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Effects Of Wait Times And Bridge Tolls On Personal Vehicle Border Crossings Into El Paso

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EFFECTS OF WAIT TIMES AND BRIDGE TOLLS ON PERSONAL VEHICLE BORDER CROSSINGS INTO EL PASO

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Abstract

Wait times at international ports of entry (POE) increase overall travel costs and negatively affect establishments at the border by raising costs and reducing efficiency. This study employs linear transfer function analysis to model northbound personal vehicle traffic flows across three international bridges that link Ciudad Juarez, Chihuahua, Mexico and El Paso, Texas, USA. The analysis attempts to build upon prior regional studies that examine the effects of tolls, exchange rates, and economic conditions on cross-border traffic volumes. This is done by incorporating a fairly unique data set of wait times into the equation specifications. Empirical results confirm inverse relationships between traffic flows and tolls, as well as between tolls and wait time, at each bridge. Substitution effects between structures are also observed. For the tolled ports of entry, dollar-equivalent toll estimates of the wait time effects are approximated using bridge-specific coefficients. A regional average of the cost effect is used to calculate a similar estimate for the un-tolled bridge. As value of time measures, wait time toll equivalents are used to estimate time-related crossing costs at each POE. To further assess model reliabilities, out-of-sample simulations are also utilized. U-statistics and error-differential regressions are deployed as tools for comparing LTF accuracies relative to those of random walk benchmarks.

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Chapter 1: Introduction

Cross-border transportation plays a major role in the economies of many United States border cities. One analysis determines that Mexican nationals directly support 10% of economic activity and employment in the Rio Grande Valley of south-central Texas (Ghaddar et al., 2004). In the same study, survey respondents further indicate that crossing times of two hours or longer act as deterrents to cross-border travel. A separate effort for the San Diego area finds that decreasing border wait times increase firm productivity while reducing shipping costs (ERB, 2008). Shorter cross-border wait times also increase the volumes of personal expenditures on both sides of the border due to improved consumer time usage efficiency.

Large numbers of cross-border shoppers and other visitors transit the United States-Mexico border each year. More than 74 million personal vehicle border crossings from Mexico to the United States are estimated to have occurred in 2015, with 12 million crossing through a port of entry (POE) located in El Paso (BTS, 2016). This analysis focuses on northbound personal vehicle crossings through El Paso POEs because of the availability of a unique dataset on personal vehicle wait times for this area. The sample period for this analysis corresponds to the interval for which border crossing wait time data are available, August 2010 to December 2016.

The cities of El Paso and Ciudad Juarez are connected by a network of four international bridges that span the Rio Grande River—the natural landmark that delineates the border between Texas and Mexico. Of the four, tolls are charged to travelers moving into and out of the country on three of the bridges. The untolled bridge is the Bridge of the Americas and the three tolled

bridges are the Paso del Norte or Santa Fe Street Bridge, the Stanton Street Bridge, and the Ysleta or Zaragoza Street Bridge. Of the tolled arteries, the Paso del Norte and Ysleta-Zaragoza POEs allow all personal vehicle traffic while northbound crossing on the Stanton Street Bridge is only allowed for vehicles enrolled in the SENTRI program.

The effect of tolls on transportation demand is mostly inelastic (Matas & Raymond, 2003). Previous research indicates that an inelastic response of cross-border traffic to bridge tolls is typical of southbound traffic through the three tolled POEs in the El Paso area (De Leon et al., 2009). Northbound traffic across the same structures is also inelastic with respect to toll tariffs (Fullerton et al., 2013).

Just as tolls can affect bridge traffic volumes, long delays can also discourage cross-border commuting. This analysis attempts to determine the effect of wait times on northbound passenger vehicle travel through regional POEs. It takes advantage of wait time data reported online by U.S. Customs & Border Protection (CBP) to model tolled northbound personal vehicle crossings through the Paso del Norte and Ysleta-Zaragoza ports (CBP, 2017). The study also examines the effects of wait times on traffic on the un-tolled Bridge of the Americas. Furthermore, wait time toll equivalents are calculated as monetary estimates of the time cost imposed on commuters using each POE. Those values quantify the monetary toll effect of each additional one-minute delay in crossing each bridge. Those estimates are also used to identifying the time threshold at which passenger cars will be induced to select an alternate route for crossing the border.

The next chapter reviews the literature on cross-border traffic, bottlenecks at POEs, and bridge tolls. The subsequent chapter summarizes the data and methodology utilized. Empirical estimation and comparative simulation results are discussed next, followed by a conclusion.

Chapter 2: Literature Review

Economies on either side of the United States-Mexico border are interconnected in a variety of ways. Cross-border shopping is an especially important type of interaction between cities on opposite sides of the international boundary (Coronado & Phillips, 2007). Factors such as price and income differentials between neighboring countries contribute to large volumes of cross-border shopping trips (Baruca & Zolfagharian, 2013). Differences in laws, policies, and consumer regulations also motivate consumers to purchase goods and services from across the border every day.

Prior studies report that the purchasing power of the Mexican peso is one factor that affects traffic at POEs. Real exchange rate fluctuations may have different effects depending on the location being examined (Fullerton, 2000). In El Paso, declines in the purchasing power of the peso reduce northbound traffic at the Bridge of the Americas, where vehicular travel is most prevalent. The Paso del Norte crossing experiences an increase in northbound pedestrian traffic when the peso weakens. In the same study, variations in the exchange rate do not noticeably affect international movements at the Ysleta-Zaragoza POE during the sample period analyzed.

Because many border crossings are tolled, it is reasonable to expect that tolls are likely to affect cross-border traffic. Governments often use tolls to aid in financing the construction and maintenance of new infrastructure. In addition, tolls sometimes generate a positive externality by alleviating congestion on roadways (Matas & Raymond, 2003). Hirschman et al. (1995) finds that the median toll elasticity for automobile traffic is around -0.10 for bridges and tunnels inside New York City. Demand tends to be more responsive to price when traffic can move quickly through

an alternative path. If the alternative path is gridlocked, the elasticity of demand is usually smaller. Elasticities for roadways frequently travelled by tourists are generally smaller than elasticities for roads traveled by a more diverse population. Inelastic tourist responses may result because tolls charged are only a small portion of the complete cost of any given trip (Matas & Raymond, 2003).

De Leon et al. (2009) analyzes the effects of exchange rate fluctuations, real bridge tolls, and economic activity on southbound traffic volumes at POEs in El Paso, Texas. Real peso depreciation is associated with statistically significant declines in passenger vehicle crossings at the Ysleta-Zaragoza Bridge. Furthermore, parameter estimates indicate that tolls negatively impact traffic volumes while economic activity positively affects bridge traffic.

In a subsequent study examining the effects on northbound crossings, Fullerton et al. (2013) finds that tolls are inversely related to automobile traffic across both the Paso Del Norte and the Ysleta-Zaragoza POEs. Increased economic activity on either side of the international border stimulates northbound crossings at these POEs, while declines in the purchasing power of the peso have the opposite effect. Price elasticities are estimated at -0.502 at the Ysleta-Zaragoza bridge and at -0.226 at the Paso Del Norte bridge, implying that small vehicle traffic is relatively non-responsive to fluctuations in the tolls charged.

Consumer demand for international travel between the United States and Mexico creates congestion, bottlenecks, and increased wait times at the POEs. In addition to the direct financial costs that cross-border travelers incur, consumers who traverse the international line are also subject to time costs. Administrative decisions undertaken immediately after 11 September 2001

created long delays at U.S. POEs, causing traffic flows to change substantially (Olmedo & Soden, 2005).

As a deterrent to cross-border travel, long wait times can negatively impact the economies of border regions (Del Castillo-Vera, 2009). One proposed approach to reducing border wait times is to increase the number of CBP inspection personnel at POEs. Roberts et al. (2014) determines that a single additional agent at each of 17 land passenger POEs included in the analysis results in 3.6 million dollars in additional U.S. output. In El Paso, Texas, the higher staffing levels are estimated to increase personal vehicle crossings by 212,113 above the 2012 level and contribute an estimated 4 million dollars per year in time saved due to lower border wait times.

Previous research examines the effects of real tolls, exchange rates, and aggregate economic activity on cross-border travel. Another strand of the literature quantifies the economic effects of border-crossing delays. This study attempts to bridge these two bodies of research and contribute to the existing literature by assessing the ways in which cross-border traffic volumes are impacted by border wait times, tolls, exchanges rates, and economic activity. Monthly frequency data from 2010 through 2016 are utilized to complete the analysis. The data and methods employed are described in the next section.

Chapter 3: Data and Methodology

This study uses data for three of the four international bridges located in the El Paso-Ciudad Juarez borderplex. The Ysleta-Zaragoza bridge is the easternmost POE within the El Paso city limits. This tolled POE is isolated from the others and is popular with professionals who commute across the border for work. The Paso del Norte bridge is the other tolled border crossing and is positioned near the city center. This bridge is used almost exclusively for small vehicle and pedestrian traffic flows to the downtown regions on both sides of the border. Lastly, the Bridge of the Americas is an untolled POE located approximately 3 miles east of the Paso del Norte crossing (De Leon et al., 2009).

In 2013, CBP selected the City of El Paso, Texas for a pilot program that allows reimbursing this federal agency for a portion of the services it provides (CBP, 2013). Under this agreement, the City of El Paso pays CBP for any overtime required to more fully staff POE lanes during peak hours (TTI, 2017). The El Paso program is one of 5 efforts that were approved at that time. Each program responds to increased trade/travel volumes across POEs and examines the effects associated with specific services (such as locally financed paid overtime) on the US economy (CBP, 2013). The effect of this program is demonstrated as decreased wait times in Figures 1, 3, and 5 despite increased traffic volumes at each bridge.

The sample period for this study is August 2010 to December 2016. Monthly bridge traffic data are collected from CBP reports (CBP, 2017). Northbound tolls at the Paso del Norte and Ysleta-Zaragoza bridges are reported by Caminos y Puentes Federales de Ingresos Conexos (CAPUFE, 2017). Nominal tolls generally remain fixed for 1 to 2 years following a price change.

Real tolls, of course, change more often. Because of this, and because tolls across the two ports are not always uniform (rates changes are not always adopted simultaneously), the real toll variable is averaged across both tolled bridges as shown in Equation (1).

$$TOLL_t = \frac{1}{2}\sum_{t=1}^{T}\left(100 * \frac{toll_{rt}/NEXR_t}{USCPI_t}\right) \quad (1)$$

$TOLL_t$ is the averaged real toll for month t. $toll_{rt}$ is the nominal toll charged at bridge r during month t. $NEXR_t$ is the nominal exchange rate between the Mexican peso and U.S. dollar during month t and $USCPI_t$ is the U.S. consumer price index for the same period (FRED, 2017). Wait times are gathered from CBP reports (CBP, 2017). Labor constraints allow data collection only on weekdays between the hours of 8am and 5pm. The data are averaged to produce a monthly average wait time variable that is measured in minutes.

Figures 1, 3, and 5 chart personal vehicle crossings and wait times for each of the international bridges during the sample period. Each graph demonstrates a reduction of wait times around the year 2013 that likely results from the overtime staffing agreement between CBP and the City of El Paso (CBP, 2013), as well as infrastructure improvements that reduced bottlenecks at the Bridge of the Americas in 2012 (GAO, 2013). All bridges experience increases in small vehicle traffic during the sample period as well as diminished wait times relative to the period when staffing was not supplemented by local overtime budgeting.

Vehicular crossings at each bridge are also are plotted against the wait times for each structure in Figures 2, 4, and 6. Negative correlations are noted throughout. The sample correlation coefficients are calculated for each crossing; they are -0.417 for the Paso del Norte bridge, -0.482 for the Ysleta-Zaragoza bridge, and -0.343 for the Bridge of the Americas. These values and the scatter plots provide preliminary evidence that northbound automobile traffic reacts to fluctuations in commuting delays at the POEs in question.

