The Value of Time: Evidence From Auctioned Cab Rides*

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Abstract

We recover valuations of time using detailed consumer choice data from a large European ride hail platform, where drivers bid on trips and consumers choose between a set of potential rides with different prices and waiting times. First, we estimate consumer demand as a function of prices and waiting times. While demand is responsive to both, price elasticities are on average four times higher than waiting-time elasticities. We show how these estimates can be mapped into values of time that vary by place, person, and time of day. Regarding variation within a day, the value of time during non-work hours is 16% lower than during work hours. Regarding the spatial dimension, our value of time measures are highly correlated both with real estate prices and urban GPS travel flows. A variance decomposition reveals that most of the substantial heterogeneity in the value of time is explained by individual differences as opposed to place or time of day. In contrast with other studies that focus on long run choices we do not find evidence of spatial sorting. We apply our measures to quantify the opportunity cost of traffic congestion in Prague, which we estimate at $469,000 per day.

Keywords: Value of time, demand in transportation markets, ride hail.
JEL classification: C73; D83; L90; R12

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1 Introduction

Allocating time is an important aspect of many economic decisions. Since Becker (1965), economists have used the labor-leisure trade-off to measure people's value of time. Credible measures of the value of time are useful for a variety of important policy decisions. For instance, they are a critical input to infrastructure planning, particularly in the transportation sector. A unique empirical challenge in measuring the value of time is that in many economic settings — unlike in labor markets — time is not always directly priced. In this paper we use data from auctioned cab rides to overcome this empirical challenge, allowing us to estimate how the value of time is distributed across individuals, across places, and across time-of-day within a large urban area.

Transportation markets are generally revealing of the value of time: consider, for instance, the various decisions involved in the daily commute from home to work (Domencich and McFadden, 1975). In this context they might trade off cheaper-yet-slower off-peak trains against more expensive express trains; choose to leave earlier than their work requires to beat the rush hour; or choose between different service tiers in a ride-hailing platform, which involve different waiting times and prices. The choices made when faced with such tradeoffs are therefore informative about the value of time, or the opportunity cost of time spent traveling.

We use detailed consumer choice data from Liftago, a large European ride-hailing application. This platform uses a unique mechanism to allocate each ride through a rapid auction process in which nearby drivers bid on ride requests and requesting consumers choose between bids based on various characteristics. Most importantly, bids often involve tradeoffs between price and waiting time, or the time it would take the taxi to pick up the customer. Contrast this with platforms like Uber and Lyft that employ "surge" pricing to equilibrate demand and supply so that consumers do not get to directly express their preferences over prices and waiting times within the platform. We are able to observe both consumers' individual choice sets as well as their ultimate selection for 1.9 million ride requests and 5.2 million bids.

The *first* contribution of this paper is to provide a direct and clean measurement of consumers' willingness-to-pay to reduce waiting times. We use the variation in choice sets and choices to estimate a demand system that depends both on prices *and* waiting times. Such measures are of first-order importance for the provision of public transportation infrastructure as well as for the ride hail industry where price and waiting time are the two key variables on which firms compete. Our setting allows us to overcome some of the empirical challenges in measuring preferences over both prices and waiting-time.

Our *second* contribution, building on the work of Small (1982), is to provide a conceptual framework to interpret the disutility of waiting and to demonstrate how the willingness-to-pay for waiting-time reductions can be used to recover the value of time. When consumers choose a shorter wait time over a lower price, they reveal that the value of their time at a particular destination and time-of-day is greater than the value at the original location. Intuitively, the willingness to pay for lower wait times is simply the difference between the *value of time* at the destination and the *value of time* at the origin. In keeping with this interpretation we will refer to the willingness to pay for waiting time reductions as the *net value of time* (abbreviated as NVOT). By leveraging high-resolution choices in a transportation market, we are able to recover a measure of the value of economic activity across place, individuals, and time of day. We formalize this mapping, demonstrate that the average value of time by place, individuals and time-of-day is identified and show how it can be recovered with a simple moment-based estimator. Rich geographic detail, including information about whether trips were ordered inside or outside of buildings as well as real estate prices and zoning conditions associated with trip origins and destinations, allows us to further decompose the value of time and interpret the prevailing patterns. New types of data can often spark fruitful new lines of research and fill in gaps where other data sources are not available or deficient, as for example the use of satellite data on night lights (Henderson et al., 2012). The type of data required for our framework is increasingly made available by platforms in the transportation sector. Although our approach relies in part on unique features of our platform, we believe that it could be easily adapted to conduct a similar study within the US context, for example, with data from Uber or Lyft. Our measurement is complementary to other long-run measures of spatial economic activity such as real estate prices.

The demand results show that consumers respond substantially to changes in both price and waiting time. MWe find that the net value of time, expressed as an hourly quantity, is \$10.80. Price elasticities are about three times higher than waiting-time elasticities, however, there is large variation in these measures within the day and across space. This heterogeneity underscores the importance of the context in which price and time tradeoffs are made. From the overnight hours to the mid-day, the willingness to pay for lower wait times approximately doubles. Geographic differences are estimated to have an order of magnitude difference from one extreme to another. Because our data includes panel identifiers of both passengers and drivers we are also able to credibly identify the individual specific heterogeneity in both the elasticities and the implied NVOT. We recover heterogeneity across passengers both in their utility of income and dis-utility to wait times. We rank individuals by their relative sensitivity to prices and wait times and find that the top quartile have NVOT measures about 3.5 times higher than the bottom quartile.

We use our estimates to investigate the sources of variation in the value of time and determine how much is driven by differences across people, locations, and times of day. Our approach is similar to a branch of the labor literature which decomposes differences in wage into firm and worker specific variation (Abowd et al. (1999)). This exercise provides a number of important insights. First, we find that almost eighty percent of the variation in the value of time is driven by differences across people. Once individual-specific variation is taken into account, differences across places play a relatively small role. We also find that people who express a higher VOT are not necessarily doing so for the same places. In fact, the relationship between high value of time people and high value of time places is slightly negative. This finding is interesting in light of recent evidence of positive sorting of high earners in the long-run residential housing market (e.g., Bayer et al. (2007)). A small survey of passengers reveals that the estimated value of time during the starting time of a typical work day is very close to the mean wage in the survey sample. This finding provides evidence that our results may be credibly extrapolated to other contexts.

When people are traveling they forgo valuable time at origin or destination. We can therefore use our value of time measures to quantify the opportunity cost of traffic congestion. Building on this, we use our estimates to quantify the cost of congestion for the population of riders on the app and, under additional assumptions, for the entire city of Prague, which has 1.3 million residents. We find that the cost of traffic congestion, counting only work days, is about \$0.5 million per day and \$75 annually for each vehicle driver on the road. This provides, to our knowledge, the first city-wide estimates of the opportunity cost of congestion directly derived from observed choices in a market setting.

Related literature The paper contributes mainly to four strands of literature, which we describe below.

The *first* strand is the literature on the opportunity cost of time. While the standard labor-leisure choice model implies that an extra hour of leisure should be valued at the shadow wage, the literature starting from the seminal work of Becker (1965) recognizes that an agent's time is also an input to other non-market activities. Recent papers in this literature have used a variety of widely available micro-data to study the trade-off between market goods and time (see, for instance, Aguiar and Hurst (2007); Aguiar et al. (2012); Nevo and Wong (2019)). Though these studies utilize rich and comprehensive datasets of consumption behavior (for example, household scanner data), they are only able to measure the opportunity cost of time indirectly through other market transactions. A related question is to what extent workers value flexible work schedules. Mas and Pallais (2017) investigate preferences for such flexibility in an experiment with call-center workers, Bloom et al. (2015) study work-from-home preferences and performance differences among workers in a large travel agency, and Chen et al. (2017) study the value of work hours flexibility among Uber drivers.[1] Our work contributes to this literature in a number of ways. First, we extend the analysis of the opportunity cost of time outside of the workplace and study how this value varies across individuals, space, and time. Second, our data allows us to directly measure consumers' opportunity costs of time and to disaggregate these measures along various dimensions.

The *second* strand is the emerging literature that utilizes high resolution spatial data to shed light on urban sorting and segregation (Athey et al., 2019; Davis et al., 2017; Couture et al., 2019; Kreindler and Miyauchi, 2019; Almagro and Domınguez-Iino, 2019).[2] Kreindler and Miyauchi (2019) use people's commuting flows to estimate a gravity model where consumers choose where to work, as a function of where they live and wage values. The model yields estimates of the relative desirability of locations. They then show that the implied values from the estimation correlate well with the empirical distribution of wages and night lights in the city. In contrast, since we directly observe how people trade-off waiting time and monetary savings when choosing to move from one location to another, we can obtain a direct measure of their value of spending time at a specific location. Our approach allows us to perform a number of important quantifications that would be hard to do based on GPS data alone. For instance, we demonstrate in our application how our measures can be used to quantify the cost of traffic congestion.

The *third* strand is the literature in transportation economics and industrial organization, dating to the pioneering work of Daniel McFadden (McFadden, 1974; Domencich and McFadden, 1975), on the value of travel time savings. While the rich spatial nature of our data allows us to link consumers' willingness to pay for reductions in waiting time to the value of time across locations, the studies in this strand measure the benefits of travel time savings through surveys or revealed preference analysis based on mode choice. Small (2012) reviews the travel time literature and presents stylized facts suggesting that the value of personal travel time is about 50% of the gross wage rate and that the value of travel time increases less than proportionally with income/hourly wage — with elasticity estimates ranging from 0.5 to 0.9. Couture et al. (2018) study the de-

[1] The taxi industry has long provided a laboratory for empirical work on flexible work hours. See, e.g., Camerer et al. (1997), Farber (2005), Farber (2008), Crawford and Meng (2011),Thakral and Tô (2017).

[2] While not using high resolution spatial data, the work of Su (2018) is also related to this strand. The author studies the causal link between the value of time and gentrification. He argues that the increase in the value of time of high-wage workers led them to seek living areas with shorter commuting times, which then leads to gentrification of former poor, but close to downtown, areas.

terminants of driving speed and the deadweight loss of travel, where hours in traffic are valued at half the average wage. In contrast, our study directly uses our VOT measure as the opportunity cost of lost time due to congestion. Bento et al. (2020) use commuter tollway choices to infer consumers' urgency from their willingness-to-pay for travel time savings. Hall (2018) analyzes the benefits of choice over toll and non-toll lanes.[3] Finally, a recent literature studies equilibrium outcomes resulting from transportation infrastructure. This includes studies that analyze the impact of new roads on driving behavior (Duranton and Turner, 2011), the impact of transit on urban development and spatial sorting (Heblich et al., 2018), the welfare effect of transportation improvements (Allen and Arkolakis, 2019), and the design of optimal transportation networks (Fajgelbaum and Schaal, 2017). Our study complements this literature by showing how transportation options and choices are related to the opportunity cost of time, an important component of the overall welfare of transit. We also provide quantification of the baseline costs associated with transit externalities in a specific setting.

Fourth, our estimates are relevant to the literature that studies taxi and ride hail markets. Recent papers analyze the supply side in ride-hail markets. Buchholz (2018) quantifies the impact of uniform pricing regulation and search frictions on the spatial allocation of drivers and passengers in the NYC taxi market; Frechette et al. (2018) assess the effect of entry restrictions and market thickness on efficiency in the NYC taxi market.[4] In these papers, the demand for taxis is estimated either as a function of prices (Buchholz (2018)) or waiting times (Frechette et al. (2018)).[5] Cohen et al. (2016) and Castillo (2019) estimate demand for rides on the Uber platform, and in particular Castillo (2019) also estimates the demand for both waiting-time and price. His paper has a different focus and quantifies the benefit of surge pricing whereas we provide a conceptual framework to link the disutility of waiting-time to the spatial distribution of the value of time. In terms of the setting, ours has the benefit that we observe a direct and

[3] There are a host of other studies. For example, the US department of transportation distinguishes in its guidance on Valuation of Travel Time between 'on-the-clock' business travelers and personal travel (Belenky, 2011). For the former, the valuation of travel time is assigned to be the nationwide median gross compensation based on the 2015 BLS National Occupational Employment and Wage Estimates. For personal travel, estimates are based on survey results from Miller (1989). Like Miller (1989) many studies that estimate time valuations are situated within the transportation literature, largely based on stated preference reports (see Abrantes and Wardman (2011) for the UK and Cirillo and Axhausen (2006) for Germany). Jara-Diaz et al. (2008) combines detailed data (travel diaries and interviews) from Chile, Germany and Switzerland with a theoretical model in the spirit of Becker (1965) to estimate people's value of leisure time. They find that the marginal valuation of leisure is 65.9% of the average hourly wage in Chile, 119.8% in Germany and 87.8% in Switzerland. Borjesson et al. (2012) study two identical surveys given to car commuters in Sweden in 1994 and 2007 and find that people with below median income have elasticity of travel time with respect to income indistinguishable from zero, and those with above median income have elasticity close to 1. Lam and Small (2001) use survey of California commuters on Route 91 which includes free lanes and tolled "express lanes." The value of time is estimated at $22.87 or 72% of the average wage. Fosgerau et al. (n.d.) study data collected from interviews with over 6,000 Danish people and obtain estimates of the value of time at 67% of the mean after-tax wage. Significance Quantitative Research (2007) find that the value of time in the Netherlands is about €8.76, with business trips valued at €24 per hour. Kreindler (2018) evaluates the welfare effect of congestion pricing using both travel behavior data and a field experiment.

[4] In a similar vein, Liu et al. (2019) and Hall et al. (2019) study various aspects of the design of DiDi and Uber, respectively. These papers, however, do not estimate demand.

[5] Brancaccio et al. (2017) and Brancaccio et al. (2020) study closely related models in the context of the oceanic bulk shipping industry.

salient choice that includes a price waiting-time trade-off and also a panel-structure for riders, which provides a convincing way to estimate the population heterogeneity. The rest of this paper proceeds as follows. Section 2 describes the institutional setting and our data. Section 3 describes the conceptual framework which motivates our analysis. Section 4 lays out the model of consumer choice and the details of identification and estimation. We present the results of our estimation in Section 5, counterfactuals in Section 6 and conclude in Section 7.

2 Setting and Data

2.1 The Platform: A Unique Approach to Matching and Price Discovery

Liftago is a ride-hail platform, which was founded in 2015 and services rides through licensed taxi drivers. In Prague, all taxis need to be operated by licensed drivers. Moreover, taxis need to be equipped with a separate meter, which captures the number of kilometers traveled in the "occupied" mode together with the billed amount.[6] A licensed driver may find fares by searching for street-hail passengers or by choosing to participate in a dispatch service. Among dispatch options, there are traditional telephone-based dispatch services and, more recently, the app-based ride-hail platform that we study. Note that this regulatory environment is different from most U.S. municipalities, in which there is nearly free entry into the ride-hail market through firms such as Uber and Lyft. Uber has also been present in Prague since 2014, but its presence is not as large as in a typical US city of similar size, partially since it is still fighting several legal battles due to various licensing and taxation issues.[7]

Drivers pay a percentage fee for each ride that is booked through the platform. By tracking both the taxi's GPS and the time of the trip, it provides an approximate fare both before the trip begins and after its completion. While the platform has a strong presence in the Czech Republic, it is still less well known in other countries. This has the advantage that few riders are tourists, making it easier to interpret our estimates in light of local economic quantities.[8]

Importantly, drivers and passengers are matched by a combination of a dispatch algorithm and an auction. Whenever a passenger requests a ride, the system looks for

[6]Licensing requires both a fee and an exam. Meters needs to be certified every two years by a state agency. Each meter records the aggregate numbers of kilometers billed together with the revenues.

[7]Since the EU court's decision from December 2017, Uber is viewed as a transportation company and hence its drivers need to be properly licensed.

[8]This is also reflected in the relatively small fraction of airport rides, which comprise about 2 percent of total trips.

nearby available cars and sends requests to a certain number of them, typically four, to elicit an offer. A cab driver who receives a request observes the details of the trip — the location of the passenger, the destination, passenger rating and payment via cash or credit. A taxi driver who is interested in performing the job submits a bid, which is chosen from a set of pre-programmed tariffs.[9] A tariff consists of a flag fee, a per-minute waiting fee and a per-kilometer fee with a regulatory cap at CZK 36 ($\approx$ \$1.41). The platform takes any tariff bids and combines them with a query to Waze, a real-time traffic mapping service and Google subsidiary, which provides estimated trip time and distance information. The tariff bids are then translated into a single expected price for a trip. The passenger then observes bids as final trip prices together with other bid-specific attributes: the waiting time until the taxi arrives (ETA), the make and model of the car, and the driver's rating. Importantly, these non-price attributes are automatically attached to the bids; in the case of waiting time, the Waze query also determines the expected ETA of each bidder to reach the passenger. The passenger may select one of the bids, in which case the ride occurs, or else may decline all bids. When the ride is completed, the passenger pays the fare shown on the meter.[10] Figure 15 shows the interface that riders see on the app before the request and after the request arrives.

A noteworthy consequence of Liftago's mechanism is that it allows for variation in both prices and waiting times: a driver with a high ETA may submit a lower bid than a driver with a low ETA, and vice-versa. Contrast this with traditional taxi services, where prices are fixed so that the market clears through adjustments in waiting time, and with other ride-hail platforms, where prices are adjusted to keep waiting times stable.

2.2 Data

Our dataset covers 1.9 million trip requests and 1.1 million actual trips on the platform between September 30, 2016 and June 30, 2018. For each request, we observe the time of the request, pick-up and drop-off location, trip price bids and estimated waiting times from each driver, and which bid the passenger chose, if any. In addition, we observe a unique identifier for each driver and passenger. There are 1,455 unique drivers and 113,916 unique passengers over the sample period.

For each ride request we complement the data with geospatial and public transportation data from Google Places and Transit Matrix APIs, based on the GPS addresses for

[9] When starting the ride, the driver selects a tariff among the options he has pre-programmed on the meter. This is also why the bidding is not completely unrestricted: a typical driver has only about 5 fare combinations on his meter, but there are notable exceptions. Some drivers who specialize in Liftago trips have over 20 different tariffs. Note that neither the passengers nor the other drivers observe tariffs that were not chosen.

[10] The app and an email receipt from Liftago only display an estimated amount. However, if the actual amount diverges from the estimated amount, customers are encouraged to report the discrepancy. Drivers can be banned from the platform if they are found regularly overcharging.

Table 1: Bid, Order, and Daily Summary Statistics

Variable	P10	Mean	P90	S.D.
PANEL A: ORDER SUMMARY ($N = 1,874,409$)				
Price of Trip (USD, across-auction)	5.65	11.66	19.75	6.261
Wait Time (minutes, across-auction)	3.00	6.8	12.00	3.816
PANEL B: BID SUMMARY ($N = 5,229,724$)				
Number of Bids (within-auction)	1.00	2.79	4.00	1.087
Price of Trip (USD, within-auction)	5.04	9.85	16.16	1.059
Wait Time (minutes, within-auction)	3.50	6.85	11.25	1.856
PANEL C: DAILY SUMMARY ($N = 638$)				
Number of Requests	1961	2938.3	4098	956.67
Number Rides	1160	1786.2	2470	557.15
Number Drivers	411	499.23	585	97.372

NOTE: The table shows summary statistics at the bid level (Panel A), the auction level (Panel B) and for entire days (Panel C). P10 refers to the 10th percentile and P90 to the 90th percentile of the respective variable.

each point of origin and destination in the Liftago data. The API data provide alternative public transit times and routes as well as a measure of over 90 types of businesses and local amenities within both 100m and 1km radii around pickup and drop-off locations.[11] Furthermore, we use hourly rainfall data to attach prevailing weather characteristics to each ride.[12] Finally, we use data on GPS-specific land values and land zoning types from GIS coded data.[13]

Table 1 summarizes the daily activity of the platform. There are on average about $3,000$ trip requests each day, of which 61% become rides. The average bid is \$11.66 and the average waiting time is 7 minutes. In addition, about one third of the drivers in the sample were active each day. The average number of drivers bidding in each auction is 2.8, and except in rare cases there are no more than four bids.[14]

Another important feature of the platform is the ability to schedule trips exactly 15 minutes in advance. Scheduled trips represent 7.8 percent of all orders on the platform. While these types of orders do not feature variable waiting times and are not included in our analysis, they suggest that the orders we do analyze most likely represent a timely need for trips.

