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Dynamic Road Pricing and the Value of Time and Reliability

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Dynamic Road Pricing and the Value of Time and Reliability

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Abstract

High Occupancy Toll (HOT) lanes that use dynamic pricing to manage congestion and generate revenue are increasingly popular but poorly understood. In this paper we estimate the behavioral response of drivers to dynamic pricing in a HOT lane. The challenge in estimation lies in the simultaneity of price and demand: the structure of dynamic tolling ensures that prices increase as more drivers enter the HOT lane. Prior research has found that higher prices in HOT lanes increase usage. We find that after controlling for simultaneity arising from autocorrelation HOT drivers instead respond to tolls in a manner consistent with economic theory. The average response to a 10% increase in the toll is a 2% reduction in usage. Drivers primarily value travel reliability over time savings, although there is heterogeneity in the relative values of time and reliability based on time of day and destination to or from work. The results highlight the importance of both controlling for simultaneity when estimating demand for dynamically priced toll roads and treating HOT lanes with dynamic prices as a differentiated product with bundled attributes.

Keywords: transportation economics; tolling; value of time; value of reliability; microeconomic behavior; congestion management; high occupancy toll lanes

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1 Introduction

Road transportation comprises a substantial proportion of the United States economy. The vast majority of infrastructure is owned, maintained, and operated by local, state, or federal agencies. According to Winston (2010) in 2007 American consumers spent over \$1 trillion dollars on gasoline and vehicles. In metropolitan areas road congestion led consumers to purchase 2.9 billion *additional* gallons of fuel and spend 5.5 billion hours sitting in traffic (Schrank et al., 2012). These costs are likely lower bounds due to unpriced congestion externalities for local air pollution (Currie and Walker, 2011; Gibson and Carnovale, 2015), carbon emissions (Weitzman, 2009), and increased sprawl (Anas and Rhee, 2006). Despite the enormous annual cost of traffic congestion most roads do not have even the simplest form of congestion pricing. Combating congestion in the short run by increasing capacity is challenging due to strained transportation budgets such as the perennial projected insolvency of the Highway Trust Fund (Kirk and Mallett, 2013). Furthermore, according to the fundamental law of highway capacity (Downs, 1962, 2004; Duranton and Turner, 2011), the long run elasticity of road supply is equal to one - meaning that any increases in supply will be met by equal increases in demand. Based on these facts, implementing appropriate congestion pricing has the potential to produce large welfare gains.

One particular example of congestion pricing that is gaining traction is the High Occupancy Toll (HOT) lane, where High Occupancy Vehicles (HOV) travel without cost and Single Occupancy Vehicles (SOV) are charged an access toll.¹ From an engineering perspective redistributing cars from congested general-purpose (GP) lanes to free-flowing HOV lanes can reduce congestion delays and associated externalities (Dahlgren, 2002). The toll, often varying by time of day or traffic conditions, also generates valuable revenue for local and state agencies. Both aging infrastructure and diminished revenue from gas taxes, declining in real terms since 1993, make this potential revenue a valuable part of infrastructure bud-

¹The definition of an HOV varies by location and roadway, but all HOV require at least two occupants and some require three or more.

gets. Furthermore, HOT lanes are politically palatable compared to unpopular uniform tolls because GP lanes are left untolled, maintaining a free alternative for low income or cost-sensitive drivers. These characteristics of HOT lanes in theory can lead to broad welfare gains (Safirova et al., 2004). However, there remain concerns over equity of access: wealthy drivers can avoid congestion while others must sit in traffic, leading to HOT lanes being disparagingly termed ‘Lexus Lanes’.

While HOT lanes are a popular form of managing valuable public roadways,² there is relatively little empirical economic research on the behavioral response of drivers to HOT implementation. Since HOT lanes often have dynamic prices that adjust to congestion the variation in price, plus the presence the free GP lanes as a veritable substitute, presents an opportunity to uncover how drivers respond to congestion management.

Our primary contributions are to generate empirical estimates for the price elasticity of demand and calculate the value of time and reliability on dynamically priced HOT lanes using micro-level data on SR167, in the Seattle-Tacoma metro area of Washington State. While most economists are not surprised by a downward sloping demand curve, the existing empirical literature on dynamically priced HOT lanes estimates a positive price response. Liu et al. (2011b) recovered coefficient values on price in a logit framework ranging from 0.214 to 0.600. More recent research by Janson and Levinson (2014) also found a positive effect of price on HOT usage with elasticities ranging from 0.03 to 0.85. In addition to identifying a more plausible demand elasticity we show that failure to properly identify the behavioral response to price produces invalid estimates of the value of time and reliability.

The most common explanation put forth for the positive effect of price on HOT demand is that price acts as a signal of future congestion (Liu et al., 2011b; Janson and Levinson, 2014), and therefore higher prices are associated with greater time savings. This explanation confounds expectations about time savings with the pure behavioral response to price.

²According to the Bureau of Economic Analysis the value of the stock of highways is equal to \$3,264.5 billion. Data were accessed from Table 7.1B. Current-Cost Net Stock of Government Fixed Assets on 1/13/2014 - <http://www.bea.gov/iTable/index.cfm>

Ceteris paribus, consumers prefer to purchase the same amount of time savings at a lower price. Not accounting for expectations of time savings introduces omitted variable bias into the coefficient on the pure price effect. A more plausible explanation for a positive price elasticity is that previous work did not adequately control for the simultaneity of price and congestion in dynamic tolling algorithms - as more drivers enter the managed lane conditions deteriorate (speed decreases) and the tolls increase, leading to a positive correlation between price and usage. Since conditions, and thus prices, are persistent there is a high degree of autocorrelation that leads to biased estimates.

Without formally addressing the problems of simultaneity and omitted variable bias in the setting of dynamic tolling algorithms it is premature to conclude that HOT usage violates a central tenet of economic theory. Our identification relies on a first-differences approach that overcomes the simultaneity of price and quantity that generates the positive demand response for Liu et al. (2011b). We also control for travel reliability and expectations of time savings using micro-level data, unlike Janson and Levinson (2014) who examine aggregate differences in usage after experimental changes in the toll rates.

Contrary to the previous literature that finds a positive demand response we estimate price elasticities ranging between -0.13 and -0.24 , with a preferred estimate of -0.21 . This is the first estimate of a negative price elasticity (to our knowledge) for dynamically priced HOT lanes, which are a critical part of many cities' future transportation management plans. Our estimation also allows us to calculate the welfare gains associated with decreased travel time and increased travel reliability for HOT lane users. In the base specification the total welfare gains are approximately \$2.3 million. Though the consumer welfare gains may seem small relative to aggregate transportation spending, the magnitude must be considered in the appropriate context. The gains to drivers are roughly equal to the total revenue generated from the project during the sample period. The welfare implications are significant when weighed alongside plans to expand HOT lanes both locally and nationally.

Our second contribution is to jointly estimate VOT and VOR for a dynamically priced

HOT lane. Prior studies (Brownstone et al., 2003; Liu et al., 2011b; Burriss et al., 2012; Janson and Levinson, 2014) of dynamically priced HOT lanes construct a simple estimate of the VOT by dividing the toll by the realized time savings. This method produces unrealistically high estimates of VOT that can exceed \$100/hr (Burriss et al., 2012; Janson and Levinson, 2014), whereas the U.S. Department of Transportation uses 50% of median household hourly income for the VOT for personal travel, which equates to roughly \$14 for Seattle Metro.³ Simply dividing the toll by time savings is problematic because the toll contains a bundle of attributes including improved reliability.⁴ Though some of the authors (Burriss et al., 2012; Janson and Levinson, 2014) mention these limitations there are no large scale revealed preference studies that jointly estimate VOT and VOR for HOT lanes.⁵

The joint estimation of VOT and VOR is axiomatically linked to the challenge of properly identifying the demand response for HOT lanes with dynamic pricing. Without identifying the demand response, which represents the (negative) marginal utility of income, it is impossible to estimate the marginal rates of substitution between time savings and money and reliability and money. This leads to severe problems in the simple methods for estimating VOT on HOT lanes that assigns all of the benefits associated with the HOT lane to time savings. Devarasetty et al. (2012) show in a stated preference study that VOR can be larger than VOT on HOT lanes, indicating that most of the simple revealed preference VOT estimates are too large. Our results are even more stark; drivers vastly value reliability over time savings on the HOT lane. We estimate that VOT is only \$3/hour for the preferred specification while VOR is over \$23/hour. In aggregate 80% of the benefits to HOT users are from increased reliability, though time savings is relatively more important for some subsets of the roadway.

In addition to estimating demand elasticity and welfare gains this article links the theoret-

³Sources are from (U.S. Department of Transportation, 2014; Bureau of Labor Statistics, 2014).

⁴There are other attributes other than VOT contained in the purchase of HOT access such as the mental stress from being in traffic, particularly when watching cars pass by in the free-flowing HOT lane.

