The Impact of the Economic Recession on Truck Traffic in Los Angeles

Final Report

METRANS Project 11-20

May 2012

Principal Investigators:

Chen Feng Ng

Elaine F. Frey

Graduate Student:

Foong Yee Law

Department of Economics

California State University Long Beach

1250 Bellflower Blvd

Long Beach, CA 90840-4607

Disclaimer

Abstract

The economic recession in 2007 coincided with rising oil prices and an overall decline in traffic volume nationwide. This project focuses on truck traffic on the Long Beach Freeway (I-710), which connects the Ports of Los Angeles and Long Beach to railyards and other freeways. We explore various factors that could have affected truck traffic on this freeway, such as economic conditions, diesel prices, possible modal substitutions, and port policies. To identify these factors and help us develop a model to disentangle the effects of these factors on truck traffic, we conduct a comprehensive literature review of the research on this topic. We present summary statistics of the data that were collected for this project, and discuss the steps for future research.

Table of Contents

List of Figures

List of Tables

Disclosure

Project was funded in entirety under this contract to California Department of Transportation.

Acknowledgments

The authors are grateful to Kristen Monaco, Andrew Ojede, Seiji Steimetz, Steven Yamarik, and participants of the CSULB Seminar Series and the WEAI Annual Conference for providing useful comments and suggestions. We also would like to thank Foong Yee Law for excellent research assistance.

1. Introduction

Traffic congestion and its implications are a major concern for modern metropolitan areas. The Los Angeles area has been consistently ranked the most congested metropolitan area in the country since the early 1980s (Texas Transportation Institute, 2009). One of the factors contributing to traffic congestion in the Los Angeles area is the high truck traffic generated from freight movement; Los Angeles is tied with Chicago for the greatest volume of intercity truck freight in the country (Federal Highway Administration, 2005). This project examines various factors that affect truck traffic in the Los Angeles metropolitan area, specifically on the Long Beach Freeway (I-710).

The high volume of truck traffic in this region is partly a result of goods movement from the Port of Los Angeles and the Port of Long Beach, which combined, is the fifth largest port in the world.[1] When the economy slid into recession in late 2007, it had a deep impact on both ports and on freight movement in general, due to lower consumer demand for goods. Around the same time, fuel prices climbed to an all-time high, increasing the costs of truck transportation. Therefore, it is hypothesized that truck traffic declined significantly during this period. Of course, we would also expect that non-truck traffic declined during this period as well, mainly because of fewer work trips as a result of unemployment and fewer discretionary trips from lower consumer spending. If fewer trucks are on the road, we should also observe less traffic congestion and possibly improved air quality as a result. Researchers have well-documented the many negative effects of traffic congestion, such as lost productivity from work due to more time spent driving and increased fuel costs and emissions from idling (Texas Transportation Institute,

---

[1] Port of Long Beach website: http://www.polb.com/about/facts.asp

2009). Trucks that burn diesel are also a major source of air pollution, which may result in health risks to local residents (South Coast Air Quality Management District, 2000).

This project focuses on truck traffic patterns on the Long Beach Freeway, which runs north and south from the Long Beach and Los Angeles ports to Alhambra, which is northeast of the city of Los Angeles. It is an integral connector between the ports and other freeways, distribution centers, and rail facilities in Southern California. We conduct an extensive review of the literature on this topic to narrow down the factors that might affect truck traffic and to explore the possible methodologies and models. In addition to economic conditions and diesel prices, we expect truck traffic on this freeway to be affected by the demand and supply of trucking based on goods shipped, policies implemented at the ports, the availability of rail as a substitute mode, holidays, and adverse weather conditions. We describe each of these factors in detail in this report. We then identified and collected the data relevant to our project. Finally, based on the available data, we propose an econometric model that we plan to use in future research to describe the relationship between truck traffic and various economic and regulatory factors.

It is expected that the results from this project will be useful to policy makers as well as of interest to researchers in this field. First, the results can be used to show how truck traffic may change due to rapid fluctuations in future economic conditions using a relatively simple model, which may be useful for future infrastructure changes and improvements. This would add to the literature because most of the current studies have very onerous data requirements and it is difficult to apply them to finer time scales such as monthly intervals. Although our project is limited by the fact that we focus on one particular freeway, we think that our study can also highlight to other researchers how policies implemented elsewhere (in our case, the ports) can also affect truck traffic on freeways.

Secondly, in considering policies aimed at reducing congestion (e.g., a congestion toll or higher gasoline taxes), it may be important for policy makers to know how truck traffic responds to changes in diesel prices. This study may also be useful to other researchers interested in studying the link between truck traffic and traffic congestion, air pollution, and accident rates.

The structure of the report is as follows. We present an overview of the previous literature in Section 2. Section 3 discusses the data and presents summary statistics, while Section 4 presents the econometric model. Section 5 concludes.

2. Background information and literature review

According to the National Bureau of Economic Research, the late 2000s recession began in December 2007 and continued well into 2009. The economic recession resulted in fewer goods being imported to and exported from U.S. ports. The Long Beach and Los Angeles ports handled almost 11.3 million TEUs (twenty-foot equivalent units) of inbound and outbound loaded containers in 2007; over the next two years this declined to 9.1 million TEUs in 2009 before climbing back up to 10.5 million TEUs in 2010.[2] Even though drayage is a small percentage of total truck traffic in Los Angeles, there is reason to believe that trucks traveling the Long Beach Freeway are primarily carrying freight that originates or is being carried into the port. Thus, measuring truck traffic along this freeway gives us an indication of how freight movement decreased in general during the recession.

[2] Calculated using inbound and outbound container data from the Port of Long Beach website (http://www.polb.com/economics/stats/teus_archive.asp) and the Port of Los Angeles website (http://www.portoflosangeles.org/maritime/stats.asp). The number of containers is measured in terms of TEUs.