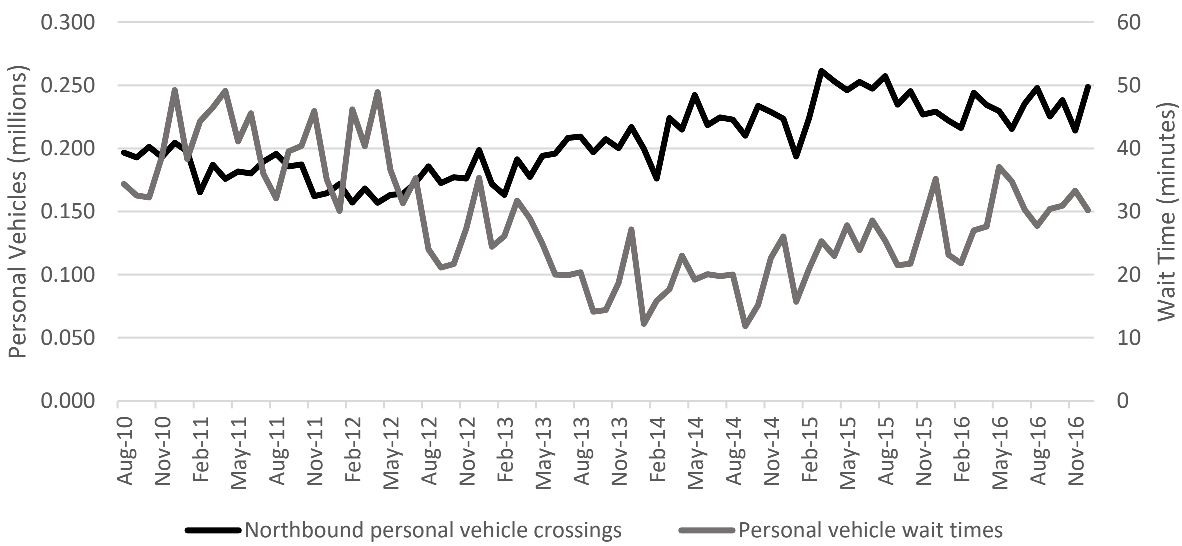

Figure 1. Paso del Norte: Time Series of Personal Vehicles and Wait Times

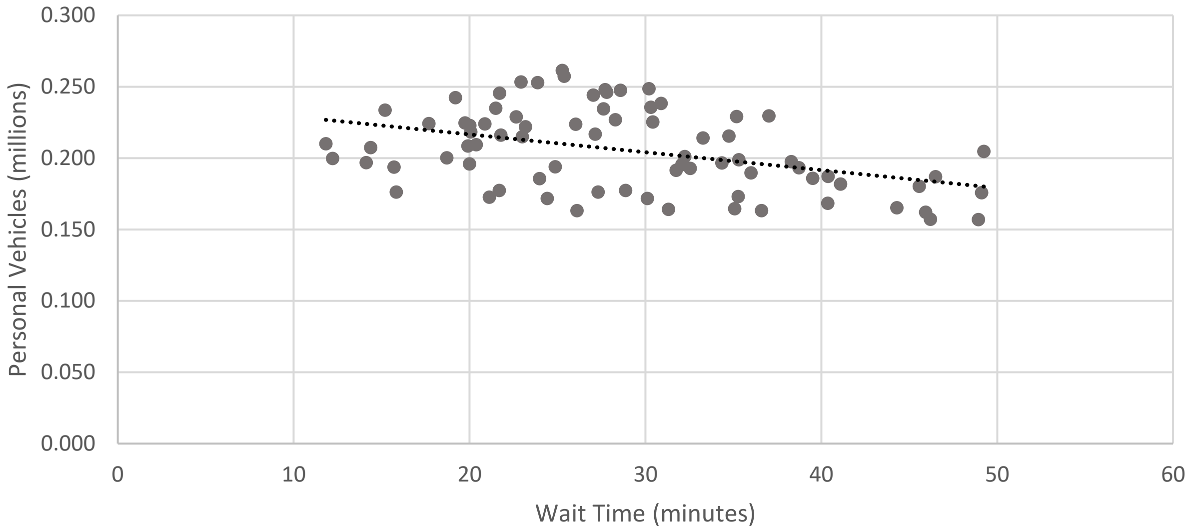

Figure 2. Paso del Norte: Personal Vehicle Traffic Against Wait Times

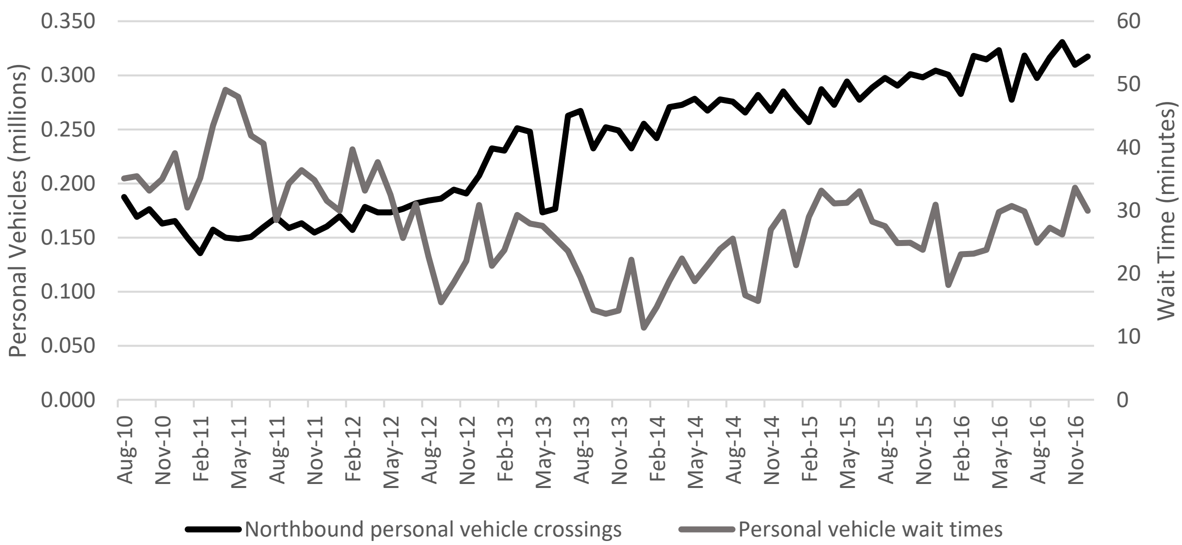

Figure 3. Ysleta-Zaragoza: Time Series of Personal Vehicles and Wait Times

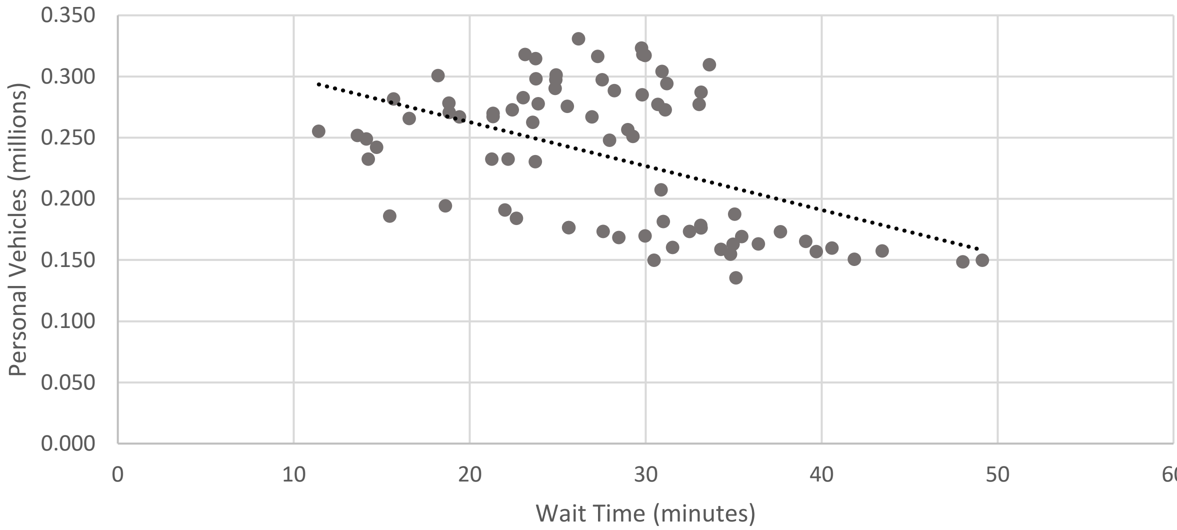

Figure 4. Ysleta-Zaragoza: Personal Vehicle Traffic Against Wait Times

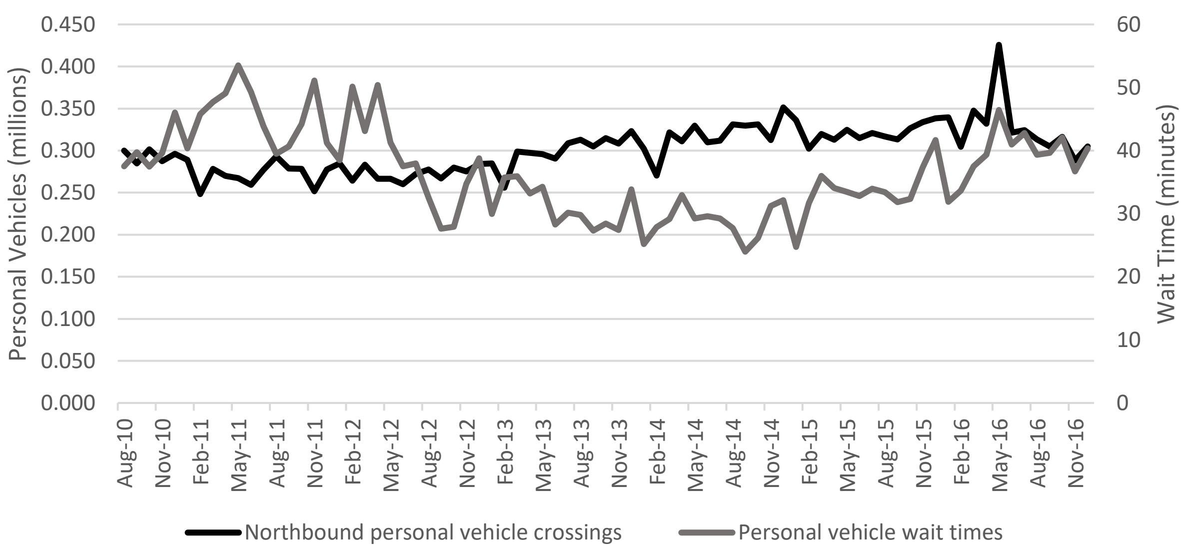

Figure 5. Bridge of the Americas: Time Series of Personal Vehicles and Wait Times

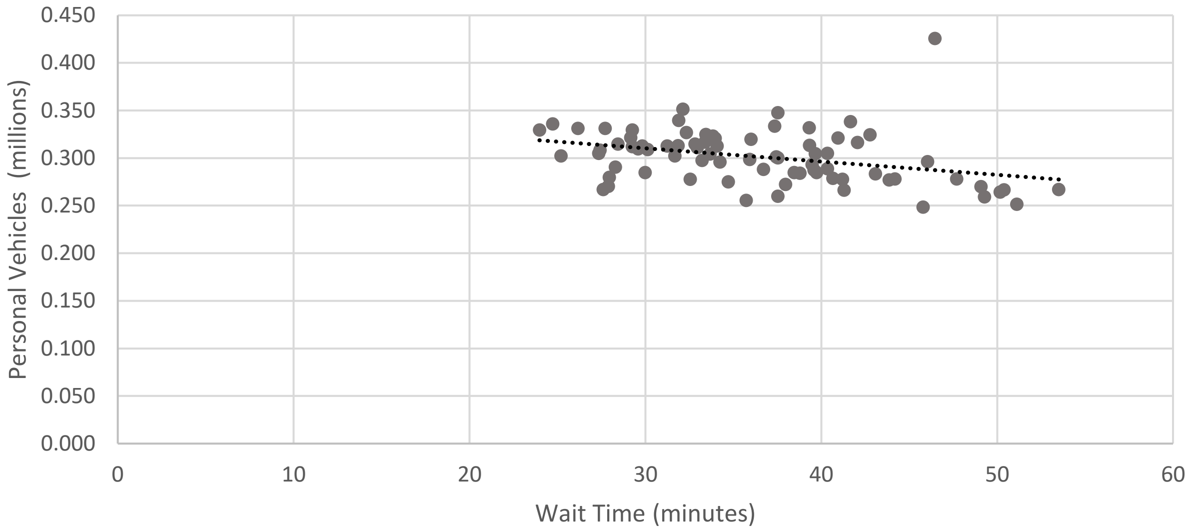

Figure 6. Bridge of the Americas: Personal Vehicle Traffic Against Wait Times

In addition to tolls, traffic volumes, and wait times, the sample data include IMMEX international manufacturing employment in Ciudad Juarez, non-agricultural employment in El Paso, the Mexican industrial production index, and a real peso-to-dollar exchange rate. IMMEX employment measures regional business cycle conditions in Ciudad Juarez. The industrial production index is a macroeconomic indicator used to assess the economic well-being of Mexico. Both IMMEX employment and industrial production index data are from Instituto Nacional de Estadistica y Geografia (INEGI, 2017). El Paso non-agricultural employment measures fluctuations in the business cycle of El Paso. It is reported by the Bureau of Labor Statistics (BLS, 2017). The real exchange rate is calculated by the Border Region Modeling Project at the University of Texas at El Paso (BRMP, 2017).

Data are differenced once to induce stationarity. Dickey-Fuller unit root tests are used to confirm stationarity. Traffic volumes at each POE are analyzed using linear transfer function

(LTF) analysis. Cross-correlation functions are generated to aid in specifying equation lag structures. Autocorrelation functions are used to determine whether any autoregressive and moving average terms are required for modeling non-random movements in the LTF residuals. An LTF with two independent variables, x and z, plus autoregressive and moving average components, is shown in Equation (2).

$$y_t = \theta_0 + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \gamma_{t-j} + \sum_{a=1}^{n} A_a x_{t-a} + \sum_{b=1}^{k} B_b z_{t-b} + \gamma_t \tag{2}$$

LTFs are estimated for northbound personal vehicle crossings across each bridge. The general implicit function used for each POE is shown in Equation (3). The algebraic signs below the equation indicate the hypothesized relationship between the independent variables and the dependent variable. Table 1 provides variable acronym definitions and units of measure. Table 2 summarizes the hypothesized relationships between explanatory variables and individual traffic flows.

$$\begin{aligned} BC_t = f\big(&\underset{(+/-)}{TOLL_{t-i}}, \underset{(+/-)}{WT_{t-j}}, \underset{(+)}{ELPM_{t-k}}, \underset{(+)}{CJIMX_{t-m}}, \underset{(+)}{MXIP_{t-n}}, \underset{(?)}{REXR_{t-u}}, AR_{t-p}, MA_{t-q}\big) \end{aligned} \tag{3}$$

Table 1. Variables and units of measure

Acronym	Definition	Unit of Measure
BCPN	Northbound personal vehicle crossings: Paso del Norte	millions
BCYN	Northbound personal vehicle crossings: Ysleta-Zaragoza	millions
BCAN	Northbound personal vehicle crossings: Bridge of the Americas	millions
TOLL	Average real toll	dollars
WTPN	Northbound personal vehicle wait times at Paso del Norte	minutes
WTYN	Northbound personal vehicle wait times at Ysleta-Zaragoza	minutes
WTAN	Northbound personal vehicle wait times at Bridge of the Americas	minutes
ELPM	Non-agricultural employment in El Paso	thousands
CJIMX	IMMEX employment in Ciudad Juarez	thousands
MXIP	Mexican industrial production index	Jan 2016 = 100
REXR	Real exchange rate	Jan 2016 = 100

Table 2. Hypothesized effects on bridge crossings

	TOLL	WTPN	WTYN	WTAN	ELPM	CJIMX	MXIP	REXR
BCPN	(-)	(-)	(+)	(+)	(+)	(+)	(+)	(?)
BCYN	(-)	(+)	(-)	(+)	(+)	(+)	(+)	(?)
BCAN	(+)	(+)	(+)	(-)	(+)	(+)	(+)	(?)

Increases in real tolls are expected to decrease traffic across tolled POEs (De Leon et al., 2009; Fullerton et al., 2013), while increasing car volumes at the untolled substitute Bridge of the Americas (Matas & Raymond, 2003). Similarly, because movement delays represent a time cost, wait times are theorized to reduce traffic at gridlocked bridges while increasing car volumes at the less congested POEs. Increases in employment and industrial growth are hypothesized to increase cross-border traffic. The effect of the real exchange rate on bridge usage is ambiguous. Prior research shows that a weakening peso negatively impacts travel by Mexican consumers into El Paso, but also incentivizes El Paso residents to travel into Mexico (Fullerton, 2000).

