Valuing Flexibility: A Model of Discretionary Rest Breaks

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Abstract

As flexible work arrangements become increasingly prevalent in the labor market, more and more workers have discretion over when they take rest breaks—a feature that is likely appealing to many. Yet we do not have a formal economic model of the decision to take breaks, nor do we know how much workers value this 'breaks' flexibility. To fill the gap, I develop and estimate the first dynamic model of daily labor supply that endogenizes rest breaks. The model includes several factors that influence the decision to take breaks: fatigue, opportunity costs, preferences across hours of the day, and random utility shocks. I estimate the model using high-frequency data on millions of taxi trips covering over 14,000 drivers in NYC during an entire year. This allows me to characterize heterogeneity across drivers in a transparent non-parametric way, estimating the model separately for each driver. Using the estimated parameters, I first evaluate the welfare loss to workers if discretionary breaks were replaced by scheduled breaks. My results show that flexibility is valued highly: the average driver in my sample would require a 23 percent increase in revenue to accept a counterfactual fixed work schedule. Further, I find substantial heterogeneity in this valuation, indicating that for some workers, discretionary breaks bestow a large non-pecuniary benefit. I then use the model to study the effects of a realistic 'mandatory breaks' policy on the frequency of breaks and labor supply. Counterfactual evidence shows that such a policy would substantially increase the frequency of breaks but would reduce labor supply by 6 to 9 percent. This result highlights the need to weigh the benefits of break-oriented policies—including a reduction in accidents—with the negative consequences for labor supply and the welfare of workers. While I use a specific industry to estimate the model, the proposed framework is quite general and can be applied in various other contexts, helping understand how workers in a given industry make their short-term labor supply decisions.

Keywords: Labor Supply; Rest Breaks; Flexibility; Alternative Work Arrangements

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1 Introduction

With the decline of traditional work arrangements—the nine-to-five workday—and the shift toward greater scheduling flexibility in the labor market,[1] discretionary rest breaks have become an increasingly common feature of many jobs. During their regular workday, freelancers, academics, white-collar managers, and taxi drivers—to name a few—can all choose when and how many rest breaks to take. This appealing flexibility allows workers to tailor the frequency of breaks to their personal preferences, and as such, is likely part of the explanation for the well-documented increase in flexible work arrangements. Yet we do not have a formal economic model of discretionary breaks, nor do we know how much workers value this 'breaks' flexibility.

In this paper, I develop and estimate the first dynamic model of daily labor supply that endogenizes rest breaks. The model focuses on forward-looking workers who need to decide each period whether to work, take a break, or end their workday. Several different factors are allowed to influence the labor supply decision: the disutility of fatigue while working, the opportunity cost of a break (forgone earnings), the fixed cost of switching from work to a break, and random utility shocks. I show that this can be structured in a dynamic discrete choice model that shares many similarities with Rust's (1987) bus engine replacement problem.

I use the model to shed light on three aspects of short-term labor supply. First, the estimates clarify the relative importance of the factors affecting short-term labor supply decisions, especially breaks. Second, I quantify workers' valuations of 'breaks' flexibility, including heterogeneity in those valuations. Third, I am able to simulate the effects of a policy seeking to increase the frequency of breaks.

To estimate the model, I focus on the New York City (NYC) taxi industry, using transaction-level data covering the universe of taxi trips. Based on more than 170 million taxi fares, I construct a dataset which contains the daily labor supply decisions of 14,190 drivers over an entire year.[2] The New York City taxi industry is a suitable setting to study the decision to take breaks given that drivers have full flexibility over

[1] Katz and Krueger (2016) show that between 2005 and 2015, 32% to 52% of net employment growth in the United States was due to 'independent workers,' which include contractors, freelancers, and 'gig-economy' workers.

[2] There are more than 40,000 unique driver identifiers in the data. I restrict my analysis to these 14,190 drivers as they display behaviors indicating that they rent their vehicles. The exact restrictions are explained in Appendix A.

when to take breaks and for how long. It also has important parallels with many recently emerging jobs that feature scheduling flexibility.

The richness of the data allows me to estimate heterogeneity across drivers in a very flexible manner. While I use all drivers to obtain the law of motion for the market wage, I estimate the parameters of the utility function separately for each driver. In doing so, I am able to recover a fully non-parametric distribution of the set of utility parameters. The interpretation of such heterogeneity is transparent: individuals have different costs of effort, different responsiveness to earnings, different preferences for taking breaks at certain hours-of-the-day, etc. Understanding this worker heterogeneity is key if we want to characterize who will be most affected by a given policy, as will be important below.

Measurement error in the labor supply decision is possible because the dataset does not contain explicit information about whether the driver is taking a break or whether he[3] is searching for a fare. Previous studies have imposed a simple fixed threshold to classify long wait times between fares as a break, an obvious problem with this being the systematic misclassification of long search times as 'breaks' when demand falls. I address this problem using the spatial nature of a taxi driver's working environment: long wait times are categorized as breaks using a threshold that varies with market conditions. I also control for longer driving times that arise when returning from a remote dropoff location by computing the optimal driving time from the previous dropoff to the next pickup.[4]

The model builds in several key reduced-form features of the data. First, it accounts for unobserved heterogeneity, given the differences in the average duration of a shift and the average time on a break observed across drivers. Second, the probability of taking a break increases with the length of continuous work time, suggesting that higher levels of fatigue increase the probability of taking a break. Third, I show that they take into account the end of their rental period, indicative of the fact that taxi drivers are forward-looking. Fourth, to show that drivers respond to varying opportunity costs, I replicate a standard methodology in the literature to estimate the labor supply elasticity of earnings. Specifically, I measure labor supply as the time working and find a much higher labor supply elasticity compared to the usual case where labor supply

[3]The taxi industry is still, to this day, male-dominated. According to a report by the NYC Taxi and Limousine Commission, fully 98.9% of taxi drivers are male (Taxi and Limousine Commission, 2014).

[4]I use a routing engine with road network data from OpenStreetMap to calculate this distance for the 170 million medallion taxi trips made in 2013.

is measured as the time working *or on breaks*. This supports the plausible view that drivers recognize that taking a break when demand is low is less costly than when demand is high.

While the basic formulation is general, I make use of a particular feature of the taxi industry in specifying the model: most taxi drivers have a rental agreement for the vehicle they drive and rent for either the day shift (5 AM to 5 PM) or the night shift (5 PM to 5 AM). The 12-hour rental period makes this a finite-horizon problem, which can be solved by backward induction. The development of the model is also guided by a short survey I conducted in July 2018 with 42 NYC medallion taxi drivers, which indicated that taking a break in the city was a complex, salient decision they faced every day.[5]

To estimate the model, I employ the nested fixed point algorithm of Rust (1987). I find that the fixed cost of taking a break is very important in the NYC taxi industry, with a monetary value of about $25 for the average driver (or about 45 minutes of revenue). Not least, taking a break for a taxi driver requires that they locate a parking place, often a challenge in Manhattan. I also find that the effect of fatigue on utility is non-negligible, with a total daily cost of fatigue being equivalent to 38% of earnings. Further, random shocks, which could include the luck of finding one of the rare taxi relief stands, are important.[6]

Using the structural estimates of the model, I run several informative counterfactual experiments. First, I look at the difference in workers' surplus between the flexible environment observed in the data and a hypothetical fixed work schedule. I find that workers value scheduling flexibility highly. To accept the hypothetical fixed work schedule, the average NYC taxi driver would require an extra $63 in revenue per day (about 23% of daily revenue), with a standard deviation of $42 indicating a high degree of heterogeneity across drivers.

Second, I study the effects of a 'mandatory breaks' policy, where workers are forced to stop working—by either taking a break or ending their shift—after a certain period of uninterrupted work. Such breaks-oriented regulations are widespread in industries where fatigue can have potentially fatal consequences (e.g. truck driving or air traffic control).

[5]Other evidence from the survey indicated that heterogeneity across drivers is important.

[6]There are 68 taxi relief stands in NYC. These street parking places give an opportunity to taxi drivers to leave their vehicles and take care of personal needs.

In a taxi context, traffic accidents and vehicle insurance create a moral hazard problem whereby the driver might take more risk than would be socially optimal, perhaps justifying policy interventions. When I compare the current laissez-faire environment (in terms of breaks) to the counterfactual 'mandatory breaks' policy, I find that a regulation of this type would achieve the goal of increasing the frequency of breaks. However, it would also decrease overall labor supply by 6 to 9 percent due to drivers taking more breaks *and* working shorter shifts. This result highlights the need to weigh the benefits of break-oriented policies—including a reduction in accidents—with the negative consequences for labor supply and the welfare of workers.

While I use a specific industry in this study, the model is quite general. Most jobs with discretionary breaks can be thought of as involving hour-by-hour decisions over when to take a break—exactly the model's focus. In this way, it can be applied to various other contexts to understand how workers in a given industry make their short-term labor supply decisions.

In the remainder of this paper, I explain the paper's contribution in the context of prior work in Section 2. Then in Section 3, I describe the data and the methodology used to infer labor supply decisions. Section 4 documents reduced-form patterns in the data that support the modeling assumptions I make. The model is set out formally in Section 5. In Section 6, I describe the estimation strategy and present the parameter estimates. Then I discuss counterfactual experiments and the results from these in Section 7. Section 8 concludes.

2 Relation to the Literature

This paper builds on several important areas of prior research. First, it adds to the recent literature quantifying the value of flexibility in the context of alternative work arrangements. The recent growth in the demand for independent contractors and other flexible work arrangements has attracted the attention of many researchers, including economists.[7] It has been suggested that the biggest benefit of independent work is the labor supply flexibility it offers, both in terms of the overall quantity of hours and being

[7] There seems to be a consensus around the fact that alternative work arrangements are growing, but the magnitude of the phenomenon is still debated (Jackson et al., 2017; Abraham et al., 2017). Stanford (2017) argues that this is not a new phenomenon, but a return to previous work organization strategies that were commonplace in previous centuries.

able to choose specific times one wishes to work (Oyer, 2016).

Two important studies look at the valuation of scheduling flexibility. In an innovative paper, Chen et al. (2017) seek to estimate the value of flexibility in the labor market using Uber drivers. Their identification strategy revolves around the idea that a driver supplying work during a given hour has a reservation wage lower than the expected wage, and vice versa. This allows them to model the reservation wage as a function of a time-varying mean and random utility shocks. They find that the drivers' surplus compared to a traditional work arrangement is equivalent to 40 percent of their total pay.[8] My study extends their work in two ways. First, I focus on a smaller time-frame per period (30-minute periods instead of one-hour), which allows me to identify the value of short discretionary rest breaks. Second, I use a dynamic discrete choice framework to model the labor supply decision rather than a static model of the reservation wage.

In a similar vein, Mas and Pallais (2017) use job postings to recover the valuation of scheduling flexibility based on revealed preference. Their randomized experiment looks at three aspects of flexible work arrangements: working from home, being able to set the number of hours in a week, and being able to choose when to work. Breaks are not the focus of their analysis. They find a small average willingness to pay for scheduling flexibility but note that the considerable heterogeneity in valuations suggests that analyses based on the mean could be misleading. Interestingly, they also consider the value of jobs that permit employers to change a worker's schedule at short notice. They find that the average applicant is willing to give up 20 percent of their wage to avoid this alternative arrangement.[9]

The second literature this paper contributes to focuses on settings with flexible hours to understand short-term labor supply decisions. Since the seminal work of Camerer et al. (1997), data on daily labor supply have been used to test the neoclassical labor supply model against models with reference-dependent preferences. Several contributions in this literature, including Camerer et al. (1997), Fehr and Goette (2007), and Crawford and Meng (2011) found evidence supporting reference dependence. This conclusion has been challenged in other papers (Oettinger, 1999; Farber, 2005, 2008a; Stafford, 2015).

[8]Other researchers have been able to use data from Uber to study labor market outcomes (e.g. Hall et al., 2017; Cook et al., 2018). In 2013, the period for which I have data, Uber accounted for a minuscule share of trips in NYC. Since then, the growth of Uber around the world has been exponential.

[9]Because of features of the jobs posted, the authors were not able to offer flexibility within a shift: only the start time and end time of a shift were allowed to vary.

In all of these studies, however, the measure of labor supply employed is always the difference between the end time and the start time of a shift, and so cannot shed light on within-shift labor supply decisions such as breaks.

More recently, the availability of the digital records of each taxi trip in New York City—the dataset used in this paper—has generated considerable interest from researchers. Most notably, Farber (2015) replicated the methodology of Camerer et al. (1997) using this newly available dataset. His findings suggest that most taxi drivers behave in a way that supports the neoclassical model. In this paper, I follow this view and model workers as neoclassical optimizing agents. Recent studies show that reference dependence can explain some specific behaviors of taxi drivers but those are not necessarily of first-order importance in my analysis.[10,11]

Instead of a reduced-form approach, two recent studies have used a structural dynamic discrete choice framework to model the daily labor supply decisions of taxi drivers. Fréchette et al. (2018) develop a general equilibrium model of the taxi industry in NYC. Within the model, taxi drivers decide endogenously how much labor to supply each hour. Their labor supply model shares some similarities with the one in this paper. First, a 'period' is defined as a unit of time. In contrast, many papers have equated a period with a fare (Farber, 2005; Thakral and Tô, 2017; Buchholz et al., 2018), giving rise to periods of different length; and it is unclear how that can be adapted to study within-shift breaks. Second, taxi drivers solve a finite-horizon problem. Third, because the time horizon is short, drivers are assumed not to discount within-day payoffs. For computational simplicity, however, they assume that breaks are exogenous. Buchholz et al. (2018) also model the decision to end a driver's shift as a dynamic discrete choice problem. They find empirical support for both neoclassical and behavioral responses and propose a new estimator that relaxes some assumptions regarding the error term.

None of these previous studies has focused on breaks within the day, although there

[10]For example, Thakral and Tô (2017) propose a model of adaptive reference points. This can be interpreted as a model midway between the standard reference dependence model and the neoclassical model. In another paper (Schmidt, 2018), I show that taxi drivers respond to idiosyncratic windfall gains in a manner consistent with reference dependence, but respond to variation in the aggregate wage in a way consistent with the neoclassical model.

[11]The NYC taxi dataset has also been used in other contexts that are further away from this paper. For instance, Haggag and Paci (2014) look at tipping behaviors; Mangrum and Molnar (2017) study the marginal congestion of a taxi; and Buchholz (2018) looks at inefficiencies created by regulations in the taxi industry. The dataset has even been used to study informational leakage from the Federal Reserve (Finer, 2018).

is an acknowledgment that breaks may be a potential confounding factor and so need to be defined. For instance, Farber (2005) and Thakral and Tô (2017) use constant thresholds of 30, 60 and 90 minutes to define breaks, depending on location. Similarly, breaks are considered exogenous in Fréchette et al. (2018), who use a fixed threshold of 45 minutes between two trips as the definition of a break. In Section 3.3, I explain in more detail the possible problems arising from previous definitions of breaks, and I also propose solutions to those issues.

My paper also relates to a third area of the literature: the consequences of fatigue and breaks. While this phenomenon has been largely ignored in economics, fields such as ergonomics, sleep research, or management have studied this question actively. Many field experiments have documented the decline in productivity or work safety due to fatigue. In turn, the modeling decisions I make are based on the well-accepted view that breaks are an important mechanism through which workers can reduce their level of fatigue (Jett and George, 2003; Hideg and Trougakos, 2009).

