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The Supply Side of Discrimination: Evidence from the Labor Supply of Boston Taxi Drivers

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Abstract

This paper investigates supply-side discrimination in the labor market for Boston taxi drivers. Using data on millions of trips from 2010–2015, I explore whether the labor supply behavior of taxi drivers differs by the gender, racial/ethnic, or age composition of Boston neighborhoods. I find that disparities in shift hours due to neighborhood demographics exist even when differences in local earnings opportunities are taken into account. I observe heterogeneity in the amount that drivers discriminate and find that this discrimination is primarily statistical rather than taste-based. As drivers gain experience and learn to better anticipate wage variation, discrimination decreases.

Keywords: discrimination, labor supply, Boston taxis, wage elasticity

JEL Classifications: J71, J22, J31, L91

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1 Introduction

Researchers have devoted much attention to understanding discrimination against legally protected classes across a variety of markets. Focusing on the labor market, economic theories and evidence regarding discrimination largely center on the market's demand side (Altonji and Blank 1999; Cain 1986). However, discrimination can also occur on the supply side of the labor market.[1] Such supply-side discrimination could be taste-based (that is, due to personal prejudice), especially if workers have some degree of market power, or it could be statistical if workers have incomplete information about the potential buyers of their labor. This discriminatory behavior is thus important to understand, particularly in light of nontrivial numbers of part-time, self-employed, and "gig" economy workers who may have a greater opportunity to engage in such actions given market structures.

Using evidence from the Boston taxicab industry, this paper investigates the extent of supply-side labor market discrimination and its mechanisms. The taxi industry has often served as a useful setting for economists to study labor supply behavior, largely due to the flexible hours that cab drivers have, unlike many other professions. Existing work has focused on whether taxi drivers dynamically respond to higher wages by working more hours, behavior that is consistent with neoclassical labor supply theory, or by working fewer hours, a choice consistent with income targeting and a behavioral model with reference-dependent preferences (for example, Camerer et al. 1997; Crawford and Meng 2011; Farber 2005, 2015). Building on the work of Farber (2015), who finds evidence of upward-sloping intertemporal labor supply, this paper examines whether the willingness of cab drivers to supply labor at a given wage differs based on the demographic composition of the areas in which they work.

I utilize data on millions of trips from taxi drivers in Boston over a six-year period from

[1]For instance, an area of discussion in Colorado and Oregon was the legality of individuals refusing to work on the basis of their religious beliefs to provide wedding cakes for same-sex couples (see American Civil Liberties Union of Colorado, "Court Rules Bakery Illegally Discriminated Against Gay Couple," from ACLU website: http://aclu-co.org/court-rules-bakery-illegally-discriminated-against-gay-couple, and see Todd Starnes, "Oregon Silences Bakers Who Refused to Make Cake for Gay Wedding," from *Fox News* website: http://www.foxnews.com/opinion/2015/07/06/state-silences-bakers-who-refused-to-bake-cake-for-lesbians.html).

2010–2015 to test for the presence of supply-side labor market discrimination. I observe that disparities exist in the supply of taxi services across Boston neighborhoods with different demographics, even when market differences in largely unanticipated local earnings opportunities are taken into account. These conditional disparities in shift hours across areas are evidenced by wage elasticities that vary by neighborhood composition. Specifically, wage elasticities are 5 to 7 percent lower as the population share of female, black, or Asian residents at trip pick-up locations rises by 1 percentage point (that is, 2 to 11 percent of the area share sample mean, depending on the demographic group). The presence of such supply-side discrimination in a driver's willingness to work longer is robust to several analysis checks, including relaxing sample restrictions, incorporating tips into local wages, adding a proxy for local costs, and assessing the role of trip drop-off locations compared to pick-up locations.

I also find heterogeneity across cab drivers and areas in the amount of estimated discrimination. Using a decomposition of this variation in discrimination estimates as well as other empirical tests, I try to determine the underlying mechanism for the observed behavior. I find evidence that the drivers' choices are primarily caused by statistical rather than taste-based discrimination, and that as drivers gain experience and learn how to better anticipate wage variation in areas, they engage in less discriminatory behavior. These results suggest that although supply-side labor market discrimination may occur under certain market conditions, it need not persist. Moreover, policies supplying earnings-relevant information to workers about those purchasing their labor might speed up the rate of learning, thereby mitigating discrimination. Lastly, the paper's findings also suggest that individuals can learn to optimize across both time and space, although perhaps at different rates. The findings are also supported by alternative, trip-level estimation I conduct that exploits the quasi-experimental exposure to neighborhoods of different demographic compositions that drivers experience based on trip drop-off locations, conditional on a given trip pick-up location.

Among existing studies, some evidence has been found of disparities in taxi services across Boston neighborhoods, although these disparities are not attributable solely to differences in driver labor supply due to the absence of controls for market wages and other variables (Austin and Zegras 2012; Nelson\Nygaard Consulting Associates 2013). In a study of the taxi industry in New York City (NYC), Haggag, McManus, and Paci (2017) examine how cab drivers engage in on-the-job learning, including the accumulation of neighborhood-specific experience, in order to improve their ability to find customers and increase earnings per shift. However, they do not examine whether differences in driver behavior across neighborhoods are potentially attributable to discrimination. Examining ridesharing rather than taxis, Ge et al. (2016) conduct an audit study in Boston and Seattle to test whether drivers of companies such as Uber and Lyft discriminate among customers. Ge et al. (2016) find a pattern of discrimination, as evidenced by longer wait times for black passengers in Seattle, and in Boston, a higher rate of trip cancellations for black passengers and longer, more expensive rides for female passengers. My paper contributes to the existing literatures on both disparities in ride transportation and intertemporal labor supply. It is a study that incorporates market wages to determine the extent of discrimination in the labor supply choices of cab drivers across neighborhoods with different demographics.

The remainder of the paper is organized as follows: section 2 provides background on the taxi industry in Boston and discusses the data used on taxi trips. Section 3 examines how these trips vary across locations. Section 4 outlines models of area-specific labor supply with discrimination, while section 5 presents the main findings regarding the existence of such discrimination. Section 6 determines the presence of driver and area heterogeneity regarding discriminatory behavior, while section 7 explores whether supply-side discrimination is taste-based or statistical. Section 8 discusses alternative, quasi-experimental estimation, and finally, section 9 concludes.

2 Background and Data on Boston Taxi Drivers

Taxicabs in Boston, historically called "Hackney Carriages," are licensed by the Police Commissioner under the authority of Chapter 392 of the Acts of 1930 and have been regulated by the Hackney Carriage Unit of the Police Department since the unit's founding in 1854.[2] There are 1,825 taxi medallions in Boston, with an upper limit on the number of cabs set by the City of Boston.[3] A Boston taxi medallion owner usually falls into one of the following categories: 1) buys or leases a vehicle, affixes the medallion, and "shifts" out the medallioned taxicab to drivers (48 percent of the 1,825 taxis); 2) buys or leases a vehicle, affixes the medallion, and operates the vehicle him/herself as an owner-operator (25 percent of the 1,825 taxis); 3) leases the medallion to a vehicle owner, who affixes the medallion and operates the taxi (20 percent of the 1,825 taxis); or 4) hires someone to manage his/her medallions, either by "shifting" out a medallioned taxicab or leasing the medallion to a vehicle owner (5 percent of the 1,825 taxis) (Nelson\Nygaard Consulting Associates 2013).

Thus, Boston cab drivers fall into one of three main categories: owner-operators (453 persons in 2013), leased medallion drivers (number unknown), or shift drivers who rent a medallioned taxicab over a weekly or 12-hour period (number unknown but likely the majority of drivers given that this is how most medallions are used) (Nelson\Nygaard Consulting Associates 2013). Drivers are free to work as few or as many hours as desired within any shift constraint, if applicable.[4] Meanwhile, in terms of expenses and earnings, drivers pay for any leasing or shift fees plus fuel and a handful of other potential authorized charges, while they

[2] See Boston Police Department, "Hackney Carriage Unit," from BPD News website: http://bpdnews.com/hackney-carriage-unit/. The most recent major revision to these regulations, Rule 403, became effective August 29, 2008 (see City of Boston, "Boston Police Department Rule 403 Hackney Carriage Rules and Flat Rate Handbook," from City of Boston website: http://www.cityofboston.gov/tridionimages/rules_tcm1-3045.pdf).

[3] New York City, with 13,238 medallions, has 7.3 times more taxi licenses than Boston (Farber 2015). However, this disparity is smaller when considering the number of medallions issued per square mile, which is 43.5 for NYC and 20.4 for Boston, or the medallions issued per 1,000 persons which, according to 2015 American Community Survey population estimates, is three in Boston versus two in NYC (Minnesota Population Center 2010).

[4] Cab fleets ("radio associations") may place constraints on the timing and duration of shifts for their drivers. By City regulation unless exempt, all medallion owners must affiliate with a radio association which primarily dispatches trips requested by customers (Nelson\Nygaard Consulting Associates 2013).

keep all fare income plus tips.[5] Because of this industry structure, as Farber (2015) argues, "the driver internalizes the costs and benefits of working in a way that is largely consistent with an economist's first-best solution to the agency problem with risk-neutral agents."

In terms of locations, pick-ups are authorized within the driver's licensed jurisdiction (that is, Boston's city limits), but drop-offs may occur outside of Boston if requested by the passenger. Within Boston, drivers are not restricted regarding where they travel or whom they pick up, whether as street hails or trips offered through the dispatch system, which they can freely accept, decline, or not respond to (Nelson\Nygaard Consulting Associates 2013). However, by regulation, drivers "may not refuse any passenger on the basis of race, sex, religion, disability, sexual orientation, national origin, or location of the passenger's pick-up or destination in any circumstance."[6] Thus, discrimination may be manifested by certain groups encountering longer wait times when hailing or requesting a taxi, or drivers being less likely to service areas where members of those groups tend to reside.[7] This paper examines the latter mechanism.

Taxi drivers only earn income when they have a passenger in the cab and the meter is running. Over the 2009–2015 period covered by my data, income in the "meter zone" is earned at the rate of \$2.60 for the first one-seventh of a mile (the "drop rate") plus either \$0.40 for every additional one-seventh of a mile (the "mileage rate") or \$28 per hour when the cab is not moving (the "waiting time rate"). Outside the "meter zone," which applies to trips from Boston to suburban cities and towns beyond a 20-mile radius from Boston, income is earned according to flat rates as published in the Official Flat Rate Handbook.[8]

[5] Authorized charges may include optional additional insurance, fees for failing to return a shifted vehicle on time, tolls from Boston proper to Logan International Airport, and so on.

[6] See City of Boston, "Boston Police Department Rule 403 Hackney Carriage Rules and Flat Rate Handbook," from City of Boston website: http://www.cityofboston.gov/tridionimages/rules_tcm1-3045.pdf. One exception to this anti-discrimination rule is that a driver may refuse a passenger if there is justifiable fear for the driver's safety or if the passenger is incapacitated.

[7] See Elisabeth Bumiller, "Cabbies Who Bypass Blacks Will Lose Cars, Giuliani Says," from *New York Times* website: http://www.nytimes.com/1999/11/11/nyregion/cabbies-who-bypass-blacks-will-lose-cars-giuliani-says.html, and see Eric Roper and Alejandra Matos, "Taxicab Drivers Skirting Minneapolis Laws," from *Star Tribune* website: http://www.startribune.com/june-29-taxi-drivers-skirting-minneapolis-laws/265066351.

[8] See City of Boston, "Boston Police Department Rule 403 Hackney Carriage Rules and Flat Rate Hand-

There are also discount coupons available for Boston residents 65 years of age and older and for disabled residents of all ages which cab drivers are required to honor.[9]

As of 2009, the City of Boston required all taxis to be equipped with electronic devices that allow for credit card processing of payments.[10] For all trips (not just those paid by credit card), these devices record information on various trip details including the fare, the trip start and end times, and the trip start and end locations via global positioning system (GPS) capabilities. The City of Boston has access to these data for planning and regulatory purposes, with two vendors supplying devices for all but a handful of cabs (Nelson\Nygaard Consulting Associates 2013).

I have obtained data from one of these two major vendors on taxi trips taken in the "greater Boston market" from April 2009 to January 2016, which I further restrict to the period running from May 1, 2009 to December 31, 2015, to better ensure complete data for all months.[11] These data identify drivers by encrypted Hackney Carriage license number and medallions (cabs) by encrypted medallion number.[12] My Boston data sample is smaller than

book," from City of Boston website: http://www.cityofboston.gov/tridionimages/rules_tcm1-3045.pdf.

[9]See Boston Police Department, "Hackney Carriage Unit," from BPD News website: http://bpdnews.com/hackney-carriage-unit/. In terms of net earnings after costs, a recent 2013 consulting report estimates that the annual pre-tax net earnings of a full-time Boston taxi driver ranges from $51,910 to $65,675 depending on the medallion ownership category, while a part-time shift driver is estimated to earn $35,883 (Nelson\Nygaard Consulting Associates 2013). However, 2010–2015 American Community Survey data on Boston taxi drivers and chauffeurs in Table A2 (pooling across six years in order to draw a larger sample of employed persons) lists earnings for this group during that period at $20,298 in 2010 dollars (Minnesota Population Center 2010).

[10]When first announced, this change was slated to become effective January 1, 2009 (see City of Boston, "Boston Police Department Rule 403 Hackney Carriage Rules and Flat Rate Handbook," from City of Boston website: http://www.cityofboston.gov/tridionimages/rules_tcm1-3045.pdf). However, the change ultimately became effective later in the year (see Eric Moskowitz, "Credit Card Use Frustrates Cabdrivers," from Boston.com website: http://archive.boston.com/news/local/massachusetts/articles/2011/05/16/credit_card_use_frustrates_cabdrivers).

[11]The "greater Boston market" largely represents data from licensed City of Boston taxicab fleets, which is why I focus here on regulations from the City of Boston. However, the "greater Boston market" also reflects data from other fleets in close vicinity (for example, Cambridge). Trips from such out-of-town fleets could start or end in Boston, albeit, illegally in the former case.

[12]When restricting the data to trips that start in Boston proper, and after correcting for some medallion numbers in the data with missing leading zeros, I observe 1,313 unique medallions. It is reassuring that this value is well below the 1,825 medallions issued in Boston, especially since trip data is missing from the second major vendor of credit card processing devices. Additionally, some subset of these 1,313 medallions likely reflects cabs not licensed in Boston that are conducting illegal pick-ups in Boston. Citations by the Boston Police Department for illegal pick-ups grew from 305 in 2011 to 513 through the first two-thirds of 2013, with drivers and medallion owners suggesting that the illegal pick-up problem is even more prevalent

the NYC sample used by Farber (2015), in part because Boston is a smaller market and also due to the absence of data from the second major device vendor. In my data, on average there are about 7.5 million trips taken annually in taxicabs in the Boston area. About 8,100 drivers earned at least one fare in a cab over the nearly seven-year period, with roughly 3,800 drivers appearing in the data during a single year. Approximately 800 drivers worked in all of the sample years, and the median driver is observed in the data for three calendar years. While I use as much of the available data as possible, much of my analysis is based on a random one-half sample of the drivers (see Appendix and section 3 for further details).

