ESTIMATING THE IMPACT OF INCIDENTS ON URBAN CONTROLLED-ACCESS HIGHWAYS: AN EMPIRICAL ANALYSIS

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ABSTRACT

An empirical analysis is developed that quantifies the impact of different types of traffic incidents on the speed and maximum flow averages of vehicles on a controlled-access highway. The incident types considered include damage to highway infrastructure, vehicle rollover, crashes (into stationary objects), collisions (with moving vehicles), rain, fog, vehicle breakdowns, pedestrians on roadway, etc. Using real-world data from Chile's most heavily used urban motorway/freeway, estimates of incident impacts on speed are generated using a multiple linear regression model incorporating instrumental variables to correct for endogeneity. Flow results are then generated using the fundamental traffic equation relating speed, flow and density. A ranking of the impacts on highway traffic of the different incident types based on incident frequency as well as impact size demonstrates that for the real case studied, the incidents with the greatest cumulative effect are (in order of magnitude) vehicle breakdown, collisions and rain.

Keywords: traffic incidents, density, speed, maximum flow, highway capacity, accidents, vehicle breakdown, collision, rain, instrumental variables, endogeneity

1. INTRODUCTION

This article presents an empirical analysis for determining the impact of different types of traffic incidents on a highway's average vehicle speeds and flows (the latter in some cases coinciding with highway capacity). The proposed analysis was applied to the real-world case of Chile's *Autopista Central*, the country's most heavily used controlled-access highway.

The effects of the selected incident types are estimated using a multiple linear regression model that incorporates instrumental variables to correct for endogeneity. The results reveal the existence of an incident hierarchy reflecting the different magnitudes of the impact the incidents could have on the normal functioning of an urban highway in terms of traffic speed and volume of traffic flow. The estimates also show that some incident types are directly related to vehicle operation such as vehicle breakdowns or accidents while others are linked to (exogenous) weather conditions such as rain or fog.

By analyzing each incident type individually, we estimate that the greatest impacts (that is, the greatest reductions in traffic speed and flow averages) are caused by the type denoted "load spill with structural damage", which reduce average speed by almost 34 km/h and maximum capacity by more than 70%. The incident type with the second greatest impact is "vehicle rollover", which cuts average speeds by about 13 km/h and maximum capacity by 26%.

Upon multiplying these individual impacts by the frequency of each incident type (taken as the number of occurrences in a one-year period), we derive each type's annual cumulative impact. The type with the greatest such effect is "vehicle breakdowns", followed by "collision" (i.e., between moving vehicles) with "rain" in third place. This implies that the two main incident types found to negatively affect service levels on an urban highway are caused by human error whereas the third type is exogenous to both humans and highway operators.

According to Giuliano (1989), estimates of incidents impacts by category are a valuable basis for evaluating alternative incident management and traffic management policies. A successful incident management policy minimizes delays and responds briefly to traffic incidents. In the design of traffic management techniques, Charles and Higgins (2002) emphasise the importance of acknowledging the effects of incidents on congestion, recognizing the nature of the incident.

The *Autopista Central* is a motorway/freeway 39.5 kilometres long running north-south through Santiago, the nation's capital and its most populous city. The first of its kind in Chile when it was inaugurated in 2004, the highway was built and continues to be run under a concession scheme in which users pay the operator through a free-flow automatic tolling system. Loop detector portals installed at various points along the route record the registration/licence plate number, speed, date and time for all vehicles using it, enabling the operator to bill the vehicle owners once a month for recorded use.

Of particular interest for our purpose, however, is that this system can also generate measurements of the average speed, flow and density of all traffic at different points along a given section of the highway for a desired period any day of the year around the clock on a permanent basis. A database can thus be constructed with abundant high-frequency data (in our case, every half hour).

The operator also has a system of television cameras monitoring the entire length of the highway 24 hours a day with no blind spots. There is thus a visual record complementing the vehicle data that allows virtually all traffic incidents occurring along the highway to be identified. Using this system we were able to identify 11 different types of traffic incidents, including those caused by weather conditions.

The remainder of this paper is divided into five sections. Section 2 is a literature survey of previous studies into urban controlled-access and other highways, which provided a set of baseline data for comparison and contrast with our empirical results; Section 3 gives a brief statistical description of our data; Section 4 introduces our methodology, specifying the econometric model we designed and its explanatory, instrumental and control variables; Section 5 sets out and discusses our main findings; and finally, Section 6 presents our principal conclusions.