The relationship between productivity, working hours, and fatigue has been recognized for a long time (see e.g. Goldmark and Brandeis, 1912 and Vernon, 1921). More recently, Brachet et al. (2012) look at the performance of paramedics over the course of their shift, finding a 0.76 percent increase in 30-day mortality of the patients treated at the end of the shift. Collewet and Sauermann (2017) use data from a call center to estimate the reduction in productivity over a work day. Interesting research by Pencavel (2015, 2016) uses data from WWI munition workers to understand how fatigue and recuperation time affect productivity, and Henning et al. (1997) and Pendem et al. (2016) use data entry-workers and fruit harvesters, respectively, to document the positive effect of rest breaks on productivity.

An extensive literature studies the effect of breaks on the risk of work accidents and road accidents (Tucker (2003) provides a review). In this literature, the most related study is by Dalziel and Job (1997). They analyze vehicle accidents and fatigue in the context of taxi drivers. Using survey data on 42 Australian drivers, they find a significant negative correlation between break time and the accident rate. Furthermore, they document optimism bias among drivers regarding their ability to avoid accidents and to drive safely while fatigued. This finding suggest that it may be optimal for authorities to implement breaks-related regulations despite possible negative effects on the direct welfare of drivers.

3 The New York City Taxi Data

An obvious barrier to study labor supply microdecisions is the scarcity of high-frequency data from a setting where these decisions are made in a decentralized way. Furthermore, studying heterogeneity requires many individuals and many observations for each individual. To address these issues, I take advantage of transaction-level data covering the universe of taxi trips in NYC to infer daily and within-day labor supply decisions of drivers. While the official purpose of this dataset was not to study labor supply decisions, it contains an incredible amount of information covering more than 40,000 drivers over an entire year, 2013. I start with a brief description of the institutional environment taxi drivers work in. Then I describe the data and explain how I construct the individual labor supply decisions.

3.1 Institutional background

The taxi industry has historically been heavily regulated throughout the world. Very much in line with that, operating a taxicab in New York City requires a medallion (attached to the vehicle) and a NYC Taxi and Limousine Commission (TLC) driver's license. In 2013, the number of medallions was capped at 13,437 (see Taxi and Limousine Commission, 2014). At that time, the market price of a medallion was at an all-time high, reaching over $1 million. In this environment, most taxi drivers did not own the medallion but rather rented it from the owner or an intermediary (called a taxi garage). The TLC imposes a lease cap whereby the owner of a medallion cannot charge more than a price ceiling. In 2013, the daily lease rate was between $115 to $139, depending on the day of the week and whether it was the day or the night shift.[12]

The NYC medallion taxi industry has one unique feature compared to the taxi industry in other North American cities: there is no central dispatcher. In other words, it is impossible for a customer to book a taxi trip, as medallion taxis almost exclusively operate by street hailing.[13] Furthermore, medallion taxis have a monopoly over street-

[12]On June 20, 2013, the TLC decreased the daily lease cap by $10 but allowed the medallion owner to charge $10 for credit card processing fees per shift, making the new rule revenue-neutral for almost everyone. See http://home.nyc.gov/html/tlc/downloads/pdf/newly_passed_rules_leasecap_updates.pdf.

[13]Since the end of 2013, the taxi environment in NYC has changed considerably. In mid-2013, the TLC started a pilot program for an E-Hail smartphone-based application to improve the matching. This pilot was negligible in 2013 and accounted for 0.25 percent of all yellow cab pickups between June

hailing customers in Manhattan and at the airports (see Figure A6 for a map of the relevant restricted zones).

Fares are regulated by the TLC. There was no fare variation during the sample period, with the last change being enacted in September 2012. The regular fare follows a two-part pricing scheme, with the fare starting at $3 (including the NY State tax surcharge) and increasing by $0.50 for every 0.2 miles traveled or each minute the cab is stationary.[14] There is also a flat fare of $52 for trips between Manhattan and JFK Airport. Because the fare is fixed, variations in average hourly earnings in the market mostly come from shorter or longer search times.

The airport taxi market is important but should be treated differently from regular street hailing as it is the only place in NYC where taxi stands truly allow a driver to take a break. That is, while a long queue of taxis would require the driver to stay in the vehicle to move forward slowly, in contrast, an airport taxi stand allows the driver to step out of the car and use facilities there while retaining his position in the queue.[15]

The transaction-level data used in this study originate from the Taxicab Passenger Enhancement Project (TPEP), spearheaded by the TLC. I use data from January to December 2013. By 2008, all NYC taxicabs were equipped with a digital system that records detailed information about each trip. This replaced hand-written logs used by the first generation of studies examining the labor supply of taxi drivers.

3.2 The TPEP data

The TPEP dataset contains an entry for each of the 173 million taxi trips made during 2013. It contains unique identifiers for the driver and the vehicle, information regarding the date, time, and precise GPS location of both the pickup and dropoff, and detailed information about the regular fare, surcharges, tolls, and tips paid by credit card. All

and November 2013 (see http://www.nyc.gov/html/tlc/downloads/pdf/ehail_q2_report_final.pdf). Another type of taxi, called the Boro taxi, made its debut in 2013. It is possible that taxi drivers changed their strategy following the introduction of Boro taxis. However, Boro taxis are not allowed to compete with yellow medallion taxis in Manhattan and at the airports, where 93.8% of all yellow taxi pickups originate (Taxi and Limousine Commission, 2014).

[14] There are also night surcharges and peak hour weekday surcharges of $0.50 and $1, respectively.

[15] The taxi airport holding areas are parking lots comprised of many lanes. The queue starts by filling the first lane. When it is filled, a second lane is opened and taxis start queuing. This process repeats with many more lanes. When customers requests taxis, the first lane advances until the lane is empty. During that time, vehicles in other lanes stay put. This general arrangement allows the drivers to use the onsite facilities: small restaurant, bathrooms, praying areas, etc.

data are stored electronically and sent automatically to the TLC.

In contrast to many datasets used by labor economists, the TPEP dataset was not created with the goal of conducting research. Most importantly, the dataset does not contain information about what would be called a 'shift.' If the raw data are grouped by drivers, what we see are many transactions, separated by periods of inactivity. It will be helpful to characterize these periods of inactivity into three categories, from shorter to longer: customer search, breaks, and 'time off work.'

I follow Farber (2015) and define a period of 'time off work' as any gap of more than six hours between two trips. This allows me to construct work shifts as all consecutive trips made by a driver between two periods of time off work.

An interesting feature of the New York City taxi industry is the '2-shift rule.' Specifically, the TLC forces the majority of medallions to be operated during two shifts per day. As will be explained in more detail in Section 5, I use the fact that almost all rental agreements between taxi fleets and drivers start or end at 5 AM or 5 PM. The *day shift* is consequently defined as starting at 5 AM and ending at 5 PM and the *night shift* starting at 5 PM and ending at 5 AM. In the estimation, I focus on drivers whose behavior during the year indicates that they follow the day-shift or night-shift schedule. The daily labor supply decision then becomes a finite-horizon problem where the driver is forced to end his shift at either 5 PM (day shift) or 5 AM (night shift).[16] In Figure A2, I show the distribution of end time of the shift. Two patterns emerge: first, most drivers in the sample respect the end time, although they sometimes spillover into the next driver's rental period; second, the end of the night shift is much more dispersed than the day shift, where most drivers finish their shift close to the end of the rental period.

3.3 Identifying breaks

As breaks are the primary focus of this study, it is important to define breaks in a way that minimizes the misclassification of breaks into customer search time (and vice versa). Previous studies have defined breaks using thresholds that depend only on the

[16] See Fréchette et al. (2018) for a more detailed explanation of the phenomenon. They argue that the reason for the 5 PM transition time is to make day and night shifts equally attractive to drivers in terms of accumulated earnings.

location of the pickup and dropoff.[17] That methodology raises three important issues: First, market conditions and misclassification errors will be correlated. Second, a fixed threshold does not account for long return trips. Third, waiting for a customer in the airport queue *is* a break. I take these in turn, in the process setting out the algorithm I develop.

3.3.1 Market Conditions

The first reason why using a fixed threshold to define a break is problematic comes from the correlation between market conditions and misclassification errors. To see why, imagine a taxi driver in a busy area in Manhattan's financial district at 4 PM on a weekday. The probability of misclassifying a 30-minute customer search time as a break is very low, given the average search time at 4 PM in that location is well below five minutes. However, at 4 AM in the same location, the average search time is much higher, and the probability of misclassifying a 30-minute customer search time as a break is therefore also much higher.

To address this issue, I compute the average search time for each location during each hour of the week. I compute the mean search time using only observations for which the last dropoff and the next pickup occur in the same region. The resulting search time in Manhattan is mapped in Figure 1 for Tuesday at 4 AM and Tuesday at 4 PM. There is a clear pattern, where the search time is generally much longer at the end of the night.

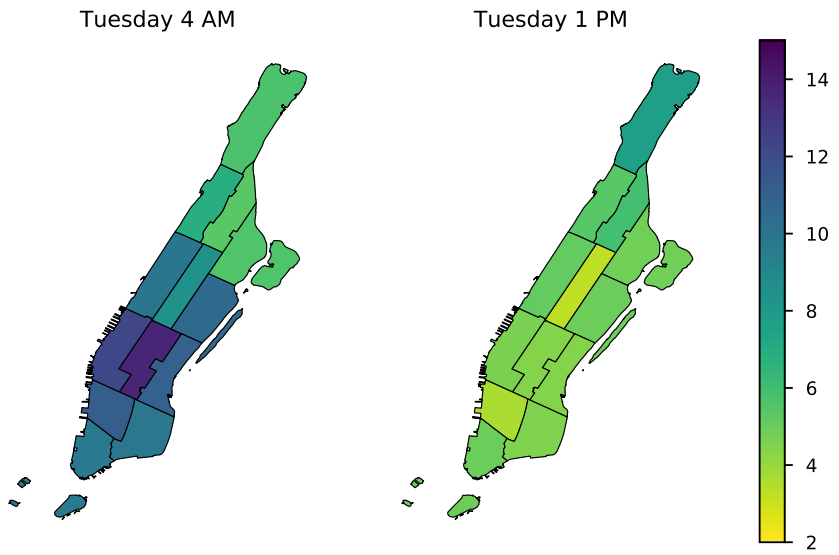
The threshold to classify a break will then depend on this measure of average search time. In areas where the mean search time is higher, a longer period of inactivity will be required to define a break. I multiply the search time by 1.5 so that a period of inactivity slightly longer than the mean search time is not considered to be a break. I also set the minimum time to classify inactivity as a break to be 20 minutes.

3.3.2 Airport Breaks

Farber (2005) and Thakral and Tô (2017) define breaks at airports to have the longest

[17] For instance, Farber (2005) defines a break as a 30-minute period between two trips within Manhattan, a 120-minute period between any trip and a trip that started at Laguardia or JFK Airport, and a 60-minute period between all other trips not covered by the first two rules. Thakral and Tô (2017) use similar thresholds.

Figure 1: Average Search Time in Manhattan



Notes: The average search time (in minutes) in each region is computed using only observations for which the last dropoff and the next pickup are in the same region. Each region is a 'community board.' See Section A.3 for further explanations.

threshold and they consider waiting in the airport queue to not be a break. In July 2018, I conducted informal interviews with taxi drivers, sixteen of whom were located at the Laguardia Airport taxi hold at the time of the interview. All of them indicated that they considered the queuing time there as a break. Based on this evidence, I consider time waiting in an airport queue as a break, and consequently set the average search time to zero in the area of Laguardia and JFK Airport.[18]

3.3.3 Driving Time

Another issue with the fixed threshold methodology relates to controlling for the driving time between the last dropoff and the next pickup. While previous studies used a longer threshold when the wait time originated or ended outside of Manhattan, the TPEP data contains the pickup and dropoff coordinates of each trip, giving one the ability to control for driving time with much more precision.

Specifically, I compute the driving distance and duration between each dropoff and

[18]See Figure A6 for a map of the neighborhoods of NYC. The two airports have their own 'neighborhood.'

pickup using a shortest path algorithm.[19] While it is possible that the driver did not take the shortest path, this will lead to a better approximation for the true duration of inactivity.

3.4 Rule to Determine Breaks

Bringing all the above considerations together, I first compute the duration of inactivity between two trips net of the driving time. More formally, the duration of inactivity before trip m is computed as the number of minutes separating the dropoff of trip $m-1$ and the pickup of trip m, net of the optimal driving time between the two locations. Denote this measure of duration of inactivity before trip m by κ_m. This value is compared to the threshold, a function of the mean search time (s_{lc}) in location l during hour c. I parametrize this function as the maximum of either 1.5 times the mean search time in the location or 20 minutes.[20] I classify the time between trip $m-1$ and m as a break if and only if:

$$\kappa_m > \max(20, 1.5 s_{lh}).$$

This rule is applied to all 170 million periods between two consecutive trips from the same driver. Using the above rule, 12.4 percent of periods within shifts are spent on break, which amount to slightly over one hour of break per 9-hour shift.

3.5 Constructing the Labor Supply Decisions

Before detailing how I reconstruct the labor supply decision, it is important to clarify what constitutes a period. Medallion taxis in NYC are mostly used for very short trips: the median trip duration is 10 minutes and 95 percent of all trips take fewer than 30 minutes. This motivates the use of relatively short periods to model the decision horizon

[19] I used the Open Source Routing Machine to compute the distance and duration for the 170 million trips. I used data from OpenStreetMap to construct the road network surrounding NYC.

[20] The 'max' function translates into a minimum threshold of 20 minutes for a break, and serves as a way to avoid overclassifying wait times as break during peak hours of the day. Indeed, during the middle of the day, the mean search time in Manhattan is often lower than 5 minutes, and would generate a threshold value of 7.5 minutes, a break duration that would be too short to reduce fatigue for taxi drivers.

of drivers. In what follows, I define periods as blocks of 30 minutes.[21]

From the transaction-level data, I reconstruct the sequence of labor supply decisions of each driver in my sample. The start of the shift is defined as the pickup time of the first customer. Then, at each subsequent 30-minute mark, I record what the driver's main activity will be during the following 30-minute period. If there is no break and the shift has not ended, I assume the driver has decided to continue working. If a break occurs in the first 15 minutes of the period, I consider that the driver decided to take a break. Finally, if the last dropoff of a shift occurs within the first 10 minutes of a period, I designate the labor supply decision in that period to be 'ending the shift.' Otherwise, the next period will be considered to be the end of the shift.

A simple illustration from an actual shift of a randomly chosen driver is shown in Figure 2. The first row represents what can be directly observed in the raw data. Each rectangle represents a trip. Then the second row shows what can be inferred from the data: the hatched sections are breaks, identified using the rule proposed in the previous subsection, and the outline represents the inferred shift start and end times. The last row presents the resulting sequence of labor supply decisions, made each 30-minute period.