In terms of data limitations, similar to Farber (2015), I cannot identify which medallions are associated with particular shift drivers, leasing drivers, or owner-operators. Because these three categories of drivers face different constraints and incentives relevant to their labor supply choices, it would be ideal to analyze their behavior separately. However, out of necessity, I group all types of drivers together.[13] Also, like Farber (2015), I do not have complete information on tip receipts. Thus, I exclude tips from fare totals (other than sensitivity analysis in section 5) and assume that tipping rates are not correlated with average hourly fare earnings.[14]

3 Variation in Trips and Demographics Across Boston

To begin the spatial analysis of taxi trips in Boston, for a given driver, I define a gap between trips of six hours or more as indicating the end of one shift and the start of another (see Appendix for details). I start with a sample of 26,602,914 trips that underlie a one-half sample of 1,788,470 shifts and 4,052 drivers used in non-spatial analysis performed to replicate Farber (2015) (see Appendix). I then impose a few additional sample restrictions, both in the estimation one-half sample as well as the non-overlapping one-half sample of 27,179,101

than the citation numbers suggest (Nelson\Nygaard Consulting Associates 2013).

[13] One possibility might be to assume that unique medallion-driver pairings are (a subset of) owner-drivers and focus some analysis on this subgroup. However, there are very few such drivers in my data (for example, in Table 1, only 18 drivers, or less than 1 percent, fall in this category).

[14] See Haggag and Paci (2014) for an examination of tipping behavior in NYC cabs.

trips associated with 1,820,251 shifts and 4,076 drivers. Specifically, across all 3,608,721 of the aforementioned shifts and 53,782,015 associated trips, observations are dropped for which a shift:

1. contains any trip without start location information (1,577,407 shifts and 22,275,790 associated trips; 41.4 percent of 53,782,015 trips);

2. contains any trip that does not start in Massachusetts (9,170 shifts and 165,373 associated trips; 0.3 percent of 53,782,015 trips);

3. starts in 2009, given that the baseline data on demographics from the U.S. Census is from 2010, as discussed below (184,021 shifts and 2,741,607 associated trips; 5.1 percent of 53,782,015 trips).

I restrict the sample at the shift level, not at the trip level, so that each shift (non-spatial) contains its full set of trips and area-specific shifts, thus not inducing bias given estimation at the area shift level. Because I'm analyzing driver behavior, I focus on the start locations of trips; compared to end locations, this is the spatial component over which drivers have more control. These restrictions result in a final spatial sample of 28,599,245 trips associated with 1,838,123 non-spatial shifts and 6,896 drivers. For the analysis, I rely on a random one-half sample of 3,435 drivers with 912,679 non-spatial shifts comprised of 14,136,226 trips.[15] In this final spatial estimation sample, 13,643,800 of the total 14,136,226 trips start in Boston proper (96.5 percent), leaving 492,426 trips (3.5 percent) starting in other parts of the greater Boston area or elsewhere in Massachusetts.

Regarding resident demographics, Figure 1 maps the area population shares across the 558 Boston block groups in the 2010 U.S. Census that are female, black non-Hispanic, Asian non-Hispanic, Hispanic, and 65 years of age and older (Minnesota Population Center 2010).[16]

[15] The final spatial non-overlapping sample contains 3,461 drivers with 925,444 non-spatial shifts comprised of 14,463,019 trips.

[16] While the full data includes areas outside of Boston proper, for visual ease, I restrict the maps to Boston. In contrast to all area residents, I also examine 2010–2015 American Community Survey data on Boston taxi drivers and chauffeurs in Table A2 (pooling across six years in order to draw a larger sample). This group of

For each of the five demographic (or "minority") groups depicted, there is variation across Boston in the local population share of the group.[17] Still, some spatial clustering exists. For instance, the Boston neighborhoods of Roxbury, Dorchester, and Mattapan tend to have some of the highest shares of black residents in the city. Meanwhile, near Logan International Airport, the East Boston neighborhood has a high concentration of Hispanic residents, while Allston, Brighton, and Chinatown are among the neighborhoods with the highest shares of Asian residents.[18] There is a less discernible pattern with the distribution of women or individuals who are 65 years of age and older, although Hyde Park and West Roxbury seem to have notable concentrations of these two groups.[19]

Turning to the taxi data, across all 52,584 clock hours in the data from January 1, 2010 to December 31, 2015, I calculate area averages for the number of trips and hourly earnings. The realization of these variables in the raw data represents drivers' labor supply as well as residents' labor demand. For a given hour × area pairing in the trip-level data, I determine the number of trips taken and total trip earnings for each driver with at least one trip in the hour × area. I then take the average of each of those variables across the given drivers within the hour × area, followed by taking the average once again across all 52,584 clock hours in the data. This calculation results in averages of driver hourly trips and driver hourly earnings for each area during the sample period.

Figure 2 shows the average driver trips per hour and hourly earnings from 2010 to 2015 for taxi trips taken in Boston areas categorized as 2010 U.S. Census block groups, focusing on the trips' starting locations.[20] Although not purged of demand-side influences and averaged

drivers, representing 12,258 persons (weighted, or 0.31 percent of the total Boston population; 108 persons unweighted), is 8.4 percent female, 61.5 percent black non-Hispanic, 1.8 percent Asian non-Hispanic, 10.7 percent Hispanic, 12.5 percent 65 years of age and older, as well as 75.6 percent foreign-born (Minnesota Population Center 2010).

[17] In the main estimation sample to be discussed, area population shares for all five groups average less than 50 percent, thus allowing the minority group description used here to be accurate.

[18] There are 133 block groups comprising quintile 1 for which the share of Asian residents is zero, ranging from a minimum overall population of 10 residents to a maximum overall population of 2,461 residents.

[19] The maximum share of residents 65 years of age and older equals 1 due to a six-person block group in Hyde Park.

[20] I also examine this figure using trip end locations. As expected, since drivers presumably have less control over end locations than start locations, the variation across block groups in trips per hour is more

over time, the spatial variation in the upper map of Figure 2 nevertheless gives some insight into how labor supply choices (on the intensive margin) by drivers might differ across areas. Conditional on working in a block group, drivers tend to work in that block group about once per hour, and up to 1.33 times per hour. Meanwhile, the lower map of Figure 2 examines spatial variation in average driver earnings per hour. Although not purged of supply-side influences and averaged over time, to the extent that the map captures labor demand-driven hourly earnings, it shows that there is substantial variation in such wages across areas. Per block group, average hourly wages range from \$7.80 to \$30.56, with values in the median block groups spanning \$11.72 to \$13.02.

In later regression analysis of cab driver labor supply, the goal will be to examine to what extent wage elasticity differences across areas are attributable to labor supply discrimination. This estimation will allow me to address shortcomings of the previous descriptive analysis by purging the influence of labor demand and non-discriminatory labor supply, and also by conditioning on the local earnings opportunities facing drivers. Such analysis will use the current intermediate dataset of 14,136,226 trips associated with 912,679 non-spatial shifts from a random one-half sample of 3,435 drivers, from which a final dataset of area shifts will be constructed for spatial regression analysis. But before proceeding to estimation, it is helpful to first consider the theoretical underpinnings of the analysis.

4 Models of Labor Supply with Discrimination

4.1 Taste-Based Discrimination

In the spirit of Becker (1957), I can model labor supply-side discrimination as due to animus. The key features distinguishing this model from a statistical discrimination framework are a wage rate that is certain and a group distaste parameter in the utility function.

The setup and results of this model are detailed in the Appendix, so I focus here on im-

compressed, with a maximum value of 1.14 for the end location map instead of 1.33 in Figure 2.

plications and testable predictions. The model shows that differentials in gross log area work hours by cab drivers, when area wages are not included as a regressor in the estimation, need not reflect taste-based discrimination. The theory also predicts that discrimination yields slope differences in labor supply across areas with high and low shares of minorities, not just intercept differences. Non-discriminatory, driver-specific tastes may generate compensating wage differentials and thus also need to be controlled for, either using driver fixed effects (if driver tastes don't differ across areas) or else alternatives (if driver tastes do differ across areas, or if it is preferable to exclude driver fixed effects). The model assumes that wages across areas are demand-driven, so empirically, this assumption requires imposing various controls for driver labor supply and using instrumental variables (IV) estimation in order to isolate the wage variation due to demand. The theory also suggests that controlling for driver fixed effects should diminish but not completely eliminate taste-based discrimination, as there is a distribution of distaste parameters across areas for a given driver. However, driver $\times$ area fixed effects should eliminate this form of discrimination.

Additionally, because the choice to engage in discrimination means drivers forgo some earnings, any increased competition that affects market wages will alter drivers' allocation of hours across areas. The model shows that if competition in low minority areas increases sufficiently more than in high minority areas, this will drive down wages in low minority areas enough compared to high minority areas to cause drivers to increase the hours supplied to high minority areas.

4.2 Statistical Discrimination

Alternatively, in the spirit of Phelps (1972) and Aigner and Cain (1977), I can model supply-side discrimination in the labor market as due to incomplete information about earnings opportunities. The key features distinguishing this model from a taste-based discrimination framework are a wage rate that is uncertain and the absence of any group-specific distaste.

Once again, the Appendix describes the detailed model setup and results, while this discussion focuses on testable predictions and implications. Similar to before, the model shows that when area wages are not included as a regressor in estimation, differences in gross log area work hours by cab drivers need not reflect statistical discrimination. The theory also predicts again that discrimination yields slope differences in labor supply across areas with high and low shares of minorities, not just intercept differences. Moreover, including controls for anticipated wage variation should not affect the amount of statistical discrimination since this behavior is driven by unanticipated wage variation. Also, the model shows that controlling for driver fixed effects should diminish but not completely eliminate this form of discrimination, given different anticipated wage means by minority share.

The theory also predicts that with increases in the "reliability ratio" — a measure of the proportion of local wage variation anticipated by a driver — differences in log hours and expected log hours across places with different minority shares will decrease. In other words, statistical discrimination is mitigated as the reliability ratio increases, since anticipated wages correspond more closely to realized wages. Following Farber and Gibbons (1996) and Altonji and Pierret (2001), if the reliability ratio approaches one over time because drivers gain more experience and are better able to increase the share of realized wage variation that is anticipated, then this form of discrimination should diminish over time. Accordingly, driver $\times$ area fixed effects should not eliminate this form of discrimination given such variation with driver experience.

5 Shift-Level Estimates of Supply-Side Discrimination

5.1 Estimation Strategy

I now turn to econometric estimation of differences across areas in the slope of taxi driver labor supply, and the extent to which such differences vary by the demographic composition of areas.[21] To do so, I need to rely on exogenous labor demand shifts within areas while hold-

[21] I cannot credibly identify differences across areas in labor supply intercepts (see Appendix).

ing driver labor supply in each area constant. As Figure 3 shows, due to potential demand differences across areas that might cause false conclusions about area-specific driver supply, the identifying demand variation must be within locations rather than across locations. To identify driver labor supply slope differences across locations (via elasticity differences), the changes in (inverse) demand causing wage changes are assumed to be identical across areas (that is, $\Delta D_j = D'_j - D_j = \Delta D_k \ \forall j \neq k$ areas, D, D').[22] Estimating differences across areas in labor supply elasticities solely from within-area variation can thus address demand or non-discriminatory supply differences across areas that are time-invariant.

To examine whether area demographic composition causes differential responses of cab driver area shift hours to area wage increases, I estimate the following equation:

$$lnH_{kidcta} = \mu + \beta lnW_{kidcta} + (lnW_{kidcta} \times \mathbf{M}_a)'\eta + \phi_d + \gamma_c + \theta_t + \pi_{dct} + \alpha_a + \varepsilon_{kidcta}. \quad (1)$$

In equation (1), for shift k, driver i, day of the week d, calendar week of the year c, year t, and area a, H is the area-specific duration of a shift in hours, $\mathbf{M}$ is a vector of "minority"/demographic population shares (that is, black, Asian, Hispanic, female, and 65 years of age and older, all as measured in the 2010 Census), W is the area-specific average hourly earnings on a shift, and ε is an error term, with standard errors clustered at the driver level.[23] Also, ϕ controls for day-of-week fixed effects, γ controls for week-of-year fixed effects, θ controls for year fixed effects, α controls for area fixed effects, and π controls for major holidays.[24] Similar to Farber (2015), these additional controls help to satisfy iden-

[22] This assumption would hold, for instance, if conditional on controls, changes in demand were random shocks. This further highlights that identifying differences in labor supply elasticities across areas will be easier than identifying intercept differences across areas if, conditional on controls, changes in demand have a greater stochastic component than levels of demand.

[23] While the demographic shares in $\mathbf{M}$ could alternatively be allowed to vary over time using American Community Survey data, there is likely little variation in many of these shares from 2010 to 2015. Also, focusing on 2010 Census data allows block group composition to be based on a much larger underlying sample. Meanwhile, the choice of 65 years as the age threshold is partly motivated by the qualifying age of the Taxi Discount Coupon Program, which reduces the cost of cabs to the elderly via coupons and may provide motivation for cab drivers to avoid such passengers (See Boston Police Department, "Hackney Carriage Unit," from BPD News website: http://bpdnews.com/hackney-carriage-unit).

[24] As in Farber (2015), major holidays are defined as New Year's Day, Easter Sunday, Memorial Day, Fourth of July, Labor Day, Thanksgiving, and Christmas Day.

tification assumptions by accounting for some anticipated variation in wages. Such wage variation likely contributes to driver labor supply differences within areas, as well as differences across areas in passenger demand and non-discriminatory driver supply. If supply-side discrimination based on area demographics exists, I expect wage elasticity parameters $\eta < 0$, reflecting diminished wage sensitivity of work hours as the minority share increases.

Since demand or non-discriminatory supply may vary over time, I can also replace fixed effects $\phi_d, \gamma_c, \theta_t$, and α_a with ϕ_{dt}, γ_{ct}, and α_{at}.[25] Driver fixed effects, κ_i, or driver $\times$ area fixed effects, κ_{ia}, may also be added to further account for supply differences within areas or non-discriminatory supply differences across areas. If such fixed effects are not actually needed for consistent estimation of discrimination parameters, then they might instead help to inform the mechanism likely generating discrimination, as discussed in the theory.

5.2 Constructing Area-Specific Shift Hours and Wages

In order to estimate equation (1), I need to define hours, H, and wages, W, so that they are area-specific variables. Regarding hours, within each shift, I assign an area to a taxi trip based on the trip's starting location. The duration of an area-specific "stint" is defined as the duration of the trip plus the duration of the driver's wait time until the start of the next trip in the shift, if applicable. The area-specific shift duration, H_{kidcta}, is the sum of all of these trip stints within a given area a. The total shift duration then generally equals the sum across locations of the area-specific shift durations, or $H_{kidct} = \sum_a H_{kidcta}$.[26] If drivers have more control over wait time than trip duration, then area shift duration captures a driver's willingness to wait for a subsequent trip (that is, willingness to work longer searching for the next fare) given a current trip that starts in area a.[27]

[25]Given the large number of fixed effects to estimate, to improve computational speed I rely on the Stata command `reghdfe`, which implements an estimator described in Correia (2016). As a check, for more basic specifications with fewer fixed effects, I compare `reghdfe` with least-squares dummy variable estimation (with and without instrumental variables) and obtain identical estimates, standard errors, and statistics.

[26]Because I truncate both area-specific and non-area-specific shifts longer than 24 hours to be equal to 24 hours (see Appendix), $H_{kidct} = \sum_a H_{kidcta}$ may not hold in these infrequent truncated shift cases.

[27]Unfortunately, I do not observe continuous information on areas traversed by a driver during trips and wait times to incorporate in the construction of area hours and wages.

