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Abstract[*]

Growing vehicle use and congestion externalities have led many to consider alternative congestion pricing mechanisms, as road pricing often has high infrastructural costs and faces public opposition. This paper explores the role of parking taxation in reducing congestion by considering a natural experiment created by the progressive January 1, 2012 Chicago parking tax increase. Exploiting differences in vehicle use across income groups, it is estimated that the approximately $2 a day parking tax increase led to a 4-6 percent reduction in total vehicle trips in high-income areas, with the largest response seen on roads more heavily used by commuters. Also found are corresponding increases in use of public transit and a 3.1 percent aggregate reduction in vehicle trips. It is concluded that parking taxes can help mitigate congestion externalities, although they are no more than about half as effective as more efficient congestion tolls.

JEL classifications: R41, R48, R52, Q53, H31
Keywords: Congestion, Second-best pricing, Traffic, Parking, Parking tax, Parking demand

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1. Introduction

Over the past 15 years, worldwide vehicles per kilometer of roadway and vehicles per person have increased by nearly 50 percent (Miller and Wilson, 2015), with vehicle miles traveled (VMT) in the United States more than doubling from 1980 to 2003 (Parry, Walls and Harrington, 2007). As the use of vehicles increases, the time, environmental, economic, and safety externalities associated with this increase in vehicle use become more pressing issues. Perhaps the most apparent and observable vehicle use externality is the time cost associated with congestion. It has been estimated that from 1982 to 2011 average annual congestion delays in the United States increased from 15.5 hours to 38 hours *per driver*, costing nearly $621 billion in wasted time (Schrank, Eisele and Lomax, 2012).[1]

The optimal mechanism proposed to internalize these externalities takes the form of a marginal use tax directly linked to the marginal social cost. In practice this usually takes the form of a road pricing mechanism that attempts to charge users for the social cost they create. Road pricing has proven to be effective at reducing congestion, but has massive infrastructural costs and faces extreme public opposition (Quddus, Carmel and Bell, 2006; Goh, 2002). For this reason it is crucial to understand the effectiveness and potential role of alternative pricing mechanisms, such as parking fees or taxation, as a short-run solution to pricing congestion related externalities.

Theoretical models of congestion and parking suggest that parking fees provide a second best pricing mechanism that can be used to reduce congestion (Verheof, Nijkamp and Reitveld, 1995a). In general these models focus on the effect of parking fees on downtown congestion from “cruising” (see Anderson and de Palma, 2004; Arnott and Inci, 2006), with little regard of behavioral effects which would change the composition and level of commuter congestion *into* the priced area. Although the theoretical literature is expansive, there is little reliable empirical work verifying these hypotheses or estimating the associated price elasticities. In this paper we evaluate the ability of parking taxes to reduce congestion and induce commuters to switch modes of transit. Using variation from a natural experiment in parking taxes created by the implementation of a city-wide parking tax on January 1, 2012 in Chicago, we estimate that the $2 daily parking tax increase led to a 4-7 percent total reduction in car traffic during AM and PM normal commuting hours. This represents approximately 3,700-6,500 cars a day. When looking

[1] This is the average annual additional time over a congestion-free commute.

at the simultaneous change in public transit ridership, we find that this decrease in driving is accompanied by an increase in public transit use.

On January 1, 2012, the City of Chicago made several price adjustments to its progressive parking tax schedule. Prior to the changes, parking providers who charged over \$12.00 a day were also to charge a \$3.00 parking tax. After the change in January 2012, the weekday parking tax was increased to \$5.00 a day while the weekend parking tax remained the same. This two-dollar-a-day increase changed the average tax rate for \$12.00 parking from 25 percent to 42 percent. Similarly, tax rates for monthly parking were increased from \$60.00 to \$90.00 for monthly fees over \$240, with two additional tax brackets at \$300 and \$400 a month (see Table 1 for a complete description). These tax increases are large, in general amounting to between \$1-2 a day, providing an ideal setting to test for behavioral responses from commuters adjusting on the extensive margin.[2] Because this new tax only applied to the top-priced tiers of parking, differences in income and driving propensities create natural counterfactual groups who were less heavily affected by the tax reform. Although only the most expensive parking faced the new tax, this policy is still expected to have a sizeable impact, as the median monthly parking price in 2012 (\$289) would have been subject to the new tax (Cook and Simonson, 2012). The response to this price adjustment can help estimate the elasticity of driving demand with respect to parking fees and understanding the effectiveness of parking taxes as a congestion pricing mechanism.

The geographic setting of Chicago makes it ideal for examining this type of question. Chicago is fairly monocentric, with a network of roadways leading to the Central Business District (CBD). Because commuters are restricted by Lake Michigan on the East, we can make fairly accurate assumptions about auto commuters' general destination if heading towards the CBD. By looking at high frequency hourly vehicle counts on roadways leading into the city, we can estimate the effect of the tax change on vehicle use. Another unique feature of Chicago's geography is the stark geographic heterogeneity in income which corresponds to parking use (Brooke, Ison and Quddus, 2014). Combining this variation with universal implementation on January 1, we estimate the effects of the Chicago parking tax on vehicle counts to infer drivers' response to the new policy, and we supplement this analysis with estimated changes in public

[2] Various news sources at the time even indicated that the parking tax was implemented to reduce congestion. (see http://articles.chicagotribune.com/2011-11-02/news/ct-met-parking-congestion-tax-1102-20111102_1_parking-tax-parking-committee-parking-industry), accessed August 14, 2015.

transportation use, and carpooling behavior, finding small but statistically significant effects, suggesting that parking taxes might have a role to play as a second best congestion pricing mechanism.

The paper proceeds as follows: in Section 2 we highlight key findings from the previous literature on congestion pricing and second best parking pricing mechanisms as well as describe the present quasi-experimental setting created by the January 1, 2012 parking tax in Chicago; in Section 3 we present the theoretical intuition for parking pricing and present a simple model to justify our identification strategy; in Section 4 we describe the data; in Section 5 we present our empirical framework; in Section 6 we present the results of our analysis and various robustness tests; and Section 7 concludes.

2. Related Literature

In environmental, urban, and public economics as well as urban planning, there is a large literature devoted to congestion-related externalities. In this paper we highlight key theoretical and empirical findings and refer interested readers to more complete reviews (Arnott, 2011; Brooke, Ison and Quddus, 2014; Inci, 2015; Miller and Wilson, 2015). Until recently, vehicles per kilometers of road and overall vehicle ownership levels have consistently risen in both developed and developing nations. Over the last 10 years, vehicle use and ownership has remained fairly constant at these high levels.[3] With more cars on the roadways than in any previous generation, the economic, social, and environmental consequences of increased traffic congestion become more pressing issues. Although motorists often internalize private time, safety, parking, and fuel costs when choosing to travel by personal vehicle, the unaccounted-for externalities of personal transport have been acknowledged dating back to Pigou (1920). These external costs are imposed on others when a motorist decides to travel to their point of destination by personal transport, and they range from time, travel, and road repair costs to costs associated with pollution, noise, and safety (Verhoef, Nijkamp and Reitveld, 1995b). As roadways approach and surpass capacity, average speeds decrease while average travel times increase. Over the last three decades, total vehicle miles traveled in urban areas of the United States has more than doubled, making roadways congested and resulting in an increase in additional congestion delays (Parry, Walls and Harrington, 2007).

[3] For example, see Milllard-Ball and Schipper (2011) or Dutzik and Baxandall (2013).

There is a vast literature exploring various regulatory and fiscal policies, and most economists agree that a Pigouvian tax is the first best method of congestion pricing. This often takes the form of road pricing, which until recently was not entirely feasible. Road pricing often requires massive infrastructural startup investments and a certain level of GPS tracking. This pricing measure has been implemented only a few times, and these attempts have often faced public rejection, political opposition, and fears of "Big Brother"-type monitoring of private activity (Goh, 2002; Verhoef, Nijkamp and Rietveld, 1995a). For these reasons, less invasive variations of road pricing are often implemented in the form of congestion toll zones where prices are either static or allowed to adjust throughout the day, such as those in London and Singapore (de Palma, Lindsey and Niskanen, 2006; Parry et al., 2014; Goh, 2002).[4] Overall, these policies have effectively reduced congestion and increased traffic speeds (Quddus, Carmel and Bell, 2006), but they are still unable to perfectly price congestion due to area restrictions and vehicle exemptions and still face some privacy concerns (Goh, 2002). Although the electronic road pricing method of congestion pricing will likely become even more feasible in the future, current technology, infrastructure, and political and privacy concerns (Anderson and de Palma, 2004) have led researchers to pursue alternative methods to correctly price externalities (Verhoef, Nijkamp and Rietveld, 1995a).

Increasing the price of parking (either directly or through taxation), is considered by some to be the second best alternative to road pricing and congestion tolls (Verhoef, Nijkamp and Rietveld, 1995a). Parking pricing allows planners to crudely mimic charge zones and congestion tolls by charging motorists who park within a designated area (Verhoef, Nijkamp and Rietveld, 1995a). It is much less technologically intensive to implement a parking tax than electronic road pricing, as it essentially amounts to a price change at parking meters and garages. This low fixed cost of startup implies that in the short run parking pricing could be an effective method of pricing externalities from motor vehicle use. Naturally, there are drawbacks to parking taxation as a means of congestion pricing, as it cannot differentiate by travel distance, route, or time, all of which affect congestion.

There is an expansive theoretical literature exploring the role of parking pricing and regulation and its effect on congestion (Anderson and de Palma, 2004; Arnott and Inci, 2006;

[4] Other examples include the Netherlands (Goh, 2002), Stockholm (Daunfeldt, Rudholm and Ramme, 2009), and Germany (Parry et al., 2014). Anas and Lindsey (2011) provide a review of road pricing case studies.

Arnott, 2006; Arnott and Rowse, 2009; Inci, 2015). Despite the theoretical support for parking pricing, there has been far less empirical work testing the ability of parking fees or taxes to reduce congestion. Much of the recent work is based on stated preferences rather than revealed preferences, making it difficult to make conclusions about policies (see Hensher and King, 2001; Tsamboulas, 2001). Perhaps the most relevant study considered the 25 percent parking tax increase in San Francisco in 1974 (Kulash, 1974). However, this study is focused on the elasticity of parking demand and does not more broadly explore the effect on congestion. He finds that parking demand was fairly inelastic to the tax increase, but it is difficult to know if the same pattern will hold among today's commuters where there are more commuters and congestion as well as more viable alternatives to driving. This is still an area of research that needs to be addressed (Inci, 2015). In general, there has been a lack of rigorous empirical work with strong identification strategies. As suggested in the introduction, the January 1, 2012 tax increase in Chicago creates an ideal natural experiment where we can obtain reliable estimates of parking tax increases on commuter driving behavior and make an important contribution to the second best congestion pricing literature.

