Accident Rates and Safety Policies for Trucks Serving the San Pedro Bay Ports

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Seiji S.C. Steimetz, Ph.D.
Principal Investigator

Steven J. Yamarik, Ph.D.
Co-Principal Investigator

Christopher Malatesta, M.A.
Research Assistant

Department of Economics
California State University at Long Beach

METRANS Transportation Center
USC CSULB

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Abstract

This study estimates three distinct measures of truck-related accident risk for several California urban highways, based on a monthly panel of accident and traffic data spanning from January 2007 through April 2010. The first of these risk measures is *average risk*, defined as the number of accidents divided by total traffic volume. The second is *marginal risk*, defined as the *change* in average risk resulting from a marginal increase in truck traffic volume. The third is *external risk*, defined as the product of marginal risk and total traffic volume.

Special attention is paid to comparisons of these risk measures between "drayage routes", which carry the highest concentrations of drayage traffic, and other urban routes. This is done to investigate the notion that drayage trucks present a greater threat to highway safety than do other types of heavy commercial trucks.

Estimation results suggest that drayage routes are indeed relatively hazardous in terms of average risk. The marginal and external risks exhibited by these routes, however, are considerably smaller than those of several other urban routes. These latter findings suggest that the exclusive targeting of drayage routes, and the trucks that travel them, may not offer the most effective approach to designing highway safety policies that target heavy commercial truck traffic.

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1. Introduction

About 87% of the truck drivers who haul ocean containers to and from the San Pedro Bay ports are independent owner operators known as "dray drivers".[1] And traffic accidents are perceived to be all too frequent on highways carrying the heaviest concentrations of drayage trucks, namely Interstates 110 and 710. Accordingly, there is a general impression that dray drivers are inherently more "dangerous" than other operators of heavy commercial trucks.

Indeed, a Los Angeles Times article entitled "Unsafe Trucks Stream Out of L.A.'s Ports" suggests that dray drivers tend to "cut corners whenever possible" when it comes to safely maintaining their trucks.[2] It describes practices such as covering cracks in their truck chassis with mud, cutting treads in bald tires with electric knives, and evading California Highway Patrol safety checkpoints when alerted by fellow drivers. Some argue that a combination of low wages and fierce competition among the roughly 16,000 dray drivers serving the ports leave them with "no choice" but to relax their safety standards. These drivers, who are paid by the load and seldom compensated for traffic delays and waiting times, earn an average wage of $8.90 per hour even before considering truck maintenance expenditures.[3] As a spokesman for the Owner-Operator Independent Drivers Association puts it, "If you want good, clean, and safe equipment, the costs for it have to be reflected in the rates that truckers receive for moving the products".[4]

One might argue, however, that drayage traffic is no more a threat to highway safety than traffic generated by other sectors of the motor carrier industry, noting that the motor carrier industry in general is highly competitive.[5] Although dray drivers might be able to cut costs by postponing safety measures or improve the number of containers they haul by driving more dangerously, doing so increases their chances of incurring accident costs. So it is not entirely clear that dray drivers have any particular incentive to "cut corners" when it comes to truck safety. And, as such, an empirical analysis is needed to determine if the presumed corner-cutting behavior of dray drivers makes the highways they travel especially dangerous.

In this study we undertake such an analysis by comparing accident risk levels among several California urban highways with varying truck volumes, paying particular attention to

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[1] "Drayage" refers to the hauling of ocean containers to and from sea ports by truck. Those who do so with their independently owned and operated trucks are referred to as "dray drivers".
[2] Sahagun (2008).
[3] Monaco and Grobar (2005 – METRANS AR04-01).
[4] The notion that higher pay corresponds to safer equipment and behavior is not limited to drayage at the ports. For instance, the truckload (TL) sector of the motor carrier industry has been characterized as "sweatshops on wheels", where hourly pay is substantially lower than for similarly-skilled manufacturing jobs (Belzer, 2002). There is some evidence that higher pay in this sector is correlated with lower accident rates (Rodriguez et al., 2003), but it is difficult to empirically distinguish the simultaneous effects of increased pay and safety initiatives implemented at the trucking firms studied.
[5] Belzer (2002).

Interstates 110 and 710, which are the most heavily traveled by dray drivers. And we develop three measures of truck-related risk to perform these comparisons. The first is "average risk", defined as the number of accidents per unit of traffic volume (i.e. the number of accidents averaged by traffic volume). This is a fairly standard measure of risk, which provides an empirical probability of an accident occurring on a given route. Our second risk measure is "marginal risk", defined as the change in average risk due to a marginal increase in truck traffic volume. This is somewhat economic measure of risk because it identifies, at the margin, the routes on which an entering truck would generate the greatest *increase* in the risk of an accident for each vehicle already travelling that route. It is especially useful for policy analysis because it identifies the routes for which reductions in truck traffic would provide the greatest risk-reduction benefits. Our third risk measure is "external risk", which calculates the cumulative change in risk across all vehicles travelling a given route due to marginal increase in truck volume; it is essentially the marginal risk for that route, multiplied by its total traffic volume. This measure is particularly useful for economists concerned with the accident externalities generated by heavy commercial trucks, and can guide road-pricing policies that target these trucks.[6]

Based on a panel of 57 California highways, or 114 routes when treating each highway's travel direction as a distinct route, spanning from January 2007 to April 2010, we find that drayage routes are relatively hazardous in terms of average risk, but not as much so in terms of marginal and external risk. For example, the northbound and southbound directions of Interstate 110 exhibit the 2nd and 3rd highest risk levels among the routes in our sample, with an average risk of about three accidents per million vehicle-miles. The average risks for the northbound and southbound directions of Interstate 710 are 2.1 and 1.8 accidents per million vehicle-mile, respectively, ranking them 11th and 21st among the 114 routes considered. When ranking these routes by marginal risk, however, the two directions of Interstate 110 are 30th and 32nd, and those of Interstate 710 are 36th and 47th. In other words, there are several other routes on which additional trucks would generate considerably greater increases in accident risk. For example, a one-percent increase in truck volume on northbound Interstate 405 would increase the risk of an accident by 0.47%, compared to a corresponding increase of 0.18% on northbound Interstate 710. Finally, trucks travelling on Interstate 110 generate the 11th and 13th highest risk externalities among the routes in our sample, and Interstate 710 ranks 25th and 38th. So it appears, for example, that road-pricing policies that target heavy commercial trucks might consider the drayage routes as relatively high priorities, noting however that trucks on other urban routes such as southbound Interstate 405 and on both directions of State Route 17 generate even greater risk externalities.

[6] See Steimetz (2008 – METRANS 06-07) for an example of a road-pricing framework designed to manage truck volumes on highways surrounding the San Pedro Bay port complex.

Overall, our findings lend a degree of credence to the notion that drayage routes are relatively hazardous, based on their average-risk rankings, providing indirect evidence that dray-drivers might indeed contribute to relatively high accident risks on the routes they travel most. Our findings also suggest, however, that safety policies which exclusively target their routes may not be warranted because, at the margin, greater risk reductions could be achieved by altering truck flows on several other routes. One particular policy that could alter truck flows, at least during certain travel periods, is to levy tolls on heavy commercial trucks based on the external risks they generate. Under such a policy, we find that such tolls would be higher-than-average for trucks on Interstate 110, but lower-than-average for trucks on Interstate 710.

More generally, our findings can be used to guide highway-safety policies irrespective of the drayage traffic carried by those highways. By providing three distinct measure of truck-related accident risk for each route in our sample, policymakers can determine which of these routes deserves the greatest attention based on their distinct policy objectives.

The remainder of this study proceeds as follows. Section 2 describes and formally derives the three risk measures that we estimate for each route in our sample. Section 3 describes our empirical framework, including our data and estimation methods, and briefly discusses our fixed-effects panel regression results. Section 4 reports and discusses our estimates for average risk, marginal risk, and external risk, and discusses the policy implications of our findings. Section 5 offers concluding remarks, including limitations of our analysis and suggestions for further research.

2. Accident Risk Analysis

2.1 Overview of Accident Risk Analysis

We assess the relative "danger" imposed by heavy commercial trucks on a given route, drayage or otherwise, primarily by answering two key questions. The first asks "what is the probability of colliding with another vehicle on that route, given the volume of trucks that travel it?" We answer this empirically by calculating the number of accidents per month on that route, divided by the number of vehicle-miles it carries.[7] This is a fairly standard measure of accident risk, which we refer to as "average risk".[8]

The second question asks "how is the risk of an accident on a given route affected by increased truck traffic?" We answer this by estimating the change in average risk that results from a marginal increase in truck volume. This risk measure helps to identify routes where increased truck volumes are likely have the biggest impact on highway safety and, likewise, where safety policies designed to alter truck volumes might be the most effective. It also helps to characterize the *external* accident risk imposed by trucks (discussed below), which can guide road-pricing and related policies that target the accident externalities imposed by heavy commercial trucks.

Between average risk and marginal risk, which is the more "appropriate" measure of how "dangerous" each route is? That depends on their application. For instance, we might say that the route with the highest average risk is the most "dangerous" with regard to truck traffic. At the same time, however, we might say that the route with the highest marginal risk carries the most "dangerous" trucks because additional trucks generate the greatest increase in average risk. And from a policy standpoint we might care more about using marginal risk to identify routes with the greatest opportunities to reduce such danger. We provide both risk measures in the following analysis and let readers decide which is better suited to their particular application.

We proceed by formally defining the risk measures discussed above. In doing so we demonstrate explicitly how average and marginal risk are related, and how marginal risk gives rise to external risk — a metric that transportation economists pay particular attention to. Readers who are not interested in these technical details should focus instead on the risk definitions given in equations (2), (4), and (6).

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[7] "Vehicle-miles" is a standard unit of traffic "volume" or "flow". It is defined here as the number of vehicles travelling a given route per month, multiplied by the number of miles traveled.