⁵Carrion and Levinson (2013) estimates value of reliability for three different lanes using GPS data, but the sample only contains 18 observations.

ical economic literature on HOT lanes with an empirical example that can help parameterize the theoretical models. While theory suggests wide benefits from HOT lanes in the presence of driver heterogeneity (Dahlgren, 2002), in practice welfare impacts depend on the distribution of value of time (VOT) and value of reliability (VOR) (Small and Yan, 2001; Small et al., 2005), trends in commuting demand, tolling structure (Chung and Recker, 2011) and distortions in connected markets (Parry and Bento, 2002). Konishi and Mun (2010) show that converting from an HOV to an HOT lane has ambiguous welfare effects, in part due to discouraging carpooling. Many of the models used in these studies include price elasticity as a parameter without providing support for its magnitude and direction.

While we focus on estimating driver demand for a HOT lane in a specific location, the overall context is critical in an attempt to generalize the welfare results. Li (2001) attempts to explain the determining characteristics of HOT use on SR91 in California by analyzing survey data. His findings indicate that income, occupancy, trip purpose and age are important factors. From a theoretical perspective Parry (2002) conducts an analysis of congestion tax alternatives using simple models with three assumptions: (1) equate the marginal social cost of trips both between peak and off-peak travel (2) equate the marginal social cost across travel modes at a given point in time, and (3) sort high and low time-cost drivers by lane. He finds that, given driver time cost heterogeneity, a two lane road with tolls to separate high and low cost users achieves the maximum efficiency, while a uniform toll across both lanes achieves 90% of the optimum by ‘spreading out the commute of lower time cost commuters to before and after the toll’. He notes that single-lane tolls are more politically feasible given the ‘hostility’ from motorists to congestion taxes. Parry and Bento (2002) partially extend this analysis by incorporating distortions into the welfare calculations of a congestion tax. They find that the distortions can cause ‘substantial’ changes to welfare that must be considered as part of a policy change.

According to these findings HOT lanes probably do not achieve the social optimum since there is still a lane with unpriced congestion externalities. However, dynamic pricing of a

HOT lane shifts policy towards internalizing congestion externalities by raising the private costs as congestion in the tolled lane increases, as well as allowing drivers with different levels of VOT and VOR to sort appropriately. This is consistent with Dahlgren (2002) who models the addition of different lane types to an existing transportation environment: ‘mixed’ lanes perform better than HOV lanes when ‘initial maximum delay is very high but the proportion of HOVs is not sufficient to fully utilize an HOV lane’.

Our estimate of a negative price response to dynamically priced HOT lanes establishes in the empirical literature that drivers do indeed adhere to theoretical predictions of HOT lanes and dynamic pricing. This has important policy implications: if the demand for HOT lanes is not downward sloping then the entire premise of dynamically priced HOT lanes as a congestion management mechanism is fatally flawed. Given a positive price response higher prices will induce higher usage, and the cycle will continue until the lanes reaches its performance constraint.⁶ Our estimates not only agree with basic economic theory but also provide empirical support for using dynamic pricing to manage congestion and provide elasticity estimates to help optimize toll rates.

The remainder of the paper is organized as follows. The next section discusses the project setting and the data utilized in the analysis. Section 3 describes the econometric methodology. The results are presented in Section 4, and Section 5 offers concluding remarks and discussion. Details on the econometric specification tests, as well as additional tables and figures are available in the Appendix.

⁶In our setting it was necessary to restrict HOT Lanes to HOV traffic between 0.33% and 0.14% of the time during toll hours. The variance arises from measuring closure rates at the road segment level.

2 Background & Data

2.1 Project Setting

Our project setting is State Route 167 (SR167) in the greater metropolitan area of Seattle, Washington. It is a connector road between the communities of Renton and Auburn south of Seattle and the I405 freeway, which then feeds either into Seattle via I5 or Bellevue via I405. Instituted in May 2008 by WSDOT, the HOT lanes pilot project converted a ten mile stretch, in both directions, of SR167's HOV lanes into HOT lanes and continues to operate to this day (Figure 1). This location was selected due to severe congestion in the GP lanes and excess capacity in the existing HOV lane. At the onset of the project the objective was to fill the excess capacity in the HOV lane by allowing some SOVs to purchase access. Congestion not only causes delays but reduces the total carrying capacity of a road, so shifting cars from the GP to the HOV lane can conceivably increase the total throughput in *both* lanes (Dahlgren, 2002).

Figure 1: SR167 HOT Lanes Map, (WSDOT, 2013)



The primary role of the toll is to regulate access to the HOT lane and maintain a minimum level of service, thereby not discouraging use of the lane by HOV and transit. Prior to implementation the GP lanes averaged 30-35 miles per hour during congested periods, with a speed limit of 60 mph, resulting in delays of roughly 50% relative to free flow. Prior to converting to HOT lanes the HOV lanes experienced little to no congestion (Wilbur Smith Associates, 2006). As of 2012 WSDOT attributes the HOT lanes with a host of desirable outcomes including: decreased congestion in the GP lanes, decreased peak congestion, maintained free flow in the HOT lanes, increased capacity of the corridor, increased safety and revenue neutrality (WSDOT, 2012). The pilot program, originally set to expire in 2012, has been extended through 2016 and the expansion of HOT lanes to other routes is underway.

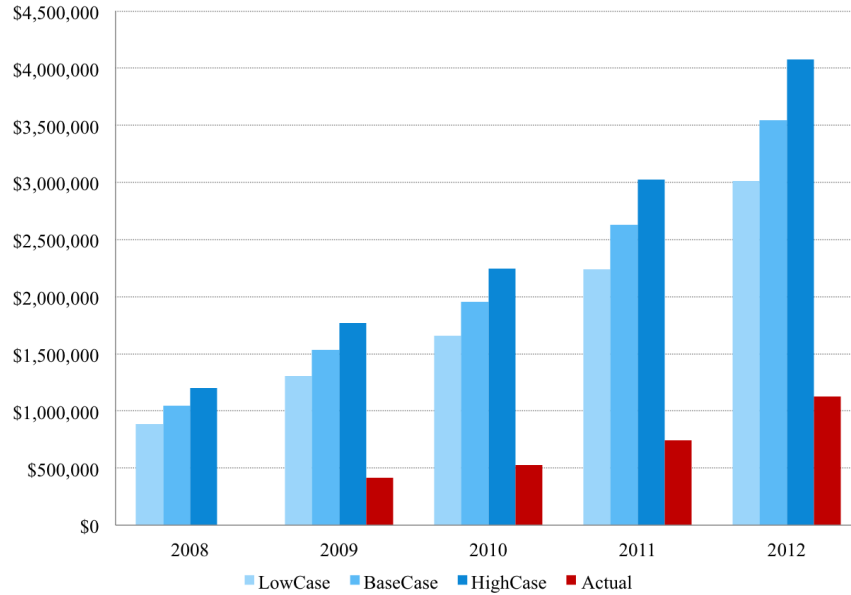
Assessing the willingness to pay for toll lanes is a requirement to determining toll levels that meet traffic volume priorities. Problematic assumptions by WSDOT in terms of the demand for HOT usage manifested in poor revenue forecasts as seen in Figure 2. Although revenue generation was not the primary objective for WSDOT, it is clear that there was a fundamental misunderstanding of the trajectory of usage and the driver response to the introduction of a tolled alternative lane.⁷

Along the ten mile stretch that comprises our project setting, SR167 has three northbound lanes and three southbound. In each direction there are two GP lanes with the third lane reserved for HOT use. HOVs require no additional equipment to use the lane, but SOVs that use the HOT lane must have purchased and installed a WSDOT ‘Good to Go’ (GTG) pass. Installed on either the license plate or an in-car windshield attachment, the pass is a transponder that registers a vehicle’s passage and collects the posted toll. Transponder detectors are installed at ‘gates’ that are the only legal entry and exit points for the HOT lane. There are six gates in the northbound direction and four gates southbound, with a double white line separating the GP and HOT lanes between gates.

GTG passes can be purchased online or at local retailers. The accounts are ‘prepaid’ in

⁷Other factors including a general decrease in travel demand due to the global financial crisis also contributed to the erroneous forecast.

Figure 2: SR167 Revenue: Forecasts vs Actual, (Wilbur Smith Associates, 2006)



that tolls are deducted upon use from funds that are preloaded into the account. Account holders can either automatically or manually replenish the balance. Users can choose between credit cards and bank accounts and services are provided online, over the phone or in person. The GTG passes can be used for all tolling facilities operated by WSDOT, including the SR520 Bridge and the Tacoma Narrows Bridge in addition to the SR167 HOT lanes. Both individuals and businesses can purchase GTG passes. While WSDOT does track both commercial and individual accounts, individuals with many users (a large family) could also purchase a commercial pass. WSDOT could not provide us with separate or tagged samples of usage broken out by account type so we were unable to uncover what effect this has on our estimates. However, purchasers of HOT access who do not bear the burden of the price would be expected to decrease our estimates of price sensitivity, and so we consider our estimates to be lower bounds.