[11] For more information see `https://developers.google.com/places/supported_types`.

[12] We obtain this from `https://www.noaa.gov/`.

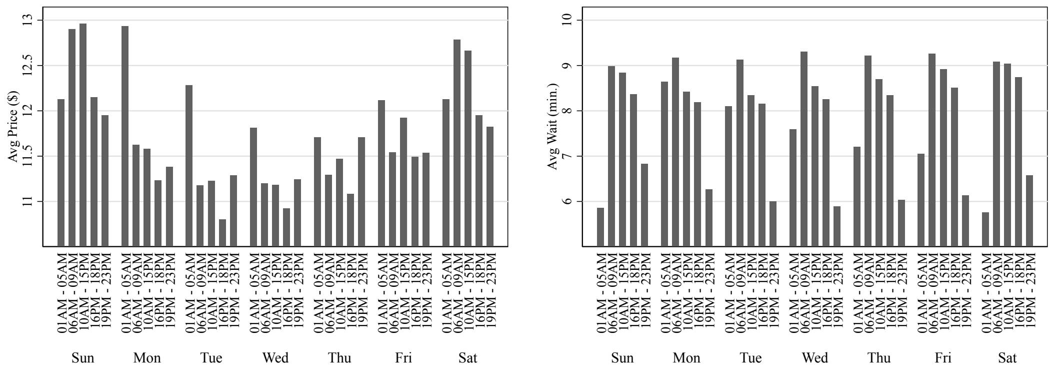
[13] Those are available at `http://www.geoportalpraha.cz`.

[14] We discard auctions with more than four bids, representing only 0.33% of the sample.

2.3 Preferences over Time and Money: Intra-daily Patterns

In this section we describe spatial and inter-temporal patterns in prices, waiting times, and choices. Those patterns show that there is large and interpretable heterogeneity in consumer choices on which our model estimates build. Figure 1, panels (a) and (b) show the average trip price and wait times by day of the week and time of the day. We see that prices are lower during the weekday afternoons and higher during the weekends, while wait times tend to be substantially higher during the day hours compared with overnight hours, across both weekday and weekend.

Figure 1: Prices and Waiting Times by Hour and Day



(a) Average Prices

(b) Average Wait Times

Consumers in our data often face a non-trivial trade-off between price and waiting time when choosing among bids. A trade-off implies that there exist options such that one has a lower waiting-time but a higher price and vice-versa. Depending on the time of day about 58-70 percent of auctions involve a trade-off between waiting less and paying more.[15]

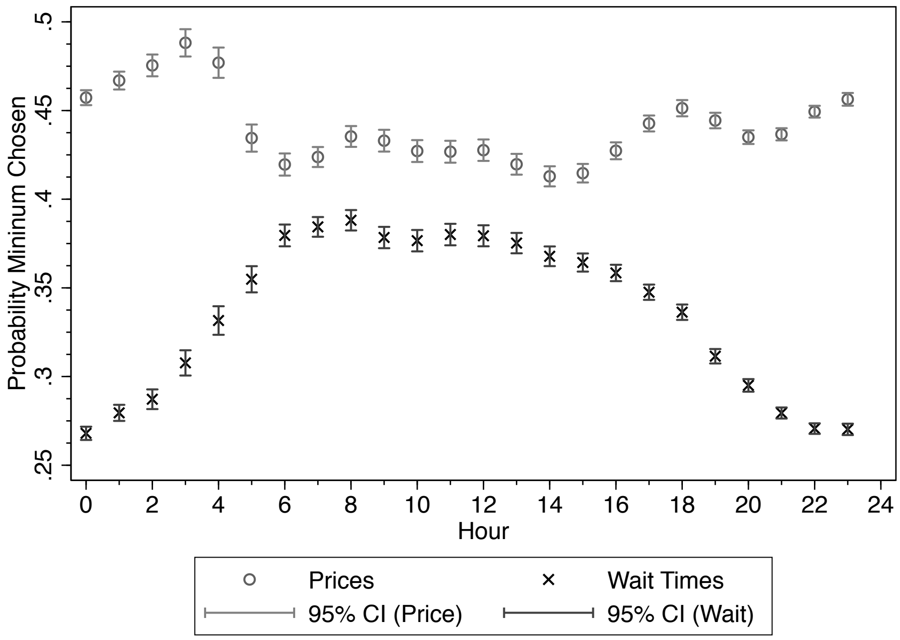
Figure 2 shows how consumers solve the trade-off between time and monetary costs at different times of the day. At all times of day, consumers are more likely to pick the minimum price option than the minimum waiting time option. The elasticities that we back out from our model are very much in line with this observation. Moreover, the magnitudes of these differences vary throughout the day. We see that during work hours, there is a a significant dip in the likelihood to choose the lowest price option and an even larger and significant increase in the likelihood to choose the lowest wait option.[16] This pattern can be attributed to some combination of preference heterogeneity across customers as well as within-customer heterogeneity across the day. Since we observe

[15] Figure 17 in Appendix A shows how the fraction of auctions with a trade-off varies hy hour of day.

[16] Note that those two do not have to add up to one since a consumer might, for example, choose a driver with the highest rating and that driver offers neither the lowest price nor provides the lowest wait time.

customer identifiers, our model leverages the variation across consumers in the timing of trips and the choices within trips.

Figure 2: Tradeoffs and Choices by Hour

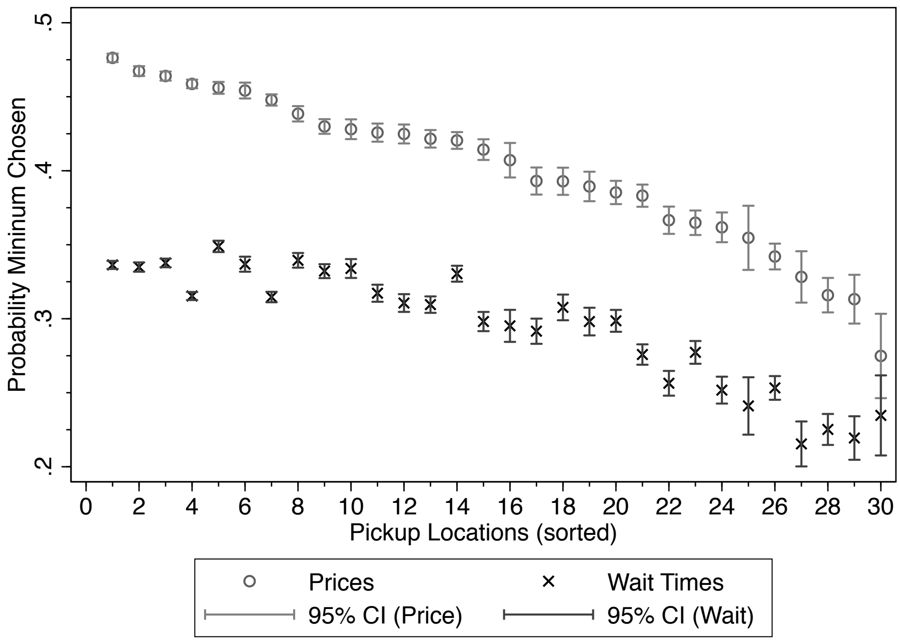


NOTE: The graph shows the mean probability that a customer who faces trade-offs between price and waiting time chooses either the lowest price or lowest waiting time. 95% confidence intervals for each series are also shown.

We next show how choices differ by locations. Instead of using administrative boundaries to arrive at a partition into smaller locations we prefer a data driven approach. We employ a clustering approach using exact GPS locations of trip origins and destinations. The partitioning is done according to a simple *k-means* procedure on latitude and longitude with the number of locations set to $A = 30$. We chose the value $k = 30$ to balance modeling the richness of spatial preference heterogeneity against sacrifices due to sample size. The resulting map is shown on Figure 23.

Figure 3 compares choices over price and wait times by location. The figure shows, within each pickup location, the probability that customers choose the lowest price and/or wait time among all available bids, computed only within auctions where a trade-off between the choices is present. Locations are sorted by the probability of choosing the lowest price. Like Figure 2, Figure 3 demonstrates that consumers exhibit preferences for lower prices and waiting times. It shows that minimum prices are chosen about 2-3 times more often than minimum waiting times, but there is substantial heterogeneity across locations. Those differences will eventually allow us to infer the different values that riders assign to different locations. We will also decompose how much of

Figure 3: Choices and Bids by Pickup Location



NOTE: This figure shows the mean probability that a customer who faces trade-offs between price and waiting time chooses either the lowest price or lowest waiting time. The locations in each are sorted by the probability on price. 95% confidence intervals for each series are also shown.

this variation is coming from place-innate characteristics and how much is driven by differences across people who travel between different locations.

3 Conceptual Framework

We now describe the conceptual framework that shows how the choices that we observe are related to the underlying value of time at different locations. A consumer's day is characterized by an allocation of time to various activities in different locations. Those activities (e.g., leisure or family time at home versus production at work) have different productivities or different intensity of pleasure at different times. Comparing her options at any given point in time, a consumer thus decides whether to move to a different location and spend her time there. Moving between locations is costly, both in terms of money and time, and a consumer has a choice between various transportation options. Liftago's auction mechanism allows us to observe a particularly clean set of decisions about these transitions.

A consumer is defined by a pair of utility functions $(\textsc{vot}^o, \textsc{vot}^d) : [0, T] \mapsto \mathbb{R}^2$, which denote their utility of spending time t at either the origin, O, or the destination, D. This specification assumes that the time spent on the ride is 0; alternatively, this means that VOT^o represents the value of spending time at the origin, net of the value of the ride, while VOT^d represents the value of spending time at the destination, net of the value of the ride.[17] In general, these functions may depend on the locations $a \in \mathcal{A}$ of the origin and the destination, which we denote by VOT^o_a, $\text{VOT}^d_{\hat{a}}$ if location a is the origin and $\hat{a}$ is the destination.

The consumer starts at time $t = 0$ at the origin. The consumer has an ideal arrival time at the destination, which is the time t^* at which $\text{VOT}^o(t^*) = \text{VOT}^d(t^*)$. However, moving from the origin to the destination involves some travel time and the time waiting for the ride. Once en route, it takes Δ periods to arrive at the destination. Then, if the consumer asks for a ride at $q \geq 0$ with an estimated time of arrival of w and a price of p, their payoff is given by:

$$u(q, w) - p = \int_0^{q+w} \text{VOT}^o(t)dt + \int_{q+w+\Delta}^{T} \text{VOT}^d(t)dt - p \tag{1}$$

Figure 4: Origin Destination Trade-Off in Waiting Time Choice

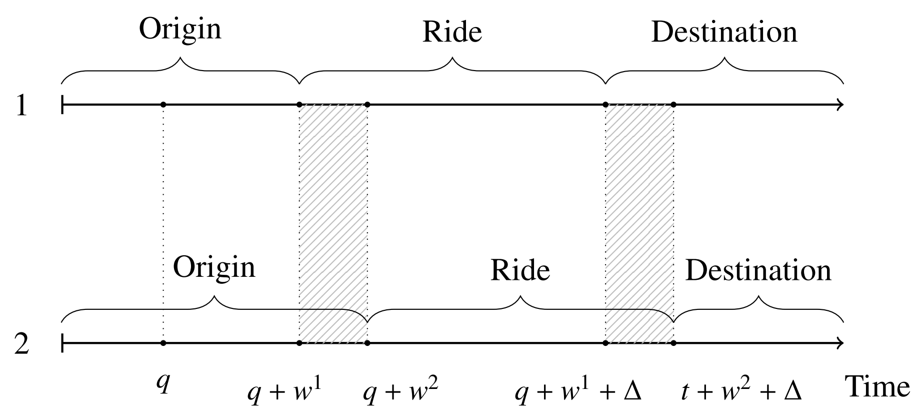


Figure 4 illustrates how the decision to accept a particular bid affects the time allocation between the origin and the destination. Suppose that when consumer requests a ride at time q, she receives two bids. Since both drivers are supposed to take the same optimal route, the time from the pickup to the destination is the same and given by Δ. The two bids differ in the estimated time of arrival of the driver. The second bid leads to a longer wait time w_2. By accepting bid 1, the passenger decides to spend $w_2 - w_1$ less time at the origin and $w_2 - w_1$ more time at the destination.

Let a and $\hat{a}$ denote the origin and destination's location, respectively. When comparing both trips, the consumer is comparing $\text{VOT}^o_a \cdot (w_2 - w_1)$ against $\text{VOT}^d_{\hat{a}} \cdot (w_2 - w_1)$, up to an approximation. Letting the difference between w_2 and w_1 be one minute, the

[17] We return to this point in our application on the opportunity cost of congestion.

willingness to pay for waiting time reductions, which we call the *net value of time*, can be expressed as:

$$\text{NVOT}_{a\to\hat{a}} = \text{VOT}^{d}_{\hat{a}} - \text{VOT}^{o}_{a} \tag{2}$$

Different people will assign different values to places and at different times. Going forward, the objects that we describe above will have i- and t-subscripts to reflect the fact that we recover a distribution of the *value of time* ($\text{VOT}^{d}_{\hat{a},t,i}$ and $\text{VOT}^{o}_{a,t,i}$) which will give rise to a distribution of the *net value of time* ($\text{NVOT}_{a\to\hat{a},t,i}$). Our data also allow us to incorporate non-linear relationships in waiting time preferences, as a result of unobserved plans or deadlines. For instance, arriving ten minutes late to an appointment could be more than twice as damaging than arriving five minutes late. In Section 4.2 we discuss the interpretation of our model and estimates in the context of these trip-specific qualities.

Since our empirical setting entails choices over trips as described above, we are able to observe distributions of the *net value of time* but not directly the underlying value of time. In Appendix C we formally derive the conditions under which the distributions of $\text{VOT}^{o}_{a,t,i}$ and $\text{VOT}^{d}_{a,t,i}$ are identified from observed distributions of the *net value of time*. The result requires one location normalization either for the origin or destination. To achieve non-parametric identification the result relies on known deconvolution techniques and for parametric identification (normal distribution) on a straightforward rank condition.

An important consideration for our measurement is that time at a destination might be more valuable per-se than time at an origin. Such differences might arise from planning and other coordinated activities. For example, people may travel to a particular destination location to be productive and then later exit the location when their productive task is completed, so that the location becomes an "origin". While we are unable to directly observe plans, our decomposition allows us to estimate the value of time at a location both for when it serves as an origin and as a destination. We are able to do this because we observe riders going in both directions and can recover both $\text{NVOT}_{a\to\hat{a}}$ and $\text{NVOT}_{\hat{a}\to a}$. With this data we can construct a reduced form measure that captures differences in productivity of time use across origin and destination.[18] To this end, let

[18]In the empirical specification we use additional data that is informative about the extent of planning. We obtained the exact location of the customer when a ride was ordered. This allows us to address how much a trip was planned in advance, since we can distinguish, for example, if a customer is standing outside of the building at the time of placing the order and hence is likely to have only limited value for her extra time at the origin.

us rewrite the relationship between the NVOT and VOT as follows:

$$\text{NVOT}_{a\to\hat{a}} = \text{VOT}^d_{\hat{a}} - \text{VOT}^o_a = \text{VOT}^d_{\hat{a}} - \frac{\text{VOT}^d_a}{\text{VOT}^d_a} \cdot \text{VOT}^o_a$$

$$= \text{VOT}^d_{\hat{a}} - \delta_a \cdot \text{VOT}^d_a = \text{VOT}_{\hat{a}} - \delta_a \cdot \text{VOT}_a$$

This measure is denoted as δ_a and given by the ratio of $\text{VOT}^o_{\hat{a}}$ to $\text{VOT}^d_{\hat{a}}$. Following Equation 12, we interpret VOT^d_a as the inherent place value and δ_a as a depreciation factor due to less (or more) productive time use at origin. Hereafter we drop superscripts o and d.

Finally, the time at which a consumer requests a ride is a choice in of itself. We discuss in Section 4.3 how to interpret our estimates in light of this.

3.1 Model of Travel Choice

So far, $\text{NVOT}_{a\to\hat{a}}$ was treated as directly observed. This section describes how to recover $\text{NVOT}_{a\to\hat{a}}$ from a standard discrete choice framework. In the next section we describe how to decompose the NVOT into the the location-specific VOTS.

There is a set of locations $\mathcal{A} = \{1, ..., A\}$ indexed by a and a set of consumers $\mathcal{I} = \{1, \ldots, I\}$, indexed by i. When presented with a menu of bids (or offers) for a ride between a and $\hat{a}$, the consumer makes a discrete choice between J options. Each alternative $j \in \mathcal{J} = \{1, \ldots, J\}$ is characterized by a tuple consisting of price, wait time, route-characteristics such as distance, characteristics of the car (model, year, color), driver (ratings and name) and the stochastic part $\epsilon_{i,j,t}$. We capture observable trip differences with $\mathbf{x}_{i,j,t}$. We also have to account for an additional term, $\xi_{a,\hat{a},t}$, that captures unobserved conditions affecting demand on a particular route, such as big sporting events, holiday travel, etc. We discuss endogeneity concerns in the estimation section. With this setup, the indirect utility from option j can be written as:

$$u_{i,j,t} = \beta^w_{i,h_t,a,\hat{a}} \cdot w_{j,t} + \beta^p_{i,h_t} \cdot p_{j,t} + \beta^x_{i,h_t} \cdot \mathbf{x}_{i,j,t} + \xi_{a,\hat{a},t} + \epsilon_{i,j,t}, \tag{3}$$

where β^p_{i,h_t} and β^w_{i,h_t} reflect preferences over waiting time and price; the subscripts h_t, a, and $\hat{a}$ in $\beta^w_{\cdot}$ indicate that we allow preferences over waiting time to vary with the hour of the day as well as by origin and destination. Finally, the coefficient β^x_{i,h_t} captures preferences for other ride-j-specific characteristics (distance, driver's rating, car type, etc.) as well as environmental conditions common to all j: hour-of-day, public transit availability, traffic speeds, trip distance and time, rainfall, origin and destination neighborhoods, and whether the order is placed on the street or in a building. Note that the latter set of variables allow us to richly condition on many determinants of the outside option.

We can then map the preference parameters in Equation 3 into NVOTs for different locations and different times of day. These NVOT's are obtained via the following equality, which compares the utility of choice j with the utility of some hypothetical option j' that adds a single minute to waiting time, but otherwise has the same characteristics. The price difference $p_{j,t} - p_{j',t}$ that solves the equation reflects the additional units of money needed to make consumers, on average, indifferent between paying or waiting more:

$$\beta^p_{i,h_t} \cdot p_{j,t} + \beta^w_{i,h_t} \cdot w_{j,t} = \beta^p_{i,h_t} \cdot p_{j',t} + \beta^w_{i,h_t} \cdot (w_{j,t} + 1) \tag{4}$$

This implies that a minute of time at destination $\hat{a}$ relative to its value at the origin a is valued as

$$\text{NVOT}_{a \to \hat{a}, h_t, i} = p_{j,t} - p_{j',t} = \frac{\beta^w_{i,h_t,a,\hat{a}}}{\beta^p_{i,h_t,a,\hat{a}}}. \tag{5}$$

Equation 5 demonstrates that individual estimates of the Net Value of Time can be recovered directly from the estimated demand model by taking a ratio of coefficients.

4 Estimation

This section discusses the details of the estimation, which involves two steps. Based on observing the individual choices over bids on the app, we first estimate a likelihood based model. To capture time- and location-specific heterogeneity in time values, we leverage the panel nature of our data to compute random coefficients on the waiting-time using an MCMC procedure. We then use the coefficient estimates from the first step to estimate the NVOT, as we outline above, and a moment-based estimator to recover the distribution $\text{VOT}^d_{\hat{a}}$ (*the value of time*) separately. For clarity in exposition and the interpretation of work and non-work hours, the analysis hereafter utilizes weekday data only.