On November 2, 2011, the Chicago City Council amended the city-wide parking tax, increasing the daily parking tax rate on all daily, weekly and monthly parking fees, as shown in Table 1; the fiscal incidence was placed on parking consumers. Essentially the tax was increased by approximately $1 a day on middle-cost monthly parking and $2 a day on more expensive parking. Although expensive, this tier of parking was not uncommon. At the Millennium Garages (over 9,000 parking stalls in the central business district) the reduced price Early Bird Special in December 2011 was $14. At these same parking garages, the monthly rate ranged from $240 to $289 a month, meaning each of these rates would have faced a $30 monthly tax increase in 2012. It is important to note that the Millennium Garages also offered reserved monthly parking for a much higher fee of $370 a month, which would have been subject to an additional $50 monthly tax (the tax rate would have increased from 16 percent to 29 percent). Needless to say, this was a substantial tax increase that was faced primarily by providers and consumers of upper-middle and high-end parking.

Chicago is a major center of economic activity and draws hundreds of thousands of workers from across Illinois and surrounding states. Between 2006 and 2010 it is estimated that nearly 400,000 workers regularly commuted to Cook County (where Chicago is located) from the surrounding five counties: DuPage, Kane, Lake, McHenry, and Will (U.S. Census, 2015). For our analysis, we restrict our focus to these five counties and Cook County to estimate how many of these commuters adjusted their commuting behavior in response to the January 1 tax increase.

3. Theoretical Intuition

To understand the response and potential heterogeneous impacts a parking tax might elicit, we present a simple modal choice model highly influenced by McFadden (1974) and Train and McFadden (1978). A representative agent gains utility from transportation mode j that depends on both consumption (x) and leisure (l). Each mode has a corresponding price (P_j) and commute time (t_j).[5] For simplicity we will assume that labor market frictions prevent workers from choosing labor supply continuously but rather that the agent works a fixed amount H at an idiosyncratic wage rate (w_i). Thus, for each transportation mode, the agent maximizes mode-specific utility $(U(x,l))$ subject to a time constraint $(T = l - H - t_j)$ and a resource constraint $(w_i H = x + P_j)$, where the price of the consumption good is normalized to one and U is concave. The agent will then choose mode k if $U(x^k, l^k) \geq U(x^j, l^j)$ for all modes j. By fixing H, this essentially becomes a tradeoff between commute times and monetary costs (Jara-Díaz, 1998). The agent's indirect utility associated with each mode j becomes
$V_j\big(P_j, t_j, w_i\big) = U\big(w_i H - P_j, T - H - t_j\big)$.

For clarity, we restrict each agent's modal choice set to two alternatives: driving and public transit.[6] This binary decision follows the simple rule for agent i

$$Drive_i = 1\big\{V_d(P_{di}, t_{di}, w_i) + \varepsilon_i^d \geq V_{pt}\big(P_{pti}, t_{pti}, w_i\big) + \varepsilon_i^{pt}\big\}. \tag{1}$$

where $V_d(\cdot)$ is the population-representative portion of the agent's indirect utility obtained from driving and $V_{pt}(\cdot)$ is the population representative portion of the agent's indirect utility obtained from taking public transit. Each agent's decision is also a function of idiosyncratic preference differences indicated by ε_i^d and ε_i^{pt}. As before, the utility of each mode depends on a mode-

[5] Commute times are actually a function of the total number of cars on the road. By considering the short run, we abstract from modeling this externality and take commute times as fixed.
[6] In reality agents have several different public transit modes available as well as alternatives such as carpooling and telecommuting.

specific price and commute time as well as the individual's wage. The price associated with driving (P_{di}) includes costs such as the price of fuel and vehicle insurance, as well as the price of parking.

First assume that prices and commute times are the same for all agents and that $\varepsilon_i^d = \varepsilon_i^{pt}$. Note that since labor supply is fixed at H the decision in equation (1) simplifies to

$$Drive_i = 1\{ U(w_i H - P_d, T - H - t_d) \geq U\left(w_i H - P_{pt}, T - H - t_{pt}\right)\}. \quad (2)$$

Consider the marginal individual who is indifferent between driving and using public transit, or

$$U(w_* H - P_d, T - H - t_d) = U\left(w_* H - P_{pt}, T - H - t_{pt}\right). \quad (3)$$

From the envelope theorem, we can observe how a small wage increase would affect the agent's decision: $\frac{\partial V_d}{\partial w} = H * U_x(w_* H - P_d, T - H - t_d)$ and $\frac{\partial V_{pt}}{\partial w} = H * U_x\left(w_* H - P_{pt}, T - H - t_{pt}\right)$. By concavity of U we know that as long as $P_d > P_{pt}$, then $\frac{\partial V_d}{\partial w} > \frac{\partial V_{pt}}{\partial w}$, meaning a small wage increase would cause the agent to strictly prefer driving over taking public transit. In fact, it will be true that at every wage greater than w_* driving will be preferred and at every wage less than w_* public transit will be preferred. Because marginal utility of consumption is falling in wages, an agent's decision to drive is completely characterized by the relation between their wage and the threshold wage w_*. Thus in this simple setting the decision to drive is completely determined by an agent's position in the wage or income distribution.[7]

Now consider a tax placed on parking such that the price of driving increases. Because the price of parking only affects the indirect utility of driving and $\frac{dV_d^i}{dp_d} < 0$ it is clear that for all individuals the indirect utility of driving will fall. The marginal individual will now find it optimal to use public transit, and total differentiation of (3) shows that the threshold wage will rise. All else equal, the total number of commuters who choose to drive will fall.

Note that if we relax the assumption that all agents face the same prices, we can no longer identify a threshold wage to characterize modal choice, but as long as $P_{di} > P_{pti}$ individual i's propensity to drive will be increasing in wages.[8] The effect of a parking tax increase would produce similar results on an individual level; for a given P_{di} and P_{pti} the wage required to make

[7] We will refer to wages and income interchangeable. By assuming H is fixed, wages and income are perfectly correlated.
[8] This is not a strong assumption as fuel, parking, and insurance costs often outweigh transit fees.

the individual indifferent between the two modes will rise and the indirect utility of driving will fall, which would result in a decrease in the number of commuters who drive if the distribution of prices is uncorrelated with the distribution of wages. If we further relax the assumption that $\varepsilon_i^d = \varepsilon_i^{pt}$, the previous results will be masked by noise. However, if the idiosyncratic component is uncorrelated with income we can still estimate marginal effects in a regression specification.

It is important to note that, as seen in Table 1, the parking tax increase on January 1, 2012 in the City of Chicago was progressively levied on the most expensive parking. This change is likely to have different impacts along the income distribution for several reasons. Even though idiosyncratic prices and preference vary in reality, the theoretical prediction that low-income workers will be less likely to drive still holds empirically (see Figure 1).[9] Among commuters to Chicago in 2011, there is a large difference in the propensity to drive between low-income and middle to high-income workers. We will exploit this preexisting variation to estimate the response in driving to a parking tax increase. Because low-income commuters are less likely to drive initially, they are less likely to be directly affected by any tax change.

Also, because the tax was progressive, it would only directly affect commuters who used the more expensive tiers of parking. For a low wage worker, paying over $300 a month in parking taxes and fees was likely not optimal prior to the tax increase. As such, it is likely that low-income commuters were not initially using expensive parking and thus less likely to be directly affected by the tax change.[10] Throughout our analysis we will operate under the assumption that low-income households are significantly less likely to be directly affected by this progressive parking tax increase. As such we will be able to estimate relative effects. Although we can only estimate relative elasticities, it is still informative to identify whether or not parking taxes are effective at reducing congestion. Given that both low and high-income workers use the same road, there will likely be indirect effects of the policy change. We look at a

[9] Low-income workers' propensity to drive is also likely lower due to large fixed costs associated with vehicle purchase and resource constraints that make driving unfeasible. For example, very low-wage workers might not be able to pay for parking, insurance, and fuel and still afford consumption.

[10] As can be seen on parking locator services such as bestparking.com, there is considerable parking available below the tax threshold, although it requires the driver to park farther from the downtown central business district. Thus low-income individuals can still drive and park in Chicago, but they would face time and convenience costs for parking farther away.

short period after the change to minimize indirect effects, but we will discuss the implications of indirect effects later on.

4. Data

Given adequate individual level data on modal choice, income, and individual demographics and characteristics a discrete choice model could be used to estimate the condition in equation (1). Although the American Community Survey (ACS) includes several questions about individuals' place of work and commute, there are several characteristics of the data that are not conducive to the question at hand. First, it does not provide a large enough sample to explore the modal choice response. Between 2008 and 2011 there were nearly 46,000 individuals in the ACS who reported working in the Chicago Public Use Micro Area work area, but because only the year of the survey is provided, we are unable to improve precision and eliminate potential omitted variable bias by controlling for changes in weather and other prices which might be correlated with the timing of the tax increase. Second, changes in ACS geographic boundaries in 2012 do not allow us to separate commuters to Chicago from the rest of Cook County, leading to potential attenuation and making it difficult to attribute a causal interpretation. We will examine what variation is possible in the ACS later, but for our main analysis we rely on road observation level data which allows us to use high frequency measures and account for a larger share of the commuting population.

In order to estimate commuter response to the January 1, 2012 tax increase, we combine geographic data on median household income with commute time vehicle counts, daily L-ridership counts, and average daily ridership on the Pace Bus system. Using these separate outcomes we are able to not only measure drivers' response but also their substitution to alternative modes of transportation. Because low-income households are less likely to utilize expensive parking and be affected by this specific tax increase, we exploit geographic variation in median household income to identify commuter response to the tax increase. Although we would ideally know the wages or income of each commuter, data limitations only allow us to proxy using local geographic measures. Measures of median household income are obtained from the U.S. Census Bureau and computed from the 2007-2011 five-year sample of the ACS. When examining vehicle counts and Pace Bus ridership, we use the county subdivision measure of median household income. Because the L-train is almost entirely contained within the City of

Chicago, we look at median household income by census tract when considering ridership, as the county subdivision estimate would be constant throughout the city. To assign income levels to each point of observation, we geocode each road measuring point and transit station and assign the median income of the closest geocoded county subdivision (or census tract).