[8] Alternatively, we could have defined average risk as the number of accidents per *truck*-mile to calculate the probability of colliding with a truck. Our study, however, is concerned with a more holistic assessment of accident risk: the probability of colliding with any other type of vehicle, and how that probability is affected by increased truck traffic. This is because the probability of, say, two cars colliding is indeed influenced by the volume of trucks that these cars must contend with.

2.2 Average Risk

We begin by writing A_{it} as the number of accidents that occur on route *i* during month *t*, where an accident is defined as a collision of any severity between two or more vehicles of any type. That number of accidents depends on the route's volume of heavy commercial trucks, $v_{T,i,t}$, and the volume of all other vehicle types, $v_{C,\mathrm{i},t}$, because the risk of an accident, *r*, depends on those volumes (and how those vehicles interact with one another). Henceforth, for simplicity, we refer to $v_{C,\mathrm{i},t}$ and $v_{T,i,t}$ as "car" and "truck" volumes. And focusing now on a given route during a given month, we can omit the *i* and *t* subscripts for ease of exposition and write

$$A(v_C, v_T) = r(v_C, v_T) \cdot (v_C + v_T) = r(v_C, v_T) \cdot v \tag{1}$$

where $v \equiv v_C + v_T$, i.e. *v* is the total traffic volume across all vehicle types. The average number of accidents per unit of traffic volume defines *average risk*, i.e. the empirical probability of an accident, given by

$$r = \frac{A}{v} \tag{2}$$

on route *i* during month *t*.

2.3 Marginal and External Risk

The change in the number of accidents resulting from a marginal increase in truck volume is given by

$$\frac{\partial A}{\partial v_T} = r + \frac{\partial r}{\partial v_T} v \tag{3}$$

To interpret this expression, consider the entry of one more truck on given a highway. The impact of the additional truck has two components. The first, *r*, is the average risk of an accident, which is the number of accidents the entering truck is expected to be involved in. From that truck driver's perspective, *r* is the risk he accepts when deciding to enter the highway. He does not consider, however, the additional risk that he imposes on the highway's existing vehicles. In other words, he does not take into account the additional risk that is *external* to his entry decision. This risk *externality* is given by the second component on the right-hand-side of (3), $\frac{\partial r}{\partial v_T} v$, which shows each vehicle's increased risk due to the additional truck, multiplied by the number affected vehicles. Thus, the increase in the number of accidents due to a marginal increase in truck volume includes the *external risk* generated by the additional trucks. Economists are interested in such externalities because they contribute to a gap between the private and social costs of truck traffic that could result in inefficiently high truck volumes.[9]

The $\frac{\partial r}{\partial v_T}$ term in (3) defines the *marginal risk* generated by increased truck traffic — the increase in average risk, r, resulting from a marginal increase in truck volume, v_T (noting that a marginal risk of zero implies no risk externality). And rearranging (3) yields

$$\frac{\partial r}{\partial v_T} v = \frac{\partial A}{\partial v_T} - r \tag{4}$$

which provides a convenient way to measure the external risk generated by trucks on each highway.[10] Further algebraic manipulation of (4) yields

$$\frac{\partial r}{\partial v_T} \frac{v_T}{r} = \frac{\partial A}{\partial v_T} \frac{v_T}{A} - \frac{v_T}{v} \tag{5}$$

which has an especially useful interpretation. The left-hand-side of (5) gives the percentage change in the (average) risk of an accident resulting from a one-percent increase in truck volume; it is the *elasticity* of accident risk with respect to truck volume. The first term on the right-hand-side of (5) is the percentage increase in the number of accidents due to a one-percent increase in truck volume; it is the elasticity of the accident rate with respect to truck volume. The remaining term in (5) is the proportion of total traffic volume that comprises trucks.

For simplicity we can write (5) as

$$E_{r,v_T} = E_{A,v_T} - \frac{v_T}{v} \tag{6}$$

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[9] This is because the marginal social cost of each truck trip exceeds its marginal private cost, but each truck's travel decision is based only on the latter. In equilibrium, then, the marginal social cost of the last truck trip exceeds its marginal social benefit, resulting in a "deadweight loss" due to excessive truck traffic. A more thorough analysis of these externalities, however, is beyond the scope of this study. Instead we simply report externality levels in the empirical analysis that follows, primarily for those interested in applying them to externality-related policies such as road pricing.

[10] Note that the dependent variable in our empirical analysis is the *number* of accidents, A, as opposed to average risk, r. Hence we must derive a way to estimate marginal risk from the marginal effect of truck volume on the number of accidents.

where $E_{r,v_T} \equiv \frac{\partial r}{\partial v_T} \frac{v_T}{r}$ and $E_{A,v_T} \equiv \frac{\partial A}{\partial v_T} \frac{v_T}{A}$. We refer to E_{r,v_T} as the "marginal risk elasticity", which provides a unit-free way to compare marginal risk across multiple routes. Moreover, it shows that marginal risk is positive when a proportional increase in accidents on a given route exceeds the proportion of trucks travelling that route.

2.3 Summary of Risk Measures

In our empirical analysis that follows, we report estimates of the *average risk*, the *marginal risk elasticity*, and the *risk externality* for each route in our dataset. Table 1 below summarizes these risk measures for easy reference.

Table 1
Summary of Accident Risk Measures

Risk Measure	**Description**	**Equation**
Average Risk	Number of accidents per million vehicle-miles	(2)
Marginal Risk Elasticity	Percentage increase in average risk due to a one-percent increase in traffic volume	(6)
External Risk	Marginal risk multiplied by traffic volume	(4)

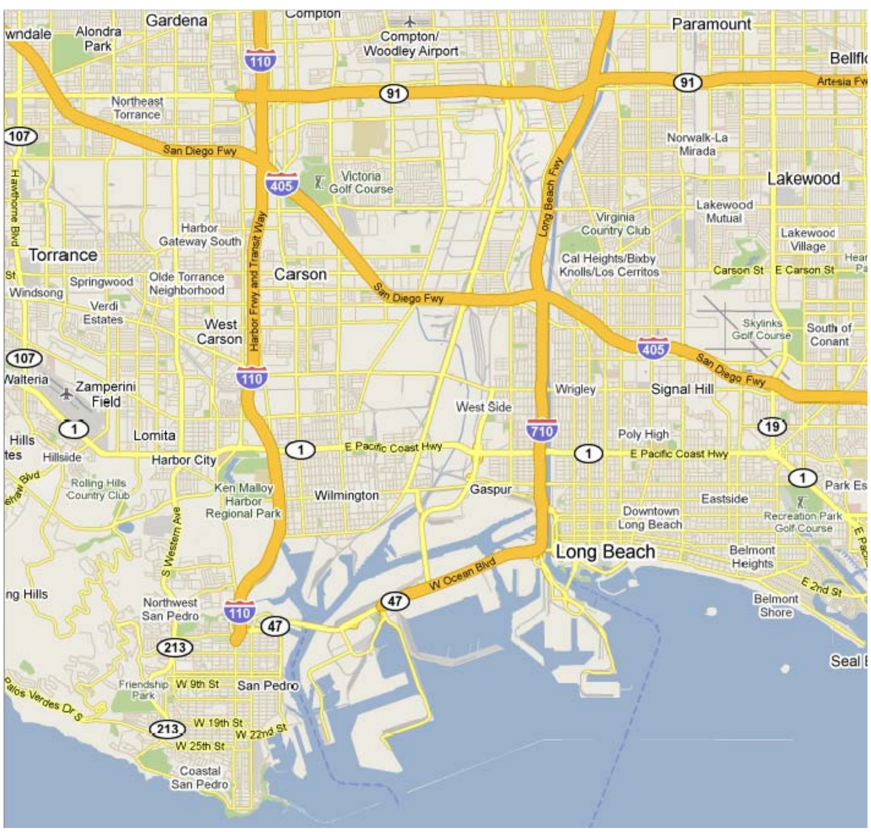
3. Empirical Setting and Estimation

3.1 Empirical Setting and Estimation Overview

Our empirical analysis is based on monthly accident and highway data for several interstates and state routes in California from January 2007 through April 2010 (40 months). We restrict our analysis to California data primarily due the availability of unusually disaggregated information from the California Department of Transportation (Caltrans). The time period for our data allows us to exploit variation in truck volumes and corresponding accident rates due to recent volatility in economic conditions.

We pay special attention to two highways that carry the heaviest concentrations of drayage traffic: Interstate 110 and Interstate 710, which terminate at the Port of Los Angeles and the Port of Long Beach, respectively. Figure 1 depicts these highways and their proximity to the San Pedro Bay port complex appearing at the bottom of the figure.

Figure 1
Map View of "Drayage Routes"



Source: Google Maps.

The figure illustrates why most ocean containers drayed in or out of these ports typically travel along Interstates 110 and 710. As such, we define their northbound and southbound segments as "drayage routes". This is not saying that other highways do not carry drayage traffic originating from the ports. Indeed, drayed ocean containers often travel along several Los Angeles highways, such as State Routes 60 and 91, and Interstate 210, on their way to warehouses in San Bernardino and Riverside counties. Interstates 110 and 710, however, indubitably carry the heaviest concentrations of drayage traffic.[11]

The basic procedure, then, is to compare their accident-risk measures to those of other urban highways in order to assess the relative risk imposed by dray drivers. We do so by estimating the relationship between the monthly number of accidents on each highway, and the truck volumes they carry, controlling for important factors such as car volumes, average vehicle speeds, highway characteristics, and temporal effects. The results of this estimation procedure are then used to calculate the risk measures described above in Section 2.