Area-specific average hourly earnings, W_{kidcta}, are defined as the total earnings from all trips that originate in area a within a non-spatial shift, divided by the area-specific shift duration, or $W_{kidcta} = E_{kidcta}/H_{kidcta}$, where E_{kidcta} is area-specific total earnings. This wage has the reasonable feature that for a given earnings amount in an area, the wage decreases either as the area trip length increases or as the wait time until the next trip increases. Thus, starting from an intermediate dataset with a random one-half sample of 3,435 drivers associated with 912,679 non-spatial shifts, this formulation of area hours and wages results in the creation of 9,890,638 area shifts.[28]

Sometimes, the average hourly earnings of an area-specific shift are quite high and may result from measurement error. In order to retain much of the sample while still removing erroneous shifts, I implement a threshold for area-specific average hourly earnings of \$25. This threshold value is guided by theory (see Appendix), and I will also explore the sensitivity of the analysis to this sample restriction. Once imposed, along with a few other sample restrictions, I obtain a dataset of 3,744,057 area-specific shifts from 2,984 drivers.[29] Average values of the demographic shares in the sample of dropped shifts do not differ substantively from their values in the retained sample.[30] Across shifts in the retained sample, area shift duration is 0.86 hours at the median and 1.25 hours on average, while average hourly area earnings are \$15.78 at the median and \$15.21 on average. Also, the number of trips per area shift is 1 at the median and 1.56 on average, while the number of trips per shift in the non-spatial analysis is 14 at the median and 14.87 on average (see Appendix).

[28]The non-overlapping sample contains 10,116,926 area shifts from 3,461 drivers.

[29]This estimation sample drops observations where the area shift hours or area wages are zero, since both are in log form for estimation. The sample also ensures a constant number of observations across all variations of equation (1) and Appendix equation (3), thus conditioning on non-missing regressors (including $\mathbf{X}_a$) in all cases. Lastly, the sample additionally imposes that the instrument for IV estimation, to be discussed, is not missing. A non-overlapping sample that applies the same restrictions as the estimation sample contains 4,094,076 area-specific shifts from 2,973 drivers. However, the relevant non-overlapping sample, which only conditions on area wages being non-zero and no greater than \$25—that is, the appropriate conditions for instrument construction, the non-overlapping sample's sole purpose—contains 4,476,441 area-specific shifts from 3,406 drivers.

[30]For instance, the difference across samples in the average Asian share is 0.04 percentage points, or 0.3 percent of the retained sample mean Asian share (13 percent).

5.3 Main Results

The upper panel of Table 1 presents OLS estimates from equation (1) of area wage elasticity β and the vector of discrimination parameters η from interactions of the area wage with area population shares.[31] Given inclusion of the interaction terms, the "baseline" elasticity β should be interpreted as the average area wage elasticity for a block group with a demographic composition of only male residents below 65 years of age, none of whom are black, Asian, or Hispanic. OLS results across all specifications display significantly negative baseline area wage elasticities while estimates of discrimination, when significant, are also generally negative.

These OLS estimates may be biased, however, because the log of area-specific average hourly earnings, lnW_{kidcta}, might not be solely driven by passenger demand, and rather could be influenced by driver supply-side factors that also affect area shift hours. Additionally, due to shift hours appearing as the dependent variable and in the denominator of the independent wage variable, measurement error may bias the wage elasticity estimate toward –1 (that is, division bias). To address these issues, following Farber (2015) and in the spirit of Camerer et al. (1997) (see Appendix), I instrument for lnW_{kidcta} with the average across other drivers of log area-specific average hourly earnings. As Farber (2015) proposes, to avoid problems arising from using an instrument derived from the dependent variable in estimation, I use the non-overlapping, randomly selected one-half subset of drivers to construct the instrument.[32] The average across drivers of log average hourly earnings of shifts k on day of week d, calendar week c, year t, and in area a ($\overline{lnW}_{kdcta}$) in the non-overlapping sample serves as the

[31] There are also significant gross disparities in area shift hours by local demographic composition. From an OLS regression of log area shift duration on a vector of area population shares, with 3,744,057 area shifts for 2,984 drivers from 2010–2015, the coefficients are all significant at the 1 percent level: –0.513 (female), –0.227 (black), –0.280 (Asian), 0.763 (Hispanic), and 0.182 (65 years of age and older). However, these associations may simply reflect area-specific differences in earnings opportunities rather than discrimination by drivers.

[32] As proposed in Angrist and Krueger (1995), unlike typical IV estimation, this split-sample IV estimation is biased toward zero rather than the probability limit of the OLS estimate. Thus, in the presence of biased estimation, using split-sample IV estimation results in wage elasticities that offer a more neutral stance between neoclassical and behavioral models of labor supply, rather than biased support for the latter.

instrument for the log of average hourly earnings for driver i with shifts k that start on day of week d, calendar week c, year t, and in area a (lnW_{kidcta}) in the estimation sample.[33] This instrument should capture demand-driven movements in the log wage that are not affected by supply-side driver choices or measurement error, thus purging from estimation any driver supply differences within areas.

The bottom panel of Table 1 presents IV estimates from equation (1). Parameter estimates are similar across specifications, although coefficient magnitudes differ. I focus on the three specifications with area $\times$ year fixed effects as the preferred, more conservative estimates. The baseline area wage elasticity $\hat{\beta}$ is positive across these specifications, albeit not significant, ranging from 0.08 to 0.10. These coefficients are in line with microeconometric estimates of the non-spatial Frisch labor supply elasticity, which tend to range from 0 to 0.5 (Altonji 1986; MaCurdy 1981; Peterman 2016), including this paper's own estimates ranging from 0.37 to 0.48 (see Appendix). This provides some reassurance that the area wage is reasonably constructed.[34]

IV estimates of the discrimination terms, $\hat{\eta}$, indicate how the baseline wage elasticity $\hat{\beta}$ differs as the demographic composition of area residents changes. These $\hat{\eta}$ terms are significantly negative for the female, black, and Asian shares, and are positive but not significant for the Hispanic and aged 65 years and older shares in preferred specifications.[35] For in-

[33]While I do not present first stage results, they are very strong. In a basic version of model (1) from Table 1 with the interaction terms omitted, the first stage F-statistic is 462. The coefficient on the instrument is 0.034, notably smaller than in the non-spatial analysis where the instrument coefficient is close to 1 (see Appendix). This indicates a weaker relationship between the wages other drivers face on a given shift and a driver's own wages faced on the same shift when that comparison is restricted to a given block group. Meanwhile, when considering the full equation (1) with six endogenous regressors, the Stock and Yogo (2005) weak instrument identification critical values for the maximal actual size of a 5 percent Wald test of the six wage instruments jointly being equal to zero are 29.18, 16.23, and 11.72 for maximal test sizes of 10, 15, and 20 percent, respectively. The joint F-statistic on the six instruments always far exceeds the first critical value when estimated separately for each of six endogenous wage regressors in all but one case, where it still exceeds the second critical value.

[34]Although drivers are not very responsive to the baseline area wage, spatial labor supply responsiveness may be greater in other cases, such as when considering the extensive margin. The intensive margin spatial analysis in this paper aligns with the non-spatial analysis in the Appendix, Farber (2015), and other microeconometric analyses of the Frisch labor supply elasticity that focus on the intensive margin response of hours to wage increases, conditional on working at least some hours.

[35]The Hispanic share coefficients become negative but not significant when the East Boston region, where Logan Airport is located, is dropped from the sample, with estimates ranging from –0.31 to –0.64.

stance, as the Asian share in a block group increases by 1 percentage point in specification (2), the baseline wage elasticity 0.100 declines by 0.0046, or 4.6 percent. If the Asian population share were to increase from 0 to 0.13, the mean value in the estimation sample, the baseline wage elasticity would decline by 0.06, or 60 percent, resulting in a wage elasticity of 0.04. Thus, in response to a 10 percent increase in the area wage, hours worked in the area increase by only 0.4 percent rather than 1 percent due to greater Asian representation. Given a mean area wage in the sample of \$15.21 and a mean area shift of 1.25 hours, on average, a \$1.52 increase in the local wage leads to an increase of 0.0125 hours worked in a baseline area (45 seconds) compared to an increase of 0.005 hours worked (18 seconds) in an area with the mean Asian population share, a disparity of 27 seconds. When this area labor supply difference for a given driver is aggregated across all drivers in a day, the disparity can become notably larger. For the 2,189 calendar days in the sample, there are on average 401 drivers on a given day.[36] Thus, across 401 drivers, given a 10 percent increase in the area wage, the average disparity in area shift length is three hours, equivalent to 2.4 area shifts and 3.75 trips (given 1.56 trips per area shift, on average). This corresponds to at least four fewer passengers served on a given day due to local demographics in a block group with average Asian representation. Moreover, this effect size becomes larger when considered across multiple areas, days, and demographic groups.

Likewise, increases of 1 percentage point in the female or black population shares lower the baseline wage elasticity by 0.0071 (7.1 percent) or 0.0057 (5.7 percent), respectively, in specification (2). Including driver fixed effects in specification (3) does not have much effect on the $\hat{\beta}$ or $\hat{\eta}$ estimates. Model (3) has more modest identification assumptions but may eliminate some supply-side discrimination if models (2) and (3) are both identified. Lastly, if models (3) and (4) are both identified, given the inclusion of driver $\times$ area fixed effects in model (4), coefficient similarity across models suggests that the primary mechanism behind driver behavior may be statistical discrimination rather than taste-based discrimination.

[36] While there are 2,191 calendar days from January 1, 2010 to December 31, 2015, January 31, 2010 and March 14, 2010 do not appear in the final estimation sample and are dropped.

With 1 percentage point increases in the female, black, or Asian shares, the baseline wage elasticity now decreases by 4.9 to 5.9 percent. The $\hat{\eta}$ female coefficient differs the most across specifications (3) and (4), perhaps indicating that taste-based discrimination plays the largest role for this demographic group. To the extent that animus is driven by demographic differences between those who discriminate and their targets, Table A2 further supports the possibility of taste-based discrimination toward women. Among the five demographic groups in $\hat{\eta}$, the largest population share disparity between Boston drivers and all residents exists for women (44 percentage points). Additional analysis in sections 6 and 7 will help further explore the relevant mechanism(s) underlying observed discrimination.

A binned scatterplot in Figure 4 provides a nonparametric view of the impact of discrimination on driver labor supply, analogous to IV estimation in Table 1.[37] To represent marginal effects of $\hat{\eta}$ that correspond to continuous changes in the area female population share, I plot supply curves for first and second decile female representation. Aligned with Table 1 regressions and the upper plot of Figure 3 (axes transposed), Figure 4 shows that labor supply is less wage sensitive when the female population share is larger.

5.4 Robustness Checks

Given that the regressor of interest in equation (1) is $lnW_{kidcta} \times \mathbf{M}_a$, I might worry about bias related to either (or both) the log area wage or area demographic share components of that term. Table 2 displays analyses testing the robustness of the discrimination findings, concentrating on analogs of specification (4) from Table 1.

Focusing first on lnW_{kidcta}, if tips in addition to fares also significantly affect driver labor supply and are correlated with area demographic shares and log area wages, then discrimination due to fare-based wages may be absent once wages based on fares plus tips are considered. Models (1) and (2) of Table 2 show that whether considering all shifts or

[37] Absent an IV estimation routine in Stata's `binscatter` command, I plot log area shift hours on fitted values of the log area shift wage (from a first stage regression), controlling for the indicators in Table 1 model (2) and five interaction terms of the observed log area shift wage and demographic shares.

only shifts where at least one trip is paid for by credit card (since tip information is only available for taxi fares paid for by credit card), evidence of discrimination still remains when wages incorporate tips. Also, baseline elasticity estimates (now significant) remain positive and in the expected range.[38]

Turning to $\mathbf{M}_a$, if some other area variable observable to drivers is correlated with area demographic shares and log area wages, then estimated discrimination may be spurious, capturing wage sensitivity to the omitted variable. Criminal activity is a candidate for such an omitted variable, but 2010 crime rates at the block group level are not readily available. Instead, in model (3) of Table 2, I examine educational attainment as measured in the 2006–2010 five-year American Community Survey (Minnesota Population Center 2010), as it is potentially relevant for explaining non-discriminatory driver labor supply.[39] While education is not observable to drivers and thus is not an ideal candidate variable, it may nevertheless be correlated with observable area amenities that drivers might care about, such as safety or infrastructure quality.[40] In model (3), there remains evidence of discrimination and a reasonable baseline wage elasticity, although there is also now a significantly positive result (10 percent level) for the age 65 years and older share.[41]

The remaining models of Table 2 now consider $lnW_{kidcta} \times \mathbf{M}_a$ in its entirety. Models (4) and (5) show that addressing potential bias from omitted time-of-day driven demand (either AM/PM or hourly) still results in sensible baseline wage elasticities and estimated discrimination. Model (6) considers that omitting area costs per hour and their interaction

[38]Some cash trips in the raw data have non-zero tip information due to measurement error and are adjusted to equal zero.

[39]Specifically, I examine the share of the area population 25 years of age and older whose educational attainment is a high school diploma.

[40]Alternatively, I attempted to include interactions between the log wage and 32 region fixed effects in order to explore non-discriminatory factors affecting driver labor supply elasticities (see Appendix for region definitions). However, I was unable to precisely estimate any of the elasticity coefficients with this approach.

[41]It is unclear how much weight to place on this specification. Since educational attainment is not directly observable to drivers, it is uncertain which neighborhood amenities, if any, attainment is correlated with that would affect driver labor supply. Consistent with this ambiguity, when the share of those with a high school diploma is replaced with the share of those with some college, I obtain an unexpected and highly negative coefficient on the interaction of the wage elasticity with the college share, as compared to the positive (but not significant) coefficient for the share of those with a high school diploma.

with area population shares may bias discrimination estimates if hourly earnings and hourly costs are correlated. I use the log of average area hourly trip distance as a proxy for fuel costs, since fuel expenditures will depend multiplicatively on distance traveled, vehicle miles per gallon, and the price of a fuel gallon. With area costs included, estimate precision is reduced since the model now tries to separately identify benefit and cost elasticities, which are both non-linearly related to distance. Thus, larger coefficient magnitudes should be given less weight, although the significantly positive baseline wage elasticity is still in line with macro and some micro estimates of the non-spatial Frisch elasticity. Interestingly, the baseline cost elasticity is of equal but opposite magnitude, revealing symmetric driver labor supply responses to benefits and costs. Evidence of wage-related discrimination is still observed, and similarly, drivers are less cost sensitive toward female and Asian demographics.[42]

Additionally, I examine the sensitivity of the results to focusing on area shifts at or below the $25 area wage threshold imposed due to measurement error considerations. First, as noted, I observe no economically significant difference between average area demographic shares in the sample with area wages at most $25 and the sample with area wages above $25. Model (7) nevertheless displays results for an expanded, combined sample of area shifts. While I still observe evidence of discrimination (although now with a significantly positive coefficient for the age 65 and older share as well), the baseline wage elasticity is now significantly negative. Sample stratification at $25 reveals that this is due to negative but imprecise wage elasticity estimates for the sample with area wages above $25. Put differently, there is a "bend" in area labor supply that the linear model masks, resulting in a substantive difference in discrimination parameters across the sample. That is, discrimination with a positive baseline wage elasticity reflects decreased neoclassical behavior, while discrimination with a negative baseline wage elasticity reflects increased income targeting behavior. Thus, this paper's results can be interpreted as focusing on the former, reflecting driver behavior for a range of area wages where the area labor supply curve is upward-sloping, and where

[42]Considering area costs via distance also helps to address one mechanism through which trip drop-off locations could matter.

area wages are more likely to be free of measurement error. Meanwhile, increased income targeting behavior can still be interpreted as a form of discrimination since, given an area wage increase, drivers are more willing to reduce work hours in high-minority areas than low-minority areas, thereby contributing to greater area disparities in access to taxi services.