4.1 Vehicle Count Data

We obtained administrative hourly vehicle counts from the Illinois Department of Transportation (IDOT) for each hour between January 2011 and May 2012 from all permanent automatic traffic recorders (ATR) in Cook County and the surrounding counties: DuPage, Kane, Lake, McHenry, and Will.[11] In 2011-2012 there were 42 permanent ATRs in the region. Occasionally the ATR will malfunction, recording a zero hourly count. To correctly identify these errors we flag all days where every hour has a zero count and construct a measure of operating frequency for each ATR direction by hour. Rather than include ATR stations that only report sporadically, we restrict our sample to those stations that operated correctly on over 85 percent of the days in our sample period, which restricts our sample to 45 ATR station directions as seen in Figure 2.[12] We will refer to this sample as the Full Sample. These observation points are distributed around most of the city and exhibit considerable variation in income and distance.

One weakness of hourly road counts relative to individual level data is an ambiguity regarding changes in commute times. Although a reduction in vehicle counts per hour will contribute to congestion reduction, it alone cannot identify improvements to congestion. As an extreme example, a road can become so heavily congested that traffic is at a standstill. By definition the hourly vehicle count (number of vehicles passing a measuring station) would be low, but this does not signal low levels of congestion. In this case peak commute hours would become longer and the hourly count would be low. In order to capture actual changes in vehicle use rather than hourly changes, we aggregate hourly vehicle counts over morning and evening commute periods to identify the change in the total number of cars during the morning, evening or combined (morning and evening) commute. When defining the morning commute, we include hourly counts between 5:00-9:00 AM, and similarly in the evening we include hourly counts

[11] 2012 hourly count data by direction and lane is publically available through the IDOT Transportation Data Management System, but the 2011 data was created by a previous system. We obtained the administrative 2011 data directly from IDOT.

[12] There are 22 ATR stations that meet the 85 percent qualification in both directions, and one station where only one of the directions meets the qualification.

between 3:00-7:00 PM. We define this period to be significantly longer than “rush hour” to avoid counting substitution to earlier or later commute times as a reduction in the total number of vehicles. We refer to this level of observation as a commute period. As morning commuters likely participate in the evening commute as well, looking at the combined morning and evening hours will give estimates of the change in the total number of trips which is likely twice as large as the number of commuters who change their behavior. When aggregating vehicle counts to the commute period level, we have nearly 15,500 daily vehicle count observations in our Full Sample. The average number of commute period trips for each road direction is 5,530.

Because it is not obvious that traffic at each of the ATR stations is Chicago-bound, we also construct a restricted sample which we refer to as the Commuter Sample. This sample is constructed by restricting our focus to roads that are displayed on the popular real-time Chicago area travel reference website, TravelMidWest.com. This sample is composed of 22 ATR station directions which are in general more heavily used roadways with a mean of 6,937 daily trips during the combined commute periods. In comparison with the ACS, this sample accounts for approximately 76,000 commuters each day. Using road count-level data provides us with a more representative and frequent measure than is provided by the ACS, which is needed to estimate potentially small or short-run effects.

The decision to drive likely depends on various external factors such as weather, the price of gasoline, and the occurrence of traffic accidents. To increase precision, we combine our hourly traffic count data with local average temperature and precipitation measures collected from the PRISM Climate Group as well as the U.S. Energy Information Administration (EIA) average weekly gasoline prices. However, we are unable to track daily accident and construction measures for each roadway over the period, this will likely reduce our precision.

4.2 Alternative Transportation Use Data

If commuters are responding to the price increase by switching transportation modes, any decrease in vehicle counts should be accompanied by an increase in use for alternate modes. To supplement our vehicle count analysis, we also test to see if there is an increase in public transit use. One of the main alternatives is the Chicago Transit Authority (CTA) L Train (the L) heavy rail/subway system. The L has over 140 stops throughout the city and close surrounding areas. To measure the L Train ridership, we make use of CTA administrative daily ridership counts by station from 2002 to present provided by the City of Chicago Data Portal. These data are then combined with the weather and gasoline price data described above as well as the median household income of the nearest census tract to each station. As seen in Figure 3, there is variation in local median income, although it is closely correlated with geography.

In addition to daily measures on the L, we use monthly daily ridership averages on the Pace Bus system from the Regional Transportation Authority Mapping and Statistics (RTAMS). The Pace Bus system includes over 150 bus routes that mostly extend from outlying areas toward the city.[13] This allows us to assign the starting point of each route to a geographic area and interpret commuter direction. We combine these data with monthly rain, temperature, and gasoline price data as well as county subdivision median household income from the U.S. Census Bureau. Unlike the L, the Pace Bus route origin exhibits considerably more variation in local median income, and it appears to be spread more uniformly over the outlying areas. At times it is difficult to geocode the exact point of origin, and for this reason we restrict our sample to routes with the origin plotted less than 10 miles from the central business district.

As stated before, we will also examine the 2008-2012 ACS sample of employed individuals who worked in the Chicago PUMA. The ACS includes questions about place of work, mode of transportation, and departure and arrival time. Between 2011 and 2012, the place of work PUMA delineation in the ACS was changed, and there was no longer a code unique to Chicago. Instead, only Cook County was identified. Although we can identify commuters to Cook County during both time periods, this will likely severely attenuate our estimates. First, many of the commuters are unaffected by the policy change. Also, if the tax increase induced commuters to park at the city boundary, and then take public transit, we would not be able to capture this change. This is only a concern if the change differentially affected individuals across income groups. As this might have occurred we interpret the ACS as suggestive evidence but do not attribute a causal interpretation to the estimated results. We restrict our sample to commuters in one of the five counties surrounding Cook County, which includes over 11,000 workers with an average commute time of 46 minutes.

[13] Although the CTA bus system covers more areas downtown, it becomes difficult to assign each route to a geographic area and it is unclear if riders are commuting toward or away from the taxed area.

5. Empirical Strategy

Because we are using aggregate road count data, it is not feasible to estimate a modal choice model, so we estimate the effect of the policy on road-level vehicle usage and expand the framework to estimate the effect of the January 2012 tax change on vehicle counts. Our reduced form estimation exploits the fact that low-income commuters should be less affected by the tax both before and after it was implemented. To estimate the model, we use a difference in differences approach comparing hourly vehicle counts before and after the January 1, 2012 implementation across income groups, where the lowest income group serves as our base. To define income groups, we divide our Full Sample into approximately equal size quartiles at \$65K, \$75K, and \$90K.[14] As the data suggest in Figure 1, this division captures the initial differences in modal choice across income groups needed for identification. In our Full Sample, there is only one station located in a county subdivision where the median household income is over \$110,000. In the Commuter Sample there are no stations in area with a median income over \$100,000. For this reason, we expect all three income groups to respond to the parking tax. Our preferred empirical specification is as follows

$$count_{sdt} = \beta_0 + \beta_1 yr2012_t * (\$65 - 75K)_{sd} + \beta_2 yr2012_t * (\$75 - 90K)_{sd} + \beta_3 yr2012_t * (\$90K\ or\ more)_{sd} + \beta_4 yr2012_t + X_{sdt}\Gamma + \phi_{\mathrm{sd}} + \varepsilon_{sdt}. \quad (4)$$

where *s* indicates recording station, *d* indicates direction, and *t* indicates day. Our dependent variable is the total commute period vehicle count reported at the station direction level. We also consider the log of this count as the dependent variable to account for nonlinearities in $count$ and to estimate the percentage change associated with the tax. The variable $yr2012$ is a binary measure equal to 1 after January 1, 2012 and zero otherwise. X_{sdt} is a matrix containing controls including local daily average temperatures and precipitation, weekly average gas prices, and day of the week, and month fixed effects to capture seasonal trends and day of the week differences in utilization. A stationXdirection fixed effect is also included to capture any directional road-specific time-invariant unobserved heterogeneity, such as road size and capacity. Because we are interested in commuters' response to the parking tax increase we restrict our analysis to the morning commute (5:00-9:00 AM), the evening commute (3:00-7:00 PM), and these two periods

[14] Actual percentiles are as follows, 25th: \$63.5K, 50th: \$76K, 75th: \$91.2K. We use rounded values for ease of interpretation.

combined. Our key parameters of interest are β_1 through β_3, which are interpreted as the expected change in vehicle counts per roadway for each income group between 2011 and 2012.

The specification in equation (4) relies on the assumption that income groups follow parallel trends in order for the low income group to represent a valid counterfactual. In Figure 4, we plot the average total vehicle count for all hours between 5:00-9:00 am and 3:00-7:00 pm for each income group. Because we restrict our sample to exclude missing days and several stations are missing data for most of August and September, we exclude these months from the figure to avoid taking averages over a smaller denominator in some months.[15] In our regression analysis we do not need to construct means, so the same problem is not present. From the figure it is apparent that although there is a difference in levels, the three higher-income groups follow a trend rather similar to that of the low-income group up until the beginning of 2012. From the figure there is a noticeably larger gap between the two highest income groups and the low-income group in 2012 than in the early 2011 pre-period. This graphic evidence suggests that a difference in difference estimation across income groups does not violate the parallel trends assumption, and it also suggests a possible small response among stations in the highest income areas, which we will test more rigorously in our regression specification.

We first estimate this relationship over the Full Sample and then restrict our analysis to the Commuter Sample to better understand the effect on commuters. As explained before, the Commuter Sample is restricted to roadways that are listed in the TravelMidWest.com travel time report section. We use this rule as a proxy for whether the road is a heavily used commuter route. Given that the parking tax applies to parking in Chicago, we expect the effect to be larger in this sample.

When examining utilization rates of alternative modes of transportation and other aspects of commuter behavior we use the same model as described in equation (4) but replace the dependent variable. As some of the data are only reported monthly or annually, we adjust the included controls appropriately. In all cases we correct the standard errors for clustering at the stationXdirection, train station, or bus route respectively to account for correlations in unobserved heterogeneity within clusters and across time.

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[15] For the two middle income groups in August and September, there is only one station a piece that reports, when we average over these months they are given full weight and deviate heavily from the mean reported in prior months because we are no longer taking an average.

6. Results

6.1 Summary of Results

We first estimate equation (4) for the full and the commuter sample over the morning (5:00-9:00 AM), evening (3:00-7:00 PM), and pooled (5:00-9:00 AM, 3:00-7:00 PM) commute hours as reported in Table 2. For all commute time periods, the tax is associated with a negative effect for the two highest quartiles of the distribution of median household income, although only the coefficient on the third quartile is statistically significant. As expected, when we limit our sample to the commuting sample, the estimated effect becomes much larger and is statistically significant for stations in both the third and fourth quartile of local median household income. In the wealthier county subdivisions we estimate that the tax led to a reduction of 176-197 vehicles in the morning commute and 212-217 vehicles in the evening commute. From the combined sample we estimate a reduction of 388-414 total trips. This represents an average 6.2-7 percent reduction in total vehicles during the morning commute and a 5.1-5.2 percent decrease in the evening commute, for a total trip reduction of 5.6-6 percent.