3.2 Data

All of our accident and traffic data are drawn from the California Freeway Performance Measurement System (PeMS), maintained by the Department of Electrical Engineering and Computer Sciences at the University of California, Berkeley. PeMS collects traffic data from sensors placed throughout the California highway network, which are installed and maintained by Caltrans.[12] And PeMS collects accident data from California Highway Patrol (CHP) incident reports and the Caltrans Traffic Accident Surveillance and Analysis System (TASAS). Our data also include monthly average retail prices for gasoline (all grades) gathered from the Federal Reserve Bank of St. Luis Economic Data depository (FRED). We use these gasoline prices to control for the general economic conditions that they are closely correlated with.

There are 254 California highways monitored in each direction by PeMS (i.e. the system monitors 508 highway directions; we refer to each direction herein as a "route"). However, the traffic sensors used for monitoring are often prone to failure. We thus devoted considerable efforts to validating our data and removing unreliable information, which reduced the number of highways available for analysis. Moreover, there is an inconsistency between the number of accidents that occurred on a given route and the traffic volume on that route. This is because accidents are reported along each highway's entire length, whereas traffic volumes are only available for the monitored portions of those highways. As such, we were forced to "impute" traffic volumes for certain routes, and discard data from highways with an insufficient proportion

[11] See, for example, Meyer, Mohaddes Associates, Inc. (2004).
[12] These sensors are usually "inductive loop detectors", which can sense metal above them to compute traffic volumes. Two detectors placed in series can classify vehicles (e.g. "car" or "truck") and measure their speeds. When only one detector is available, vehicle classifications and speeds must be imputed — see Kwon et al. (2002).

of monitored miles.[13] Finally, the accident-reporting link between PeMS and the CHP and TASAS systems failed on occasion, which compelled us to painstakingly remove anomalous accident data.

This left us with reliable data on 114 directional routes, or 57 highways. From these data we assembled an unbalanced panel of 4,249 observations, corresponding to the 40-month time span for these data.[14] Table 2 provides summary statistics for these panel data.

Table 2
Panel Data Summary Statistics

Variable	Mean	Std. Dev.
Drayage Routes		
Accidents (count)	209.79	74.70
Truck Volume (millions of truck-miles)	3.04	0.73
Car Volume (millions of car-miles)	64.09	15.11
Average Vehicle Speed (miles per hour)	57.58	3.06
Truck Concentration (truck percentage of total volume)	4.62%	1.04%
Other Routes		
Accidents (count)	167.70	243.54
Truck Volume (millions of truck-miles)	8.00	16.04
Car Volume (millions of car-miles)	171.47	320.36
Average Vehicle Speed (miles per hour)	61.30	3.82
Truck Concentration (truck percentage of total volume)	4.01%	1.74%
All Routes		
Accidents (count)	169.28	239.48
Truck Volume (millions of truck-miles)	7.81	15.76
Car Volume (millions of car-miles)	167.42	314.95
Average Vehicle Speed (miles per hour)	61.16	3.86
Truck Concentration (truck percentage of total volume)	4.04%	1.72%
Number of Routes		114
Number of Panel Observations		4,249

[13] Specifically, we omit data from highways that are monitored for less than 60% of their lengths. This criterion is based on out-of-sample forecasting experiments using data from highways with 100% monitored miles. In those experiments, predictive models of traffic volumes that included at least 60% of the available conditioning data performed reasonably well.

[14] "Panel" refers to a combination of cross-sectional and time-series data. A balanced panel would have comprised 114 x 40 = 4,560 observations. Unreliable observations were sometimes removed only for certain months, however, yielding an unbalanced panel.

Note that each observation in our panel corresponds to one route during one month. The mean values reported in Table 2 are thus averaged over routes and months. For example, the mean number of accidents per month across all routes is 169.28.

3.3 Estimation Methods

The panel nature of our data allows us to exploit information across highways and time using panel-data regression methods. Our dependent variable is the number of accidents, of any severity, between two or more vehicles of any type. Our independent variables, chosen after numerous model-specification searches, are heavy-truck volume (millions of truck-miles), car volume (millions of car-miles), average vehicle speed (miles per hour), average retail gas price (dollars per gallon), and a "dummy variable" set equal to one for observations after December 2009 — corresponding to when the most recent phase of the Clean Truck Program was implemented at the San Pedro Bay ports.[15]

We estimate the relationship between our dependent and independent variables using "fixed-effects panel regression", with both route-specific and temporal fixed effects that allow us to control for both observable and unobservable characteristics of each route and month that are not included as independent variables. Of particular interest are "interactions" between the route fixed effects and truck volumes. The effects of these interaction terms tell us how a marginal increase in truck volume on a *specific route* affects the number of accidents we would expect on that route in a given month. This effect is measured by the "coefficient" on a given route's interaction term and corresponds to equation (3) in Section 2. That coefficient allows us to calculate the marginal risk elasticity for each route, given by equation (6).

The fact that our dependent variable is the *number* of accidents may seem ponderous, given that marginal risk and its elasticity could be estimated using *average risk* as the dependent variable. In short, the empirical relationship between the number of accidents and truck volume is quite strong, whereas the relationship between average risk and truck volume is rather "noisy".[16] Moreover, interpreting the coefficients of a model with average risk as the dependent variable can be troublesome, given that the coefficient purports to hold truck volumes constant, but average risk itself changes with truck volumes. Figure 2 plots the number of accidents on each highway for each month against their corresponding truck volumes to illustrate their empirical relationship.

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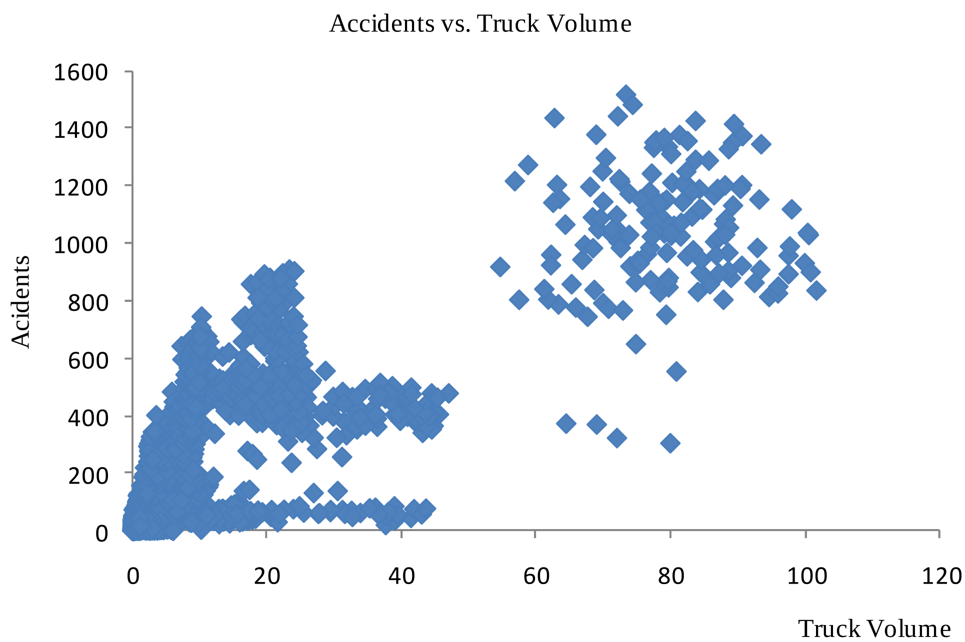
[15] In an effort to reduce diesel emissions from port trucking operations, both ports banned trucks built prior to 1989, effective October 1, 2008 (with some delay, however, in actual enforcement). Beginning January 1, 2010, the ports further banned trucks built before 1994, and trucks built before 2004 that had not been retrofitted with clean-diesel emissions systems. Moreover, the Port of Los Angeles has attempted to ban trucks operated by independent owners (i.e. "non-company" drivers), although this policy is currently being challenged in court.

[16] For instance, on a given route we might expect an increase in truck volume to increase the risk of an accident, but at the same time that increased volume naturally reduces average risk, r, by increasing its denominator.

Figure 2



We proceed now with a more formal exhibition of our estimation framework. The basic structure of our fixed-effects panel regression framework takes the form

$$A_{it} = x_{it}\beta + h_i\lambda_i + m_t\gamma_t + z_{it}\theta_i + u_{it} \tag{7}$$

where A_{it} is the number of accidents on route i during month t, and x_{it} is a 1xk vector of independent variables including car volume, average vehicle speed, average retail gasoline price, and a Clean Truck Program indicator variable, for that route and month, and β is a kx1 vector of coefficients to be estimated. The route and month fixed effects are h_i and m_t with coefficients λ_i and γ_t, and u_{it} is a mean-zero disturbance term assumed to be normally distributed. Of particular interest are the interactions of route fixed effects, reflecting route-specific characteristics such as road geometry, number of lanes, frequency of onramps, etc., with truck volume. These interactions are contained in z_{it}, and its coefficient, θ_i, measures the marginal effect of increased truck volume on the monthly number of accidents for each route, i.

The coefficients of the fixed-effects regression specification in (7) are estimated using ordinary least squares regression methods, after transforming (7) into mean-deviation form (to accommodate the fixed effects). Robust, clustered standard errors are calculated to account for heteroskedasticity while accommodating the model's panel structure.

3.4 Estimation Results

Table 3 reports the coefficient estimates and standard errors from our fixed-effects panel regression model.[17] Note that the coefficient estimates for the interactions of route fixed effects and truck volumes are listed by route designations such as "I110-N" indicating the northbound segment of Interstate 110 and "SR91-E" indicating the eastbound segment of State Route 91.