2. LITERATURE REVIEW

Congestion caused by traffic incidents has had a growing relevance for traffic managers. Tavassoli-Hojati et al. (2013a) report that traffic incidents account for 25% of delays on urban highways in the U.S. On the other hand, Ikhrata and Michell (1997) calculated that incidents are the cause of approximately 50% of additional delay (what the authors call "non-recurring congestion").

The impact of incidents on highway congestion is frequently analyzed in spatio-temporal contexts (Kerner et al., 2004). Li and Bertini (2010) compares the most commonly used methods to describe the influence of traffic disturbances in freeways through space and time. Secondary incidents, or incidents related to an existing primary incident, have also been a focus of attention, because secondary incidents have a clearer dependence of traffic management than primary incidents. Charles and Higgins (2002) address the issue of incident management on congested highways. Lindberg (2001) and Parry (2004) examined incentives for better highway driving in order to reduce accidents. Nolan and Quddus (2005) analyzed the relationship between vehicle flows and accident severity. Zhang and Khattak (2010) study the probability of having secondary incidents depending on the characteristics of the primary incident and the road. Crashes, long durations, multiple-vehicle involvement, lane blockage and incidents occurring in short segments were associated with more secondary incidents.

The definition of an incident as secondary has also been a matter of discussion. A simple approach is to define a fixed temporal or spatial region of influence of the primary incident. For instance, Raub (1997) considers incidents occurring within 15 minutes and less than 1 mile (1,609 m) upstream the primary incident. Sun and Chilukuri (2010) and Imprialou (2014) introduce more sophisticated criteria to define secondary incidents.

We are interested in determining how various incident types differ in their highway speed and flow impacts. These incidents may be classified by three types of causal factors: weather conditions, seasonality and the vehicles themselves (i.e., accidents). In the articles surveyed, data is usually collected using loop detectors.

Regarding weather conditions, Pisano et al. (2008) examined accidents in the United States due to adverse weather conditions. They concluded that bad weather reduces highway capacity for two reasons: first, a greater number of accidents, and second, drivers tend to reduce speed. The authors report data compiled from various studies showing that on U.S. freeways, light rain or snow reduces flow volumes by 5% to 10% and average speed by 3% to 13%. The corresponding figures for heavy rain are 14% and 3% to 16% while for heavy snow they are 30% to 44% and 5% to 40%. A study by Chung (2012) concluded that the behaviour of freeway traffic varies depending on weather conditions and the days of the week (i.e., seasonal factors) and that these characteristics should therefore be included in analyses of freeway incidents and their effects on non-recurring congestion. Similar analyses of the effect of weather and seasonal factors on accident occurrence and severity are found in articles by Massie et al. (1995), Hijar et al. (2000), Valent et al. (2002) and Lam et al. (2003).

In an evaluation of both weather and seasonal factors on accidents along California state highways, Satterthwaite (1976) found that weather factors were the most important. On very wet days, the number of accidents was often double that of dry days. Andrey and Yagar (1993), on the other hand, estimated that on rainy days the probability of an accident was 70% higher. Similarly, Khattak and Knapp (2000) concluded using data for interstate highways in Iowa (U.S.) that during snow events, driver capabilities were reduced by about 30%. They also reported that accident frequencies on days with snow were higher than on rainy or dry days. Using data for the United States and Israel, Brodsky and Hakkert (1988) analyzed accident risk in rainy weather. They estimated that the risk of injury in such an accident was 2 to 3 times higher than in dry conditions. The authors further concluded that accident risk was even greater when rains follow a dry spell.

Also related to seasonality, Kwon et al. (2006) investigated freeway delays during morning and afternoon peak periods as compared to free-flow conditions in San Francisco, California. The authors designed a linear regression model with explanatory variables for various incident types, special events, weather conditions and other factors, but were not able to isolate their individual effects on normal and non-recurring congestion levels. Nor did their modelling address the possible effects of endogenous variables. Laapotti and Keskinen (1998) also found that accidents were more frequent at night.

Tavassoli-Hojati et al. (2013b) use parametric models to predict traffic incident duration. Their findings were that the duration of different incident types, including accidents and stationary vehicle incidents, varied greatly. In another paper Tavassoli-Hojati et al. (2014) develop a complementary analysis demonstrating that the factors determining incident duration include incident severity, whether or not injuries occurred, whether or not medical treatment was required, etc. Other relevant incident characteristics were infrastructure, time of day and traffic conditions. Abdel-Aty and Radwan (2000) reported that accidents were more likely to occur in the presence of heavy traffic volumes. Skabardonis et al. (1999) studied the impact of traffic incidents on frequency, duration and delay along freeways in Los Angeles, California. They used longitudinal data collected by loop detectors on flow volumes and speeds.