Lastly, given the focus of the analysis on trip pick-up locations, I also consider the role of drop-off locations. Examining how demographics correlate between pick-up and drop-off locations reveals that there tends to be only a mild, positive relationship between start and end location residential composition. Thus, observed discrimination based on trip start locations is unlikely to be conflating discrimination based on trip end locations.[43]

6 Discrimination Variation By Driver and Area

Having estimated average labor supply discrimination, I now examine variation in these discrimination estimates by driver and area. I take advantage of the large sample of 3,744,057 area-specific taxi shifts to explore this heterogeneity. Focusing on one demographic group at a time and stratifying by driver-region-experience cells, I want to decompose how much of the variation in discrimination occurs: (a) within driver-areas, (b) across areas for a given driver, and (c) across drivers but area-invariant, where (b) and (c) combined account for variation between driver-areas.[44] The more variation in discrimination that exists within the driver-area dimension, the greater the credence that such discrimination is statistical rather than taste-based. This reasoning follows directly from the theory outlined in section 4 and the Appendix, where only statistical discrimination may vary within the driver-area dimension due to driver learning over time, whereas variation between driver-areas could be due to statistical or taste-based discrimination.

[43] However, even if so, estimated coefficients would still reflect unbiased estimates of location-based discrimination, even if not unbiased estimates of start-location discrimination specifically.

[44] Regions are large Boston neighborhoods or Massachusetts counties, rather than block groups, to ensure a sufficient number of block group shifts for estimation. Driver experience "periods" occur every six weeks, where a week is seven non-spatial shifts (and one to six shifts are rounded up to a week). Further details are in the Appendix.

Table 3 displays the results from the variance decomposition. For each demographic group, the mean wage elasticity-population share interaction across driver-region-experience (ire) cells is negative for all three demographic shares. Each mean lies within a confidence interval of 95 percent (female, Asian) or 99 percent (black) of the IV estimates from model (4) of Table 1, despite specification differences (for instance, examining one demographic group at a time here for $\hat{\eta}_{ire}$). Meanwhile, regarding the decomposition of total variance, the majority of the variation for all three sets of $\hat{\eta}_{ire}$ estimates occurs as experience varies within driver-regions: with 85.8 percent for the female share, 90.9 percent for the black share, and 67.6 percent for the Asian share. This finding suggests that it is possible that the majority of labor supply discrimination by taxi drivers is statistical.

The remaining variation in the $\hat{\eta}_{ire}$ estimates occurs across driver-regions and is experience-invariant, thus providing scope for taste-based and/or statistical discrimination. Variation across regions for a given driver can be thought of as discrimination taking place on the "intensive margin," as it depends on a demographic group's concentration in an area. This margin accounts for 12.5 percent of $\hat{\eta}_{ire}$ variation for the female share, 3.9 percent for the black share, and 30.1 percent for the Asian share. Meanwhile, the variance proportion across drivers that is region-invariant can be thought of as "extensive margin" discrimination, as it does not depend on the concentration of a demographic group in an area. This margin represents 1.7 percent of $\hat{\eta}_{ire}$ variation for the female share, 5.2 percent for the black share, and 2.3 percent for the Asian share.

7 Do Drivers Discriminate for Different Reasons?

7.1 Taste-Based Discrimination

To further explore the potential role of driver preferences and taste-based discrimination in my findings, I begin by examining how the discrimination term η varies with driver experience in Figure 5, now stratifying the estimation sample by experience bins only, rather than also by driver and region.[45] As discussed in section 4 and the Appendix, if the discrimination estimated in this paper is taste-based, I would expect η to be relatively constant as driver experience increases, since tastes are assumed to be time-invariant.[46] However, if discrimination is statistical, then I might expect η to approach zero as drivers gain experience and learn to better anticipate area-specific wage variation, thereby placing less weight on neighborhood demographics to assess wages.

Focusing on estimates for the female demographic group, Figure 5 shows that the wage elasticity-population share interaction term generally remains negative as driver experience increases (plots for the black and Asian shares, not shown, are similar).[47] This largely time-invariant pattern would seemingly be consistent with taste-based discrimination. However, due to wide confidence intervals, I cannot rule out the possibility that drivers may initially discriminate but that this discrimination diminishes and approaches zero as experience increases, consistent with statistical discrimination. It is only in the case of the female population share specifically that I observe somewhat stronger evidence in favor of taste-based discrimination, as η is significantly below zero in months 4–6 and year two, fairly late in a driver's experience cycle. The possibility that discrimination against women may be driven by both taste-based and statistical mechanisms is consistent with the results presented in Table 1, where inclusion of driver $\times$ area fixed effects in specification (4) reduces the magnitude of η by the most for the female group.[48]

[45] Rather than six-week experience bins, the experience period lengths now match those in Farber (2015) and follow the non-spatial analysis in Appendix Figure A11, except for the aggregation of weeks 1–2 and weeks 3–4 in order to obtain more reasonably precise estimates.

[46] As noted in the Appendix, while discrimination preferences might change over time for some individuals, it seems plausible to assume that they are stable for Boston cab drivers given the older age of this population (see Table A2).

[47] Figure 5 reflects IV estimation of specification (1) from Table 1. Given fewer observations obtained from restricting the sample to new drivers, especially within an experience category, specification (1) is more feasible to estimate with some precision than specification (2). However, because experience categories often fall within a calendar year, estimating specification (1) in Figure 5 should closely approximate estimating specification (2) in Table 1. Although Figure 5 restricts the sample to 1,000 new drivers with more than 28 non-spatial shifts (that is, approximately four weeks of experience), analogous figures for a sample of all new drivers look nearly identical, suggesting that driver exit is not particularly related to estimates of labor supply discrimination.

[48] Following the theory set forth in section 4 and the Appendix, I also examine the influence of increased market competition from ridesharing companies on discriminatory behavior and industry exit by

7.2 Statistical Discrimination

To further explore the potential role of statistical discrimination in my findings, one test I can run, guided by the theory in section 4 and the Appendix, is to examine whether the amount of estimated discrimination varies with a proxy for the reliability ratio, ψ.[49] The reliability ratio, which ranges from 0 to 1, reflects the share of total wage variation that is anticipated, and thus somewhat captures a driver's degree of wage certainty. To generate the ratio, I run an OLS regression of lnW_{kidcta} on indicators for day of week, calendar week, year, area, and major holiday. The predicted values from this regression capture anticipated log area average hourly earnings, $\widehat{AlnW}_{dcta}$, while the residuals from this regression capture unanticipated log area average hourly earnings, $\widehat{UlnW}_{kidcta}$. The numerator of the reliability ratio is the sample variance across days and weeks of anticipated log area average hourly earnings by area-year, $\widehat{Var}(AlnW)_{at}$. The denominator of the reliability ratio is the sum of the sample variance of anticipated log area average hourly earnings by area-year, $\widehat{Var}(AlnW)_{at}$, and the sample variance across shifts, days, and weeks of unanticipated log area average hourly earnings by driver-area-year, $\widehat{Var}(UlnW)_{iat}$. Thus, I generate the reliability ratio proxy, $\widehat{\psi}_{iat} = \frac{\widehat{Var}(AlnW)_{at}}{\widehat{Var}(AlnW)_{at} + \widehat{Var}(UlnW)_{iat}}$, which I calculate in each year in order to allow the ratio to

cab drivers. I utilize entry into the Boston market by Uber on October 24, 2011 (see Scott Kirsner, "Test-riding Uber, the Populist Car Service You Summon with a Mobile App," from Boston.com website: http://boston.com/business/technology/innoeco/2011/10/test-riding_uber_the_populist.html), SideCar on March 15, 2013 (see Janelle Nanos, "SideCar Launches in Boston," from *Boston Magazine* website: http://www.bostonmagazine.com/news/blog/2013/03/15/sidecar-launches-in-boston/), and Lyft on June 1, 2013 (see Michael Farrell, "Lyft is Latest Ride-Sharing App to Offer Service in Boston," from *Boston Globe* website: https://www.bostonglobe.com/business/2013/05/31/car-sharing-app-lyft-arrives-boston/g2fi9ixj707RU9MSXKWQ8O/story.html), limiting the sample to shifts undertaken by new drivers (that is, no shifts in 2010) who are "active" with at least one shift from January 1, 2011 to October 23, 2011 before the entry of ridesharing firms. Once again, I observe no evidence of driver exit due to market competition that is correlated with η values. However, this result may be partly due to the identification of ridesharing competition effects solely from entry dates of ridesharing firms, given the lack of accessible spatial data on ridesharing trips.

[49]Section 4 and the Appendix also show that statistical discrimination results solely from unanticipated wage variation, not predicted wage variation. This finding suggests that if including controls for predicted wage variation reduces the magnitude of the discrimination parameter estimates, at least some of the discrimination is taste-based. However, this test cannot be performed because, as discussed in section 5, these controls are necessary for valid identification of parameters. Alternatively, one could examine deviations from wage expectations within area × day × hour bins, to see if driver behavior varies in bins with more uncertainty. However, unlike the reliability ratio, such an approach would not allow wage uncertainty to be caused in part by drivers, as the theory in the Appendix suggests.

vary roughly by driver experience.[50]

I estimate equation (1) with IV, as in Table 1, but now add a regressor for the reliability ratio proxy as well as the interaction of the ratio with $lnW_{kidcta} \times \mathbf{M}_a$.[51] According to the model (see Appendix), if the underlying mechanism for discrimination is statistical, then the coefficients from the interaction of the reliability ratio with the relevant log area wage $\times$ demographic share regressors will be positive. In other words, as the reliability of anticipated wage variation increases, statistical discrimination should be reduced.

Table 4 presents IV estimates of how discrimination varies with the reliability ratio proxy. The ratio itself has a mean of 0.02 in the estimation sample, with a standard deviation of 0.07, a minimum very close to 0 (1.4×10^{-6}), and a maximum of 1. Baseline wage elasticity estimates, $\hat{\beta}$, and interactions with demographic shares, $\hat{\eta}$, are very similar to results in Table 1, although interpretation across tables differs since Table 1 estimates correspond to a reliability ratio of zero. I focus on specification (4) which isolates variation that is more likely specific to statistical discrimination. For instance, as the reliability ratio increases by 0.01, the negative effect of 0.0060 on the baseline wage elasticity from a 1 percentage point increase in the black share is reduced by 0.0017, or about 28 percent. I likewise observe a significantly positive effect on the Asian population share η. Across specifications, these results suggest that a reliability ratio in the 0.03 to 0.05 range, or 50 to 150 percent above the mean ratio, would eliminate labor supply discrimination for black and Asian residents.[52] For the female population share η, the ratio has a positive but not quite significant effect that is also smaller in magnitude. This result further confirms that female share discrimination may be driven by both statistical and taste-based mechanisms. Strikingly, the reliability ratio also has *negative*

[50] Experience is not a dimension of the area shift data. But since more experienced drivers appear in the data for more years, allowing the reliability ratio proxy to vary by year approximates variation by experience.

[51] Given the additional estimation error arising from inclusion of the generated reliability ratio regressor, standard errors are calculated using block bootstrapping by driver (1,000 replications per specification). Also, compared to Table 1, there is a small loss in observations of 237,909 area shifts and 27 drivers because, in these cases, there are not multiple observations with which to calculate at least one of the necessary sample variances for the reliability ratio.

[52] However, given estimate uncertainty, the ratio magnitude needed to eliminate taxi labor supply discrimination could also be several times higher.

effects on the positive (but not significant) η terms for both the Hispanic share and share aged 65 years and older, with the latter effect being significant. Thus, not only does improved anticipation of wage variation reduce labor supply discrimination against some residents, but it also reduces labor supply "favoritism" for other residents, thereby increasing the similarity of wage elasticities across all area demographics. Still, given controls in estimation for some anticipated wage variation in order to identify parameters, the paper's results reflect driver behavior in response to largely unanticipated wage changes. The possibility thus remains that drivers could exhibit taste-based discrimination when facing anticipated wage changes.

Lastly, I examine whether the reliability ratio grows as driver experience accumulates, to see if drivers learn over time to be better at anticipating wage variation. For each experience bin, I run an OLS regression of the reliability ratio proxy, $\widehat{\psi}_{iat}$, on a constant to estimate the ratio mean and standard errors. Surprisingly, Figure 6 shows that the ratio decreases over the first six months of experience when examining a sample of 1,000 new drivers with more than 28 non-spatial shifts (about four weeks). To reduce the potential influence of driver exit across experience bins, I further restrict the sample to 300 new drivers with more than 364 non-spatial shifts (about one year). However, the resulting pattern in the ratio is largely unchanged. It may be the case that non-spatial learning by drivers (that is, working longer shifts on high-wage days, as evidenced by Appendix Figure A11) occurs more quickly than spatial learning (that is, working in areas where a greater share of wage variation is anticipated). Thus, the initial decline in the ratio might reflect greater area exploration by drivers, followed by a ratio increase once drivers learn about new areas and acquire area-specific experience (for example, Haggag, McManus, and Paci 2017). Consistent with this hypothesis, the last plot of Figure 6 shows that by redefining the experience bins and examining more narrow bins in later periods, I observe that the reliability ratio increases with experience after the first six months.[53]

[53] Regarding the number of non-spatial shifts for each experience bin: year 0.1–0.5 is 1–182 shifts, year 0.6–1.0 is 183–364 shifts, year 1.1–1.5 is 365–546 shifts, year 1.6–2.0 is 547–728 shifts, year 2.1–2.5 is 729–910 shifts, year 2.6–3.0 is 911–1,092 shifts, year 3.1–3.5 is 1,093–1,274 shifts, and year 3.6 and over is 1,275 shifts or more. The last bin is not further disaggregated because it contains only six drivers, and only three drivers

Thus, among drivers who stay in the taxi industry for at least one year, the drivers most likely to statistically discriminate are relatively new ones with a few weeks or months of experience, a finding that is consistent with these drivers possibly being in the process of learning about wage variation in new areas.[54] However, as indicated by the 0.02 sample mean of the reliability ratio, drivers who exit the taxi industry after less than one year tend to have lower reliability ratios, suggesting that short-term drivers may discriminate the most.

Analyzing areas worked, I observe that in months one to six of experience, drivers work in 68 unique block groups per month on average, compared to 57 unique block groups in months 43 to 48.[55] Meanwhile, in the first six months of experience, on average there is an overlap of 34 to 36 percent of driver areas worked during proximal months, while in months 43 to 48, there is an overlap of 23 to 31 percent. Moreover, when comparing months one and two, there is 35 percent overlap in areas worked, compared to only 19 percent overlap in months one and 48.[56] Put together, with greater experience, drivers tend to work in fewer areas, work in different areas, and also reduce the core set of areas that they work in regularly, with all factors possibly contributing to higher reliability ratios in later years.

would be contained in a bin for year 4.1 and over.

[54] Very new drivers may have high ratios because of some initial familiarity with the areas they choose to work in (for example, perhaps their own residential areas, or Logan Airport). I also examine a version of the reliability ratio proxy that does not vary by year and then average it across areas for a given driver, obtaining $\widehat{\psi}_i$. Examining the third plot of Figure 6 with this alternative ratio, I still observe an upward trend but with a flatter slope, ranging from a ratio of approximately 0.02 in year 0.1–0.5 to roughly 0.05 in year 3.6 and over. This suggests that while some of the upward trend in the final plot of Figure 6 is due to industry exit by drivers with lower ratios, some of the growth in the ratio with experience remains attributable to on-the-job learning.

[55] I first calculate the number of unique block groups worked in by each driver in a monthly experience bin. I then calculate the within-bin average across drivers, before then examining the average across bins 1–6 and 43–48. Every month of experience is 28 non-spatial shifts or four weeks, with the exception of every third month, which is 35 non-spatial shifts or five weeks.