3.6 Market Hourly Earnings

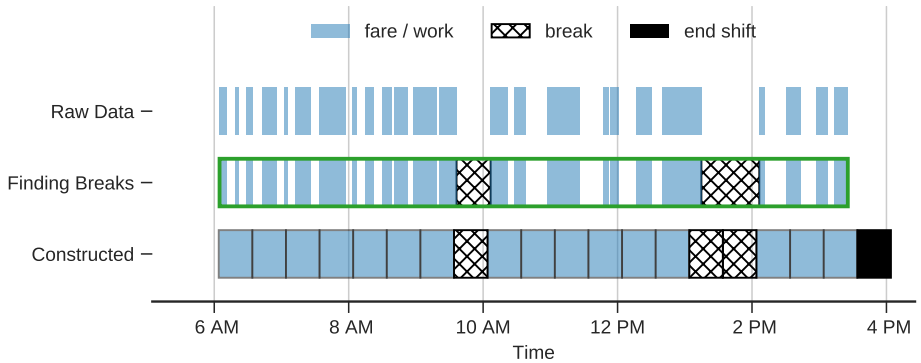
As stated earlier, hourly earnings in the taxi industry are determined in large part by the search time required to find a customer: the lower the search time, the higher the hourly earnings. In the following empirical framework, I define the market hourly earnings (or potential earnings) as the average earnings per hour averaged over *all* drivers.

Conceptually, the method I use to compute the market hourly earnings is simple. For each trip, I compute its revenue per hour by dividing the total fare received by the amount of time spent searching for the customer and spent on the trip.[22] To get the

[21] As noted above, many previous papers model a period as being one taxi fare (e.g. Farber, 2005, 2008b; Crawford and Meng, 2011; Thakral and Tô, 2017; Buchholz et al., 2018). In a way, this assumption is natural for taxi drivers as the decision to stop or end a shift can be taken at the end of each fare. However, using this definition, a period is only defined when the taxi driver is working. This becomes problematic when we want to study non-terminal actions (e.g. rest breaks), as in the current analysis.

[22] For example, suppose a driver searches for his next customer for 10 minutes, spends 20 minutes getting to the customer's destination, and receives a fare of $20. Then, this trip has a revenue per hour

Figure 2: Construction of the Data



Notes: This figure illustrates the transformations made to the raw data to infer labor supply decisions. The 'Raw Data' row represents raw transactions for a driver in the sample. There are no other trips made by this driver in the 6 hours before or after any trips shown here. The 'Finding Breaks' row adds the hatched portions where I identify rest breaks. Finally, the 'Constructed' row shows the resulting sequence of labor supply decisions for every 30-minute period.

market hourly earnings at a given moment, I take the average revenue per hour of all trips that where active (searching or driving to the destination) at that point in time.

3.7 Sample Selection

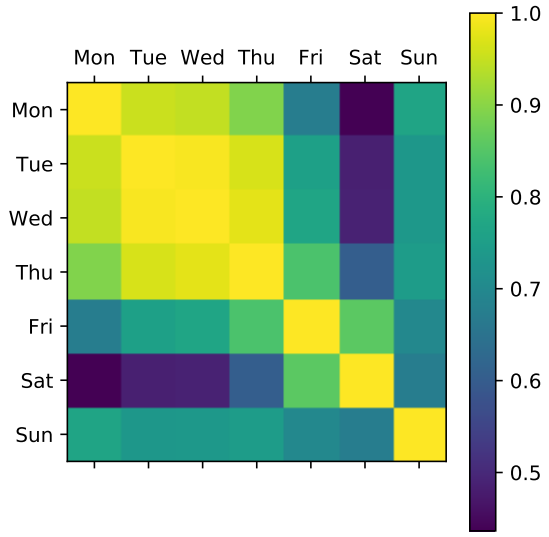
I restrict the sample in several ways to reduce measurement error. First, I only look at drivers who drove 90 percent of the time within the day shift or the night shift. Furthermore, I restrict the analysis to Monday through Thursday because labor supply patterns across those days are very similar, and I select drivers with more than 75 Monday through Thursday shifts during the year. I also drop irregular shifts with durations below 3 hours or over 12 hours.

To show why I selected shifts from Monday to Thursday, Figure 3 plots the Pearson's correlation coefficient between the time series of market wages per minute during each day of the week. We can clearly see a very high correlation during the first four days of the week. Including Friday, Saturday, or Sunday in the analysis would require that we add another level of fixed effects, which would be computationally expensive.

Summary statistics for the resulting shifts are shown in Table A1. There, we observe patterns that are consistent with the selection rules: selected drivers, based on the

of $40. See A.2 for more details.

Figure 3: Correlations Across Weekdays in Hourly Earnings Variations



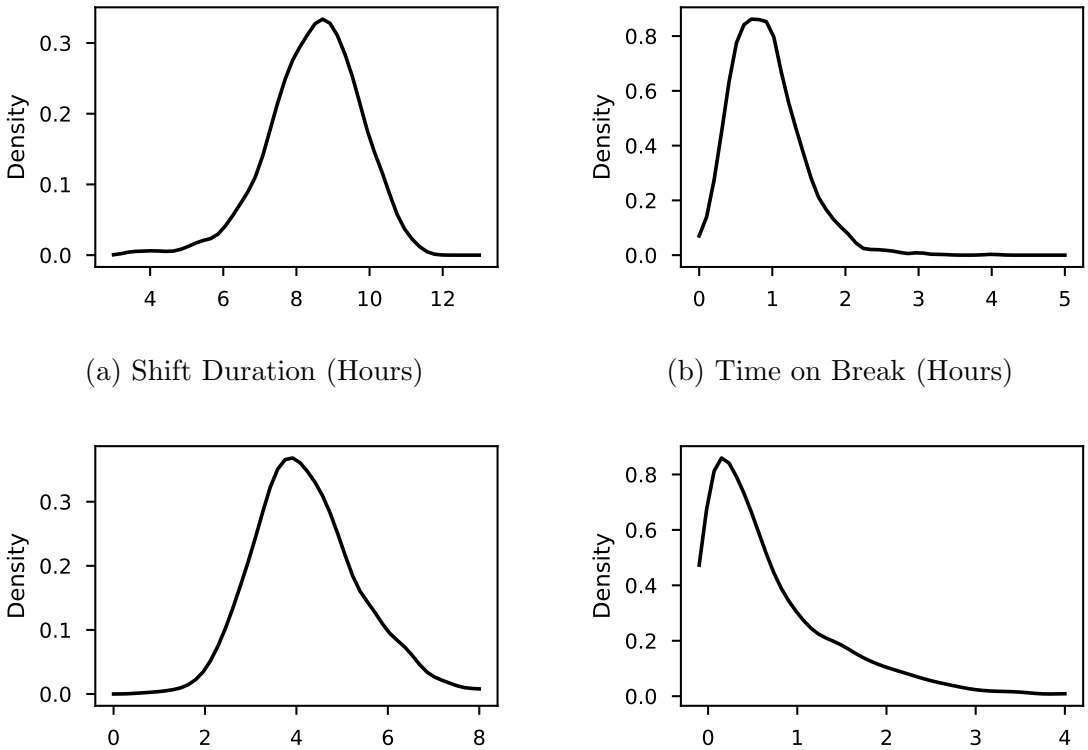
Notes: This heatmap shows the Pearson's correlation coefficient between average market hourly earnings for each minute of the day, across each day of the week. The top right cell, for example, shows the correlation coefficient between the sequence of hourly earnings on Monday and Sunday. The methodology to compute the market hourly earnings is detailed in Section A.2. I count the first 5 hours of a day (from midnight to 5 AM) as belonging to the previous day because drivers working during those hours are on the previous day's shift.

criteria just described, are earning less per shift than the remaining drivers. The first reason is that they work shorter shifts because they are restricted by the 12-hour limit. The second reason is that they face lower hourly earnings. This can be explained by the fact that owner-drivers are usually much more experienced than rental drivers. Selected drivers also work more shifts per year because I select only the drivers with enough observations to estimate the model consistently.

4 Descriptive Evidence

In this section, I document four patterns related to breaks that can be found in the data. These patterns motivate the major features of the model: allowing heterogeneity across drivers, the duration dependence of breaks, forward-looking behaviors, and opportunity costs affecting the decision to take a break.

Figure 4: Distributions of Annual Means Across Drivers



(a) Shift Duration (Hours)

(b) Time on Break (Hours)

(c) Duration of Uninterrupted Work (Hours)

(d) Number of Airport Pickups

Notes: To construct these distributions, I first obtain the mean of the selected statistic for each driver. Then I plot the resulting distributions of these averages. The PDFs are estimated using a non-parametric kernel density estimation technique with a Gaussian kernel.

4.1 Heterogeneity across drivers

A central issue with dynamic discrete choice models is the presence of unobserved heterogeneity. Previous studies have already documented significant heterogeneity across taxi drivers. Farber (2015), also using the TPEP dataset, estimates a labor supply elasticity for each individual driver. He finds substantial variation across drivers in estimated labor supply elasticities, ranging from well into negative territory to more than 0.75. In a different setting, Mas and Pallais (2017) also find considerable evidence of heterogeneity in valuations, and caution researchers that any analysis that ignores heterogeneity will potentially lead to misleading conclusions.

As a starting point when accounting for this heterogeneity in my analysis, I present distributions of summary statistics across drivers in Figure 4. Each panel shows the

distribution of annual averages over drivers: Figure 4(a) shows the distribution of average shift duration; Figure 4(b) shows the distribution of hours spent on breaks during a shift; Figure 4(c) shows the distribution of average duration of uninterrupted work (i.e. the frequency of breaks); and Figure 4(d) shows the average number of pickups from either Laguardia or JFK Airport per shift. A significant amount of heterogeneity in all dimensions of labor supply is apparent.

To explore whether this heterogeneity can simply be explained by statistical randomness, I conduct a simple thought experiment: if hours on break per shift were drawn from the same distribution for all drivers (i.e. there was no heterogeneity across drivers), then only about 5 percent of all drivers should be statistically different (at the 5% level) from the average driver. Instead, the data indicate that the mean driver (in terms of time on break) is statistically different from 66.3 percent of all other drivers.

It is possible that heterogeneity is present in other dimensions. In Table A2, I perform a variance decomposition exercise, finding that differences across weeks of the year (capturing seasonality effects) can only explain between 0.3 percent to 2.1 percent of all heterogeneity in the statistics presented in Figure 4. Similarly, differences across weekdays only explain 0.5 percent to 3.9 percent of the heterogeneity. In contrast, between 20.2 percent and 38.7 percent of heterogeneity can be explained by differences across *drivers*. This supports the decision to focus on heterogeneity across drivers while abstracting from seasonality effects.

4.2 Duration Dependence of Breaks

In this subsection, I present descriptive evidence showing that breaks exhibit positive duration dependence, a feature that supports the presence of fatigue in the decision to take a break. In contrast, a model with random breaks (due, for example, to idiosyncratic utility shocks) would have no duration dependence: there is a constant arrival rate of shocks that create a break. The properties of models with duration dependence have been studied extensively in the literature examining unemployment spells. In the current context, instead of looking at the relationship between the job-finding probability and the duration of the unemployment spell, I look at the probability of taking a break with respect to the duration of a continuous work 'spell.' In this case, the data would exhibit positive duration dependence when the probability of the event (a break) increased

with the spell duration.

Duration dependence is represented graphically in Figure 5, where the hazard function of taking a break is plotted for different cases. The dashed line represents a world where breaks have a constant arrival rate and no driver heterogeneity exists. The dashed line is flat because the probability of taking a break does not depend on the duration of continuous work.

The above discussion compares the data to a case where breaks arrive at a constant rate throughout the day and the arrival rate is common to all drivers. The previous discussion relating to the presence of heterogeneity across drivers makes it clear that the data reject this assumption. When relaxing the assumption that the rate is common to all drivers, it is well known that unobserved heterogeneity affects the shape of the hazard function seen in aggregate data (Baker and Melino, 2000; Van Den Berg, 2001). As shown by the dotted line of Figure 5, the resulting slope of the hazard function will be negative, even with no duration dependence.[23] Therefore, unobserved heterogeneity would bias the result toward finding negative duration dependence.

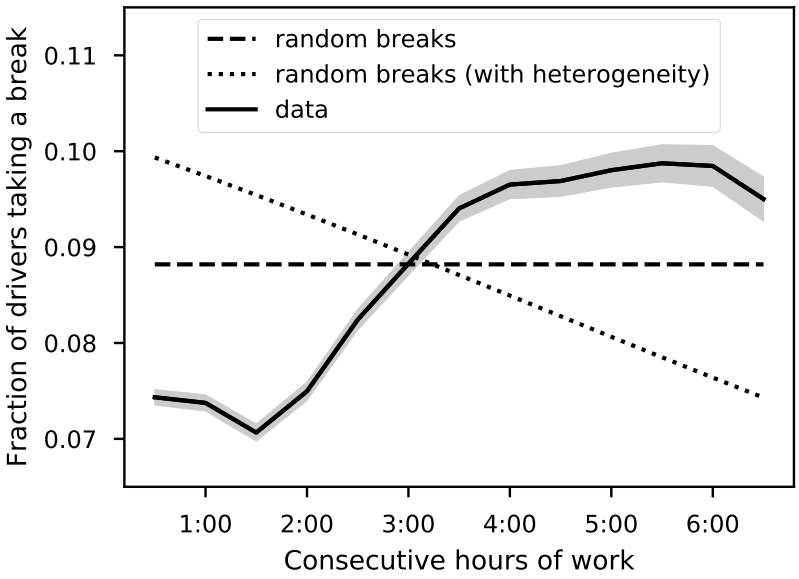
In contrast, the solid line illustrates the hazard function estimated from the data, showing that taking a break is a process that exhibits clear positive duration dependence. While a random component is still most likely present, positive duration dependence suggests that worker fatigue plays a role in the decision to take a break. For example, a driver is more likely to take a break after five hours of continuous work than after one hour because the accumulation of fatigue has decreased the net utility of continuing to work.

4.3 Forward-looking behavior

The hazard function of taking a break is helpful not only for showing that fatigue is likely to play a role in the break decision, but also to demonstrate that drivers are forward-looking within the day. Indeed, if drivers were not forward-looking, then the end of the taxi rental period should not be correlated with a reduction in the probability of taking a break in previous periods. This is because, as a driver approaches the end of a shift, the utility of taking a break decreases since its fatigue-reducing benefits would

[23] Intuitively, the reason for this decreasing hazard function is that individuals with a low probability of taking a break represent a larger fraction of drivers who have worked continuously for a longer period of time.

Figure 5: Hazard Function of Breaks



Notes: The hazard function of a break under the hypothesis of no duration dependence and heterogeneity assumes that there are two equal-sized groups of drivers. The first group takes a break each period with a probability of 5 percent while the second group does so with a probability of 13 percent.

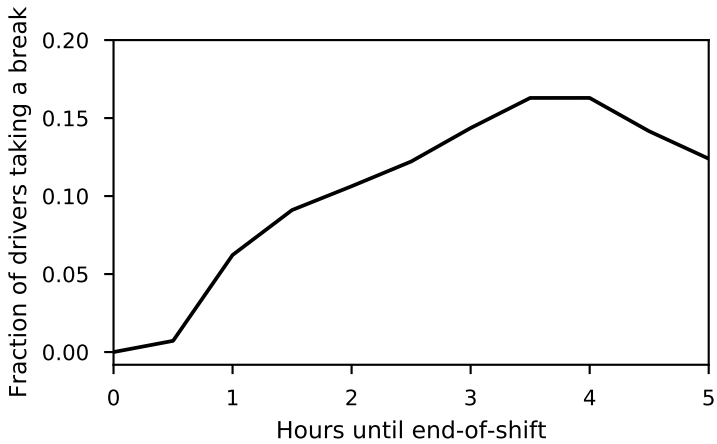
have an impact on only a relatively short period of time.