Other works such as Newbery (1988), Jansson (1994) Dickerson et al. (2000) and Edlin and Karaca-Mandic (2006) have focussed on the relationship between accidents and traffic volumes. Zhang et al. (2013) studied the link between traffic violations and accident severity, correcting for human factors, type of vehicle, type of road and environmental factors.

Our approach is based on the estimation of an empirical version of macroscopic traffic models, expressing the average speed as a linear function of traffic density, the occurrence of incidents and control variables. We use two stages least squares to control for potential endogeneity in the regression model, as density may be related to shocks in speed (the dependent variable). With these estimates we make predictions of the effects that different incidents have on highway capacity. Macroscopic traffic models consider a non-linear relationship between flow and speed, but a linear relationship between speed and density, which is our base econometric model. Wang et al. (2009) conclude that stochastic speed-density models are suitable describing empirical observations, while Lu and Meng (2013) analyse traffic in China using speed-density regression models.

3. DATA

As explained in the introduction, the data for our model were collected and supplied by the loop detector and camera monitoring systems run by the Santiago *Autopista Central* operator. For every vehicle using the highway the loop detectors generate automatic measurements on a permanent basis from which average traffic speed (kilometres per hour), total flow volume (vehicles per hour) and flow density (the ratio of the previous two calculations, in vehicles per kilometre) were calculated for various points along each highway segment. The incidents captured by the monitoring systems provided the necessary data for their classification into 11 main incident types defined as follows:

i) Load spill with infrastructure damage: load falling from a vehicle and causing damage requiring structural repairs to the highway

ii) Load spill without infrastructure damage: load falling from a vehicle without causing damage to the highway; spilled load must be removed.

iii) Vehicle rollover

iv) Crash: vehicle colliding with stationary object (e.g., retaining walls, barriers)

v) Collision: vehicle colliding with other moving vehicle(s)

vi) Rain

vii) Fog

viii) Roadway debris (pieces of wood, tires, parts of vehicles, etc.)

ix) Pedestrian on the roadway

x) Stationary vehicle

xi) Vehicle breakdown (due to dead battery, running out of gas, engine overheating, electrical or mechanical fault, flat tire, etc. In all cases, vehicles were towed away)

In 2012, the year chosen for our study, there were 102,010 occurrences of these 11 incident types along the entire highway, accounting for 96% of all incidents recorded by the operator over the 12-month period. The remaining 4% were distributed among 13 other incident types of minor importance. A breakdown by type is given in Table 1 (percentages shown are adjusted to add up to 100 after excluding minor incidents).

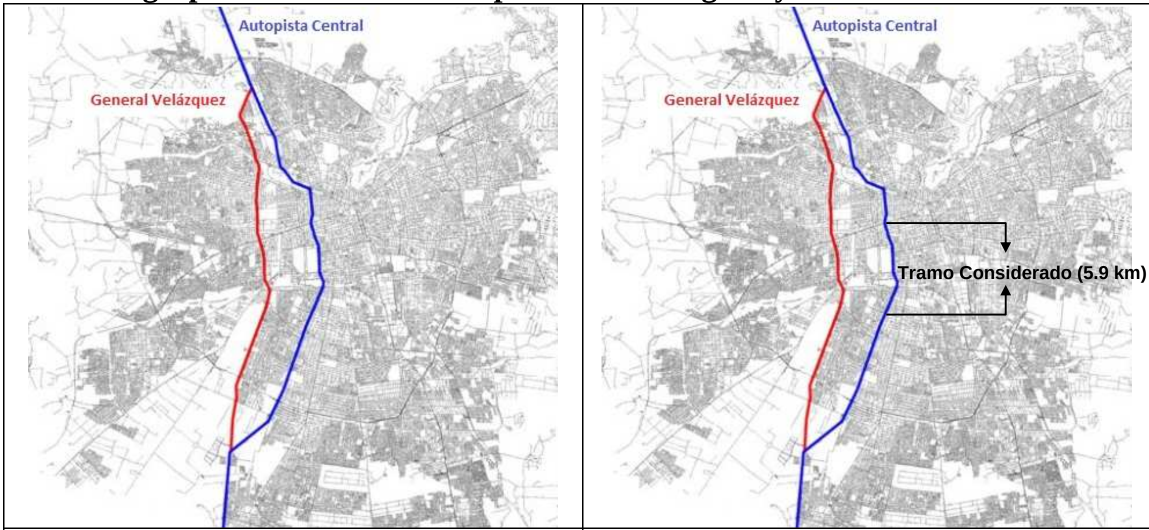
Table 1
Number of recorded incidents by type (*Autopista Central*, 2012)