There is also evidence that after the recession began, there was a noticeable change in traffic patterns, although thus far there have been no studies looking specifically at truck traffic. According to the Federal Highway Administration (2011), the estimated amount of travel in the U.S. fell by nearly 2 percent to about 2.97 trillion vehicle-miles in 2008 compared to 2007, and remained at about the same level in 2009 and 2010. The decrease in vehicle-miles traveled during the economic recession can be attributed to two factors. Total traffic flow decreases due to consumers taking fewer trips to work as a result of higher unemployment and fewer discretionary trips from lower consumer spending. Truck traffic decreases due to lower demand for goods and thus a decrease in freight movement. It is expected that decreases in vehicle-miles traveled lead to reduced congestion, and INRIX (2010) shows that delays due to traffic congestion in 2008 and 2009 were well below 2007 levels.

Aside from the recession, other factors such as diesel prices, policy changes, and seasonal effects may also affect traffic flow. A study from the Congressional Budget Office (2008) shows that rising fuel prices prior to the recession are correlated with a decrease in total traffic volume. Specifically, between the period 2003 and 2007, the number of freeway trips in California decreased by 0.7 percent and drivers decreased their average driving speed by three quarters of a mile for every 50 cent increase in the price of gasoline. Goodwin et al. (2004) and Graham and Glaister (2004) both provide overviews of the traffic demand literature and report various elasticities related to traffic. Graham and Glaister (2004) give a useful summary of the literature relating specifically to truck traffic.[3] They report that in the literature, price elasticities for truck traffic with respect to truck services fall between -7.92 to 1.72, but the majority of elasticities lie between -0.5 and -1.3. They note that the literature relating to truck traffic is quite limited and

[3] The study actually looks at total freight traffic which encompasses truck traffic as well as rail and waterway carriers.

elasticities tend to vary with estimation method, level of aggregation and commodity type. It is also important to point out that there are no studies looking at the difference in truck traffic elasticities with respect to fuel for the long run versus the short run.

There are several models developed explicitly for the purposes of estimating and predicting freight flows, which encompasses truck flows; Holguín-Veras et al. (2001) and Giuliano et al. (2010) provide useful overviews of these models. They can be broadly classified into two types of models: trip-based and commodity-based. The data requirement for these studies can be onerous, with detailed data on many aspects for each sector of the economy needed.

Trip-based models for truck flows typically follow three steps: trip generation, trip distribution and traffic assignment (Holguín-Veras et al. 2001). Trip generation is based either on trip generation rates or zonal regression models and tracks truck volume per acre or per employee for each sector of the economy. The trip distribution phase typically uses gravity or direct demand models and this phase involves estimating an origin-destination matrix of truck trips. These truck trips are then assigned to various links of the highway system. Cambridge Systematics and O'Neil Associates (1992) use trip-based modeling to develop an urban truck travel model for the Phoenix metropolitan area. Fernandez, de Cea and Soto (2003) develop a supply and demand model that estimates intercity freight that depends on the perceived transportation costs to shippers and carriers. Not only are the methods of trip-based models very data intensive, they also rely on the assumption that the market for truck services, not the market for goods, explains truck trips (Holguín-Veras and Zorrilla 2006).

Commodity-based models therefore assume that freight flow is driven by the market for goods in each economic sector and estimate commodity flows and freight flows to particular areas. Commodity-based models involve five steps (which are similar to those in trip-based models): commodity generation, commodity distribution, commodity mode split, vehicle-trip estimation, and traffic assignment (Holguín-Veras et al. 2001). Input-output or IO models (first developed by Leontieff 1936) that formulate the relationship between the inputs and outputs of a regional economy and then estimate the flow of products within the economy are often used in the commodity generation and distribution phases. A very important assumption in IO models is that the inputs used in production are proportional to the output (Sorratini 2000). If there is more than one mode in the model, a mode split model (typically using logit estimation) is used and commodity flows are then converted to the number of trips for each mode. Holguín-Veras and Thorson (2003) argue that it is important to take into account the flow of empty trips as well.

Commodity-based models often use data from the Commodity Flow Survey (published by the Bureau of Transportation Statistics), which has been conducted every five years since 1993. Among other things, this dataset provides information on the types, modes, values, and origins and destinations of commodities shipped in various industries (mining, manufacturing, retail, etc). Commodity-based models have been estimated for Nebraska (Jones and Sharma 2003), Wisconsin (Sorratini 2000), Virginia (Brogan, Brich and Demetsky 2001), and other states. Data at finer geographical scales (e.g., metropolitan areas) are more difficult to obtain; Giuliano et al. (2010) estimate a model for the Los Angeles metropolitan area by integrating various datasets, including the Commodity Flow Survey, IMPLAN county-level input output data, imports/exports, and small area employment data.

Due to the data requirements of both trip-based and commodity-based models, it is very difficult to apply them to truck flows on finer time scales (e.g., monthly intervals) since for instance, the Commodity Flow Survey is published only every five years. Developing a model that can estimate truck flows using monthly or even weekly data is crucial for the purposes of our project because economic conditions deteriorated very rapidly during the recession, and diesel prices also rose and fell significantly within a relatively short period of time. Therefore, we consider other possible approaches as well.

There is growing interest in using agent-based microsimulation techniques to model freight flows. Liedtke (2009) provides a basic overview of the framework and a summary of the literature. The key decision makers in microsimulation models are the shippers and receivers of goods, and transportation firms plan tours based on the shipment of goods. Hunt and Stefan (2005) apply an agent-based microsimulation model to freight movements in Calgary, Canada. To calibrate their model, the authors conducted an extensive set of interviews with firms in the region and collected data on the movements of their fleet (including origin and destination, commodity, and purpose).

Meanwhile, Boile and Golias (2006) estimate trucking volume using different linear regression techniques. They argue that using ordinary least squares (OLS) regression techniques with limited data may lead to multicollinearity problems (where the independent variables are very highly correlated with one another), which result in unstable coefficients and coefficients that have the "incorrect" sign, e.g., an independent variable that is known to have a positive effect on the dependent variable has a negative sign. To overcome these problems, they discuss various linear regression techniques, most of which place constraints on the coefficients and are therefore constrained versions of OLS. They estimate trucking volume with sales, employment, and number of establishments for various industries as independent variables. They conclude that due to their limited dataset, generalizations regarding the different models could not be made and in practice, different models should be used and the best one should be selected based on the fit of the model (typically measured by the adjusted R^2) and the significance of the parameters.