While we do not observe each unique driver in our HOT usage data we do have a summary of those who use the HOT lane by zip code and frequency of use. One factor that impacts HOT use is the penetration of GTG passes. The unique number of HOT users on SR167 has

been rising steadily, from 21,623 unique drivers in 2008 to 38,025 in 2011.⁸ We also obtained summary statistics for the frequency of use for individual drivers. We find that most drivers use the HOT lane only sparingly. The mean annual number of tips is just under seventeen, but the median is only two with a large number of drivers only paying once or twice in a year. While we may expect there to be different behavior between frequent and infrequent users, Liu et al. (2011a) find that the behavior is very similar between these two user classes. We therefore are not concerned about the skewness of the frequency data.

2.2 Data

Our primary dataset consists of information collected by highway loop detectors and automated tolling systems.⁹ Loop detectors yield volume and occupancy (percentage of time occupied) of individual lanes at five minute intervals is publicly available through the Washington State Transportation Center. Tolling data, obtained from the Washington State Department of Transportation (WSDOT) through a public disclosure request, includes date and time of toll collection, entry-exit gate combination and the price paid.

2.3 Loop Detectors

WSDOT maintains a network of loop detectors on SR167 both for traffic analysis and as inputs to the tolling algorithm. We obtained 5 minute aggregated volume and occupancy data from loop detectors along SR167 from the Washington State Transportation Center (TRAC) based at the University of Washington. There are several challenges in generating a viable dataset from the loop detector data. First we remove all observations that have a data quality flag indicating infrastructure malfunction.¹⁰ Next we drop all observations on

⁸It should be noted that the HOT lanes were implemented in May 2008 so the 2008 figure is incomplete. Likewise through the end of September 2012 the HOT had 29,623 unique paying users.

⁹Prior analysis also accounted for weather and gas price. Weather variables are reported hourly from SeaTac airport, at a distance of 4.1 miles from SR167. Gas prices are the weekly average for the area of study. In pursuing a first-difference estimation at the five-minute level these other controls vary too infrequently to contribute.

¹⁰Of the 16,870,248 loop detector observations 4.8% were removed due to quality flags.

weekends and holidays as these are not representative of normal commuting behavior. This leaves us with a time series of volume and occupancy for all loop detectors on the route for every valid five minute interval during our sample period. Speed is computed from volume data based on Athol (1965)'s formula. Using imputed speed, TRAC also provides estimated whole-route travel times for the northbound and southbound directions, divided into HOT and GP, at five minute intervals.

2.4 HOT Tolls

The tolling algorithm is designed to determine the price at five minute intervals using data from the HOT lane and ensuring a minimum speed of 45 mph in the HOT lane. The algorithm compares the current speed and flow with an average of the previous four minutes. *Ceteris paribus* when speed or flow is increasing (decreasing) the toll rate will decrease (increase). We obtained the tolling algorithm without exact parameter values from WSDOT under the condition that we not reproduce it, since it is proprietary to the consulting company that designed it. Importantly for our study, the algorithm only incorporates HOT data and does not consider traffic in the GP lanes. Additionally, while the toll at a given gate is based upon data from loops around the gate, the toll may be overridden if downstream gates are computing a higher toll. WSDOT provided anonymous transponder recordings from SR167 including time of day, amount charged, as well as entry and exit gate. The prevalent usage pattern, in both directions, is to enter at the first gate and stay in the HOT lane until it ends (NB1 to NB6 and SB1 to SB4; see Figure A.1). The next greatest usage is characterized by entering at the second gate and staying through the end, etc. A small minority of drivers pay the toll and exit before the HOT terminates. Figure A.2 in the Appendix displays the toll rates by time of day and gate location.

2.5 Survey

To capture demographic characteristics we obtained yearly surveys of SR167 HOT users from WSDOT. The survey is sent to all email addresses attached to a GTG account that have used the SR167 HOT lane at least once.¹¹ It covers a broad range of topics including questions about demographics and attitudes towards the HOT lanes.

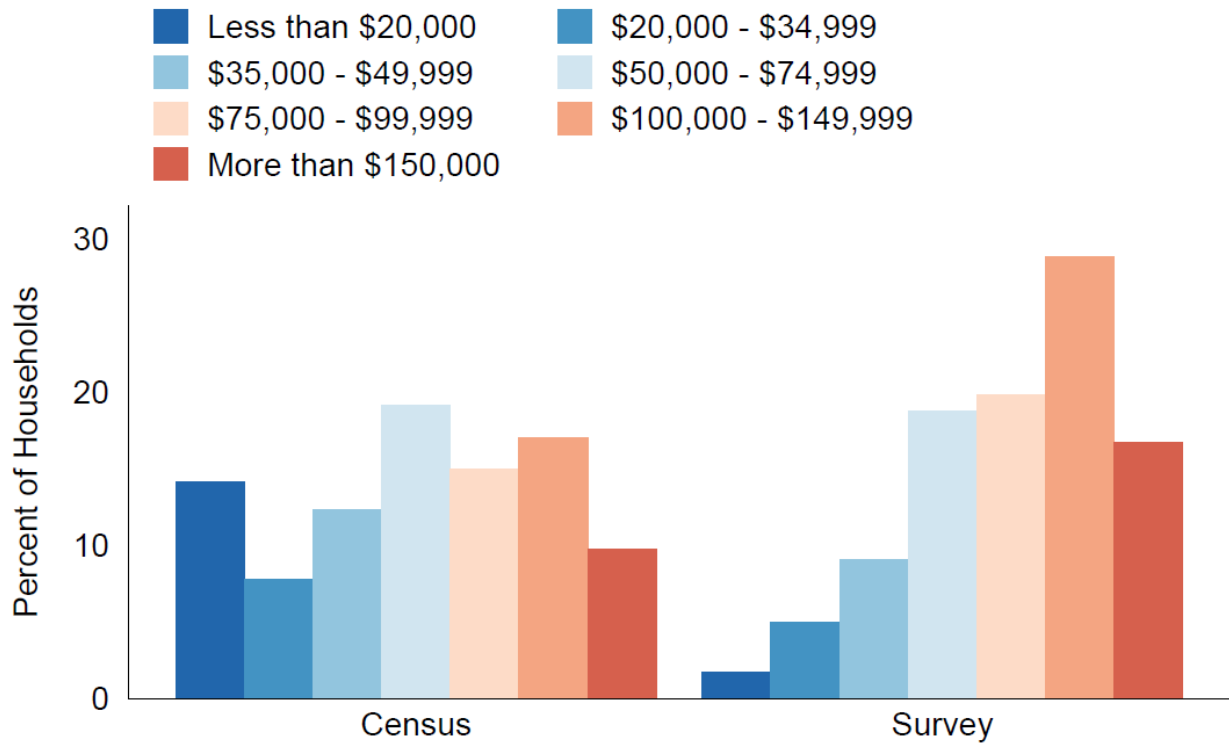
We focus on the income of HOT users since previous research (Li, 2001) has identified this as an important characteristic of use. Income is also a driver of VOT and will help put the VOT and VOR results in context for generalizing the results. While the survey captures the income information of some HOT users we are interested in the income distribution of *all* HOT users and the income distribution of *all* SR167 users. To approximate these distributions we use income at the ZIP code level from the 2010 US Census and weight by the intensity of HOT use within each ZIP code. The weights represent the proportion of all HOT users that came from a specific ZIP code. We assume that the spatial distribution of HOT users and GP users are the same, and, since HOT users are more likely to come from affluent ZIP codes, if we relax this assumption we can think of this income distribution as an upper bound on the income of GP users. Figure 3 presents the income from the survey of HOT users compared to our estimate of the income of GP users from the weighted census data. It is clear that even the upper bound of GP users' income is substantially lower than the HOT users. This implies that any VOT and VOR estimates will be upper bounds and that direct welfare effects from HOT usage are accruing to the wealthier segment of the commuting population.

2.6 Travel Time and Reliability

To illustrate the difference in average travel time and reliability between the GP and HOT lanes we plot the distribution of travel time over the course of the day in Figure 4 for both the northbound and southbound routes. The travel times were computed by TRAC for every

¹¹We do not claim that the survey is representative and use the results primarily for exploratory purposes.

Figure 3: Differences in Income



Notes: Census data are weighted by ZIP code frequency of 167 GTG users, and may be considered an upper bound of income. Survey data are from annual WSDOT surveys of HOT users.

five minute interval for both the HOT and GP lanes. The thick line represents the average travel time at a given time of day and the shaded region is one standard deviation in travel times at that time over all days in the sample. There are several noteworthy features in Figure 4. First, the peak congestion periods are dramatic: there is a steep spike in traffic for the GP lanes during the morning in the northbound direction and during the evening in the southbound direction. The free flow rate, as evidenced by travel times in the middle of the night, is approximately 10 minutes in either direction. On average the HOT lane maintains close to free flow conditions throughout the day in the northbound direction and experiences very minimal congestion during the evening peak in the southbound route. Comparing mean HOT travel times to the average GP travel times during the peak commute shows that drivers are saving roughly 3-6 minutes by paying for HOT access. For the overall sample drivers saving 1.85 minutes on average by using the HOT lane.