Incident type	**Number**	**%**
Vehicle breakdown	62,715	61.5%
Rain	10,697	10.5%
Fog	8,530	8.4%
Crash	7,892	7.7%
Roadway debris	4,764	4.7%
Collision	2,996	2.9%
Stationary vehicle	2,686	2.6%
Load spill without infrastructure damage	899	0.9%
Vehicle rollover	482	0.5%
Pedestrian on the roadway	293	0.3%
Load spill with infrastructure damage	56	0.1%
Total	**102,010**	100.0%

The data we used for our estimates related to a specific section of the *Autopista Central* selected to be representative of its status as an urban motorway/freeway. The two selection criteria were a high level of incidents and high daily traffic demand, given that on segments where congestion is infrequent (e.g., the city outskirts), incident impacts will likely be relatively insignificant or very heterogeneous.

The selected section was the one with both the highest number of incidents and the highest demand. Measuring 5.9 kilometres in length, it is located within a stretch of highway that passes through the centre of the city, competing with the *Autopista General Velázquez* (see Figure 1). The section has 8 loop detector points that supplied average speed and flow measurements for every half hour period, the experimental unit employed in our analysis. The corresponding density values were derived from these calculations. The monitoring systems also indicated for each period and incident type whether or not an incident occurred. Together these measurements forms a set of panel data with a small cross-sectional dimension N and a large longitudinal dimension T.

Figure 1
Geographical location of *Autopista Central* highway and selected section



(a) *Autopista Central* (Santiago, Chile) | (b) Section studied

Table 2
Number of incidents recorded by type (*Autopista Central*, selected section, 2012)

Incident type	**Number**	**%**
Vehicle breakdown	7,128	68.2%
Rain	1,082	10.3%
Fog	320	3.1%
Crash	673	6.4%
Roadway debris	366	3.5%
Collision	175	1.7%
Stationary vehicle	246	2.4%
Load spill without infrastructure damage	283	2.7%
Vehicle rollover	98	0.9%
Pedestrian on the roadway	45	0.4%
Load spill with infrastructure damage	40	0.4%
Total	**10,456**	100.0%

The number of incidents recorded in 2012 on the selected section are set out in Table 2. Interestingly, the type distribution is similar to that for the entire highway as given in Table 1.

Note that previous to estimating our model, the data were filtered to eliminate inconsistent observations due to loop detector system errors caused by temporary technical faults. This left 128,729 observations for the selected section on which to base our estimates, or 92% of the original total in the database; the other 8% were discarded.

4. METHOD

The fundamental traffic equation for a section or arc a of the highway relates the volume of traffic flow (f_a) to its density (d_a) and speed (v_a) as follows (Greenshields, 1935; May, 1990):

$$f_a = v_a \cdot d_a \quad , \quad \forall a \tag{1}$$

The relationship between speed and density is thus decreasing so that as density increases, speed decreases (Greenshields, 1935; May, 1990). In light of this, we propose the following functional form for the decreasing linear relationship between speed and density:

$$v_a = \beta_{a,0} + \beta_{a,d} \cdot d_a \quad , \quad \forall a \tag{2}$$

where $\beta_{a,0}$ is a parameter equal to the free-flow speed of our selected highway section a and must be positive, while $\beta_{a,d}$ is a parameter representing the marginal effect on speed of an increase in density and must be negative.

To estimate the effect of a given incident on the average speed of section a we use the following multiple linear regression model, based on (2) and similar to formulations proposed elsewhere (Garib et al., 1997; Abdel-Aty and Radwan, 2000; Wirtz et al., 2005; Kau, 2007; Boyles et al., 2007):

$$v_{a,i,t} = \beta_{a,0} + \beta_{a,d} \cdot d_{a,i,t} + \sum_k \delta_k \cdot I_{a,k,i,t} + \varepsilon_{a,i,t} \tag{3}$$

where δ_k represents the effect of an incident of type k on average speed over section a at measurement point i in period t, and $\varepsilon_{a,i,t}$ is the modelling error. $I_{k,i,t}$ is a set of dichotomous variables that are equal to 1 when a type k incident is recorded at measurement point i in period t, and 0 otherwise. Each observation or experimental unit is represented by an i, t pair corresponding to a half hour of traffic flow at a measurement point. Since speed is expressed in kilometres per hour and density in vehicles per kilometre, flow (4) is then vehicles per hour.