4.1 Mixed Logit Discrete Choice Model

Under the assumption that $\epsilon_{i,j,t}$ are independently and identically distributed according to a Type I extreme value distribution, choosing the maximum among J alternatives with utilities given by Equation 3 reduces to the standard logit. The probability that an alternative j will be chosen depends on its relative mean utility and is given by:

$$l(w_{j,t}, p_{j,t}, \mathbf{x}_{i,j,t}; \theta) = \frac{exp(\beta^w_{i,h_t,a,\hat{a}} \cdot w_{j,t} + \beta^p_{i,h_t,a,\hat{a}} \cdot p_{j,t} + \beta^x_{i,h_t} \cdot \mathbf{x}_{i,j,t})}{exp(-\xi_{a,\hat{a},t}) + \sum_j exp(\beta^w_{i,h_t} \cdot w_{j,t} + \beta^p_{i,h_t,a,\hat{a}} \cdot p_{j,t} + \beta^x_{i,h_t} \cdot \mathbf{x}_{i,j,t})}, \tag{6}$$

Endogeneity concerns: For bid-specific attributes we the econometrician are on almost equal footing with consumers because we observe all relevant bid attributes up to the drivers' names and photos. These unobserved features are therefore part of $\epsilon_{i,j,t}$. However, because drivers might condition their bids on $\xi_{a,\hat{a},t}$, bids could still be correlated with unobservable demand conditions and thereby bias the price coefficients. To deal with this concern, we exploit persistent differences in bids among different drivers.[19] These differences might, for example, come from pre-programmed bid increments in the meter. However, a straightforward GMM implementation is not feasible since our model relies on individual choice data and is likelihood-based. This prevents us from using standard inversion techniques to isolate $\xi_{a,\hat{a},t}$ and directly instrument. To get around this we, instead, concentrate $\xi_{a,\hat{a},t}$ out using a control function approach (Petrin and Train, 2010). This step consists of a simple regression of trip prices on a set of driver fixed effects, from which we recover a residual which then enters the likelihood as a control. In Figure 19 in Appendix A we show the resulting distribution of fixed effects, which demonstrates that there is large and persistent variation in driver bids. The interquartile range is \$1.9 or 20% of the average fare and the range from the 10th to the 90th percentile is \$4 or 43% of the average fare. Without the control function we find smaller price and waiting time elasticities resulting in an overall mean NVOT which is 19% lower than with the control function.

Control variables: We specify h_t as follows: the price coefficient is allowed to vary across work hours (defined to be 9am-6pm) and non-work hours, and the waiting time coefficient is allowed to vary across five blocks of time. The omitted category is the midnight hour, 12am to 1am. The remaining blocks are 1am to 5am, 6am to 9am, 10am to 3pm, 4pm to 6pm, and 7pm to 12am. We also control for drivers' quality ratings, car type, traffic speed and the distance of the trip. Further, we add controls rain. In Equation 3, β^x_{i,h_t} captures preferences for other ride-j-specific characteristics, which are the distance, the driver's rating, the car type, and environmental conditions common to all j.

Outside option: We allow the outside option to vary spatially at the level of each specific order in the data. This includes controlling for the environmental conditions (such as weather), and whether or not the trip was ordered from within a building or outside on the street. We also incorporate detailed public transit data including the time-of-day-specific presence of public transit availability within walking distance between each individual order's origin and destinations points. These characteristics impact the value of the outside option available to consumers, which is earned by choosing no

[19] This approach is similar to a literature that exploits different leniency standards of judges and known as the *judge design*. See Waldfogel (1995) for the first such strategy.

alternative from $\mathcal{J}$. We normalize the value of the outside option to zero during 12pm and 1am at a location without any nearby public transit option, when it is not raining and when the order is place inside a building. Note that this specification allows for spatial (across different origin-destination pairs) and time-of-day variation in the outside option.

Estimation details MCMC: The estimation exploits the panel structure of our data to capture the full heterogeneity in time values in a tractable way. In particular, we opt for a hierarchical Bayes mixed-logit model to obtain individual specific estimates for the dis-utility of waiting via an MCMC method using data augmentation of latent variables as in Tanner and Wong (1987). In this approach the unobserved random coefficients are simulated and then these simulations are treated as data, which sidesteps the need to evaluate multidimensional integrals by sampling from a truncated Normal distribution instead. We follow techniques described in Rossi and Allenby (2003), Rossi et al. (2005) and Train (2009) and now describe the particular version of the Gibbs sampler that we construct.

We assume that the waiting time and price coefficients for each individual are additive in time of day, location, and an individual specific shifter that is normally distributed.

$$\beta^w_{i,h_t,a,\hat{a}} = \beta^w_i + \beta^w_a + \beta^w_{\hat{a}} + \beta_{h_t} \tag{7}$$

$$\beta^p_{i,h_t,a,\hat{a}} = \beta^p_i + \beta^w_a + \beta^w_{\hat{a}} + \beta_{h_t} \tag{8}$$

Suppose that $\boldsymbol{\beta}_i \sim N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$, where $\boldsymbol{\beta}_i = (\beta^w_i, \beta^p_i)$, the vector of coefficients that vary at the individual level. The matrix $\boldsymbol{\Sigma}$ denotes the variance of the individual specific components of the coefficients as well as their covariance. The covariance $\sigma_{w,p}$ tells us whether ot not people who are more elastic to waiting times are also more elastic to price. We would expect this to be true as the utility of income should be related to opportunity costs. However, one can also imagine segments of the population who are wealthy and yet have an abundance of disposable time, such as individuals who may be well-off and retired.

$$\boldsymbol{\Sigma} = \begin{pmatrix} \sigma_w & \sigma_{w,p} \\ \sigma_{w,p} & \sigma_p \end{pmatrix} \tag{9}$$

We assume that $\boldsymbol{\mu} \sim N(\mu_0, \Sigma_0)$, where Σ_0 is a diffuse prior (unboundedly large variance). We assume that the hyper-parameters of the variance are Inverse-Wishart, $\Sigma_0 \sim IW(v_0, S_0)$. One can then iteratively update the $\boldsymbol{\beta}_i$-coefficient vector, the mean of the coefficients as well as the standard deviations. The specific assumptions on the priors lead to conjugate distributions where the posterior mean of $\boldsymbol{\beta}_i$ is itself normal and the variance again in the family of inverse gamma distributions. To describe the updating algorithm, let $\overline{\boldsymbol{\mu}}^l$ be the sample mean of coefficients of iteration l in the chain and S^l be the sample variance of the Inverse-Wishart.

The key simplification exploited in the Gibbs sampler is that one does not have to obtain an analytical expression for the posterior distribution of the $\boldsymbol{\beta}_i$'s, which instead only needs a proportionality factor that can be easily computed at each step. In particular, we have

$$K(\beta_i|\boldsymbol{\mu}^l, \boldsymbol{\Sigma}^l, \mathbf{y}_i) \propto \Pi_t^{T_i}\ l(y_{ti}; \boldsymbol{\beta}_i) \cdot \phi(\boldsymbol{\beta}_i|\boldsymbol{\mu}^l, \boldsymbol{\Sigma}^l) \tag{10}$$

where $\mathbf{y}_i$ is the vector of choices and covariates observed for passenger i with T_i observations and $l(y_{ti}; \boldsymbol{\beta}_i)$ is the likelihood contribution of a particular choice.

1. Draw a new posterior mean $\boldsymbol{\mu}^l$ for the distribution of coefficients from $N(\overline{\boldsymbol{\mu}}^{l-1}, \frac{W}{N})$.
2. Draw $\boldsymbol{\Sigma}^l$ from $IW(K+N, S^l)$, where $S^l = \frac{K \cdot I + N \cdot S_1}{K+N}$, and $S_1 = \frac{1}{N} \cdot \sum_i^N (\boldsymbol{\beta}_i^{l-1} - \overline{\boldsymbol{\mu}}^{l-1}) \cdot (\boldsymbol{\beta}_i^{l-1} - \overline{\boldsymbol{\mu}}^{l-1})'$.
3. For each i, draw $\boldsymbol{\beta}_i^l$, according to the Metropolis Hastings algorithm, with new proposal $\boldsymbol{\beta}_i^{pl}$ starting from $\boldsymbol{\beta}_i^{l-1}$ using density $\phi(\boldsymbol{\beta}_i|\boldsymbol{\mu}^l, \boldsymbol{\Sigma}^l)$.

Such an MCMC procedure is known to be slow for a large dimensional parameter space. To avoid slow convergence we, therefore, first estimate the model without the random coefficients using standard maximum likelihood and then employ the above Gibbs sampler to obtain the distribution of random coefficients separately, starting from the maximum likelihood estimates.

4.2 Value of Time: Estimation Details

From the logit model above we obtain the NVOT as the ratio of the price and waiting time coefficients. To decompose those NVOT into the value of time an additional estimation step is required. Appendix C provides the conditions for identification and shows that we need one location normalization. While our framework allows us to identify the individual-specific VOT at arbitrarily fine geographic and temporal resolutions, practical data limitations require us to recover these measures as coarser partitions that aggregate to our locations as defined in Figure 23, at hourly intervals, and in five-percentile bins of individual-specific price versus waiting time preferences, β_i^p/β_i^w. We use a moment estimator that is based on the simple relationship between the observed $\text{NVOT}_{i,h_t,a\to\hat{a}}$ and the unknown pairs of $\text{VOT}_{i,\hat{a},h_t}$ and $\delta_{i,a,h_t} \cdot \text{VOT}_{i,a,h_t}$:

$$\text{NVOT}_{i,h_t,a\to\hat{a}} = \text{VOT}_{i,\hat{a},h_t} - \delta_{i,a,h_t} \cdot \text{VOT}_{i,a,h_t} + \eta_{i,h_t,a\to\hat{a}}, \tag{11}$$

where we interpret $\eta_{i,h_t,a\to\hat{a}}$ as orthogonal measurement error. From this equation we see that for each i and h_t there are $2 \cdot N_a - 1$ parameters after normalizing one origin value. For each of those sets we observe N_a^2 equations.

Denoting the collection of VOT's as $\overline{\text{VOT}}$, requiring that all VOT are positive.[20]

$$\begin{aligned} \underset{\overline{\text{VOT}}}{\text{minimize}} \quad & \sum \eta^2_{i,h_t,a\to\hat{a}} \\ \text{subject to} \quad & 0 \leq \text{VOT}_{i,a,h_t},\ \forall i, h_t, a \ \text{ and } \ \delta_{i,1,h_1} = 0\ \forall i \end{aligned}$$

We also normalize the origin VOT of location one to zero, consistent with the 12am, location one reference category normalization imposed in Equation 3. The normalization does not matter much because N_a is large and the system heavily over-identified. In fact, we get very similar values for almost all location normalizations.

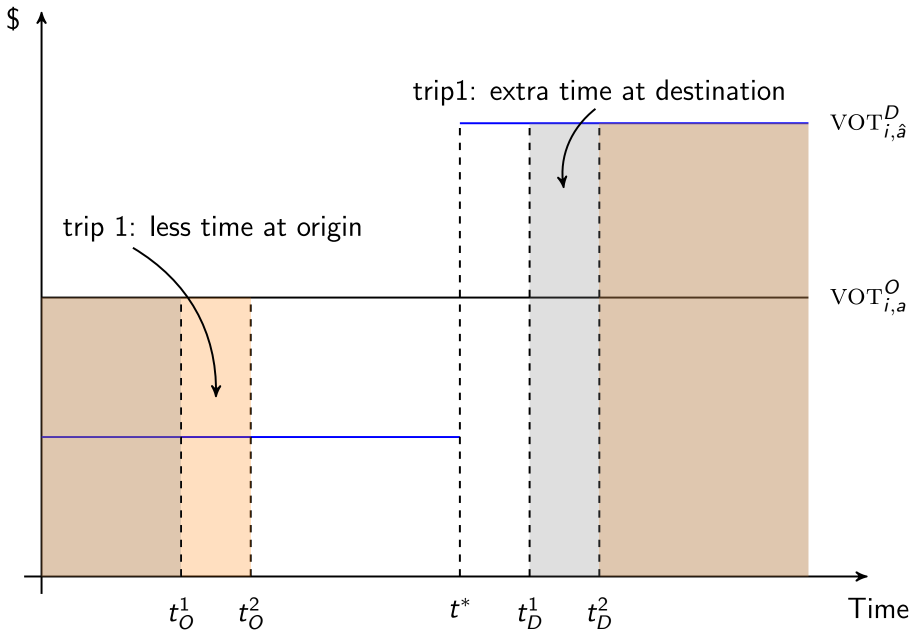
4.3 Optimal Query Times and Interpretation

Given that the decision to move from the origin to the destination is revealing that time at the destination has become more valuable than at the origin, it is natural to ask how to interpret our estimates when the time at which the ride is requested is itself endogenous. This is illustrated in Figure 5. The origin value in this example is constant and the destination becomes more valuable at t^*. If the trip duration is Δ and expected wait times under the optimal trip choice $E[w^*]$ they will query the app at a time q, anticipating that under the optimally chosen wait time they arrive at the destination at t^*. One the query is made the consumer receives wait times and prices from different drivers and makes a selection. Importantly, we only use the trip selection to estimate VOT^d and VOT^o and do not make use of query times. Furthermore, so far we have not introduced the notion of an optimal arrival time and only distinguish between productive time use at the destination and less productive time use at the origin through a reduced form depreciation factor δ. It is, however, worthwhile contemplating whether t^* is identified, which would allow us to more explicitly account for the changing origin and destination values around appointments and plans.

In Appendix B elaborate on the identification of a model in which we are more explicit about the fact that query times are optimally chose. We are able to show that t^* is identified under a variety assumptions. Key to this identification is that even though the consumer optimizes on the time at which the ride is requested, they still face uncertainty over the waiting times and prices they will face when making a choice. This allows us to infer when a ride would make the consumer late, so that they are willing to pay for shorter ETAs, and when it would make them arrive too early, so that they are willing

[20] To estimate the model we use JuMP (Dunning et al. (2017)).

Figure 5: Optimal query times and trip choices



NOTE: This graph shows the differences in value that two trips create. It also shows how the destination value changes after t^*.

to pay for longer ETAs.[21] Furthermore, we show that, even though the observed trip choices reveal preferences about local deviations from the optimal departure time, all parameters of the model are identified under two versions of the model in Equation 1.[22] The simplest way for observed choices over local deviations to inform us about the value of time more generally is to assume that an individual's underlying value of time at origin and destination is constant over some time interval. This assumption would imply that the value expressed over small deviations from the optimal arrival time is linear in time and therefore fully informative about the value of time further away from the optimal arrival time. This is, for instance, what Small (1982) implicitly assumes by letting preferences be linear in the distance to the optimal arrival time. A look at the data can help us discern whether or not linearity is a good assumption. Figure 18 in Appendix A shows the likelihood of picking a particular trip as a function of the wait time and the likelihood of choosing the inside option as a function of the minimum wait time. While more explicit conditioning on t^* is possible we interpret our distinction between the origin value of time and the depreciated destination value of time as a

[21] Using the language of Equation 1, we can infer when a ETA w is to the left or to the right of the ideal arrival time, t^*.

[22] In Appendix B we assume that the consumer can *finely tune* his query time. This is a stylized assumption. However, any friction that prevents the consumer from fully optimizing over the request time would only make our identification argument stronger since it would allow us to measure the consumer's willingness to pay for reductions in waiting times at moments where the value at the origin and the destination are further apart.

reduced form that captures the essence of appointment driven changes in the value of time.

5 Results

We first present the results from the logit-demand model and the implied waiting time and price elasticities. We then present the results on the value of time.

5.1 Logit Model Results

Table 2 shows the coefficients and standard errors that we obtain from the demand model. The dis-utility of money is higher and almost identical across working and non-working hours. The intra-daily coefficients on waiting time vary over time-of-day, increasing in absolute magnitude (more negative) into the mid-day peak and declining into the evening. In addition to the time dimension, an important component of our subsequent analysis is to what extent the willingness to pay for waiting time reductions scales both with the origin and destination. In addition, there is a large amount of origin- and destination-specific heterogeneity in utility. Due to the large number of coefficients we show those separately in Figure 25.

The outside option is chosen about 33% of the time. Several coefficients measure an interaction effect between waiting time and additional factors related to the outside option: public transit availability, whether the trip is ordered on the street or not, and the presence of rain. Since the latter two of these interact with waiting time their net effects are not immediately apparent. We compute marginal effects to see the impact: rainfall confers a 0.59% increase in choosing the outside option. On-street ordering leads to a 0.16% increase. Within the auction, consumers prefer drivers with higher ratings and better cars. They prefer taxis for longer distance trips.

Table 3 show the elasticities of price and waiting time, computed as the percent change in selecting the bid with respect to a percent change in price and waiting time, respectively.

The table shows a set of bid-level elasticities, which measure the competitiveness of alternative bids, as well as a set of order-level elasticities, which measure the competitiveness of the outside option. We see a general pattern that consumers are much more price elastic than waiting-time elastic: price elasticities range from four to eleven times higher, with starker differences in the evening compared to the day time.

In column 2 we use the estimated joint distribution of random coefficients to categorize four types of individuals as high (H) and low (L) sensitivity to price and waiting

Table 2: Model Coefficient Estimates

Description	Coefficient	Std Error
Price 6pm-6am	-1.183	0.002
Price 6am-6pm	-1.175	0.003
Waiting Time 1am-5am	-0.018	0.011
Waiting Time 6am-9am	-0.081	0.011
Waiting Time 10am-3pm	-0.089	0.01
Waiting Time 4pm-6pm	-0.062	0.01
Waiting Time 7pm-11pm	-0.031	0.01
Waiting × On-Street Order	-0.036	0.002
Waiting × Raining	0.015	0.004
Waiting Time Squared	-0.006	0.0
Driver Rating	11.063	0.097
Car: Mid Quality	0.248	0.005
Car: High Quality	0.708	0.009
Trip Speed	-0.051	0.002
Alt. Transit Available	0.044	0.007
Order on Street	0.211	0.014
Rain	-0.148	0.034
Trip Distance	5.65	0.071
Waiting × Pickup Location FE 1-30		
Waiting × Dropoff Location FE 1-30		
Pickup Location FE 1-30	Omitted - See Figure 25	
Dropoff Location FE 1-30		
Hour FE		

Note: This table shows coefficient estimates and standard errors of the logit demand model for each consumer type. The final 120 rows are omitted for exposition. These parameter estimates comprise outside option shifters and waiting time preference interactions with each of 30 pickup and dropoff locations as defined in Section D.1. The omitted results are instead depicted graphically in Figure 25.

times. High price-sensitivity individuals have *below* median β_i^p, meaning they experience the highest disutility from price. Likewise, high waiting-time-sensitivity individuals have *below* median β_i^w. Consumers have highly heterogeneous elasticities: between the two extreme groups both price and waiting time elasticities differ by about a factor of four. We estimate a modest positive correlation between the sensitivity to price and waiting times: more price-sensitive passengers are also more waiting time sensitive, and vice-versa.

These elasticity estimates convey that both price and waiting time are important factors in the consumer decision and that waiting time elasticities vary throughout the day in ways that reflect the varying value of work and non-work related tasks.[23]

Table 3: Estimated Elasticities

Time of Day	Individual Type	Bid Level Elasticities		Order Level Elasticities	
		PRICE	WAITING TIME	PRICE	WAITING TIME
Daytime 6am-6pm	Overall	-4.37	-1.01	-3.9	-0.89
	H Price, H Wait Sensitivity	-8.59	-1.81	-7.36	-1.53
	H Price, L Wait Sensitivity	-2.86	-0.85	-2.8	-0.76
	L Price, H Wait Sensitivity	-5.1	-1.04	-4.47	-0.96
	L Price, L Wait Sensitivity	-2.03	-0.52	-2.06	-0.51
Evening 6pm-6am	Overall	-5.49	-0.5	-4.9	-0.49
	H Price, H Wait Sensitivity	-8.72	-0.8	-7.48	-0.75
	H Price, L Wait Sensitivity	-3.4	-0.37	-3.43	-0.37
	L Price, H Wait Sensitivity	-6.16	-0.52	-5.39	-0.52
	L Price, L Wait Sensitivity	-2.49	-0.22	-2.63	-0.24

NOTE: This table shows the demand elasticity of price and waiting time across daytime and evening hours and individual type groupings. We distinguish as *high (H) price sensitivity* individuals who have below median values for β_i^p and *low (L) price sensitivity* individuals as those with above median values for β_i^p, and similarly for waiting time sensitivity. The first two columns show these elasticities among competing bids, reflecting the change in demand due to a 1% change in price or waiting time on a single bid. The second two columns show them with respect to choosing the outside option, reflecting a change in demand due to a 1% change in price or waiting time on *all* bids.