Table 1: Summary Stats

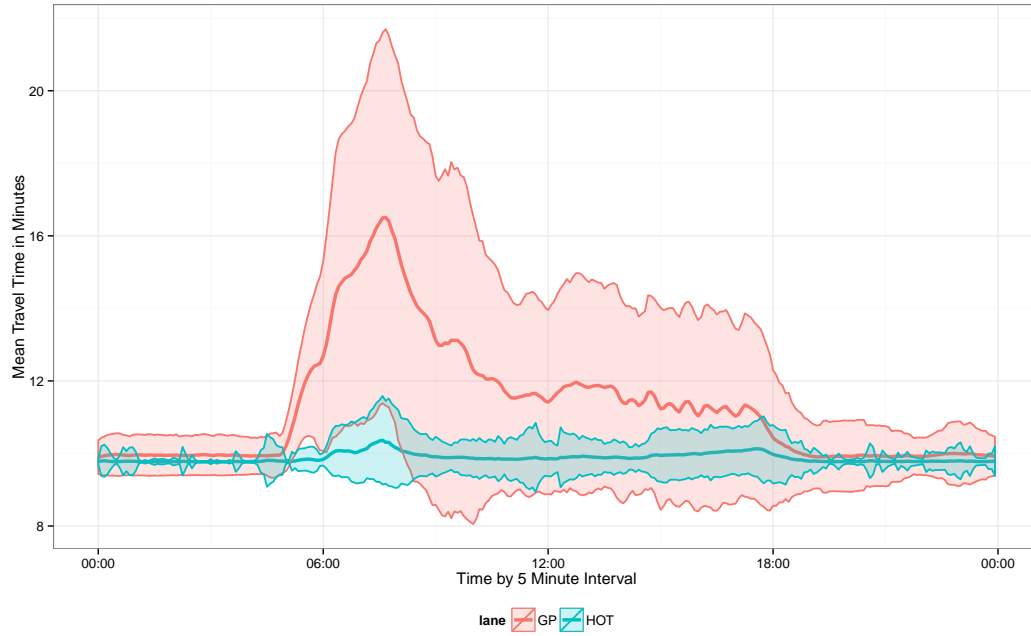
Statistic	N	Mean	St. Dev.	Min	Max
Count	1,071,743	2.41	3.96	0	46
Price	1,071,743	0.68	0.44	0.50	6.50
SOV	1,071,743	102.78	38.85	0.00	209.00
GP Speed	1,071,743	53.52	11.18	5.00	70.00
Reliability	1,071,743	1.17	0.93	-0.00	5.31
Expected Time Savings	1,071,743	1.85	1.56	-2.16	13.55

Previous research by Small et al. (2005) suggests that reliability is also an important determinant of the HOT use decision. The shaded region shows that one standard deviation in travel times in the GP lane can often exceed 20 minutes during the commuting period. There is little variation in travel times in the HOT lane, indicating that reliability is also a key attribute of the good. We follow Small et al. (2005) in constructing a reliability measure, estimating the median and 80th percentiles in travel-time savings for each 5-minute interval throughout the day for both the GP and HOT lanes using quantile regressions. Coefficients for northbound and southbound directions are estimated separately. The difference between the fitted values for the 80th and 50th quantiles is a measure of dispersion that approximates reliability for each lane. The reliability variable in the regression is the difference in reliability between the GP and HOT lanes. Expected travel-time savings are estimated from the fitted values of a linear regression of time savings on 5-minute fixed effects, HOV counts, and GP speeds.¹² This produces a forward thinking prediction of drivers' expectation of travel time savings when they make the decision to enter the HOT lane. Our specification assumes drivers form their expectation of travel time savings from the HOT lane based on the time of day and traffic conditions.

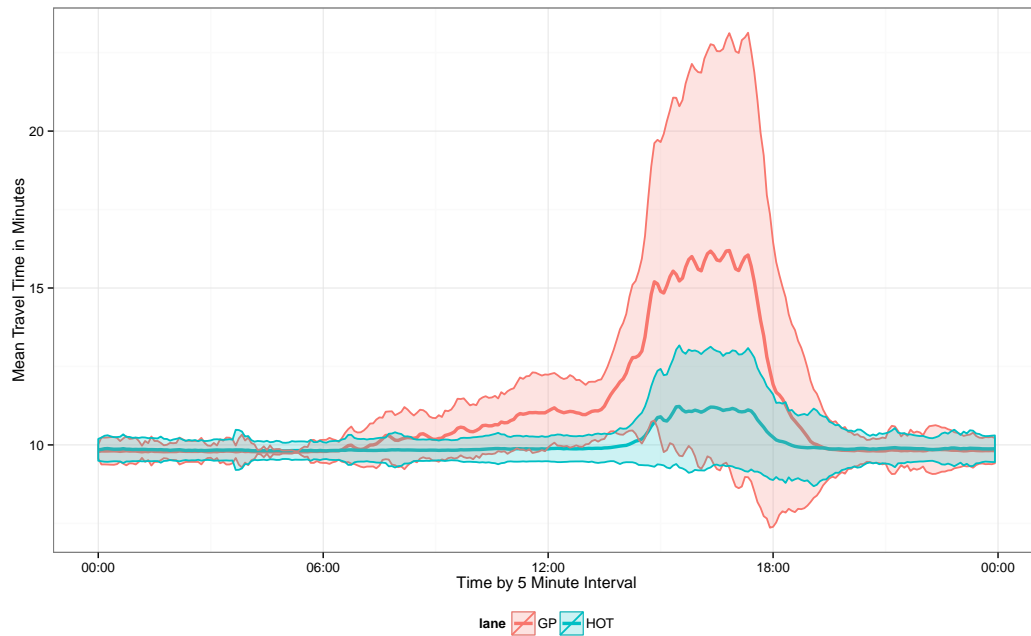
¹²Our specification is $TTSave_{it} = \beta_1 HOV_{it} + \beta_2 GP_{it} + D_m + e_{it}$, where $TTSave_{it}$ is realized travel time savings, GP_{it} is GP speed, HOV_{it} is the count of HOV drivers in the HOT lanes, and D_m are fixed effects for each 5-minute period in the day.

Figure 4: Travel Time and Reliability

Northbound



Southbound



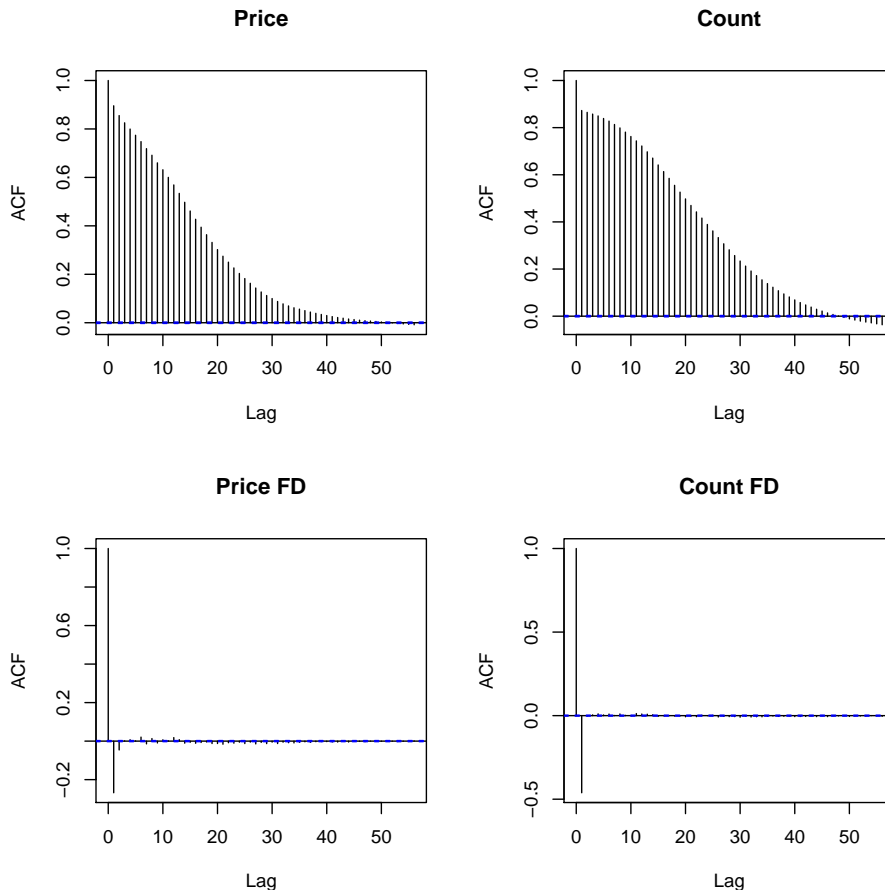
Notes: The thick line the mean travel time and the shaded region bounded by the thin lines represents one standard deviation in travel time. The colors distinguish between the GP and HQT lanes. Free flow travel time is approximately 10 minutes in either direction.

3 Methodology

Our objective is to identify the pure behavioral response of toll prices on the demand for purchasing access to the HOT lane. The structure of the tolling algorithm dictates that prices increase as HOT speeds decrease and HOT volume increases. The changes in speed and volume are computed every five minutes taking the difference between data at the five minute mark and the average of the previous four minutes. For instance, conditions from 7:59-8:00 are compared to the average conditions from 7:55 through 7:59 to calculate the price at 8:00-8:05. In this sense the price is not strictly endogenous since it is predetermined for any driver by the conditions prior to their entry. However, traffic conditions exhibit a high degree of persistence leading to autocorrelation in the variables of interest (see Figure 5). Not accounting for such a high degree of autocorrelation results in biased coefficients.