Table 3
Fixed-Effects Panel Regression Estimates

Variable	Coefficient	Std. Error.	t Stat.	p Value
Car Volume	0.50	0.12	4.23	0.00
Car Volume Squared	0.00	0.00	-3.62	0.00
Avg. Vehicle Speed	70.28	30.76	2.28	0.02
Avg. Vehicle Speed Squared	-1.23	0.53	-2.32	0.02
Avg. Vehicle Speed Cubed	0.01	0.00	2.32	0.02
Avg. Retail Gas Price Squared	-18.60	7.09	-2.62	0.01
Avg. Retail Gas Price Cubed	3.19	1.45	2.20	0.03
Clean Truck Program Period Indicator	19.81	7.21	2.75	0.01
Clean Truck Program Indicator Interaction with Drayage Route Indicators	-7.92	5.45	-1.45	0.15
Truck Volumes Interacted with Route Fixed Effects				
Drayage Routes				
I110-N	40.75	2.88	14.16	0.00
I110-S	34.06	2.45	13.90	0.00
I710-N	9.93	2.88	3.45	0.00
I710-S	18.02	1.86	9.68	0.00
Other Routes				
I10-E	23.80	1.77	13.45	0.00
I10-W	16.13	1.59	10.12	0.00
I105-E	11.16	4.20	2.66	0.01
I105-W	0.21	4.91	0.04	0.97
I15-N	7.31	1.23	5.96	0.00
I15-S	2.28	1.56	1.47	0.15
I205-E	-14.38	3.09	-4.66	0.00
I205-W	19.66	3.88	5.07	0.00
I210-E	6.11	1.82	3.36	0.00
I210-W	6.38	1.79	3.57	0.00
I215-N	3.91	0.95	4.10	0.00
I215-S	11.68	1.96	5.96	0.00
I280-N	9.41	2.56	3.67	0.00
I280-S	3.33	3.44	0.97	0.34

[17] Coefficients for time fixed effects are omitted, however, for ease of exposition — a common convention when reporting fixed-effects panel regression estimates.

Variable	Coefficient	Std. Error.	t Stat.	p Value
I405-N	32.09	1.97	16.28	0.00
I405-S	40.69	2.28	17.82	0.00
I5-N	8.20	1.01	8.10	0.00
I5-S	8.51	0.95	8.97	0.00
I580-E	1.43	1.22	1.18	0.24
I580-W	-0.64	1.75	-0.37	0.72
I605-N	22.54	2.56	8.80	0.00
I605-S	24.61	2.48	9.92	0.00
I680-N	7.48	2.87	2.61	0.01
I680-S	-0.61	2.96	-0.21	0.84
I8-E	-9.78	2.93	-3.33	0.00
I8-W	-10.12	2.88	-3.52	0.00
I80-E	11.69	1.17	10.00	0.00
I80-W	7.95	1.06	7.50	0.00
I805-N	-17.32	4.98	-3.48	0.00
I805-S	-12.04	4.84	-2.49	0.01
I880-N	17.18	2.27	7.58	0.00
I880-S	13.17	1.75	7.53	0.00
SR1-N	-3.09	0.65	-4.73	0.00
SR1-S	-5.68	1.18	-4.80	0.00
SR101-N	6.06	0.96	6.31	0.00
SR101-S	4.81	0.74	6.52	0.00
SR113-N	66.40	9.15	7.26	0.00
SR113-S	24.53	5.28	4.65	0.00
SR118-E	-2.37	3.90	-0.61	0.54
SR118-W	-0.46	2.77	-0.17	0.87
SR120-E	-4.86	1.29	-3.75	0.00
SR120-W	13.00	2.75	4.73	0.00
SR134-E	-28.34	9.13	-3.11	0.00
SR134-W	16.49	7.69	2.14	0.03
SR14-N	-13.06	2.88	-4.53	0.00
SR14-S	-2.54	2.02	-1.26	0.21
SR152-E	-10.56	2.14	-4.93	0.00
SR152-W	10.77	1.61	6.68	0.00
SR160-N	66.95	21.80	3.07	0.00
SR160-S	-20.05	35.32	-0.57	0.57
SR163-N	-34.63	19.94	-1.74	0.09
SR163-S	-71.05	26.01	-2.73	0.01
SR17-N	64.62	12.25	5.27	0.00
SR17-S	44.77	5.17	8.66	0.00
SR170-N	-45.05	24.68	-1.83	0.07
SR170-S	78.85	15.44	5.11	0.00
SR180-E	-12.75	2.45	-5.20	0.00
SR180-W	-3.54	2.93	-1.21	0.23
SR22-E	-10.51	4.76	-2.21	0.03
SR22-W	-17.75	6.04	-2.94	0.00
SR23-N	-15.94	2.75	-5.80	0.00
SR23-S	-17.20	3.07	-5.60	0.00
SR237-E	16.93	4.37	3.87	0.00
SR237-W	28.58	8.24	3.47	0.00
SR238-N	21.91	3.36	6.53	0.00
SR238-S	-25.70	3.43	-7.50	0.00
SR24-E	13.29	2.41	5.52	0.00
SR24-W	68.36	11.21	6.10	0.00
SR37-E	-44.17	7.98	-5.53	0.00

Variable	Coefficient	Std. Error.	t Stat.	p Value
SR37-W	-39.19	9.55	-4.10	0.00
SR4-E	-12.08	2.53	-4.77	0.00
SR4-W	-10.24	1.96	-5.24	0.00
SR41-N	-5.62	1.14	-4.92	0.00
SR41-S	-5.31	0.86	-6.17	0.00
SR51-N	-7.21	11.02	-0.65	0.52
SR51-S	-10.99	9.60	-1.14	0.26
SR52-E	-69.93	16.55	-4.23	0.00
SR52-W	-72.27	19.88	-3.63	0.00
SR55-N	-17.78	7.39	-2.40	0.02
SR55-S	-7.07	6.74	-1.05	0.30
SR56-E	17.02	13.65	1.25	0.22
SR56-W	38.62	57.03	0.68	0.50
SR57-N	0.37	3.25	0.11	0.91
SR57-S	10.62	3.89	2.73	0.01
SR60-E	24.31	1.98	12.29	0.00
SR60-W	22.56	1.71	13.15	0.00
SR65-N	45.19	7.19	6.28	0.00
SR65-S	-11.53	2.52	-4.58	0.00
SR71-N	-25.16	5.96	-4.23	0.00
SR71-S	-61.57	9.02	-6.82	0.00
SR73-N	6.41	3.20	2.00	0.05
SR73-S	-4.55	3.64	-1.25	0.21
SR78-E	-8.90	1.64	-5.42	0.00
SR78-W	-8.37	1.30	-6.46	0.00
SR84-E	-5.04	1.01	-4.98	0.00
SR84-W	1.01	2.14	0.47	0.64
SR85-N	2.96	5.75	0.51	0.61
SR85-S	-5.17	6.27	-0.82	0.41
SR87-N	83.40	31.68	2.63	0.01
SR87-S	-5.11	6.51	-0.78	0.43
SR91-E	33.28	1.86	17.93	0.00
SR91-W	27.50	1.84	14.98	0.00
SR92-E	-47.32	11.21	-4.22	0.00
SR92-W	59.09	11.60	5.09	0.00
SR94-E	-39.81	5.22	-7.62	0.00
SR94-W	-5.64	3.71	-1.52	0.13
SR99-N	3.12	0.61	5.12	0.00
SR99-S	2.64	0.61	4.33	0.00
US50-E	-8.75	2.98	-2.93	0.00
US50-W	-10.83	3.18	-3.40	0.00
Observations				4,249
Routes				114
R^2 Within Routes				0.61
R^2 Between Routes				0.94
R^2 Overall				0.92

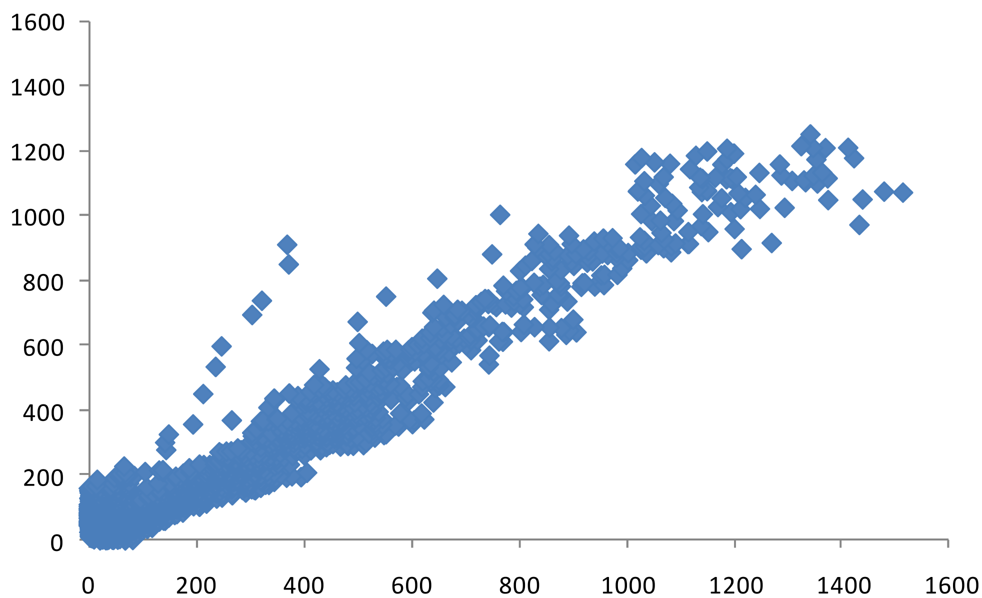
The R^2 values reported at the bottom of Table 3 demonstrate a fairly strong statistical fit between our regression model and data. The model explains about 61% of the variation in accident rates within each route over time, 94% of the variation between routes, and 92% overall.