[56] I construct a matrix to explore the similarity of areas worked when comparing pairs of monthly driver experience bins. For a given driver i and experience bins j and k where $j < k$, I calculate $S_i(j,k) = N_{i,sh}(j,k)/N_{i,tot}(j,k) \in [0,1]$, where $N_{i,tot}(j,k)$ is the total number of unique areas that exist across bins j and k, while $N_{i,sh}(j,k)$ is the shared number of unique areas that exist across those bins. I then calculate the average S across drivers for any pair of experience bins j and k based on the number of drivers $N(k)$ who remain in the industry in bin k, $\overline{S(j,k)} = \sum_{i(k)} S_i(j,k)/N(k)$, which corresponds to the in-text values.

8 Quasi-Experimental Trip-Level Estimation

Despite the main results being guided by labor supply theory, aligning with prior microeconometric estimates of the Frisch elasticity, being robust, and having a clear mechanism, some hesitation regarding the findings may nevertheless remain. Because I do not have continuous information on areas travelled by drivers during trips and intervening wait times, in order to create area shift hours and wages, I construct proxies for the ideal, continuous-information analogs of those variables. As a result, and since area wages in the paper are tied to trip start locations (albeit reasonably, as discussed), some confusion may still arise regarding the preferred interpretation of the estimated labor supply elasticities. Namely, as mentioned, I interpret those elasticities as reflecting how wages received for trips starting in area a affect driver willingness to work longer searching for subsequent fares following trips starting in area a.

Alternatively, one could implement a different strategy to identify driver discrimination, sacrificing some of the useful theoretical interpretation of the current approach in order to take further advantage empirically of the taxi industry framework. The alternative strategy exploits the quasi-experimental exposure to neighborhoods of different demographic compositions that drivers experience based on trip drop-off locations, conditional on a given trip pick-up location (since drivers have almost no legal control over the drop-off location after accepting a trip, as noted in section 2). The outcome of interest is the log distance from a trip's drop-off location to the subsequent trip's pick-up location, which proxies for the time, fuel, and/or effort expended to secure a driver's next trip on a (non-spatial) shift. Using this distance measure, I can then examine if drivers are less sensitive to economic opportunities in areas with higher minority shares, estimating separate effects for local wages at the drop-off and subsequent pick-up locations in order to account for economic "push" and "pull" factors, respectively. All else equal, higher area wages at the drop-off location should decrease the distance between the drop-off and subsequent pick-up locations, as drivers would be less willing to travel far for the next trip given economic opportunities close by. Meanwhile, all else equal, higher area wages at the subsequent pick-up location should increase the distance between the drop-off and subsequent pick-up locations, as drivers would be more willing to travel far for the next trip given economic opportunities far away.

However, one might also anticipate an important difference in driver responses to area wages at the current drop-off location versus the subsequent pick-up location. Upon completion of a given trip, drivers likely have a relatively high degree of certainty regarding economic opportunities at the current drop-off location, as demand in the area is directly observable. However, drivers likely have a relatively low degree of certainty about economic opportunities at possible subsequent pick-up locations, where demand is not directly observable from the current drop-off location. Thus, given such differences in area wage certainty and the paper's earlier results in section 7, one might expect driver discrimination to be more prevalent in response to wage variation at the subsequent pick-up location rather than the current drop-off location, as the former area likely has a greater share of wage variation that is unanticipated.

To execute the alternative approach, I estimate the following trip-level equation:

$$lnDES_{kidctoe} = \mu + \beta_e lnW_{kidcte} + \beta_s lnW_{kidcts} + (lnW_{kidcte} \times \mathbf{M}_e)'\eta_e + (lnW_{kidcts} \times \mathbf{M}_s)'\eta_s$$

$$+ \phi_d + \gamma_c + \theta_t + \pi_{dct} + \alpha_o + \alpha_e + \alpha_s + \varepsilon_{kidctoe}. \tag{2}$$

In equation (2), $DES_{kidctoe}$ is the straight-line intervening distance between a trip's end location and the subsequent trip's start location, defined for a given shift k, driver i, day of the week d, calendar week of the year c, year t, and trip originating in block group o and ending in block group e.[57] Analogous to area-specific average hourly earnings, W_{kidcta}, in

[57]Without loss of generality, the straight-line distance measure is defined for the current trip in the data sample rather than the subsequent trip. Straight-line distance should be a reasonable first-order approximation for route distance. Estimating routes given a large number of trip-level observations presents computational challenges, in addition to not necessarily reflecting the circuitous route a driver may take between the location of a trip's drop-off and the location of the subsequent trip's pick-up while searching for a new fare. For observations where the initial measured intervening distance is zero, I set the adjusted final intervening distance equal to the smallest positive intervening distance in the estimation sample (0.000012 miles, equal to 0.06 feet). I prefer intervening distance rather than intervening hours (that is, intervening

equation (1) (where a corresponds to current trip pick-up locations), W_{kidcts} reflects average hourly earnings in the block group s of the subsequent trip's pick-up. This pick-up-area-specific wage is an area-shift-level wage, not a trip-level wage, constructed identically as W_{kidcta} but now used in estimation to reflect economic opportunities at the pick-up location of the subsequent trip rather than the current trip.

In contrast, W_{kidcte} reflects average hourly earnings in the block group e of the current trip's drop-off. Because there is no analogous area-shift-level wage in equation (1), this variable is constructed anew. Specifically, regarding hours, within each (non-spatial) shift, I assign an area to a taxi trip based on the current trip's ending location. The duration of an area-specific "stint"—here, drop-off-area-specific—is defined as the driver's wait time until the start of the next trip in the shift, if applicable, plus the duration of the subsequent trip. The drop-off-area shift duration, H_{kidcte}, is the sum of all of these trip stints within a given, current trip end area e. The total shift duration then generally equals the sum across locations of these area-specific shift durations, or $H_{kidct} = \sum_e H_{kidcte}$. As previously discussed, if drivers have more control over wait time than trip duration, then drop-off area shift duration captures a driver's willingness to wait for a subsequent trip (that is, willingness to work longer searching for the next fare) given a current trip that ends in area e. Drop-off-area average hourly earnings, W_{kidcte}, are defined as the total earnings from all trips in stints associated with current trip drop-off area e within a (non-spatial) shift, divided by the drop-off-area duration, or $W_{kidcte} = E_{kidcte}/H_{kidcte}$, where E_{kidcte} is drop-off-area total earnings. As with the pick-up area wage, W_{kidcts}, the drop-off area wage, W_{kidcte}, has the reasonable feature that for a given earnings amount in an area, the wage decreases either as the area trip length increases or as the wait time until the next trip increases.

All fixed effects have identical definitions as in equation (1), except that they are now specific to current trips originating in area o, current trips ending in area e, or subsequent

wait time) since the latter better captures the willingness to deviate from a trip's drop-off location. For instance, a driver willing to remain geographically close to the drop-off location and who eventually finds a subsequent fare there may experience a longer intervening wait time than a driver who actively seeks to depart the drop-off location and finds the next passenger at a distant location but relatively quickly.

trips starting in area s. Indicator α_o captures time-invariant factors at current trip start locations and thus helps to implement the quasi-experiment. Other indicators serve functions similar to their roles in equation (1), accounting for some anticipated variation in wages that likely contributes to differences in passenger demand and non-discriminatory driver supply. Lastly, ε is a trip-level error term, with standard errors clustered at the driver level.

As in estimation of (1), I will estimate equation (2) by IV (OLS results omitted for brevity) using instruments $\overline{lnW}_{kdcte}$ and $\overline{lnW}_{kdcts}$ for lnW_{kidcte} and lnW_{kidcts}, reflecting the average across drivers of the relevant log average area hourly earnings variable in the non-overlapping sample.[58] I use the sample of trips underlying the 3,744,057 area-specific shifts for 2,984 drivers from 2010–2015 shown in Table 1, applying a few additional restrictions on the trip sample, resulting in 1,097,819 trips.[59] If drivers respond to local economic opportunities in a baseline area with no minority representation, I expect $\beta_e < 0$ and $\beta_s > 0$. If supply-side discrimination based on area demographics also exists, I expect wage elasticity

[58] As in the paper's primary analysis, while I do not present first stage results, they are once again strong. In a basic version of model (1) from Table 5 with the interaction terms omitted, the first stage F-statistics reflecting the endogenous subsequent pick-up area wage and current drop-off area wage are 139 and 127, respectively. The coefficients on the two instruments in the two regressions range from 0.036 to 0.100, similar to the instrument coefficient of 0.034 in the basic version of paper's primary spatial analysis. Meanwhile, when considering the full equation (2) with twelve endogenous regressors, the Stock and Yogo (2005) weak instrument identification critical values for the maximal actual size of a 5 percent Wald test of the twelve wage instruments jointly being equal to zero are 43.27, 23.24, and 16.35 for maximal test sizes of 10, 15, and 20 percent, respectively. The joint F-statistic on the twelve instruments always exceeds the first or second critical values when estimated separately for each of twelve endogenous wage regressors in all but two cases (the wage interactions with the black share), where it still exceeds the third critical value.

[59] I drop trips that meet any of the following criteria: (1) trip is part of a non-spatial shift containing any trip with no drop-off location (all trips already have a start location, per inclusion in the paper's spatial analysis); (2) trip is part of a non-spatial shift containing any trip that does not end in Massachusetts; (3) trip has a missing value for the log intervening distance, $lnDES_{kidctoe}$ (including observations where the trip is the last route of a driver's non-spatial shift); (4) trip has a missing value for any component of either vector of demographic shares, $\mathbf{M}_e$ or $\mathbf{M}_s$; (5) trip has a missing value for either log area wage, lnW_{kidcte} or lnW_{kidcte} (that is, in cases where there area wage equals 0); (6) trip has a value of either log area wage, lnW_{kidcte} or lnW_{kidcts}, that exceeds \$25 (this restriction already holds for lnW_{kidcts}, per inclusion in the paper's spatial analysis); (7) trip has a missing value for either of the wage instruments, $\overline{lnW}_{kdcte}$ or $\overline{lnW}_{kdcts}$; and (8) trip(s) for which the most exhaustive set of fixed effects cannot be estimated. These restrictions result in 4,744,052 trips being dropped in the estimation sample. When I compare the log area wage and minority shares for the next trip in the estimation sample versus the sample of trips in non-spatial shifts with missing or out of state drop-off locations (that is, sample restrictions [1] and [2]), mean values of these variables are very similar. For instance, the mean log area wage for the subsequent trip pick-up location is 2.662 in the estimation sample, equivalent to approximately \$14.32, and 2.697, or approximately \$14.83, in the sample of trips dropped due to restrictions (1) and (2).

parameters $\eta_e > 0$ and $\eta_s < 0$, reflecting diminished wage sensitivity regarding intervening trip distance as the local population share of certain demographic groups increases.

Table 5 presents IV estimates from equation (2). Consistent with the earlier findings in Table 1 and likewise focusing on specification (4) here, the alternative analysis shows that the distance between the current trip drop-off location and the subsequent trip pick-up location responds positively (negatively) to the local wage at the subsequent pick-up (current drop-off) location. Regarding the subsequent pick-up area wage for example, a 1 percent increase in this wage increases the intervening trip distance by 2.66 percent. As the population share at the pick-up location increases for the female and Asian groups, such wage sensitivity is mitigated, consistent with the primary analysis. For instance, as the Asian share in the subsequent pick-up block group increases by 1 percentage point in Table 5 specification (4), the baseline intervening distance elasticity 2.66 declines by 0.0186, or 0.7 percent. If the subsequent pick-up Asian population share were to increase from 0 to 0.12, the mean value in the estimation sample, the baseline intervening distance elasticity would decline by about 0.22, or 8 percent, resulting in an intervening distance elasticity of 2.44. Thus, in response to a 10 percent increase in the pick-up area wage, intervening distance increases by 24 percent rather than 27 percent due to greater Asian representation. Given a mean pick-up area wage of \$14.32 and a mean intervening trip distance of 0.97 miles, on average, a \$1.43 increase in the pick-up wage leads to an increase of 0.26 miles between a driver's current drop-off location and the subsequent pick-up location when the latter is a baseline area, compared to an increase of 0.23 intervening miles in a pick-up area with the mean Asian population share, a disparity of 0.03 miles. In the non-spatial data, the median driving speed is 3 miles per hour.[60] The distance disparity of 0.03 miles therefore corresponds to approximately 36 seconds less area work (driving) time due to local demographics in an area with average Asian representation, comparable to the 27-second disparity in average area shift length

[60]Miles per hour is calculated based on the hourly average distance traveled with a passenger across each of the 58,464 clock hours in the taxi data from May 1, 2009 to December 31, 2015.

observed from a similar example in the primary analysis.[61]

However, unlike the primary analysis, I do not estimate any such labor supply discrimination for the black demographic group, and propose reasons for this below. Additionally, as hypothesized, I likewise do not estimate any labor supply discrimination regarding the current drop-off area wage. Assuming that this drop-off wage is more certain than the subsequent pick-up area wage for reasons already discussed, this result is also consistent with the previous findings in Table 4 showing that discrimination diminishes with increases in the reliability ratio proxy—the share of total wage variation that is anticipated and, thus, more certain.[62]

One reason for the lack of estimated discrimination regarding the black share is that some unobservables might remain unaccounted for in the IV estimation of equation (2) that result in a non-random sorting of drivers across trip drop-off locations, even conditional on the same trip origin location. For instance, perhaps some drivers only pick up passengers of a certain racial/ethnic group, gender, or age, all of which may vary even within the pick-up location of the current trip and could be observable to the driver but not to the researcher. While driver fixed effects would account for this supply-side behavior to an extent, such actions might vary even for a given driver (for example, based on demand for rides during a shift, or depending on driver experience). Such strategic behavior could bias the discrimination coefficients toward zero and, if relatively more problematic for the black group, could result in the appearance of no discrimination for this group when, in fact, discriminatory sorting would occur regarding who drivers pick up at a trip's start location.[63]

Another reason for no observed discrimination against the black demographic group might

[61] Alternatively, based on a driving speed of 8.2 miles per hour at the 90th percentile in the non-spatial data, the distance disparity of 0.03 miles corresponds to approximately 13 seconds less area work time due to local demographics in an area with average Asian representation.

[62] Due to correlation between the drop-off area wage variables and the subsequent pick-up area wage variables, I do not estimate equation (2) with pick-up variables only, as this would result in biased coefficients.

[63] To try to address such concerns, following Haggag and Paci (2014), I try limiting estimation to only trips that originate from Logan Airport. For such trips, customers and drivers queue at taxi stand lines, ensuring a more quasi-random pairing of drivers and drop-off locations. Unfortunately, such analysis results in only 32,105 trips. This sample is too small to perform credible estimation of equation (2), as the first stage becomes quite weak and the coefficients, now potentially biased, also become very imprecise.

be that, for this group compared to the others, notably less of the total variance in the drop-off location population share occurs conditional on the pick-up location (that is, "within" variation), as opposed to across pick-up locations (that is, "between" variation). Specifically, the "within" share is 57.7 percent for the black group, and ranges from 93.4 percent (female) to 98.7 percent (age 65 years and older) for the other four demographic groups. This leaves much less identifying wage variation (when interacted with demographic group shares) with which to estimate discriminatory behavior towards the black group using the research design in this additional analysis, especially since the analysis is restricted to mainly unanticipated wage variation. More substantively, these variance decomposition findings indicate that trip pick-up locations explain area demographics much more for black residents than for other groups.[64]

9 Conclusion

This paper tests for the presence of supply-side discrimination in the labor market for Boston cab drivers. I find evidence of supply-side discrimination, in the form of wage elasticities that are 5 to 7 percent lower as the area population share of female, black, or Asian residents at trip pick-up locations increases by 1 percentage point (that is, 2 to 11 percent of the area share sample mean, depending on the demographic group). I find that this discrimination regarding a driver's willingness to work longer searching for the next fare, in response to largely unanticipated wage changes, is primarily statistical rather than taste-based, especially for black and Asian residents. As drivers learn with experience and are better able to

[64]This result could be demand-driven, supply-driven, or both. Regarding a demand-side explanation, perhaps taxi trip requests from passengers are relatively more likely (or less likely, if negatively correlated) to originate from places of residence versus other locations for black passengers. Alternatively, regarding a supply-side explanation, perhaps taxi trip acceptances and/or searching by drivers occurs relatively more frequently (or less frequently, if negatively correlated) at places of residence versus other locations for black passengers. To the extent that the result is supply-driven *and* discriminatory, however, it cannot be identified by the research design of this supplementary analysis, which does not utilize "between" variation. An additional caveat regarding the interpretation of results, as in the primary estimation, is that the supplementary analysis generally cannot assess the extent of discrimination based on anticipated wage variation, as the identifying variation is primarily based on unanticipated wage variation. Nevertheless, the findings of this additional, trip-level analysis lend support to the validity of the paper's main approach and findings.

anticipate wage variation in areas, they discriminate less. However, such spatial learning takes time and seems to occur at a slower rate than non-spatial learning regarding the optimal duration of shifts in response to wage variation.