Because morning and evening traffic patterns are not independent, we would expect similar responses in both the morning and evening. Only observing a response in one direction would not be consistent with commuters responding to the parking tax increase. We find that the change after the January tax is consistent over the morning and evening periods and not statistically different, an intuitive condition for the observed change to be a response to the tax.

Rather than imposing that each recording station experience the same effect in levels, we also consider the log hourly count and interpret the effect as the percentage change associated with the new tax. The results looking at the log hourly count are consistent with our estimates in levels suggesting a negative effect for more wealthy stations in the full sample, which becomes more pronounced as we focus on more commuter-oriented stations. Our estimates suggest the tax led to a 4.2-6.5 percent reduction in total vehicle trips in more wealthy areas in the pooled time sample.

The results across all three time groups with both outcomes consistently estimate negative effects for high-income areas (top two quartiles) on the order of 4-7 percent for the Commuter Sample. By aggregating up 2011 vehicle counts during both the morning and evening commute across all roads in our Commuter Sample by income group, we estimate that an average of 25,000 vehicles passed ATRs on roads in the third quartile and 52,000 vehicles passed ATRs on roads in the fourth quartile each day. Our estimates suggest that on these roadways approximately 2,200 ((0.056*52,000+0.06*25,000)/2) commuters in high-income areas stopped driving due to the tax increase. Because we do not have data on all unique routes in the city, this is likely a lower bound. From the ACS we estimate that in 2011 approximately 94,000 individuals outside of Cook County commuted to Chicago by car. Applying a 4-7 percent reduction uniformly would imply between 3,700 (0.04*94000) and 6,500 (0.07*94000) commuters quit driving.

In the Commuter Sample we estimate that ATR stations in the second quartile also experience a non-significant reduction in total vehicle counts. As there is no a priori reason to believe that the propensity to drive would jump discontinuously precisely at $65,000, this group is likely measured with error. If an important share of commuters in this income group do not initially drive or utilize expensive parking and are not directly affected by the tax change, then this group would contain both treated and untreated participants, which would attenuate the estimates toward zero. In reality, each individual's idiosyncratic preferences are likely to yield heterogeneous thresholds, meaning that the $65,000 cutoff likely introduces some level of measurement error. Although our specification in equation (4) should provide a lower bound estimate, we estimate a variant of equation (4) but enter median household income continuously rather than as separate quartiles to verify that our estimates are not dependent on our selection of cohorts. This removes the measurement error associated with the threshold but imposes linearity restrictions. The estimation results provided in Table 3 support our findings in Table 2, and suggest that ATR stations in high-income areas experienced a statistically significantly larger reduction in total vehicle counts. For the morning Commuter Sample we estimate a reduction of 43 vehicles per station (or 1.5 percent) for every $10,000 increase in median household income. This would suggest that an ATR station assigned to an area with a median income of $90,000 would have seen an additional reduction of 107.5 vehicles during the morning commute relative to a station assigned to a $65,000 area. This estimate is smaller than those reported in Table 2, although within the confidence intervals. Estimates for the evening and combined commute times are also consistent with the previous estimates. Even when imposing linearity, the results suggest that stations in high-income areas experienced an additional 2-4 percent reduction in vehicles per hour relative to low-income areas.

As seen in Figure 4, it appears that the drop in vehicle trips occurs prior to the tax change. To test this hypothesis and explore effect heterogeneity over time we set up the estimation as an event study. First we group observations into six periods corresponding to quarters one through four of 2011 and the first two quarters of 2012.[16] Rather than estimating the 15 quarters by income group parameters, for clarity and ease of interpretation we include median household income linearly as in Table 3 rather than looking at the differences across median household income quartiles. We plot the coefficients in Figure 5, with regression results available in the Appendix. We use the fourth quarter of 2011 as our omitted quarter.

In the Commuter Sample, during both the morning and the evening, there is a noticeable reduction starting in the first quarter of 2012 (see Figure 5). This pattern is most pronounced in the evening commute times. Prior to the 2012 tax change, none of the interaction coefficients are statistically different from zero. In all quarters after the change the coefficient is large, significant and negative, although the coefficient on the first quarter of 2012 for the morning commute times is only significant at the 10 percent level. A similar pattern holds for the combined time periods as well as when looking at log counts, although the pattern is not as obvious. As Figure 5 shows, there appears to be a discrete break from the previous trend in 2012, although it only becomes pronounced in the second quarter.

As we move further away from the time of the intervention, it becomes difficult to interpret whether the large effects are due to gradual changes in commuting behavior or indirect effects on the control group. For example, if fewer commuters choose to drive, the commute time required to drive might fall in the long run, increasing the indirect utility of driving.[17] If this differentially impacts low-income workers we would see an increase in their driving behavior which would be viewed as a larger reduction in the difference in differences estimation. It is unclear how long this general equilibrium adjustment would take, and as such we recognize that the effects we estimate might overstate the negative effect of the tax change. From Figure 4 it appears that total trip counts in low-income areas did increase, but not by as much as our estimated coefficient. From our regression on the combined commute times for the Commuter Sample, we estimate a coefficient of 274 on $yr2012$, significant at the 10 percent level. This

[16] We only use data through May 31, 2012, so the second quarter of 2012 only contains data from the first two months, April and May.

[17] Recent work has shown that it is still the case that increased capacity does not reduce congestion, as more commuters find it optimal to drive. A reduction driving could be seen as a capacity increase (Duranton and Turner, 2011).

represents the change in total trips for the omitted group between 2011 and 2012. If we attribute this entire shift to indirect effects (essentially assuming there is no secular trend in vehicle usage) then the tax increase would still be associated with a 111-138 total vehicle reduction (1.5-1.9 percent) for the two highest quartiles. Even allowing for indirect effects on low-income areas, we find that total vehicle trips fall after the tax is put in place.

As stated before, a reduction in total vehicle or trip counts due to the tax should be accompanied by an increase in usage on alternative modes. To verify this we look at transit data. In the Chicago metropolitan area there are several major public transit options, two of which are the L Train (heavy rail system) and the Pace Bus (commuter bus system).[18] Using the framework identified in equation (4) we look at the effect of the policy by median household income groups on ridership rates. Unfortunately we are only able to get daily station entry counts for the L Train, meaning we do not know where riders exit and we cannot look at differences across time in a day. Pace Bus data are only available as monthly daily average ridership counts along given routes. As with the L Train, we do not know where riders exit as well as where riders enter. Thus we must assume that any changes in non-Chicago bound ridership after the tax was implemented is uncorrelated with median household income of station of origin. Given these data limitations, we interpret our estimated coefficients with caution and consider them suggestive.

As reported in Table 4, L Train ridership counts increased after the tax was implemented in all specifications. First we restrict our sample to 2011 and 2012, the same years observed in our hourly road count data. Under this specification ridership significantly increased for all income groups, with the largest increases for stations in the wealthiest census tracts, although the estimates are not statistically significantly different. When we expand the sample to include a longer pre-trend the estimate becomes much larger in magnitude, suggesting that after the tax over 500 people per station substituted toward the L Train for all median household income levels over $65,000. This seems too large and is likely due to a growing trend not uniform to all income groups.

When estimating changes in Pace Bus ridership, we estimate positive coefficients for all median household income groups in most specifications but have very low precision. This is likely due to our inability to control for daily weather fluctuations and other day-to-day

[18] Two other important sources of public transportation are the Metra system (commuter train) and the CTA Bus (city bus system). Unfortunately, data limitations do not allow us to consider the response on these systems.

differences. Only one of the estimates is statistically significant for the $75-90,000 median household income group, although this is only marginally significant at the 10 percent level. Our estimates from both public transit systems suggest that there was an actual change in commuter modal composition and that total vehicle counts did respond to the tax increase. Our most conservative estimates suggest that L Train ridership increased by between 2 percent and 3.5 percent per station depending on the local income level. Combining this with average daily ridership rates in 2011, we estimate that approximately 4,600 more commuters (each commuter enters twice) rode the L in 2012 than in 2011 due to the tax increase. Although this is larger than our estimated aggregate effect for the roads with count data, it falls within the range we calculated from the ACS for the entire commuting population. Although not conclusive, the transit data support the hypothesis that commuters substituted away from driving after the tax increase.

When commuters make a transportation modal choice decision, there are more alternatives in their choice set than simply driving or public transit. For example, commuters can choose to carpool, ride a bike, walk, or work from home. Unfortunately, the only data available to test these alternatives are the ACS place of work and commute supplement. As described above, some geographic definitions in the ACS changed between 2011 and 2012, and although we do not expect the change to systematically impact high and low-income families differently, we interpret the ACS results as suggestive. We consider the probability of carpooling, the probability of walking or biking, and the probability of working at home as well as driving and taking public transit as reported in Table 5. In each case our estimates are insignificant. Although the signs are as expected for bus transit, driving, and carpooling, the ACS is inconclusive. In addition to looking at carpooling, we look at the number of riders among drivers. We find that this rate significantly increased for all income groups, which might suggest movement along the intensive margin. However, it is possible that this would no longer be significant once we correct for multiple hypothesis testing. We also look at commute times in the ACS and find no significant difference.

6.2 Robustness and Falsification Tests

Our identification relies on the assumption that ATR stations in high-income and low-income areas face parallel trends and that there were no other changes at the same time that differentially impacted high and low-income individuals. Although we are unable to directly test these assumptions, we impose several tests and discuss possible alternatives.[19]

First, although the parking tax was imposed on January 1, 2012, it was amended by the City Council on November 2, 2011. It is possible that commuter modal choice responded to the announcement, which could bias our comparison. If commuters responded by substituting away from driving in November, this would bias our estimates down, but if commuters responded by driving more, our estimates would be biased upward. We test to see if commuters responded to the announcement by including an indicator for November and December of 2011 interacted with each income group. In essence we now have three periods: pre, post-announcement, and post-tax change. In this specification there is only one significant post-announcement coefficient for ATR stations in areas with median income between $75,000 and $90,000 for the full sample. Our estimates for the post-tax change estimates are similar to those in Table 2 but larger in some cases, and they can be found in Appendix Table A1.

To test that our income groups have similar enough pre-trends and that our specification is not just capturing trending differences, we estimate the same specification but specify August 1, 2011 as the start of the new tax increase and only use observations from 2011.[20] As seen in Appendix Table A2, under this specification none of the treatment effects by income group are significant, and in many cases they are opposite signed. This suggests that we are not just capturing a secular trend that varies by income group.