A similar approach is proposed by Nam and Mannering (2000) except that the authors use a logistic regression formulation. Other works base their models on Poisson or negative binomial regression (Jovanis and Chang, 1987; Miaou and Lum, 1993; Joshua and Garber, 1990; Kockelman and Ma, 2007). Since for present purposes we are interested in statistical inference rather than prediction, however, the use of linear regression should be adequate.

It is well established that in the presence of congestion, the density of highway traffic flows may be affected by the speed of the flows and vice versa. This implies that $d_{a,i,t}$ is an endogenous variable. To address this we use lagged density variables as instruments (i.e., instrumental variables) representing lags of 1 hour, 24 hours and 1 week. These variables are exogenous but are also correlated with the endogenous variable, thus making good instruments. Using alternative sets of recent lags does not have a relevant incidence on the magnitudes or significance of the estimates. Applications of lagged variables as valid instruments are discussed in Chowdhury (1987) and Oxley and Greasley (1998); a good example from the field of transport is offered in Andrikopoulos and Loisides (1998).

To complete our econometric model, we add a number of seasonal dichotomous variables to the speed-density relationship (3) in order to control for time of day, day of the week and month of the year. The definitive specification of the formulation for estimating the impact of an incident on average speed recorded by a loop detector *i* on highway section *a* may then be stated as follows:

$$v_{a,i,t} = \beta_{a,0} + \beta_{a,d} \cdot \hat{d}_{a,i,t} + \sum_k \delta_{a,k} \cdot I_{a,k,i,t} + \sum_j \theta_{a,j} \cdot C_{a,j} + \varepsilon_{a,i} \qquad (5)$$

where $\hat{d}_{a,i}$ is the instrumentalized density, generated using the following auxiliary regression:

$$d_{a,i} = \gamma_{a,0} + \phi_{a,1h} \cdot d_{a-1h,i} + \phi_{a,1d} \cdot d_{a-1d,i} + \phi_{a,1w} \cdot d_{a-1w,i} + \sum_k \delta_{a,k} \cdot I_{a,k,i} + \sum_j \theta_{a,j} \cdot C_{a,j,i} + e_{a,i} \qquad (6)$$

The estimator $\hat{d}_{a,i}$ obtained upon estimating the parameters of model (6) can then be substituted into (5). The estimation method is therefore just the classical two-stage least squares (2SLS). To test the model's robustness we also derive estimates with fixed effects (FE) and random effects (RE) models, using instrumental variables for the panel data structures (on panel data models, see Baltagi, 2013).

The $\{\delta_{a,k}\}$ parameters in (5) can be directly interpreted as the average speed reduction--the impact on speed--caused *ceteris paribus* by incident type *k* on highway section *a*. The incident's impact on flow can then be indirectly derived simply by evaluating the fundamental traffic equation (1) with our estimate of $\hat{v}_a$ obtained from (5) and its corresponding density $\hat{d}_a$ in the presence of a type *k* incident $(I_{a,k} = 1)$, and comparing the resulting value with the case where no incident is detected $(I_{a,k} = 0)$. If we use the density associated with the maximum flow on section *a*, the result is an estimate of the impact of a type *k* incident on the section's capacity.

5. RESULTS

The estimates generated by the model (5) using the three different above-mentioned regression methods (two-stage least squares, fixed effects and random effects) and instrumental variables for the panel data are given in **¡Error! No se encuentra el origen de la referencia.** for the density parameter $\beta_{a,d}$ and the incident type parameters $\{\delta_{a,k}\}$. To simplify the presentation, the estimates for the seasonal control variable parameters and the intercept are not shown.

¡Error! No se encuentra el origen de la referencia.
Parameter estimates for model (5)

Dependent variable: Speed (Km/h)	2SLS	FE	RE
Density	-0.939*** (0.003)	-0.97*** (0.003)	-0.939*** (0.004)
Load spill with infrastructure damage	-34.18*** (1.031)	-33.882*** (0.992)	-34.172*** (1.251)
Vehicle rollover	-12.474*** (0.658)	-12.603*** (0.633)	-12.472*** (0.799)
Load spill without infrastructure damage	-9.946*** (0.391)	-10.124*** (0.377)	-9.944*** (0.475)
Crash	-7.858*** (0.264)	-7.781*** (0.254)	-7.855*** (0.32)
Pedestrian on the roadway	-5.545*** (0.97)	-5.655*** (0.934)	-5.548*** (1.178)
Stationary vehicle	-5.107*** (0.419)	-4.963*** (0.403)	-5.103*** (0.508)
Rain	-3.543*** (0.201)	-3.565*** (0.194)	-3.541*** (0.244)
Vehicle breakdown	-2.621*** (0.082)	-2.569*** (0.079)	-2.618*** (0.099)
Collision	-2.241*** (0.492)	-2.39*** (0.473)	-2.239*** (0.597)
Fog	-1.321*** (0.367)	-1.317*** (0.353)	-1.318*** (0.446)
Roadway debris	-0.787** (0.342)	-0.809** (0.329)	-0.883** (0.415)
R2	0.717	0.7179	0.5831
No. of observations	128,729	128,729	128,729

Standard errors in parentheses. ** Significant at the 5% level. *** Significant at the 1% level.