There have been some other studies relating economic conditions to traffic-related factors, not just truck traffic. One such study, Burger and Kaffine (2009), looks at the effect of gas price fluctuations on traffic speeds in Los Angeles, controlling for fluctuations in the economy and other variables. They use weekly traffic data from the Performance Monitoring System (PeMS), which provides traffic counts, speeds, and other information from loop detector data in California. The authors use OLS techniques and instrumental variables (IV) techniques because gasoline prices may not be exogenously determined (e.g., it may depend on traffic volumes). They find that increased fuel costs from driving faster are roughly offset by the value of time saved. In a finding that is related to our topic, they find that gasoline prices have a statistically significant effect on freeway speeds during rush hour: they find that a one dollar increase in gasoline prices is associated with a 2.6 to 4.1 miles per hour increase in freeway speed. They hypothesize that this could be a result of people responding to higher prices by driving less, which therefore reduces congestion and increases freeway speeds. They also find that an increase in the unemployment rate is associated with an increase in freeway speed (since a higher unemployment rate would mean fewer drivers during rush hour), although this is not always statistically significant. Since this relationship is conceptually similar to the topic of our project, we think that this approach can be used for our project.

Our literature review shows that although there have been many studies in this general area, to the best of our knowledge, no current studies exist that examine the effect of state and national economic factors on truck flows and traffic composition on a weekly or monthly basis. Moreover, since data that is required to use trip-based or commodity-based models are not always publicly available, in order to address this research question, we propose using OLS models. The next two sections of this report discusses how our literature review has allowed us to narrow down the factors that might affect truck traffic on the Long Beach Freeway and what model is appropriate in examining the relationship between these factors and truck traffic.

3. Factors that affect truck traffic and data sources

To reiterate, the focus of our project is to study how the recession affected truck traffic on the Long Beach Freeway, while accounting for other possible determinants of truck traffic such as diesel prices, policies implemented at the Ports of Los Angeles and Long Beach, modal substitution, and other factors. The time period that we are interested in would encompass 2007 to 2011. Giuliano et al. (2010) provide a very thorough model of how to estimate and predict freight flows for a given year on highway networks in the Los Angeles metropolitan area, and our aim is to supplement the literature by providing a simpler framework with which we can see how truck flow changes on a particular freeway on a finer time scale.

Based on Burger and Kaffine (2009), we identify California Department of Transportation's Performance Measurement System (PeMS) as a potential source of traffic volumes. PeMS relies on data gathered from thousands of loop detectors on the freeway system and provides information about traffic flow, composition, speed, and congestion delay.[4] PeMS data are available from 2001 for the study area. The number of trucks is either directly measured by loop detectors or estimated by PeMS using an algorithm developed by Kwon et al. (2003),

[4] A loop detector is an induction loop embedded in the road that electrically detects metal objects (in this case, vehicles) as they pass over the loop.

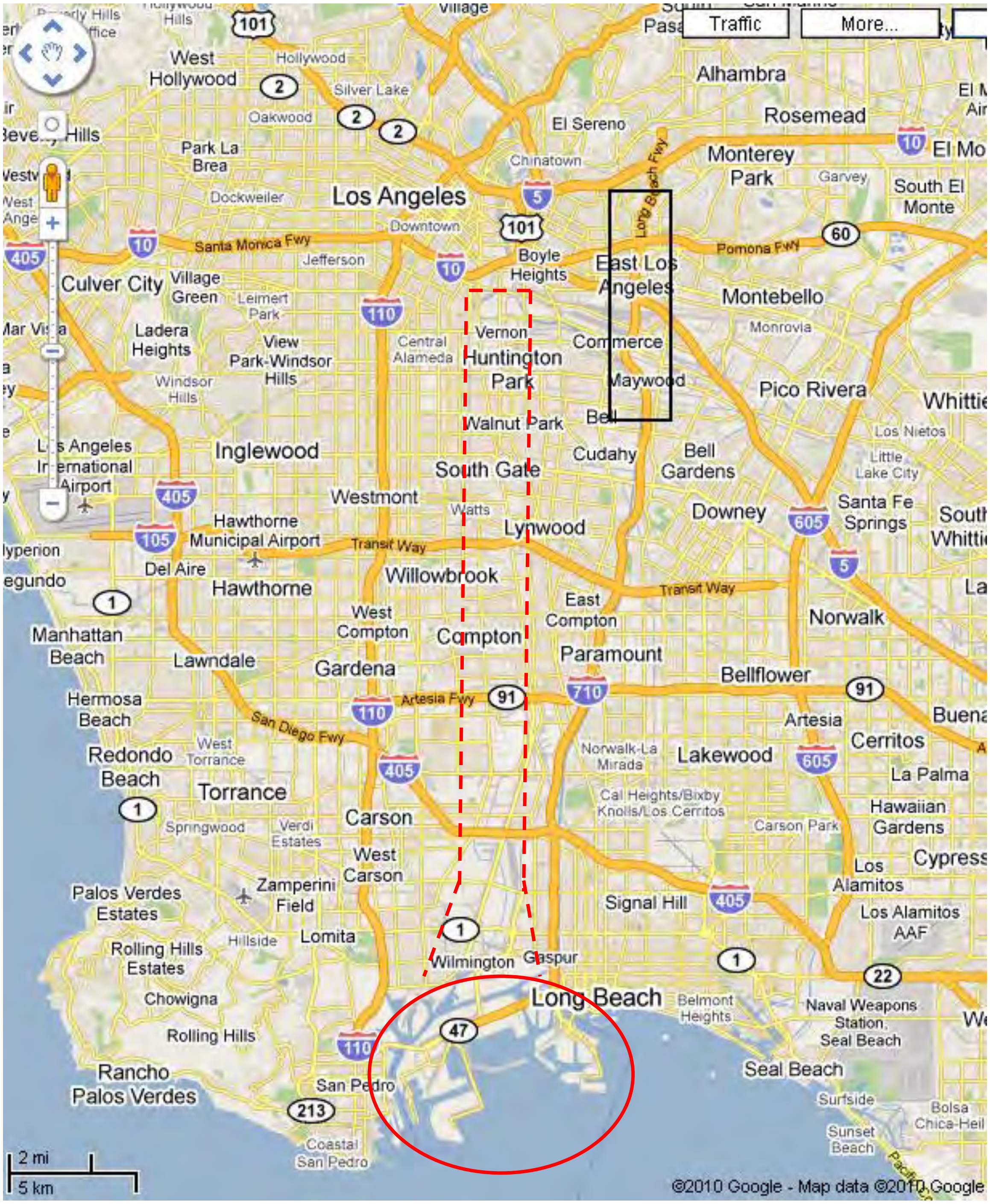
with the assumption that trucks are 60 feet in length, on average.[5] The study area contains 23 individual detectors.