Given that each ATR station records traffic in separate directions, one might expect that roadways heading toward Chicago in the morning experience a greater effect than roadways leading away from the city, and vice versa for the evening commute. To exploit this variation, a triple difference could be constructed to compare hourly counts before and after the tax change across income groups and direction of travel. To determine direction of travel, one would combine road direction information (e.g., South Bound) with latitude and longitude coordinates

[19] In studying the Chicago parking tax setting, we have also found that there were two additional changes made on January 1, 2012 that affect commuters. First, the Metra commuter train system reduced the amount of pre-tax transit benefits that could be deposited from $230 to $125. Although this is a large reduction, it would induce Metra users to substitute away from public transit, working against us. Second, the Illinois Tollway system increased several tolls by 15-25 cents. None of the roadways we consider face tolls, although they might lead to toll roads. Overall this would result in at most an $11.50 increase each month (.25*2*23 commuting days), significantly less than the $30-60 dollar increase for parking. It is likely that drivers from low income areas would respond more elastically to such small tolls, which would work against our estimates as well.

[20] We look at August 1, 2011 so as to include the same time frame of 5 months of “post treatment” without including any of the actual treatment period.

of each station and the central business district to classify roadways as "toward Chicago" or "away from Chicago." For example, if a station is north of the central business district and South Bound then that roadway is flagged as "toward Chicago."

Although intuitive, it is not clear that this comparison would yield unbiased estimates. First this simple classification likely has a considerable amount of measurement error, which would attenuate the coefficient on the triple interaction. For example, although a station might be west of the central business district and West Bound, it might be the most convenient path to the nearest freeway entrance leading to the city. By flagging this roadway as "away from Chicago" we are attributing any response at this point to the tax change to unobserved changes in the counterfactual, thus introducing noise. Without an understanding of local commuters' travel paths, it is difficult to eliminate this measurement error. Second, the tax applies to all non-private parking in the city. As such, residents and recreational drivers who pay for parking and often travel opposite the flow of commuter traffic might also respond, contaminating the directional counterfactual. Both of these concerns would attenuate the coefficient on the triple difference. We estimate the proposed triple difference model and, although the coefficient on the triple interaction is almost always negative (suggesting an effect larger in magnitude for roadways in the direction of the Chicago commute), it is never statistically significant.[21]

Although we have focused mainly on commuting hours, previous literature has suggested that recreational drivers and those with more flexible schedules might be more responsive to parking taxes (Tsamboulas, 2001). To estimate the response of flexible drivers, we estimate the same specification but limit our sample to the daytime hours of 10:00 AM–2:00 PM. We understand that not all drives during this time are made by recreational drivers, but it is likely that workers commuting at this time also have more flexible work schedules. We find that the reduction in vehicles in both samples is large and significant (see Appendix Table A4). We also expand our morning and evening commute periods to 4:00-10:00 AM and 2:00-8:00 PM to see if our main analysis is not capturing substitution to earlier or later times outside of our defined commute periods. We find that the effects are still significant, negative, and larger, suggesting that the reduction in total vehicle counts is due to the parking tax increase.

When considering any question of taxation, it is important to consider questions of incidence. Although the fiscal incidence falls on the commuter, it is not clear to what extent the

[21] These results are displayed in Appendix Table A3.

supply side responded to the tax increase. To examine this question, we looked at Internet archives of parking garage and street parking websites. We found evidence that some garages did not change their prices, while other parking providers updated their prices to include the full tax. Chicago Parking Meters, which are privately operated, report that they were required by law to add the tax to the parking price and not absorb the cost.[22] Overall only limited historical pricing information was available. Although we cannot measure the degree of supply side incidence, there is evidence that some share of commuters were exposed to the price change. Given that some suppliers likely bore part of the tax, our estimated results would correspond to a lower tax faced by the commuter, suggesting larger elasticities. The data suggest that the observed changes in vehicle counts are due to actual reductions in vehicle use, which are accounted for by substitution toward public transit. Our results have remained robust to various alternative specifications, and although we cannot directly verify tax incidence, our estimates would provide lower bounds.

7. Conclusion

The growing amount of vehicles and congestion has led many to consider feasible methods of congestion pricing. In this paper we explore the effectiveness of parking taxation at reducing congestion. Using natural variation created by geographic income differences and a city-wide parking tax on expensive parking in Chicago, we estimate the effect of an additional $1-2 daily parking tax on commuters' modal choice response. We find that commuter roadways in high income areas, where drivers were more likely to be affected by the tax saw a reduction in total vehicle counts ranging from 175-217 cars over the daily commute period. This corresponds to a 4-6 percent reduction in total vehicle counts. Even when accounting for possible indirect effects we estimate a small direct effect reduction in vehicle counts of at least 1.5-1.9 percent.

To verify that we are capturing an actual reduction in congestion, we examine changes in total commute period vehicle counts as well as public transit ridership and carpooling behaviors, finding a significant drop in the total number of vehicles and a 2-3 percent increase in L Train ridership, and suggestive evidence of increased carpooling behavior. We also find that the response cannot be explained by substituting driving to earlier or later times.

[22] See http://chicagometers.com/news/2012/2/13/city-of-chicago-and-cook-county-parking-lot-and-garage-operations-tax.aspx (accessed August 14, 2015).

In 2012 the median monthly parking rate in Chicago was $289, with an additional tax of $30 a month (10.38 percent). If we construct an aggregate response from the estimates for the combined commute periods in the Commuter Sample we estimate a -3.1 percent direct response to the increase.[23] Using a response rate of 3.1 percent we estimate an approximate aggregate vehicle count elasticity of 0.3 (0.031/0.1038). The total response is nearly 10 times smaller than the 30 percent reduction in car traffic associated with the introduction of the 2003 5£ (nearly $10 in 2012 US dollars) London toll zone (Quddus, Carmel and Bell, 2006). However, given that the Chicago parking tax only increased by $2 (one fifth of the 2003 London toll fee), a linear extrapolation of our estimate would yield a 15.5 percent reduction (3.1 percent*5) in vehicle trips. Although it is not clear that the response would continue linearly and the settings are not completely comparable, the data suggest that parking taxation can be used as a method of congestion pricing, although it does not perform as efficiently as a congestion toll.

As previously noted, parking taxation is unable to differentiate between length, route, and mode of travel all of which affect the size of the driving externality. Additionally, parking taxes can only induce those who park to internalize the social costs they create. For these reasons, it is not expected that parking taxes will be as efficient as a congestion toll. Our setting only allows us to estimate relative changes, but suggest that parking taxes can be used to reduce vehicle trips and congestion in the short run. As a reduction in vehicle trips reduces congestion, it is unclear how large the long-run effect will be (Duranton and Turner, 2011).

Although parking taxation presents unique challenges of tax incidence and an inability to charge all commuters their social marginal cost, the data suggest that moderately large parking taxes can reduce vehicle use and congestion, providing a potential second best congestion pricing short-run alternative. Although road pricing and dynamic congestion tolls are more efficient, parking taxation can be viewed as a short run solution to congestion pricing. The results of this paper suggest that field experiments designed to isolate the impact of parking taxes on driving behavior can help identify how efficiently parking taxes can reduce congestion. Governments and communities seeking to reduce congestion-related externalities in the near future should consider implementing parking taxation policies to price the social costs of driving.

[23] Assuming the low income group had no response, we multiple the response of each quartile by 0.25 to obtain the aggregate expected response, (0-0.016*0.25-0.065*0.25-0.042*.25)*100=-3.075 percent. If the lowest income group did respond this estimate would be larger.

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Tables and Figures

Table 1. January 1, 2012 Weekday Parking Tax Changes

	Before January 1		After January 1	
Base Price	Rate	Percentage	Rate	Percentage
		Daily Rate		
<$2	$0	0	$0	0
$2-5	$1.00	20-50%	$1.00	20-50%
$5-12	$1.75	14.6-35%	$1.75	14.6-35%
≥$12	$3.00	≤25%	$5.00	≤41.7%
		Weekly Rate		
$10-25	$5.00	20-50%	$5.00	20-50%
$25-60	$8.75	14.6-35%	$8.75	14.6-35%
≥$60	$15	≤25%	$25	≤41.7%
		Monthly Rate		
$40-100	$20	20-50%	$20	20-50%
$100-240	$35	14.6-35%	$35	14.6-35%
$240-300	$60	20-25%	$90	30-37.5%
$300-400	$60	15-20%	$110	27.5-36.7%
≥$400	$60	≤15%	$120	≤30%

Notes: Tax rates apply to all weekday public parking within the City of Chicago. Daily weekend taxation did not adjust. In December 2011, the publicly owned but privately operated Millennium Garages at Millennium Park offered daily parking for $24-29 and monthly rates for $240-289. These combined garages account for over 9,100 parking spaces in the Central Business District. The median monthly parking rate for all of Chicago in 2012 was $289.

Table 2. Change in Total Vehicle Counts in Response to Jan 1, 2012 Parking Tax Increase

	5:00-9:00 AM		3:00-7:00 PM		5:00-9:00 AM & 3:00-7:00 PM	
	Full Sample	Commuter Sample	Full Sample	Commuter Sample	Full Sample	Commuter Sample
	Total Vehicle Count					
Yr2012*Median$90k+	-39.480	-175.607**	-29.924	-211.931**	-69.403	-387.538**
	(48.360)	(81.200)	(49.361)	(82.563)	(89.310)	(153.941)
Yr2012*Median$75-90k	-102.392*	-197.154**	-110.592**	-217.002***	-212.985**	-414.156***
	(52.518)	(69.793)	(53.693)	(69.908)	(98.567)	(125.619)
Yr2012*Median$65-75k	2.272	-117.073	61.441	-61.741	63.713	-178.815
	(52.460)	(83.701)	(61.744)	(104.953)	(108.312)	(181.434)
Mean Total Count	2295	2806	3236	4131	5530	6937
Observations	15,456	7,555	15,456	7,555	15,456	7,555
	Log(Total Vehicle Count)					
Yr2012*Median$90k+	-0.009	-0.038	-0.017	-0.048***	-0.012	-0.042**
	(0.013)	(0.023)	(0.011)	(0.016)	(0.010)	(0.017)
Yr2012*Median$75-90k	-0.043**	-0.073**	-0.047***	-0.068**	-0.042***	-0.065***
	(0.018)	(0.031)	(0.015)	(0.025)	(0.012)	(0.020)
Yr2012*Median$65-75k	0.020	-0.018	0.014	-0.016	0.017	-0.016
	(0.016)	(0.025)	(0.015)	(0.022)	(0.014)	(0.021)
Number of Clusters	45	22	45	22	45	22
Observations	15,438	7,540	15,456	7,555	15,456	7,555