The following results in **¡Error! No se encuentra el origen de la referencia.** are of particular interest:

a) The parameters for all of the explanatory variables representing incident types have the expected sign (negative) and have satisfactory statistical significance (all significant with a 95% confidence interval and almost all at 99%).

b) Ordering the incident types from greatest to smallest (absolute) parameter value reveals that the type with the biggest impact on highway speed is “load spill with infrastructure damage,” whose parameter was estimated at -34.18. In line with what was developed in Section 4, this can be interpreted as a reduction in average speed of 34k/hr.

c) The second most influential incident type on average speed is “vehicle rollover,” as indicated by its parameter estimate of -12.47.

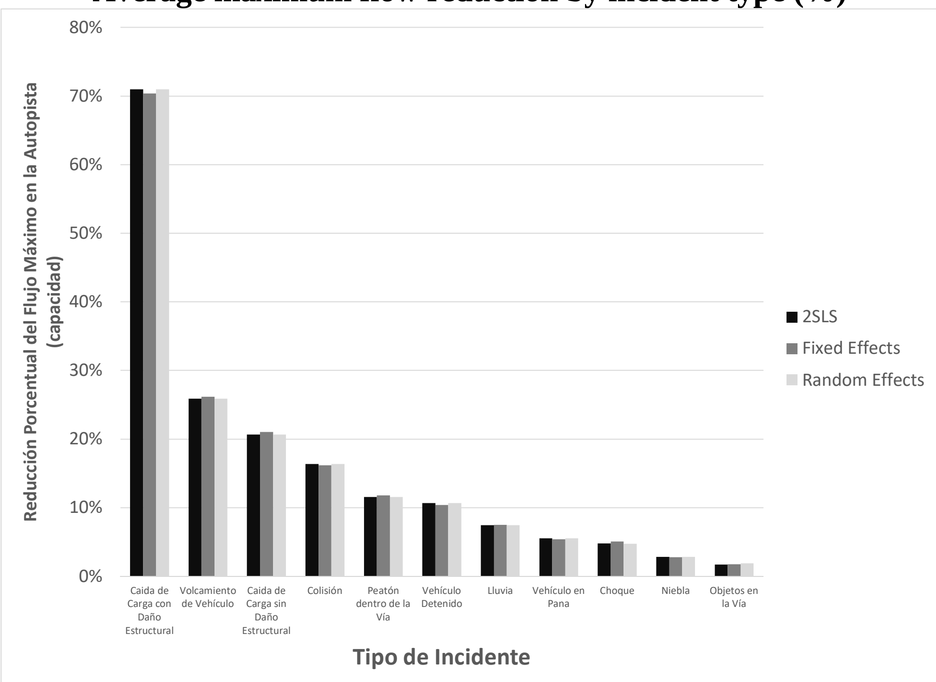
d) The parameter estimate for the “collision” incident type (between vehicles in motion) was significantly higher (in absolute value) at -8 than a “crash” (colliding with a stationary object).

e) Weather variables such “rain” and “fog” impact to a lesser degree, though still significantly, on average highway speed. The same applies to “vehicle breakdown.”

To calculate the impact on flow, we must first obtain a value for density. The value corresponding to the maximum flow capacity of section *a* can be derived by substituting the parameters in (5) into (1), then differentiating with respect to density and setting the derivative to 0. The result is a maximum flow density of 98 vehicles per kilometre $\left(d^* = 98 \ veh/k\right)$. At this level, the average maximum flow is 4,718 veh/h.