The estimated model fits the data well. In Appendix Section E.3, we show quality of our model fit on both aggregate moments and specific choices.

5.2 The Net Value of Time

We now present results for the willingness-to-pay for waiting time reductions implied by our estimates, which we refer to as the *net value of time* (NVOT), scaled to USD per hour. NVOT represents the difference between the value of time attainable at a *destination* from the value of time attainable at the trip *origin*, given the activities and features

[23]We can also decompose elasticities by trip origins and destinations as with Table 9 and Table 10. Broadly similar patterns between demand types are revealed, though we see that there are large differences in each elasticity measure from one location to another. In general, price elasticities are more variable than waiting time elasticities.

of each location at each time for each person. They are computed using the above coefficients together with Equation 5, where we account for all trip-specific and environmental factors that affect valuations of the trip and the outside option, such as public transit and rainfall.

Table 4 summarizes the NVOT results. The overall mean value is \$13.47 per hour, an average NVOT across all trips and individuals. The most prominent source of heterogeneity is between individuals. We again report four groups of individuals, those with above- and below-median random coefficient estimates on both price preferences and waiting time preference. The low price sensitivity and high waiting time sensitivity group exhibits NVOT nearly twice the overall average at \$23.39 per hour, while individuals with low sensitivity to price and high sensitivity to waiting time have average NVOT of \$5.00. All groups have similar time-of-day patterns, with the highest values in the morning hours between 6am and 9am. Going forward, to be able to extrapolate form our specific context, we will interpret our VOT measure during this time of day as the wage rate. Not only is this the highest VOT measure during the day it is also most plausibly the value assigned to work related activities. Supporting evidence for this interpretation comes from a small survey that we conducted among passengers together with Liftago. We find that that wage rate among these survey participants is \$15.23, very close to our measurement of the VOT during work hours, which is \$15.44.

The individual-specific parameters reveal stark differences in valuation, but there is also substantial heterogeneity by time-of-day as well as place. We see that late morning to mid-day hours have estimated values that are approximately 50% higher compared to evening and overnight hours. Finally, we divide Prague's spatial regions into *core* and *non-core*, where core regions are the locations including and adjacent to regions 11 and 20 as depicted in Figure 23. In Table 4 we label as *urban core trips* any trip that involves one of these regions as origin or destination. We find that NVOT in core regions are on average 41% higher than non-core trips.

To interpret our results in finer detail, we note that even a given rider may have higher or lower NVOT when the circumstances surrounding a ride are more or less urgent. We can therefore view any NVOT estimate that fixes an individual, time-of-day and location to still be an average across the circumstances facing that individual. In Section E.6 we demonstrate that our data can be used to recover different NVOT estimates between trips with a drop-off time close to the start of a new hour, which are more likely to involve deadlines, and those at different times. This analysis provides an example of trip-specific heterogeneity that is averaged in the results reported in Table 4.

One important application of these results is that they provide insight into the interpretability of geographic (GPS) time-use data, such as cell phone location data. In

Table 4: Net Value Of Time Estimates

Subsample	Net Value of Time (NVOT) 12a-6a	6a-9a	10a-2p	3p-6p	7p-12a	All Hours
All Types	12.56	16.38	16.63	13.91	10.96	13.47
H Price, H Wait Sensitivity	14.44	17.29	17.46	15.53	13.52	15.03
H Price, L Wait Sensitivity	4.34	6.76	7.08	5.19	3.82	5.0
L Price, H Wait Sensitivity	22.51	26.21	26.44	23.96	20.01	23.39
L Price, L Wait Sensitivity	8.99	12.41	12.91	9.85	2.33	10.02
Urban Core Trips	12.96	17.1	17.31	14.37	11.4	13.97
Non-Core Trips	9.93	11.78	9.61	10.57	7.6	9.94

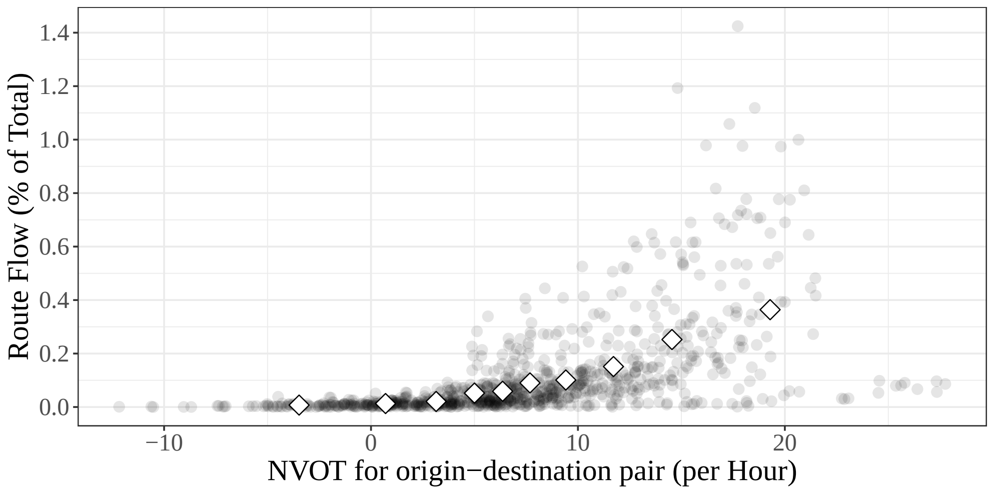
Note: This table shows NVOT estimates implied by the logit demand model. All estimates are presented in US dollars.

several studies, for example Kreindler and Miyauchi (2019), authors use this type of data and interpret aggregate location decisions as a measure of place-specific amenities or productive capacity.

Our analysis is, to our knowledge, the first to pair highly granular spatial data, that records where people go within a city, with direct NVOT measures, the latter of which capture the relative attractiveness of locations as per our illustration in Figure 4. A natural question is, therefore, how close binary measures of time spent are to our direct measures of the relative attractiveness of locations. To answer this question we correlate our WTP for waiting time reductions for going from a to $\hat{a}$ with the fraction of all trips that go from a to $\hat{a}$. The two different measures line up well but not perfectly. Figure 6 shows a scatter plot of the nine hundred different directional data points as well as the binscatter points on top. As the plot illustrates, the two are highly significantly correlated with a correlation coefficient of 0.56 and *t-statistic* of 20.46. We can further condition this analysis on different times of day. We find that at 0.43 this correlation is highest during the middle of the day, which falls into work hours (10am-3pm), and lowest during midnight at 0.38. Both of these correlations are significant at all conventional levels.

These results convey a number of important insights. First, travel flows appear to be a good but not perfect measure of time valuations. The variation in those correlations throughout the day gives further guidance on when those travel flows align better with place-specific time valuations. Time valuations that are based on revealed preferences in transportation markets can therefore serve as an additional important quantification of the relative attractiveness of locations. In the next section, we explore this idea further by estimating the model outlined in Section 3, which micro-founds the expressed willingness to pay to reduce waiting times through place specific values of time.

Figure 6: Relationship between Travel Flows and the NVOT



NOTE: This graph shows the scatter (transparent round dots) and binscatter (white diamonds) relationship between the NVOT for an origin-destination pair and the respective traffic flow (as a fraction of total).

5.3 The Value of Time

Equation 2 expresses how a transportation-specific measure – the willingness to pay for waiting time reductions, or NVOT – is related to the value of time. A measure of the *value of time* (VOT) is useful outside the context of transportation and can be seen as a summary measure of the value that a person expresses for the set of activities at a place and time of day. In this section we highlight several stylized facts about the distribution of VOT across places, time, and individuals.

An important consideration for our measurement is that time at a destination might be more valuable per-se than time at an origin. Such differences might arise from planning and other coordinated activities. For example, people may travel to a particular destination location to be productive and then later exit the location when their productive task is completed, so that the location becomes an "origin". While we are unable to directly observe plans, our decomposition allows us to estimate the value of time at a location both for when it serves as an origin and as a destination. We are able to do this because we observe riders going in both directions and can recover both $\text{NVOT}_{a\to\hat{a}}$ and $\text{NVOT}_{\hat{a}\to a}$. With this data we can construct a reduced form measure that captures differences in productivity of time use across origin and destination.[24] To this end, let

[24] In the empirical specification we use additional data that is informative about the extent of planning. We obtained the exact location of the customer when a ride was ordered. This allows us to address how much a trip was planned in advance, since we can distinguish, for example, if a customer is standing outside of the building at the time of placing the order and hence is likely to have only limited value for her extra time at the origin.

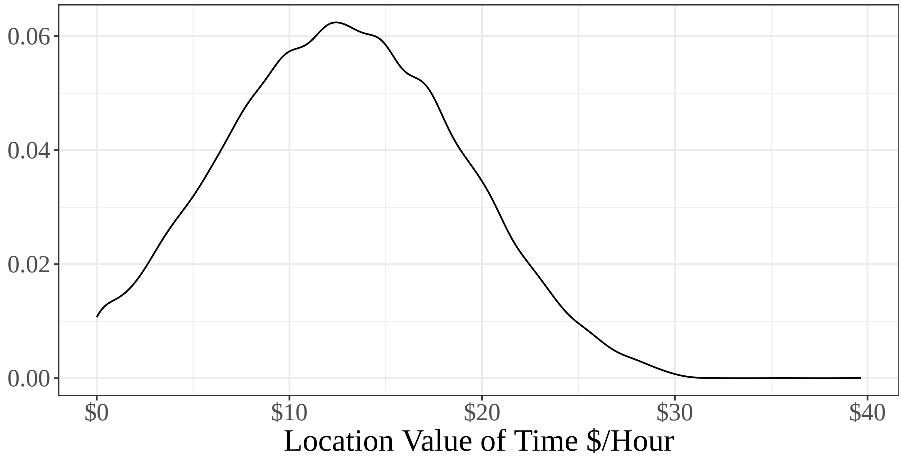
us rewrite the relationship between the NVOT and VOT as follows:

$$\text{NVOT}_{a\to\hat{a}} = \text{VOT}^d_{\hat{a}} - \text{VOT}^o_a = \text{VOT}^d_{\hat{a}} - \frac{\text{VOT}^d_a}{\text{VOT}^d_a} \cdot \text{VOT}^o_a = \text{VOT}^d_{\hat{a}} - \delta_a \cdot \text{VOT}^d_a = \text{VOT}_{\hat{a}} - \delta_a \cdot \text{VOT}_a \quad (12)$$

This measure is denoted as δ_a and given by the ratio of $\text{VOT}^o_{\hat{a}}$ to $\text{VOT}^d_{\hat{a}}$. Following Equation 12, we interpret VOT^d_a as the inherent place value and δ_a as a depreciation factor due to less (or more) productive time use at origin. Hereafter we drop superscripts o and d.

Figure 7 shows the unconditional distribution of the value of time v_a (USD/hour) that we back out. The histogram reveals large variation. The interquartile range goes from \$6.8/h to \$16.3/h. The tenth percentile of the distribution is \$3.7/h and the ninetieth percentile is \$21.3/h.

Figure 7: Histogram VOT

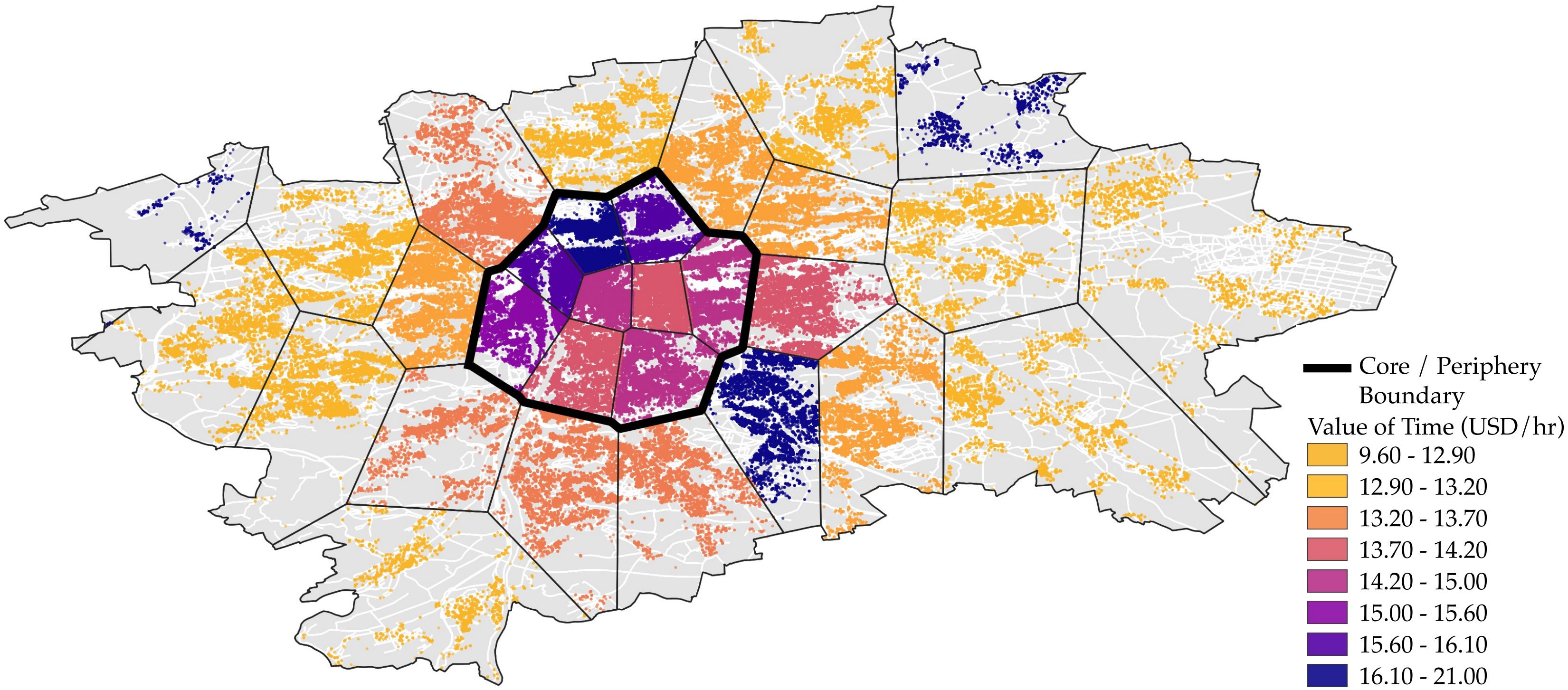


NOTE: This graph shows the unconditional distribution of the values of time that we back out.

Spatial Heterogeneity Figure 8 shows VOT heterogeneity by location. Going from the lowest-value location to the highest-value location implies a difference of \$10.83 in the hourly value of time. This corresponds to a 51.96% increase in percentage terms. However, the interquartile range is already substantially smaller with a difference of \$2.89, which in percentage terms is 17.78%. This suggests a relatively small contribution of places to the variance in the value of time. However, both the location breakdown and the person-specific breakdown mask the variation from the respective other source. For example, to the extent that they are correlated one may mistake variation in the value of time in the spatial dimension for person-specific variation and vice versa.

These results offer a direct measure of the short-run monetary value that people assign to spending time at different places. This distribution is distinctive from other

Figure 8: Map of VOT Estimates in Prague

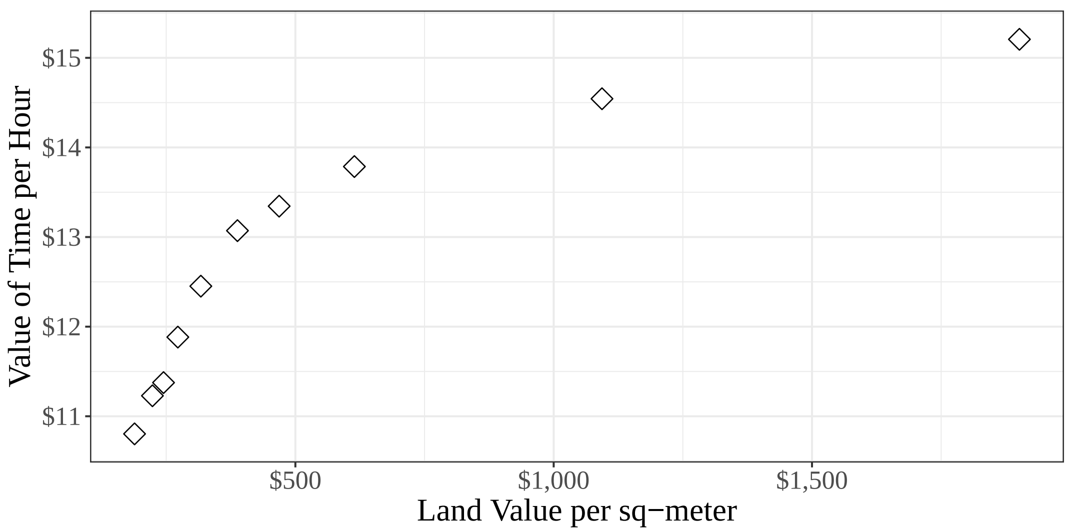


NOTE: This figure depicts each GPS destination point in the Liftago data shaded by the average value of time in that destination, or VOT_a^d across places $a \in \{1, ..., 30\}$ within the city limits of Prague. White lines depict the city's street map. The bold black line delineates the boundaries which we specify as the urban core in presenting results.

similar measures studied in the literature. For example, economists have devoted considerable attention to measuring the long run effect of place of residence on individual outcomes (Chetty et al., 2018; Couture et al., 2019). However, place of residence might be an imperfect measure of the extent to which people benefit from the resources that different places have to offer. However, a study of "experienced segregation" based on GPS data reveals that time use across different spatial regions is less segregated than residential locations (Athey et al., 2019). Another example is Davis et al. (2017) who use Yelp data to show that restaurant consumption is only half as segregated as residences. Our VOT measure encompasses the valuations stemming from the full set of activities of individuals in our sample.

To explore how our value of time estimates compare to other quantities that capture spatial differences in economic activity, we correlate our VOT measures with property prices. A binscatter plot of the relationship is shown in Figure 9. There is a strong positive relationship between real estate prices and our VOT measures. However, the "returns" to higher land values are diminishing. From a regression of log-VOT on log land-values we measure an elasticity of 0.25 ($p < 0.001$). So for every 1% higher land value we measure a value of time that is 0.25% higher. On the one hand, this strong positive relationship serves as a validation of our measures since we have not used land values at any point in the estimation. On the other hand, we find that with an R^2 of less than 0.02 that real estate prices can only explain a very small percentage of the variation in VOT. This re-emphasizes the point that the value of time is a useful complementary measure of short run economic activity across space.

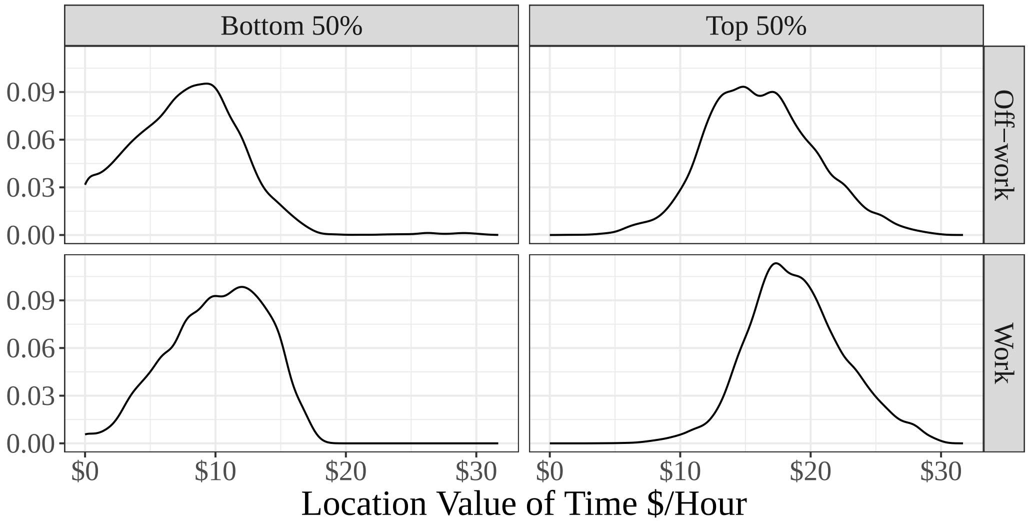
Figure 9: Place-specific VOT and Land Values



NOTE: The x-axis orders the thirty locations by their average value. The y-axis in the left panel shows the values of both types during work times and right panel during non-work times.