De Leon et al. (2009) reports that real peso depreciation is associated with decreased volumes of southbound traffic across the Ysleta-Zaragoza bridge. A subsequent study of northbound traffic determines that tolls significantly reduce crossings at both Paso del Norte and Ysleta-Zaragoza bridges (Fullerton et al., 2013). As the expected effect on border traffic in response to increasing wait times is also negative, the proposed outcome of the two variables imply that wait times can be measured as a fee separate from the actual toll charged at the border crossing.

The monetary value placed on an additional unit of time represents the marginal value of time (Small, 2013). Much transportation research analyzes the valuation of time. In a study on toll saturation, Hensher et al. (2016) explains that the value of travel time savings is equal to the ratio of the marginal utility of time to the marginal utility of travel cost. Earnhart (2004) compares data on the time and monetary costs affecting actual demand for a recreational good, quantified by visits to a lake, with survey data indicating hypothetical responses to those factors. The effect of time (opportunity) costs on the demand for recreation is denoted βo and the effect of access fees on demand is denoted βa. If time costs are properly measured in monetary terms, then $\beta o / \beta a = 1$ so that both time-related and non-time-related components of the cost of travel to the lake generate the same marginal effect on demand. This approach provides a ratio by which to adjust the monetary valuation of time costs using access fees as a benchmark.

Other studies apply comparable techniques to quantify the cost of time using ordinary least squares. McConnell and Strand (1981) employ a system where the opportunity cost of time is some variable, k, multiplied with average income. The variable k equals the ratio of the OLS coefficients for travel cost and travel time expressed as a proportion of income. A separate but

comparable study utilizes a log-log specification to study the marginal value of time through elasticities of demand for air travel (De Vany, 1974). Adjusting this technique for a linear model produces a marginal value of time also equal to the coefficient of travel time divided by the coefficient of price.

Small (2013) presents a technique for determining the value of time using implicit differentiation. For simplicity, only contemporaneous lags of the regressors are used in Equation (4). $\hat{X}_{rt}^{LTF}$ represents the estimated total crossings at POE r. $TOLL_t$ is the average toll of both bridges, and WT_{rt} is the wait time at each bridge.

$$\hat{X}_{rt}^{LTF} = \beta_0 + \beta_1 TOLL_t + \beta_2 WT_{rt} \tag{4}$$

The total differential of Equation (4) is shown as Equation (5). The value of time for bridge crossers can be computed as the change in tolls that would exactly offset the effect of a given change in wait times so that total bridge crossings would remain unchanged. The change in crossings is set equal to zero in Equation (6) which is then transformed into Equation (7).

$$d\hat{X}_{rt}^{LTF} = \frac{\partial \hat{X}_{rt}^{LTF}}{\partial TOLL_t} dTOLL_t + \frac{\partial \hat{X}_{rt}^{LTF}}{\partial WT_{rt}} dWT_{rt}, \qquad and\ d\hat{X}_{rt}^{LTF} = 0, \tag{5}$$

$$0 = \frac{\partial \hat{X}_{rt}^{LTF}}{\partial TOLL_t} dTOLL_t + \frac{\partial \hat{X}_{rt}^{LTF}}{\partial WT_{rt}} dWT_{rt} \tag{6}$$

$$\frac{\partial \hat{X}_{rt}^{LTF}}{\partial TOLL_t} dTOLL_t = -\frac{\partial \hat{X}_{rt}^{LTF}}{\partial WT_{rt}} dWT_{rt} \tag{7}$$

$$\frac{dTOLL_t}{dWT_{rt}} = -\frac{\partial \hat{X}_{rt}^{LTF} / \partial WT_{rt}}{\partial \hat{X}_{rt}^{LTF} / \partial TOLL_t} = -\frac{\beta_2}{\beta_1} \quad (8)$$

Isolating the derivative of tolls with respect to wait time yields Equation (8). Small (2013) uses the absolute value of the resulting implicit differentiation ratio, β_2/β_1, in describing the value of time. Here, Equation (8) indicates that a one-minute change in wait times is equal to an increase in tolls of a magnitude β_2/β_1, defined as the ratio of the estimated $TOLL_t$ and WT_{rt} coefficients from each LTF equation. This is shown in Equation (9).

$$\frac{dTOLL_t}{dWT_{rt}}(\Delta WT_{rt}) = Opportunity\ Cost\ of\ Bridge\ Crossing_r \quad (9)$$

Though subject to transaction costs, commuters intent on using a specific border crossing can elect to use one of the alternative bridges to minimize their cost of crossing. South of the border, transactional costs are affected by factors such as the distance between the original and alternate crossings and the potential for congestion on roadways that link the two bridges. Longer-than-planned distances from the substitute POE to the intended destination in El Paso can also influence the selection of a crossing point. Considering these costs, rational commuters are expected to use their preferred bridge if the crossing cost at that bridge (the sum of the $Opportunity\ Cost\ of\ Bridge\ Crossing_r$ and $TOLL_t$) is below the crossing cost at the other structures plus any transactional costs, or total cost.

In a frictionless system which ignores transactional costs, the untolled Bridge of the Americas is always the ideal primary crossing, but the $Opportunity\ Cost\ of\ Bridge\ Crossing_r$ cannot be directly evaluated there because a toll is not available for monetizing the wait time. Instead, the average of $TOLL_t$ coefficients from the Paso del Norte and Ysleta-Zaragoza regressions is applied to generate a mean monetary cost effect for crossings within the borderplex area. This method requires the assumption that the own-price elasticity of Bridge of the Americas traffic, with respect to tolls, is equal to the average of the own-price elasticities at the other bridges should the untolled bridge charge a fare. The wait time required for crossing costs at the Bridge of the Americas to exceed those of either tolled crossing is calculated by dividing the nominal toll by the nominal $Opportunity\ Cost\ of\ Bridge\ Crossing_r$ at the Bridge of the Americas.

To asses LTF equation reliability, a sequence of 24-month out-of-sample forecasts are generated for the period between January 2013 and December 2016. This type of forecast simulation employs an expanding sample of historical data. The first step of the simulation utilizes a historical sample ranging from August 2010 to December 2012 and generates monthly forecasts for the term spanning January 2013 to December 2014. In the second step, the historical sample expands by one month, now incorporating a bank of historical observations that stretch from August 2010 to January 2013. The second step provides forecasts for the period between February 2013 and January 2015. This sample expansion, model re-estimation, and simulation process is repeated through the end of the sample period, resulting in 48 1-month ahead forecasts, 47 2-month ahead forecasts, 46 3-month ahead forecasts and so forth.

Forecast reliability is assessed by comparing out-of-sample forecast results from the LTF model with those from random walk benchmarks. Two types of random walk models are used in this study. The first is a simple random walk (RW). At crossing r and time t, RW predictions, $\hat{X}_{rt}^{RW}$, are equal to the actual number of northbound small vehicle crossings in the previous month, or Y_{rt-1}, as shown in Equation (10).

$$\hat{X}_{rt}^{RW} = Y_{rt-1} \tag{10}$$

The second benchmark is a random walk with drift (RWD). The processes for developing RW and RWD estimates are similar, but RWD methods include a drift component to consider differences in the last and second-to-last months of historical data. In Equation (11), RWD predictions are illustrated by the variable $\hat{X}_{rt}^{RWD}$. The drift component is defined as $(Y_{rt-1} - Y_{rt-2})$.

$$\hat{X}_{rt}^{RWD} = Y_{rt-1} + (Y_{rt-1} - Y_{rt-2}) \tag{11}$$

Relative accuracy is evaluated via two approaches. U-statistics provide descriptive information for each set of forecasts (Pindyck & Rubinfeld, 1998). A formal regression-based F-test based on pairwise error-differentials is also deployed (Ashley et al., 1980). First, stepwise U-statistics and U-statistic decompositions are calculated for LTF, RW, and RWD forecasts at each international crossing. Accuracy is determined by comparing these values across the three models. Then, error-differential regression analysis indicates if the differences between the LTF and benchmark forecasts are statistically significant.

U-statistics for each step, s, of the rolling regression are defined in Equation (12). X_{rt}^{f} is the forecast value of northbound personal automobile crossings at bridge r and time t as calculated by LTF, RW, and RWD models. Y_{rt} is the actual observed value.

$$U_r^s = \frac{\sqrt{1/T \sum_{t=1}^{T} \left(X_{rt}^{f} - Y_{rt}\right)^2}}{\sqrt{1/T \sum_{t=1}^{T} \left(X_{rt}^{f}\right)^2} + \sqrt{1/T \sum_{t=1}^{T} (Y_{rt})^2}} \tag{12}$$

U-statistic values are always between 0 and 1. When equal to zero, a U-statistic describes a perfect forecast where X_{rt}^{f} is equal to Y_{rt}. A value near 1 indicates poor forecasting performance. U-statistic second-moments can be decomposed into three proportions of inequality, the sum of which is equal to 1. These are bias, variance (var), and covariance ($covar$) proportions, illustrated in Equations (13), (14), and (15).

$$bias_r^s = \frac{\left(\bar{X}_r^{f} - \bar{Y}_r\right)^2}{1/T \sum_{t=1}^{T} \left(X_{rt}^{f} - Y_{rt}\right)^2} \tag{13}$$

The bias proportion is a measure of the degree by which the averages of forecast and observed values differ from each other. These are $\bar{X}_r^{f}$ and $\bar{Y}_r$, respectively. As an indication of systematic error within the model, it is preferable that the value of bias be close to zero.

$$var_r^s = \frac{\left(\hat{\sigma}_r^{f} - \sigma_r\right)^2}{1/T \sum_{t=1}^{T} \left(X_{rt}^{f} - Y_{rt}\right)^2} \tag{14}$$

Further measuring systematic error, the variance proportion reflects model ability to replicate the variability in the actual series. In equation (14), $\hat{\sigma}_r^f$ and σ_r describe the standard deviations from forecast and observed series. A large var value indicates that variability is much larger in one series than in the other. Large values imply that a model is poorly specified.

$$covar_r^s = \frac{2(1-\rho_r)\hat{\sigma}_r^f \sigma_r}{1/_T \sum_{t=1}^{T} \left(X_{rt}^f - Y_{rt}\right)^2} \tag{15}$$

The covariance proportion is an assessment of unsystematic error. Equation (15) introduces ρ, the correlation coefficient between the forecast and actual series. It is defined in Equation (16).

$$\rho_r = \frac{1}{\hat{\sigma}_r^f \sigma_r T} \sum_{t=1}^{T} (X_{rt}^f - \bar{X}_r^f)(Y_{rt} - \bar{Y}_r) \tag{16}$$

Ideally, bias and variance proportions equal zero, while the covariance proportion equals 1. That represents a situation in which all forecast errors are exclusively due to random shocks (Pindyck & Rubinfeld, 1998).

Following descriptive assessment with U-statistics, pairwise error-differential tests (Ashley et al., 1980) determine if there is a significant difference between the mean squared errors of LTF and benchmark forecasts. This method involves regressions of error terms from LTF and benchmark forecasts for each step-length. As shown in Equation (17), forecast errors (e_{rt}) are

calculated by subtracting observed values from forecast estimates, $\hat{X}_{rt}$. The process applies to LTF, RW, and RWD models at each of the three border crossings.

$$e_{rt} = \hat{X}_{rt} - Y_{rt} \tag{17}$$

Using errors corresponding to step s of the out-of-sample simulations, two new series are generated. In Equation (18), LTF error is added to the corresponding benchmark error. In Equation (19), it is subtracted from the same benchmark error. e_{rt}^{BK} denotes the error from a benchmark forecast, either RW or RWD, at time t. e_{rt}^{LTF} is the LTF forecast error.

$$\Sigma_t^s = e_t^{BK} + e_t^{LTF} \tag{18}$$

$$\Delta_t^s = e_t^{BK} - e_t^{LTF} \tag{19}$$

With Σ_t^s and Δ_t^s as the dependent variable, error-differential tests are executed as shown in Equations (20) and (21). In those equations, α_1, α_2, α_3, and α_4 are regression coefficients to be estimated. $\mu(\Sigma_t^s)$ and $\mu(\Delta_t^s)$ are the sample means of the Σ_t^s and Δ_t^s series at step s. η_t and ε_t are stochastic error terms of the error-differential equation. Significant differences between LTF and benchmark errors are determined by examining stepwise error means in combination with computed t-statistics and F-statistics for Equations (20) and (21). Error means are calculated as shown in Equation (22).

$$\Sigma_t^s = \alpha_1 + \alpha_2[\Delta_t^s - \mu(\Delta_t^s)] + \eta_t \tag{20}$$

$$\Delta_t^s = \alpha_3 + \alpha_4[\Sigma_t^s - \mu(\Sigma_t^s)] + \varepsilon_t \tag{21}$$

$$\bar{e}_r^s = \frac{1}{T}\sum_{t=1}^{T} e_{rt} \tag{22}$$

The algebraic sign of the error mean dictates how error-differential tests are completed. If LTF and benchmark error means are of opposing signs, Equation (20) is employed. Otherwise, Equation (21) is utilized. The error mean also serves in differentiating between the forecast accuracy of benchmark and LTF models. If the error mean of the benchmark forecast is positive, a positive value of α_1 or α_3 suggests that the accuracy of the LTF model is superior to the benchmark model if the value of α_2 or α_4 is also positive at that step. Given positive values for α_2 or α_4, a negative benchmark error mean in conjunction with negative values for α_1 or α_3 also implies that LTF forecast accuracy is better (Fullerton & Kelley, 2008).

The benchmark error mean further governs how significant differences between LTF and benchmark accuracy are determined. Whenever the error mean is positive, opposing signs of the α coefficients in either equation indicate that a one-sided t-test should be employed to verify the statistical significance of each coefficient. The same is true whenever the error mean is negative and both α coefficients are either positive or negative. LTF forecast accuracy is significantly better than benchmark forecast accuracy if the coefficient favoring the benchmark model is statistically insignificant while the coefficient favoring the LTF model is statistically significant.

Alternately, if both α coefficients concur on which set of forecasts is most accurate, a non-standard F-test is adopted which examines the hypothesis that $\alpha_1 = \alpha_2 = 0$ or that $\alpha_3 = \alpha_4 = 0$. Contrary to usual F-tests, this 4-pronged test requires significance levels at less than half of those

found in F-distribution tables (Ashley et al., 1980). Rejecting the null hypothesis establishes that differences in forecast accuracy between LTF and benchmark models are statistically significant.