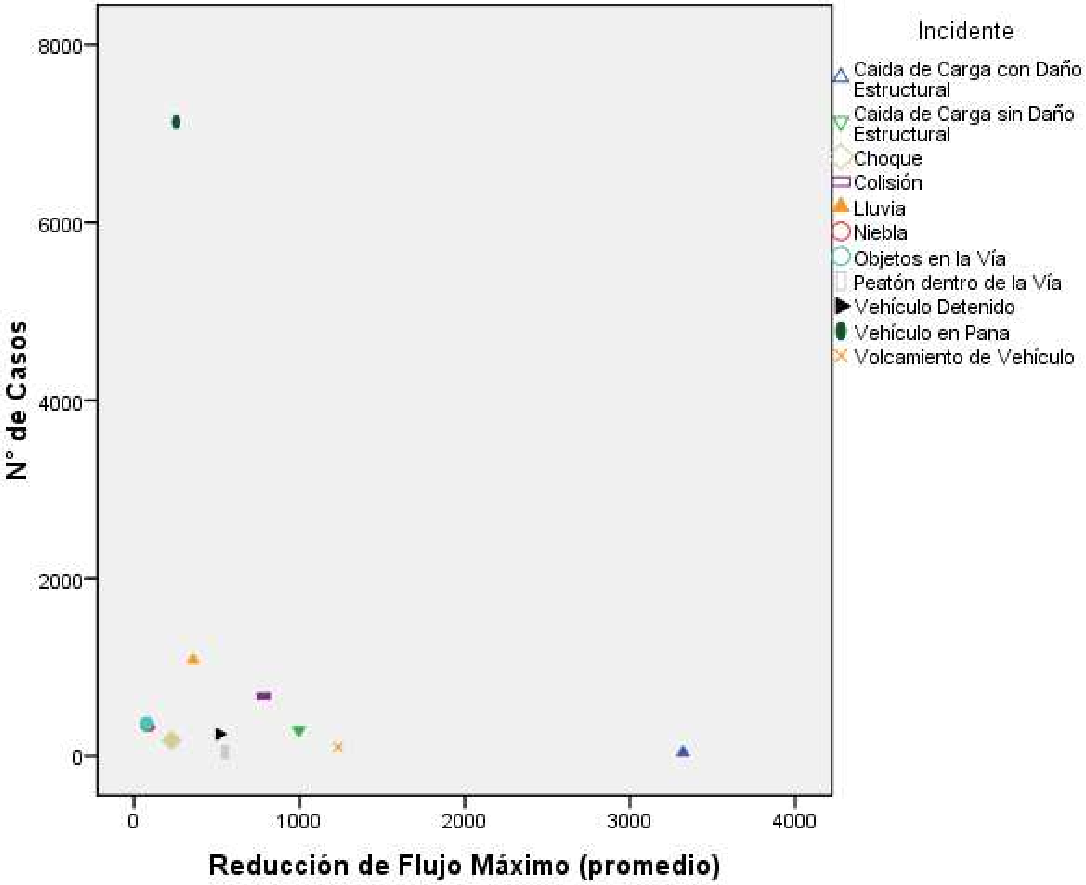
If we utilize this density level as a baseline value, we can then directly estimate the impact of each incident type on the average maximum flow. The results of this estimation are given in Figure 2. As can be seen, they show that “load spill with infrastructure damage” reduces average maximum flow by just over 70%. Next in order of magnitude is “vehicle rollover” with a reduction of 26%.

Figure 2
Average maximum flow reduction by incident type (%)



Observe, however, that according to Table 2 the number of times a “load spill with infrastructure damage” occur is very low, amounting to only 0.4% of all incidents. By contrast, a “vehicle breakdown” accounts for 68.2% of cases. Thus, we have one incident that is high impact but low occurrence and another that is low impact but high occurrence. The flow reduction and frequency variables are shown in Figure 3 for the 11 incident types. Note that since the results for 2SLS, FE and RE were similar, only the estimates obtained with 2SLS are shown.