Time and Person Heterogeneity For clarity of exposition, we group time of day into two categories – work-time, defined as the hours 6am-6pm, and non-work-time – and group individuals into the bottom 50% and top 50% in terms of VOT. Figure 10 show VOT estimates within each of these four groups. We see that both groups express a higher value of time during work hours.

Figure 10: VOT by Group and Time



NOTE: The x-axis orders the thirty locations by their average value. The y-axis in the left panel shows the values of both types during work times and right panel during non-work times.

Table 5 gives an overview of means and standard deviations for the top and bottom 50% in the distribution of VOT. During both work and non-work time, the top 50% exhibit a VOT that is almost twice that of the bottom part of the population. Within type, however, the difference between work-time and non-work-time is modest. For the top 50% the value of time is 15% higher during work than during non work times. For the bottom 50% the discrepancy is larger, their value of time is 19% higher during work hours.

5.3.1 Variance Decomposition

Our estimates also allow us to study whether or not different strata of society value different places differently. We exploit the fact that our data contain a panel of riders in which we can observe the same rider making decisions about time allocations across many different places. If we found that most of the variation in the value of time is driven by places and not people, this would suggest that place-specific factors accrue equally to different people. For example, there might be differences in the provision of public goods across places, which are typically equally available to all people. On

Table 5: Summary Statistics of Value of Time

	Work Time (USD)		**Non Work Time** (USD)		**Non Work Time** VOT /
	MEAN	STD	MEAN	STD	**Work Time** VOT (%)
Location Values (v_{i,a,h_t})					
All	17.15	10.29	14.02	10.39	0.82
H Price, H Wait Sensitivity	19.18	7.0	15.95	7.05	0.83
H Price, L Wait Sensitivity	9.79	4.82	7.25	6.24	0.74
L Price, H Wait Sensitivity	27.05	12.43	23.45	12.73	0.87
L Price, L Wait Sensitivity	12.66	4.64	9.83	5.85	0.78

NOTE: This table shows summary statistics on the estimates that capture how much less productive time at the origin is relative to the destination separate by type. The last column shows the relative magnitude of the non work-time VOT over the work-time VOT in percent.

the other hand, differences in the value of time might be predominantly driven by differences across people. This would be true, for example, if wealthy people with productive jobs enjoy activities that are equally exclusive across different places.

To separate out the respective sources of variation and investigate their relationship in more detail we now turn to a variance decomposition. A variance decomposition will allow us to investigate whether people with high average VOT spent more time in places with high average VOT.[25] The extent of such sorting effects has been of long standing interest in the economics of marriage markets (Becker (1973)), labor markets, (Abowd et al., 1999; Eeckhout and Kircher, 2018; Shimer and Smith, 2000) and housing markets (Couture et al. (2019)). Our approach is similar to the labor literature that tries to decompose wages into firm specific components and worker specific components, most importantly Abowd et al. (1999). For the variance decomposition we derive an accounting equation from the following regression model:

$$\text{VOT}_{i,a,h_t} = \alpha_i + \eta_{h_t} + \gamma_a + \epsilon_{i,t}, \tag{13}$$

where α_i is a person fixed effect η_{h_t} is a time-period fixed effect, γ_a is a place fixed effect, and $\epsilon_{i,t}$ is a residual. Due to the curse of dimensionality, we run this specification by replacing individual values with the percentile means, so that i becomes an indicator of the percentile bin.[26] This regression then gives rise to the following variance

[25] The place specific estimates should not necessarily be interpreted as deep structural parameters that are inherent to a place. They could capture certain agglomeration effects, such as the taste for meeting certain people who typically can be found at a given place.

[26] Our panel is not long enough to observe a given individual in all possible combinations of origin, destination and time of day.

decomposition.

$$Var(\textsc{vot}) = Var(\alpha) + Var(\eta) + Var(\gamma) + 2 \cdot Cov(\alpha, \eta) + 2 \cdot Cov(\alpha, \gamma) + 2 \cdot Cov(\gamma, \eta) + Var(\epsilon) \quad (14)$$

Table 6 shows the results from this exercise. At 78%, by far the largest contributor to the observed variance of the VOT are differences across people. In comparison, place-specific variance is small and accounts for 10% of the total. Intra-daily changes in the VOT contribute another 9%.

Table 6: Variance Decomposition of the Value of Time

$Var(\alpha_i)$	$Var(\eta_{h_t})$	$Var(\gamma_a)$	$2 \cdot Cov(\alpha_i, \gamma_a)$	$2 \cdot Cov(\alpha_i, \gamma_{h_t})$	$2 \cdot Cov(\gamma_a, \eta_{h_t})$	$Var(\epsilon_{i,t})$
27.7	3.25	3.5	-0.4	-0.1	0.3	1.6
0.78	0.09	0.1	-0.01	-0.002	0.008	0.04

NOTE: The first row of this table shows the variances of each of the components of the model above. The second row shows the variance of each of the components divided by the total variance, which can loosely be interpreted as fractions of the total variance.

Moreover, the covariances show that high VOT people do not spend more time in high VOT places. With a covariance of -0.4 we measure a slightly negative sorting effect. Similarly, there is a negative correlation between people who express a high value of time the times of day with higher average VOT.[27]

5.3.2 Discrepance between Value of Time at Origin and Destination

We next discuss our estimates of differentially effective time use at origin and destination, as measured by δ_{i,a,h_t}. Table 7 gives an overview. Across the entire population, unplanned time at the origin is only 31% as valuable as time at the destination during work hours while it is 36% as valuable during non-work time. Holding the location fixed, meetings and other types of work-required planning therefore lead to a larger discrepancy in the value of planned and unplanned time. Moreover, we find that there is a large difference in δ within the population. Not surprisingly, people that we have labeled as more time sensitive ($\beta_i^w > median(\beta^w)$) have a larger discrepancy in the value of planned and unplanned time. This shows that higher willingness to pay for lower waiting times is driven both by a larger inherent value of time at any given location and also a bigger discrepancy between planned and unplanned time.

[27] We have also repeated this same exercise with the NVOT as opposed to VOT.Location fixed effects in this exercise are defined over directional pairs since the net value of time is defined over those. Under this alternative exercise, we come to a very similar conclusion. Most of the variation is driven by differences across people instead of differences across places. This should dissuade any concern that our results are driven by specific aspects of the decomposition that we perform.

Table 7: Summary Statistics for δ_{i,a,h_t}

	Work Time		**Non Work Time**	
	Mean	STD	Mean	STD
Location Values ($\textsc{vot}_{i,a,h_t}$) in USD				
All	0.18	0.17	0.2	0.24
H Price, H Wait Sensitivity	0.14	0.11	0.12	0.11
H Price, L Wait Sensitivity	0.32	0.34	0.5	0.79
L Price, H Wait Sensitivity	0.14	0.12	0.14	0.12
L Price, L Wait Sensitivity	0.18	0.18	0.21	0.25

Note: This table shows summary statistics on the estimates that capture how much less productive time at the origin is relative to the destination separate by type.

To summarize our results, we find large differences in the value of time across individuals and also large differences in differentially productive time use across origin and destination. Most of the variation in the value of time comes from person-specific heterogeneity as opposed to place specific heterogeneity. Interestingly, this suggests that, in the short run, different places do not confer benefits that are equally valued by everyone. These results are an important short-run complement to the recent debate around the importance of place-specific factors for long-run outcomes. Another interesting implication lies in the finding that the value of time of high types can, in part, be explained by a larger necessity for planning as measured by the ratio between origin and destination flow values for the same area. This suggests that high VOT types depend to a larger extent on complementary inputs with whom a need for coordination arises. For example, high skilled work places might require more meetings and coordination with others to use time productively.

6 Application: The Time Cost of Traffic Congestion

Traffic congestion is a growing phenomenon across the globe. The 2019 Urban Mobility Report estimates that the average urban commuter in the United States spent an extra 54 hours of travel time on roads as a result of congestion.[28] INRIX reports a similar global measure taken across 220 cities among 38 countries to estimate that congestion increases traffic time on average by 108 hours in 2018, a 1% increase over the previous year.[29] This problem has the attention of regulators. Large metropolitan cities are experimenting with a variety of policy instruments including congestion pricing,

[28] See Schrank, Lomax and Eisele (2012).

[29] See https://inrix.com/scorecard/.

variable tolling and stricter limits to parking. While congestion is a salient problem for commuters and businesses alike, the costs are normally difficult to quantify precisely because commuters' opportunity costs in traffic are hard to measure. In this section, we use our framework to quantify the opportunity cost of congestion in Prague.

Our approach has two ingredients. First, we use time and distance data from the 1.9 million trips in our sample to measure average traffic speed by time of day and route. We find the hour of day at which 75th percentile traffic speeds are highest and denote this as the free-flowing or un-congested traffic speed. By comparing each observed trip time against the counterfactual trip time under un-congested conditions, we compute a measure of extra travel time due to congestion. Figure 11 panel (a) plots average excess travel times by hour across Prague. During peak times, trips take an extra 5-6 minutes or about 25% longer. In evening and overnight hours, congestion falls substantially as average traffic speeds become close to the free-flowing speeds.

The second ingredient is our measure of time cost. Our time of day and place-specific VOT estimates serve as these measures and can be interpreted as a summary of the value of activities at certain places throughout the day. When we estimate a positive WTP for transiting from one place to another, this reveals that the destinations must be higher valued than the origins *at that time*. Thus, the time cost of congestion will depend on whether congestion reduces time spent at a productive destination ($\text{VOT}_{a,h_t,i}$) or a less productive origin ($\delta_{a,h_t,i} \cdot \text{VOT}_{a,h_t,i}$). One feature of our value of time estimates is that we can distinguish between anticipated and unanticipated congestion costs. Anticipated congestion costs, which would arise, say, during an hour in which a road is typically congested, will induce travelers to leave early and thereby sacrifice time at the origin instead of the destination. Conversely, unanticipated congestion costs will cost travelers time at their destinations, which are most often higher valued.

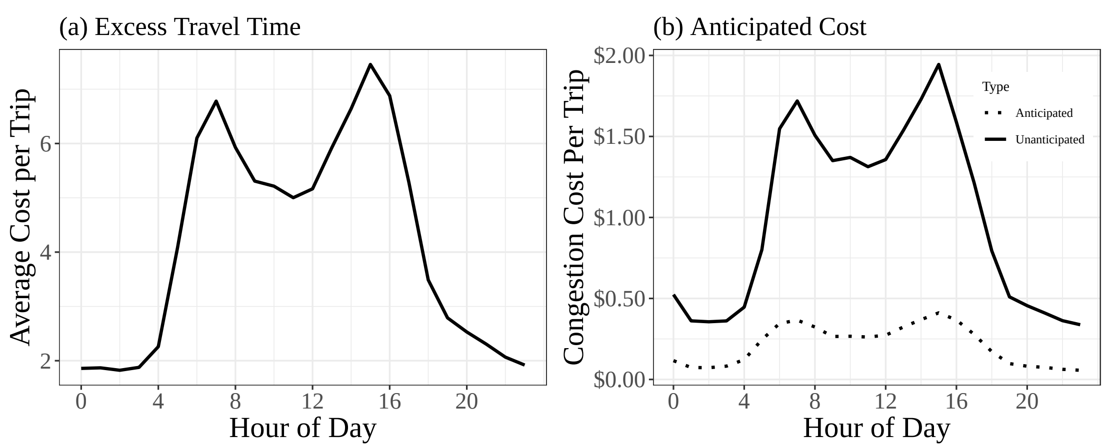
To compute congestion costs, we multiply the number of excess minutes in traffic by the value of time at origin or destination, depending on whether congestion is anticipated or unanticipated.

We make a baseline assumption that the value of time spent in a vehicle is equal to zero, consistent with our normalization of time spend waiting unproductively in a particular location. Several studies have measured the opportunity cost of travel time, known in the literature as the value of travel time (VTT). This value has been frequently estimated to be approximately 50% of the gross wage rate, and higher in congested conditions (Small, 2012). By design, VTT can be interpreted as a willingness to pay to reduce travel time, which implies it is a *net* value or difference between the value of time spent at an origin or destination and the value of time spent in the car. Thus if we take our VOT measure to be equal to the one times the wage rate, as discussed in Section 5.2, and accept that VTT is equal to 0.5 times the wage rate, then we could infer that the consumption value of time within a car is equal to the difference, or 0.5 times wages. However, as we are studying congestion, we note that evidence from Abrantes and Wardman (2011) reports that the VTT under congested conditions is equal to 1.54 times the wage rate. This would imply that the time spent in the car is valued negatively. In this case, our assumption that in-car time is valued at zero would yield an underestimate of the cost of congestion.

We also note that our measure of cost is implicitly relative to the value of an identical trip volume occurring under conditions of free-flow traffic speed. This is distinct from a deadweight loss measure which would measure costs relative to counterfactual speeds given an alternative arrangement of roads or congestion pricing (Couture et al., 2018). There are two useful ways to interpret our measurement. First, it can be regarded as an upper bound on the welfare gain associated with reducing congestion among drivers currently on the road. Second, we can use it to compute marginal benefits due to smaller reductions in congestion to enable quantification of costs associated with policies such as tolling that may induce reductions in congestion without eliminating it all together.

Figure 11 panel (b) combines trip-specific excess travel times and their associated VOT measures to plot the cost of congestion. We find congestion cost patterns that mirror the daily commute. If this were completely anticipated by travelers, then an average rush-hour trip would impose around \$0.25 – \$0.30 of time cost as passengers would choose to replace less valuable time at origins with time in congested traffic. When delays are unanticipated, however, the average per-trip cost to travelers is between \$1.00 – \$1.30 during rush-hour.

Figure 11: Excess Time in Traffic and Estimated Congestion Costs



The above figures make clear that congestion costs are borne most heavily in the rush-hour periods, and, when traffic accidents and other shocks to commute time impose unanticipated delays, the costs can grow five-fold. We now explore congestion cost heterogeneity across space. Higher congestion costs in core sections of urban areas has led some municipalities to implement zone-based congestion pricing, as London did in 2003.[30] Figure 12 and Figure 13 separate trips by *urban core* or *non-core*. Urban core designates routes that begin or end in the high density center of Prague (Locations including and adjacent to 11 and 20 and in Figure 23).

Figure 12: Excess Travel Time in Center and Periphery

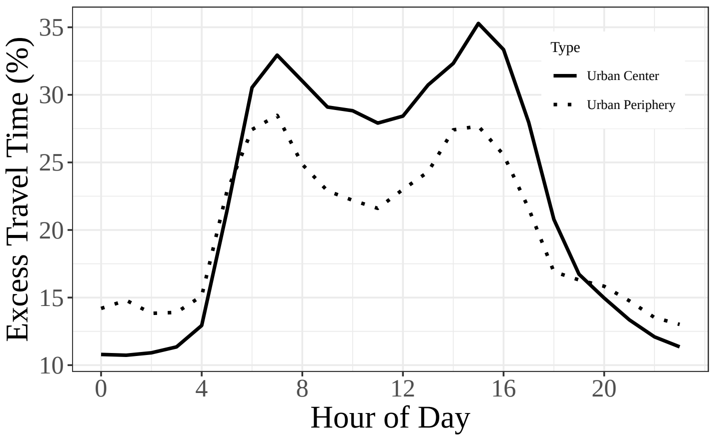
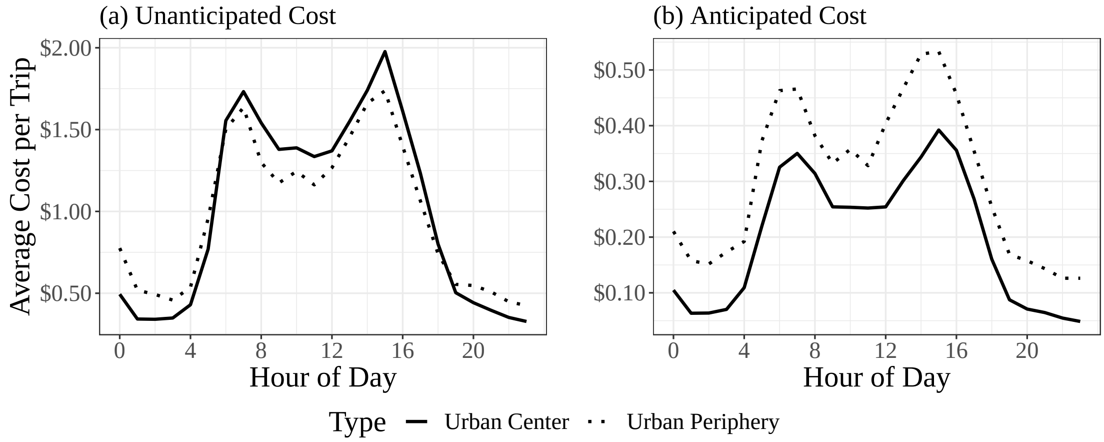


Figure 12 shows that, on average, the extra time spent driving relative to time in free-flowing traffic is larger by a factor of 2-3 throughout the day on routes connecting to the urban core. Trips in the city periphery exhibit similar time of day patterns, but with less extreme differences across night and day. In Figure 13 we show congestion costs across core and non-core routes. Unexpected congestion costs (Panel (a)) in the urban core are mostly higher during the day time, but evening congestion is more costly outside of the urban core. This is consistent with our finding that VOT at peripheral destinations, which are largely residential, are higher valued than core origins in the evening hours. This is because anticipated Panel (b) shows anticipated congestion costs in and out of the core over the day. Since peripheral residential areas outside of the urban core tend to have higher values as origin-locations than non-residential areas, we see that anticipated costs, which impose costs on origin time rather than destination time, are higher on average outside the core.

Individual heterogeneity in VOT can induce disparate impacts of congestion. We denote high-VOT individuals, denoted as individuals with above-median WTP for waiting time reductions, as *time-sensitive* types. The remaining individuals are denoted *time-insensitive* types. Figure 13 Panel (b) shows that unanticipated congestion costs

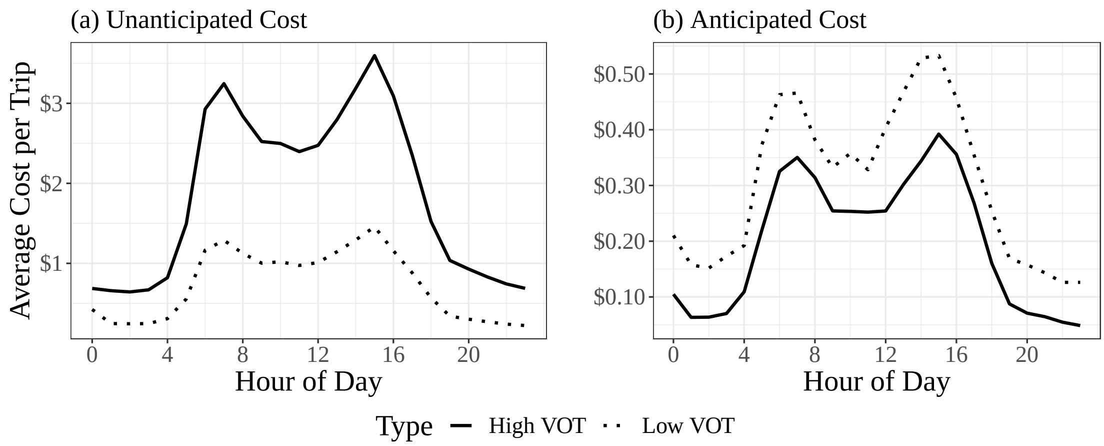
[30]Similar programs are being planned for New York City. See http://www.mta.info/press-release/bridges-tunnels/mta-announces-selection-transcore-build-nation-leading-central.