Empirical results are reported in the next two chapters. First, estimation results for LTF equations at each POE are discussed. Those results include the effect of wait times, tolls, and other variables on northbound personal vehicle volumes at each POE. The opportunity cost of crossing is also examined. The subsequent chapter discusses out-of-sample simulation results plus forecast accuracy comparisons between LTF, RW, and RWD models.

Chapter 4: Empirical Results

Estimation results for each POE are presented in Tables 3 through 5. All series are differenced prior to estimation to remove non-stationarity. Price elasticities of demand are included in the second-to-last row. Persons crossing into the United States from Ciudad Juarez face both tolls and time costs, both of which affect traffic volume across the area's POEs. The change in tolls required to achieve the same reduction in traffic as a one-minute change in wait time is reported in the final row of each table as the wait time toll estimate. The tolled bridge LTF results are discussed first, followed by the results for the untolled bridge.

Estimation results for the LTF equation for northbound personal vehicle travel across the Paso del Norte bridge are shown in Table 3. The magnitude of the toll coefficient implies that a price hike in real tolls diminishes the amount of traffic using the Paso del Norte bridge. A one-dollar increase in the average toll charged for northbound passage reduces monthly traffic by nearly 17 thousand monthly personal vehicles. Fullerton et al. (2013) also reports decreased personal vehicle crossings in response to toll hikes at the Paso del Norte POE, though the magnitude of that toll coefficient is larger. Including wait times as explanatory variables may help to buffer the effect of tolls on traffic volume.

Table 3. Paso del Norte northbound small vehicles (BCPN)

Variable	Coefficient	Std. Error	t-statistic	Probability
Constant	9.86E-06	0.001375	0.007177	0.9943
BCPN(-1)	-0.414681	0.097972	-4.232632	0.0001
TOLL(-1)	-0.016767	0.033832	-0.495604	0.6221
WTPN(-2)	-0.000641	0.000285	-2.251661	0.0284
WTYN(-1)	0.000766	0.000327	2.343822	0.0227
WTAN	0.001225	0.000407	3.010488	0.0039
CJIMX(-10)	0.000512	0.000671	0.763283	0.4486
ELPM(-10)	0.001226	0.000805	1.523140	0.1335
REXR(-1)	-0.001147	0.000494	-2.321186	0.0240
MXIP	0.002182	0.000630	3.462960	0.0010
AR(2)	-0.432013	0.133117	-3.245366	0.0020
R-squared	0.558165	Mean Dep. Var.		0.001035
Adj. R-Sq	0.477832	S.D. Dep. Var.		0.017175
Std. Err. Reg	0.012411	Akaike Info. Crit.		-5.783266
Sum Sq. Resid	0.008471	Schwarz Info. Crit.		-5.418324
Log-Likelihood	201.8478	F-statistic		6.948094
Durbin-Watson	1.680352	Prob(F-statistic)		0.000001
Paso del Norte northbound small vehicle toll elasticity				-0.151
Paso del Norte northbound small vehicle wait time toll estimate				$0.038

Sample Period: August 2010 – December 2016
Number of Observations: 66

All three wait time coefficients are statistically significant at the 5% level. Traffic across the Paso del Norte POE responds negatively to increased northbound wait times across the same POE at a rate of 641 fewer personal vehicles per month for each additional minute of wait time. Increased wait times at the other international crossings, all else equal, repel traffic to the Paso del Norte POE.

On average, an additional minute of wait time at the far-east Ysleta-Zaragoza bridge increases personal vehicle traffic across the Paso del Norte bridge by 766 cars, implying that border crossers are willing to drive a substantial 13.5 miles to a different area of the city to avoid the time cost of waiting. Wait times across the Bridge of the Americas produce a similar effect on Paso del

Norte traffic. An additional minute of wait time at the Bridge of the Americas is associated with an additional 1,225 personal vehicles across Paso del Norte. The somewhat larger effect probably results from the shorter distance between the Bridge of the Americas and the Paso del Norte bridge, which are less than 3 highway miles apart.

IMMEX employment in Ciudad Juarez and El Paso non-agricultural employment are positively correlated with northbound traffic across the Paso del Norte bridge. An increase of 1,000 in IMMEX and El Paso non-agricultural employment increases traffic by 512 and 1,226 personal vehicles, respectively. The $REXR$ parameter indicates that decreases in the purchasing power of the peso reduce the number of monthly personal vehicles. A one percent depreciation of the peso leads to a 1.15 thousand decline in the number of cars traversing this bridge, similar to what is documented in Fullerton et al. (2013). $MXIP$ shows that a one-point increase in Mexican industrial activity raises the monthly traffic volume by nearly 2.2 thousand vehicles.

The estimated price elasticity of demand is -0.151. The coefficient for average tolls is not statistically significant, but the magnitude is comparable to that reported in Fullerton et al. (2013) for the same POE. Furthermore, an elasticity of -0.151 is comparable to elasticities described in the literature on toll road elasticity outlined by Matas and Raymond (2003). The estimate for the value of time spent on the bridge is included in the final row of Table 3. As expressed in Equation (8) above, it is calculated as the absolute value of the quotient of the $WTPN$ and $TOLL$ coefficients at this bridge, or $\beta_{wait} / \beta_{toll}$. Consumers traveling northward across the Paso del Norte POE are estimated to value their wait time at $0.04 per minute. Increasing the wait time at this POE by 1

hour relative to the other POEs has the same negative effect on personal vehicle cross-border activity at the bridge as adding $2.40 to the toll, or $2.50, in 2018 nominal terms.

Table 4. Ysleta-Zaragoza northbound small vehicles (BCYN)

Variable	Coefficient	Std. Error	t-statistic	Probability
Constant	0.002924	0.001696	1.723500	0.0900
BCYN(-1)	-0.493328	0.106128	-4.648422	0.0000
BCYN(-2)	-0.473362	0.103641	-4.567327	0.0000
TOLL(-1)	-0.031899	0.045744	-0.697328	0.4883
WTPN	0.000531	0.000340	1.563390	0.1233
WTYN(-2)	-0.001266	0.000508	-2.491280	0.0156
WTAN(-2)	0.001348	0.000628	2.145338	0.0361
CJIMX(-5)	0.000465	0.000840	0.553600	0.5819
ELPM(-5)	0.001982	0.000969	2.045563	0.0453
REXR(-1)	-0.001045	0.000589	-1.775486	0.0810
MXIP	0.001999	0.000813	2.459597	0.0169
AR(3)	-0.476038	0.125994	-3.778254	0.0004
R-squared	0.509385	Mean Dep. Var.		0.002358
Adj. R-Sq.	0.417914	S.D. Dep. Var.		0.020743
Std. Err. Reg.	0.015826	Akaike Info. Crit.		-5.290642
Sum Sq. Resid	0.014776	Schwarz Info. Crit.		-4.908217
Log-Likelihood	199.8178	F-statistic		5.568838
Durbin-Watson	1.849027	Prob(F-statistic)		0.000005
Ysleta-Zaragoza northbound small vehicle toll elasticity				-0.251
Ysleta-Zaragoza northbound small vehicle wait time toll estimate				$0.040

Sample Period: August 2010 – December 2016
Number of Observations: 71

Regression results for northbound personal vehicle crossings across the Ysleta-Zaragoza bridge are summarized in Table 4. Higher tolls also decrease northbound personal vehicle traffic volumes through the Ysleta-Zaragoza POE. A one-dollar increase in tolls reduces monthly northbound traffic by nearly 32 thousand personal vehicles. The larger negative toll elasticity at Ysleta-Zaragoza than at Paso del Norte is similar to that reported in Fullerton et al. (2013).

All wait time coefficients at this bridge satisfy the 5% significance criterion. Congestion related substitution effects are also confirmed for this parabolic span. A one-minute increase in the wait times at the Ysleta-Zaragoza POE reduces monthly traffic across this bridge by 1,266 personal vehicles. This is the largest effect of own wait times on traffic across any of the three bridges and is consistent with the magnitude of the Ysleta-Zaragoza correlation coefficient discussed in conjunction with Figure 4.

Each minute of increased wait time at Paso del Norte increases personal vehicle traffic at Ysleta-Zaragoza by 531. The effect of wait times at the Bridge of the Americas on traffic at the easternmost POE is more dramatic. An additional one-minute delay `at the Bridge of the Americas increases traffic at the Ysleta-Zaragoza crossing by 1,348 cars per month. The larger $WTAN$ coefficient may result from the closer proximity and easier access from the Bridge of the Americas to the Ysleta-Zaragoza bridge than from the Paso del Norte structure.

Coefficients for IMMEX employment in Ciudad Juarez and El Paso non-agricultural employment confirm positive relationships with northbound traffic. An increase of 1,000 in Ciudad Juarez IMMEX employment increases monthly traffic across Ysleta-Zaragoza by 465 personal vehicles. The same increase in El Paso non-agricultural employment increases northbound personal vehicle travel by 1,982.

As the easternmost POE into El Paso, the Ysleta-Zaragoza bridge links Mexican consumers to large shopping centers on the east side of the city (De Leon et al., 2009). That geographic location makes the negative response of passenger vehicle crossings to real exchange rate, $REXR$,

movements plausible and logical due to the consequent loss of purchasing power on the north side of the border (Fullerton et al., 2013). Mexican industrial production, $MXIP$, is positively correlated with northbound traffic across the Ysleta-Zaragoza bridge. One-unit increases in the Mexican industrial production index are associated with an increase of 1,999 personal vehicles per month.

The price elasticity of demand at the Ysleta-Zaragoza crossing is also inelastic at -0.251. As in Table 3, the coefficient for average tolls is not significant, but the value of the elasticity at Ysleta-Zaragoza is akin to that reported in Fullerton et al. (2013) and is also within the range outlined by Matas and Raymond (2003). Cross-border commuters at the Ysleta-Zaragoza bridge value their time at \$0.04 per minute, as well. For this bridge, the value of time spent waiting in line to cross is estimated by dividing the $WTYN$ coefficient by the Ysleta-Zaragoza $TOLL$ coefficient, or β_{wait} / β_{toll}. The absolute value is equal to \$0.04. Equal time valuations between Paso del Norte and Ysleta-Zaragoza bridges imply that both tolled POEs are indistinguishable in terms of utility provided to persons engaging in northbound passage into the United States.

In 2018 nominal terms, the average toll is equal to \$1.46 and the per hour wait time toll estimate is \$2.50 at both tolled crossings. If a commuter prefers a tolled POE currently gridlocked with a one-hour wait, the total cost at the other POE must be less than \$3.96 for the same commuter to consider using the secondary crossing. The geospatial location of primary and secondary selections will influence the extent of transactional costs, but it is possible that smaller wait times at the other crossing will reduce total costs by a large enough margin to incentivize using the alternative bridge.

Table 5 summarizes the LTF estimation results for northbound traffic across the untolled Bridge of the Americas. The effects of increasing tolls are as expected. The toll coefficient indicates that toll hikes at the neighboring bridges result in significantly more traffic through the Bridge of the Americas at approximately 106.5 thousand additional personal vehicles per month for each dollar increase.

Table 5. Bridge of the Americas northbound small vehicles (BCAN)

Variable	Coefficient	Std. Error	t-statistic	Probability
Constant	-0.000887	0.001637	-0.541615	0.5902
BCAN(-1)	-0.650255	0.079283	-8.201658	0.0000
TOLL	0.106597	0.042727	2.494832	0.0155
WTPN	0.000613	0.000400	1.533126	0.1308
WTYN(-1)	0.001049	0.000563	1.864895	0.0673
WTAN(-1)	-0.000731	0.000660	-1.107421	0.2728
CJIMX(-7)	0.002216	0.000986	2.248942	0.0284
ELPM(-1)	0.002060	0.000952	2.164176	0.0347
REXR(-1)	-0.001092	0.000563	-1.938507	0.0575
MXIP	0.001937	0.000822	2.356601	0.0219
AR(2)	-0.391462	0.134088	-2.919434	0.0050
MA(6)	-0.319493	0.155444	-2.055351	0.0444
R-squared	0.611453	Mean Dep. Var.		0.000388
Adj. R-Sq.	0.536471	S.D. Dep. Var.		0.024707
Std. Err. Reg.	0.016821	Akaike Info. Crit.		-5.160283
Sum Sq. Resid	0.016129	Schwarz Info. Crit.		-4.771743
Log-Likelihood	190.0298	F-statistic		8.154598
Durbin-Watson	1.815802	Prob(F-statistic)		0.000000
Bridge of the Americas northbound small vehicle toll elasticity				0.652
Bridge of the Americas northbound small vehicle wait time toll estimate				$0.030

Sample Period: August 2010 – December 2016
Number of Observations: 69

All three wait time coefficients exhibit the hypothesized signs, albeit with computed t-statistics that do not satisfy the standard significance criterion. As wait times at the Bridge of the Americas increase by one-minute, total monthly traffic across the same POE decreases by 731

cars. A one-minute increase in the average wait times at the Paso del Norte crossing is shown to increase monthly traffic across the Bridge of the Americas by 613 personal vehicles. Likewise, a one-minute increase in the wait time for personal vehicles at Ysleta-Zaragoza is expected to increase northbound personal vehicle crossings at the Bridge of the Americas by 1,049 automobiles per month.

Changes in $CJIMX$ and $ELMP$ are positively correlated with traffic volumes at the untolled Bridge of the Americas. As IMMEX employment in Ciudad Juarez grows by 1,000 employees, monthly personal vehicle traffic across the Bridge of the Americas is expected to increase by 2,216. An increase of 1,000 in El Paso non-agricultural employment raises monthly traffic flows across the bridge by 2,060 personal vehicles.

The coefficient for the real exchange rate is negative. Fullerton (2000) finds that an increase in the real exchange rate decreases the amount of total traffic through the free POE. These results corroborate those findings. Personal vehicle traffic over the Bridge of the Americas responds to decreases in the valuation of the peso in the same way that personal vehicle traffic responds at the Paso del Norte and Ysleta-Zaragoza bridges. The similarity in magnitude of the $REXR$ coefficients suggest that northbound travel into El Paso is reduced uniformly across all three POEs whenever the peso weakens.

The estimated coefficient for $MXIP$ is also positive in Table 5. As in Tables 3 and 4, it is also statistically significant. As $MXIP$ goes up by one unit, personal vehicle traffic across the Bridge of the Americas will increase by 1,937 personal vehicles per month.