In addition to the finding that individuals learn to optimize across both time and space but at different rates, the paper's results also have important policy implications. Unequal taxi route service in Boston stemming primarily from statistical discrimination due to wage uncertainty suggests that a helpful recourse to reduce such uncertainty might be some form of incentivized training to increase driver knowledge of consumer demand across neighborhoods. Infrastructure changes to broaden transportation options in underserved areas may also be desirable, in order to compensate for differences in taxi access in instances when driver information about local wages is low.

More generally, this study adds to our knowledge of the extent to which adjustments in hours worked result not only from the wages faced, but also from non-price determinants like individual preferences or uncertainty. This worker response is important to understand, particularly given large numbers of part-time, self-employed, and "gig" economy workers who may have the ability to make such adjustments to their work hours. The findings reported in this paper can thus aid our exploration of potential discrimination on the supply side of the labor market in other industries where workers have flexibility over their hours and may face non-trivial uncertainty regarding the potential buyers of their labor or be able to use their market power to exercise certain preferences regarding those buyers. Further work might examine other transportation industries like ridesharing (adding to the work by Ge et al. 2016), or non-transportation industries, to see if similar behavior is exhibited. Exploring whether supply-side labor market discrimination exists on the extensive margin of hours worked would also be of interest.

References

Aigner, Dennis J., and Glen G. Cain. 1977. "Statistical Theories of Discrimination in the Labor Market." *Industrial and Labor Relations Review* 30(2): 175–187.

Altonji, Joseph G. 1986. "Intertemporal Substitution in Labor Supply: Evidence from Micro Data." *Journal of Political Economy* 94(3): S176–S215. Part 2: Hoover Institution Labor Conference.

Altonji, Joseph G., and Rebecca M. Blank. 1999. "Race and Gender in the Labor Market." In Ashenfelter, Orley C. and David Card, eds., *Handbook of Labor Economics*, Vol. 3C, Amsterdam: Elsevier.

Altonji, Joseph G., and Charles R. Pierret. 2001. "Employer Learning and Statistical Discrimination." *Quarterly Journal of Economics* 116(1): 313–350.

Angrist, Joshua D., and Alan B. Krueger. 1995. "Split-Sample Instrumental Variables Estimates of the Return to Schooling." *Journal of Business & Economic Statistics* 13(2): 225–235.

Austin, Drew, and P. Christopher Zegras. 2012. "Taxicabs as Public Transportation in Boston, Massachusetts." *Transportation Research Record* 2277: 65–74.

Becker, Gary S. 1957. *The Economics of Discrimination.* Chicago: University of Chicago Press.

Boston Planning & Development Agency. 2010. *2010 Census Tracts & Neighborhoods.* Available at http://www.bostonplans.org/getattachment/d09af00c-2268-437b-9e40-fd06d0cd20a2.

Cain, Glen G. 1986. "The Economic Analysis of Labor Market Discrimination: A Survey." In *Handbook of Labor Economics*, Vol. 1, ed. Orley C. Ashenfelter and Richard Layard, 693–785. Amsterdam: Elsevier.

Camerer, Colin, Linda Babcock, George Loewenstein, and Richard Thaler. 1997. "Labor Supply of New York City Cabdrivers: One Day at a Time." *Quarterly Journal of Economics* 112(2): 407–441.

Correia, Sergio. 2016. "Linear Models with High-Dimensional Fixed Effects: An Efficient and Feasible Estimator." Working Paper. Durham, NC: Duke University.

Crawford, Vincent P., and Juanjuan 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(5): 1912–1932.

Farber, Henry S. 2005. "Is Tomorrow Another Day? The Labor Supply of New York City Cabdrivers." *Journal of Political Economy* 113(1): 46–82.

Farber, Henry S. 2015. "Why You Can't Find a Taxi in the Rain and Other Labor Supply Lessons from Cab Drivers." *Quarterly Journal of Economics* 130(4): 1975–2026.

Farber, Henry S., and Robert Gibbons. 1996. "Learning and Wage Dynamics." *Quarterly Journal of Economics* 111(4): 1007–1047.

Ge, Yanbo, Christopher R. Knittel, Don MacKenzie, and Stephen Zoepf. 2016. "Racial and Gender Discrimination in Transportation Network Companies." Working Paper No. 22776. Cambridge, MA: National Bureau of Economic Research.

Haggag, Kareem, Brian McManus, and Giovanni Paci. 2017. "Learning By Driving: Productivity Improvements by New York City Taxi Drivers." *American Economic Journal: Applied Economics* 9(1): 70–95.

Haggag, Kareem, and Giovanni Paci. 2014. "Default Tips." *American Economic Journal: Applied Economics* 6(3): 1–19.

MaCurdy, Thomas E. 1981. "An Empirical Model of Labor Supply in a Life-Cycle Setting." *Journal of Political Economy* 89(6): 1059–1085.

Minnesota Population Center. 2010. *National Historical Geographic Information System: Version 2.0* Minneapolis, MN: University of Minnesota.

Nelson\Nygaard Consulting Associates. 2013. "The City of Boston Taxi Consultant Report." Available at http://nelsonnygaard.com/wp-content/uploads/2014/05/BOSTON-Taxi-Consultant-RPT.pdf.

Peterman, William B. 2016. "Reconciling Micro and Macro Estimates of the Frisch Labor Supply Elasticity: A Sensitivity Analysis." *Economic Inquiry* 54(1): 100–120.

Phelps, Edmund S. 1972. "The Statistical Theory of Racism and Sexism." *American Economic Review* 62(4): 659–661.

Stock, James, and Motohiro Yogo. 2005. "Testing for Weak Instruments in Linear IV Regression." In *Identification and Inference for Econometric Models: Essays in Honor of Thomas J. Rothenberg*, ed. James H. Stock and Donald W. K. Andrews, 80–108. Cambridge: Cambridge University Press.

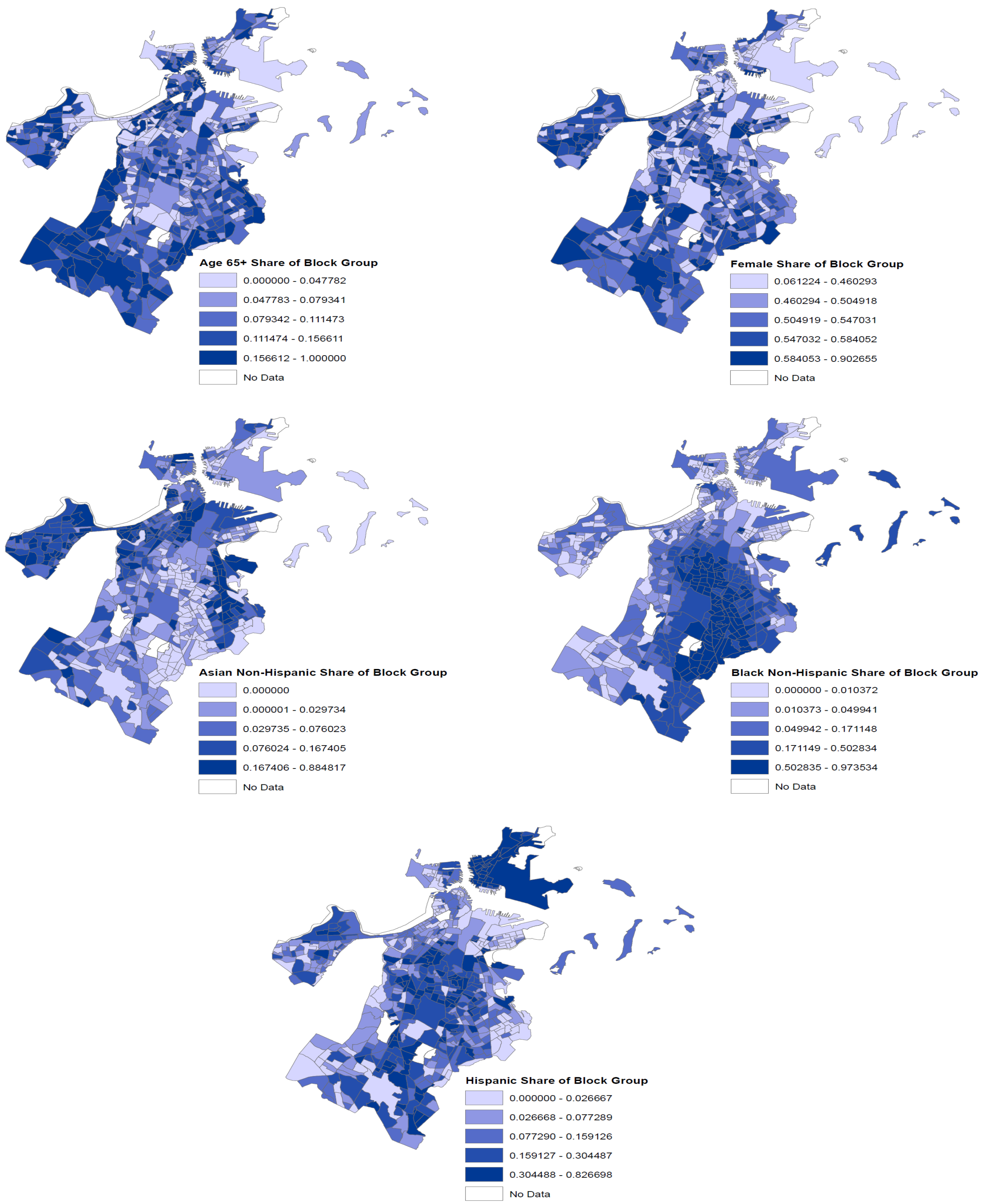

Figure 1: Boston Block Group 2010 Population Shares, by Demographic Group and Quintile
Source: 2010 U.S. Census and author's calculations.

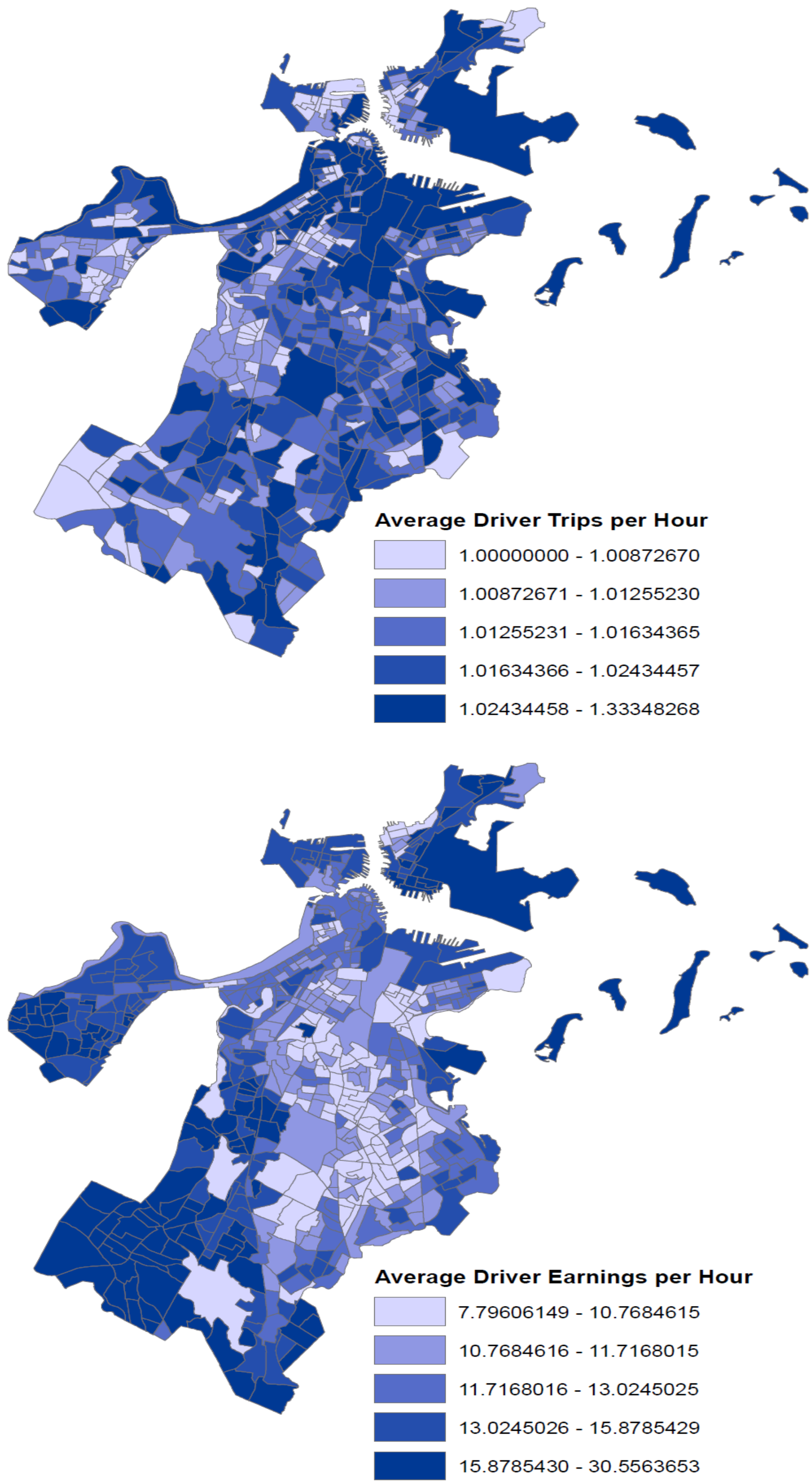

Figure 2: Boston Block Group 2010–2015 Average Hourly Driver Trips and Earnings, by Quintile

Source: Boston taxi data and author's calculations.