Figure 6 shows the hazard function associated with starting a break but this time with respect to time until the *end* of the taxi rental period. Notice here that the '0' on the horizontal axis represents the end of a shift. We can observe a steadily decreasing probability of taking a break as we get closer to the end of the rental period (moving from right to left).[24] This suggests that drivers are forward-looking whereby they make their decisions incorporating the continuation value, which depends on the terminal period. If they did not expect their shift to end, their probability of taking a break would be constant.

While forward-looking behavior can explain the pattern observed in Figure 6, other explanations cannot be ruled out by this simple reduced-form exercise. Time until the end of the rental period is highly correlated with the hour-of-the-day fixed effects, for instance. These confounding factors will be accounted for in the structural model

[24]Only shifts where the driver worked until the end of the rental period are included here because the decision to end could lead to a similar pattern without forward-looking preferences.

Figure 6: Probability of Taking a Break at the End of Shift



Notes: Only the drivers who worked until the end of their rental period are included in this figure.

presented in the next section.

4.4 Opportunity cost

Simple economic intuition tells us that drivers should be responsive to pecuniary incentives: If the potential earnings are high, taking a break will be costly. Conversely, in times of low demand and low potential earnings, it would be efficient for drivers to take a break. The extent to which drivers respond to pecuniary incentives in their decision to take a break is unclear.

As a simple test, Figure A3 shows the probability of taking a break in $1 increments of a period's deviation from usual potential earnings (i.e. the market hourly earnings). As expected, we see a negative correlation, indicating that drivers are more likely to take a break when earnings are low. This suggests that potential earnings during the period are a factor in the decision to take a break.

Many studies focus on estimating the daily labor supply elasticity. I replicate the methodology of Camerer et al. (1997) to assess how much the elasticity would change if we account for breaks not as a control variable, but in the measure of labor supply itself. Define the 'gross' labor supply as the time between the start and end of a shift. Then 'adjusted' labor supply can be defined as the 'gross' labor supply net of all breaks taken during the shift. If breaks occur randomly and are not correlated with potential

Table 1: Estimates of Labor Supply Elasticity (2SLS)

	All	Day Shift	Night Shift	Owner
	(1)	(2)	(3)	(4)
Panel A: Gross shift				
log Hourly Earnings	0.256***	0.071***	0.438***	0.463***
	(0.004)	(0.004)	(0.006)	(0.015)
Panel B: Adjusted shift (net of breaks)				
log Hourly Earnings	0.821***	0.624***	1.098***	1.216***
	(0.007)	(0.009)	(0.011)	(0.032)
Controls	Yes	Yes	Yes	Yes
Observations	4,894,002	2,148,223	2,151,782	566,344

Notes: Clustered standard errors in parentheses (driver-level). Controls include weather (temperature and precipitation), location fixed effects (modal pickup neighborhood – 72), holiday fixed effects (9), and fixed effects for the month of the year (11) and the hour of the week (167).

earnings, we should observe the same labor supply elasticity for both measures of labor supply.

Table 1 shows the estimated labor supply elasticities (the details of the regression, the variables, and the instrument for hourly earnings are explained in Appendix B). In Panel A, the labor supply elasticities are estimated using the gross measure of labor supply. When I use the adjusted measure of labor supply in Panel B, the elasticities become significantly higher. This is intuitive: some drivers use breaks as a margin of labor supply adjustment since lower potential earnings reduce the opportunity cost of taking a break.

5 A Labor Supply Model with Breaks

In this section, I set out the model of daily labor supply with discretionary breaks. The model reflects the flexible environment taxi drivers operate in by letting the drivers make labor supply decisions along two dimensions: taking breaks and ending the shift. This can be formulated using a standard dynamic discrete choice framework.

5.1 Fatigue

There is a general consensus in the literature that rest breaks during the workday reduce fatigue (Tucker, 2003; Jett and George, 2003; Hideg and Trougakos, 2009). In the model I now outline, I define fatigue as the net effect of all duration-dependent processes affecting utility during the day. For instance, the need to eat or go to the bathroom are examples of duration-dependent processes with an associated disutility that grows over time. I will use 'fatigue' as an umbrella term to simplify the discussion.

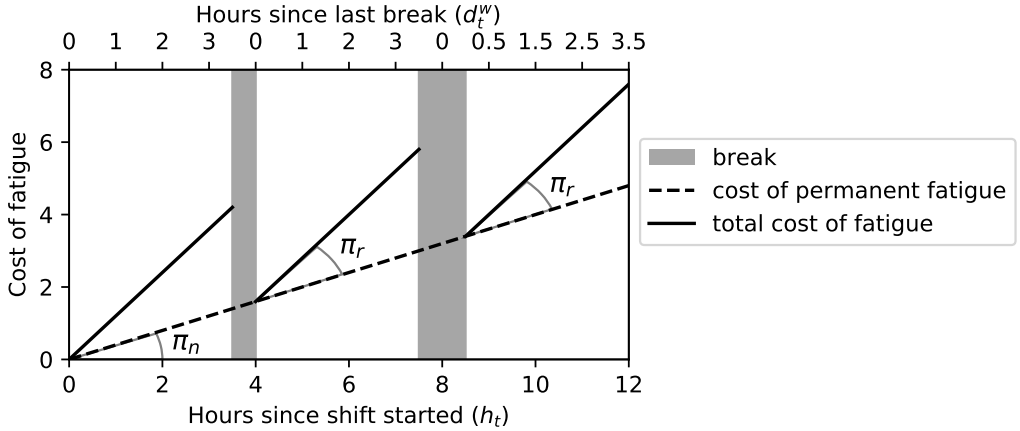
The way I parametrize fatigue captures two crucial features of resource depletion and recovery over the workday. First, breaks serve as a recovery mechanism and lead to a reduction in accumulated fatigue. Second, sleep is crucial to completely recuperate from a workday. This also means that we expect the fatigue level of a worker to be higher later in the day (compared to earlier), even if the worker is just back from a break. To model those two features, I define fatigue accordingly as the sum of two components: recoverable fatigue and non-recoverable fatigue.

In the following subsection and in the estimation, non-recoverable fatigue enters utility as a function of the accumulated *hours* on shift (h_t), where time is denominated in the number of 30-minute periods. Recoverable fatigue is defined as a function of the *duration* of uninterrupted work (d_t^w), again denominated in number of 30-minute periods. In terms of their parametrization, I assume these two components have a linear and additively separable effect such that the total cost of fatigue is $\pi_n h_t + \pi_r d_t^w$, where π_n and π_r indicate the speed at which fatigue accumulates.

In the model, breaks are assumed to reset recoverable fatigue, but have no effect on non-recoverable fatigue. Following the literature on resource recovery, I make the strong assumption that any breaks of at least 30 minutes eliminate recoverable fatigue completely. In contrast, the only way to reduce non-recoverable fatigue is to end one's shift.

As shown in Section 4, the probability of taking a break increases with the time since the last break. It is useful to understand the fatigue process through the lens of Figure 7. Parameters π_n and π_r inform us as to the nature of the fatigue process. The larger they are, the more quickly total fatigue accumulates.

Figure 7: Graphical Representation of the Fatigue Process



5.2 Per-Period Utility

Given the above treatment of fatigue, I now define the utility function of the agents. In dynamic discrete choice models, the agent derives utility each period, utility depending on the value of the state variables as well as the action taken by the agent. While forward-looking agents seek to maximize more than just their utility in the current period, understanding the factors that influences per-period utility is key to understanding the intuition behind the main parameters and how they affect the driver's decision.

Formally, an agent derives per-period (flow) utility, which depends on his action ($a_t \in (w)$ork, (b)reak, (e)nd shift) as well as the state space (x_t). Taking these actions in turn, when the agent works, his flow utility is characterized by the expected earnings to be made during that period (I_t), as well as the disutility from fatigue. The utility when the agent works ($a_t = w$) is given by

$$u_t(a_t, x_t | a_t = w) = \gamma I_t - \pi_n h_t - \pi_r d_t^w + \alpha_c^w + \epsilon_t^w,$$

where α_c^w is an intercept that varies with the hour-of-the-day (*clock* time). It can capture the fact that working is less pleasant at certain times of the day (e.g. rush hour); it can also be viewed as an hour-of-the-day fixed effect. In the estimation, it is treated as a nuisance parameter. The error term ϵ_t^w is an idiosyncratic utility shock. For tractability, I make the assumption that all idiosyncratic utility shocks follow an extreme value type I distribution. This is the logit assumption and is standard in the dynamic discrete

choice literature.[25]

The contribution of earnings to utility is represented by γI_t. In the estimation, I use the average hourly wage in period t across all drivers as a measure of I_t. For computational purposes, I discretize I_t into eight bins, each of which has a width of \$1 per 30-minute period, and is expressed in terms of deviations from the mean. To be more precise about the evolution of potential earnings, it is possible to decompose it into four separate components: (a) the hourly market earnings, (b) the average deviation from the hourly market earnings, (c) driver-specific productivity, and (d) a driver-specific idiosyncratic shock. In this model, the hourly market earnings and the driver-specific productivity (a and c) are captured by the hour-of-the-day fixed effects. I assume that the driver-specific idiosyncratic shock (component d) is i.i.d. and that the drivers are not able to predict this, making it irrelevant for the decision they make at the start of the period. Potential earnings (I_t) are then normalized to represent the deviation from usual hourly market earnings (component b).

The utility when the agent chooses a break ($a_t = b$) is

$$u_t(a_t, x_t | a_t = b) = -\tau \cdot \mathbb{1}[a_{t-1} \neq b] - \psi d_t^b + \alpha_c^b + \epsilon_t^b.$$

At the start of a break, the agent incurs a fixed cost (τ). The duration of the break is denoted by d_t^b. The term ψd_t^b captures the idea that breaks have decreasing marginal utility, so the utility of a two-hour break is not double the utility of a one-hour break. In addition, the utility from rest breaks also contains an intercept that varies with the time of the day (α_c^b) and an idiosyncratic utility shock (ϵ_t^b). The hour-of-the-day fixed effect for breaks represents the fact that workers may have preferences across hours of the day for taking breaks (e.g. having lunch at the same time every day).

Finally, the value of ending the shift ($a_t = e$) is normalized to 0 plus an idiosyncratic

[25] Using similar data, Buchholz et al. (2018) relax this assumption in a simpler model that only tracks the decision to end a shift. Relaxing the logit assumption in dynamic models with breaks is left for future research.

utility shock. Putting everything together, per-period utility is then:

$$u_t(a_t, x_t) = \begin{cases} \gamma I_t - \pi_n h_t - \pi_r d_t^w + \alpha_c^w + \epsilon_t^w & \text{if } a_t = w; \\ -\tau \cdot \mathbb{1}[a_{t-1} \neq b] - \psi d_t^b + \alpha_c^b + \epsilon_t^b & \text{if } a_t = b; \\ \epsilon_t^e & \text{if } a_t = e. \end{cases} \tag{1}$$

The vector of state variables, x_t, consists of: I_t, h_t, d_t^w, d_t^b, a_{t-1}, and the clock time c. It is also useful to define $\epsilon_t \equiv (\epsilon_t^w, \epsilon_t^b, \epsilon_t^e)$, as well as the vector of parameters $\theta \equiv (\gamma, \pi_n, \pi_r, \tau, \psi, \alpha^w, \alpha^b, \theta_f)$, where θ_f is the set of parameters capturing the evolution of the state space, discussed next.

5.3 Evolution of the State Space

The agents' beliefs about the future are an essential component of the model. Intuitively, because the utility in future periods is part of the optimization problem, a rational agent must keep track of the evolution of the state space. In the problem outlined here, only potential earnings are stochastic and carry some uncertainty concerning their evolution.

Recall that I_t is a discretized measure of the market's deviation from usual earnings in the period. I model the law of motion of I_t as a Markov process that can be represented using an 8×8 transition matrix (θ_f). The elements of θ_f are parameters of the model and are assumed to be identical across drivers (i.e. all drivers have the same expectation about the evolution of potential earnings).

The other laws of motion in this model are deterministic. The hour of the day follows the clock cycle. The accumulated hours on shift (h_t) and the durations of uninterrupted work and breaks (d_t^w and d_t^b) follow the laws of motion:

$$h_{t+1} = h_t + 1$$

$$d_{t+1}^w = \begin{cases} d_t^w + 1, & \text{if } a_t = w, \\ 0, & \text{otherwise.} \end{cases}$$

$$d_{t+1}^b = \begin{cases} d_t^b + 1, & \text{if } a_t = b, \\ 0, & \text{otherwise.} \end{cases}$$

The fact that these variables evolve in a deterministic fashion is the key to the computational efficiency of the estimation technique and a central reason for why the model can be estimated separately for each driver in a reasonable amount of time.

5.4 Forward-looking value function

Agents in this model are forward-looking during the day, as stated earlier. This implies that when deciding their action at the beginning of each period, their objective is to maximize the utility of the current and future periods within the shift, stopping at most at the end of their rental period.

The agent's problem is then to choose a_t to maximize the discounted sum of future flow utilities:

$$\max_{a_t} \left[u(a_t, x_t, \epsilon_t) + E\left(\sum_{t'=t+1}^{T} \beta^{t'-t} \left[u(x_{t'}, a_{t'}, \epsilon_{t'}) \right] \right) \right].$$

This is a standard dynamic programming problem. It can be written in a recursive form with the ex-ante value function $\bar{V}_t(x_t)$:

$$\bar{V}_t(x_t) = \max_{a_t} u(a_t, x_t, \epsilon_t) + \beta \int \bar{V}_{t+1}(x_{t+1}) f(x_{t+1}|a_t, x_t) dx_{t+1}.$$

In the above recursive representation, $f(x_{t+1}|a_t, x_t)$ is the transition function and maps the probability of going from the current state x_t to x_{t+1}, given action a_t. The value of the state variables depends only on the last period's value and the last period's decision. It is helpful to define the conditional value function $v_t(a_t, x_t)$—also called the choice-specific value function—as the present discounted value of choosing a_t and behaving optimally in the following periods:

$$v_t(a_t, x_t) = \tilde{u}(a_t, x_t) + \beta \int \bar{V}_{t+1}(x_{t+1}) f(x_{t+1}|a_t, x_t) dx_{t+1}, \tag{2}$$

where $\tilde{u}$ is defined as the utility net of the error terms. The problem becomes very similar to a static conditional logit model in which the agent maximizes v_t instead of u_t. Among the options available, the agent chooses the option yielding the highest forward-looking utility. The researcher does not know what the error term is, but makes

an assumption about its distribution. Then, for a given set of parameters θ, we can compute the conditional choice probability $p(a_t|x_t, \theta)$—the probability that an action is taken given the current values of the state space. This conditional choice probability is the central object of the estimation strategy.

A large literature studies at the identification of dynamic discrete choice models (e.g. Rust, 1994; Magnac and Thesmar, 2002). The discount factor (β) is known from the literature to be non-parametrically unidentified. While the choice of discount factor is an important modeling decision when the time horizon of the forward-looking decision is long, it is less of an issue for within-day applications. Because my periods have a duration of 30 minutes, even a discount factor of 0.99 translates to an implausibly large annual discount rate.[26] I follow Fréchette et al. (2018) and set $\beta = 1$, assuming there is no discounting within a shift.