Since data on an hourly and daily basis can fluctuate greatly and loop detectors occasionally fail, we follow PeMS' recommendations and group the detectors by location (I-710N and north of I-5, I-710N and south of I-5, I-710S and north of I-5, and I-710S and south of I-5).[6] We then calculate the median daily truck flow in terms of vehicles per day over the course of the five weekdays from each group. This gives us panel data with 904 total weekly observations and 226 observations in each detector group. We also calculate truck traffic as a percentage of total traffic flow to analyze how truck flow was affected by various factors relative to total traffic flow. There were no major construction projects in the study area, although there was a pavement rehabilitation project to the south which occurred on weekends and did not directly impact weekday traffic in the study area.

Figure 1 shows a map of the freeway with the ports of Los Angeles and Long Beach at the southernmost end. The black box in the figure indicates area for which PeMS data were collected, the red circle indicates the general location of the Los Angeles and Long Beach ports, and the area between the red-dashed lines that lies between I-710 and I-110 is the approximate location of the 20 mile Alameda Corridor rail line. The Alameda Corridor is parallel to the Long Beach Freeway and connects the ports to two major railyards at the northern end. The PeMS detector data cover the area from Imperial Highway to just after SR-60. Although some of the truck traffic in this area is from the ports heading towards warehouses and the railyards, it should be noted that there may also be substantial non-port truck traffic here carrying domestic freight.

[5] The data therefore does not include smaller (Class7 and 8) trucks. However, given that we are primarily interested in the impacts of freight trucks, this would not bias our results.
[6] In the event that a loop detector is not accurately reporting data, PeMS imputes the data using several methods. For more information on this and on the estimation of truck volumes, see http://pems.dot.ca.gov/.

Figure 1: Map of the Long Beach Freeway (I-710)



Source: Google maps (http://maps.google.com)

Table 1 shows trends in total traffic flow and truck flow from January 2007 to April 2011. We can see that total traffic flow fell about 4.6 percent in 2009 compared to 2007, while truck flow fell about 26.0 percent. The decrease in the percentage of truck traffic during this period indicates that there was a bigger decrease in truck flow, relative to total traffic flow.

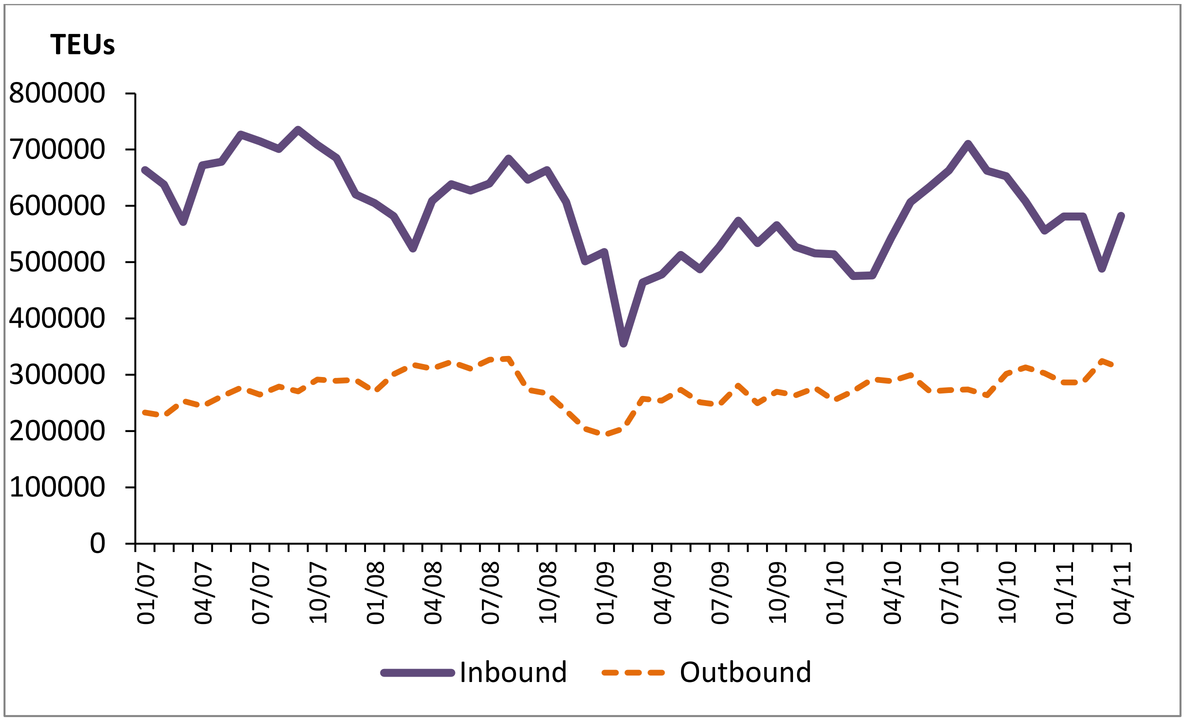
Table 1: Traffic Flow and Truck Flow (averaged over the year)

	Total traffic flow (veh/day)	Truck flow (veh/day)	Truck flow as % of total traffic flow
2007	90,991.4	5,201.9	5.91
2008	88,917.5	5,213.1	6.31
2009	87,391.3	4,345.5	5.45
2010	85,388.0	3,977.4	4.75
2011 (till Apr)	86,839.0	3,946.7	4.80

Note: The four detector groups (I-710N north of I-5, I-710N south of I-5, I-710S north of I-5, and I-710S south of I-5) had fairly similar percentages of truck traffic, with the averages ranging from 4.2% to 6.9%. The detector groups south of I-5 tended to have lower percentages than their same-directional counterparts north of I-5.