The table also shows that the coefficients pertaining to car volume, average vehicle speed, and average gasoline price each carry their expected sign, and are statistically significant at the 5% level or better. The estimates for car volume and car volume squared, speed, speed squared, and speed cubed, and gasoline price and gasoline-price-squared reflect significant, nonlinear relationships with accident rates.[18] Although these variables are not of direct interest, it is important to control for their influences when examining the relationship between accident rates and truck volumes. In other words, omitting them would "pollute" our estimates of this relationship to the extent that those variables are correlated with truck volumes.

Figure 3 shows the relationship between the accident rates observed in the data and the those predicted by our regression model, further illustrating the model's "goodness of fit" (noting that a "perfect fit" would produce a straight line from the origin at a 45-degree angle).

Figure 3

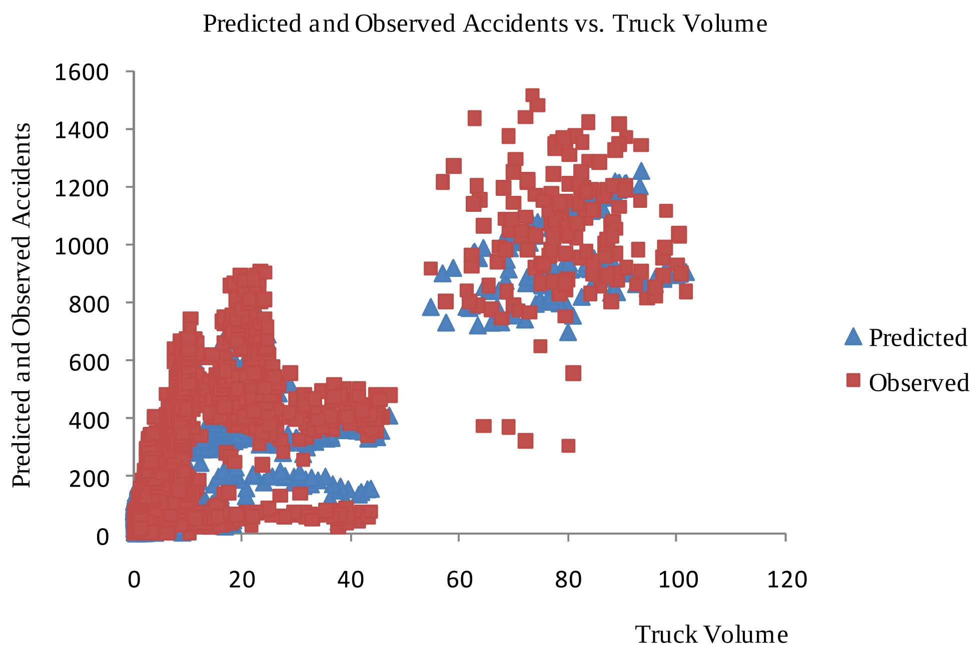
Predicted vs. Observed Accidents



Likewise, Figure 4 plots both our predicted and observed accident rates against truck volumes, showing their fairly strong relationship when conditioned on truck volumes.

[18] Level values of gasoline prices were omitted, curiously, due to multicollinearity with their squared values.

Figure 4



In Table 3, the coefficient for the Clean Truck Program variable is positive and significant, showing an average rise in accident rates on all routes in our sample after December, 2009. We also interacted this variable with combined fixed effects for the drayage routes (northbound and southbound directions of Interstates 110 and 710) to loosely examine the effects of the Clean Truck Program on those routes. Table 3 reports a negative coefficient for this interaction term, suggesting a decline in accident rates on the drayage routes after December, 2009, although this effect is only distinguishable form zero at the 15% level of significance. Again, this variable is only of ancillary interest and serves primarily as a control variable.

Our key estimates of interest are coefficients on the interactions of truck volumes with route-specific fixed effects, including those for the drayage routes. Table 4 shows that most, although not all, of these coefficient estimates are significant at the 5% level or better. Among the statistically-significant estimates, 52 are positive and 37 are negative. In other words, a marginal increase in truck volume increases the accident rate on 52 of the routes in our sample, including the drayage routes, but decreases the accident rate on 37 of them. The finding that accident rates on some routes actually fall with increased truck traffic may be counterintuitive at first glance. This is consistent, however, with the results of previous empirical studies that estimate a negative relationship between accident rates (and even average risk) and traffic volume.[19] One way to make sense of this finding is to consider an urban route where increased truck traffic generates visibly more hazardous driving conditions. Motorists might then respond by driving more vigilantly — a phenomenon known in the accident literature as "risk compensation" — and the net effect in some cases could be a reduction in accident rates (and, perhaps, average risk as well).[20]

The mean of the statistically-significant coefficients is 5.31, suggesting that on average a one-million vehicle-mile increase in truck volume results in an increase of 5.31 accidents per month. Note, however, that these coefficients are estimated for routes with varying traffic volumes, i.e. at various levels of exposure to accident risk. As such they cannot be used alone to compare the relative danger of the trucks traveling them. This comparison is accomplished instead by using these coefficient estimates to calculate the risk measures defined in Section 2 and discussed below in Section 4, which take into account the traffic volumes on each route.

[19] See, for example, Newbery (2005).
[20] See Steimetz (2008).

4. Risk Measurement and Policy Implications

4.1 Risk Measurement Overview

Following the analysis developed in Section 2, we assess the relative danger of trucks travelling on each route by estimating and comparing three route-specific risk measures: average risk, marginal risk (elasticity), and external risk. In other words, we make indirect comparisons of truck risk by assessing the risk generated on the routes they travel, using these three risk metrics. And in our comparisons we pay particular attention to drayage routes to explore the notion that dray drivers are inherently more dangerous than drivers of other heavy commercial trucks.

4.2 Average and Marginal Risk

Recall that average risk is the number of accidents on a given route, divided by the total number of vehicle-miles (millions of vehicle-miles in our case) traveled on that route. This provides an empirical estimate of the probability that a vehicle travelling that route will be involved in a collision (with any other type of vehicle). In calculating average risk for each of the 114 routes in our sample, we use the median number of accidents and vehicle-miles from January through April of 2010 (i.e. from the last four months of observations in our sample). We use medians from these latter months to reasonably reflect the most recent conditions on the routes we study. Table 4 reports these average-risk measures for each route, ranked in descending order with drayage routes indicated in boldface type.

Also recall that marginal risk gives the change in the (average) risk of an accident on a given route due to a marginal increase in truck volume on that route. This is a somewhat economic way of characterizing truck risk because it identifies, at the margin, routes where an additional truck is likely to "do the most damage"; likewise, it identifies the routes for which reductions in truck traffic are likely to have the biggest risk-reduction impact. Table 5 reports marginal risk elasticities for each route, based on the coefficient estimates given in Table 3 and on median truck volumes, accident rates, and the proportions of truck volumes out of total vehicle volumes from January through April of 2010. These elasticities are only reported for routes with statistically-significant coefficient estimates in Table 3, based on a 5% significance level. They give the percentage increase in the risk of an accident on each route due to a one-percent increase in truck volume on that route, and are ranked in descending order with drayage routes indicated in boldface type. Note that negative elasticities are reported for 37 of the 89 routes in the table, suggesting that increased truck traffic actually reduces the risk of an accident on those routes. Again, this finding may be somewhat counterintuitive, but is consistent with several earlier findings in the accident literature.[21] Moreover, our mean risk elasticity across all routes is roughly zero, which is coincides with the "official" estimates of the United States Federal Highway Administration and United Kingdom Department of Transport for risk elasticities with respect to overall traffic volumes.[22]

Table 4

Ranking of Routes by Average Risk

Rank	Route	Average Risk	Rank	Route	Average Risk	Rank	Route	Average Risk	Rank	Route	Average Risk
1	SR87-N	3.08	30	SR71-N	1.59	59	SR17-N	0.99	88	SR4-W	0.34
2	**I110-S**	**3.02**	31	I210-W	1.57	60	SR73-N	0.98	89	I8-E	0.34
3	**I110-N**	**2.97**	32	SR85-N	1.56	61	SR56-E	0.97	90	SR94-E	0.32
4	SR87-S	2.84	33	I280-N	1.55	62	I580-E	0.95	91	SR180-W	0.29
5	SR51-N	2.49	34	I280-S	1.54	63	SR52-W	0.93	92	SR180-E	0.23
6	I605-N	2.41	35	SR237-W	1.51	64	SR14-S	0.93	93	SR41-S	0.22
7	SR22-E	2.36	36	SR170-S	1.51	65	SR14-N	0.90	94	SR238-N	0.20
8	I605-S	2.33	37	I215-S	1.50	66	US50-E	0.89	95	SR41-N	0.20
9	SR51-S	2.22	38	SR163-S	1.47	67	SR170-N	0.86	96	SR152-W	0.19
10	SR134-W	2.09	39	SR22-W	1.45	68	SR73-S	0.84	97	SR152-E	0.18
11	**I710-N**	**2.06**	40	I805-S	1.38	69	I580-W	0.82	98	SR65-N	0.17
12	SR57-S	2.05	41	SR92-E	1.33	70	SR37-W	0.81	99	SR113-N	0.17
13	I405-N	1.98	42	SR55-N	1.31	71	SR56-W	0.78	100	SR78-E	0.16
14	SR134-E	1.98	43	SR55-S	1.31	72	I5-N	0.76	101	SR23-N	0.16
15	I215-N	1.97	44	I80-E	1.27	73	SR99-N	0.70	102	SR23-S	0.15
16	SR91-E	1.92	45	SR163-N	1.26	74	SR99-S	0.69	103	SR160-S	0.14
17	SR60-E	1.91	46	I10-W	1.25	75	I15-S	0.67	104	SR238-S	0.14
18	I880-N	1.90	47	I10-E	1.24	76	I15-N	0.66	105	SR78-W	0.14
19	SR60-W	1.90	48	SR37-E	1.23	77	SR52-E	0.65	106	SR65-S	0.12
20	I105-W	1.86	49	SR71-S	1.20	78	I5-S	0.65	107	SR120-E	0.12
21	**I710-S**	**1.82**	50	I680-N	1.16	79	SR17-S	0.64	108	SR160-N	0.12
22	I405-S	1.82	51	I80-W	1.14	80	SR92-W	0.63	109	SR1-S	0.09
23	I880-S	1.81	52	SR118-E	1.13	81	SR94-W	0.48	110	SR1-N	0.08
24	I105-E	1.79	53	SR118-W	1.10	82	SR4-E	0.43	111	SR84-W	0.06
25	SR91-W	1.74	54	SR237-E	1.09	83	I8-W	0.41	112	SR120-W	0.05
26	SR57-N	1.68	55	SR24-W	1.06	84	SR101-N	0.40	113	SR113-S	0.05
27	I210-E	1.67	56	I680-S	1.04	85	I205-E	0.38	114	SR84-E	0.05
28	I805-N	1.66	57	SR24-E	1.00	86	SR101-S	0.36			
29	SR85-S	1.62	58	US50-W	0.99	87	I205-W	0.36			
										Mean	1.08
										Median	1.00
										Std. Dev.	0.76

[21] See Vitaliano and Held (1991), Elvik (1994), Newbery (1988), Dickerson et al. (2000), and Newbery (2005).
[22] U.K. Department of Transport (1981) and U.S. Federal Highway Administration (1982).