To summarize, in this section, I have set out a dynamic model of daily labor supply with discretionary rest breaks. The model features several components affecting the decision to take a break. First, breaks allow the worker to reduce accumulated fatigue through its recoverable component (d_t^w). Second, breaks offer higher utility at certain hours of the day because of differences in the taste for breaks across hours (e.g. lunchtime) or differences in average hourly earnings, through α_c^w and α_c^b. Third, demand shocks affect expected earnings and modify the opportunity cost of a break. Other factors influencing the decision to take a break are then included in the random utility shocks (error terms).

6 Estimation

The estimation of this dynamic discrete choice model is carried out by maximum likelihood. The central parts of the log-likelihood function are the conditional choice probabilities, $p(a_t|x_t)$. In this section, I first describe the log-likelihood. Then I discuss intuitively how one might think of the identification of each parameter and describe how heterogeneity is handled. Finally, I present the estimates and describe how well the model fits the data.

[26] The results presented in the following section are not sensitive to changing the discount factor to take on any value between 0.95 and 1.

6.1 Estimation Strategy

Define the probability of choosing an action given a realization of the state space by $p_t(a_t|x_t)$. According to the model, this will be equal to the probability that action a is the optimal action at time t. Assuming that the idiosyncratic utility shocks follow a type I extreme value distribution, the probability of an arbitrary choice a_t is given by

$$p_t(a_t|x_t) = \frac{\exp\left[v_t(x_t, a_t)\right]}{\sum_{a_t'} \exp\left[v_t(x_t, a_t')\right]}. \tag{3}$$

The above conditional choice probability is essential to the estimation strategy, with the maximum likelihood function being comprised of each observation's conditional choice probability associated with the realized action.

The maximum likelihood function is formed by calculating the probabilities of the observed actions in the data. Specifically, the log-likelihood function is

$$l(\theta) = \sum_{t=0}^{T} \sum_{n=0}^{N} \left(\ln\left[p_t(a_{nt}|x_{nt}, \theta)\right] + \ln\left[f(x_{nt+1}|x_{nt}, a_{nt}, \theta_f)\right]\right).$$

For each period and each agent, the likelihood can be factored into two pieces: the conditional choice probability and the transition density function.

Because θ_f only enters the second part of the likelihood, it can be obtained independently in a first step. Although this is not as efficient as estimating everything jointly, it greatly reduces the computational cost. This first step is carried out nonparametrically using a simple bin estimator (based on empirical frequencies):

$$f(x_{t+1}|x_t, a_t) = \frac{\sum_{n=1}^{N} \sum_{t'=1}^{T} \mathbb{1}(x_{nt'+1} = x_{t+1}, x_{nt'} = x_t)}{\sum_{n=1}^{N} \sum_{t'=1}^{T} \mathbb{1}(x_{nt'} = x_t)}.$$

Taking the estimate of θ_f as given, I then estimate the model using a finite-horizon version of the nested fixed point algorithm developed in Rust (1987). This technique is known to be computationally intensive because the agent's problem needs to be solved at every iteration of the likelihood optimization algorithm, hence the 'nested' structure of the problem. First, for a given draw of the utility parameters, the algorithm solves the agent's problem by backward induction. During the last 30 minutes of the rental period, the agent knows that he is forced to end the shift. Thus, regardless of

his action choice, the continuation value will be the same. In other words, at $t = T$, the forward-looking value function is equivalent to the static utility function ($v_T = u_T$). Using this feature, we can compute the value function at the preceding period (v_{T-1}). Iterating this process allow us to recover the value function at every period of the shift.

Once v_t is recovered, the estimation is identical to a static conditional logit model. I make the assumption that the error terms are drawn from an extreme value type I distribution, generating the closed form solution in Equation (3) for the conditional choice probabilities. Standard maximum likely optimization techniques can be used to iterate over different draws of the parameter, until convergence.

The identification of each parameter can be understood intuitively from the respective sources of identifying variation. First, the coefficient on hourly earnings (γ) is identified from unexpected variation in potential earnings. Following the literature (see e.g. Farber, 2015), I assume that the hour-of-the-day fixed effect captures all expected variation in potential earnings. I estimate the model with shifts from Monday to Thursday to avoid the need to include day-of-the-week fixed effects, since this would be too computationally costly. On this point, Fréchette et al. (2018) find that shifts on Monday through Thursday are very similar, suggesting that the identification of parameters does not originate from variation across weekdays.

The parameters governing the cost of fatigue (π_r and π_n) captures most of the duration dependence embodied in the model. The parameter of recoverable fatigue (π_r) can be understood graphically from Figure 5. Positive duration dependence imply that the probability of taking a break increases as the duration of uninterrupted work increase. This would translate into a positive coefficient, and the magnitudes are identified out of the slope of the change in the probability of taking a break. The parameter of non-recoverable fatigue, is identified similarly with the difference in the probability of ending the shift at different shift duration. Intuitively, if we see a driver starting a shift at 6 AM and another otherwise similar shift at 10 AM, the cost of fatigue will be identified out of the fact that at a given hour, the level of recoverable and non-recoverable fatigue will be different and lead to different probability of taking a break.

The parameter governing the rate of breaks utility decline (ψ) is identified out of the duration dependence of breaks. If the probability of ending a break is constant with respect to the duration of the break, this would indicate that $\psi = 0$. However, if the

utility of an additional period of break is lower as the total length of a break increases, then ψ will be identified out of the speed at which marginal utility of a break decreases.

The fixed cost of taking a break (τ) is identified out of the frequency of switching between work and break. Keeping the number of periods on break a driver takes, a large fixed cost would translate into an individual that bunches his periods on breaks in one large break. In contrast, an individual that switches frequently between work and break would have a low fixed cost.

Finally, the hour-of-the-day fixed effects (α_c^w and α_c^b) are constraining all previous parameters to be identified within the same hour. Indeed, the linear fixed effects will remove the average conditional choice probability of each action for a given hour of the day. Notice that the identification of all the above parameters does not necessitate multiple drivers, only multiple work shifts. This will be important for the next subsection where I explain how the estimation strategy accounts for unobserved heterogeneity across drivers.

6.2 Unobserved Heterogeneity

The model presented in Section 5 and the estimation strategy described in this section do not distinguish between data from one driver or thousands of them. As stated by Aguirregabiria and Mira (2010), "in microeconomic applications of single-agent models, we typically have that N is large and T_i is small," where N is the number of agents and T_i is the number of periods the researcher observes agent i. This is not the case in the current application: in both dimensions, the number of observations is large. It is possible to see the data as having a completely new dimension: the shift. For each driver, N can be thought of as the number of shifts and T_j as the number of periods for shift j, where we see the agent's detailed period-by-period labor supply decisions.

Using the richness of the data, I handle unobserved heterogeneity in possibly the *most* flexible way: the model is estimated independently for each driver. This is more flexible than using a fixed effects model because heterogeneity is allowed to enter non-linearly in each parameter. In most applications of dynamic discrete choice models, the preferred method to account for unobserved heterogeneity is to use finite mixture distributions (Arcidiacono and Jones, 2003; Arcidiacono and Miller, 2011). One major limitation of that estimation strategy is that increasing the number of 'types' is computationally

prohibitive. In fact, most applications typically use fewer than 10 types. In contrast, I allow each taxi driver to have his *own* type. The resulting heterogeneity is therefore non-parametrically identified.

The interpretation of such heterogeneity is also intuitive. Because of genetic reasons or age, for example, some individuals may have better recuperation capabilities than others. Therefore, their values of π_n and π_r can vary. Similarly, the fixed cost of taking a break (τ) can differ across individuals. I also allow hour-of-the-day preferences to vary from driver to driver. This is necessary if we believe, for instance, that drivers are heterogeneous in their taste for when to take lunch or if some of them have stronger distaste for rush-hour traffic.

Allowing this degree of flexibility in heterogeneity demands a lot from the data. In order to balance this flexibility with precision in the estimation, I force the hour-of-the-day fixed effects to be the same for each three-hour block. This increases the precision of the estimates while still capturing the fact that drivers have different preferences for breaks across the day.

6.3 Results

As a benchmark, I start by showing the estimation results ignoring heterogeneity. The main reason for doing so is to compute standard errors and compare the implied confidence intervals of the parameters to the distributions I obtain after accounting for heterogeneity.

Table 2 presents the results. The estimation exercise is conducted separately for day-shift and night-shift drivers. All parameters have the expected sign. The estimate of the fixed cost appears to indicate that it is a crucial factor in the decision to take a break. Recall that medallion taxi drivers operate mainly in Manhattan, where the fixed cost of taking a break includes the time cost of finding a parking space—a difficult challenge.

To interpret the estimates of the fatigue parameters, we must remember that we are dealing with (a) a cost that is paid *each working period* and (b) a cost per *accumulated* unit of working period. For example, a coefficient of \$0.54 for the non-recoverable fatigue during a 9-hour shift entails a total cost of non-recoverable fatigue of \$92.34. The cost of recoverable fatigue, while smaller, is still significant. With $\pi_r = \$0.09$, when

Table 2: Parameter Estimates (*homogeneous* drivers)

	Day shift	Night shift	Equal (p-value)
Potential earnings (γ)	0.0458 (0.0050) [\$1]	0.0923 (0.0044) [\$1]	< 0.001
Non-recoverable fatigue (π_p)	0.0155 (0.0060) [\$0.34]	0.0132 (0.0032) [\$0.14]	0.649
Recoverable fatigue (π_r)	0.0038 (0.0004) [\$0.08]	0.0031 (0.0004) [\$0.03]	0.434
Rate of break util. decline (ψ)	0.2295 (0.0194) [\$5.01]	0.3150 (0.0184) [\$3.41]	< 0.001
Fixed cost (τ)	2.6827 (0.0704) [\$58.57]	2.7368 (0.0666) [\$29.65]	0.991
Number of drivers	1397	1039	
Observations	2,295,383	1,635,429	

Notes: Standard errors in parentheses are obtained by bootstrap at the shift-driver level. In brackets are the estimates normalized by the utility value of a \$1 deviation in market-level earnings (i.e. dividing by γ). The estimates are obtained from a random 15% sample of drivers.

a driver takes no break during a shift (as with about 30% of the shifts in my sample), the total cost of recoverable fatigue will amount to \$15.39 (or 5.5 percent of average daily earnings) for a 9-hour shift. If instead the driver had taken a break in the middle of the shift, the total cost of recoverable fatigue would diminish by 47 percent to \$8.10, for the same number of periods worked.

It is also possible that some of the cost of fatigue gets absorbed by the hour-of-the-day fixed effects. Indeed, if taxi drivers use a heuristic method for determining when to take breaks that involves taking breaks at similar clock times each day, the cost of fatigue will be included in the hour-of-the-day effect. For example, if a taxi driver always starts between 6 AM and 9 AM, and always take a break at 11 AM, the cost of fatigue in this case would be zero. Intuitively, this situation creates case where, after controlling for the hour-of-the-day, the probability of taking a break is the same (i.e. no duration dependence or $\pi_r = 0$).

It is important to note that almost all the difference in valuations between day-shift and night-shift drivers is due to the difference in γ. If we normalize γ to be the same across both groups, then the cost of fatigue and the fixed cost is statistically similar.

Table 3: Mean Parameter Estimates (*heterogeneous* drivers)

	Day Shift		Night Shift	
	Mean	Std. Dev.	Mean	Std. Dev.
Potential earnings (γ)	0.0951	0.1748	0.1757	0.0944
	[\$0.73]		[\$1.35]	
Non-recoverable fatigue (π_p)	0.0700	0.0890	0.0624	0.0517
	[\$0.54]		[\$0.48]	
Recoverable fatigue (π_r)	0.0120	0.0143	0.0116	0.0114
	[\$0.09]		[\$0.09]	
Rate of break util. decline (ψ)	0.2899	1.0287	0.5119	1.8163
	[\$2.24]		[\$3.95]	
Fixed cost (τ)	3.1545	1.3072	3.2377	2.0826
	[\$24.32]		[\$24.96]	
Number of drivers	8100		6090	

Notes: The estimates normalized in brackets are obtained by dividing by the utility value of a \$1 deviation of market-level earnings averaged across day-shift and night-shift drivers (i.e. dividing by the average γ across all drivers).

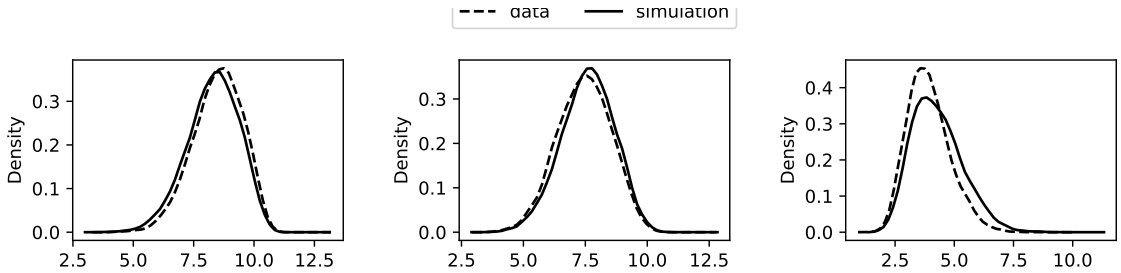
Figure A4 provides a graphical representation of the transition matrix of the hourly earnings. The same estimates are used for the model with homogeneous drivers and for the model with heterogeneous drivers given the assumption that the market conditions apply to everyone. We observe a significant amount of persistence in this measure; the probability of remaining in the same earnings state is always the highest.

The results from the estimation strategy accounting for heterogeneity are presented in Table 3. The parameter estimates have the same magnitude, but the fixed cost (in dollars) is lower while the parameters governing the cost of fatigue are higher. The full distributions are presented in Figure A5. We observe significantly more heterogeneity in every parameter when compared to the standard errors of the estimates from the homogeneous drivers estimation of Table 2. This heterogeneity will be driving the large range of valuations of labor supply flexibility I find below.

To get a sense of the fit of the model, I simulate shifts for every driver and compare the distribution of summary statistics describing a work shift at the driver-level. For a given driver, I draw values for potential earnings (I) and hour-of-the-day (c) from the empirical initial values of these variables.[27] The starting values for the other state

[27]Because I do not model the decision to start a shift, I take these values as given. If I observe a

Figure 8: Distributions of Annual Means Across Driver



(a) Shift Duration (Hours) (b) Labor Supply (Hours) (c) Continuous Work (Hours)

Notes: To construct these measures, I first obtain the mean of the selected statistic for each driver. Then I plot the resulting distribution of these averages. The PDFs are estimated using a non-parametric kernel density estimation technique with a Gaussian kernel.

variables (h_t, d_t^w, and d_t^b) are set to zero. Then I use the model parameters to infer the driver's sequence of decisions and the values of the state variables in the next period. I iterate over every period until the driver decides to end the shift or reaches the end of the rental period.

With the simulated shifts in hand, I compare the resulting distributions to their empirical counterparts in the data along three dimensions: shift duration, working hours, and duration of uninterrupted work. Figure 8 shows the three distributions. The solid line represents the distribution found in the data. The fit is very good along all dimensions. The largest disparity can be found in Figure 8(c). However, the difference in means between the data and the simulation is small—only 21 minutes on a mean of 3 hours and 55 minutes.