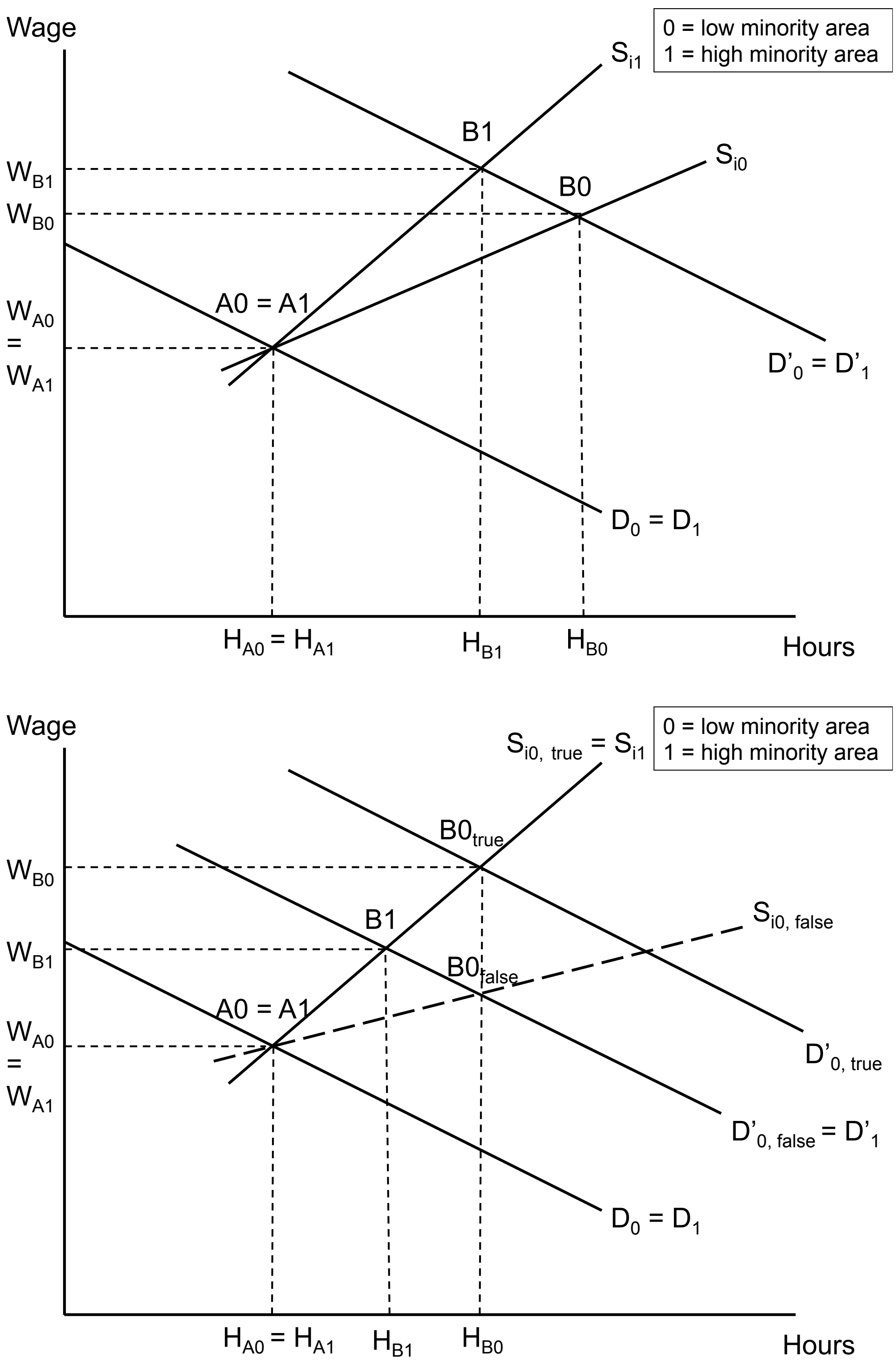

Figure 3: Valid and Invalid Identification of Driver i's Labor Supply Across Areas
Source: Author's illustrations.

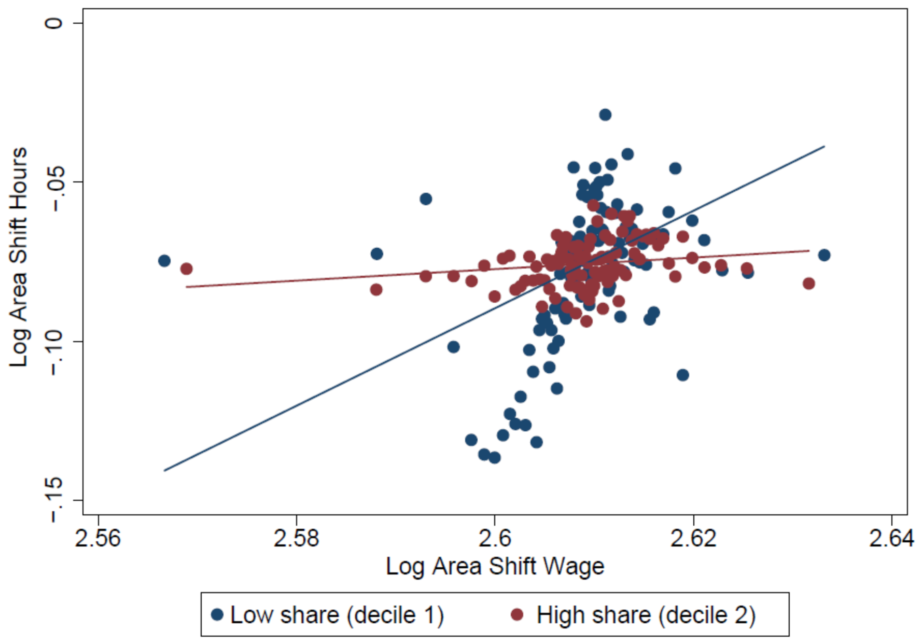

Figure 4: Driver Labor Supply Across Areas, IV Estimates by Female Population Share
Source: Boston taxi data, 2010 U.S. Census, and author's calculations.

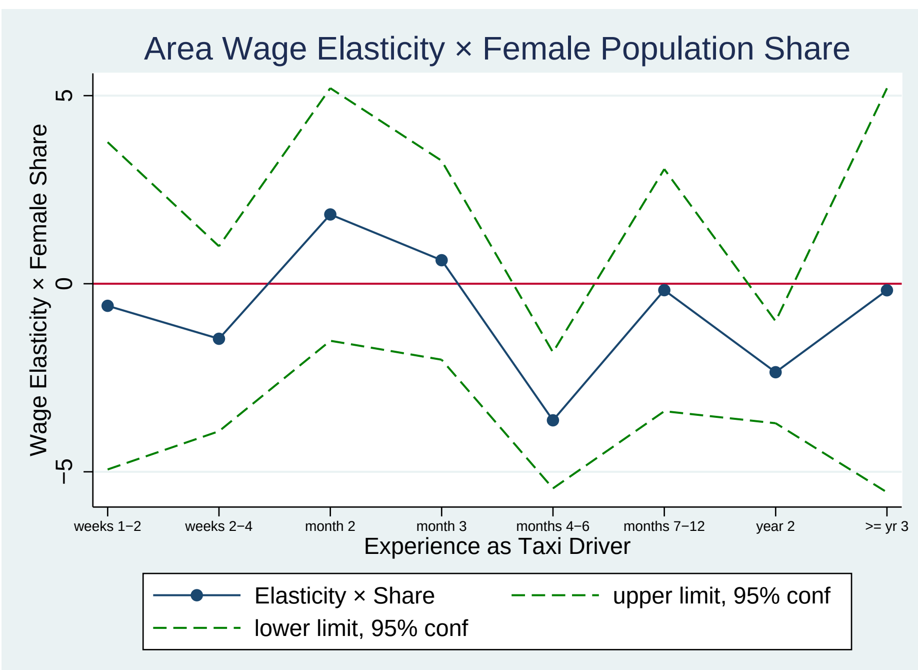

Figure 5: Area Wage Elasticity of Labor Supply x Area Population Shares, IV Estimates by Experience (New Drivers with More than 28 Non-Spatial Shifts)
Source: Boston taxi data, 2010 U.S. Census, and author's calculations.

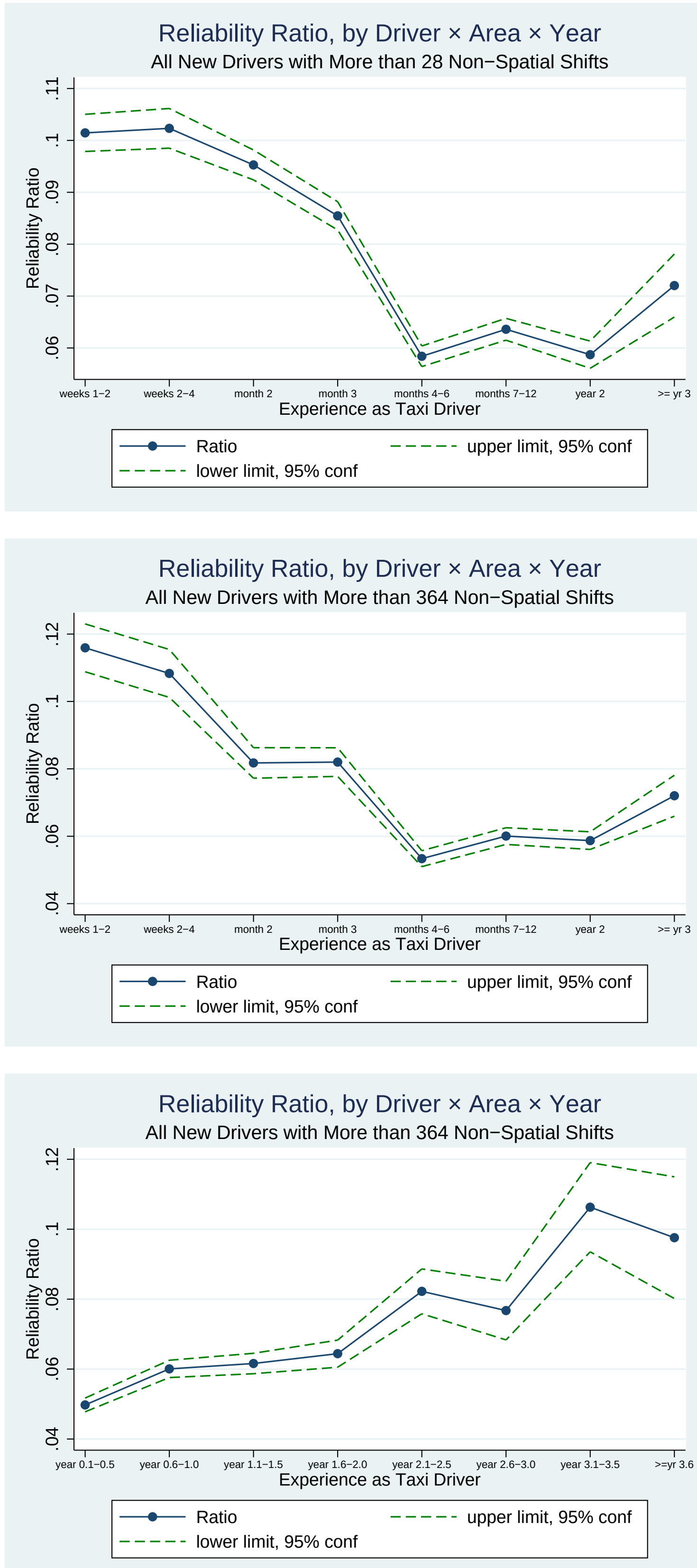

Figure 6: Reliability Ratio Mean, by Experience (New Drivers as Indicated)
Source: Boston taxi data, 2010 U.S. Census, and author's calculations.

Table 1: Area Wage Elasticity and Area Wage Elasticity × Area Population Shares, Regressions of Log Area Shift Duration in Hours

Model (OLS)	(1)	(2)	(3)	(4)
Key F.E.'s	Area	Area × Year	Area × Year, Driver	Area × Year, Driver × Area
Elasticity	–0.370***	–0.372***	–0.350***	–0.441***
	(0.016)	(0.016)	(0.015)	(0.012)
× Female	–0.264***	–0.262***	–0.264***	–0.129***
	(0.029)	(0.029)	(0.027)	(0.025)
× Black	–0.020	–0.017	–0.047**	–0.036
	(0.024)	(0.023)	(0.024)	(0.024)
× Asian	–0.077***	–0.073***	–0.076***	–0.063***
	(0.022)	(0.022)	(0.021)	(0.022)
× Hispanic	0.476***	0.464***	0.400***	0.315***
	(0.033)	(0.032)	(0.032)	(0.027)
× Age 65+	0.029	0.029	0.017	–0.045**
	(0.026)	(0.026)	(0.025)	(0.022)

Model (IV)	(1)	(2)	(3)	(4)
Key F.E.'s	Area	Area × Year	Area × Year, Driver	Area × Year, Driver × Area
Elasticity	0.169	0.100	0.080	0.100
	(0.127)	(0.137)	(0.130)	(0.118)
× Female	–0.925***	–0.712***	–0.700***	–0.488**
	(0.237)	(0.257)	(0.247)	(0.218)
× Black	–0.846***	–0.574**	–0.628**	–0.579**
	(0.261)	(0.293)	(0.294)	(0.262)
× Asian	–0.616***	–0.464**	–0.415**	–0.593***
	(0.195)	(0.213)	(0.206)	(0.188)
× Hispanic	1.011***	0.110	0.124	0.543
	(0.334)	(0.409)	(0.404)	(0.365)
× Age 65+	0.130	0.194	0.165	0.235
	(0.175)	(0.187)	(0.176)	(0.154)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Author's calculations using Boston taxi data. Each column displays a set of estimated elasticities from a single OLS or IV regression of log area shift duration, as noted. "Elasticity" is the estimated coefficient of log area average hourly earnings, where an "area" is a 2010 U.S. Census block group. "× 'Group' " is the estimated coefficient of log area average hourly earnings interacted with a vector of demographic group area population shares, where "Group" is either female, black non-Hispanic, Asian non-Hispanic, Hispanic, or 65 years of age and older. In IV regressions, the instrument for log area average hourly earnings is the log average across drivers of area average hourly earnings for a non-overlapping sample of drivers on the same day and in the same area, with additional instruments also interacted with "Group." All regressions include an indicator for major holiday (1) as a control. Model 1's additional controls are indicators for day of week (6), calendar week (51), year (5), and area (668). Model 2 replaces Model 1's additional controls with indicators for day of week × year (41), calendar week × year (306), and area × year (3,570). Model 3 has all of Model 2's additional controls plus indicators for driver (2,983). Model 4 has all of Model 2's additional controls plus indicators for driver × area (241,090). Estimated using a sample of 3,744,057 area-specific shifts for 2,984 drivers from 2010–2015. Standard errors clustered by driver are in parentheses.