In Table 4 we see that the mean average risk across all 114 routes in our sample is 1.08 accidents per million vehicle-miles, with a standard deviation of 0.76. The highest average risk belongs to the northbound segment of State route 87, — an urban route running through downtown San Jose. Following closely behind are two of the drayage routes: the northbound and southbound directions of Interstate 110, with average risks that are about 2.50 standard deviations above the mean. The other drayage routes, northbound and southbound Interstate 710, rank 11th and 21st, respectively, with average risks that are about 0.80 to 1.29 standard deviations above the mean. Thus it appears that the drayage routes — especially Interstate 110 — can be characterized as relatively hazardous from the standpoint of average risk, lending a degree of credence to the notion that drayage trucks are "more dangerous" than other types of heavy commercial trucks. Note, however, that other routes carrying less drayage traffic do indeed rank ahead of Interstate 710, which arguably carries the nation's highest concentration of dray drivers.[23]

In Table 5, however, we see that the risk rankings change considerably in terms of marginal risk.[24] The highest marginal risk is on the northbound segment of State route 160, which runs through downtown Sacramento. The drayage routes rank 30th, 32nd, 36th, and 47th out of the 89 routes — 52 of which have positive marginal risk elasticities. Among those routes with positive risk elasticities, the mean is 1.32 with a standard deviation of 1.95, suggesting that, on average, a one-percent increase in truck volume yields a 1.32% increase in accident risk. For the drayage routes, the marginal risk elasticity ranges from 0.18 to 0.43, i.e. 0.46 to 0.58 standard deviations below the mean of the positive marginal risk elasticities. The drayage route risk elasticities are still above the overall average of 0.12 when also considering routes with negative risk elasticities, but they still rank considerably behind several other routes. Thus, from the standpoint of marginal risk, it would be difficult to characterize drayage routes (or the dray drivers travelling them) as especially "dangerous". Put differently, increasing the truck volume on westbound State Route 120 by one percent would generate about forty-two times the percentage increase in average risk that a one-percent increase in truck traffic on northbound Interstate 710 would, despite the fact that both routes carry similar concentrations of heavy trucks (5.31% vs. 5.18%).

[23] Sahagun (2008).
[24] Only estimates that are statistically-significant at the 5% significance level are reported.

Table 5
Ranking of Routes by Marginal Risk Elasticity

Rank	Route	Marginal Risk Elasticity	Rank	Route	Marginal Risk Elasticity	Rank	Route	Marginal Risk Elasticity	Rank	Route	Marginal Risk Elasticity
1	SR160-N	8.51	**24**	SR101-N	0.52	**47**	**I710-N**	**0.18**	**70**	SR163-S	-0.99
2	SR120-W	7.69	**25**	SR101-S	0.52	**48**	SR73-N	0.18	**71**	SR52-W	-1.00
3	SR65-N	5.97	**26**	I405-N	0.47	**49**	SR57-S	0.17	**72**	SR71-S	-1.18
4	SR113-S	5.84	**27**	SR60-W	0.46	**50**	I210-W	0.16	**73**	SR92-E	-1.49
5	I205-W	4.70	**28**	I605-S	0.45	**51**	I210-E	0.13	**74**	SR180-E	-1.53
6	SR238-N	3.12	**29**	I5-N	0.45	**52**	I215-N	0.03	**75**	SR1-S	-1.57
7	SR17-S	3.06	**30**	**I110-N**	**0.43**	**53**	SR22-E	-0.14	**76**	SR52-E	-1.64
8	SR152-W	3.04	**31**	I605-N	0.42	**54**	US50-E	-0.18	**77**	SR41-N	-1.65
9	SR92-W	3.02	**32**	**I110-S**	**0.41**	**55**	US50-W	-0.26	**78**	SR78-E	-2.05
10	SR17-N	2.33	**33**	SR24-E	0.37	**56**	I805-S	-0.32	**79**	SR65-S	-2.06
11	SR113-N	2.22	**34**	I880-N	0.35	**57**	SR22-W	-0.33	**80**	SR120-E	-2.47
12	SR24-W	1.77	**35**	I880-S	0.33	**58**	SR134-E	-0.35	**81**	SR1-N	-2.78
13	SR237-E	1.48	**36**	**I710-S**	**0.33**	**59**	SR55-N	-0.35	**82**	SR23-N	-2.86
14	SR170-S	1.22	**37**	I15-N	0.30	**60**	I805-N	-0.39	**83**	I205-E	-2.99
15	SR237-W	1.00	**38**	I80-E	0.26	**61**	SR14-N	-0.39	**84**	SR94-E	-2.99
16	SR87-N	0.82	**39**	SR134-W	0.25	**62**	SR37-E	-0.39	**85**	SR152-E	-3.05
17	SR91-E	0.71	**40**	I215-S	0.24	**63**	SR71-N	-0.41	**86**	SR23-S	-3.22
18	I405-S	0.70	**41**	I80-W	0.23	**64**	I8-W	-0.62	**87**	SR78-W	-3.31
19	I10-E	0.68	**42**	SR99-N	0.21	**65**	SR4-W	-0.76	**88**	SR238-S	-5.29
20	SR91-W	0.63	**43**	I280-N	0.21	**66**	SR4-E	-0.80	**89**	SR84-E	-5.45
21	I5-S	0.57	**44**	I680-N	0.20	**67**	SR37-W	-0.80			
22	I10-W	0.57	**45**	SR99-S	0.19	**68**	I8-E	-0.84			
23	SR60-E	0.57	**46**	I105-E	0.19	**69**	SR41-S	-0.90			
				Mean	0.12			**Mean of Positive Elasticities**			1.32
				Median	0.19			**Median of Positive Elasticities**			0.47
				Std. Dev.	2.24			**Std. Dev. of Positive Elasticities**			1.95

Table 6 reports the lower and upper bounds of the 95% confidence intervals for the marginal risk elasticity estimates given in Table 5. Those intervals can be used to gauge statistical differences in the elasticity estimates across routes (at the 5% significance level).

Table 6
95% Confidence Intervals for Marginal Risk Elasticity Estimates

Route	Lower Bound	Upper Bound	Route	Lower Bound	Upper Bound	Route	Lower Bound	Upper Bound	Route	Lower Bound	Upper Bound
SR160-N	3.07	13.95	SR101-N	0.35	0.70	**I710-N**	**0.05**	**0.31**	SR163-S	-1.69	-0.29
SR120-W	4.49	10.89	SR101-S	0.35	0.68	SR73-N	-0.03	0.39	SR52-W	-1.54	-0.47
SR65-N	4.10	7.83	I405-N	0.41	0.53	SR57-S	0.02	0.33	SR71-S	-1.51	-0.85
SR113-S	3.37	8.31	SR60-W	0.39	0.54	I210-W	0.04	0.28	SR92-E	-2.16	-0.82
I205-W	2.85	6.54	I605-S	0.35	0.55	I210-E	0.02	0.24	SR180-E	-2.09	-0.96
SR238-N	2.17	4.07	I5-N	0.33	0.57	I215-N	0.00	0.06	SR1-S	-2.20	-0.94
SR17-S	2.35	3.76	**I110-N**	**0.37**	**0.50**	SR22-E	-0.24	-0.04	SR52-E	-2.39	-0.89
SR152-W	2.13	3.95	I605-N	0.31	0.52	US50-E	-0.29	-0.07	SR41-N	-2.28	-1.02
SR92-W	1.85	4.20	**I110-S**	**0.35**	**0.48**	US50-W	-0.40	-0.12	SR78-E	-2.77	-1.32
SR17-N	1.45	3.20	SR24-E	0.23	0.51	I805-S	-0.54	-0.09	SR65-S	-2.94	-1.19
SR113-N	1.62	2.83	I880-N	0.25	0.45	SR22-W	-0.53	-0.13	SR120-E	-3.72	-1.21
SR24-W	1.19	2.35	I880-S	0.23	0.43	SR134-E	-0.55	-0.14	SR1-N	-3.91	-1.66
SR237-E	0.68	2.29	**I710-S**	**0.26**	**0.40**	SR55-N	-0.62	-0.08	SR23-N	-3.82	-1.90
SR170-S	0.74	1.69	I15-N	0.19	0.41	I805-N	-0.59	-0.19	I205-E	-4.21	-1.76
SR237-W	0.40	1.59	I80-E	0.20	0.31	SR14-N	-0.55	-0.23	SR94-E	-3.76	-2.23
SR87-N	0.19	1.45	SR134-W	-0.01	0.52	SR37-E	-0.53	-0.26	SR152-E	-4.24	-1.86
SR91-E	0.63	0.79	I215-S	0.15	0.33	SR71-N	-0.59	-0.23	SR23-S	-4.33	-2.10
I405-S	0.62	0.78	I80-W	0.16	0.30	I8-W	-0.95	-0.29	SR78-W	-4.30	-2.32
I10-E	0.58	0.79	SR99-N	0.11	0.31	SR4-W	-1.03	-0.48	SR238-S	-6.67	-3.92
SR91-W	0.54	0.72	I280-N	0.07	0.34	SR4-E	-1.11	-0.48	SR84-E	-7.57	-3.32
I5-S	0.44	0.71	I680-N	0.02	0.39	SR37-W	-1.17	-0.42			
I10-W	0.45	0.69	SR99-S	0.07	0.31	I8-E	-1.31	-0.36			
SR60-E	0.47	0.66	I105-E	0.02	0.36	SR41-S	-1.18	-0.63			