7 Counterfactual Experiments

The estimated structural model can be used to conduct various counterfactual experiments. In this section, I focus on two hypothetical experiments. First, I compare the utility generated by the current environment, where breaks are unconstrained, to one in which a fixed schedule applies. This allows me to compute the compensation that a worker would require in order to accept this fixed working schedule. Second, I study how the frequency of breaks, labor supply, and worker welfare would be affected if a

day-shift driver starting at 7AM half the times and 7:30AM the other half, I draw his initial value from this distribution.

'mandatory breaks' policy that sought to limit the number of uninterrupted work hours were imposed.

Both counterfactuals can be seen as a modification of the choice set. First, the fixed-schedule counterfactual is the more extreme, as the driver must select the action dictated by the schedule, completely eliminating any choice over within-day labor supply. The second, the 'mandatory breaks' policy, affects the choice set in a similar fashion, but is more flexible. In this counterfactual, the option to work is removed (for one period) after a predetermined number of periods of uninterrupted work.

7.1 The Value of Discretionary Breaks

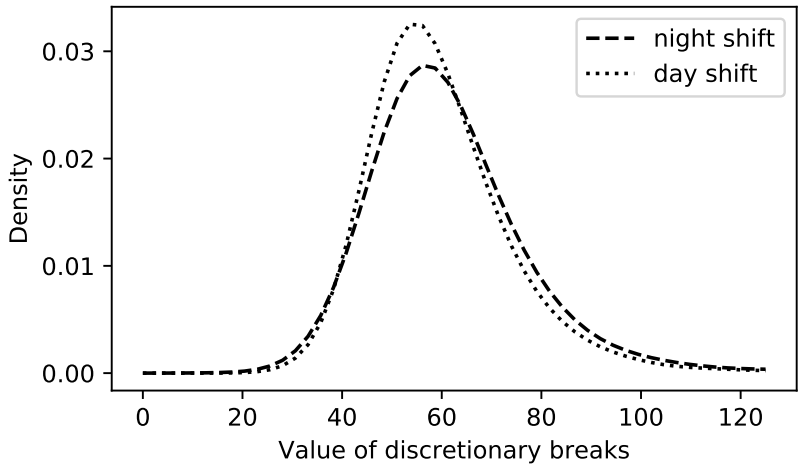
In the first simulation, I quantify the value of discretionary breaks by computing the reduction in utility per shift in switching from the unconstrained environment to a hypothetical fixed schedule. Because the model is estimated separately by worker, this value is driver-specific.

It should be noted that the value of discretionary breaks depends on how far the fixed schedule deviates from the optimal schedule. For example, an extreme schedule forcing drivers to take a 30-minute break every hour would lead to very low utility due to the high estimated fixed cost. Therefore, the counterfactual schedule I explore follows a realistic work schedule with two breaks: a 30-minute break after 2.5 hours and a 60-minute break after another 2.5 hours of uninterrupted work. After the last break, the driver works for another 2.5 hours. In total, the shift's duration is 9 hours, with 7.5 hours of work and 1.5 hours given to breaks.

The distribution of the value of discretionary rest breaks is presented in Figure 9. The average value for day-shift and night-shift drivers is \$61 and \$63, respectively. This indicates that the average driver would require an increase in revenue of about 23 percent to accept the counterfactual fixed schedule. While the distribution for day-shift and night-shift drivers is similar, we see a larger mass at higher values for night-shift drivers. There is a significant amount of heterogeneity over the value of discretionary rest breaks, irrespective of shift type. The standard deviation is \$41 (equivalent to 14.7 percent of average daily earnings).

The high degree of heterogeneity in the value of flexibility has implications for employers wishing to give their employees discretionary rest breaks. Having the ability to

Figure 9: Value of Discretionary Breaks per Shift



Notes: The PDFs are estimated using a non-parametric kernel density estimation technique with a Gaussian kernel.

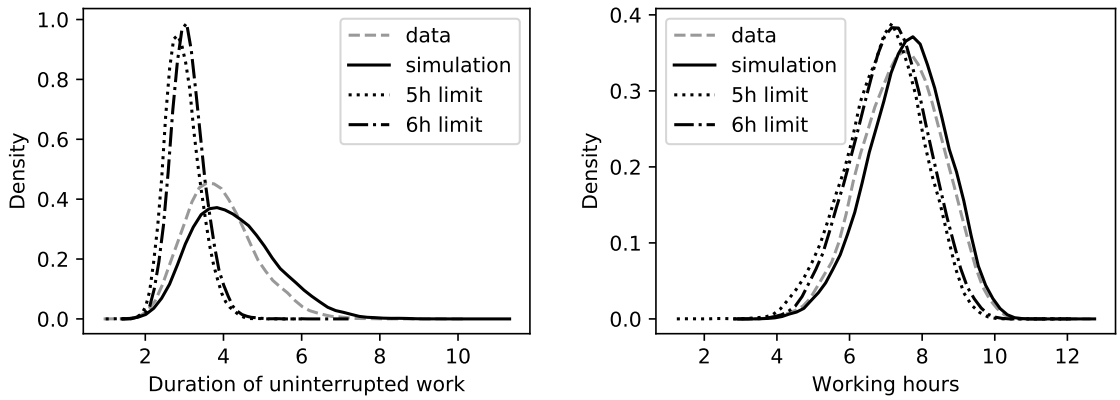
choose the timing and the length of breaks is likely to be highly valuable to some workers, as my findings indicate, giving employers another tool to attract better employees without increasing their payroll. It is also worth noting that the subjects of this study, taxi drivers, have self-selected into this career with highly flexible work hours. Therefore, it is perhaps unsurprising to see a high average valuation for discretionary breaks in an industry where discretionary breaks represent the status quo.

7.2 The Effect of a Mandatory Break Policy

Policymakers have long recognized the adverse effects of lengthy uninterrupted working hours on worker safety. This is why it is common to see regulations in this area. While the most prevalent type of policy limits the total length of a shift, many jurisdictions impose rules on breaks. For instance, in the United Kingdom, air traffic controllers cannot work for more than two hours without taking a break of at least 30 minutes. In the European Union, commercial truck drivers are required to take a break or breaks totaling at least 45 minutes after no more than four and a half hours of driving. This last rule is enforced with the aid of a digital device called a tachograph, which monitors the speed of the vehicle over a period of time and is mandatory on large vehicles.

The different thresholds for the policy I consider are 5 and 6 hours. After reaching the threshold, the driver must either take a break or end his shift. In this counterfactual

Figure 10: Effects of Mandatory Breaks Policies



(a) Duration of Time Between Breaks

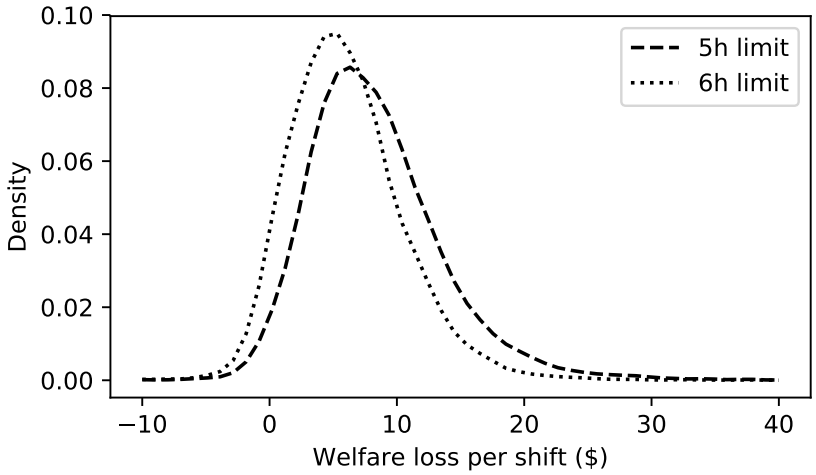
(b) Working Hours

experiment, I use the estimated model to simulate the decisions of each driver. As a starting point, I draw starting values for the state space from the distribution of start times for the same driver. I will then be shutting down this potential margin of adjustment.

As we have seen above, taxi drivers value the ability to decide when to take breaks highly. A 'mandatory breaks' policy, by construction, removes some of the discretion over when to take a break. However, this policy does not imply that drivers will wait until the end of their allowed uninterrupted work time to take a break. In this counterfactual experiment, a driver could take a break before reaching the limit if he receives a large shock to utility (e.g. dropping off a customer at the airport in the previous period).

In terms of the results, following the introduction of the policy, I estimate a significant drop in driver fatigue levels. Figure 10(a) shows the distribution of average duration of uninterrupted work. There is a clear shift to the left, indicating that the frequency of breaks becomes higher. The difference between the 5-hour and 6-hour policy is rather small. Figure 10(b) shows the distribution of working hours per shift (i.e. labor supply). We observe a reduction in overall labor supply. Interestingly, while a part of the explanation for this reduction is that drivers take more breaks, I also find that they reduce the overall duration of their shifts—a reduction of 3.4 percent for the 6-hour limit versus 4.4 percent for the 5-hour limit. Overall, labor supply, measured by the number of periods worked, decreases by 6.4 percent for the 6-hour limit and 8.5 percent

Figure 11: Welfare Loss from Mandatory Break Policy, per Shift



Notes: The PDFs are estimated using a non-parametric kernel density estimation technique with a Gaussian kernel.

for the 5-hour limit.

Because this policy places a restriction on taxi drivers, welfare can be affected. I compute welfare using the same method as described in Section 7.1. The results are shown in Figure 11. Even though a mandatory breaks policy would still preserve a lot of flexibility, the average driver would experience a reduction in welfare equivalent to 2.1% to 3.0% of daily revenue.

Overall, these results highlight the importance of understanding the incentives at play for taxi drivers. While a 'mandatory breaks' policy will increase the frequency at which drivers take break, they also significantly reduce the average labor supply of drivers.

8 Conclusion

The labor market is currently undergoing a profound structural transformation as we move away from traditional employer-employee relationships toward a more decentralized pattern of working in many industries. In this context, my paper has sought to understand how workers decide when to take breaks and how much they value this 'breaks' flexibility. Extending the work of Chen et al. (2017) and Fréchette et al. (2018), I develop the first dynamic model of labor supply with discretionary breaks. The model

uses a dynamic discrete choice framework and captures worker fatigue, hour-of-the-day effects, fixed costs of taking a break, and the opportunity cost of forgone earnings. To estimate the model, I use high-frequency data from NYC taxi drivers. The richness of the data allows me to account for unobserved heterogeneity in a very flexible way, recovering the utility parameters separately for each driver.

I find that taxi drivers value discretionary breaks highly: they would require a 23 percent increase in daily revenue in order to be induced to accept a fixed break schedule. Furthermore, I explore the effects of a mandatory break policy that limits the number of uninterrupted hours of work. While the policy achieves its goal of increasing the frequency of breaks, I find a significant reduction in labor supply of between 6.4 and 8.5 percent. This result is driven by taxi drivers taking more breaks *and having shorter shifts.*

These results have potentially broad labor market implications. The high value placed on discretionary breaks that I find may help explain the rapid growth of the 'gig' economy in recent years and the move of many employers towards greater employee flexibility. Moreover, quantifying the value of this non-pecuniary benefit is an understudied way to improve the efficiency of labor contracts. The results presented in this paper suggest that some employees would be willing to accept reduced wages if they were compensated by having greater work flexibility.

The framework developed in this paper constitutes a general model of labor supply with discretionary rest breaks. While the estimation strategy was implemented in a setting with millions of observations, datasets containing information on labor supply decisions are getting larger, more detailed, and span more sectors than ever before, broadening the likely applicability of my framework. This paper also calls attention to promising future research focusing on the interaction between discretionary breaks and labor supply decisions over a medium horizon, such as weekly or monthly hours. Finally, as non-traditional work arrangements become more and more prevalent, my analysis highlights the need for economists to account for new margins of labor supply adjustment, including breaks.

References

Abraham, K. G., J. C. Haltiwanger, K. Sandusky, and J. R. Spletzer (2017): "Measuring the Gig Economy: Current Knowledge and Open Issues," Working Paper.

Aguirregabiria, V. and P. Mira (2010): "Dynamic Discrete Choice Structural Models: A Survey," *Journal of Econometrics*, 156, 38–67.

Arcidiacono, P. and J. B. Jones (2003): "Finite Mixture Distributions, Sequential Likelihood and the EM Algorithm," *Econometrica*, 71, 933–946.

Arcidiacono, P. and R. A. Miller (2011): "Conditional Choice Probability Estimation of Dynamic Discrete Choice Models With Unobserved Heterogeneity," *Econometrica*, 79, 1823–1867.

Baker, M. and A. Melino (2000): "Duration Dependence and Nonparametric Heterogeneity: A Monte Carlo Study," *Journal of Econometrics*, 96, 357–393.

Borjas, G. J. (1980): "The Relationship between Wages and Weekly Hours of Work : The Role of Division Bias," *Journal of Human Resources*, 15, 409–423.

Brachet, T., G. David, and A. M. Drechsler (2012): "The Effect of Shift Structure on Performance," *American Economic Journal: Applied Economics*, 4, 219–246.

Buchholz, N. (2018): "Spatial Equilibrium, Search Frictions and Dynamic Efficiency in the Taxi Industry," Working Paper.

Buchholz, N., M. Shum, and H. Xu (2018): "Dynamic Labor Supply of Taxicab Drivers: A Semiparametric Optimal Stopping Model," Tech. rep.

Camerer, C., L. Babcock, G. Loewenstein, and R. Thaler (1997): "Labor Supply of New York City Cabdrivers: One Day at a Time," *Quarterly Journal of Economics*, 112, 407–441.

Chen, M. K., J. A. Chevalier, P. E. Rossi, and E. Oehlsen (2017): "The Value of Flexible Work: Evidence from Uber Drivers," Working Paper 23296, National Bureau of Economic Research.

Chou, Y. K. (2002): "Testing Alternative Models of Labour Supply: Evidence from Taxi Drivers in Singapore," *Singapore Economic Review*, 47, 17–47.

Collewet, M. and J. Sauermann (2017): "Working Hours and Productivity," *Labour Economics*, 47, 96–106.

Cook, C., R. Diamond, J. Hall, J. A. List, and P. Oyer (2018): "The Gender Earnings Gap in the Gig Economy: Evidence from over a Million Rideshare Drivers," Working Paper.

Crawford, V. P. and J. Meng (2011): "New York City Cab Drivers' Labor Supply Revisited: Reference-Dependent Preferences with Rational-Expectations Targets for Hours and Income," *American Economic Review*, 101, 1912–1932.

Dalziel, J. R. and R. F. S. Job (1997): "Motor Vehicle Accidents, Fatigue and Optimism Bias in Taxi Drivers," *Accident Analysis & Prevention*, 29, 489–494.

Farber, H. S. (2005): "Is Tomorrow Another Day? The Labor Supply of New York City Cabdrivers," *Journal of Political Economy*, 113, 46–82.

——— (2008a): "Employment Insecurity: The Decline in Worker-Firm Attachment in the United States," Working Paper 530.

——— (2008b): "Reference-Dependent Preferences and Labor Supply: The Case of New York City Taxi Drivers," *American Economic Review*, 98, 1069–1082.

——— (2015): "Why You Can't Find a Taxi in the Rain and Other Labor Supply Lessons from Cab Drivers," *Quarterly Journal of Economics*, 130, 1975–2026.

Fehr, E. and L. Goette (2007): "Do Workers Work More If Wages Are High? Evidence from a Randomized Field Experiment," *American Economic Review*, 97, 298–317.

Finer, D. A. (2018): "What Insights Do Taxi Rides Offer into Federal Reserve Leakage?" Working Paper.