Many of the studies reviewed in the previous section rely on commodity flow data for the underlying demand of truck travel. Although commodity flow data are very useful, the studies are conducted infrequently (every five years) and therefore do not capture rapid fluctuations in the economy. Therefore, since we are focused more narrowly on a particular freeway, the Long Beach Freeway, and we are not directly interested in the origins and destinations of the truck traffic, one potential indicator of the demand for truck traffic is the import and export of goods at the Ports of Los Angeles and Long Beach. As stated in Giuliano et al. (2010), the websites of the ports contain monthly records of container traffic (in TEUs), which are depicted in Figure 2. We can see from this graph that imports are far more important than exports at the ports and that inbound container volumes dropped significantly in 2009.

Figure 2: Inbound and Outbound Containers at the Ports of Los Angeles and Long Beach

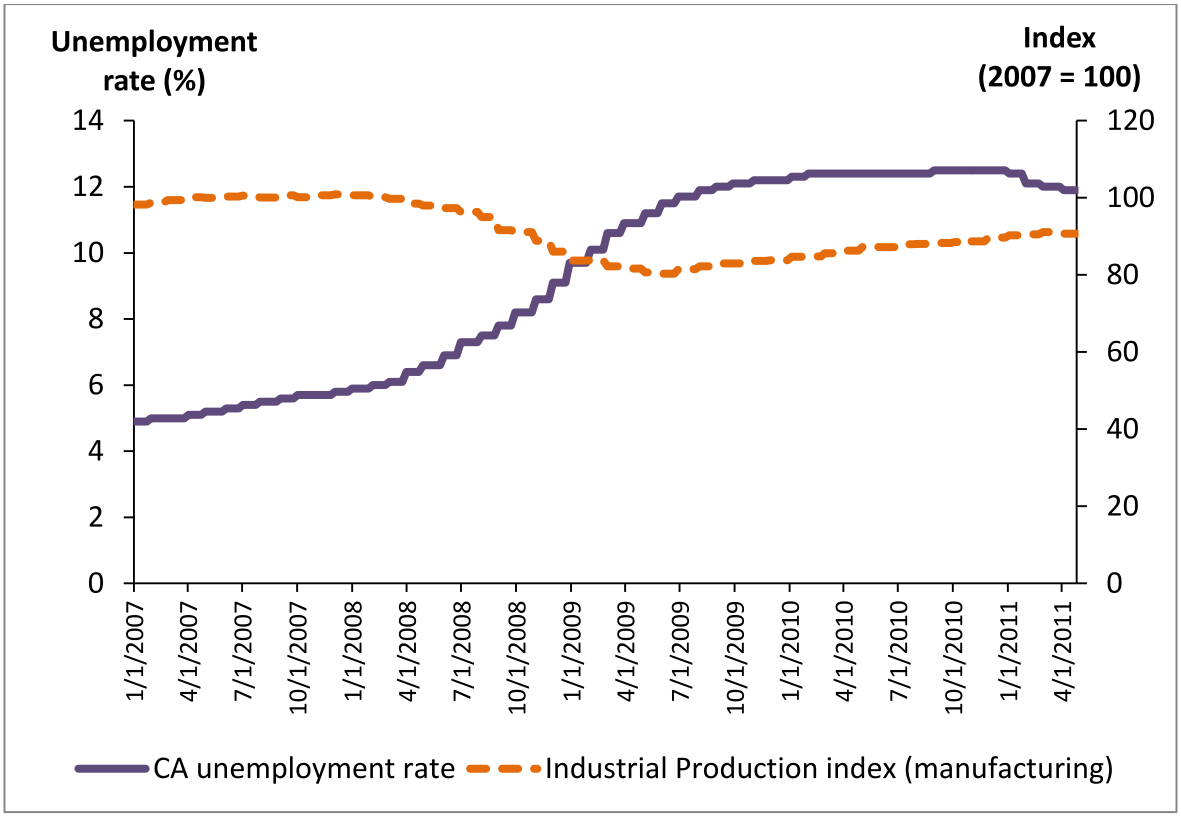


In terms of the bigger picture, the amount of goods shipped is based on consumer demand, which can be proxied by economic variables such as income, the unemployment rate, industrial production, personal consumption expenditures, and retail sales. All of these variables are available at the national level on a monthly basis and we argue that using national data rather than state level data (which is not always available) is appropriate because more than half of the cargo that go through the ports originate or arrive outside the Los Angeles region (Giuliano et al. 2005). However, these variables are highly correlated. That is, we would expect to see a negative relationship between the unemployment rate and household income, and a negative relationship between the unemployment rate and industrial production as well. Therefore, depending on our econometric model, we might not want to include all of these variables since they could cause multicollinearity problems (which were briefly discussed in the previous section). In fact, we would expect these economic variables to be highly correlated with container volumes as well. Having looked at the data for the economic variables, we think that the most appropriate variables to use in our study are the industrial production index and personal consumption expenditures, especially since these have the lowest correlation among the variables.

We collect data on the national industrial production index for the manufacturing sector, published by the Federal Reserve. The industrial production index measures real output each month as a percentage of real output in a base year (2007 in this case). To illustrate the change in economic conditions between January 2007 and April 2011, Figure 3 provides a graph of the unemployment rate and industrial production index. The two variables are highly correlated; the unemployment rate steadily increased from 4.9 percent in January 2007 to 12.5 percent at the end of 2010, while the industrial production index fell from 98.2 in January 2007 to 80.6 in May 2009, before recovering slightly thereafter.

Data for personal consumption expenditures are from the Bureau of Economic Analysis, and are adjusted for inflation using the Consumer Price Index for urban consumers from the U.S. Bureau of Labor Statistics, with January 2009 as the base year.