4.3 External Risk

As discussed in Section 2, external risk characterizes the additional accident risk imposed on all of the highway's (affected) travelers when an additional truck joins them. Economists care about external risk because it corresponds directly to the deadweight loss that could result from "too many" truck trips in terms of accident risk. And when multiplied by what these motorists are collectively willing to pay to avoid such additional risk, external risk can (*inter alia*) determine the tolls levied on trucks to reduce their travel to an economically-efficient level.[25]

Table 7 reports our external risk calculations for each route, ranked in descending order with drayage routes indicated in boldface type.[26] State Route 87 northbound tops the list, due to a combination of high marginal risk and traffic volume, suggesting that trucks traveling this route impose the largest risk externalities among the routes in our sample.[27]

[25] See Jansson (1994).
[26] Only estimates that are statistically-significant at the 5% significance level are reported.
[27] Put differently, this route carries the most inefficiently-high volume of trucks with regard to accident risk.

Table 7

Ranking of Routes by External Risk

Rank	Route	External Risk	Rank	Route	External Risk	Rank	Route	External Risk	Rank	Route	External Risk
1	SR87-N	80.32	**24**	I205-W	19.31	**47**	I210-W	4.81	**70**	SR180-E	-12.97
2	SR170-S	77.34	**25**	**I710-S**	**16.20**	**48**	SR101-S	4.45	**71**	I805-S	-13.42
3	SR24-W	67.29	**26**	SR237-E	15.84	**49**	I210-E	4.44	**72**	SR14-N	-13.96
4	SR160-N	66.83	**27**	I880-N	15.28	**50**	SR99-N	2.42	**73**	I205-E	-14.77
5	SR113-N	66.23	**28**	I10-W	14.88	**51**	SR99-S	1.95	**74**	SR23-N	-16.10
6	SR17-N	63.63	**29**	SR134-W	14.39	**52**	I215-N	1.94	**75**	SR23-S	-17.35
7	SR92-W	58.46	**30**	SR120-W	12.95	**53**	SR1-N	-3.16	**76**	I805-N	-18.98
8	SR65-N	45.02	**31**	SR24-E	12.29	**54**	SR120-E	-4.98	**77**	SR55-N	-19.09
9	SR17-S	44.13	**32**	I880-S	11.36	**55**	SR84-E	-5.08	**78**	SR22-W	-19.20
10	I405-S	38.87	**33**	SR152-W	10.59	**56**	SR41-S	-5.53	**79**	SR238-S	-25.85
11	**I110-N**	**37.78**	**34**	I80-E	10.42	**57**	SR1-S	-5.77	**80**	SR71-N	-26.75
12	SR91-E	31.37	**35**	I215-S	10.18	**58**	SR41-N	-5.81	**81**	SR134-E	-30.32
13	**I110-S**	**31.04**	**36**	I105-E	9.37	**59**	SR78-W	-8.51	**82**	SR37-W	-40.00
14	I405-N	30.11	**37**	SR57-S	8.57	**60**	SR78-E	-9.06	**83**	SR94-E	-40.13
15	SR237-W	27.07	**38**	**I710-N**	**7.87**	**61**	US50-E	-9.64	**84**	SR37-E	-45.39
16	SR91-W	25.76	**39**	I280-N	7.86	**62**	I8-E	-10.12	**85**	SR92-E	-48.66
17	SR113-S	24.48	**40**	I5-S	7.86	**63**	I8-W	-10.52	**86**	SR71-S	-62.77
18	I10-E	22.56	**41**	I5-N	7.44	**64**	SR4-W	-10.58	**87**	SR52-E	-70.58
19	SR60-E	22.40	**42**	I80-W	6.81	**65**	SR152-E	-10.74	**88**	SR163-S	-72.51
20	I605-S	22.28	**43**	I15-N	6.65	**66**	SR65-S	-11.65	**89**	SR52-W	-73.20
21	SR238-N	21.71	**44**	I680-N	6.32	**67**	US50-W	-11.83			
22	SR60-W	20.66	**45**	SR101-N	5.66	**68**	SR4-E	-12.51			
23	I605-N	20.13	**46**	SR73-N	5.43	**69**	SR22-E	-12.87			
				Mean	4.25		**Mean of Positive External Risk**				23.25
				Median	5.66		**Median of Positive External Risk**				15.56
				Std. Dev.	30.63		**Std. Dev. of Positive External Risk**				21.11

The table also shows that the drayage routes rank 11th, 13th, 25th, and 38th among these routes. The average external risk across all routes is 4.25, and the average across routes with positive risk externalities is 23.25. Among these routes with positive risk externalities, Interstate 110 in both directions exhibits larger than average truck risk externalities, whereas Interstate 710 in both directions exhibits smaller than average externalities. Although it is difficult to draw any general conclusions about the drayage routes from these findings, it may be worth noting that none of them are among the top ten routes in terms of the external risk generated by heavy trucks. In other words, none of the drayage routes are among the top-ten least-efficient routes due to risk externalities generated by excessive truck volume.

Table 8 reports the lower and upper bounds of the 95% confidence intervals for the external risk estimates given in Table 7.

Table 8
95% Confidence Intervals for External Risk Estimates

Route	Lower Bound	Upper Bound	Route	Lower Bound	Upper Bound	Route	Lower Bound	Upper Bound	Route	Lower Bound	Upper Bound
SR87-N	18.24	142.40	I205-W	11.71	26.90	I210-W	1.31	8.32	SR180-E	-17.78	-8.17
SR170-S	47.08	107.60	**I710-S**	**12.56**	**19.85**	SR101-S	3.00	5.89	I805-S	-22.90	-3.94
SR24-W	45.33	89.26	SR237-E	7.27	24.41	I210-E	0.88	8.00	SR14-N	-19.61	-8.31
SR160-N	24.11	109.55	I880-N	10.84	19.73	SR99-N	1.22	3.61	I205-E	-20.82	-8.71
SR113-N	48.30	84.16	I10-W	11.75	18.00	SR99-S	0.75	3.14	SR23-N	-21.49	-10.71
SR17-N	39.61	87.65	SR134-W	-0.68	29.47	I215-N	0.08	3.81	SR23-S	-23.37	-11.32
SR92-W	35.71	81.20	SR120-W	7.56	18.33	SR1-N	-4.44	-1.89	I805-N	-28.74	-9.21
SR65-N	30.93	59.12	SR24-E	7.57	17.00	SR120-E	-7.52	-2.45	SR55-N	-33.57	-4.60
SR17-S	33.99	54.26	I880-S	7.94	14.79	SR84-E	-7.06	-3.10	SR22-W	-31.03	-7.37
I405-S	34.39	43.34	SR152-W	7.42	13.75	SR41-S	-7.22	-3.85	SR238-S	-32.56	-19.13
I110-N	**32.14**	**43.42**	I80-E	8.13	12.72	SR1-S	-8.09	-3.45	SR71-N	-38.43	-15.08
SR91-E	27.73	35.01	I215-S	6.34	14.02	SR41-N	-8.05	-3.58	SR134-E	-48.21	-12.43
I110-S	**26.24**	**35.84**	I105-E	1.14	17.61	SR78-W	-11.05	-5.97	SR37-W	-58.72	-21.28
I405-N	26.24	33.97	SR57-S	0.94	16.20	SR78-E	-12.28	-5.84	SR94-E	-50.37	-29.89
SR237-W	10.92	43.22	**I710-N**	**2.22**	**13.52**	US50-E	-15.49	-3.80	SR37-E	-61.04	-29.75
SR91-W	22.16	29.36	I280-N	2.83	12.89	I8-E	-15.87	-4.36	SR92-E	-70.62	-26.69
SR113-S	14.14	34.82	I5-S	6.00	9.72	I8-W	-16.16	-4.89	SR71-S	-80.46	-45.09
I10-E	19.09	26.03	I5-N	5.46	9.42	SR4-W	-14.41	-6.75	SR52-E	-103.01	-38.14
SR60-E	18.52	26.27	I80-W	4.73	8.88	SR152-E	-14.94	-6.54	SR163-S	-123.49	-21.53
I605-S	17.42	27.15	I15-N	4.25	9.05	SR65-S	-16.59	-6.72	SR52-W	-112.17	-34.23
SR238-N	15.13	28.29	I680-N	0.70	11.94	US50-W	-18.06	-5.59			
SR60-W	17.30	24.02	SR101-N	3.78	7.54	SR4-E	-17.47	-7.54			
I605-N	15.11	25.15	SR73-N	-0.84	11.71	SR22-E	-22.19	-3.55			

4.4 Policy Implications

The results presented in Tables 4–8 demonstrate that the relative risk generated by additional trucks on a given route depends on how such risk is characterized. For example, it might be reasonable to deem trucks on northbound Interstate 710 as relatively "dangerous" because that route's average risk is among the highest in our sample. In terms of marginal risk, however, it ranks below the median of those routes.