The issue of simultaneity can be interpreted in a time series context as autocorrelation in traffic patterns. A driver paying to enter the HOT lane will not influence the price that she pays, nor will she influence the price of any other driver in her 5 minute interval. Rather, as more drivers enter the price in the subsequent time interval increases. Therefore, without autocorrelation we do not expect the error term to be correlated with HOT usage, since the price is predetermined from the prior five minute interval. However, traffic is highly persistent and unobserved factors in the previous five minutes are correlated with current HOT usage, biasing the coefficient on price. We therefore first difference (FD) the data to reduce the serial correlation (see Figure 5). The interpretation of differenced data is also more attractive in the context of dynamic tolling. We know that both the toll and usage will be high during periods of congestion, but what we hope to recover is how drivers respond to *changes* in the toll rate. Increasing the toll as congestion increases is the central tenant of dynamic congestion pricing and is critical to managing HOT lanes. Prior to estimation we perform several test for unit roots adapted for time series data do not find unit roots in the data. This allows us to estimate the first-difference (FD) equation using OLS. Details can be found in Section A.3 in the Appendix.

Figure 5: Price and Count ACF



Notes: The autocorrelation function (ACF) of price and count and their respective first differences.

3.1 Econometric Specification

Our estimation equation takes the form

$$y_{it} = \beta p_{it} + \theta HOV_{it} + \gamma GP_{it} + \phi E[TTsave|t] + \lambda R_t + c_i + h_t + d_t + u_{it} \quad (1)$$

where the dependent variable, y_{it} , is the count of SOVs in the HOT lane at gate i and time t , and takes values $y = \{0, 1, 2, 3, \dots\}$. Our parameter of interest is β , the coefficient on the displayed HOT price, p_{it} . We also want to recover the VOT and VOR, the marginal rates of substitution between time and money and reliability and money. VOT and VOR are represented by the ratios $-\frac{\phi}{\beta}$ and $-\frac{\lambda}{\beta}$ respectively. Estimating all the preference parameters jointly presents a more reliable methodology for estimating VOT and VOR compared to

simply dividing the toll by time savings, which is confounded with unobservables (Janson and Levinson, 2014). We include the expected time savings ($E[TTSave|t]$) based on the information available to drivers at time t as described in Section 2.6. Unlike Liu et al. (2011b), who include realized travel time, we model this as an expectation based on the expected difference in travel time since the actual time savings are unknown to the driver when she makes the HOT purchase decision. Reliability (R_t) is the difference in reliability between the GP and HOT lanes based on the reliability metric advocated in Small et al. (2005). Additional controls include count of HOV users in the HOT lanes (HOV_{it}) and the speed in the GP lanes (GP_{it}). We also include fixed effects for the gate of entrance (c_i), hour of day (h_t), and day-of-week (d_t). The idiosyncratic error term is represented by u_{it} .

First-differencing equation 1 gives

$$\Delta y_{it} = \beta \Delta p_{it} + \theta \Delta HOV_{it} + \gamma \Delta GP_{it} + \phi \Delta E[TTsave|t] + \lambda \Delta R_t + c_i + h_t + d_t + \Delta u_{it} \quad (2)$$

where the coefficient of interest is β . We perform the first-differencing between time periods on the same day and at the same gate. Fixed effects are not first-differenced because we want to control for unobserved heterogeneity in the change in HOT usage by gate, day-of-week, and time of day as advocated by Wooldridge (2003).

4 Results

Coefficient estimates for both the OLS and FD HOT counts are presented in Table 2. Standard errors in OLS models (columns (1) and (2)) are robust to heteroskedasticity and clustered at the gate of entrance and the FD (columns (3) and (4)) are adjusted using a first-difference robust variance matrix clustered at the gate of entrance (Wooldridge, 2010). The OLS estimates are presented to show the impact of both simultaneity due to autocorrelation and the omitted variable bias from not including expected travel time and reliability. Column (1) shows that in a simple OLS framework the price response is positive, significant,

and reasonably large in magnitude.¹³ Simply controlling for travel time and reliability, as the seen in column (2), vastly decreases the magnitude of the estimate of the demand response but it is still positive and significant. Columns (3) and (4) show the results of the first-differenced model that both produce a demand response that is negative and statistically significant at the 1% level.

The preferred specification in column (4) estimates that a \$1 increase in the price decreases HOT users by 0.737 within a 5 minute interval. This finding stands in contrast to earlier research that identified a positive price response (Liu et al., 2011b; Janson and Levinson, 2014). Transforming this to an elasticity at the average quantity and price yields an estimated elasticity of -0.21 . There is not a significant difference in the price response when adding travel time and reliability in the first-difference model. As expected more HOV drivers and higher GP speeds decrease SOV purchases of HOT access since both variables decrease the benefits of the HOT lane relative to the GP lane. The point estimates of VOT and VOR are \$3.11 and \$23.43 respectively indicating that drivers care more about reliability than time savings when using the HOT lanes. VOT and VOR are investigated in more detail in Section 4.3.

¹³Since the data in columns (1) and (2) are counts we also estimate count models including Poisson and negative binomial that produce similar results and are available upon request.

Table 2: First Difference OLS Regressions

	OLS		First-Difference	
	(1)	(2)	(3)	(4)
Price	2.376*** (0.014)	0.484*** (0.013)	-0.732*** (0.019)	-0.737*** (0.019)
SOV	0.011*** (0.0001)	-0.002*** (0.0001)	-0.035*** (0.0002)	-0.035*** (0.0002)
GP Speed	-0.085*** (0.001)	-0.027*** (0.001)	-0.011*** (0.001)	-0.010*** (0.001)
Reliability		1.208*** (0.009)		0.288*** (0.027)
E[TT Save]		0.759*** (0.006)		0.038*** (0.008)
Constant	7.158*** (0.042)	3.650*** (0.040)	0.278*** (0.013)	0.263*** (0.013)
Weekday FEs	Yes	Yes	Yes	Yes
Hour FEs	Yes	Yes	Yes	Yes
Gate FEs	Yes	Yes	Yes	Yes
Observations	1,071,743	1,071,743	1,056,997	1,056,997
Adjusted R ²	0.403	0.529	0.039	0.039

Note: The dependent variable is the count of HOT users in a five minute interval. The dependent and all independent variables are in levels in columns (1) and (2) and first-differenced in columns (3) and (4). Standard errors are robust to heteroskedasticity and clustered at the entry gate. *p<0.1; **p< 0.05; ***p<0.01

4.1 Heterogeneity in Demand Elasticity

The price elasticity, as well as the VOT and VOR, depend on the features of the trip so we investigate two important sources of heterogeneity: the time of day and trip direction. Time of day is associated with congestion and also captures drivers on the traditional daily commute to and from work. The peak period is defined as 6:00am-9:00am in the northbound direction and 3:00pm-6:00pm in the southbound direction corresponding to the morning and evening commutes.¹⁴ The heterogeneity with respect to route direction is motivated by the argument that drivers face different incentive structures for utilizing the HOT lanes driving to and from work.

Table 3 presents results of regressions that interact price, reliability, and expected time savings with the variables of interest. Column (1) displays the base specification (column

¹⁴The peak period can be seen on the travel time graphs in Figure 4.

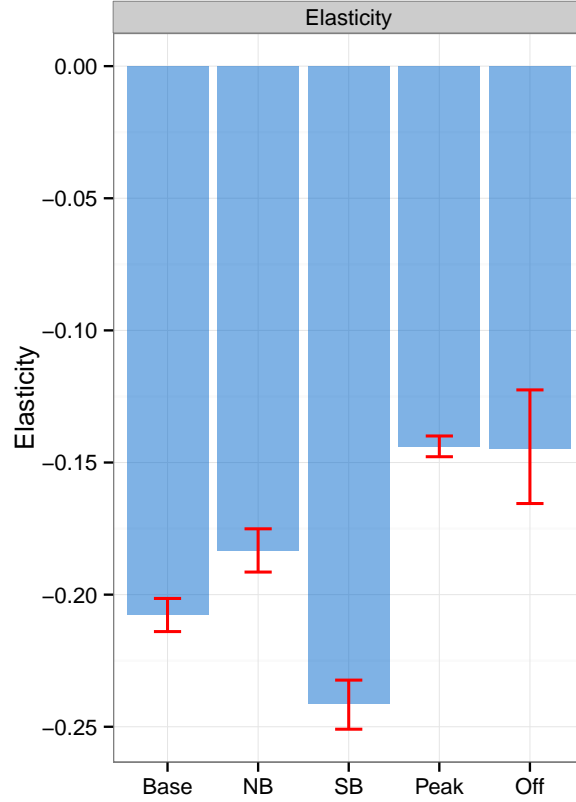
(4) of Table 2) for reference. The elasticities for each subgroup based on the estimates are presented in Figure 6 with bootstrapped 95% confidence intervals. Column (2) presents interactions with dummies for the peak period and shows that the demand response is greater during the peak period in levels. However, when converting these demand responses to elasticities the peak and off-peak periods have similar elasticities, as shown in Figure 6. The distinction between the point estimate and elasticities is in part due to more drivers being on the the road during the peak period. Interactions with directions, presented in column (3), show that drivers are more sensitive to the toll in the southbound direction. This is intuitive because drivers may have more flexibility when returning home compared to going to work. Unlike the peak/off-peak distinction, drivers are not only absolutely more responsive in the southbound direction but also proportionally more responsive as revealed by the elasticities for each direction in Figure 6. The next section discusses both base effects of the value of time and reliability and issues of heterogeneity.