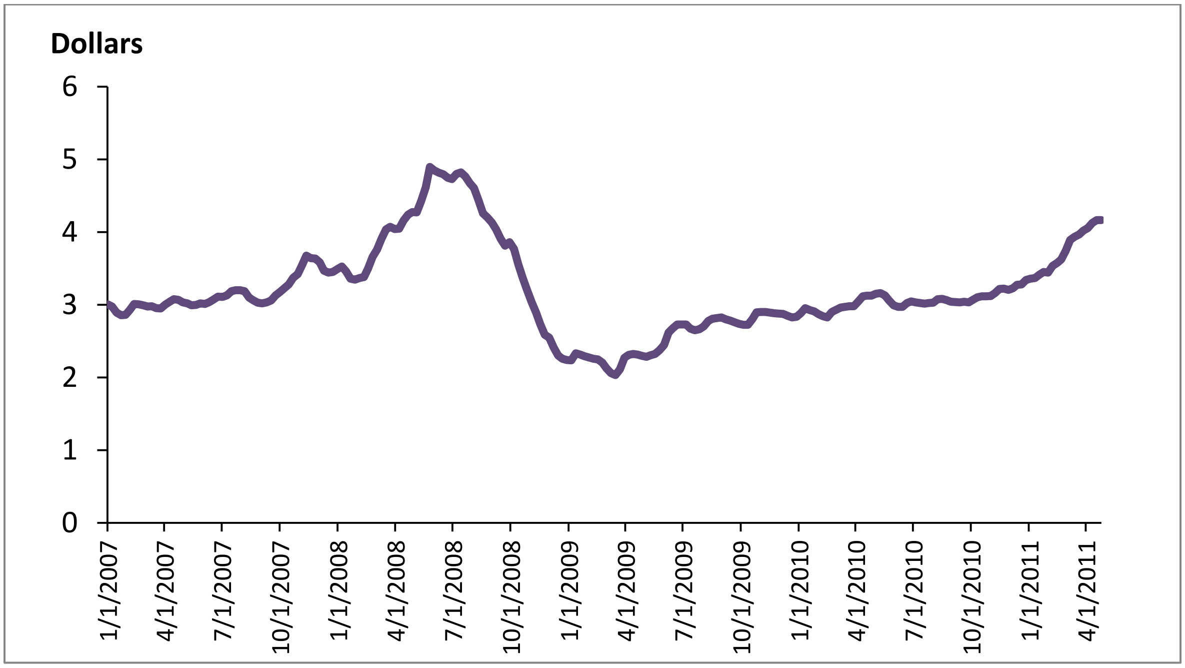
Figure 3: The Unemployment Rate and Industrial Production Index



Ideally, to accurately estimate the demand and supply of trucking, we would like to have the price of trucking services. However, there are no publicly available data on price. Moreover, delivery contracts are often written with prices set in advance, and therefore, current prices may not have much of an effect on actual truck traffic. From our interviews with trucking companies, prices are relatively stable from year to year and the biggest fluctuations would be due to fuel prices, with surcharges imposed if diesel prices rise above a certain level. Therefore, we think that diesel prices might be a potential factor in determining truck traffic, although we expect truck traffic to be relatively inelastic to the price of diesel, at least in the short run. Average weekly diesel prices for California are obtained from the U.S. Energy Information Administration and are adjusted in the same manner as personal consumption expenditures.

Figure 4 shows that the price of diesel increased in 2007 to its peak in the early summer of 2008 ($4.89, adjusted for inflation in January 2009 dollars) and then fell dramatically thereafter.

Figure 4: Average Weekly Price of Diesel



Following Burger and Kaffine's (2009) lead, we think that truck traffic – since we measure it at weekly intervals – may be affected by rainfall and seasonal effects, including holidays. Average weekly rainfall data for downtown Los Angeles were obtained from the National Climatic Data Center. In terms of holidays, we can use a dummy variable to indicate the week in which a federal U.S. holiday occurred. Figure 2, which shows container volumes at the ports, shows that there are periodic dips in container volumes at the beginning of every year. Although these dips could be explained in part by the post-holiday season decrease in consumer spending, we think that it is also due to the Lunar New Year, which is a major celebration in China that usually occurs in January or February and lasts 15 days. Many factories will shut down from one to two weeks during this time, resulting in a significant decrease in port container volumes. The U.S. then experiences a lagged effect, since goods take four to five weeks to be transported across the ocean. Therefore, we use a dummy variable that controls for the four weeks after the first day of the Lunar New Year.

Any possible policies that occurred at the port that affect trucks might also have an impact on truck traffic along the Long Beach Freeway. In particular, an important policy change that occurred during the time period of this study was the implementation of the Clean Trucks Program by the ports of Los Angeles and Long Beach, which is aimed at reducing pollution generated by trucks using the ports. The Clean Trucks Program was implemented in phases. Trucks with engines built prior to1989 were completely banned from the port starting on October 1, 2008. Subsequently, trucks with pre-1994 engines and many with 1994-2003 engines were banned starting on January 1, 2010.[7] To incorporate this into a model, we can use a dummy variable for each phase of this policy, starting three months after the respective implementation date to account for the delayed reaction from the trucking companies and the hiccups that they encountered.

We believe that the Clean Trucks Program may result in the substitution of rail for trucks as a mode of freight transportation. In an attempt to measure this substitution in our analyses, we look at the ratio of truck traffic to the number of trains, which are obtained from the Alameda Corridor Transportation Authority website. We calculate the average daily number of trains running through the Alameda Corridor, which connects the ports to the railyards near the intersection of I-710 and I-5, by dividing the number of trains per month (obtained from the Alameda Corridor Transportation Authority) by the number of days in the corresponding month. This variable also gives us a proxy for on-dock and near-dock rail. Of course, there are also

[7] See http://www.polb.com/environment/cleantrucks for more information.

other factors that may have impacted the substitution of rail for trucks. During our study period, on-dock rail capacity has been steadily increasing. Between 2005 and 2010, on-dock rail capacity has increased by about 40 percent. We believe that our proxy variable will also capture these changes.

Having collected all of these data and created dummy variables for the relevant factors, we present the summary statistics for our data in Table 2.