Notes: Observations are the sum of hourly counts during the specified period for each station direction. Sample restricted to unique stationXdirection ATRS that were functioning over 85 percent of the days from January 1, 2011 to May 31, 2012. Days where 0 vehicles were recorded for all hours are excluded. All regressions include local temperature and precipitation controls as well as weekly average gasoline prices and hour of day, day of week, month, and station direction fixed effects. Weekends, federal holidays, and other major holidays are excluded. Standard errors clustered at the stationXdirection level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3. Change in Total Vehicle Counts in Response to Jan 1, 2012 Parking Tax Increase, Imposing Linearity in Income

	5:00-9:00 AM		3:00-7:00 PM		5:00-9:00 AM & 3:00-7:00 PM	
	Full Sample	Commuter Sample	Full Sample	Commuter Sample	Full Sample	Commuter Sample
	Total Vehicle Count					
Yr2012*Median H.H. Income	-18.002	-42.975**	-22.089	-66.976***	-40.091	-109.951***
	(12.334)	(19.781)	(13.860)	(18.805)	(24.302)	(36.190)
Yr2012	144.530	366.832**	132.559	502.076***	277.089	868.908***
	(98.688)	(153.562)	(114.563)	(156.672)	(199.193)	(291.174)
Mean Total Count	2295	2806	3236	4131	5530	6937
Observations	15,456	7,555	15,456	7,555	15,456	7,555
	Log(Total Vehicle Count)					
Yr2012*Median H.H. Income	-0.007*	-0.011*	-0.007*	-0.014***	-0.006**	-0.012***
	(0.003)	(0.006)	(0.004)	(0.004)	(0.003)	(0.004)
Yr2012	0.054*	0.093*	0.043	0.100***	0.044*	0.094**
	(0.027)	(0.045)	(0.028)	(0.035)	(0.024)	(0.034)
Number of Clusters	45	22	45	22	45	22
Observations	15,438	7,540	15,456	7,555	15,456	7,555

Notes: Observations are the sum of hourly counts during the specified period for each station direction. Sample restricted to unique stationXdirection ATRS that were functioning over 85 percent of the days from January 1, 2011 to May 31, 2012. Days where 0 vehicles were recorded for all hours are excluded. Median household income reported in $10,000 units. All regressions include local temperature and precipitation controls as well as weekly average gasoline prices and hour of day, day of week, month, and station direction fixed effects. Weekends, federal and other major holidays are excluded. Standard errors clustered at the stationXdirection level. *** p<0.01, ** p<0.05, * p<0.1.

Table 4. Transit Ridership Response to Jan. 1, 2012 Parking Tax Increase

	L Train Daily Ridership			Pace Bus Average Daily Ridership		
Sample Years	2011-2012	2002-2012	2002-2014	2011-2012	2002-2012	2002-2014
Post*Median$90k+	142.530***	530.042**	524.384**	50.089	77.357	166.128
	(54.423)	(212.082)	(204.017)	(64.120)	(74.117)	(122.028)
Post*Median$75-90k	130.278***	524.518***	416.193*	-3.648	78.001*	61.694
	(46.704)	(163.375)	(223.892)	(22.357)	(41.039)	(44.179)
Post*Median$65-75k	86.076*	500.671**	567.701**	-9.330	39.670	35.712
	(46.059)	(225.706)	(255.652)	(14.373)	(43.291)	(46.098)
Post*Median	21.168***	74.370***	67.050***	0.064	5.726	8.364
H.H. Income	(6.740)	(22.865)	(24.520)	(5.606)	(9.361)	(11.528)
Post	-43.717	150.763	322.874**	53.617	-96.564	-53.455
	(41.937)	(124.959)	(127.177)	(37.111)	(85.776)	(81.358)
Mean Station/Route Ridership	4054	3629	3705	651	681	683
Observations	72,701	398,712	471,603	2,328	12,784	15,112

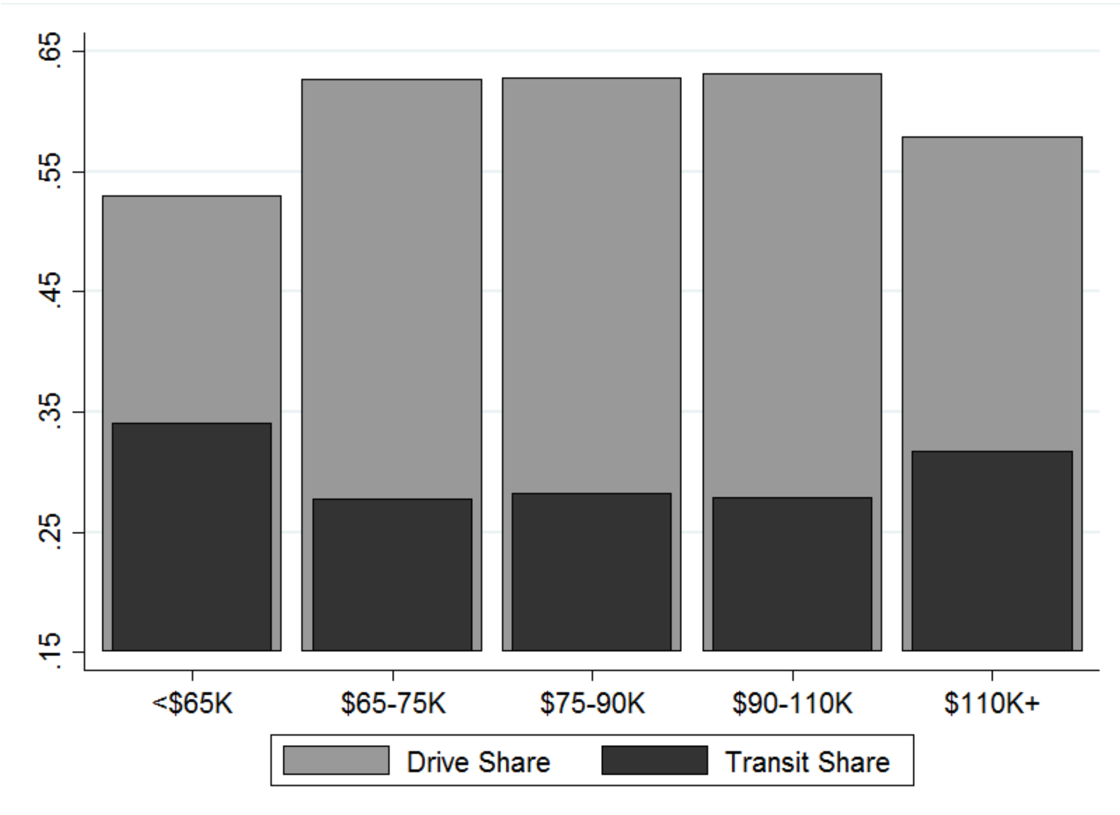
Notes: L Train observations are daily counts for each station. Pace Bus observations are monthly average daily route ridership counts. Median household income in $10,000 units. Each station is assigned the median household income of the census tract (for L Train) or county subdivision (for Pace Bus) it is located in. In specifications ending in 2012, "Post" indicates the year 2012. In specifications ending after 2012, "Post" indicates all years after the tax increase. All L Train regressions include local temperature and precipitation controls as well as average weekly gasoline price and day of week, month, and station fixed effects. Weekends, federal and other major holidays are excluded. Pace Bus regressions include local monthly average temperature and precipitation controls as well as average monthly gasoline prices and month and route fixed effects. Standard errors clustered at the stationXdirection level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 5. Alternative Responses to Jan. 1, 2012 Parking Tax Increase, ACS

	Train	Bus	Bike or Walk	Drive Alone	Carpool	Number of Riders
Yr2012* Household Income $90k+	-0.0095	0.0029	-0.0001	-0.0128	0.0236	0.0679*
	(0.023)	(0.004)	(0.004)	(0.034)	(0.016)	(0.033)
Yr2012*Household Income $75-90k	-0.0093	0.0037	-0.0001	-0.0280	0.0405	0.1359**
	(0.037)	(0.005)	(0.003)	(0.053)	(0.027)	(0.066)
Yr2012*Household Income $65-75k	0.0083	0.0077	-0.0014	-0.0364	0.0280	0.0888**
	(0.036)	(0.005)	(0.003)	(0.039)	(0.028)	(0.041)
Observations	11,258	11,258	11,258	11,258	11,258	9,170

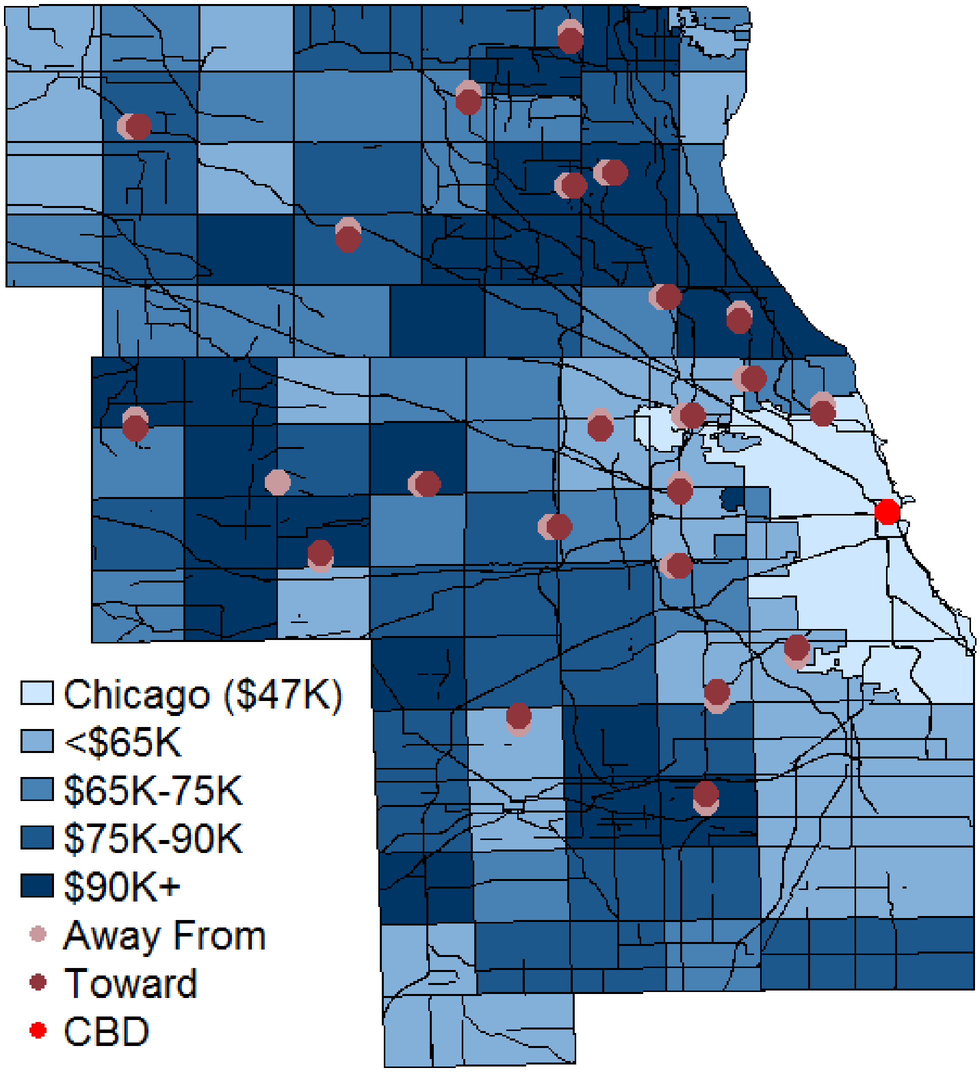
Notes: Observations are at the individual level and sample restricted to the 5 counties surrounding Cook County. Changes in geographic measures in the ACS in 2012 allows us to look only at travel patterns into Cook County, and not Chicago more specifically. All regressions include controls for gender as well as PUMA of residence, year, and age fixed effects. The sample for the Number of Riders is smaller because it is restricted to only those who used a car to get to work. Regressions are weighted using ACS individual probability weights and standard errors are clustered at the PUMA of residence. *** p<0.01, ** p<0.05, * p<0.1.