Fréchette, G. R., A. Lizzeri, and T. Salz (2018): "Frictions in a Competitive, Regulated Market: Evidence from Taxis," Working Paper 24921, National Bureau of Economic Research.

Goldmark, J. and L. D. Brandeis (1912): *Fatigue and Efficiency: A Study in Industry*, Charities publication committee.

Haggag, K. and G. Paci (2014): "Default Tips," *American Economic Journal: Applied Economics*, 6, 1–19.

Hall, J. V., J. J. Horton, and D. T. Knoepfle (2017): "Labor Market Equilibration: Evidence from Uber," Working Paper.

Henning, R. A., P. Jacques, G. V. Kissel, A. B. Sullivan, and S. Alteras-Webb (1997): "Frequent Short Rest Breaks from Computer Work: Effects on Productivity and Well-Being at Two Field Sites," *Ergonomics*, 40, 78–91.

Hideg, I. and J. P. Trougakos (2009): "Momentary Work Recovery: The Role of within-Day Work Breaks," in *Current Perspectives on Job-Stress Recovery*, Emerald Group Publishing Limited, vol. 7 of *Research in Occupational Stress and Well-being*, 37–84.

Jackson, E., A. Looney, and S. Ramnath (2017): "The Rise of Alternative Work Arrangements: Evidence and Implications for Tax Filing and Benefit Coverage," Office of Tax Analysis Working Paper 114.

Jett, Q. R. and J. M. George (2003): "Work Interrupted: A Closer Look at the Role of Interruptions in Organizational Life," *The Academy of Management Review*, 28, 494–507.

Katz, L. F. and A. B. Krueger (2016): "The Rise and Nature of Alternative Work Arrangements in the United States, 1995-2015," Working Paper 22667, National Bureau of Economic Research.

Magnac, T. and D. Thesmar (2002): "Identifying Dynamic Discrete Decision Processes," *Econometrica*, 70, 801–816.

Mangrum, D. and A. Molnar (2017): "The Marginal Congestion of a Taxi in New York City," Working Paper, 00000.

Mas, A. and A. Pallais (2017): "Valuing Alternative Work Arrangements," *American Economic Review*, 107, 3722–3759.

Oettinger, G. S. (1999): "An Empirical Analysis of the Daily Labor Supply of Stadium Vendors," *Journal of Political Economy*, 107, 360–392.

Oyer, P. (2016): "The Independent Workforce in America: The Economics of an Increasingly Flexible Labor Market," Technical Report.

Pencavel, J. (2015): "The Productivity of Working Hours," *The Economic Journal*, 125, 2052–2076.

——— (2016): "Recovery from Work and the Productivity of Working Hours," *Economica*, 83, 545–563.

Pendem, P., P. Green, B. R. Staats, and F. Gino (2016): "The Microstructure of Work: How Unexpected Breaks Let You Rest, But Not Lose Focus," SSRN Scholarly Paper ID 2888477, Social Science Research Network, Rochester, NY.

Rust, J. (1987): "Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher," *Econometrica*, 55, 999–1033.

——— (1994): "Structural Estimation of Markov Decision Processes," in *Handbook of Econometrics*, Elsevier, vol. 4, 3081–3143.

Schmidt, M.-A. (2018): "The Daily Labor Supply Response to Worker-Specific Earnings Shocks," Working Paper.

Stafford, T. M. (2015): "What Do Fishermen Tell Us That Taxi Drivers Do Not? An Empirical Investigation of Labor Supply," *Journal of Labor Economics*, 33, 683–710.

Stanford, J. (2017): "The Resurgence of Gig Work: Historical and Theoretical Perspectives," *The Economic and Labour Relations Review*, 28, 382–401.

Taxi and Limousine Commission (2014): "2014 Taxicab Factbook," Tech. rep.

Thakral, N. and L. T. Tô (2017): "Daily Labor Supply and Adaptive Reference Points," Working Paper.

Tucker, P. (2003): "The Impact of Rest Breaks upon Accident Risk, Fatigue and Performance: A Review," *Work & Stress*, 17, 123–137.

Van Den Berg, G. J. (2001): "Duration Models: Specification, Identification and Multiple Durations," in *Handbook of Econometrics*, ed. by J. J. Heckman and E. Leamer, Elsevier, vol. 5, 3381–3460.

Vernon, H. M. (1921): *Industrial Fatigue and Efficiency*, G. Routledge.

Appendix A Data Construction and Cleaning

A.1 Data Cleaning Procedures

I conduct several data cleaning procedures to ensure that the results are not driven by measurement errors or outliers. I describe them in this section.

- I flag trips that have faulty location data or that are not located within NYC 5 boroughs or in New Jersey.
- I flag trips that have negative or zero fares.
- I flag trips that 'end' after they start.
- I flag trips that 'start' before the previous trip has ended.

After aggregating trips into shifts, I remove the entire shift if it contains a flagged trip. I do this because only removing the problematic trip would create the possibility for a false break. Using the resulting dataset, I compute the market wage and the average search time by region without any further restrictions. For the final analysis, I remove the shifts that are outliers following these rules:

- Shifts shorter than 3 hours.
- Shifts longer than 12 hours.[28]
- Drivers with fewer than 75 observed Mon-Thu day shifts or 75 observed Mon-Thu night shifts.

I also further restrict the analysis to drivers exhibiting behavior suggesting they rent the medallion from a taxi garage.

A.2 Market Hourly Earnings

I construct the measure of market hourly earnings in a way similar to Thakral and Tô (2017).

[28] A shift longer than 12 hours suggests the driver is not bound by the regular rental agreement.

The measure of hourly earnings depends on how many drivers are working. Drivers who are not working are not included in the measure of average hourly earnings. Each trip is associated with the preceding wait time. As mentioned in the main text, we can categorize wait times into three groups: search time, breaks, and 'time off work.' For the purpose of computing average hourly earnings, only the search time is relevant. I impute an average search time of 7 minutes to the first trip of the shift and to the first trip after a break.

The measure of revenue per minute from a trip i can be expressed as

$$R_i = \frac{F_i}{S_i + T_i},$$

where F_i is the total fare paid by the customer, S_i is the amount of time the driver searched for the customer, and T_i is the amount of time the trip lasted.

For every minute that the driver was either searching for the customer or driving the customer on trip i, R_i will contribute to the measure of average earnings. The average hourly earnings in minute m can then be defined as 60 multiplied by the average of all search time or trips occuring during this minute.

I construct the measure of hourly earnings for every minutes of the year (all 525,600 of them). When constructing the potential earnings I_t, I compute the average of the next 30 minutes.

A.3 NYC Neighborhoods and Average Search Time

One major solution to correctly identify breaks is to control for market demand. I do this by computing the average search time in an area. In this section, I describe the methodology for doing so.

The simplest way of computing a measure of average search time would be to compute the average search time of all pickup in an area. One issue with this methodology arises because it combines drivers that started looking for a customer directly after a dropoff and drivers that drove to the location. To get a precise measure of search time, I compute search time in a location using only pickups that follow a dropoff in the same neighborhood.

I define a neighborhood in my analysis as a 'community board'[29] plus some large

[29]Community boards are comprised of volunteers and only act in an advisory capacity. They can

non-residential areas, such as Laguardia Airport, JFK Airport, and Central Park. I also create a zone in New Jersey to capture trips going to Newark Airport or Jersey City. The size and location of each neighborhood can be seen on Figure A6.

If I relied only on pickups during the same hour of the year to estimate the average search time, sample error would be a large issue. It is not rare to observe location-hour pairs with less than 20 observations. To solve this, I instead aggregate the yearly data at the weekly level so that for each location-hour pair, I have about 52 times more observations. This generates a measure of average search time for a maximum of 12,096 location–hour-of-the-week pairs.

The resulting distribution of search time for two specific hours of the week is presented in Figure A7. Not all neighborhood have data. Because more than 93% of all pickups are located in Manhattan or at the airports, some neighborhoods do not have enough observations to consistently estimate an average search time. I drop the shifts for which I do not have data on average search time for a trip.

Appendix B Labor Supply Elasticity

In Section 4.4, I described how the estimates of the labor supply elasticity was affected by the inclusion of breaks in the measure of labor supply. Here, I explain in more detail the underlying model and why an instrumental variables approach is required.

One of the strategies used by the daily labor supply literature has been to estimate a regression of hourly earnings on hours worked.[30] The regression equation is:

$$\ln(H_{is}) = \delta \ln\left(E_{is}/H_{is}\right) + \beta X_{is} + \mu_i + \nu_{is}, \tag{4}$$

where H_{is} is the duration of shift s for worker i; (E_{is}/H_{is}) is the hourly earnings; X_{is} are covariates such as date, time, or weather; and μ_i is a driver fixed effect. The labor supply elasticity is measured by δ. There are two issues with this strategy: First, anticipated variation in hourly earnings cannot be used to identify this elasticity because it is possible that workers wanting to work longer shifts only do so when the hourly earnings

advice the authorities on zoning or service delivery in their community.

[30]This strategy has been employed by Camerer et al. (1997), Chou (2002), Farber (2015), and Schmidt (2018). Here I replicate this methodology to get a sense of how the the labor supply elasticity would vary.

are higher. Second, the long-recognized issue of division bias (Borjas, 1980) is present in this setting because H_{is} appears in both the RHS and the LHS of the equation.

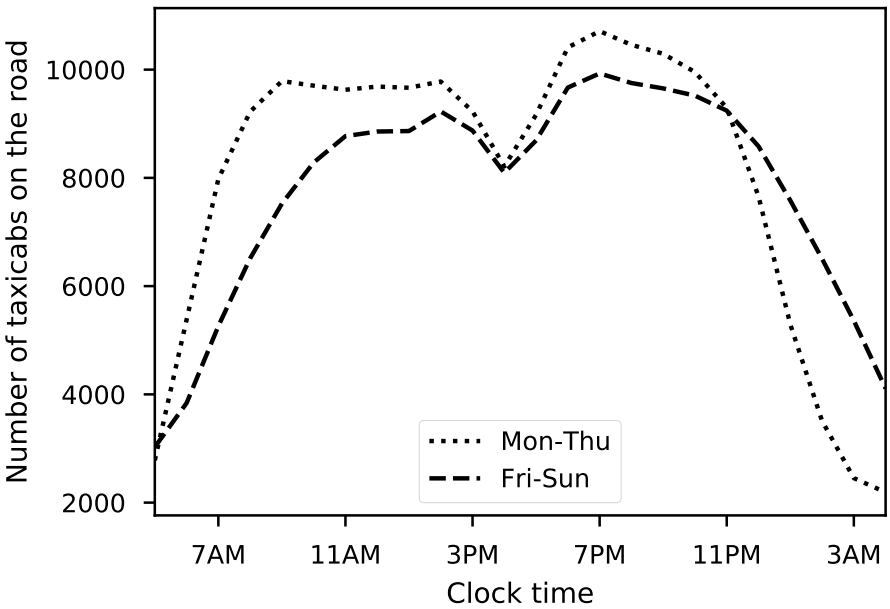
To address the first issue, I follow the literature and use a comprehensive set of controls which leaves only unanticipated hourly earnings variations to identify the labor supply elasticity. The controls include hour-of-the-week dummies, holidays, month of the year, precipitation, temperatures below 0 degree Celsius, and modal neighborhood (the neighborhood with the maximum number of pickups during a shift). The second issue is addressed by instrumenting the hourly earnings of the driver by the average hourly earnings of other drivers with an overlapping shift. To construct the instrument, I use a random sample of 1/3 of the drivers, while the other 2/3 are used for the estimation.

Because elasticities are computed in percentages, reducing labor supply by a constant amount would also increase the elasticity. A 30-minute increase over 7.5-hour shift is proportionately larger than a 30-minute increase over a 9-hour shift. However, we can carry out a simple back-of-the-envelope calculation to compute how much this would mechanically affect the elasticity. For simplicity, suppose the average shift duration is nine hours and drivers take on average one hour of break per shift. The elasticity of 0.256 in Table 1 means that a 10% increase in wage will result in a shift that is 13.8 minutes longer. When breaks are taken into account, the average labor supply is now 8 hours. The 13.8 minutes increase is now equivalent to 2.88% (elasticity of 0.288) instead of 2.56%. This mechanical relationship can only explain a difference of 0.032 between the elasticities, representing only 1/20th of the observed difference.

For comparison with the instrumental variables approach, the corresponding OLS regression is presented in Table A3. We can see that, rather than attenuating the negative labor supply elasticity of Panel A, netting out the breaks reduces the estimates even more. This can be explained by the fact that another variable is introduced on both the RHS and the LHS, increasing the scope for the division bias.

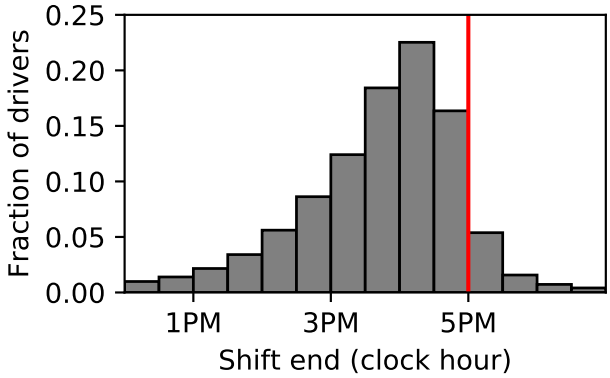
Appendix C Additional Figures and Tables

Figure A1: Number of Taxicabs on the Road, by Clock Time

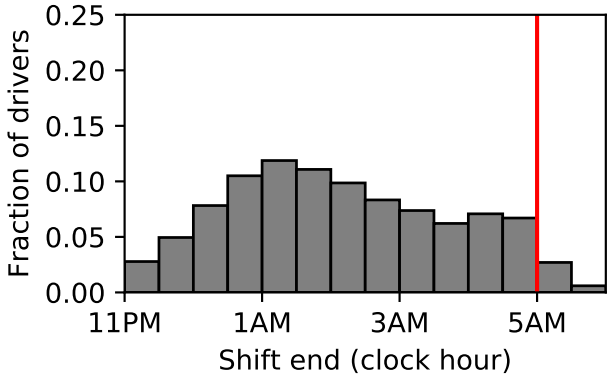


Notes: This plot contains the supply of taxicabs on the road at each hour of the day and shows the average number of unique medallions that were active (had picked up customer) during a particular hour. The fall in supply in the late afternoon is due to the transition time between day-shift and night-shift drivers. The hours from midnight to 5 AM are associated with the previous day to match the drivers' schedules.