Bridge of the Americas small vehicle toll elasticity is calculated using $TOLL_t$ and $BCAN$ series averages along with the regression coefficient for $TOLL$. At 0.652, the magnitude of the toll elasticity is larger than those calculated for the Paso del Norte or Ysleta-Zaragoza bridges. While still falling within the inelastic range, it suggests that northbound traffic across the un-tolled Bridge of the Americas is more responsive to toll hikes than the traffic flows at either of the tolled POEs. As indicated by the positive sign of the parameter estimate for the $TOLL$ variable, the Bridge of the Americas functions as a substitute route for the other bridges.

The absence of a toll prevents direct calculation of a wait time toll equivalent at this bridge. To circumvent that, a regional average toll effect is generated using the $TOLL$ coefficients reported in the Paso del Norte and Ysleta-Zaragoza tables. The Small (2013) method is slightly modified such that the $WTAN$ coefficient is divided by the average of the $TOLL$ coefficients from the two other bridges, or $2 * \beta_{wait} / (\beta_{tollPDN} + \beta_{tollYZ})$. Numerically, the opportunity cost of crossing at the Bridge of the Americas is determined with the absolute value of the following: $2 * -0.000731 / (-0.016767 - 0.031899) = \$0.03$.

On average, the Bridge of the Americas experiences a larger number of personal vehicle crossings than either of the tolled bridges. This effect is likely due to the absence of a toll. At \$0.03 a minute, the wait time toll equivalent is smaller than that of the Paso del Norte or Ysleta-Zaragoza crossings. Commuters utilizing this bridge as their primary selection are expected to continue using it until the crossing cost exceeds the total cost at either of the alternatives. Because it is untolled, the Bridge of the Americas can absorb a greater wait time cost than the other bridges before commuters employ alternative routes, depending on transactional costs. In a frictionless

system, that exchange occurs when the wait time cost at this crossing is greater than $TOLL_t$. In 2018, that is expected to occur after approximately 49 minutes.

Out-of-sample simulation accuracy of the LTF models is assessed in the next chapter. Random walk benchmarks for each bridge are used for that exercise. The accuracy analysis attempts to determine whether the LTF models provide more accurate traffic volume forecasts than the random walks. Thiel U-coefficients are generated for LTF forecast errors at each step-length for 1-month-ahead all the way to 24-months-ahead. The reliability of the LTF models is then assessed by comparing those U-statistics against the values calculated for the random walks (Pindyck & Rubinfeld, 1998). A second approach is utilized wherein error-differentials between LTF and random walk forecasts are included in a regression equation to determine if any difference in the accuracy of the two approaches is statistically significant (Ashley et al., 1980).

Chapter 5: Comparative Simulation Results

Out-of-sample forecast accuracy is examined in this chapter. Using an expanding window of historical observations, the forecast errors of LTF models are compared to those of RW and RWD benchmarks. Descriptive U-statistics determine comparative accuracy rankings among the three types of forecasts at each POE. Those results are then supplemented with outcomes of the Ashley et al. (1980) error-differential regression technique to establish whether pairwise differences in precision between LTF and RW or LTF and RWD models are statistically significant.

Paso del Norte simulation accuracy results appear in Tables 6 through 8, followed by results from the Ysleta-Zaragoza crossing in Tables 9 through 11. The Bridge of the Americas outcomes are summarized in Tables 12 through 14. Of the three tables assigned to each POE, the first compares U-statistics between LTF, RW, and RWD models throughout the steps of the simulation. The second table shows U-statistic second-moment decompositions. Results from Ashley et al. (1980) error-differential tests are shown in the last of the tables for each bridge. The final table in this chapter, Table 15, compares accuracy from U-statistic and error-differential analyses across the three sets of forecasts for each of the international bridges.

Table 6 summarizes U-statistics from LTF and benchmark forecasts at the Paso del Norte bridge. Figures in bold typeface highlight the smallest U-statistic, which represents the most accurate reading at that step (Pindyck & Rubinfeld, 1998). U-statistics show that the LTF approach is most accurate at step-lengths 1 through 11. At steps 7 and 8, the RW U-statistics are equal in magnitude to those of the LTF approach. After the 11-month step-length, all LTF U-statistics are

larger than corresponding values for RW forecasts. Both LTF and RW U-statistics are consistently smaller than any from the RWD model at those longer step-lengths.

Table 6. Paso del Norte northbound small vehicles U-statistics

Step-Length	Observations	LTF	RW	RWD
1-Month	48	**0.026**	0.042	0.071
2-Month	47	**0.032**	0.042	0.069
3-Month	46	**0.034**	0.042	0.069
4-Month	45	**0.035**	0.041	0.069
5-Month	44	**0.037**	0.041	0.068
6-Month	43	**0.040**	0.041	0.068
7-Month	42	**0.042**	**0.042**	0.068
8-Month	41	**0.042**	**0.042**	0.069
9-Month	40	**0.040**	0.042	0.069
10-Month	39	**0.040**	0.042	0.070
11-Month	38	**0.042**	0.043	0.070
12-Month	37	0.046	**0.043**	0.071
13-Month	36	0.049	**0.043**	0.071
14-Month	35	0.050	**0.043**	0.071
15-Month	34	0.050	**0.043**	0.071
16-Month	33	0.050	**0.039**	0.067
17-Month	32	0.049	**0.040**	0.064
18-Month	31	0.048	**0.039**	0.064
19-Month	30	0.045	**0.038**	0.062
20-Month	29	0.042	**0.039**	0.062
21-Month	28	0.042	**0.039**	0.062
22-Month	27	0.046	**0.040**	0.063
23-Month	26	0.050	**0.039**	0.063
24-Month	25	0.053	**0.040**	0.063

Table 7 describes the decompositions for each Paso del Norte U-statistic in Table 6. Bias and variance components indicate systematic forecast errors. The covariance proportion measures unsystematic errors. If forecast errors are entirely random, the sum of bias and variance components equals 0 and the covariance component is equal to 1. The sum of the three components always equals 1 (Pindyck & Rubinfeld, 1998). For all three approaches, the greatest source of error is random at each step-length.

Table 7. Paso del Norte U-statistic decompositions

	LTF			RW			RWD		
Step-Length	Bias	Var	Covar	Bias	Var	Covar	Bias	Var	Covar
1-Month	0.001	0.006	0.993	0.003	0.000	0.997	0.000	0.125	0.875
2-Month	0.003	0.001	0.996	0.008	0.002	0.990	0.002	0.160	0.838
3-Month	0.005	0.010	0.986	0.010	0.006	0.984	0.001	0.159	0.840
4-Month	0.007	0.020	0.973	0.005	0.000	0.995	0.000	0.137	0.863
5-Month	0.013	0.037	0.951	0.008	0.002	0.990	0.001	0.176	0.822
6-Month	0.012	0.035	0.952	0.005	0.000	0.995	0.000	0.159	0.841
7-Month	0.009	0.044	0.947	0.004	0.000	0.995	0.001	0.173	0.826
8-Month	0.008	0.047	0.944	0.003	0.000	0.997	0.000	0.171	0.829
9-Month	0.011	0.069	0.920	0.003	0.000	0.997	0.001	0.177	0.822
10-Month	0.015	0.097	0.889	0.005	0.000	0.995	0.001	0.193	0.806
11-Month	0.017	0.109	0.874	0.003	0.000	0.997	0.000	0.183	0.816
12-Month	0.015	0.115	0.870	0.004	0.000	0.995	0.001	0.201	0.798
13-Month	0.013	0.099	0.888	0.002	0.000	0.998	0.000	0.192	0.808
14-Month	0.017	0.103	0.880	0.005	0.001	0.995	0.002	0.219	0.779
15-Month	0.030	0.128	0.842	0.012	0.016	0.973	0.003	0.271	0.726
16-Month	0.039	0.120	0.840	0.002	0.000	0.998	0.000	0.215	0.785
17-Month	0.052	0.081	0.867	0.003	0.000	0.997	0.002	0.222	0.776
18-Month	0.058	0.057	0.886	0.000	0.000	1.000	0.000	0.224	0.775
19-Month	0.083	0.024	0.893	0.003	0.000	0.997	0.005	0.227	0.768
20-Month	0.131	0.011	0.858	0.002	0.000	0.998	0.001	0.211	0.788
21-Month	0.169	0.005	0.826	0.003	0.000	0.997	0.002	0.216	0.782
22-Month	0.175	0.014	0.810	0.006	0.000	0.994	0.003	0.237	0.759
23-Month	0.152	0.013	0.835	0.001	0.000	0.999	0.000	0.223	0.777
24-Month	0.131	0.017	0.852	0.002	0.000	0.998	0.003	0.221	0.777

Error-differential regression results for the Paso del Norte forecasts are summarized in Table 8. Asterisks are used to highlight statistical significance. Rejection of the null hypothesis implies that LTF forecasts are significantly more accurate than RW or RWD forecasts at that step (Ashley, et al., 1980).

Table 8. Paso del Norte Ashley et al. (1980) error-differential regression results

Step-Length	Benchmark Forecast	Error Mean	α_1 or α_3 t-statistic	α_2 or α_4 t-statistic	F-statistic	Conclusion[†]
1-Month	RW	Negative	-0.341	4.488*	10.130*	Reject
	RWD	Negative	0.072	8.671*	37.599*	Reject
2-Month	RW	Negative	-0.345	1.994*	2.047	Fail to Reject
	RWD	Negative	-0.150	5.807*	16.874*	Reject
3-Month	RW	Negative	-0.273	1.406*	1.025	Fail to Reject
	RWD	Negative	0.035	5.140*	13.210*	Reject
4-Month	RW	Negative	0.006	1.086	0.590	Fail to Reject
	RWD	Negative	0.276	4.815*	11.631*	Reject
5-Month	RW	Negative	0.088	0.727	0.268	Fail to Reject
	RWD	Negative	0.183	4.259*	9.085*	Reject
6-Month	RW	Negative	0.226	0.217	0.049	Fail to Reject
	RWD	Negative	0.343	3.623*	6.624*	Reject
7-Month	RW	Negative	0.140	-0.043	0.011	Fail to Reject
	RWD	Negative	0.197	3.273*	5.376*	Reject
8-Month	RW	Negative	0.206	0.026	0.021	Fail to Reject
	RWD	Negative	0.239	3.329*	5.570*	Reject
9-Month	RW	Negative	0.237	0.378	0.099	Fail to Reject
	RWD	Negative	0.209	3.666*	6.742*	Reject
10-Month	RW	Negative	0.228	0.399	0.106	Fail to Reject
	RWD	Negative	0.200	3.685*	6.810*	Reject
11-Month	RW	Negative	0.363	0.117	0.073	Fail to Reject
	RWD	Negative	0.357	3.308*	5.536*	Reject
12-Month	RW	Negative	0.312	-0.371	0.117	Fail to Reject
	RWD	Negative	0.255	2.717*	3.725*	Reject
13-Month	RW	Negative	0.395	-0.730	0.345	Fail to Reject
	RWD	Negative	0.340	2.310*	2.725*	Reject
14-Month	RW	Negative	0.350	-0.801	0.382	Fail to Reject
	RWD	Negative	0.235	2.147*	2.332	Reject
15-Month	RW	Negative	0.393	-0.821	0.415	Fail to Reject
	RWD	Negative	0.344	2.220*	2.524*	Reject
16-Month	RW	Negative	0.853	-1.260	1.157	Fail to Reject
	RWD	Positive	-0.631	1.829*	1.871	Reject
17-Month	RW	Negative	0.932	-1.087	1.025	Fail to Reject
	RWD	Negative	0.608	1.681*	1.598	Reject
18-Month	RW	Negative	1.128	-0.965	1.101	Fail to Reject
	RWD	Negative	0.789	1.809*	1.948	Reject
19-Month	RW	Negative	1.132	-0.650	0.852	Fail to Reject
	RWD	Negative	0.657	1.962*	2.141	Reject
20-Month	RW	Negative	1.419*	-0.023	1.007	Fail to Reject
	RWD	Negative	1.040	2.489*	3.638*	Reject

21-Month	RW	Negative	1.655*	0.186	1.387	Fail to Reject
	RWD	Negative	1.176	2.671*	4.258*	Reject
22-Month	RW	Negative	1.688*	-0.224	1.450	Fail to Reject
	RWD	Negative	1.173	2.233*	3.181*	Reject
23-Month	RW	Negative	1.830*	-0.783	1.982	Fail to Reject
	RWD	Negative	1.288	1.625*	2.149	Reject
24-Month	RW	Negative	1.580*	-0.999	1.748	Fail to Reject
	RWD	Negative	1.003	1.253	1.289	Fail to Reject

$^{\dagger}H_o: MSE(e^{BK}) = MSE(e^{LTF})$, where MSE is the mean square error of benchmark and LTF forecast errors.

One-month-ahead LTF forecasts are significantly more accurate than the RW forecasts. After that, differences in accuracy are not statistically significant at any other step-length, including those for 12- to 24-months when the RW errors are slightly smaller (Table 6). The LTF forecast errors are significantly smaller than those of the RWD models at all but the longest step-length. Favorable LTF forecasting outcomes for the Paso del Norte bridge may result from adopting a measure of the total cost of crossing that involves both time and physical tolls. A study by Fullerton et al. (2013) uses tolls and other explanatory variables, but omits wait times. Indeterminate forecasting results in that effort imply that tolls alone may not adequately measure travel costs across this POE.

Table 9. Ysleta-Zaragoza northbound small vehicles U-statistics

Step-Length	Observations	LTF	RW	RWD
1-Month	48	**0.028**	0.044	0.070
2-Month	47	**0.031**	0.044	0.071
3-Month	46	**0.029**	0.044	0.071
4-Month	45	**0.026**	0.044	0.071
5-Month	44	**0.025**	0.045	0.072
6-Month	43	**0.026**	0.040	0.069
7-Month	42	**0.026**	0.040	0.066
8-Month	41	**0.026**	0.033	0.063
9-Month	40	**0.025**	0.033	0.060
10-Month	39	**0.026**	0.032	0.059
11-Month	38	**0.027**	0.032	0.058
12-Month	37	**0.027**	0.032	0.058
13-Month	36	**0.028**	0.032	0.058
14-Month	35	**0.027**	0.032	0.058
15-Month	34	**0.029**	0.032	0.058
16-Month	33	**0.030**	0.031	0.057
17-Month	32	**0.031**	0.032	0.057
18-Month	31	**0.031**	0.032	0.058
19-Month	30	**0.031**	0.032	0.059
20-Month	29	**0.031**	0.033	0.059
21-Month	28	**0.030**	0.033	0.060
22-Month	27	**0.032**	0.033	0.061
23-Month	26	**0.033**	0.034	0.061
24-Month	25	**0.034**	**0.034**	0.061

Table 9 reports the U-statistics for the Ysleta-Zaragoza bridge simulations. The LTF U-statistics are smaller than RW U-statistics for all step-lengths other than that for 24-months-ahead. The LTF and RW U-statistics are lower than those from the RWD model across all 24 step-lengths.