Table 3: Heterogeneity by Gates, Congestion, and Direction

	Base (1)	Congestion (2)	Direction (3)	Congestion & Direction (4)
Price	-0.737*** (0.019)			
Price:Off-peak		-0.559*** (0.027)		
Price:Peak		-0.861*** (0.027)		
Price:NB			-0.637*** (0.025)	
Price:SB			-0.903*** (0.031)	
Price:Off-peak:NB				-0.477*** (0.032)
Price:Off-Peak:SB				-0.714*** (0.048)
Price:Peak:NB				-0.764*** (0.036)
Price:Peak:SB				-1.015*** (0.039)
Reliability	0.288*** (0.027)			
Reliability:Off-peak		0.180*** (0.031)		
Reliability:Peak		0.382*** (0.042)		
Reliability:NB			0.466*** (0.037)	
Reliability:SB			0.147*** (0.037)	
Reliability:Off-peak:NB				0.222*** (0.032)
Reliability:Off-peak:SB				0.130** (0.057)
Reliability:Peak:NB				0.856*** (0.078)
Reliability:Peak:SB				0.090* (0.049)
E[TT Save]	0.038*** (0.008)			
E[TT Save]:Off-peak		-0.0002 (0.008)		
E[TT Save]:Peak		0.130*** (0.020)		
E[TT Save]:NB			-0.004 (0.011)	
E[TT Save]:SB			0.103*** (0.012)	
E[TT Save]:Off-peak:NB				-0.023** (0.011)
E[TT Save]:Off-peak:SB				0.029** (0.012)
E[TT Save]:Peak:SB				0.040 (0.025)
E[TT Save]:Peak:SB				0.359*** (0.035)
Weekday FEs	Yes	Yes	Yes	Yes
Hour FEs	Yes	Yes	Yes	Yes
Gate FEs	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	1,056,997	1,056,997	1,056,997	1,056,997
Adjusted R ²	0.039	0.039	0.039	0.040

Note: Column (1) is the same regression as Column (4) of Table 2. Columns (2) and (3) show the interactions of price, time savings, and reliability with a dummy for peak period and direction respectively. Column (4) shows the results of a regression that interacts price, time savings, and reliability with both the peak dummy and the direction variable. There are no based effects included so the coefficients represent marginal effects for the relevant subgroup. *p<0.1; **p<0.05; ***p<0.01

Figure 6: Price Elasticities by Model



Notes: The thick bars represent the mean estimates for average elasticity and the thin bars are bootstrapped 95% confidence intervals. The estimates are based on the price parameter as well as average quantity and price in the relevant subsample for regressions in column (1) - (3) of Table 3.

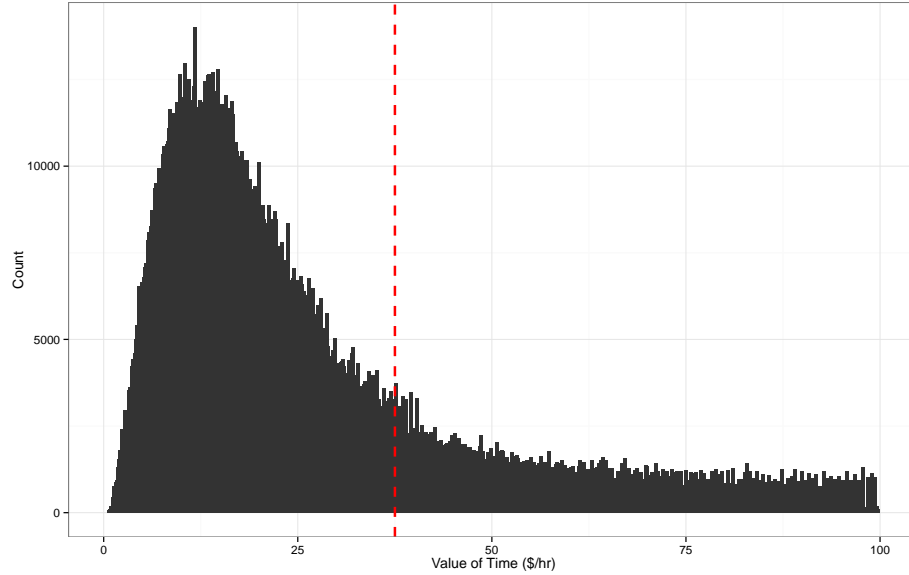
4.2 Value of Time and Reliability

A simple estimate of the Value of Time (VOT) is just the toll divided by the realized time savings. Though as stated above this measure produces unrealistically high VOT estimates on dynamically priced HOT lanes.

$$VOT = \frac{\text{Toll}}{TT_{GOP} - TT_{HOT}}$$

Before presenting the jointly estimated VOT and VOR from the regressions we show the distribution of the simple VOT from SR167 in Figure 7. VOT is constructed by simply dividing the toll by the difference in travel time between the GP and HOT lane for each

Figure 7: Simple Value of time



Notes: Simple VOT is based on toll and loop detector data. The red dashed line is the median and simple VOT is curtailed at \$1000/hour. The figure is curtailed at \$100/hour to avoid showing the far right tail.

5-minute interval in the sample.¹⁵ The average VOT using the simple method is \$38 dollar per hour and is designated by the red dashed line in Figure 7.

Figure 8 presents the estimates of VOT and VOR defined as the ratio of the preference parameters. It is important to note that this requires a negative coefficient on price in order to obtain a valid estimate of the marginal utility of income defined as negative one times the dis-utility of the toll. The estimates in Figure 8 are based on the regression models in columns (1) - (4) of Table 3. Since VOT and VOR are nonlinear combinations of parameters Figure 8 reports the mean and 95% confidence interval from bootstrapping each regression model. In models with interactions the VOT (VOR) is the ratio of the appropriate interactions for both $E[TT\ Save]$ (Reliability) and price. For example, the VOT for the peak period is the ratio of coefficients on $E[TT\ Save]:Peak$ and $Price:Peak$. Thus, Figure 8 represents variation in both the preferences for time savings (reliability) and the sensitivity to price.

The main result is that VOR is vastly more important than VOT; in fact in several speci-

¹⁵All observations with negative time savings and time savings above \$1000 are dropped.

fications the VOT is insignificant. In the base specification the reliability ratio (VOR/VOT), is 7.5 indicating that reliability is much more important in using the HOT lane than time savings. These results suggest that the simple estimates of VOT on HOT lanes vastly overestimate the true VOT, and that much of the purchase decision is actually based on improved reliability.

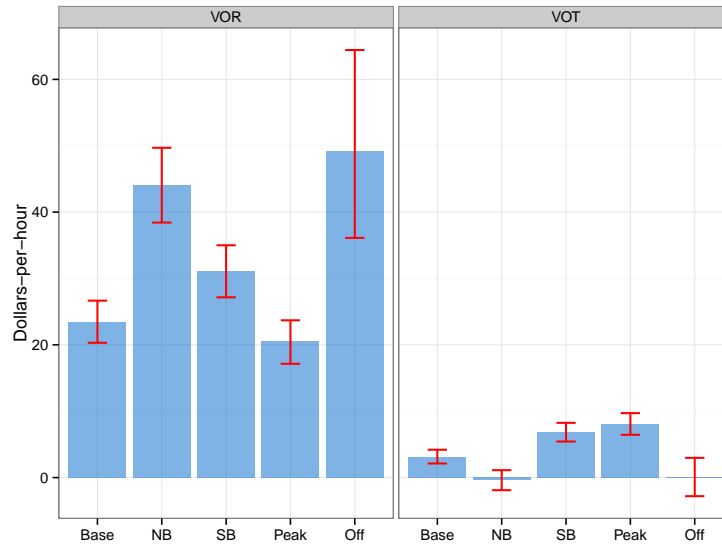
There is substantial heterogeneity in VOT and VOR. Northbound travelers greatly prefer reliability to time savings, which may indicate the need to arrive at work at a specified time. The peak VOT is statistically significantly larger than the base specification and the reliability ratio falls to 2.5 during the primary commuting period. The off-peak period has an insignificant VOT and a very high VOR of over \$40/hour. However, the confidence intervals are relatively large and the estimates in part are driven by the insensitivity to the toll in the off-peak period. Drivers that use the toll during off-peak periods may purchase the toll under a commercial account, which would explain the low sensitivity to the toll rate.