Figure 13: Planned and Unplanned Congestion Cost in Center and Periphery



for time-sensitive individuals are slightly more than double that of time-insensitive individuals, with average rush-hour costs up to $2.02 per trip. Anticipated congestion costs both types nearly the same amount, which suggests that travelers' time costs in unproductive states (i.e. periods in which anticipated time costs can be borne more cheaply) is much more equal than in productive states. These differences are relevant because many solutions to urban congestion involve pricing through tolls, zone-pricing, or automotive taxes. Nevertheless, this distinction suggests that price-based solutions to congestion will result in time-sensitive drivers and passengers choosing to pay while time-insensitive drivers exit the road.

Figure 14: Estimated Hourly Congestion Costs by Individual Differences



Total Cost of Congestion in Prague

Finally, we ask what our congestion cost measures imply for traffic in Prague as a whole. The 2016 Prague Transportation Yearbook uses survey data to estimate that $1,646,600$

automobile trips occur during each workday.[31] This study also provides estimates of the volume of traffic across each workday hour, each day of week and each month as well as average vehicle occupancy rates.

To determine the total costs of congestion, we first note that the population within Prague from which our estimates are drawn (i.e., taxi passengers) is likely to be selected on high-VOT individuals compared with the average Prague commuter. In order to extrapolate from our hourly congestion cost estimates, we first adjust these costs to reflect opportunity cost of car commuters who are *not* on the Liftago platform. To do this we make the assumption that at 9:00am, a typical workday starting time, our VOT estimate is equal to users' average wage. This value is equal to \$13.78 per-hour. The mean wage among Prague residents, however, is \$9.15 per-hour. Using this, we specify an adjustment factor $\alpha = 9.15/13.78 = 0.67$ and scale all VOT results by α. A second assumption we make is that the spatial distribution of trips in each hour is the same between Liftago users and car commuters. Combining these assumptions allows us to infer, for example, that at 5pm when Liftago riders face an unanticipated congestion cost of \$1.50 per trip, the average car commuter would face a cost of \$1.00 per trip.

We can now combine our hourly congestion costs with the hourly distribution of all traffic provided by the Prague Transportation Yearbook. We assign the annual number of car trips in Prague to each hour given by the yearbook, and multiply the number of trips per hour by the α-scaled average congestion costs. We again scale these measures by the average occupancy rate in Prague of 1.30. Finally, we determine how much congestion is anticipated by computing the mean traffic speeds by day of week and hour and treated any trip in which actual trip time is at or below the time implied by this expectation as a trip faced with anticipated congestion. Any additional trip time is treated as unanticipated.

Table 8 summarizes the results. Panel A compares the distributions of Liftago rides and all Prague car trips and shows that most car trips occur in the same hours in which our speed data imply the greatest congestion, as shown in Panel B. The next two panels compare congestion costs that can be planned ahead (Panel C) with those that are unplanned (Panel D). The last row of panel D shows that between 11 and 15 percent of congestion time is unplanned. The last row, Panel E, combines the data above to estimate total congestion costs of \$468,753 during each workday in Prague. At 254 work days per year, this implies that Prague drivers face \$119 million in annual congestion costs or about \$75 per driver.[32] Because this estimate is relative to an impractical benchmark of equal traffic volume with no congestion, we can use this estimate to interpret

[31] See http://www.tsk-praha.cz/static/udi-rocenka-2016-en.pdf.

[32] Statistics on work-days per quarter come from the European Commission's Eurostat data for the Czech Republic.

the value of a smaller 10% decline in congestion by scaling accordingly.

Table 8: Estimated Congestion Costs

	Time-of-Day								Aggregate
	3:00am	**6:00am**	**9:00am**	**12:00pm**	**3:00pm**	**6:00pm**	**9:00pm**	**12:00am**	**Total**
A. Trip Volume Density*									
Liftago	0.08	0.08	0.1	0.08	0.09	0.15	0.17	0.27	1.0
All Vehicles	0.02	0.02	0.18	0.18	0.18	0.21	0.15	0.06	1.0
B. Mean Excess Travel Time/Trip (min.)									
All	1.85	1.85	6.27	5.17	5.91	6.54	2.94	2.1	4.19
Core-Locations	1.67	1.67	6.09	5.02	5.72	6.45	2.79	1.95	4.02
Non-Core	2.54	2.54	6.25	4.77	5.74	5.8	3.09	2.49	4.28
C. Anticipated Congestion Costs/Trip (USD)									
All	0.08	0.08	0.32	0.22	0.25	0.3	0.11	0.06	0.18
Core-Locations	0.6	0.6	1.6	1.26	1.49	1.39	0.63	0.47	0.17
Non-Core	0.16	0.16	0.42	0.29	0.35	0.36	0.17	0.13	0.27
High-VOT Types	0.02	0.02	0.14	0.11	0.12	0.15	0.06	0.03	0.08
Low-VOT Types	0.02	0.02	0.13	0.09	0.1	0.12	0.04	0.02	0.07
D. Unanticipated Congestion Costs/Trip (USD)									
All	0.41	0.41	1.74	1.43	1.62	1.69	0.64	0.4	1.06
Core-Locations	0.39	0.39	1.76	1.46	1.64	1.74	0.64	0.39	1.07
Non-Core	0.07	0.07	0.31	0.21	0.23	0.29	0.1	0.05	1.02
High-VOT Types	0.09	0.09	0.39	0.29	0.33	0.41	0.16	0.1	0.24
Low-VOT Types	0.09	0.09	0.33	0.2	0.24	0.29	0.09	0.05	0.18
Unanticipated Delays Fraction	0.11	0.11	0.14	0.15	0.15	0.15	0.12	0.11	0.13
E. Daily Estimated Congestion Costs ($,000)*									
All Prague Traffic	2.71	2.71	112.24	85.33	99.47	122.46	31.2	7.55	468.75
All Prague Traffic (10 %)	0.27	0.27	11.22	8.53	9.95	12.25	3.12	0.75	46.88

NOTE: This tables reports a summary of our hourly congestion cost estimates. Each column aggregates results into three-hour bins so that, for example, *3:00am* refers to the period between 12:01am-3:00am. The final column reports means across all hours, except for panels indicated with an asterisk (*), in which the final column reports the sum over all hours.

Our congestion cost estimates only incorporate the cost of time. We do not quantify the added cost of pollution, noise, accidents or other costs. This estimate also averages over potentially important heterogeneity; a driver who only commutes into the city core at 9:00am and leaves at 6:00pm on each workday would face average annual costs of about $281 over 46.7 lost hours. If we were to restrict attention to high congestion routes only, this number would likely grow further.

The ability to draw insights from market behavior to quantifying the cost of congestion can be valuable for local policy makers and regulators in a variety of contexts. For example, suppose a city needs to write a procurement contract for road repairs which specifies bonus payments to contractors for timely completion. In order to determine what incentives to offer, our method could be used to measure the costs of congestion due to each additional day of construction, as long as anticipated delay time estimates for the particular project were available. Another use for congestion cost estimates is in determining the value of new infrastructure itself, such as the benefits to adding a new lane to a road, upgrading an intersection, or adding public transportation services.

In each of these cases we would need to have information about the specific project to explicitly characterize its impact on traffic speeds and any spillover effects to nearby roads, but such an analysis remains feasible with our approach.

7 Conclusion

The trade-off between time and money is at the heart of many important economic decisions. In this project we use data from a large European ride share platform that offers menus with explicit trade-offs between time and money. We use this unique feature to estimate a demand model based on choices from these menus. This allows us to recover riders' preferences and demand elasticities over time and money as well as their implied willingness-to-pay to reduce waiting time. Building on ideas in Small (2012) we then provide a framework to translate the estimates from this demand model into the implied *value of time* across different locations, times and types of individuals.

Our demand model reveals noteworthy patterns in how individuals value time and money. Consumers are about four times more price elastic than waiting time elastic. There are also large differences in willingness to pay for waiting time reductions in the population of riders. The top fifty percent of riders are willing to pay on average $17.14 per hour of waiting time reduction, compared to $4.54 for the bottom fifty percent. We show how these differences vary over the day, and we find that work hours lead to higher willingness-to-pay compared to evening hours. We also find that the origin-destination-specific WTP measures are highly correlated with the fraction of travel flows across the same routes, lending insight into studies using travel flows as a proxy for place-specific values.

We decompose the demand model estimates to quantify the value of time. We estimate the average value of time in Prague at $14.48 per hour during work hours and $12.55 per hour during non-work hours. We again find substantial heterogeneity by place, time and individuals. A variance decomposition reveals that 85% of the overall heterogeneity is driven by individual differences. Only a small fraction of the variation is due to place and time of day, once individual differences are accounted for. The model also allows us to distinguish between the value of time in planned and unplanned activities. We find that there are large differences in the population of riders in terms of the ratio of planned and unplanned time values and these differences are again increasing during work time. This finding suggests that more time-elastic demand might be driven by the need to coordinate with coworkers and other complementary production factors at work.

There are several qualitative insights that arise from our model. First, it provides a measure of the short-run value of places due to their set of features, amenities and activities, as it is based on directly observed decisions about same-day time allocation. Using other common methods to measure the value of places, such as housing prices, will risk confounding the short-run valuations with the long-run expectations that make up real estate demand. In contrast with literature on residential sorting, our results suggest that people with a higher value of time do not sort into places with a higher value of time. This suggests that the use of places may be more egalitarian than residential choices. Finally, our approach shows that data generated by ride hail companies and other transportation services can be exploited to better understand urban infrastructure and potentially be used to detect and evaluate missing transport links.

To demonstrate how our estimates can be used in a policy context, we quantify the cost of traffic congestion in Prague. This is done by combining our high-resolution traffic speed data with our measures of planned and unplanned time costs. By recovering per-trip time costs across each hour of the day, we estimate that congestion imposes approximately $469 thousand per day in time costs.

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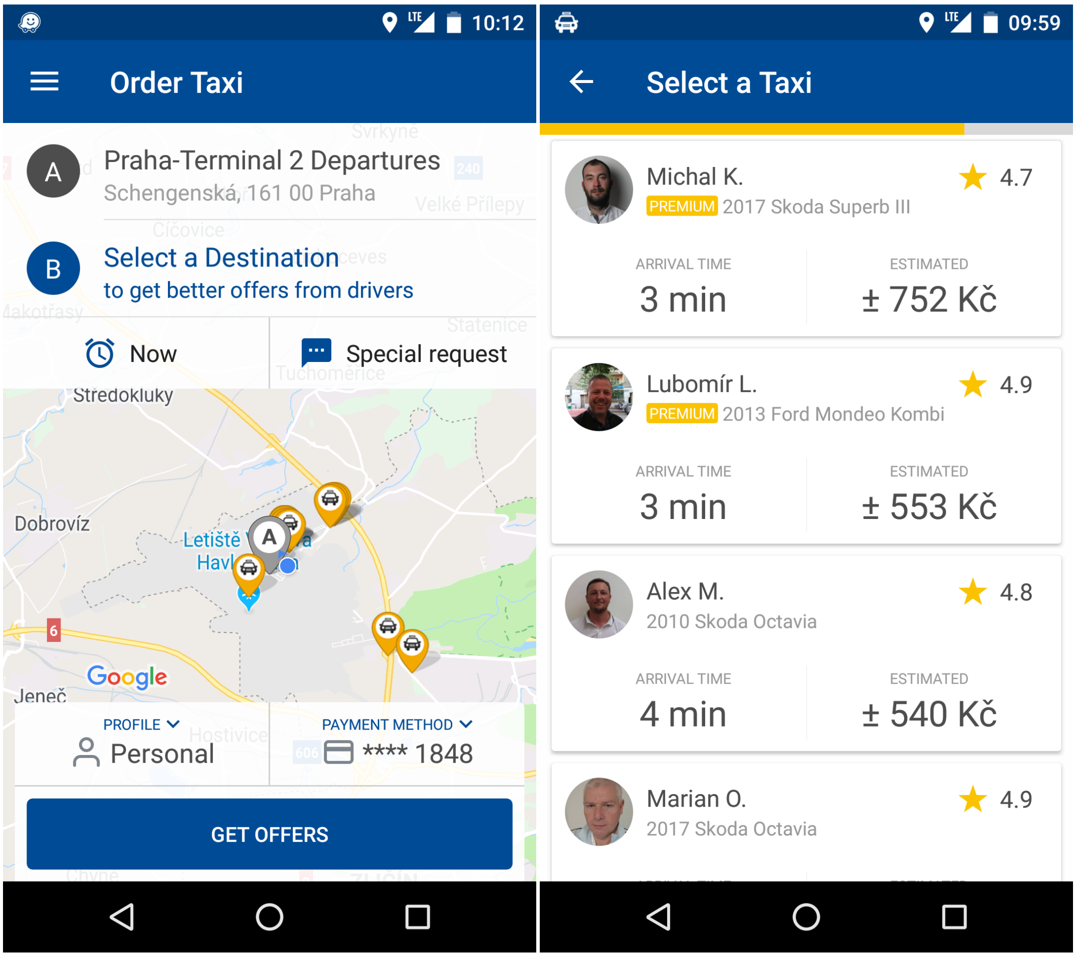
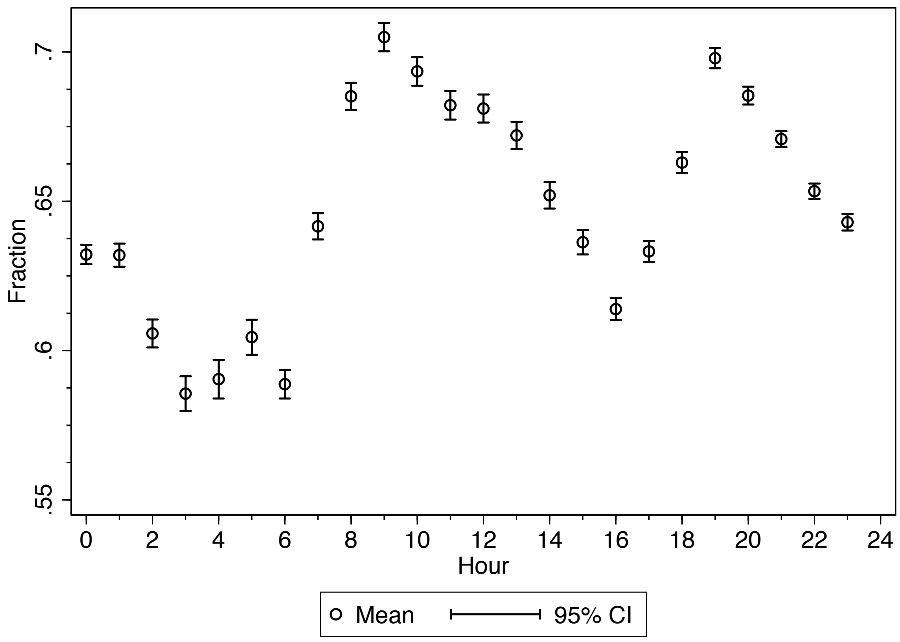
A Omitted Graphics

Figure 15: Picture of the Liftago App



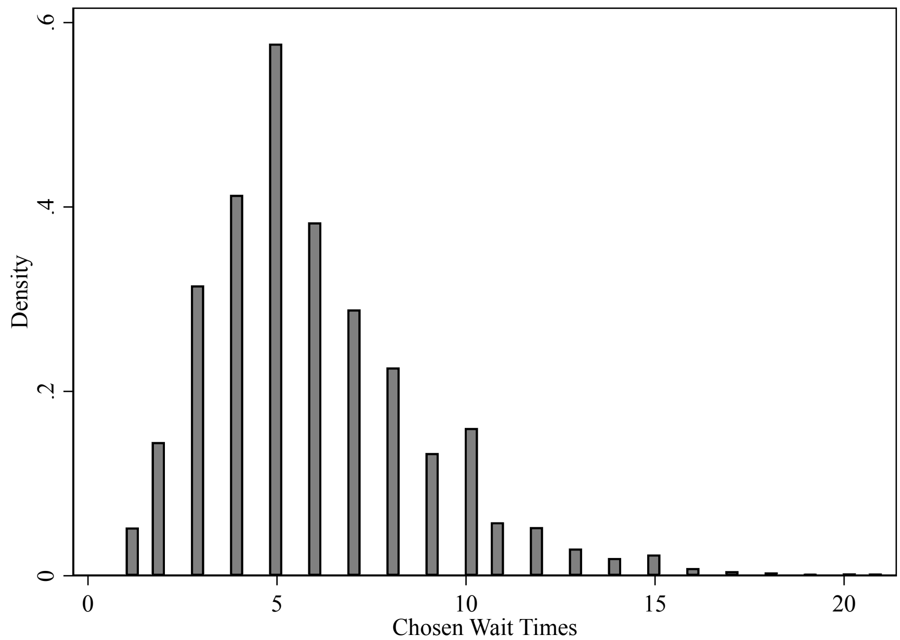
NOTE: This Graph shows the interfact of the Liftago App.

Figure 16: Trips with Price/Waiting Tradeoff



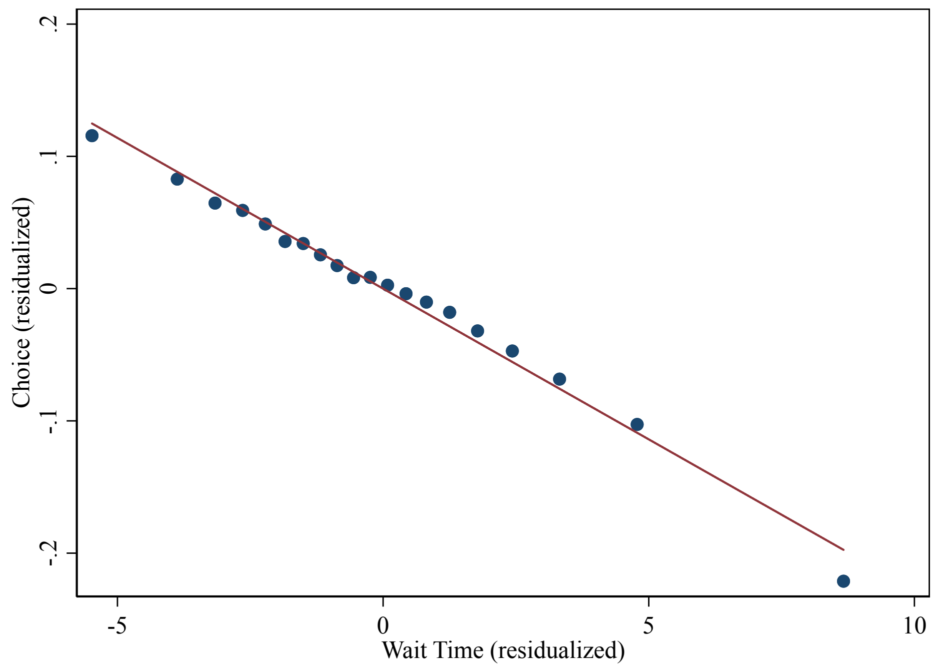
NOTE: The graph shows the proportion of trips that involve an option to spend more and wait less.

Figure 17: Histogram of the Wait Time Distribution

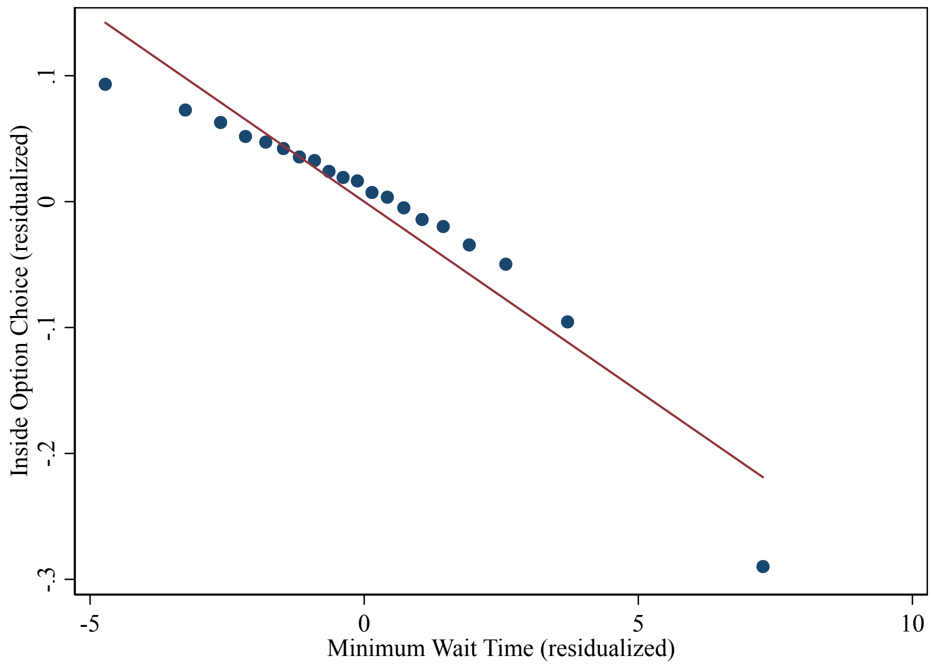


NOTE: This graph shows the histogram of wait times.