Figure 1. Modal Choice Proportions by Income Group



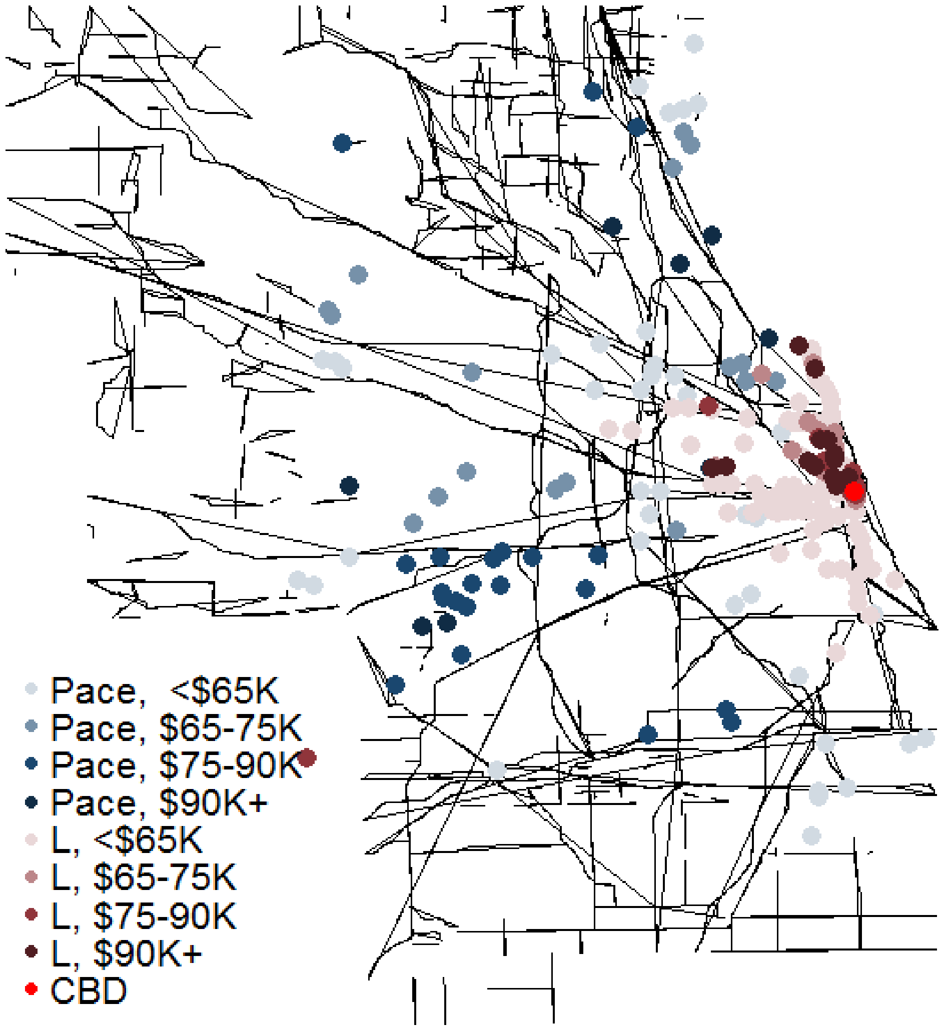
Notes: Figure created from the 2008-2011 ACS. Sample restricted to commuters living in Cook County or one of the surrounding 5 counties. Estimates weighted by ACS individual weights.

Figure 2. ATR Measurement Stations and County Subdivision Median Household Income



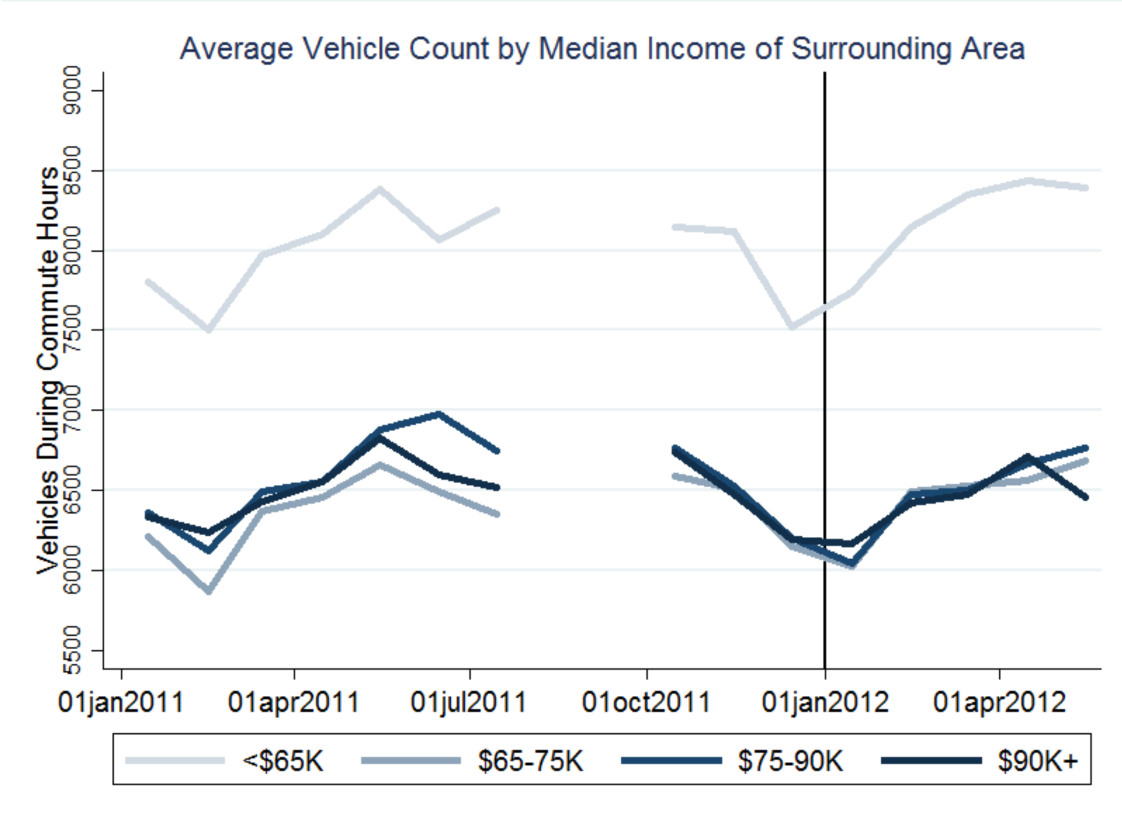
Notes: ATR stations in the Full Sample are indicated. County Subdivision median household income collected from the U.S. Census Bureau 2011 five-year ACS sample.

Figure 3. L Train and Pace Bus Station Location and Median Household Income of Nearest Community Subdivision or Census Tract



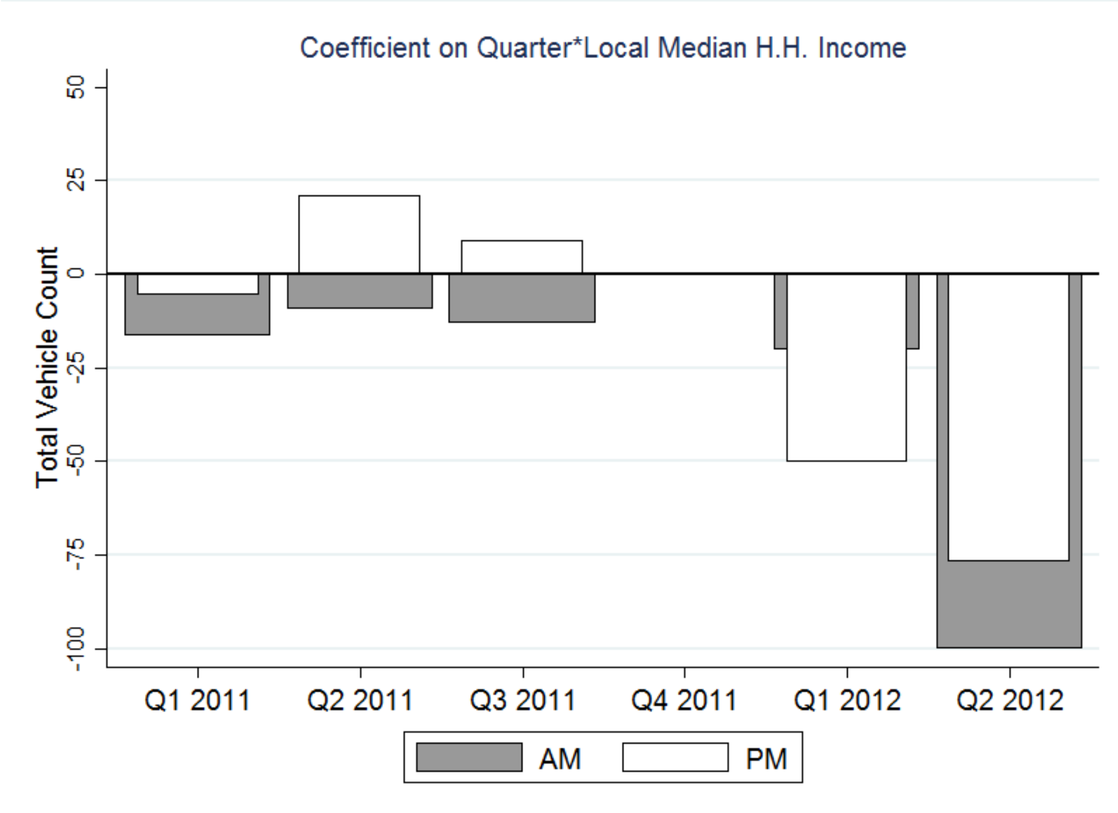
Notes: L Train stations and Pace Bus route points of origin plotted by median household income of nearest census tract (L Train) or county subdivision (Pace Bus).