Table 10. Ysleta-Zaragoza U-statistic decompositions

	LTF			RW			RWD		
Step-Length	Bias	Var	Covar	Bias	Var	Covar	Bias	Var	Covar
1-Month	0.001	0.000	0.999	0.009	0.001	0.990	0.000	0.132	0.868
2-Month	0.000	0.001	0.999	0.006	0.000	0.994	0.000	0.132	0.868
3-Month	0.001	0.001	0.999	0.006	0.000	0.994	0.000	0.145	0.855
4-Month	0.011	0.002	0.988	0.004	0.000	0.996	0.000	0.140	0.860
5-Month	0.021	0.000	0.979	0.004	0.000	0.996	0.000	0.147	0.853
6-Month	0.006	0.066	0.928	0.022	0.027	0.951	0.002	0.249	0.749
7-Month	0.001	0.275	0.724	0.022	0.037	0.941	0.000	0.174	0.826
8-Month	0.005	0.261	0.734	0.005	0.000	0.994	0.003	0.125	0.872
9-Month	0.019	0.280	0.701	0.004	0.001	0.995	0.000	0.116	0.884
10-Month	0.025	0.251	0.724	0.014	0.002	0.984	0.001	0.150	0.849
11-Month	0.027	0.322	0.651	0.009	0.000	0.991	0.000	0.111	0.889
12-Month	0.032	0.355	0.612	0.010	0.000	0.990	0.000	0.128	0.872
13-Month	0.025	0.387	0.587	0.016	0.005	0.978	0.000	0.157	0.843
14-Month	0.032	0.415	0.553	0.009	0.000	0.991	0.000	0.129	0.871
15-Month	0.028	0.424	0.549	0.014	0.004	0.982	0.000	0.172	0.828
16-Month	0.033	0.447	0.519	0.006	0.000	0.994	0.000	0.144	0.856
17-Month	0.037	0.399	0.564	0.006	0.000	0.994	0.000	0.153	0.847
18-Month	0.053	0.394	0.553	0.005	0.000	0.995	0.000	0.154	0.846
19-Month	0.066	0.398	0.535	0.008	0.000	0.992	0.000	0.168	0.832
20-Month	0.079	0.397	0.524	0.005	0.000	0.995	0.000	0.158	0.842
21-Month	0.099	0.399	0.502	0.006	0.000	0.994	0.000	0.166	0.834
22-Month	0.102	0.322	0.575	0.009	0.000	0.990	0.000	0.181	0.819
23-Month	0.108	0.330	0.562	0.005	0.000	0.995	0.000	0.168	0.832
24-Month	0.093	0.348	0.559	0.010	0.000	0.989	0.001	0.195	0.804

Second-moment U-statistic decompositions in Table 10 follow the same general patterns as those for the Paso del Norte summary in Table 7. Though forecasts for each of the three models are essentially unbiased, the LTF model struggles to replicate some of the variability for forecasts beyond 6 months in the future. Based on U-statistics alone, the LTF model is more precise than either benchmark, but it may be possible to improve the quality of those forecasts by replicating more of the series variability.

Table 11. Ysleta-Zaragoza Ashley et al. (1980) error-differential regression results

Step-Length	Benchmark Forecast	Error Mean	α_1 or α_3 t-statistic	α_2 or α_4 t-statistic	F-statistic	Conclusion[†]
1-Month	RW	Negative	-0.978	5.040*	13.178*	Reject
	RWD	Positive	-0.070	8.221*	33.798*	Reject
2-Month	RW	Negative	-0.579	2.856*	4.247*	Reject
	RWD	Positive	0.054	6.394*	20.444*	Reject
3-Month	RW	Negative	-0.297	3.221*	5.230*	Reject
	RWD	Negative	0.057	6.868*	23.585*	Reject
4-Month	RW	Negative	0.001	4.287*	9.191*	Reject
	RWD	Positive	-0.309	8.139*	33.168*	Reject
5-Month	RW	Negative	0.104	4.747*	11.272*	Reject
	RWD	Negative	0.416	8.456*	35.839*	Reject
6-Month	RW	Negative	-0.510	3.173*	5.165*	Reject
	RWD	Negative	-0.186	7.528*	28.352*	Reject
7-Month	RW	Negative	-0.616	3.081*	4.937*	Reject
	RWD	Negative	0.099	6.976*	24.335*	Reject
8-Month	RW	Negative	-0.060	1.422*	1.013	Fail to Reject
	RWD	Positive	0.194	6.171*	19.059*	Reject
9-Month	RW	Negative	0.169	1.859*	1.742	Reject
	RWD	Negative	0.417	6.278*	19.797*	Reject
10-Month	RW	Negative	0.041	1.408*	0.992	Reject
	RWD	Negative	0.265	5.967*	17.839*	Reject
11-Month	RW	Negative	0.179	1.184	0.717	Fail to Reject
	RWD	Positive	-0.530	5.370*	14.557*	Reject
12-Month	RW	Negative	0.204	1.224	0.770	Fail to Reject
	RWD	Negative	0.493	5.426*	14.840*	Reject
13-Month	RW	Negative	0.044	0.907	0.412	Fail to Reject
	RWD	Negative	0.351	5.066*	12.892*	Reject
14-Month	RW	Negative	0.225	0.916	0.445	Fail to Reject
	RWD	Positive	-0.539	4.908*	12.188*	Reject
15-Month	RW	Negative	0.126	0.490	0.128	Fail to Reject
	RWD	Negative	0.385	4.352*	9.545*	Reject
16-Month	RW	Negative	0.348	0.327	0.114	Fail to Reject
	RWD	Positive	-0.509	4.074*	8.429*	Reject
17-Month	RW	Negative	0.385	0.192	0.092	Fail to Reject
	RWD	Negative	0.526	3.880*	7.667*	Reject
18-Month	RW	Negative	0.543	0.205	0.169	Fail to Reject
	RWD	Negative	0.655	3.772*	7.327*	Reject
19-Month	RW	Negative	0.552	0.257	0.186	Fail to Reject
	RWD	Negative	0.633	3.838*	7.565*	Reject
20-Month	RW	Negative	0.662	0.441	0.316	Fail to Reject
	RWD	Positive	-0.956	3.980*	8.376*	Reject

21-Month	RW	Negative	0.712	0.704	0.502	Fail to Reject
	RWD	Negative	0.806	4.251*	9.359*	Reject
22-Month	RW	Negative	0.655	0.469	0.324	Fail to Reject
	RWD	Negative	0.766	3.965*	8.155*	Reject
23-Month	RW	Negative	0.801	0.320	0.372	Fail to Reject
	RWD	Positive	-1.010	3.613*	7.039*	Reject
24-Month	RW	Negative	0.617	0.180	0.206	Fail to Reject
	RWD	Negative	0.678	3.427*	6.102*	Reject

†$H_o: MSE(e^{BK}) = MSE(e^{LTF})$, where MSE is the mean square error of benchmark and LTF forecast errors.

Results from Ashley, et al. (1980) error-differential regression tests at the Ysleta-Zaragoza POE are arranged in Table 11. This analysis determines that LTF models are significantly more accurate than RW models at steps 1 through 7 as well as at steps 9 and 10. At longer step-lengths, error-differential regression tests are unable to determine a significant difference between either forecast. Table 10 illustrates this LTF inefficiency through large LTF variance components beyond the 6th step-length. These results contrast with the Paso del Norte findings, where a statistically significant difference exists only at a single step. Error differences between LTF and RWD models at Paso del Norte and Ysleta-Zaragoza are similar, nonetheless. Against the RWD benchmark, significant differences are present at every step, indicating that the LTF forecasts are significantly more accurate than RWD forecasts. It is difficult to distinguish between the LTF and RW approaches in terms of accuracy at this bridge. This stands in contrast to the results for the Ysleta-Zaragoza analysis completed by Fullerton et al. (2013) where the predictive superiority of the LTF model is established at every step.

Table 12. Bridge of the Americas northbound small vehicles U-statistics

Step-Length	Observations	LTF	RW	RWD
1-Month	48	**0.025**	0.044	0.077
2-Month	47	**0.027**	0.044	0.078
3-Month	46	**0.028**	0.044	0.078
4-Month	45	**0.030**	0.044	0.077
5-Month	44	**0.032**	0.044	0.077
6-Month	43	**0.033**	0.044	0.078
7-Month	42	**0.033**	0.045	0.079
8-Month	41	**0.031**	0.045	0.079
9-Month	40	**0.030**	0.046	0.080
10-Month	39	**0.031**	0.046	0.081
11-Month	38	**0.031**	0.047	0.082
12-Month	37	**0.030**	0.047	0.083
13-Month	36	**0.030**	0.048	0.084
14-Month	35	**0.030**	0.048	0.084
15-Month	34	**0.031**	0.048	0.085
16-Month	33	**0.030**	0.046	0.083
17-Month	32	**0.032**	0.047	0.083
18-Month	31	**0.035**	0.047	0.084
19-Month	30	**0.035**	0.048	0.084
20-Month	29	**0.037**	0.049	0.085
21-Month	28	**0.038**	0.049	0.087
22-Month	27	**0.039**	0.050	0.088
23-Month	26	**0.038**	0.051	0.090
24-Month	25	**0.038**	0.052	0.091

Bridge of the Americas out-of-sample simulation U-statistics are shown in Table 12. The LTF model yields smaller values than either benchmark at each of the 24 steps. Bridge of the Americas RW U-statistics are also smaller than those from the RWD model. Among the three bridges for which the personal vehicle traffic flows are analyzed, the LTF forecasts perform best for the Bridge of the Americas in terms of U-statistic comparisons with random walk benchmarks.

Table 13. Bridge of the Americas U-statistic decompositions

	LTF			RW			RWD		
Step-Length	Bias	Var	Covar	Bias	Var	Covar	Bias	Var	Covar
1-Month	0.000	0.066	0.934	0.000	0.000	1.000	0.000	0.207	0.793
2-Month	0.001	0.043	0.956	0.000	0.000	1.000	0.000	0.213	0.787
3-Month	0.000	0.035	0.964	0.001	0.004	0.995	0.000	0.246	0.754
4-Month	0.000	0.029	0.970	0.000	0.000	1.000	0.000	0.221	0.779
5-Month	0.000	0.032	0.968	0.000	0.000	1.000	0.000	0.227	0.773
6-Month	0.002	0.034	0.963	0.000	0.000	1.000	0.000	0.230	0.770
7-Month	0.003	0.034	0.963	0.000	0.000	1.000	0.000	0.236	0.764
8-Month	0.007	0.066	0.927	0.000	0.000	1.000	0.000	0.233	0.767
9-Month	0.005	0.079	0.916	0.000	0.000	1.000	0.000	0.234	0.766
10-Month	0.004	0.124	0.872	0.000	0.000	1.000	0.000	0.237	0.763
11-Month	0.005	0.127	0.867	0.000	0.000	1.000	0.000	0.236	0.764
12-Month	0.006	0.162	0.832	0.000	0.000	1.000	0.000	0.238	0.761
13-Month	0.006	0.154	0.840	0.000	0.000	1.000	0.000	0.238	0.762
14-Month	0.006	0.150	0.844	0.000	0.000	1.000	0.000	0.244	0.756
15-Month	0.015	0.133	0.853	0.001	0.003	0.996	0.001	0.269	0.731
16-Month	0.015	0.147	0.838	0.000	0.000	1.000	0.000	0.245	0.754
17-Month	0.015	0.171	0.814	0.000	0.000	1.000	0.000	0.244	0.756
18-Month	0.014	0.117	0.869	0.001	0.000	0.999	0.000	0.243	0.757
19-Month	0.016	0.116	0.868	0.000	0.000	1.000	0.000	0.247	0.752
20-Month	0.020	0.105	0.874	0.000	0.000	1.000	0.000	0.244	0.756
21-Month	0.016	0.109	0.875	0.001	0.000	0.999	0.000	0.245	0.755
22-Month	0.012	0.138	0.850	0.001	0.000	0.999	0.000	0.242	0.757
23-Month	0.013	0.140	0.847	0.001	0.000	0.999	0.000	0.243	0.757
24-Month	0.019	0.159	0.822	0.000	0.000	1.000	0.001	0.246	0.753

Bias, variance, and covariance second-moment decompositions for Bridge of the Americas U-statistics are in Table 13. Similar to results from the Paso del Norte and Ysleta-Zaragoza bridges, LTF, RW, and RWD forecasts for the Bridge of the Americas are unbiased, but LTF and RW forecasts have a smaller variance decomposition than the RWD model. After 9-months-ahead, LTF forecasts do not capture variability as well as RW forecasts. The disparity in variance components between the two is small, however, with a difference of less than 0.2 at step-lengths larger than 9-months-ahead.