Figure 18: Choices as a Function of Wait Time



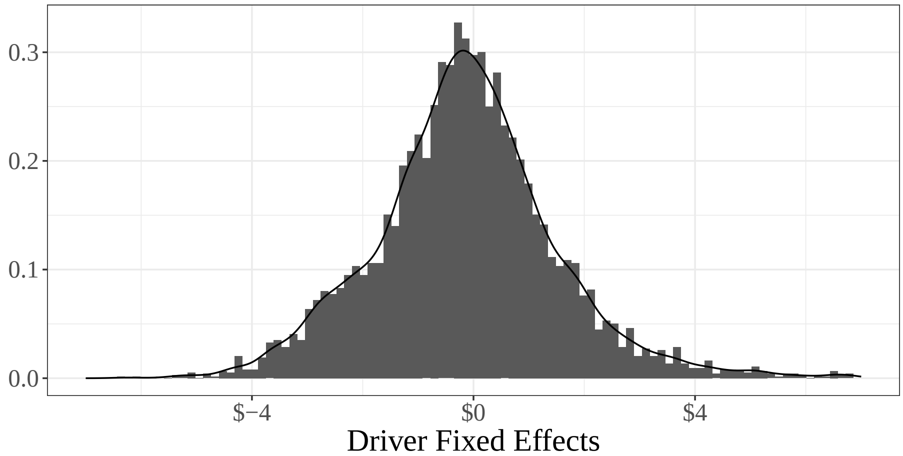
(a) Trips Choice as Function of Waiting Time



(b) Inside Option Choice as Function of the Minimum Waiting Time

NOTE: The graph on top shows the probability of choosing a trip as a function of the wait time, both residualized after taking into accound time of day, origin and destination location, weather conditions, and the respective other prices and wait times. The graph on the bottom shoes the probability of choosing any trip over the outside option as a function of the minimum waiting time, both residualized for time of day, origin and destination locations, and weather conditions.

Figure 19: Driver Fixed Effects



B Relation to the model in Small (1982)

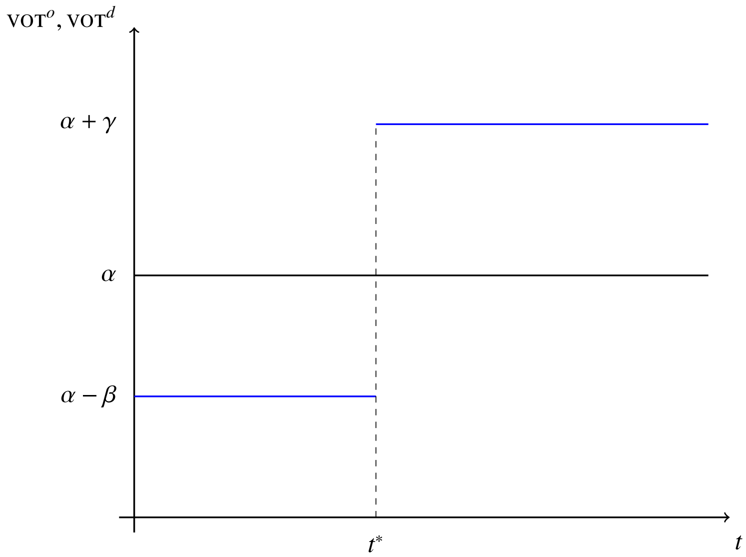
The model described in Equation 1 is the workhorse model of the transportation literature on travel time savings (see, e.g., Tseng and Verhoef (2008) and Engelson and Fosgerau (2016)). It has its origins in the work of Small (1982), which is inspired by the work of of Vickrey (1969). Small (1982) considers a special case of the above model where:[33]

$$
\begin{aligned}
\textsc{vot}^o(t) &= \alpha \\
\textsc{vot}^d &= \alpha - \beta \mathbb{1}[t \leq t^*] + \gamma \mathbb{1}[t \geq t^*]
\end{aligned}
\tag{15}
$$

Note that under this specification, $\alpha = \textsc{vot}^o$, $\beta = (\textsc{vot}^o(t) - \textsc{vot}^d(t))\mathbb{1}[t \leq t^*]$, and $\gamma = (\textsc{vot}^d(t) - \textsc{vot}^o(t))\mathbb{1}[t > t^*]$.

[33] Small (1982) is expressed in terms of opportunities cost of time. Equation 15 in terms of the values is equivalent (see Tseng and Verhoef (2008) and Engelson and Fosgerau (2016)).

Figure 20: Value at origin (black) and destination (blue) as a function of time in the constant model



This version of the model, where over the relevant time intervals, VOT^o and VOT^d are constant, is the one to which the approximation described in Section 3 maps to. Whereas Small (1982), assumes that VOT^o and VOT^d are constant everywhere, it is important to note that this is not the case in the exercise that we carry out. Indeed, we only assume that this holds over $[q, q+w+\Delta]$; however, we allow these values to vary across different times of day, different locations, and different types of riders.

B.1 Optimal query time

In reality, riders may plan the time at which they request a ride. Thus, the rider's problem is given by:

$$\max_q \mathbb{E}\left[\max_{i \in \mathcal{I}} u(q, w_i) - p_i\right] \tag{16}$$

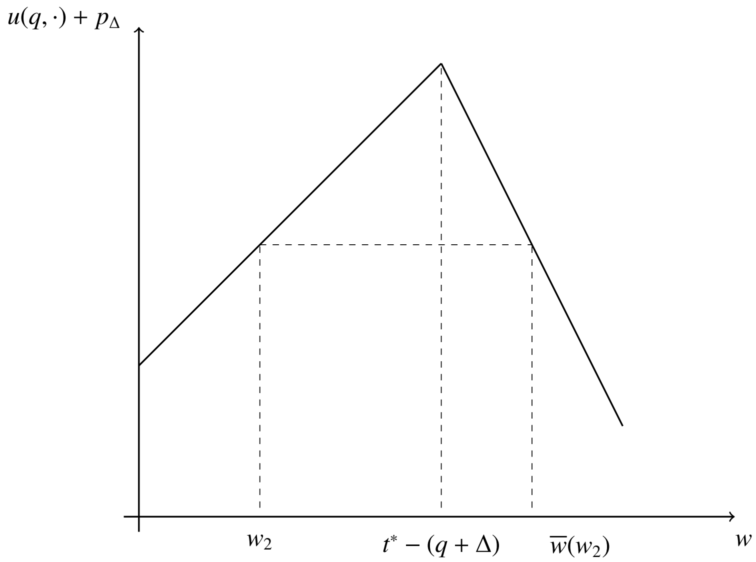
where the expectation is over the price and waiting times that the rider will face. Let $u^*(q, (w_i, p_i)_{i \in \mathcal{I}})$ denote the term inside the expectation and let q^* denote the solution to the problem in Equation 16. Note that what we observe in the data corresponds to $u^*(q^*, (w_i, p_i)_{i \in \mathcal{I}})$. In what follows, we show that in spite of this there are two versions of the model where the relevant parameters are identified, and hence the values of time, for all q and not just q^*. Furthermore, to convey the main ideas we focus on the case in which w_2, p_2, p_1 are known, and the rider just faces uncertainty about the ETA of the first ride, $w_1 \sim F$.

The analysis that follows implicitly assumes that conditional on the trip, all riders are identical. Buchholz et al. (2020) shows how to extend the arguments presented here to the case in which, conditional on a trip, there is heterogeneity in the preferences of the riders who need to take that trip.

B.1.1 Small (1982)

Consider first the specification in Small (1982), described in Equation 15. We assume that $t^* \leq T$. Fix a query time $q \geq 0$ such that $q + \Delta < t^*$[34]. Figure 21 plots the function $u(q, w_2) + p_\Delta$:[35]

Figure 21: The function $u(q, w_2) + p_\Delta$



In a world without uncertainty in which the rider anticipates the waiting time w, she would simply choose $q = t^* - (\Delta + w)$, so that the effective function (given the optimal choice of q^*) would be always decreasing.[36]

Given a waiting time w_2, we can think of the waiting times w_1 that are chosen over w_2 for a given price differential p_Δ,

$$C(w_2, p_\Delta) = \{w_1 : u(q, w_1) \geq u(q, w_2) + p_\Delta\} \tag{17}$$

[34] We show below that the optimal query time always satisfies this, so this is the relevant case

[35] The figure implicitly assumes that the price differential is not "very" negative so that

$$p_\Delta + \alpha(T - \Delta) + \gamma(T - t^*) \geq 0.$$

Otherwise, the entire figure would be below the w-axis.

[36] To see this, note that even though the above is the picture as a function of w, for fixed w, we would have the same picture as a function of q, once we flip the roles of q and w.

As Figure 21 suggests, $C(w_2, p_\Delta)$ is an interval with one of its endpoints being w_2. Intuitively, if the consumer arrives before their ideal time under w_2, then w_2 is the lowest ETA that the consumer is willing to accept instead of trip 2 given p_Δ. Similarly, if the consumer arrives after their ideal time under w_2, then w_2 is the highest ETA that the consumer is willing to take instead of trip 2 given p_Δ. Thus, the shape of $C(w_2, p_\Delta)$ reveals whether w_2 is below or above $t^* - (q + \Delta)$.[37]

To infer the parameters β, γ, consider the case in which $p_\Delta = 0$. Fix w_2 such that $\min\{w : w \in C(w_2, 0)\} = w_2$. For $\epsilon > 0$, β is identified as the parameter such that the rider is indifferent between (w_2, p) and $(w_2 - \epsilon, p - \beta\epsilon)$. That is, $\beta\epsilon$ is how much we have to pay the rider to take a trip that leaves $\epsilon > 0$ earlier than trip 2. On the other hand, γ is identified as the parameter such that the rider is indifferent between (w_2, p) and $(w_1 + \epsilon, p - \gamma\epsilon)$. That is, $\gamma\epsilon$ is how much we have to pay the rider to take a trip that leaves $\epsilon > 0$ later than trip 2.

Finally, note that with β, γ identified, we can identify $t^* - (q + \Delta)$ from solving:

$$\frac{\beta w_2 + \gamma \overline{w}(w_2, q, 0)}{\beta + \gamma},$$

where $\overline{w}(w_2, q, 0)$ is the maximum element of $C(w_2, p_\Delta)$. A similar experiment identifies β, γ and $t^* - q$ when $w_2 = \max\{w : w \in C(w_2, p_\Delta)\}$. Clearly, α cannot be identified.

When $q + \Delta \geq t^*$, then the rider is always late. This would correspond to a case where Figure 21 only displays the downward sloping branch. In this case, the rider always prefers shorter ETAs for a given price differential. However, one can show that in this model the rider always chooses q^* so that $q^* + \Delta < t^*$:

Proposition 1. *Let* $\text{VOT}^o, \text{VOT}^d$ *be as in Equation 15. Then, the optimal choice of query time,* q^**, satisfies that* $q^* + \Delta < t^*$.

The proof, while straightforward, is involved because of the many cases one needs to consider, so it is relegated to Buchholz et al. (2020). However, it is intuitive why such a result should be true. Inspection of Figure 21 reveals that the rider is risk averse in w; by choosing q smaller than $t^* - \Delta$, the rider makes sure that he has a chance to arrive early.

[37] Formally, one can show that if $w_2 < t^* - (q + \Delta)$, then $C(w_2, p_\Delta) = [w_2, \overline{w}_2(w_2, q, p_\Delta)]$ where

$$\overline{w}(w_2, q, p_\Delta) = \max\left\{\frac{p_\Delta + (\beta + \gamma)(t^* - (q + \Delta)) - \beta w_2}{\gamma}, t^* - (q + \Delta)\right\},$$

whereas if w_2 is to the right of $t^* - (q + \Delta)$, then $C(w_2, p_\Delta) = [\underline{w}_2(w_2, q, p_\Delta), w_2]$, where

$$\underline{w}(w_2, q, p_\Delta) = \min\left\{\frac{p_\Delta + (\beta + \gamma)(t^* - (q + \Delta)) - \gamma w_2}{\beta}, t^* - (q + \Delta)\right\}.$$

B.1.2 Linear specification

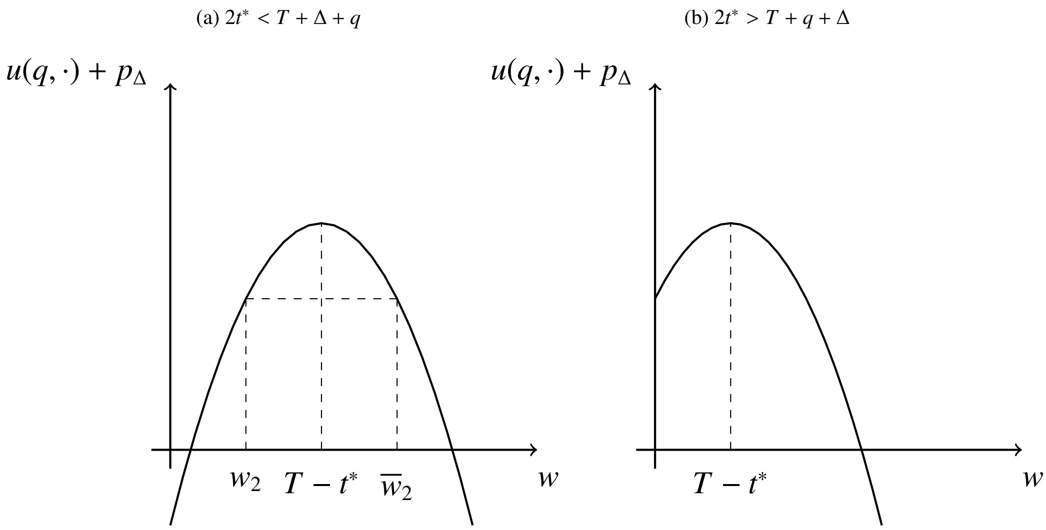
Another common specification of the model is the linear case (see Engelson and Fosgerau (2016)):

$$\begin{aligned} \text{VOT}^o(t) &= \alpha, \\ \text{VOT}^d(t) &= \alpha + \gamma(t - t^*), \end{aligned} \tag{18}$$

where $\alpha, \gamma > 0$ and t^* is the desired arrival time. We continue to assume that the trip length, Δ is less than t^* so that the rider can potentially arrive at her ideal arriving time.

As before, it will not be possible to identify α from the choices. However, a similar exercise allows us to identify γ, t^*. Figure 22 plots the function $u(\cdot, q) + p_\Delta$ for $q < t^* - \Delta$:

Figure 22: The function $u(q, w_2) + p_\Delta$



To understand how choices reveal γ, t^*, consider the case in which $p_\Delta = 0$. When $2t^* < T + \Delta + q$, we have that $C(w_2, p_\Delta)$ is an interval with w_2 as its lower or upper end (see Figure 22a). Moreover, $T - t^*$ is always the center of that interval. Thus, we can identify $T - t^*$ from the midpoint of this interval. Given $T - t^*$, we can write

$$u(q, w_2) = \frac{\gamma}{2}(w_2 - (T - t^*))^2 + u(T - t^*, q)$$

Using this, let k be such that the rider is indifferent between (w_2, p) and $(w_2 - \epsilon, p - k\epsilon)$. Then, it follows that

$$\frac{\gamma}{2} = \frac{k}{2(w_2 - (T - t^*)) - \epsilon}.$$

On the other hand, when $2t^* > T + q + \Delta$, the function $u(\cdot, q) + p_\Delta$ is as in Figure 22b. For $p_\Delta = 0$ and w_2 low enough, however, $C(w_2, 0)$ is an interval with w_2 as its lower bound and $T - t^*$ as its midpoint. Thus, a similar experiment identifies $\gamma/2$.

The above discussion implicitly assumes that $q < t^* - \Delta$. Indeed, this is without loss of generality:

Proposition 2. *Let* $\text{VOT}^o, \text{VOT}^d$ *be as in Equation 18. Then, the optimal choice of query time,* q^**, satisfies that* $q^* + \Delta < t^*$.

The proof, while straightforward, is involved because of the many cases one needs to consider, so it is relegated to Buchholz et al. (2020).

C Identification of Location Values

The following are the three assumptions that will be used in our main theorem below.

Assumption 1. (Independence across locations) $F\left(V_a^{i,k}, V_{a'}^{i,k'}\right) = F_{i,a,k}(V) \cdot F_{i,a',k'}(V)$ $\forall (a, a') \in \mathcal{J}^2$ *and* $(k, k') \in \{o, d\}^2$

The following assumption imposes the existence of at least one location where the mean of the values is known either when this location is the destination or it is the origin. For example, the mean (local) wage per minute might be a good approximation of the mean value per minute for trips originating in a typical business area.

Assumption 2. (Location Normalization) $\exists a \in \mathcal{A}, k \in \{o, d\} : \mathbb{E}\left[v_{i,a}^k\right] = \mu_0$.

While we will establish non-parametric identification of the value distributions, for the empirical application it will be useful to consider a special case of normal distributions.

Assumption 3. (Normal Distributions) $V_{i,a}^k \sim N\left(\mu_a^k, \sigma_a^k\right) \forall i, a \in \mathcal{A}, k \in \{o, d\})$*, iid across* (i, a, k)*.*

With these assumptions we can state the following identification result. The first part is straightforward, but requires the knowledge of a subset of trips, such that one of the two values in the difference $V_{i,a}^d - V_{i,a'}^o$ is a known constant. The second part imposes a potentially weaker requirement: only that we know the mean value at one location (whether it is the origin or the destination) and that one part of difference can be held constant across a subset of observations. The last part is a special case, which imposes more parametric structure.

Theorem 3. (Sufficient Conditions for Identification)

1. *Under Assumption 1, if* $\exists\left(X^o, X^d, a\right) \subset X \times X \times \mathcal{A} : \Pr\left[V^k_{i,a} = \hat{v}_k | X^k, a\right] = 1$ *for* $k \in \{o, d\}$*, then* $F_{a,k}(v)$ *is identified* $\forall a \in \mathcal{A}, k \in \{o, d\}$.

2. *Under Assumptions 1 and 2 , when either* $\exists k \in \{o, d\} : v^k_{i,a,t} = v^k_{i',a,t} \forall (i, i', a, t)$ *or* $\exists k \in \{o, d\} : v^k_{i,a,t} = v^k_{i,a,t'} \forall (i, a, t, t')$*, then* $F_{a,k}(v)$ *is identified* $\forall a \in \mathcal{A}$ *and* $k \in \{o, d\}$ *whenever* $|\mathcal{A}| \geq 3$.

3. *Under Assumptions 2 and 3,* $\left(\mu^k_a, \sigma^k_a\right)$ *is identified* $\forall a \in \mathcal{A}, k \in \{o, d\}$ *whenever* $|\mathcal{A}| \geq 3$.

Proof: See Appendix C. The theorem says that we can identify the distributions of valuations non-parametrically whenever (1) values are independent across locations and we can isolate cases for which the value either at the origin or at the destination is known to be equal to some constant, (2) when values are independent and are location- and time-, but not individual-specific either at the origin or at the destination (e.g., everyone has the same value of spending a minute in a residential area) or values are location and individual, but not time-specific (e.g., an individual has always the same value of a minute of being at his business location at 8am every Monday), we know the mean value in at least one location and there are at least 3 locations. Given the previous result, we can of course also identify the values parametrically. However, this approach is particularly easy when the values are iid normal, when there are at least 3 locations and we have one location normalization for both mean and variance. (1) follows from restricting attention to cases where one part of the difference is known to be a constant, and hence the distribution can be fully recovered from the distribution of the differences. (2) follows from a deconvolution argument as in Li and Vuong (1998) since under the hypothesis of the theorem we can construct a sample in which we hold one part of the difference fixed. By applying the Kotlarski Lemma, one can then recover the distributions of both pieces of the difference (up to the location). The additional location normalization pins down the means separately. (3) follows since adding an additional location to the existing set of L locations comes with 4 new parameters (two means and two standard deviations) and generates $2 \cdot (L - 1)$ additional equations and hence one needs $L \geq 3$ together with the two normalizations.