Choosing an "appropriate" risk measure from these results depends on the policy it is intended to guide. For instance, average risk suggests that the drayage routes are relatively hazardous, arguably due to their heavy concentration of drayage traffic. Marginal risk, however, may be more useful for policy analysis when considering the scarce resources that risk-reduction policies require. For example, consider a choice between reducing truck traffic on the drayage routes by 10% by diverting containers to on-dock rail, or reducing truck traffic on State Route 17 — a winding, hilly route from San Jose to Santa Cruz — by simply diverting trucks to alternative routes. The former would reduce the accident risk on the drayage routes by 1.8% to 4.5%, whereas the latter would reduce the accident risk on State Route 17 by 23.% to 30.1%. A similar example could be constructed for several other highways that rank ahead of the drayage routes in terms of marginal risk. It seems, then, that the biggest safety-policy "value" might come from re-routing (or at least redistributing, perhaps during peak periods) truck traffic on several routes other than the drayage routes, such as State Route 113, running through Oakland, and Interstate 405, running from Orange County to the Los Angeles County border. External risk takes into account the number of vehicles affected by the marginal risk imposed by increased truck traffic. So, for example, if tolls are levied on trucks to address the risk externalities they generate, then such tolls would be similar for trucks travelling on Interstates 110 and 405, but considerably lower than for those travelling on State Route 17. And Truck tolls on Interstate 710 would be lower than average if such tolls were levied only on routes with positive levels of external risk.

In summary, our results suggest that drayage routes may indeed be relatively dangerous in terms of average risk, but that several other highways might be more suitable targets for safety policies designed to reduce accident risk by altering truck flows. In other words, it may not be efficient to exclusively target drayage routes, and the dray drivers travelling them, when formulating truck-related highway safety policies.

5. Concluding Remarks

5.1 Summary of Analysis and Findings

We estimate three accident-risk measures — average risk, marginal risk, and external risk — to assess the relative danger of several California highways carrying varying concentrations of heavy commercial truck traffic. We do so by exploiting fixed-effects panel regression methods using a large panel of California highway traffic and accident data from January 2007 through April 2010. We also develop a somewhat novel analytic model that enables us to calculate marginal and external risk using from our panel regression results. Table 9 summarizes how each route in our study ranks according to our three risk measures.

Table 9

Summary of Route Rankings by Average, Marginal, and External Risk

Route	AR	MR	ER	Route	AR	MR	ER	Route	AR	MR	ER	Route	AR	MR	ER
I105-E	24	46	36	I805-N	28	60	76	SR17-S	79	7	9	SR57-N	26	-	-
I105-W	20	-	-	I805-S	40	56	71	SR180-E	92	74	70	SR57-S	12	49	37
I10-E	47	19	18	I80-E	44	38	34	SR180-W	91	-	-	SR60-E	17	23	19
I10-W	46	22	28	I80-W	51	41	42	SR1-N	110	81	53	SR60-W	19	27	22
I110-N	**3**	**30**	**11**	I880-N	18	34	27	SR1-S	109	75	57	SR65-N	98	3	8
I110-S	**2**	**32**	**13**	I880-S	23	35	32	SR22-E	7	53	69	SR65-S	106	79	66
I15-N	76	37	43	I8-E	89	68	62	SR22-W	39	57	78	SR71-N	30	63	80
I15-S	75	-	-	I8-W	83	64	63	SR237-E	54	13	26	SR71-S	49	72	86
I205-E	85	83	73	SR101-N	84	24	45	SR237-W	35	15	15	SR73-N	60	48	46
I205-W	87	5	24	SR101-S	86	25	48	SR238-N	94	6	21	SR73-S	68	-	-
I210-E	27	51	49	SR113-N	99	11	5	SR238-S	104	88	79	SR78-E	100	78	60
I210-W	31	50	47	SR113-S	113	4	17	SR23-N	101	82	74	SR78-W	105	87	59
I215-N	15	52	52	SR118-E	52	-	-	SR23-S	102	86	75	SR84-E	114	89	55
I215-S	37	40	35	SR118-W	53	-	-	SR24-E	57	33	31	SR84-W	111	-	-
I280-N	33	43	39	SR120-E	107	80	54	SR24-W	55	12	3	SR85-N	32	-	-
I280-S	34	-	-	SR120-W	112	2	30	SR37-E	48	62	84	SR85-S	29	-	-
I405-N	13	26	14	SR134-E	14	58	81	SR37-W	70	67	82	SR87-N	1	16	1
I405-S	22	18	10	SR134-W	10	39	29	SR41-N	95	77	58	SR87-S	4	-	-
I580-E	62	-	-	SR14-N	65	61	72	SR41-S	93	69	56	SR91-E	16	17	12
I580-W	69	-	-	SR14-S	64	-	-	SR4-E	82	66	68	SR91-W	25	20	16
I5-N	72	29	41	SR152-E	97	85	65	SR4-W	88	65	64	SR92-E	41	73	85
I5-S	78	21	40	SR152-W	96	8	33	SR51-N	5	-	-	SR92-W	80	9	7
I605-N	6	31	23	SR160-N	108	1	4	SR51-S	9	-	-	SR94-E	90	84	83
I605-S	8	28	20	SR160-S	103	-	-	SR52-E	77	76	87	SR94-W	81	-	-
I680-N	50	44	44	SR163-N	45	-	-	SR52-W	63	71	89	SR99-N	73	42	50
I680-S	56	-	-	SR163-S	38	70	88	SR55-N	42	59	77	SR99-S	74	45	51
I710-N	**11**	**47**	**38**	SR170-N	67	-	-	SR55-S	43	-	-	US50-E	66	54	61
I710-S	**21**	**36**	**25**	SR170-S	36	14	2	SR56-E	61	-	-	US50-W	58	55	67
I805-N	28	60	76	SR17-N	59	10	6	SR56-W	71	-	-				

We pay particular attention to risk measures for the four routes that carry the heaviest concentrations of drayage traffic: Interstates 110 and 710 in both directions, which we refer to as "drayage routes" (indicated by boldface type in the above table).[28] We do this to investigate a general notion that drayage traffic is inherently more hazardous than heavy commercial truck traffic in general, perhaps due to the intensely-competitive nature of drayage operations.

Our empirical findings are somewhat mixed. All of the drayage routes exhibit an average risk well above the mean of the 114 routes considered in our study. The northbound and southbound directions of Interstate 110, in particular, carry the second and third highest average risk among these routes. In terms of marginal risk, however, the drayage routes rank from 30th to 47th — well behind several other urban routes. The external risk rankings for the drayage routes range from 11th to 38th, demonstrating that inefficiently-high truck volumes, in terms of accident risk, are not unique to drayage routes.

In short, our findings suggest that drayage routes are relatively hazardous from the standpoint of average risk. In terms of marginal and external risk, however, we find that several urban highways carrying smaller concentrations of drayage traffic may be more suitable targets for safety policies designed to alter the flow of heavy truck traffic.

5.2 Caveats

Three key variables in our analysis are the truck volumes, car volumes, and the number of accidents on each route. Car and truck volumes, however, are only available for the monitored portions of each route, whereas accident rates are reported for the entire length of each route. We were thus forced to impute traffic volumes on each route in order to make them consistent with the accident rate data. And in the process of validating out imputations we were forced to discard "unreliable" information for several routes.

Moreover, the PeMS data facility from which we collected our traffic and accident data is not capable of exactly matching accidents to routes in all cases. That facility is also at the mercy of disabled traffic sensors and failed links with the CHP and TASAS reporting systems. Hence, our estimates may reflect "noise" due to data measurement error, although we devoted considerable effort to culling anomalous observations from our database.

A more reliable means of collecting data for our analysis would be to request car and truck volumes directly from Caltrans, and accident data directly from their TASAS system, on a route-by-route basis. Doing so for California's 508 or so urban routes, or even for the 114 routes

[28] In Table 9, blank entries for marginal and external risk estimates indicate that those estimates were not statistically-significant at the 5% significance level.

in our sample, would have been prohibitively costly. Instead we made every effort to construct a reliable database using the PeMS facility, which allowed us to exploit rich, cross-sectional information in a cost-effective manner.

5.3 Suggestions for Further Research

Our analysis is related to a broader literature on the relationship between product safety, firm profitability and market structure.[29] In the context of drayage operations, further research could examine possible changes in accident risk on the drayage routes after the implementation of the Clean Truck Program at the San Pedro Bay ports. The truck-age and engine-retrofitting restrictions imposed by this program, and the attempted ban of independent owner operators at the port of Los Angeles, are likely to result in reduced competition among drayage operators. And economic theory predicts that reduced competition leads to greater firm profitability. So a useful hypothesis would be whether or not this increased profitability has improved the safety of the highways most commonly traveled by drayage trucks. This hypothesis could be tested using time-series data from these drayage routes, using analytic methods similar to those developed in our present study.

Further research could also focus on whether or not independent owner operators actually have an incentive to "cut corners" when it comes to safely maintaining their trucks, noting that maintenance is costly, but so are accidents.[30] A safety "production function" approach, similar to that proposed by Friedlander and Spady (1980), could be employed to conduct the analysis. Doing so, however, would require data on truck-maintenance expenditures, drayage revenues and pay rates, drayage output (such as the number of containers hauled per month), and so forth — perhaps gathered using survey instruments.

[29] In the context of freight movement by truck, see Monaco and Williams (2000), Belzer (2002), and Rodriguez et al. (2003).
[30] In a related study, Monaco (2007 – METRANS 06-02) examines the feasibility of subsidies in a truck-retrofitting context and finds that owner-operators would be willing to increase their share of maintenance investment if subsidized.

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