figure 5, it shows the hourly evolution of traffic flow in the City of Buenos Aires during the day of the event (August 7, 2021) and the two Saturdays before and after. From this graph, we can extract an interesting observation: on August 7, compared to the other 4 Saturdays, there was not only a higher traffic flow during 4:00 PM to 7:00 PM (the time of the internet outage), but also a more pronounced upward trend for these 3 hours of analysis. In other words, we could speculate that the internet outage could be explained by the idea that people, bored or with nothing to do without internet during those hours, decided to venture out more onto the streets than on other Saturdays.

Figure 5: Hourly evolution of Traffic Flow in the Autonomous City of Buenos Aires



4 Conclusions

The massive internet outage and mobile phone service in Argentina on August 7, 2021, represented an unprecedented event that affected millions of users across the country. Driven by an interest in understanding how a total disconnection of communications could impact in the number of traffic accidents, this study aimed to examine the effects of this phenomenon on road accidents that occurred in the City of Buenos Aires during the period from 2019 to 2021.

By using high-frequency data on injury records resulting from road accidents in the City of Buenos Aires, this study documented an increase in the occurrence of traffic accidents between 4:00 PM and 7:00 PM following the internet service interruption. This finding has remained consistent across different study periods and has been supported by placebo analyses and randomization techniques of the results, confirming the robustness of the findings.

Considering factors related to traffic flow around the internet outage and relevant climatic variables according to the specialized literature, allowed for clarifying the impact of the internet outage on road safety. The results suggest that even after adjusting for these variables, the internet service interruption remains a significant factor in the incidence of traffic accidents in the City of Buenos Aires.

As explored in the section on Potential Mechanisms, while it is not possible to definitively determine the intrinsic mechanisms that could explain how the internet outage affects the number of traffic accidents, for instance, through changes in traffic patterns or cell phone usage during the event, the findings have significant implications for road safety management and accident prevention policy planning. Identifying the impact of an internet outage in the City of Buenos Aires on traffic accidents underscores the necessity to comprehend how these events contribute to traffic accidents and to develop effective damage control strategies.

The analysis and discussion presented in this document justify the development of future research that combines the analysis of these exogenous events to road accidents with new data and technologies for detecting cell phone usage violations in the City of Buenos Aires.[9] This integration would be an optimal resource to strengthen the study by corroborating the mechanisms and the relationship between problems in cell phone networks and their influence on cell phone usage while driving.

[9]For more details, see https://www.infobae.com/sociedad/2023/02/02/nuevas-fotomultas-en-caba-que-se-puede-hacer-y-que-no-dentro-del-auto/.

5 Appendix

Robustness Check: Utilizing Data from the Buenos Aires Observatory

Table 4: *Regression with Controls Using Buenos Aires Observatory Data*

	Dependent Variable: *Injuries from Traffic Accidents*						
Variables	Model 1A	Model 2A	Model 3A	Model 4A	Model 5A	Model 6A	Model 12A
Internet Outage	4.097**	3.868**	3.861**	4.059**	4.018**	4.000**	3.822
	(1.953)	(1.923)	(1.919)	(1.915)	(1.907)	(1.909)	(1.001)***
							[1.065]***
Observations	156	156	156	156	156	156	1096
R^2	0.028	0.066	0.075	0.090	0.104	0.108	0.451
Traffic Flow	No	Yes	Yes	Yes	Yes	Yes	Yes
Average Temperature	No	No	Yes	Yes	Yes	Yes	Yes
Wind Speed	No	No	No	Yes	Yes	Yes	Yes
Total Precipitation	No	No	No	No	Yes	Yes	Yes
Average Visibility	No	No	No	No	No	Yes	Yes
Day of the Week	No	No	No	No	No	No	Yes
Month	No	No	No	No	No	No	Yes
Day of the Month	No	No	No	No	No	No	Yes
Time Trend	No	No	No	No	No	No	Yes

Notes: In Models 1A to 6A, the sample corresponds to Saturdays available from 2019 to 2021. In contrast, the sample of Model 12A includes the 1096 days between 2019-2021. Average temperature is calculated as the mean of the 24 hours of the day, while average wind speed (in km/h) and visibility (in km) are based on values observed between 16:00 and 19:00 hours, coinciding with the internet service outage. Total precipitation represents the accumulation of levels in mm throughout the day. Robust standard errors are reported in parentheses. Newey-West robust standard errors accounting for heteroskedasticity and autocorrelation (Newey and West, 1994) are reported in brackets.
*Significant at the 10% level
**Significant at the 5% level
***Significant at the 1% level

Traditional Standard Errors versus Robust Standard Errors

To begin with, for the sake of simplicity in the demonstration, we confine ourselves to a two-variable model without an intercept, meaning that we only have "Internet Outage" as the explanatory variable. Thus, in the following equation, we define what we already know as the variance of the estimated β when using traditional standard errors:

$$\hat{V}(\hat{\beta}) = \frac{\sigma^2}{\sum_i (X_i - \overline{X})^2} = \frac{\sigma^2}{nV(X)}$$

where n is the number of observations and $V(X)$ is the variance of the independent variable. Therefore,

$$\hat{V}(\hat{\beta}) = \frac{\sigma^2}{156 \cdot \frac{155}{156}} \cong \sigma^2$$

In contrast, according to the well-known definition of White-Huber robust standard errors, we have:

$$\hat{V}_R(\hat{\beta}) = \frac{\sum_i (X_i - \overline{X})^2 \hat{\epsilon}_i^2}{\left(\sum_i (X_i - \overline{X})^2\right)^2} = \frac{\sum_i (Y_i - \hat{Y}_i)^2 (X_i - \overline{X})^2}{\left(\sum_i (X_i - \overline{X})^2\right)^2}$$

Then, it is evident to see that, since we have one observation affected by the event and only one regressor, we know that "Internet Outage" (the only independent variable) will fully and accurately explain the number of accidents that occurred on August 7, 2021 (our Y in the model). Mathematically, and generalizing this result, we have $\hat{Y}_{event} = Y_{event}$. So, focusing on what happens with the numerator, since the denominator remains unchanged between strategies, we arrive at:

$$\Rightarrow \sum_i (Y_i - \hat{Y}i)^2 (X_i - \overline{X})^2 = \left[\underbrace{(0 - \frac{1}{156})^2}_{\cong 0} \underbrace{(Y_i - \hat{Y}i)}_{=Y_i} + (1 - \frac{1}{156})^2 \underbrace{(Y_{event} - \hat{Y}_{event})}_{=0}^2 \right] \cong 0$$

where $i \neq event$, meaning that observations i do not correspond to the day of the Internet Outage, implying that $\hat{Y}_{event}$ is the estimation for the day this event occurred in Argentina. Thus, we finally arrive at:

$$\hat{V}R(\hat{\beta}) \cong 0 \;\; \Rightarrow \;\; t_{obs} = \frac{\hat{\beta}}{V_R(\hat{\beta})} \xrightarrow[V_R(\hat{\beta}) \underset{+}{\to} 0]{} +\infty$$

However, when adding a large number of regressors, it is evident that some noise is introduced into the estimations, so it is no longer necessarily the case that $\hat{Y}_{event} \neq Y_{event}$, implying a clear increase in the estimator's variance. Moreover, for calculating the estimator's variance, both for traditional and robust standard errors, multicollinearity among the different independent variables must now be considered. Indeed, although these changes technically represent a loss of efficiency, they open up the possibility of using White-Huber robust standard errors without biased inference towards the significance of the estimations.

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