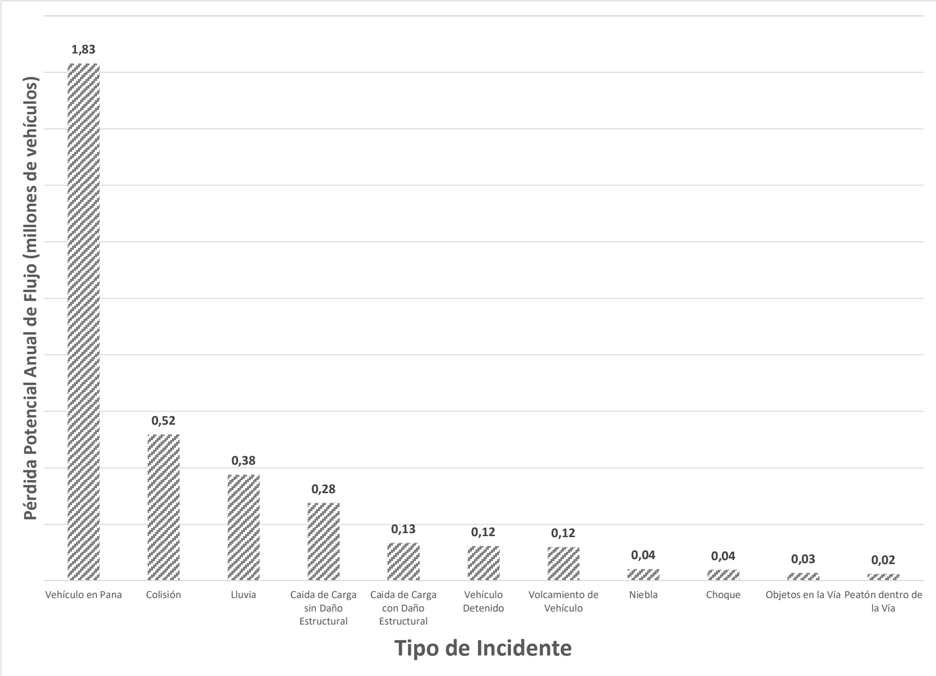
Figure 3
Relation between reduction of average maximum flow and occurrences by incident type (2SLS parameter estimates)



Finally, if we multiply the incidents’ individual average maximum flow reductions by their frequency as measured by the number of occurrences, we obtain a particularly important result, which is the potential maximum flow loss for the incident types over the course of a year. This is an indicator of their respective annual cumulative impacts. Using our flow reduction estimates and the occurrence figures given in Table 2, the 11 incident types can then be ranked by cumulative impact as is done in Figure 4.

As can be seen, the incident type responsible for the greatest loss is “vehicle breakdown,” followed by “collision”. In third place, surprisingly enough, is “rain.” These annual impacts represent not only a loss of vehicle flow for the highway operator but also a potential reduction in use of the infrastructure by travellers.

Figure 4
Annual potential flow loss or cumulative impact, by incident type (2SLS parameter estimates)



6. CONCLUSIONS

This article presented an empirical analysis to determine the impact of different types of incident types on the speed and volume of traffic flows on an urban controlled-access highway. The case study focussed on a section of the main urban motorway/freeway in Santiago, Chile, that registered the highest demand and the greatest number of incidents.

Incident data recorded by the highway's monitoring systems were classified into 11 main incident types: i) load spill with infrastructure damage; ii) load spill without infrastructure damage; iii) vehicle rollover; iv) crash; v) collision; vi) rain; vii) fog; viii) roadway debris; ix) pedestrian on the roadway; x) stationary vehicle; and xi) vehicle breakdown. Together these types accounted for 96% of all recorded incidents, with vehicle breakdown being the most numerous at 60% of the total and collision the next most numerous at 8.4%. Load spill with infrastructure damage was the most infrequently recorded incident type at 0.1%.

The methodology employed consisted in formulating a multiple linear regression model between speed and the different incident types, controlling for traffic density and seasonal factors. Since density is known to be an endogenous variable, density lags of various dimensions were incorporated as instrumental variables. The model was estimated using the method of two-stage least squares.

Analyzing each incident occurrence in isolation, it was found that the greatest impacts, if measured in terms of average speed and average maximum flow reductions, was caused by the "load spill with infrastructure damage" incident type, which reduced speed by about 34 km/h and flow by more than 70%. The next greatest impact was due to "vehicle rollover", which cut speed by about 13 km/h and flow by around 26%.

If, however, we take the incidents' respective frequencies into account by multiplying these impact estimates by their corresponding numbers of cases, the incident with the greatest annual cumulative impact turned out to be "vehicle breakdown", followed by "collision" and then by "rain". This suggests that the two main incidents negatively impacting highway service levels were attributable to some sort of human error.

These results are highly interesting for the light they shed on the relative importance of different incidents on the highway section in our study. Vehicle breakdown is enormously disruptive of the its normal operation, causing a potential reduction in traffic flows of more than 1.8 million vehicles per year whose drivers are either prevented from taking the highway or are forced to change or delay their trips. Collisions diminish annual flows by the equivalent of 0.53 million vehicles while rain (exogenous to the road network) reduces volumes by an amount equivalent to 0.39 million vehicles.

Finally, our results point to the existence of a clearly defined hierarchy of incident impacts on urban motorway/freeway functioning, some of which are directly related to vehicle operation and others to outside factors such as weather conditions. Estimates of the effects of incidents on congestion are a valuable input for the design of traffic management policies.

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