Table 2: Summary Statistics (904 observations)

	Mean	Std. dev.	Min	Max
Industrial production index (2007 = 100)	91.20	7.00	80.35	100.93
Unemployment rate (%)	9.31	2.98	4.90	12.50
Personal consumption (billions of $)	9,993.78	95.24	9,821.10	10,186.26
Diesel price ($ per gallon)	3.20	0.62	2.03	4.90
Average rainfall (inches)	0.03	0.11	0.00	0.85
Holiday (dummy)	0.09	0.28	0	1
Lunar New Year (dummy)	0.09	0.28	0	1
Clean Trucks Oct 2008 (dummy)	0.54	0.50	0	1
Clean Trucks Jan 2010 (dummy)	0.25	0.43	0	1
Total traffic flow (vehicles per day)	88,084.25	12,618.38	50,275.00	110,457.00
Truck flow (vehicles per day)	4,631.26	1,327.10	1,352.50	7,738.50
Truck flow as % of traffic flow	5.55	1.43	2.25	9.04
Average number of trains per day	41.74	5.39	33.71	51.50
Trucks/trains	111.56	32.02	31.72	193.36

Table 2 provides interesting information on truck traffic, economic factors, and other relevant information. During the study period from 2007 to 2011, the average unemployment rate is 9.31 percent and ranges from 4.90 percent to 12.50 percent. The average diesel price is $3.20 per gallon (in 2009 dollars) with a maximum of $4.90 per gallon. Truck flow over this period has varied dramatically, with a minimum of 1,352.50 trucks per day and a maximum of

7,738.50 trucks per day. Finally, the measure of trucks per trains means that on average, there are 112 trucks for each train in the study area.

4. Model

In this section, we develop a simple model to explain truck flow, or the quantity of trucks measured at each location over a period of time. The quantity (flow) of trucks can be interpreted as the equilibrium of supply and demand for trucking services. Although we do not observe the price of trucking services, we do observe major factors that determine this price, including diesel price and economic conditions such as the industrial production index and personal consumption expenditure.[8] There is also evidence suggesting that drayage is a competitive market (Port of Los Angeles 2008). As a result, this information is not needed in the model since there is little difference between drayage prices across firms. Personal consumption expenditure is correlated with the demand for trucking services and is used as a proxy for overall economic activity. The supply of trucks is likely to be shifted by the Clean Trucks program, whereas economic factors will likely shift the demand for trucking services.

The reduced form economic model that we plan to estimate using OLS is given by the equation below. A similar model can be used to analyze the proportion of truck flow.

$$TruckFlow_{it} = \alpha + \beta_1 IndustrialProduction_t + \beta_2 X_{it} + \upsilon D_i + \gamma M_t + \varepsilon_{it} \qquad (1)$$

where *i* indicates the detector group and *t* indicates the time period (weeks). The dependent variable $TruckFlow_{it}$ on the left hand side of the equation is median truck flow during that week (in terms of vehicles per day) for a given detector group. One particular variable of interest on the right hand side is $IndustrialProduction_t$, which will be used as the primary measure of

[8] As mentioned earlier, prices for trucking services are actually quite stable throughout time and are often specified in yearly contracts (Fernando Bogarin, Total Transportation Services, Inc., personal communication, April 21, 2011). These prices are altered indirectly through fuel and other surcharges.

economic conditions. The estimated coefficient for this variable, β_1, will tell us the direction and magnitude of the recession's effect on truck traffic patterns. The matrix X_t captures independent variables such as diesel prices, personal consumption expenditure, amount of rainfall and control variables for holidays and the Clean Trucks Program. We account for the fact that truck flow may not instantly react to changes in diesel prices by using the diesel price averaged over the current week and the previous three weeks; using diesel price as a contemporaneous variable and other lags did not significantly change the results. We also use the square and cube of the diesel price variable to see if the relationship between truck flow and diesel prices is nonlinear. To capture individual variation in the data across detector groups, we use detector fixed effects represented in the equation by D_i. Similarly, variation across time will be captured by monthly fixed effects represented by M_t. Finally, ε_{it} captures random unobserved variation in the data.

Based on previous work in this area, we have several hypotheses regarding the results of this model. First, we expect that during periods of economic decline, the volume of truck traffic, as well as the proportion of truck traffic to total traffic will decrease. Second, since we are examining a relatively short time period, we expect that truck traffic will be relatively inelastic to changes in diesel prices. This prediction is based on the fact that trucking service prices are negotiated on a yearly basis and have changed very little over the entire time period. Factors such as U.S. holidays, Lunar New Year, and rainfall should have a negative impact on truck volume. Since the Clean Trucks Program limited the number of trucks that can service the ports, we believe that its implementation will also have a negative effect on truck volume and the proportion of trucks on the road. Finally, as average trains per day increases, we expect truck volume to increase, since trains are substitutes for trucks to some extent in this area.

It should be noted that Burger and Kaffine (2009) instrument for gasoline price using oil price due to the endogeneity of gasoline price. However, since we are looking at only one freeway, we do not think that truck volumes on the Long Beach Freeway are sufficiently high to affect diesel prices overall in the region and therefore an instrumental variables approach is not necessary.

We considered using time series methods to analyze the relationship between truck traffic and economic indicators, like a vector autoregression (VAR) model or the estimation techniques used in Monaco and Brooks (2001). The panel data we use in this paper are grouped by detector, so converting this to time series data would either require aggregation of weekday traffic means, over detector and over time, or using data from only one detector. Neither of these methods would be ideal since traffic levels vary significantly across detectors in the study area, and using only one detector would lead to less reliable data. Our current model also has the advantage of accounting for the effects of rainfall and holidays on weekly traffic levels, which would not be possible under time series methods. Future extensions of this research project could include a time series approach, perhaps using an alternative source with data for a longer time period, since PeMS data are only available for this area from 2001.

5. Conclusion

This project examines the relationship of the economic recession and other factors on truck traffic on the Long Beach Freeway (I-710) in the Los Angeles metropolitan area. In this report we provide an overview of the related literature, describe data to be used in an empirical model, and propose a model to examine these relationships. Factors such as diesel prices, personal consumption expenditures, rainfall, holidays, the Clean Trucks Program, and rail substitutes should be controlled for in the analysis. Based on previous research, we believe that Los Angeles truck traffic, specifically port-related truck traffic, will be significantly affected by the economic downturn, controlling for these other factors.