Figure 4. Total Vehicle Count Pre-Trend by Income Groups



Notes: Hourly counts for 5:00-9:00 AM are averaged over income groups for the commuter sample. In August and September, multiple stations in the two middle income groups had reporting errors and were eliminated from the sample, we omit these months from the figure rather than changing the denominator of the average.

Figure 5. Event Study Coefficients



Notes: Regression coefficients presented in Appendix Table A5. The fourth quarter of 2011 is the omitted period. All post period coefficients are statistically different than zero, and none of the pre-period coefficients are statistically different from zero.

Appendix Tables

Table A1. Driving Response to January 1, 2012 Parking Tax Increase, Adjustment Period after the Announcement

	5:00-9:00 AM & 3:00-7:00 PM			
	Full Sample		Commuter Sample	
	Total Count	Log(Total Count)	Total Count	Log(Total Count)
Yr2012*Median$90k+	-105.608	-0.019*	-365.720**	-0.042**
	(90.899)	(0.011)	(169.903)	(0.019)
Yr2012*Median$75-90k	-281.590***	-0.055***	-432.555***	-0.074**
	(103.580)	(0.015)	(147.750)	(0.026)
Yr2012*Median$65-75k	42.423	0.014	-137.626	-0.008
	(118.802)	(0.017)	(210.843)	(0.025)
Nov-Dec 2011	-209.694	-0.037	127.603	0.002
*Median$90k+	(240.641)	(0.040)	(155.235)	(0.028)
Nov-Dec2011	-389.162	-0.073*	-88.738	-0.044
*Median$75-90k	(243.504)	(0.040)	(158.438)	(0.040)
Nov-Dec2011	-124.531	-0.019	231.965	0.043
*Median$65-75k	(249.451)	(0.039)	(192.996)	(0.029)
Number of Clusters	45		22	
Observations	15,456		7,555	

Notes: Observations are the sum of hourly counts during the specified period for each station direction. Sample restricted to unique stationXdirection ATRS that were functioning over 85 percent of the days from January 1, 2011 to May 31, 2012. Days where 0 vehicles were recorded for all hours are excluded. All regressions include local temperature and precipitation controls as well as weekly average gasoline prices and hour of day, day of week, month, and station direction fixed effects. Weekends, federal and other major holidays are excluded. Standard errors clustered at the stationXdirection level. *** p<0.01, ** p<0.05, * p<0.1.

Table A2. Falsification Test, Treating August 1, 2011 as Beginning of Treatment Period

	5:00-9:00 AM & 3:00-7:00 PM			
	Full Sample		Full Sample	
	Total Count	Total Count	Total Count	Total Count
Post*Median$90k+	-60.796	-0.001	159.230	0.027
	(139.606)	(0.021)	(231.900)	(0.029)
Post*Median$75-90k	-102.792	-0.025	71.980	-0.023
	(158.570)	(0.028)	(257.822)	(0.043)
Post*Median$65-75k	-61.339	0.010	191.032	0.038
	(144.287)	(0.021)	(235.642)	(0.029)
Number of Clusters	45		22	
Observations	11,081		5,338	

Notes: Observations are hourly counts for each station direction. Sample restricted to observations from stationXdirection locations with hourly count data for over 85 percent of the days from January 1, 2011 to December 31, 2011. All regressions include local temperature and precipitation controls as well as weekly average gasoline prices and hour of day, day of week, month, and station direction fixed effects. Weekends, federal and other major holidays are excluded. Standard errors clustered at the stationXdirection level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A3. Driving Response to Jan. 1, 2012 Parking Tax Increase, Direction of Chicago Traffic

	Total Vehicle Count				Log(Total Vehicle Count)			
	5:00-9:00 AM		3:00-7:00 PM		5:00-9:00 AM		3:00-7:00 PM	
	Full Sample	Commuter Sample	Full Sample	Commuter Sample	Full Sample	Commuter Sample	Full Sample	Commuter Sample
Yr2012*Median$90k+	-28.049	-149.219***	-27.971	-194.408	-0.003	-0.030**	-0.014	-0.045*
	(55.534)	(26.214)	(75.771)	(131.461)	(0.014)	(0.014)	(0.016)	(0.024)
Yr2012*Median$75-90k	-133.606*	-250.950***	-130.967*	-217.636**	-0.063**	-0.102**	-0.057***	-0.083**
	(66.830)	(42.860)	(72.943)	(99.598)	(0.027)	(0.045)	(0.021)	(0.039)
Yr2012*Median$60-75k	-10.997	-132.058**	72.232	-29.055	0.008	-0.030	0.018	-0.012
	(64.835)	(54.742)	(86.487)	(154.024)	(0.016)	(0.019)	(0.023)	(0.035)
Yr2012*Median$90k+*DCT	-25.976	-52.882	-4.726	-35.077	-0.013	-0.015	-0.005	-0.006
	(95.951)	(153.085)	(99.726)	(160.065)	(0.025)	(0.045)	(0.021)	(0.030)
Yr2012*Median$75-90k* DCT	62.420	107.592	40.748	1.268	0.040	0.059	0.022	0.031
	(104.038)	(132.738)	(104.228)	(126.765)	(0.035)	(0.058)	(0.026)	(0.043)
Yr2012*Median$60-75k* DCT	26.463	29.969	-21.589	-65.372	0.025	0.023	-0.007	-0.008
	(104.067)	(162.840)	(123.036)	(204.916)	(0.031)	(0.049)	(0.030)	(0.043)
Number of Clusters	45	22	45	22	45	22	45	22
Observations	15,456	7,555	15,456	7,555	15,438	7,540	15,456	7,555

Notes: DCT stands for Direction of Chicago Traffic, which is opposite in the morning and in the evening. Observations are the sum of hourly counts during the specified period for each station direction. Sample restricted to unique stationXdirection ATRS that were functioning over 85 percent of the days from January 1, 2011 to May 31, 2012. Days where 0 vehicles were recorded for all hours are excluded. All regressions include local temperature and precipitation controls as well as weekly average gasoline prices and hour of day, day of week, month, and station direction fixed effects. Weekends, federal holidays, and other major holidays are excluded. Standard errors clustered at the stationXdirection level. *** p<0.01, ** p<0.05, * p<0.1.

Table A4. Driver Response to January 1, 2012 Parking Tax Increase at Different Times

	10:00 AM – 2:00 PM		4:00-10:00AM		2:00-8:00 PM	
			Total Vehicle Count			
	Full Sample	Commuter Sample	Full Sample	Commuter Sample	Full Sample	Commuter Sample
Yr2012*Median$90k+	-82.571**	-210.766***	-54.626	-225.685**	-56.989	-311.908**
	(36.765)	(59.814)	(57.820)	(99.095)	(68.138)	(110.371)
Yr2012*Median$75-90k	-137.315**	-189.518***	-134.534**	-251.390***	-179.233**	-343.094***
	(53.351)	(47.039)	(66.025)	(87.153)	(76.519)	(91.401)
Yr2012*Median$65-75k	7.305	-64.375	-1.204	-146.017	70.481	-111.922
	(46.111)	(77.790)	(68.688)	(112.759)	(82.119)	(136.212)
Average Total Count	2458	3128	2960	3628	4442	5650
Observations	15,456	7,555	15,456	7,555	15,456	7,555

Notes: Observations are hourly counts for each station direction. Sample restricted to observations from stationXdirection locations with hourly count data for over 85 percent of the days from January 1, 2011 to December 31, 2011. All regressions include local temperature and precipitation controls as well as weekly average gasoline prices and hour of day, day of week, month, and station direction fixed effects. Weekends, federal and other major holidays are excluded. Standard errors clustered at the stationXdirection level. *** p<0.01, ** p<0.05, * p<0.1.

Table A5. Driving Response to Jan. 1, 2012 Parking Tax Increase, Event Study

	5:00-9:00 AM		3:00-7:00 PM		5:00-9:00 AM & 3:00-7:00 PM	
	Full Sample	Commuter Sample	Full Sample	Commuter Sample	Full Sample	Commuter Sample
	Total Vehicle Count					
Q1 2011*Median	17.974	-16.328	3.439	-5.556	21.413	-21.884
H.H. Income	(24.715)	(31.185)	(24.533)	(26.798)	(47.483)	(53.529)
Q2 2011*Median	30.520	-9.486	39.095**	20.878	69.615*	11.392
H.H. Income	(19.273)	(18.590)	(19.215)	(26.984)	(36.363)	(41.500)
Q3 2011*Median	33.744	-13.009	35.974*	9.078	69.718*	-3.931
H.H. Income	(20.829)	(13.812)	(18.575)	(20.202)	(37.343)	(24.833)
Q1 2012*Median	16.801	-20.382*	-5.680	-50.239***	11.121	-70.620***
H.H. Income	(17.381)	(10.664)	(15.842)	(11.705)	(31.241)	(18.332)
Q2 2012*Median	-16.616	-100.159**	1.784	-76.747*	-14.832	-176.906**
H.H. Income	(28.334)	(39.079)	(27.309)	(37.598)	(54.166)	(75.263)
Observations	15,456	7,555	15,456	7,555	15,456	7,555
	Log(Total Vehicle Count)					
Q1 2011*Median	0.003	-0.001	-0.009	-0.004	-0.004	-0.005
H.H. Income	(0.009)	(0.010)	(0.007)	(0.006)	(0.008)	(0.006)
Q2 2011*Median	0.011	-0.000	0.014*	0.006	0.014*	0.003
H.H. Income	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.006)
Q3 2011*Median	0.012	-0.003	0.012	0.001	0.012	-0.003
H.H. Income	(0.009)	(0.006)	(0.007)	(0.004)	(0.008)	(0.004)
Q1 2012*Median	0.000	-0.007*	-0.008*	-0.015***	-0.004	-0.013***
H.H. Income	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.003)
Q2 2012*Median	-0.001	-0.018	0.004	-0.010	0.003	-0.014
H.H. Income	(0.009)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)
Number of Clusters	45	22	45	22	45	22
Observations	15,438	7,540	15,456	7,555	15,456	7,555

Notes: See notes to Table 3 and Figure 5.