Proof. (1) Restricting attention to X^o and trips originating in a going to destination a' identifies $F_{D,a'}(v)$ trivially from the observed distribution of the differences by shifting the distribution of the data by the relevant constant, $\hat{v}_O$. Similarly, $F_{O,a'}(v)$ is identified from using only data from X^d and trips that originated in a and went to a'.

(2) Consider $|\mathcal{A}| = 3$ and the case $v^o_{i,a,t} = v^o_{i',a,t} \forall(i, i', a, t)$,i.e., that values at a given origin and time are the same for all individuals i. Since values at origin are the same, the deconvolution argument identifies (using variation over time) the distribution of values at origin and the distribution of the values at each destination (using variation across individuals going to each destination) - up to a location normalization, i.e., the two means cannot be identified separately directly.[38] With 3 locations we can setup the following system of 6 equations in 6 unknowns (in the means of values at origin and at destination), where the objects on the LHS are recovered from the deconvolution argument: $\mu_{12} = -\mu^o_1 + \mu^d_2, \mu_{13} = -\mu^o_1 + \mu^d_3, \mu_{21} = -\mu^o_2 + \mu^d_1, \mu_{23} = -\mu^o_2 + \mu^d_3, \mu_{31} = -\mu^o_3 + \mu^d_1, \mu_{32} = -\mu^o_3 + \mu^d_2$. This system is not identified since the matrix of coefficients has a rank of 5. Substituting equation from Assumption 2 for one of the equations including that mean restores the full rank of the coefficient matrix. For any additional location, 2 new parameters and $L - 1$ new equations are introduced, but the rank is still (2L-1). Substituting equation from Assumption 2 brings the rank to 2L, and we have $L \cdot (L - 1)$ equations. Hence we can simply keep any subset with rank 2L as at true parameters all of these equations will hold simultaneously.

The case $v^o_{i,a,t} = v^o_{i,a,t'} \forall(i, a, t, t')$, is analogous, except variation over individuals is used for the deconvolution argument and the distribution of values at origin and destination is identified using variation within individuals as they go to different destinations. The means are then recovered as above.

(3) Since sum of two normally distributed random variables is also normally distributed with mean being the sum of means and the variance being the sum of the variances, the means can be recovered directly by using the argument in (2). However, the system of equations involving the variances is also less than full rank - and hence to identify these directly, one needs another location normalization (such as the knowledge of the variance at some location) or one needs to appeal to case (2), which establishes that the variances are identified non-parametrically.

□

D Data Details

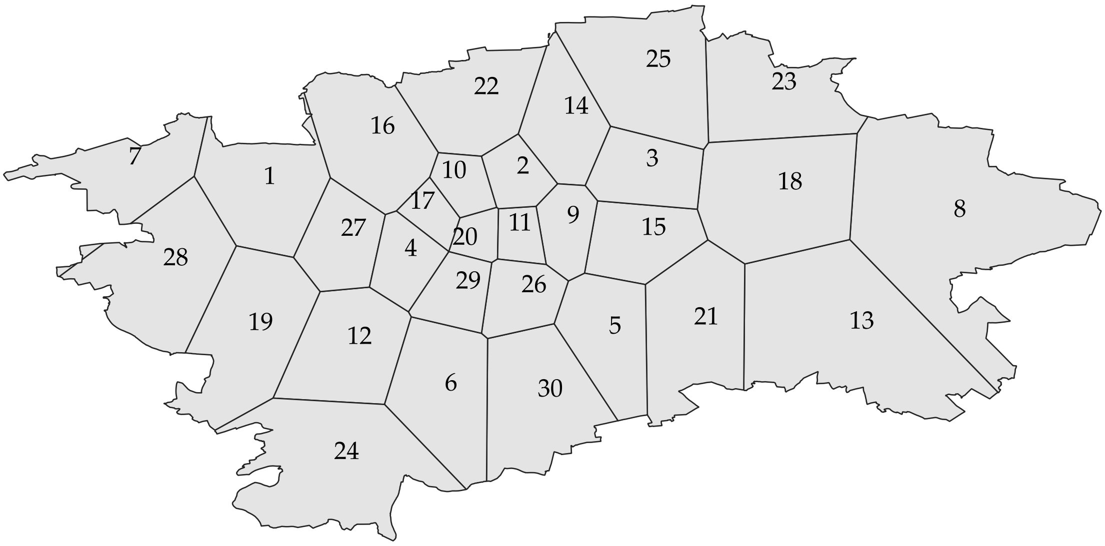
D.1 Locations

Using the exact GPS points of trip origin, we partition our data into 30 locations. Figure 23 shows these locations together with an index value for comparing results in Sec-

[38] In the measurement literature setup $Y_1 = X + \varepsilon_1, Y_2 = X + \varepsilon_2$, the distributions $F(X), G(\varepsilon)$ are identified from $H(Y_1, Y_2)$ whenever the usual iid assumption holds, when the characteristic functions of F and G are non-vanishing everywhere and when $E(\varepsilon) = 0$.

tion 5. The partitioning is done according to a simple *k-means* clustering procedure on the requested pickup locations with $k = 30$. This procedure minimizes the straight-line distance between each point and the weighed center of all points within the same cluster, with the constraint that each cluster has an equal number of points. The depicted locations are close approximations, displayed as Voronoi cells that contain the clustered points. This process allows location definitions to be independent of any political boundaries and better representative of places in which demand is concentrated.

Figure 23: Locations in Prague

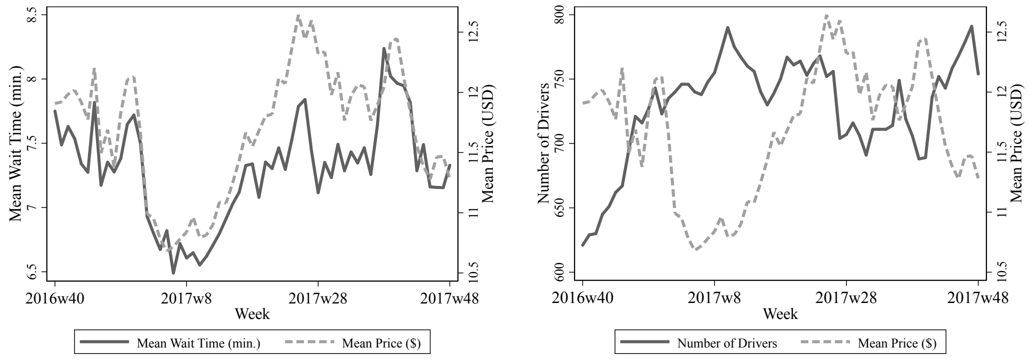


Note: This figure maps the boundaries of the city of Prague with locations defined by a kmeans-clustering procedure on GPS-locations of trip origins and depicted as Voronoi cells that contain the clustered points. Displayed index values correspond to indices used in the paper.

D.2 Market Time Series Summary

Figure 24, panels (a) and (b) summarize the week-over-week trends in prices. Beginning 2017 the ridership and drivers stop to grow and enter a relatively stationary period, although there are some large swings in the number of passengers towards the end of 2017. It shows the relationship between labor supply and price during the sample period. As expected, price decreases as supply increases during the winter holiday seasons and increases as supply falls during the summer. The second panel shows how average waiting time and average price evolve during the sample period.

Figure 24: Weekly Waiting Times and Number of Drivers Compared to Prices



(a) Average Prices

(b) Price and Driver Count

E Estimation Details

E.1 Recovering Latent Types: Conditional *K-Means*-Clustering Procedure

The clustering procedure allocates passengers to initial latent classes using a "*k-means++*" algorithm and then reallocates passenger types to best explain individual choices after controlling for observable features of the environment. This approach is based on Bonhomme et al. (2017) and uses Julia's *Clustering* package implementation of *k-means++*. Our discussion here is mainly based on the two.

E.2 Location Parameter Estimates

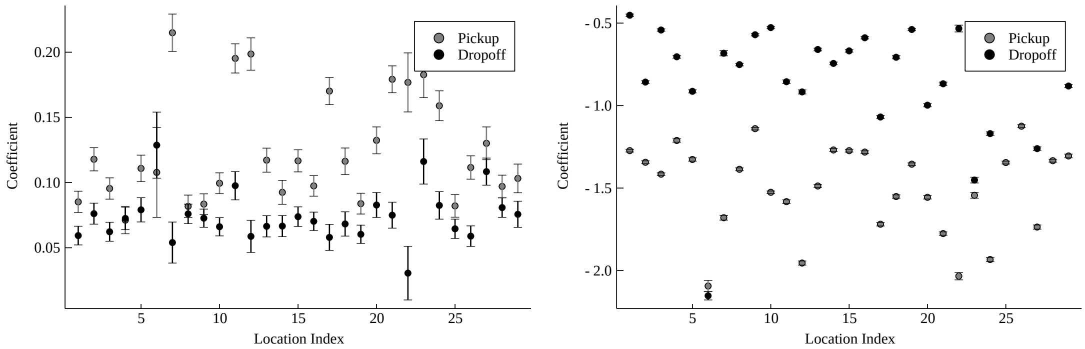
Here we offer additional details on location-specific parameter estimates. Figure 25 plots these estimates across origins and destinations.

E.3 Model Fit

Figure 26 illustrates the model's ability to fit the observed choices in the data. For each trip and corresponding driver bids, we use our estimates to predict whether each customer will pick the outside-option and plot the average prediction for each week.

Figure 27 Demonstrates the model's ability to correctly predict specific choices across auctions. We do this in two ways: first we use our estimates to predict which option each customer will pick inclusive of simulated draws of $\epsilon_{i,j,t}$. Because the $\epsilon_{i,j,t}$ represent unobservable attributes associated with each choice, this simulation will tend

Figure 25: Location-Specific Coefficient Estimates

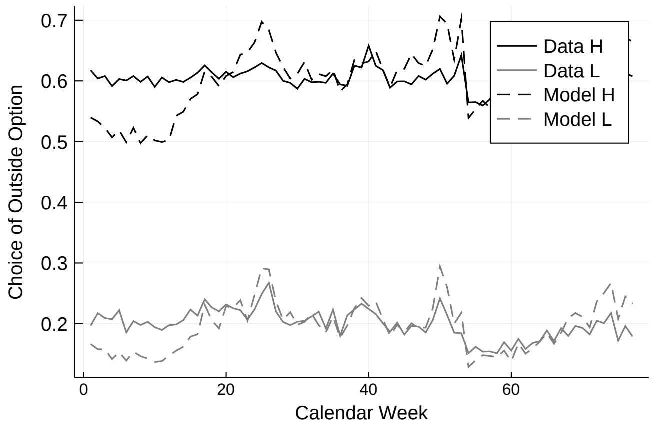


(a) Waiting Times × Locations

(b) Location Means

Note: This figure shows coefficient estimates for 120 location-specific parameters omitted from Table 2. Standard errors are depicted as bars around each point. Location indices may be cross-references with Figure 23. Panel (a) displays results for the coefficients on the interaction between waiting time and location, and Panel (b) displays results for the coefficients on location indicators, which can be interpreted as location-specific utility shifters relative to location index 1.

Figure 26: Model Fit On Outside Option Selection



to add additional noise to our choice predictions. We also make the same predictions but set $\epsilon_{i,j,t} = 0$ for all i, j, t, which improves our predictions by about 10%.

E.4 Elasticities by Area

See Table 9 and Table 10 below.

E.5 Estimation Results Omitting Control Function

Table 11 below presents the price and waiting time elasticity estimates in which the control function is omitted.

Table 9: Bid Level Elasticities by Origin Area

Origin Area	High VOT-Type Elasticities		Low VOT-Type Elasticities	
	Price	Waiting Time	Price	Waiting Time
1	-4.82	-0.98	-5.22	-0.93
2	-2.71	-0.37	-3.66	-0.3
3	-3.98	-0.56	-4.26	-0.46
4	-2.95	-0.38	-3.79	-0.29
5	-4.47	-0.37	-4.53	-0.38
6	-5.05	-0.59	-5.37	-0.57
7	-9.64	-0.27	-9.7	-0.22
8	-10.0	-0.55	-9.75	-0.48
9	-2.78	-0.46	-3.38	-0.41
10	-2.62	-0.33	-3.7	-0.25
11	-2.41	-0.36	-3.19	-0.26
12	-5.26	-0.47	-5.55	-0.43
13	-7.81	-0.47	-7.58	-0.44
14	-3.95	-0.51	-4.34	-0.44
15	-3.45	-0.49	-3.69	-0.44
16	-3.69	-0.38	-4.54	-0.31
17	-2.79	-0.34	-3.89	-0.24
18	-6.75	-0.78	-6.45	-0.7
19	-5.63	-0.56	-5.93	-0.53
20	-2.52	-0.31	-3.43	-0.22
21	-5.48	-0.52	-5.41	-0.47
22	-5.06	-0.7	-5.45	-0.6
23	-6.9	-0.64	-7.09	-0.6
24	-10.31	-0.44	-9.6	-0.38
25	-5.82	-0.44	-6.17	-0.41
26	-2.98	-0.39	-3.59	-0.34
27	-3.89	-0.56	-4.33	-0.5
28	-6.66	-0.43	-6.56	-0.39
29	-2.84	-0.36	-3.64	-0.29
30	-4.98	-0.57	-5.2	-0.51

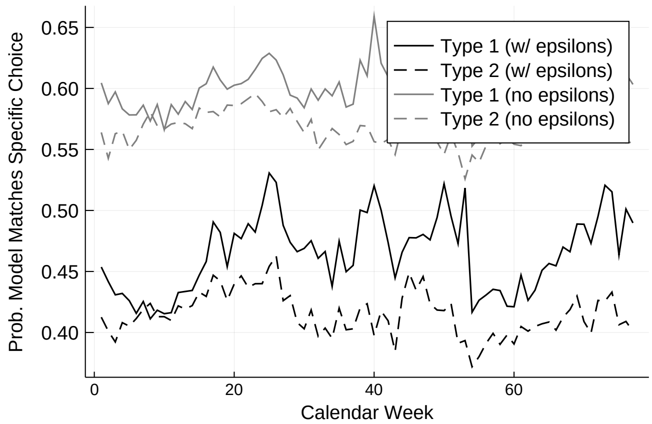
Note: This table shows price and waiting time elasticities across the thirty different origin places separated by high and low VOT types. Figure 23 shows location indices on a map of Prague.

Table 10: Bid Level Elasticities by Destination Area

	High VOT-Type Elasticities		Low VOT-Type Elasticities	
Destination Area	Price	Waiting Time	Price	Waiting Time
1	-4.3	-0.47	-4.44	-0.42
2	-2.45	-0.47	-3.09	-0.45
3	-3.6	-0.32	-3.88	-0.26
4	-2.67	-0.45	-3.31	-0.47
5	-4.16	-0.43	-4.39	-0.32
6	-4.75	-0.28	-4.96	-0.21
7	-9.35	-0.38	-8.33	-0.39
8	-8.75	-0.32	-8.48	-0.28
9	-2.64	-0.37	-3.16	-0.36
10	-2.52	-0.44	-3.29	-0.45
11	-2.32	-0.35	-2.87	-0.35
12	-4.81	-0.34	-4.69	-0.24
13	-7.02	-0.26	-7.06	-0.21
14	-3.55	-0.32	-3.93	-0.27
15	-3.18	-0.32	-3.51	-0.3
16	-3.18	-0.41	-3.75	-0.37
17	-2.57	-0.45	-3.41	-0.46
18	-5.86	-0.3	-5.98	-0.24
19	-5.24	-0.33	-5.13	-0.26
20	-2.42	-0.48	-3.26	-0.5
21	-5.04	-0.33	-5.3	-0.28
22	-4.27	-0.31	-4.37	-0.23
23	-6.14	-0.19	-5.77	-0.17
24	-8.21	-0.38	-7.69	-0.31
25	-5.42	-0.36	-5.51	-0.28
26	-2.84	-0.41	-3.24	-0.37
27	-3.35	-0.35	-3.46	-0.29
28	-6.0	-0.37	-5.84	-0.27
29	-2.72	-0.36	-3.19	-0.34
30	-4.58	-0.33	-4.67	-0.26

Note: This table shows price and waiting time elasticities across the thirty different destination places separated by high and low VOT types. Figure 23 shows location indices on a map of Prague.

Figure 27: Model Fit On Outside Option Selection



E.6 Trip-Specific Heterogeneity Results

The baseline results in Table 4 show the average NVOT across different hours of the day. Within each time-of-day and within each individual's *type*, however, there is additional heterogeneity due to the fact that some trips are more or less time-sensitive. For example, a given person may express higher NVOT if she is late for an appointment compared.

To analyze this type of heterogeneity, we define *time-sensitive* trips as the subset of trips in which a rider, having requested a ride, is faced with a set of bids in which (1) the arrival time falls around a rounded hour increment such as 9:00am or 2:00pm, (2) only bid would provide a trip that arrives before the hour and all others would provide a trip which arrive after the hour, and (3) a trip occurs on the platform. Because the NVOT estimated on trips generated on this subset is inherently selected due to point (3), we compare this against a similar subset of trips around a placebo clock-time. We thus define *placebo* trips by selecting orders where the arrival time falls around a clock time ending in :23 or :53, such as 8:23am or 2:53pm. We then apply criteria (2) and (3) to these trips. The difference NVOT between time-sensitive and placebo trips reveals the relevant heterogeneity in time-sensitivity.

To augment our baseline results, Table 12 reports results for *time sensitive* trips and shows that the NVOT for this subset is about 58% greater than a comparable measure in the placebo group. The first column reports NVOT for all trips, as in Table 4, as a comparison. Our baseline NVOT results, therefore, can be interpreted as averages across this type of trip-specific heterogeneity.

Table 11: Estimated Elasticities

Time of Day	**Individual Type**	**Bid Level Elasticities**		**Order Level Elasticities**	
		PRICE	WAITING TIME	PRICE	WAITING TIME
Daytime 6am-6pm	Overall	-1.83	-0.63	-1.74	-0.64
	H Price, H Wait Sensitivity	-4.08	-1.18	-3.83	-1.09
	H Price, L Wait Sensitivity	-0.95	-0.51	-1.04	-0.53
	L Price, H Wait Sensitivity	-2.15	-0.6	-2.05	-0.68
	L Price, L Wait Sensitivity	-0.65	-0.3	-0.75	-0.38
Evening 6pm-6am	Overall	-2.58	-0.25	-2.4	-0.28
	H Price, H Wait Sensitivity	-4.32	-0.39	-4.12	-0.4
	H Price, L Wait Sensitivity	-1.25	-0.2	-1.33	-0.22
	L Price, H Wait Sensitivity	-3.09	-0.26	-2.87	-0.31
	L Price, L Wait Sensitivity	-1.04	-0.15	-1.12	-0.18

NOTE: This table shows the demand elasticity of price and waiting time across daytime and evening hours and individual type groupings. This table replicates Table 3 except that the model is estimated with no control function. We distinguish as *high (H) price sensitivity* individuals who have below median values for β_i^p and *low (L) price sensitivity* individuals as those with above median values for β_i^p, and similarly for waiting time sensitivity. The first two columns show these elasticities among competing bids, reflecting the change in demand due to a 1% change in price or waiting time on a single bid. The second two columns show them with respect to choosing the outside option, reflecting a change in demand due to a 1% change in price or waiting time on *all* bids.

Table 12: Trip-Specific Heterogeneity in NVOT

	All Trips	**Time-Selected Trips**	
		Placebo	*Time-Sensitive*
NVOT ($/hour)	$13.47	$17.92	$28.34
N Trips	1,021,007	86,786	62,229
N Individuals	80,161	32,438	21,651

NOTE: This table shows baseline mean NVOT estimates in the first column. The second column reports mean NVOT estimates for trips in which exactly one bid occurs before the 23rd and 53rd minute of each hour and additional bids fall beyond this time. The third column similarly reports NVOT estimates for trips in which exactly one bid occurs before the first minute of each hour. All estimates are presented in US dollars.