Our proposed model is designed to accommodate readily available data and requires relatively simple statistical techniques. This model also allows for weekly or monthly data, which is not possible using commodity-based or trip-based modes. Despite this simplicity, we believe that our method will provide useful information to policy makers and transportation researchers who are interested in issues like traffic congestion alleviation, the effects of port policies, and highway infrastructure planning.

Future extensions to this project could analyze other freeways in the Los Angeles area with significant truck traffic, including I-5, I-10, and I-405. In addition, it would also be interesting to see if decreased truck travel leads to changes in air pollution and congestion delay in the area. This would enable policy makers to see if policies targeting truck travel, such as the Clean Trucks Program, are effective in achieving reductions in pollution and congestion.

References

Alameda Corridor Transportation Authority, 2010. http://www.acta.org

Boilé, Maria and Michail Golias, 2006. "Truck Volume Estimation via Linear Regression Under Limited Data." *Journal of the Transportation Research Forum,* 45 (1): 41-58.

Brogan, James J., Stephen C. Brich, and Michael J. Demetsky, 2001. *Application of a Statewide Intermodal Freight Planning Methodology*, Final Report.

Bureau of Economic Analysis, 2010. http://www.bea.gov

Bureau of Labor Statistics, 2010. http://www.bls.gov

Bureau of Transportation Statistics, various years. *Commodity Flow Survey*. http://www.bts.gov/publications/commodity_flow_survey/

Burger, Nicholas E., and Daniel T. Kaffine, 2009. "Gas Prices, Traffic, and Freeway Speeds in Los Angeles." *The Review of Economics and Statistics*, 91 (3): 652-657.

Cambridge Systematics and O' Neil Associates (1992) Development of an urban truck model for the Phoenix Metropolitan Area, Final Report.

Congressional Budget Office, 2008. *Effects of Gasoline Prices on Driving Behavior and Vehicle Markets*. Pub. No. 2883.

Energy Information Administration, 2010. http://www.eia.doe.gov/

Federal Highway Administration, 2005. *Assessing the Effects of Freight Movement on Air Quality at the National and Regional Level.*

Federal Highway Administration, 2011. *Traffic Volume Trends: December 2010*.

Federal Reserve, 2010. http://www.federalreserve.gov/

Fernandez, L. J. Enrique, Joaquin C. de Cea and Alexandra O. Soto, 2003. "A multi-modal supply–demand equilibrium model for predicting intercity freight flows." *Transportation Research Part B: Methodological*, 37(7): 615-640.

Giuliano, Genevieve, Thomas O'Brien, Sara Hayden, Paul Dell'aquila, 2005. *The Terminal Gate Appointment System at the Ports of Los Angeles and Long Beach: An Assessment*, METRANS Final Report.

Giuliano, Genevieve, Peter Gordon, Qisheng Pan, JiYoung Park, and LanLan Wang, 2010. "Estimating Freight Flows for Metropolitan Area Highway Networks Using Secondary Data Sources." *Networks and Spatial Economics*, 10 (1):73-91.

Goodwin, Phil, Joyce Dargay, and Mark Hanl, 2004. "Elasticities of Road Traffic and Fuel Consumption with Respect to Price and Income: A Review." *Transport Reviews*, 24 (3): 275-292.

Graham, Daniel J., and Stephen Glaister, 2004. "Road Traffic Demand Elasticity Estimates: A Review." *Transport Reviews*, 24 (3): 261-274.

Holguín-Veras, José and Ellen Thorson, 2003. "Modeling Commercial Vehicle Empty Trips with a First Order Trip Chain Model," *Transportation Research Part B: Methodological*, Vol. 37, No. 2, pp. 129-148.

Holguin-Veras J., G.F. List, A.H. Meyburg, K. Ozbay, H. Teng, and S. Yahalom, 2001. "An Assessment of Methodological Alternatives for a Regional Freight Model in the NYMTC Region." http://www.utrc2.org/research/assets/6/regionalfreight1.html

Holguin-Veras J, and J.C. Zorrilla, 2006. "A First Approximation to Longitudinal Modeling of Commercial Vehicle Empty Trips." *Transportation Research Board Annual Meeting Paper* #06-0263.

Hunt, J.D. and K.J. Stefan, 2007. "Tour-based Microsimulation of Urban Commercial Movements," *Transportation Research Part B: Methodological*, Vol. 41, No. 9, pp. 981-1013.

Hymel, Kent, 2009. "Does Traffic Congestion Reduce Employment Growth?" *Journal of Urban Economics*, 65: 127-135.

INRIX, 2010. *National Traffic Scorecard: 2009 Annual Report*.

Jones, Elizabeth G. and Anshul Sharma, 2003. *Development of Statewide Freight Forecasting Model for Nebraska*. Presented at the Transportation Research Board Annual Meeting.

Kwon, Jaimyoung, Pravin Varaiya, and Alexander Skabardonis, 2003. "Estimation of truck traffic volume from single loop detector using lane-to-lane speed correlation." *Transportation Research Record*, 1856: 106-117.

Leontief, W. 1936, 'Quantitative Input-Output Relations in the Economic System of the United States,' *Review of Economic Statistics*, Vol. 18, No. 3.

Liedtke, Gernot, 2009. "Principles of Micro-behavior Commodity Transport Modeling," *Transportation Research Part E: Logistics and Transportation Review*, Vol. 45, pp. 795-809.

Monaco, Kristen A, and Taggert J. Brooks, 2001. "Deregulation in Wages in Trucking: A Time Series Phenomenon – A Time Series Approach." *Research in Transportation Economics*, 6 (1): 55-69.

National Climatic Data Center, 2010. http://www.ncdc.noaa.gov

Port of Long Beach, 2010. http://www.polb.com/

Port of Los Angeles, 2010. http://www.portoflosangeles.org/

Port of Los Angeles, 2008. *San Pedro Bay Ports Clean Trucks Program: CTP Options Analysis*.

South Coast Air Quality Management District. 2000. *Multiple Air Toxic Exposure Study in the South Coast Air Basin (MATES-II)*.

Sorratini, Jose A., 2000. "Estimating Statewide Truck Trips Using Commodity Flows and Input-Output Coefficients." *Journal of Transportation and Statistics*, 3 (1): 53-67.

Texas Transportation Institute, 2009. *2009 Urban Mobility Report*.