Breaking down the heterogeneity further panel (b) presents the means and confidence intervals for VOT and VOR based on column (4) of Table 3 that interacts price, time savings, and reliability with both direction and peak period. Focusing on the peak period shows that drivers in the morning commute to work (NB) value reliability over time savings while drivers returning home (SB) prefer time savings. This is intuitive given that drivers need to get to work on time and they just want to return home quickly.

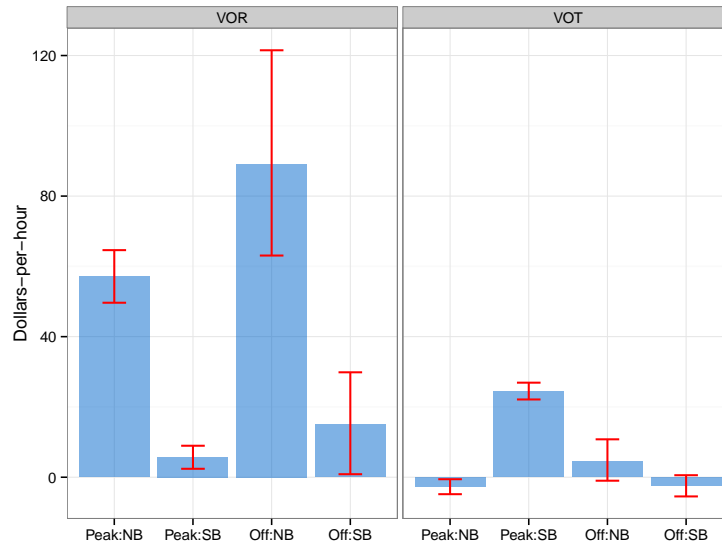
The heterogeneity also suggests that transportation managers can optimize the toll algorithms for HOT lanes based on simple observable differences in usage behavior. Drivers that value reliability may not be as sensitive to the toll rate and will purchase HOT access at a wide range of prices. Conversely those who value time savings may be more sensitive to the toll rate and traffic conditions when deciding to use the HOT. However, since time savings and reliability are correlated a more detailed analysis is required to investigate the relationship between VOT, VOR, and price elasticity.

Figure 8: Value of Time and Reliability Heterogeneity

(a) Base Specification and Single Interactions



(b) Double Interactions: Direction and Peak Period



Notes: The thick bars are the mean value of time and reliability and the thin error bars represent bootstrapped 95% confidence intervals. Panel (a) is based on the regressions in columns (1) - (3) of Table 3 and Panel (b) is based on column (4) of Table 3. The horizontal axis shows the estimates based on the main parameters (price, reliability, and expected time savings) as well as interactions with either direction and congested period (Panel (a)) or the double interactions of the main parameters with both direction and congested period (Panel (b)).

4.3 Aggregate Welfare Effects

Combining the VOT and VOR estimates with the realized time savings and improvements in reliability produces aggregate welfare estimates for the HOT users on SR167. The welfare estimates focus on the dollar value of time savings and reliability for those that purchase access to the HOT lane and omits other attributes of the toll, such as reducing the disutility of being stuck in traffic or improved safety. Thus, the estimates presented should be considered lower bounds of the benefits to HOT drivers. Our base specification produces aggregate benefits of \$2.3 million, which is roughly equivalent to the revenue generated by the toll during this period. 80% of the benefits come from improved reliability, with only 20% due to travel time savings. Examining heterogeneity in the aggregate effects shows that the vast majority of benefits are due to improved reliability during the morning commute period. The welfare estimates exclusively focus on the benefits to SOV drivers purchasing access to the HOT lane. WSDOT claims (WSDOT, 2012) that during the sample period HOT lane usage increased while maintaining 45 MPH over 99% of the time so there are unlikely to be negative impacts on HOV users and public transit riders. Additionally, GP speeds increased during peak periods according to WSDOT. WSDOT's estimates should not be interpreted as causal impacts of HOT implementation on traffic on SR167, but if the GP lane experiences improvements in reliability and decreases in travel times then substantial benefits will accrue to drivers on the GP lanes. However, since HOT users are wealthier on average we caution the extrapolation of VOT and VOR parameters from HOT users to the GP lane.

5 Conclusion

The scale of congestion costs in the United States warrants new approaches to managing our roads. In addition to alleviating congestion, better road management will decrease accidents and reduce both local and global pollutants. A burgeoning approach to managing congestion

is to introduce a HOT lane, either by converting existing HOV lanes or when adding new road capacity. The use of new technology, such as real time congestion pricing, gives road operators a powerful tool for managing congestion while at the same time collecting much-needed revenue. While there has been applied work in the transportation literature, as well as theoretical economic research on HOT lanes, there has been little empirical economics research using revealed preference data on how consumers respond to HOT lanes. The few studies using revealed preference data on HOT lanes have estimated a positive price response that is inconsistent with economic theory. If higher prices actually cause drivers to move into the HOT lane the basic premise of dynamically priced HOT lanes is flawed. We provide evidence that prior results are due to a failure to address issues of serial correlation and simultaneity inherent in dynamic pricing, as well as not accounting for the bundle of attributes that HOT lanes deliver.

We employ a first difference estimation strategy to recover a negative price elasticity by overcoming simultaneity in the dynamic pricing structure due to autocorrelation in travel demand. The negative demand response enables us to jointly estimate the value of time and reliability. We find a negative and substantial elasticity of approximately -0.21 , indicating that drivers do indeed reduce usage as the toll rate increases. The analysis of VOT and VOR show that drivers primarily value reliability rather than time savings. There is heterogeneity in VOT and VOR; drivers value reliability during the morning commute and time savings during the evening commute. The aggregate welfare to HOT users on STR167 is estimated to be \$2.3 million, approximately the value of the toll revenues. The welfare estimate show that there are large benefits to drivers from using HOT lanes. If the the GP lanes also the benefit from decreased congestion due to traffic diverted to the HOT lanes the benefits may be significantly larger.

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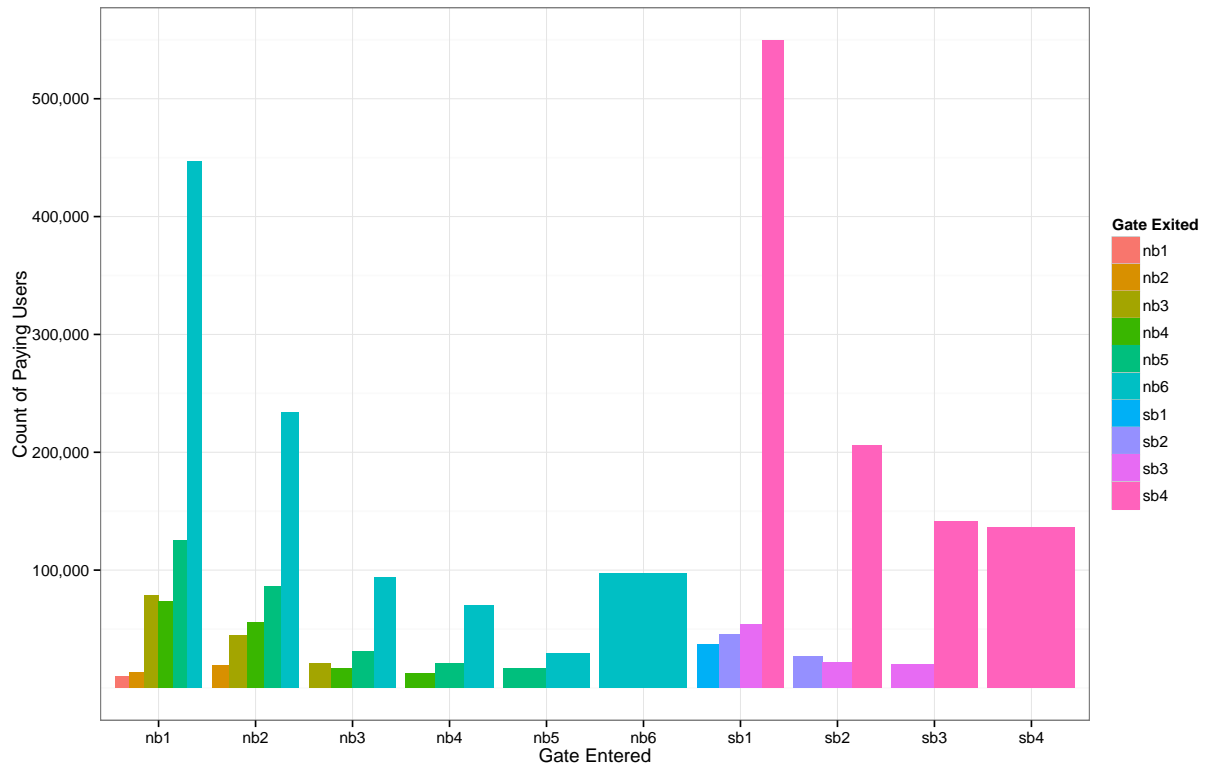
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A Appendix