Table 14. Bridge of the Americas Ashley et al. (1980) error-differential regression results

Step-Length	Benchmark Forecast	Error Mean	α_1 or α_3 t-statistic	α_2 or α_4 t-statistic	F-statistic	Conclusion†
1-Month	RW	Negative	-0.027	5.128*	13.151*	Reject
	RWD	Negative	0.032	10.034*	50.338*	Reject
2-Month	RW	Negative	-0.007	3.977*	7.908*	Reject
	RWD	Negative	0.011	8.793*	38.662*	Reject
3-Month	RW	Negative	-0.139	3.352*	5.628*	Reject
	RWD	Negative	-0.123	8.149*	33.209*	Reject
4-Month	RW	Negative	0.035	2.742*	3.759*	Reject
	RWD	Positive	0.050	7.317*	26.769*	Reject
5-Month	RW	Negative	-0.003	2.233*	2.493*	Reject
	RWD	Negative	-0.046	6.536*	21.362*	Reject
6-Month	RW	Negative	0.199	2.121*	2.269	Reject
	RWD	Negative	0.108	6.341*	20.110*	Reject
7-Month	RW	Negative	0.192	2.165*	2.362	Reject
	RWD	Negative	0.112	6.366*	20.268*	Reject
8-Month	RW	Positive	-0.257	2.697*	3.670*	Reject
	RWD	Positive	-0.260	7.009*	24.599*	Reject
9-Month	RW	Positive	-0.191	2.912*	4.258*	Reject
	RWD	Negative	0.194	7.231*	26.165*	Reject
10-Month	RW	Negative	0.339	2.850*	4.119*	Reject
	RWD	Negative	0.128	7.050*	24.860*	Reject
11-Month	RW	Positive	-0.187	2.941*	4.342*	Reject
	RWD	Negative	0.226	7.121*	25.379*	Reject
12-Month	RW	Positive	-0.221	3.235*	5.256*	Reject
	RWD	Negative	0.159	7.468*	27.897*	Reject
13-Month	RW	Positive	-0.146	3.291*	5.427*	Reject
	RWD	Negative	0.252	7.492*	28.095*	Reject
14-Month	RW	Negative	0.352	3.174*	5.098*	Reject
	RWD	Negative	0.081	7.276*	26.476*	Reject
15-Month	RW	Negative	0.328	3.059*	4.734*	Reject
	RWD	Negative	0.167	7.221*	26.086*	Reject
16-Month	RW	Positive	-0.274	2.846*	4.087*	Reject
	RWD	Positive	-0.193	6.947*	24.149*	Reject
17-Month	RW	Positive	-0.316	2.654*	3.571*	Reject
	RWD	Negative	0.268	6.497*	21.140*	Reject
18-Month	RW	Positive	-0.237	2.041*	2.110	Reject
	RWD	Positive	-0.322	5.697*	16.278*	Reject
19-Month	RW	Positive	-0.334	1.909*	1.878	Reject
	RWD	Negative	0.233	5.485*	15.068*	Reject
20-Month	RW	Positive	-0.368	1.726*	1.558	Reject
	RWD	Negative	0.388	5.206*	13.629*	Reject

21-Month	RW	Positive	-0.245	1.537*	1.212	Reject
	RWD	Positive	-0.325	4.946*	12.285*	Reject
22-Month	RW	Positive	-0.192	1.510*	1.158	Reject
	RWD	Negative	0.248	4.843*	11.756*	Reject
23-Month	RW	Positive	-0.189	1.634*	1.354	Reject
	RWD	Negative	0.263	4.948*	12.276*	Reject
24-Month	RW	Positive	-0.323	1.754*	1.590	Reject
	RWD	Negative	0.241	5.078*	12.924*	Reject

†$H_o: MSE(e^{BK}) = MSE(e^{LTF})$, where MSE is the mean square error of benchmark and LTF forecast errors.

Ashley et al. (1980) error-differential regression results for the Bridge of the Americas are presented in Table 14. Unlike forecast simulation results from the tolled Paso del Norte and Ysleta-Zaragoza bridges, the analysis of the untolled Bridge of the Americas indicates that LTF forecasts are reliably more accurate than those of the RW and RWD models. Past studies regarding traffic volumes through POEs in El Paso have focused on the effect of tolls and either omit the Bridge of the Americas as a point of study or do not include an error-differential analysis.

Table 15 consolidates model optimality results from the preceding tables. LTF U-statistics and Ashley et al. (1980) results are contrasted against the two benchmarks at all three POEs. Figures in the RW column indicate which model performs best when comparing LTF and RW simulation accuracy at each step-length. Figures under the RWD heading reflect comparisons between LTF and RWD models. An octothorpe (#) in the U-statistic columns signals that LTF and benchmark accuracy is equivalent at that step. A hyphen (-) under an AGS heading means that the LTF forecast is not a significant improvement over the benchmark forecast at that step.

Table 15. U-statistic and Ashley et al. (1980) accuracy comparisons

	Paso del Norte				Ysleta-Zaragoza				Bridge of the Americas			
	U-statistic		AGS		U-statistic		AGS		U-statistic		AGS	
Step	RW	RWD	RW	RWD	RW	RWD	RW	RWD	RW	RWD	RW	RWD
1	LTF	LTF	LTF	LTF	LTF	LTF	LTF	LTF	LTF	LTF	LTF	LTF
2	LTF	LTF	-	LTF	LTF	LTF	LTF	LTF	LTF	LTF	LTF	LTF
3	LTF	LTF	-	LTF	LTF	LTF	LTF	LTF	LTF	LTF	LTF	LTF
4	LTF	LTF	-	LTF	LTF	LTF	LTF	LTF	LTF	LTF	LTF	LTF
5	LTF	LTF	-	LTF	LTF	LTF	LTF	LTF	LTF	LTF	LTF	LTF
6	LTF	LTF	-	LTF	LTF	LTF	LTF	LTF	LTF	LTF	LTF	LTF
7	#	LTF	-	LTF	LTF	LTF	LTF	LTF	LTF	LTF	LTF	LTF
8	#	LTF	-	LTF	LTF	LTF	-	LTF	LTF	LTF	LTF	LTF
9	LTF	LTF	-	LTF	LTF	LTF	LTF	LTF	LTF	LTF	LTF	LTF
10	LTF	LTF	-	LTF	LTF	LTF	LTF	LTF	LTF	LTF	LTF	LTF
11	LTF	LTF	-	LTF	LTF	LTF	-	LTF	LTF	LTF	LTF	LTF
12	RW	LTF	-	LTF	LTF	LTF	-	LTF	LTF	LTF	LTF	LTF
13	RW	LTF	-	LTF	LTF	LTF	-	LTF	LTF	LTF	LTF	LTF
14	RW	LTF	-	LTF	LTF	LTF	-	LTF	LTF	LTF	LTF	LTF
15	RW	LTF	-	LTF	LTF	LTF	-	LTF	LTF	LTF	LTF	LTF
16	RW	LTF	-	LTF	LTF	LTF	-	LTF	LTF	LTF	LTF	LTF
17	RW	LTF	-	LTF	LTF	LTF	-	LTF	LTF	LTF	LTF	LTF
18	RW	LTF	-	LTF	LTF	LTF	-	LTF	LTF	LTF	LTF	LTF
19	RW	LTF	-	LTF	LTF	LTF	-	LTF	LTF	LTF	LTF	LTF
20	RW	LTF	-	LTF	LTF	LTF	-	LTF	LTF	LTF	LTF	LTF
21	RW	LTF	-	LTF	LTF	LTF	-	LTF	LTF	LTF	LTF	LTF
22	RW	LTF	-	LTF	LTF	LTF	-	LTF	LTF	LTF	LTF	LTF
23	RW	LTF	-	LTF	LTF	LTF	-	LTF	LTF	LTF	LTF	LTF
24	RW	LTF	-	-	#	LTF	-	LTF	LTF	LTF	LTF	LTF

At the Paso del Norte bridge, the RW model is highly competitive with the LTF. At that crossing, the LTF approach is a better alternative for most of the shorter forecast horizons. However, Ashley et al. (1980) results indicate that LTF forecasts are not significantly more accurate than RW forecasts beyond the initial step. At the Ysleta-Zaragoza bridge, U-statistics determine that the LTF methodology is superior to the benchmark models in all but the final step, where the accuracy of the LTF forecast is equal to that of RW forecasts. Ashley et al. (1980) error-

differential tests confirm significant differences between LTF and RW forecast accuracy for nine of the first 10 simulations, but significance in error differences cannot be established after that. For the Bridge of the Americas, U-statistics and Ashley et al. (1980) assessments establish that the LTF model is a significant improvement over the benchmark models at each step. Additionally, U-statistic and Ashley et al. (1980) methods determine that LTF equations at each POE yield better accuracy than RWD models in all but one case. The single exception to this pattern occurs for the final step-length for the Paso del Norte bridge. Overall, the information in Table 15 confirms substantial predictive superiority for the LTF equations estimated for these three POEs.

Incorporating border wait times as an independent variable to model northbound traffic volumes across El Paso POEs produces mixed results when compared to the Fullerton et al. study from 2013. For the Paso del Norte analysis, the inclusion of wait times improves forecast accuracy against a RW benchmark as determined by both U-statistic and error-differential assessment. U-statistics results for the Ysleta-Zaragoza bridge are similar in both studies, but error-differential tests suggest that the forecasting performance of the 2013 LTF model is superior. Those outcomes imply that the Ysleta-Zaragoza model may be better-specified without a measure of time cost. Wait times are also included for the Bridge of the Americas forecast. Though forecasting results overwhelmingly favor the LTF model at this POE, there are no upstream studies by which to assess the effect of wait times on forecast precision.

Chapter 6: Conclusion

Border wait times have been shown to impose a negative effect on the economic activity of some border cities (Ghaddar et al., 2004). Long wait times imply increased time costs which, in conjunction with fuel usage and tolls, contribute to the overall burden of crossing. While previous studies have reported an inelastic response to tolls at El Paso POEs, the effect of wait times across these international crossings has not been studied very extensively.

Three LTFs are developed to analyze northbound personal vehicle traffic volumes from Ciudad Juarez, Mexico to El Paso, Texas. Each equation applies to one of the bridges included in the study: Paso del Norte, Ysleta-Zaragoza, or Bridge of the Americas. Sample data include real tolls, wait times at the same bridge, wait times at the other bridges, business cycle fluctuations in Ciudad Juarez and El Paso, the real peso-to-dollar exchange rate, and the Mexican industrial production index.

Overall, toll hikes negatively influence traffic at the Paso del Norte and Ysleta-Zaragoza POEs, but increase volumes across the Bridge of the Americas. That occurs because the latter structure is untolled and serves as a substitute route for the tolled bridges. Increased wait times at any of the three bridges are linked to decreased traffic volumes through those POEs, while simultaneously increasing traffic flows at the other two crossings. An increase in either IMMEX employment in Ciudad Juarez, or non-agricultural employment in El Paso, produces a positive effect on crossings at all three bridges. Increases in the real exchange rate have negative effects on bridge traffic flows that may result from decreased spending power for Mexican consumers following a peso depreciation. At each POE, personal vehicle traffic volumes escalate in response

to gains in industrial production in Mexico, as well. Wait time toll-equivalent estimates at the Paso del Norte and Ysleta-Zaragoza crossings are estimated at around $0.04 per minute, or $2.40 per hour of wait time. At the Bridge of the Americas, the toll-equivalent estimate is $0.03, or $1.80 per hour of wait time. The 2018 nominal hourly time costs are $2.50 and $1.88, respectively.

With long wait times, the cost of crossing at a specific POE can become prohibitive. Using easily accessible real-time sources to monitor wait times throughout the El Paso area, border crossers can make educated choices between structures to reduce the cost burden. Distances between bridges in Ciudad Juarez, traffic congestion, and extended drives from the alternative crossing to the El Paso destination contribute to transactional costs which also influence commuter POE selection. If an alternate route is selected, the total cost of using the substitute POE will generally be lower than the crossing cost at the preferred selection.

The fidelity of the estimation results is examined by comparing the accuracy of out-of-sample LTF forecasts against RW and RWD benchmark forecasts. In general, U-statistics and error-differential regression statistics indicate that LTF equations achieve superior predictive accuracy relative to either benchmark, but caution should be exercised in interpreting these results. The inclusion of wait times as a regressor for the Paso del Norte LTF model appears to improve northbound personal vehicle crossing forecast accuracy. The same improvement is not apparent for the Ysleta-Zaragoza bridge. The effect of wait times on forecast precision for the Bridge of the Americas is indeterminate because LTF forecasts have not previously been assembled for this structure.

Consumers respond to price and income differentials across international boundaries. Because these differentials are often large between the United States and Mexico, it would be helpful to examine the cost and effect of border wait times at POEs between countries with more similar economic profiles, such as those in western Europe. Replication of this study for pedestrian traffic flows across the bridges used in this study may help shed light on substitution effects between driving and walking. The methodology can also be applied to any other region where infrastructure and/or administrative bottlenecks create wait times that potentially affect commerce.

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Data Appendix

Table 16. USCPI, NEXR, and Northbound Border Crossings Data

	USCPI 1982-1984=100	NEXR	BCPN (millions)	BCYN (millions)	BCAN (millions)
Aug-10	217.923	12.766	0.300	0.197	0.187
Sep-10	218.275	12.798	0.285	0.193	0.169
Oct-10	219.035	12.439	0.301	0.201	0.176
Nov-10	219.590	12.338	0.287	0.193	0.163
Dec-10	220.472	12.390	0.296	0.205	0.165
Jan-11	221.187	12.128	0.289	0.198	0.150
Feb-11	221.898	12.065	0.248	0.165	0.136
Mar-11	223.046	11.996	0.278	0.187	0.157
Apr-11	224.093	11.706	0.270	0.176	0.150
May-11	224.806	11.654	0.267	0.182	0.149
Jun-11	224.806	11.806	0.259	0.180	0.151
Jul-11	225.395	11.674	0.277	0.190	0.160
Aug-11	226.106	12.237	0.293	0.196	0.168
Sep-11	226.597	13.064	0.279	0.186	0.159
Oct-11	226.750	13.438	0.278	0.187	0.163
Nov-11	227.169	13.696	0.252	0.162	0.155
Dec-11	227.223	13.775	0.278	0.164	0.160
Jan-12	227.842	13.383	0.285	0.172	0.170
Feb-12	228.329	12.783	0.264	0.157	0.157
Mar-12	228.807	12.752	0.283	0.168	0.178
Apr-12	229.187	13.056	0.267	0.157	0.173
May-12	228.713	13.620	0.266	0.163	0.173
Jun-12	228.524	13.919	0.260	0.164	0.177
Jul-12	228.590	13.364	0.272	0.173	0.181
Aug-12	229.918	13.179	0.278	0.186	0.184
Sep-12	231.015	12.924	0.267	0.173	0.186
Oct-12	231.638	12.898	0.280	0.177	0.194
Nov-12	231.249	13.064	0.275	0.176	0.191
Dec-12	231.221	12.865	0.284	0.199	0.207
Jan-13	231.612	12.696	0.285	0.172	0.233
Feb-13	232.985	12.725	0.256	0.163	0.230
Mar-13	232.299	12.500	0.299	0.191	0.251
Apr-13	231.795	12.206	0.297	0.177	0.248
May-13	231.916	12.299	0.296	0.194	0.173
Jun-13	232.374	12.964	0.290	0.196	0.177
Jul-13	232.889	12.762	0.309	0.208	0.263
Aug-13	233.323	12.912	0.313	0.209	0.267
Sep-13	233.632	13.055	0.305	0.197	0.232