Figure A2: Distribution of End Time of Shifts



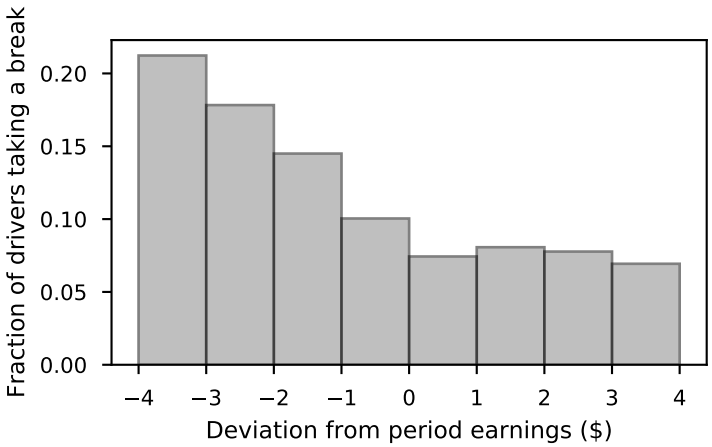
(a) Day-Shift Drivers



(b) Night-Shift Drivers

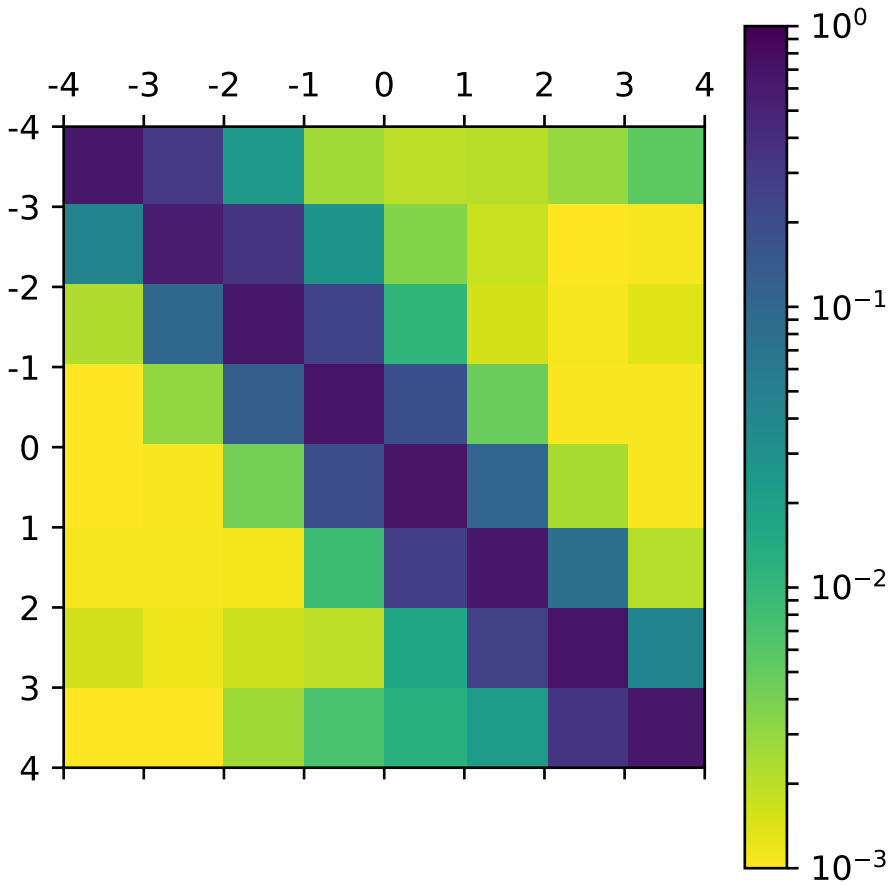
Notes: The end time is the start of the period in which the driver ended his shift. The vertical lines represent the usual transition time (5 AM or 5 PM). Because the drivers need to bring the car back to the garage, typically located in Queens or in Brooklyn, the end of their shift is usually around 45 minutes earlier.

Figure A3: Probability of Taking a Break, by Deviation from Usual Earnings



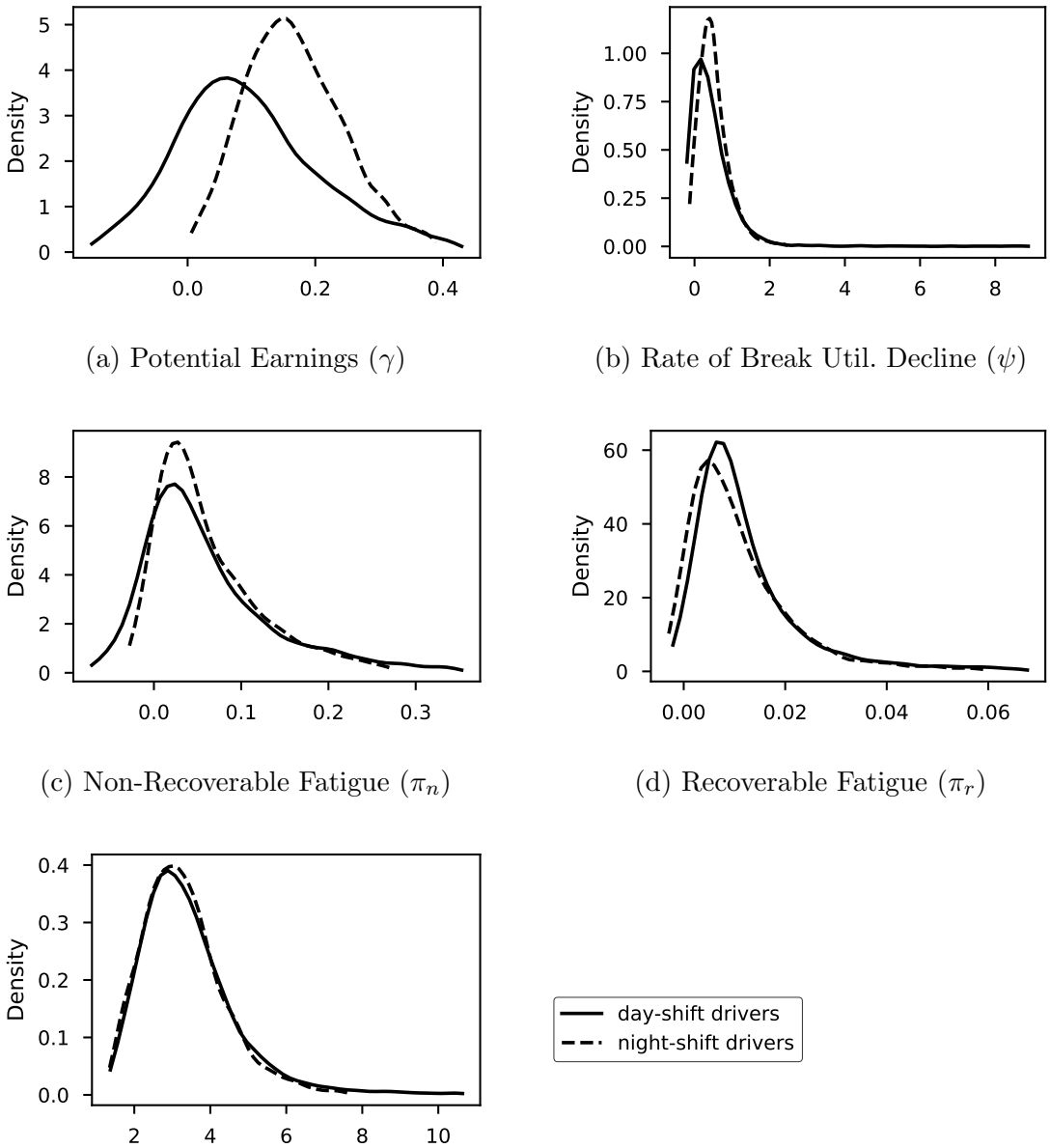
Notes: Each bin represents a $1 increment in the deviation from anticipated earnings. See Section A.2 for a more detailed explanation of the way market hourly earnings are constructed.

Figure A4: Markov Transition Matrix of Hourly Earnings



Notes: The figure represents transition probabilities between period t (y-axis) and period $t+1$ (x-axis). Because there is persistence, most of the probability mass is located on the diagonal. Notice that the shading is normalized to a log-scale to show the out-of-diagonal values more clearly.

Figure A5: Distribution of Parameter Estimates



(a) Potential Earnings (γ)

(b) Rate of Break Util. Decline (ψ)

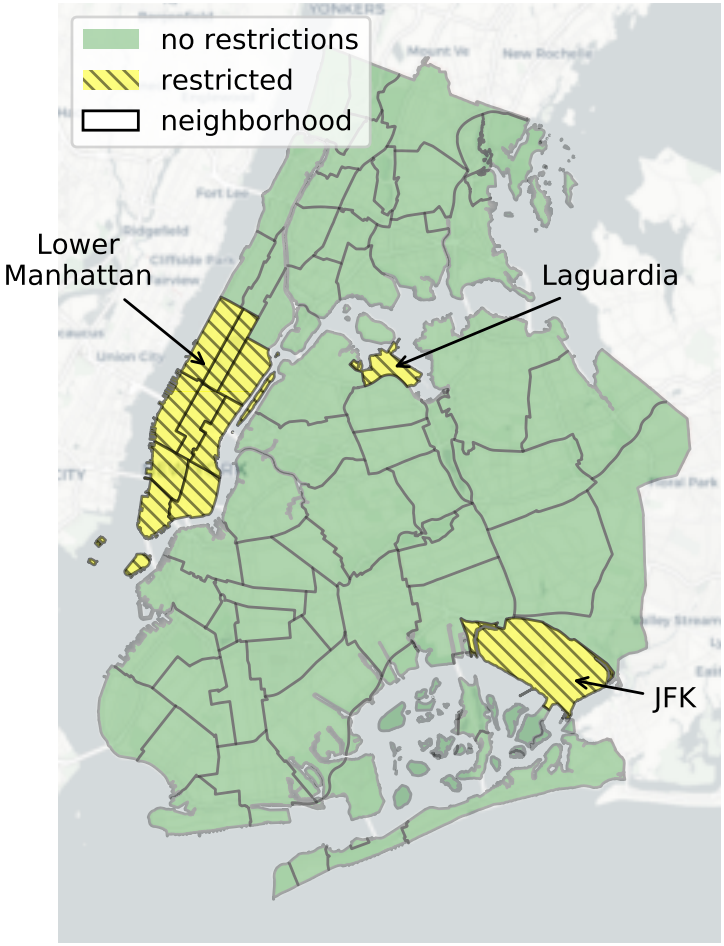
(c) Non-Recoverable Fatigue (π_n)

(d) Recoverable Fatigue (π_r)

(e) Fixed Cost (τ)

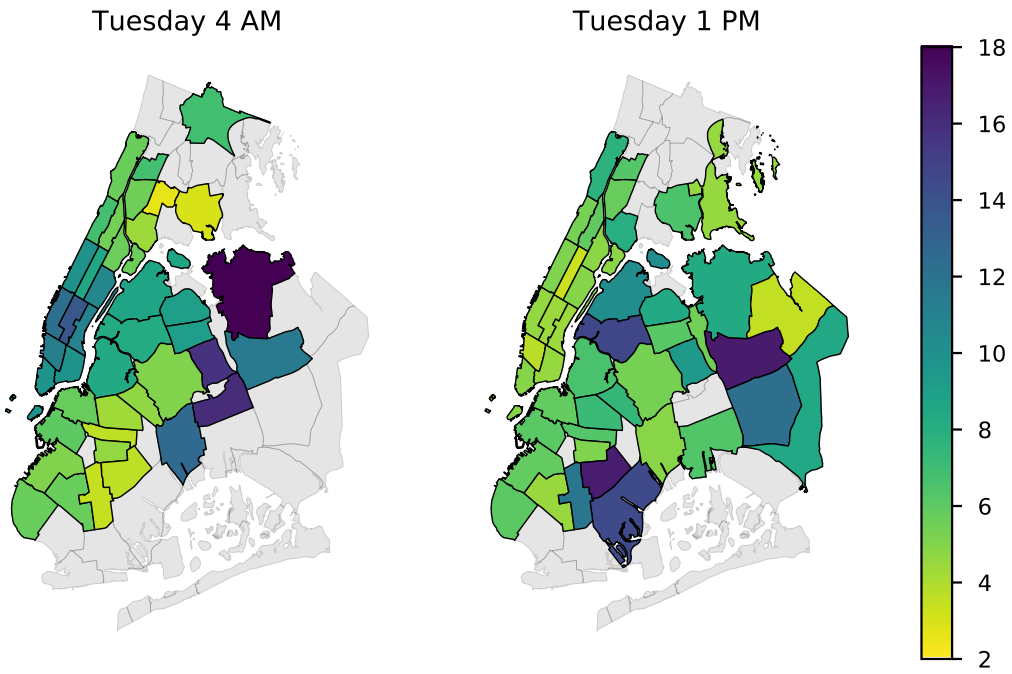
Notes: The PDFs are estimated using a non-parametric kernel density estimation technique with a Gaussian kernel. In each panel, the solid line plots the distribution for day-shift drivers and the dashed line, the distribution for night-shift drivers.

Figure A6: Map of NYC with Neighborhoods



Notes: The neighborhoods referred to in this map are called 'community boards' by NYC officials. Yellow (medallion) taxis have the monopoly over street hailing in 'restricted' neighborhoods.

Figure A7: Average Search Time



Notes: The average search time (in minutes) in each region is computed using only observations with the last dropoff and the next pickup in the same region, where a region is a 'community board.' Further explanation is given in Section A.3. The locations of the two airports have been removed because, as explained in Section 3.3.2, I set search time at airports to zero.

Table A1: Summary Statistics

	Selected Drivers			Non-Selected Drivers		
	mean	median	std. dev.	mean	median	std. dev.
Shifts per year	248.2	253	54.8	154.5	151	101.8
Shift length (hours)	8.6	8.8	2.1	9.0	9.0	2.6
Trips per shift	21.8	22	7.8	22.2	22	8.7
Earnings per shift	269.4	266.5	81.0	285.1	280.0	93.0
Hourly Earnings	31.4	31.4	6.0	32.1	32.2	6.5
Number of drivers		14,190			26,079	

Notes: Selected drivers display behaviors that indicate they are renting their medallion from a taxi garage and follow the 5 AM and 5 PM transition times. In general, the selected drivers exhibit a lower level of heterogeneity. Non-selected drivers either do not display behaviors suggesting they rent, or they are occasional or irregular drivers and do not appear in enough shifts to allow the consistent estimation of the model. See Section 3.7 for more details describing the selection criteria.

Table A2: Variance Decomposition

Var. explained by:	Week of the year	Day of the week	Driver
Shift duration	0.4%	3.9%	38.7%
Time on break	1.7%	0.5%	27.7%
Frequency of breaks	2.1%	2.1%	20.2%
Airport pickups	0.3%	1.6%	31.4%

Notes: The percentage of the variation explained by each variable is computed in a fixed effect model where the only regressor is a constant. The percentage of the variation explained is therefore the proportion of the variation explained by the associated fixed effects.

Table A3: OLS Elasticity Estimates

	All	Day Shift	Night Shift	Owner
	(1)	(2)	(3)	(4)
Panel A: Gross shift				
log Hourly Earnings	-0.278^{***}	-0.131^{***}	-0.285^{***}	-0.359^{***}
	(0.003)	(0.003)	(0.003)	(0.008)
Panel B: Adjusted shift (net of breaks)				
log Hourly Earnings	-0.480^{***}	-0.462^{***}	-0.507^{***}	-0.544^{***}
	(0.002)	(0.003)	(0.003)	(0.007)
Driver	Yes	Yes	Yes	Yes
Weather	Yes	Yes	Yes	Yes
Location	Yes	Yes	Yes	Yes
Date/Time	Yes	Yes	Yes	Yes
Observations	4,894,002	2,148,223	2,151,782	566,344

Notes: Clustered standard error are in parentheses (driver level). Controls include weather (temperature and precipitation), location fixed effects (modal pickup neighborhood – 72 in total), holiday fixed effects (9), and fixed effects for the month of the year (11) and the hour of the week (167).