A.1 Trip Combinations

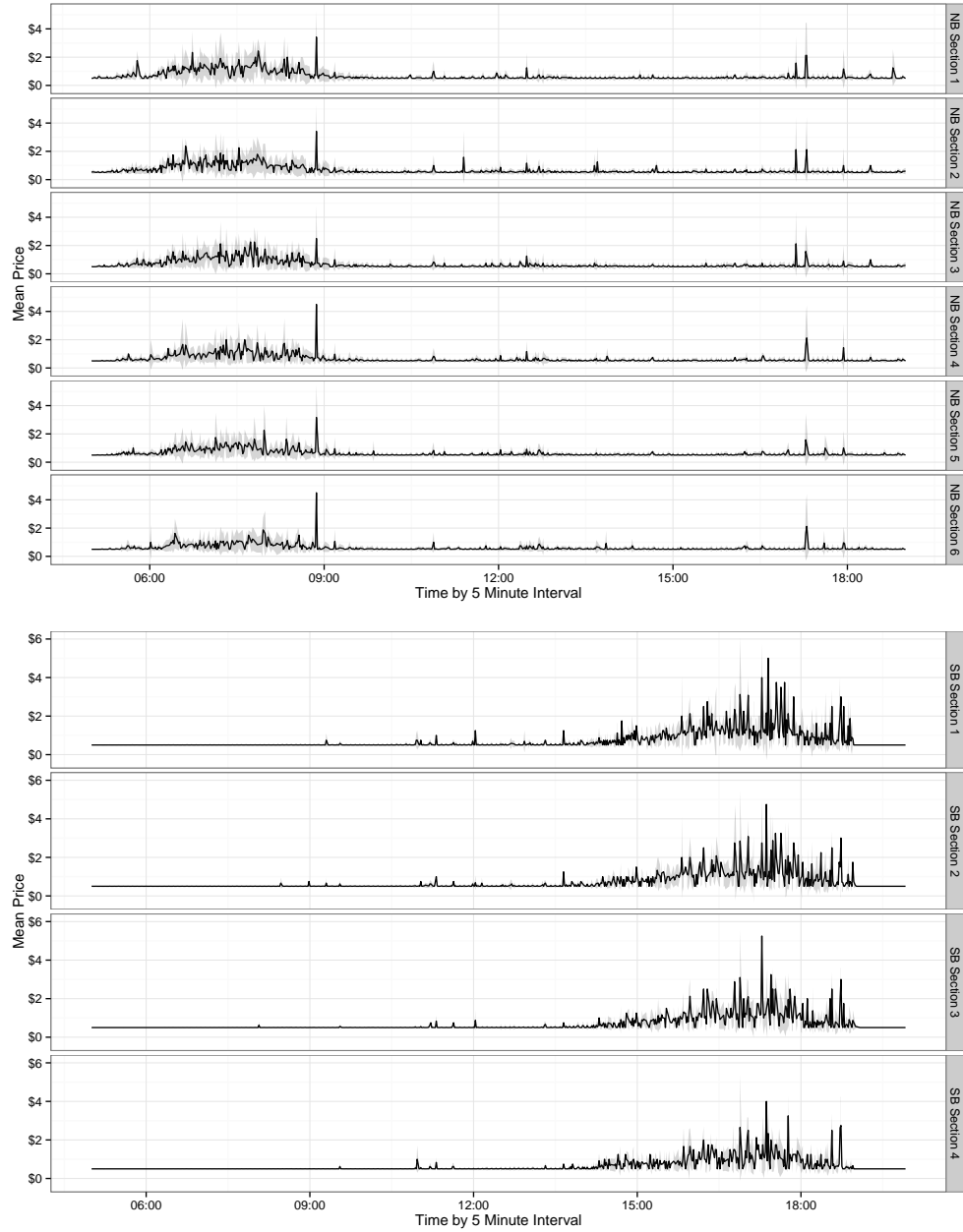
Figure A.1: SR167 trip combinations



Notes: The horizontal axis indicates the entry gate and the colors designate exit gates. The number of purchased tolls for each combination is on the vertical axis. The thickness does not convey variation in the data, and is meant to properly space the figure.

A.2 Prices by gate

Figure A.2: Price by Section



Gate locations were determined using [this tool](#).

North Bound:

- NB1 13.83
- NB2 15.10
- NB3 16.60
- NB4 18.61
- NB5 20.28
- NB6 22.90
- ends 25.09

South Bound:

- SB1 25.64
- SB2 23.70
- SB3 20.53
- SB4 18.99
- ends 17.03

A.3 Panel Data

Our data can be interpreted as a ‘pseudo’ panel in the sense that we repeatedly observe usage at individual entry gates. Structured this way, $N = 10$ (six northbound plus four southbound gates) and $T = 1,215,000$ (although T will vary according to different missing data at different gates). ‘Pseudo’ panels such as we are proposing here are likely to violate the dynamic homogeneity assumption underlying true panel data models (Im et al., 2003). Understanding that the data might display dynamic heterogeneity informs our choice of unit-root tests presented later in this section.

We employ three tests to explore the heterogeneity of our ‘pseudo’ panel based on Holtz-Eakin et al. (1988); Holtz-Eakin (1988):

1. an F-test for parameter equality from an Augmented Dickey-Fuller estimation with third order lag (ADF(3)),
2. another F-test from a third order autoregressive (AR(3)) regression across all variables and
3. finally White’s test for groupwise heteroskedasticity.

A rejection of the null in the F-tests indicates heterogeneity across parameters while a rejection of the null in White’s test indicates an inequality of variance. We performed White’s test using a regression of the residuals from the ADF(3) regression on the original regressors and their squares. The test statistic is $(NT) * R^2 \sim \chi^2$, where the degrees of freedom are the number of regressors from the second stage. Table A.1 presents the statistics, all of which reject the null of parameter and variance homogeneity at the 1% significance level.

Table A.1: Dynamic Heterogeneity Tests

Test	White	ADF	AR
F Statistic	261017.62	2037.24	1018.45

Notes: White’s test tests the equality of variance, the ADF(3) and AR(3) test for parameter equality across an ADF and AR equation respectively. The number of observations is 1,282,349

Given parameter and variance heterogeneity we employ two unit root tests for panel data: that developed by Im et al. (2003) and a cross-sectionally augmented version of Im et al. (2003) proposed by Pesaran (2007). We begin with the following formula:

$$y_{it} = \alpha_i + \beta_i y_{i,t-1} + \epsilon_{it} \tag{3}$$

where $i = 1, \dots, N$ for each gate, $t = 1, \dots, T$ represents the time periods and y_{it} represents each series in the panel. The traditional panel unit root test developed by Im et al. (2003) fits the following ADF equation

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \sum_j^{p_i} \rho_{ij} \Delta y_{i,t-j} + \epsilon_{it} \tag{4}$$

where p_i is the number of lags (here three). This is estimated for each variable in the panel across each cross section. A ‘t-bar’ statistic is formed as the average of the individual cross sectional ADF(3) statistics according to the following equation

$$t\text{-bar} = \frac{1}{N} \sum_{i=1}^N t_{\rho_i} \quad (5)$$

The null is that each series in the ‘pseudo’ panel contains a unit root. Rejection of the null indicates that there is no unit root in any cross sectional series. Im et al. (2003) show that the statistic is normally distributed under the null and provide critical values for given N and T . The t-bar for each series is presented in Table A.2 and reject the null of unit roots at about the 1% significance level.

This traditional Im et al. (2003) unit root test can be modified to account for cross-sectional dependence. Pesaran (2006) shows that the effects of unobserved common factors in panel data can be eliminated by filtering the cross-sectional mean. Extending this work to unit roots in Pesaran (2007) leads to the following cross-sectionally augmented DF (CADF) regression

$$\Delta y_{it} = \alpha_i + \beta_i y_{it-1} + \gamma_i \bar{y}_{t-1} + \delta_i \Delta \bar{y}_t + \epsilon_{it} \quad (6)$$

where \bar{y}_t is the cross-sectional mean. The t -statistics on the β coefficient are estimated from each unit i of the panel, with the average forming the CIPS statistic

$$\text{CIPS} = t\text{-bar} \frac{1}{N} \sum_{i=1}^N t_{\beta_i} \quad (7)$$

Results from the tests are presented in Table A.2 and indicate there are no unit roots in the series.

Table A.2: IPS Panel Unit Root Tests

Variables	ADF	AD Ftrend	CADF	CADFtrend
Count	-56.67	-56.79	-57.55	-57.69
Price	-45.67	-45.80	-42.48	-42.51
Volume After Gate	-56.25	-56.97	-60.10	-64.28
Speed Before Gate	-68.20	-68.25	-68.55	-68.92
Speed at Gate	-56.74	-57.07	-61.90	-62.54
Speed After Gate	-63.15	-64.50	-66.17	-69.22
Value of Reliability	-40.68	-40.68	-28.83	-28.83
Expected Time Savings	-29.38	-29.38	-15.53	-15.51
Proportion	-59.75	-61.07	-61.84	-64.23

Notes: All tests are conducted using three lags. Columns with 'trend' include an individual time trend in the regression. All tests reject the null of a unit root at greater than 1% significance. Total number of observations is 1,282,349.