Oct-13	233.718	12.992	0.315	0.207	0.252
Nov-13	234.121	13.060	0.308	0.200	0.249
Dec-13	234.723	13.010	0.323	0.217	0.232
Jan-14	235.385	13.222	0.302	0.200	0.255
Feb-14	235.672	13.293	0.270	0.176	0.242
Mar-14	235.978	13.193	0.322	0.224	0.271
Apr-14	236.471	13.067	0.311	0.215	0.273
May-14	236.832	12.933	0.330	0.242	0.278
Jun-14	237.029	12.993	0.310	0.218	0.267
Jul-14	237.424	12.991	0.312	0.225	0.278
Aug-14	237.256	13.144	0.331	0.223	0.276
Sep-14	237.486	13.237	0.330	0.210	0.266
Oct-14	237.506	13.480	0.331	0.234	0.282
Nov-14	237.118	13.615	0.313	0.229	0.267
Dec-14	236.290	14.521	0.352	0.224	0.285
Jan-15	234.913	14.697	0.336	0.194	0.270
Feb-15	235.489	14.917	0.302	0.224	0.257
Mar-15	235.989	15.238	0.320	0.261	0.287
Apr-15	236.201	15.194	0.313	0.253	0.273
May-15	236.891	15.280	0.325	0.246	0.294
Jun-15	237.419	15.479	0.315	0.253	0.277
Jul-15	237.876	15.952	0.321	0.247	0.289
Aug-15	237.811	16.534	0.317	0.257	0.297
Sep-15	237.467	16.839	0.313	0.235	0.290
Oct-15	237.792	16.570	0.327	0.245	0.301
Nov-15	238.153	16.631	0.334	0.227	0.298
Dec-15	237.846	17.070	0.338	0.229	0.304
Jan-16	238.106	18.065	0.340	0.222	0.301
Feb-16	237.808	18.433	0.304	0.216	0.283
Mar-16	238.078	17.630	0.348	0.244	0.318
Apr-16	238.908	17.480	0.332	0.234	0.315
May-16	239.362	18.136	0.426	0.230	0.323
Jun-16	239.842	18.654	0.321	0.215	0.277
Jul-16	239.898	18.616	0.324	0.236	0.318
Aug-16	240.389	18.474	0.313	0.248	0.297
Sep-16	241.006	19.244	0.305	0.225	0.316
Oct-16	241.694	18.891	0.316	0.238	0.331
Nov-16	242.199	20.009	0.288	0.214	0.310
Dec-16	242.821	20.499	0.305	0.249	0.317

Table 17. Northbound Personal Vehicle Toll data

	Paso Del Norte (Pesos)	**Ysleta-Zaragoza (Pesos)**
Aug-10	$23.00	$23.00
Sep-10	$23.00	$23.00
Oct-10	$23.00	$23.00
Nov-10	$23.00	$23.00
Dec-10	$23.00	$23.00
Jan-11	$23.00	$24.00
Feb-11	$23.00	$24.00
Mar-11	$23.00	$24.00
Apr-11	$23.00	$24.00
May-11	$23.00	$24.00
Jun-11	$23.00	$24.00
Jul-11	$23.00	$24.00
Aug-11	$23.00	$24.00
Sep-11	$23.00	$24.00
Oct-11	$23.00	$24.00
Nov-11	$23.00	$24.00
Dec-11	$24.00	$24.00
Jan-12	$24.00	$25.00
Feb-12	$24.00	$25.00
Mar-12	$24.00	$25.00
Apr-12	$24.00	$25.00
May-12	$24.00	$25.00
Jun-12	$24.00	$25.00
Jul-12	$24.00	$25.00
Aug-12	$24.00	$25.00
Sep-12	$24.00	$25.00
Oct-12	$24.00	$25.00
Nov-12	$24.00	$25.00
Dec-12	$24.00	$25.00
Jan-13	$24.00	$25.00
Feb-13	$24.00	$25.00
Mar-13	$24.00	$25.00
Apr-13	$24.00	$25.00
May-13	$24.00	$25.00
Jun-13	$24.00	$25.00
Jul-13	$24.00	$25.00
Aug-13	$24.00	$25.00
Sep-13	$24.00	$25.00
Oct-13	$24.00	$25.00
Nov-13	$24.00	$25.00
Dec-13	$24.00	$25.00

Jan-14	$26.00	$26.00
Feb-14	$26.00	$26.00
Mar-14	$26.00	$26.00
Apr-14	$26.00	$26.00
May-14	$26.00	$26.00
Jun-14	$26.00	$26.00
Jul-14	$26.00	$26.00
Aug-14	$26.00	$26.00
Sep-14	$26.00	$26.00
Oct-14	$26.00	$26.00
Nov-14	$26.00	$26.00
Dec-14	$26.00	$26.00
Jan-15	$26.00	$26.00
Feb-15	$26.00	$26.00
Mar-15	$26.00	$26.00
Apr-15	$26.00	$26.00
May-15	$26.00	$26.00
Jun-15	$26.00	$26.00
Jul-15	$26.00	$26.00
Aug-15	$26.00	$26.00
Sep-15	$26.00	$26.00
Oct-15	$26.00	$26.00
Nov-15	$26.00	$26.00
Dec-15	$26.00	$26.00
Jan-16	$26.00	$26.00
Feb-16	$26.00	$26.00
Mar-16	$26.00	$26.00
Apr-16	$26.00	$26.00
May-16	$26.00	$26.00
Jun-16	$26.00	$26.00
Jul-16	$26.00	$26.00
Aug-16	$26.00	$26.00
Sep-16	$26.00	$26.00
Oct-16	$26.00	$26.00
Nov-16	$26.00	$26.00
Dec-16	$26.00	$26.00

Table 18. WTPN, WTYN, and WTAN Data

	WTPN	**WTYN**	**WTAN**
Aug-10	34.348	35.067	37.524
Sep-10	32.542	35.450	39.730
Oct-10	32.231	33.149	37.447
Nov-10	38.737	34.976	39.589
Dec-10	49.245	39.091	46.051
Jan-11	38.301	30.480	40.347
Feb-11	44.293	35.129	45.786
Mar-11	46.503	43.450	47.704
Apr-11	49.116	49.129	49.087
May-11	41.098	48.029	53.506
Jun-11	45.566	41.868	49.275
Jul-11	36.000	40.589	43.863
Aug-11	32.078	28.477	39.484
Sep-11	39.514	34.284	40.667
Oct-11	40.392	36.409	44.194
Nov-11	45.943	34.828	51.125
Dec-11	35.079	31.530	41.200
Jan-12	30.107	29.962	38.459
Feb-12	46.199	39.703	50.168
Mar-12	40.368	33.132	43.079
Apr-12	48.944	37.663	50.389
May-12	36.601	32.494	41.288
Jun-12	31.315	25.631	37.528
Jul-12	35.271	31.010	37.975
Aug-12	23.991	22.659	32.543
Sep-12	21.121	15.451	27.602
Oct-12	21.690	18.611	27.952
Nov-12	27.319	22.000	34.721
Dec-12	35.314	30.878	38.786
Jan-13	24.411	21.250	29.977
Feb-13	26.113	23.729	35.725
Mar-13	31.743	29.274	35.932
Apr-13	28.877	27.948	33.214
May-13	24.879	27.578	34.249
Jun-13	20.000	25.616	28.297
Jul-13	19.910	23.580	30.137
Aug-13	20.385	19.420	29.817
Sep-13	14.132	14.238	27.344
Oct-13	14.380	13.611	28.435
Nov-13	18.703	14.116	27.413
Dec-13	27.143	22.179	33.843

Jan-14	12.220	11.424	25.208
Feb-14	15.843	14.708	27.897
Mar-14	17.685	18.827	29.162
Apr-14	23.005	22.419	32.949
May-14	19.208	18.818	29.255
Jun-14	20.067	21.333	29.580
Jul-14	19.739	23.894	29.252
Aug-14	20.021	25.545	27.714
Sep-14	11.831	16.559	23.974
Oct-14	15.200	15.670	26.167
Nov-14	22.646	26.950	31.242
Dec-14	26.043	29.806	32.138
Jan-15	15.702	21.330	24.736
Feb-15	20.866	28.989	31.683
Mar-15	25.281	33.153	36.000
Apr-15	22.928	31.105	34.086
May-15	27.797	31.212	33.437
Jun-15	23.873	33.039	32.819
Jul-15	28.591	28.227	33.976
Aug-15	25.376	27.525	33.382
Sep-15	21.487	24.847	31.857
Oct-15	21.718	24.909	32.335
Nov-15	28.294	23.773	37.356
Dec-15	35.181	30.931	41.667
Jan-16	23.179	18.195	31.895
Feb-16	21.782	23.035	33.676
Mar-16	27.031	23.139	37.526
Apr-16	27.618	23.747	39.316
May-16	37.027	29.773	46.464
Jun-16	34.749	30.703	40.944
Jul-16	30.318	29.843	42.765
Aug-16	27.706	24.885	39.341
Sep-16	30.422	27.281	39.656
Oct-16	30.902	26.187	42.062
Nov-16	33.277	33.620	36.723
Dec-16	30.203	29.966	40.356

Table 19. CJIMX, ELPM, REXR, and MXIP Data

	CJIMX (thousands)	ELPM (thousands)	REXR 1997=100	MXIP 2008=100
Aug-10	180.171	277.400	98.440	100.551
Sep-10	179.698	281.700	98.215	99.857
Oct-10	179.327	282.300	94.968	102.858
Nov-10	176.351	284.200	93.508	100.362
Dec-10	178.282	285.400	93.580	99.856
Jan-11	176.824	281.200	91.584	97.106
Feb-11	178.382	281.600	91.273	94.207
Mar-11	179.420	283.100	91.445	102.180
Apr-11	179.126	284.200	89.888	97.703
May-11	181.908	284.400	90.475	101.502
Jun-11	180.401	282.700	91.567	101.523
Jul-11	178.535	280.600	90.180	101.674
Aug-11	177.150	281.900	94.612	103.675
Sep-11	178.454	285.700	100.803	102.620
Oct-11	178.289	283.000	102.912	106.868
Nov-11	177.606	285.400	103.727	104.952
Dec-11	178.185	286.800	103.149	103.140
Jan-12	179.598	282.800	100.251	100.708
Feb-12	182.594	284.900	95.735	99.904
Mar-12	183.568	286.600	96.208	104.985
Apr-12	186.888	287.600	98.976	100.652
May-12	188.730	288.900	103.678	105.882
Jun-12	188.650	285.800	104.980	105.085
Jul-12	186.650	284.100	100.082	105.343
Aug-12	188.028	286.200	98.975	106.406
Sep-12	190.031	288.600	97.140	104.416
Oct-12	192.339	290.100	96.252	108.837
Nov-12	195.271	292.400	96.505	107.284
Dec-12	194.657	292.800	94.525	102.457
Jan-13	196.017	287.000	93.058	101.641
Feb-13	199.320	289.300	93.536	98.320
Mar-13	202.315	290.500	91.647	101.080
Apr-13	202.947	291.100	89.156	103.386
May-13	202.968	292.300	90.395	104.558
Jun-13	199.378	289.100	95.440	102.643
Jul-13	202.388	287.500	94.081	105.480
Aug-13	201.608	290.500	95.051	106.171
Sep-13	201.616	293.300	95.959	102.974
Oct-13	206.301	294.600	94.700	109.447
Nov-13	206.154	297.500	94.213	106.598
Dec-13	205.355	297.600	93.152	103.347

Jan-14	208.539	292.900	94.205	103.562
Feb-14	204.340	294.600	94.726	99.974
Mar-14	207.531	295.700	94.462	105.991
Apr-14	209.940	296.300	94.056	103.247
May-14	212.739	297.400	93.629	107.629
Jun-14	214.956	294.700	94.156	105.854
Jul-14	215.202	290.900	93.822	108.801
Aug-14	215.407	293.000	94.409	108.312
Sep-14	217.871	294.300	94.742	107.092
Oct-14	221.369	296.100	95.696	112.749
Nov-14	223.231	298.500	95.436	108.916
Dec-14	224.294	299.700	100.611	107.051
Jan-15	225.228	296.100	101.469	105.102
Feb-15	226.654	297.900	103.300	102.226
Mar-15	230.908	298.800	105.623	108.239
Apr-15	235.631	300.200	106.098	105.031
May-15	236.911	302.000	105.619	106.518
Jun-15	241.867	301.000	107.317	107.246
Jul-15	244.578	298.200	110.327	109.761
Aug-15	247.730	300.300	114.058	109.560
Sep-15	250.754	302.600	115.658	108.890
Oct-15	254.941	305.600	113.009	112.935
Nov-15	253.226	307.700	112.644	108.839
Dec-15	247.675	307.800	114.559	107.249
Jan-16	247.754	304.200	121.200	105.121
Feb-16	250.577	305.700	123.446	104.555
Mar-16	251.778	306.300	118.273	105.879
Apr-16	253.328	309.200	118.122	106.686
May-16	256.705	310.100	123.675	106.928
Jun-16	254.873	307.300	127.357	107.839
Jul-16	256.069	306.800	126.469	108.181
Aug-16	259.037	308.800	125.361	109.905
Sep-16	264.595	311.300	129.750	107.318
Oct-16	263.463	313.600	127.110	111.703
Nov-16	265.006	316.000	134.100	110.496
Dec-16	266.251	316.300	136.198	106.633

Vita

Omar Solis was born in El Paso, Texas. He is an alumnus of the University of Texas at El Paso. In 2007, Omar earned a Bachelor of Science degree in Biology as a Presidential scholar and completed a Bachelor of Science in Psychology in 2011 with cum laude honors. Omar began work toward a Master of Science in Economics in the summer of 2015. In 2016, he was named a James Foundation Scholar by the Department of Economics & Finance.

Omar has been employed by the university throughout his graduate studies. Initially hired as a Teaching Assistant for the Department of Economics & Finance, he was later re-assigned as a Research Assistant for the Border Region Modeling Project where he has contributed to multiple reports related to the El Paso Borderplex area. During the Summer of 2018, he worked as a full-time Economic Analyst for the Border Region Modeling Project. Omar has been involved with many community outreach organizations, including the University Lions, the American Red Cross, and the El Paso International Music Foundation.

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This thesis was typed by Omar Solis