Table 2: Robustness Checks, IV Regressions of Log Area Shift Duration in Hours

Model	(1)	(2)	(3)	(4)
Description	Tips, All Shifts	Tips, CC Shifts	Education, HS Diploma	Time F.E.'s, AM/PM
Elasticity	0.231**	0.380***	0.044	0.082
	(0.104)	(0.145)	(0.127)	(0.119)
× Female	–0.704***	–0.605**	–0.445**	–0.446**
	(0.196)	(0.280)	(0.225)	(0.222)
× Black	–0.530**	–0.737**	–0.719**	–0.594**
	(0.258)	(0.313)	(0.296)	(0.271)
× Asian	–0.455***	–0.996***	–0.677***	–0.582***
	(0.163)	(0.232)	(0.215)	(0.188)
× Hispanic	0.501	0.799	0.518	0.579
	(0.314)	(0.585)	(0.367)	(0.364)
× Age 65+	0.105	–0.063	0.269*	0.190
	(0.138)	(0.197)	(0.162)	(0.154)
× Education			0.392	
			(0.311)	
Area Shifts	3,744,057	1,792,521	3,744,057	3,730,676
Drivers	2,984	2,877	2,984	2,983

Model	(5)	(6)	(6) *continued*	(7)
Description	Time F.E.'s, Hour	Elasticity, Wage	Elasticity, Cost (Distance)	Expanded Sample
Elasticity	0.104	1.322***	–1.313***	–0.657***
	(0.116)	(0.365)	(0.264)	(0.022)
× Female	–0.450**	–1.347**	0.803*	0.031
	(0.218)	(0.624)	(0.449)	(0.039)
× Black	–0.577**	–1.335*	0.932	–0.140***
	(0.285)	(0.781)	(0.577)	(0.019)
× Asian	–0.630***	–1.448**	0.951*	–0.342***
	(0.189)	(0.679)	(0.494)	(0.031)
× Hispanic	0.577	1.275	–0.899	–0.057*
	(0.376)	(1.115)	(0.815)	(0.032)
× Age 65+	0.157	0.002	0.130	0.301***
	(0.155)	(0.429)	(0.309)	(0.033)
Area Shifts	3,730,676		3,263,915	8,429,180
Drivers	2,983		2,943	3,040

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Author's calculations using Boston taxi data from 2010–2015. Each model displays a set of estimated elasticities from a single IV regression of log area shift duration, as noted. "Elasticity" is the estimated coefficient of log area average hourly earnings, where an "area" is a 2010 U.S. Census block group. "× 'Group' " is the estimated coefficient of log area average hourly earnings interacted with a vector of demographic group area population shares, where "Group" is either female, black non-Hispanic, Asian non-Hispanic, Hispanic, or 65 years of age and older. The instrument for log area average hourly earnings is the log average across drivers of area average hourly earnings for a non-overlapping sample of drivers on the same day and in the same area, with additional instruments also interacted with "Group." All regressions include as controls indicators for major holiday, day of week × year, calendar week × year, area × year, and driver × area. Singleton observations (area shifts) within a given fixed effect indicator are dropped. In models (1) and (2), average hourly earnings include tips, and model (2) restricts to shifts where at least one trip per shift is paid for by credit card. In model (3), "Group" is also the educational attainment level (a high school diploma) for those 25 years of age and older. Indicators for time-of-day are included in model (4) (AM vs PM) and model (5) (hour-of-day), interacted with the indicators for day of week × year, calendar week × year, and area × year. Model (6) includes an estimate of log average area hourly trip distance (using trip start and end location pairings when both are available, rounded to two-decimal point latitude-longitude coordinates, and estimating trip routes via an Open Source Routing Machine at `http://project-osrm.org`) as a proxy for area hourly costs. Model (7) expands the sample to include area wages above $25. Standard errors clustered by driver are in parentheses.

Table 3: Variance Decomposition of Area Wage Elasticity × Area Population Shares, IV Regressions of Log Area Shift Duration in Hours, By Driver-Region-Experience

		Total Variance		
Wage Elasticity × Pop. Share ($\hat{\eta}_{ire}$)	Mean	Proportion Within Driver-Regions	Proportion Across Regions, Given Driver	Proportion Across Drivers, Region-Invariant
Female	–0.539	0.858	0.125	0.017
Black	–0.057	0.909	0.039	0.052
Asian	–0.376	0.676	0.301	0.023

Notes: Author's calculations using Boston taxi data. Based on 4,182 IV regressions from 2011–2015 of log area shift duration, stratified by driver-region-experience bins of 50 or more area shifts, on log area average hourly earnings and log area average hourly earnings interacted with one demographic group area population share. The demographic groups for each set of regressions are female, black non-Hispanic, and Asian non-Hispanic (the Hispanic and 65 years of age and older groups are omitted from the table given their lack of significance in Table 1, column (2)). These regressions estimate 4,182 $\hat{\eta}_{ire}$ terms, where i is driver, r is region, and e is experience. A "driver" is a new taxi driver whose first shift in the data does not occur for at least one year, starting in January 2011. A "region" is a large Boston neighborhood or Massachusetts county, as discussed in the Appendix. An "experience" period occurs every six weeks of experience, where a week is defined as seven non-spatial shifts. The instrument for log area average hourly earnings is the log average across drivers of area average hourly earnings for a non-overlapping sample of drivers on the same day and in the same area. All regressions include the same controls as Table 1, column (1). There are two stages for the decomposition: 1) OLS regression of $\hat{\eta}_{ire}$ on driver × region fixed effects; 2) OLS regression of the predicted values from the first regression on driver fixed effects. "Mean" is the average $\hat{\eta}_{ire}$, weighted by the inverse sampling variance of each $\hat{\eta}_{ire}$. "Total Variance" is the raw total variance of $\hat{\eta}_{ire}$. "Proportion Within Driver-Regions" is the variance of the residuals from the first regression divided by the total variance. "Proportion Across Regions, Given Driver" and "Proportion Across Drivers, Region-Invariant" are the variances of the residuals and predicted values, respectively, from the second regression, each divided by the total variance.

Table 4: Area Wage Elasticity × Area Population Shares × Reliability Ratio,
IV Regressions of Log Area Shift Duration in Hours

Model	(1)	(2)	(3)	(4)
Key F.E.'s	Area	Area × Year	Area × Year, Driver	Area × Year, Driver × Area
Elasticity	0.160	0.102	0.094	0.119
	(0.134)	(0.134)	(0.130)	(0.118)
× Female	–0.850***	–0.629**	–0.636**	–0.484**
	(0.249)	(0.250)	(0.250)	(0.226)
× Black	–0.950***	–0.687**	–0.698**	–0.601**
	(0.297)	(0.325)	(0.315)	(0.289)
× Asian	–0.708***	–0.581***	–0.551***	–0.673***
	(0.197)	(0.214)	(0.212)	(0.188)
× Hispanic	1.275***	0.354	0.321	0.669*
	(0.367)	(0.451)	(0.421)	(0.365)
× Age 65+	0.118	0.166	0.161	0.244
	(0.174)	(0.195)	(0.179)	(0.151)
× Female × $\widehat{\text{RR}}$	0.097	0.037	0.019	0.092
	(0.072)	(0.076)	(0.073)	(0.065)
× Black × $\widehat{\text{RR}}$	0.267***	0.198**	0.167**	0.168**
	(0.074)	(0.082)	(0.081)	(0.077)
× Asian × $\widehat{\text{RR}}$	0.081	0.047	0.062	0.138***
	(0.056)	(0.059)	(0.056)	(0.047)
× Hispanic × $\widehat{\text{RR}}$	–0.092	0.154	0.077	–0.024
	(0.106)	(0.129)	(0.119)	(0.096)
× Age 65+ × $\widehat{\text{RR}}$	0.101	0.077	0.047	–0.105**
	(0.062)	(0.068)	(0.063)	(0.046)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Author's calculations using Boston taxi data. Each column displays a set of estimated elasticities from a single IV regression of log area shift duration, as noted. "Elasticity" is the estimated coefficient of log area average hourly earnings, where an "area" is a 2010 U.S. Census block group. "× 'Group' " is the estimated coefficient of log area average hourly earnings interacted with a vector of demographic group area population shares, where "Group" is either female, black non-Hispanic, Asian non-Hispanic, Hispanic, or age 65 years of age and older. "× 'Group' × $\widehat{\text{RR}}$" is the estimated coefficient of log area average hourly earnings interacted with a vector of demographic group area population shares interacted with a reliability ratio measure. The numerator of the reliability ratio is the sample variance of anticipated log area average hourly earnings by area-year, $\widehat{Var}(AlnW)_{at}$, where a day × calendar week × year × area estimate of anticipated log area average hourly earnings, $\widehat{AlnW}_{dcta}$, is obtained from the predicted values of an OLS regression of lnW_{kidcta} on indicators for day of week, calendar week, year, area, and major holiday. The denominator of the reliability ratio is the sum of the sample variance of anticipated log area average hourly earnings by area-year, $\widehat{Var}(AlnW)_{at}$, and the sample variance of unanticipated log area average hourly earnings by driver-area-year, $\widehat{Var}(UlnW)_{iat}$, where a shift × driver × day × calendar week × year × area estimate of unanticipated log area average hourly earnings, $\widehat{UlnW}_{kidcta}$, is obtained from the residuals of the aforementioned OLS regression of lnW_{kidcta} on indicators for day of week, calendar week, year, area, and major holiday. The instrument for log area average hourly earnings is the log average across drivers of area average hourly earnings for a non-overlapping sample of drivers on the same day and in the same area, with additional instruments also interacted with "Group" and "Group" × $\widehat{\text{RR}}$. All regressions include the reliability ratio and an indicator for major holiday as controls. Additional controls for Models 1 to 4 are as defined in Table 1. Estimated using a sample of 3,506,148 area-specific shifts for 2,957 drivers from 2010–2015. This sample differs from the Table 1 sample because for 237,909 area-specific shifts (and 27 drivers), there are not multiple observations with which to calculate at least one of the necessary sample variances for the reliability ratio. Bootstrapped standard errors clustered by driver are in parentheses (1,000 replications per specification).

Table 5: Alternative Area Wage Elasticity and Alternative Area Wage Elasticity × Area Population Shares, Trip-Level IV Regressions of Log Intervening Trip Distance in Miles

Model	(1)	(2)	(3)	(4)
Key F.E.'s	Area	Area × Year	Area × Year, Driver	Area × Year, Driver × Area
End Elasticity	–2.228	–2.166	–1.854	–1.716*
	(1.359)	(1.637)	(1.369)	(1.042)
× Female	–2.307	–1.846	–1.582	–0.710
	(1.724)	(1.577)	(1.413)	(1.116)
× Black	1.793	2.293**	1.897*	0.847
	(1.132)	(1.098)	(1.015)	(0.712)
× Asian	0.419	0.583	0.217	0.597
	(1.406)	(1.283)	(1.149)	(0.840)
× Hispanic	0.975	0.860	0.492	0.990
	(1.847)	(2.040)	(1.722)	(1.322)
× Age 65+	2.169*	1.930	1.485	1.055
	(1.206)	(1.304)	(1.131)	(0.949)
Start Elasticity	3.946***	4.256**	3.547**	2.659**
	(1.205)	(1.784)	(1.499)	(1.336)
× Female	–2.243*	–3.866***	–3.014**	–1.856*
	(1.202)	(1.487)	(1.254)	(1.033)
× Black	–1.687	–1.936	–1.712	–0.540
	(1.231)	(1.231)	(1.087)	(0.896)
× Asian	–1.217	–0.608	–0.709	–1.858*
	(1.322)	(1.349)	(1.169)	(1.113)
× Hispanic	2.419*	3.824**	3.274**	0.418
	(1.451)	(1.510)	(1.300)	(0.984)
× Age 65+	–0.157	0.106	–0.240	–0.008
	(0.784)	(0.872)	(0.733)	(0.565)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Author's calculations using Boston taxi data. Each column displays a set of estimated elasticities from a single IV regression of log intervening trip distance, as noted. " 'Location' Elasticity" is the estimated coefficient of log area average hourly earnings, where an "area" is a 2010 U.S. Census block group, and "Location" is either the current trip ending block group ("End") or the next trip starting block group ("Start"). "× 'Group' " is the estimated coefficient of log area average hourly earnings interacted with a vector of demographic group area population shares, where "Group" is either female, black non-Hispanic, Asian non-Hispanic, Hispanic, or 65 years of age and older, and "area" corresponds to "End" or "Start" as indicated. The instrument for log area average hourly earnings is the log average across drivers of area average hourly earnings for a non-overlapping sample of drivers on the same day and in the same area ("end" or "start"), with additional instruments also interacted with "Group." All regressions include an indicator for major holiday as a control. Model 1's additional controls are indicators for day of week, calendar week, year, and area (three area types: current trip start [origin], current trip end, and next trip start). Model 2 replaces Model 1's additional controls with indicators for day of week × year, calendar week × year, and area × year (for each of the three area types). Model 3 has all of Model 2's additional controls plus indicators for driver. Model 4 has all of Model 2's additional controls plus indicators for driver × area (for each of the three area types). The sample is estimated using 1,097,819 trips for 2,386 drivers from 2010–2015. Standard errors clustered by driver are in parentheses.

A Appendix

A.1 Spatial Analysis: Labor Supply Models with Discrimination

A.1.1 Taste-Based Discrimination

Let $j = 0, 1$ serve to index demographic group concentration, where 0 denotes a low minority share and 1 indicates a high minority share, $p = 0, 1$ indexes large geographic places, and $i = 1, ..., N$ indicates cab drivers. Places have no demographic profile unless paired with groups to form "areas" a (group-place pairings). I assume: 1) driver utility is intertemporally separable, and 2) driver period-specific utility functions are identical. Assumption 2 simplifies the setup but could be relaxed if desired. Assumption 1, while strong, allows for two stage budgeting, where in stage 1, a driver allocates total per period consumption and leisure/labor across periods, and in stage 2, a driver allocates total within-period consumption and leisure/labor between those two choice variables.

I focus on the stage 2 problem for a given period t, thereby suppressing time notation. In choosing total leisure and labor within a period, a driver also simultaneously decides across which areas to allocate labor. The driver i problem is:

$$\max_{C_i, H_{i1}, ..., H_{iA}} U = U(C_i, H_{i1}, ..., H_{iA}),$$

where C is consumption and H_a is hours driven in area a. If T is defined as the total available hours within a period (for example, 24 hours in a day), H is total hours, and L is leisure, $T = H_i + L_i = \sum_a H_{ia} + L_i$ and is fixed. In words, driver i's choice regarding the amount of leisure time pins down the amount of total hours driven, which is jointly determined with how those labor hours are allocated across areas, so in the driver problem, labor hours can be used as the choice variables instead of leisure.

For simplicity but without loss of generality, assume that there are only two areas: $a = 0 \equiv \{j = 0, p = 0\}$ (a low minority share-place 0 pairing), and $a = 1 \equiv \{j = 1, p = 1\}$ (a high minority share-place 1 pairing).[65] The cost to driver i of not supplying labor to a given area a is $H_{ia}(W_a - d_{ia})$, where W_a is the area wage, common to *all* drivers (that is, the area wage is demand-driven, so it varies by area a but not driver by i), and d_{ia} is area-specific distaste on the part of driver i, where $\forall i$, $d_{i0} = 0$ and $d_{i1} \neq 0$. In words, d_{ia} measures the strength of prejudice for area a by driver i due to area a's minority composition. This area-specific distaste lowers the cost of *not* working in that area.[66]

For a high-minority area (here, area 1), there is a distribution of distaste parameters d_{i1} across drivers, $f_1(d)$. In a low-minority area (here, area 0), the distribution of distaste parameters across drivers is degenerate at 0. Also, for a given driver (for example, driver 1), there is a distribution of distaste parameters d_{1a} across areas, $g_1(d)$. Thus, the heterogeneity of discrimination across drivers or areas, respectively, is captured by the f and g distributions. Within the driver-area dimension, there is no variation in distaste.

[65] In other words, $\{j = 0, p = 1\}$ and $\{j = 1, p = 0\}$ pairings do not exist.

[66] Even without time notation suppressed, d_{ia} is assumed to be time-invariant. While discrimination preferences might change over time for some individuals, it seems plausible to assume that they are stable for Boston cab drivers given the older age of this population (see Table A2).

The extensive margin choice to supply any labor in an area will be dependent on the area-specific wage net of the distaste ($W_a - d_{ia}$) being greater than some driver-specific reservation wage, r_i, constant across areas. Assuming an interior solution, the within-period tradeoff between hours worked in a low minority area and a high minority area is:

$$\frac{\partial U(C_i, H_{i1}, ..., H_{iA})/\partial H_{i0}}{\partial U(C_i, H_{i1}, ..., H_{iA})/\partial H_{i1}} = \frac{W_0}{W_1 - d_{i1}}.$$

If I assume a functional form for U, using MaCurdy (1981) as a guide, I can specify $U(C_i, H_{i1}, ..., H_{iA}) = \gamma_i C_i^{\omega_c} - (\sum_a \phi_{ia} H_{ia}^{\omega_a})$. Here, ω is related to how consumption and hours are substituted across periods, where ω_a specifically relates to the intertemporal wage elasticity of substitution for area a, $\beta_a = 1/(\omega_a - 1)$. Additionally, γ and ϕ represent taste shifters that vary across individuals or individual-area pairings, respectively, and are unrelated to area-specific discrimination. The within-period hours tradeoff across areas is now:

$$\frac{\omega_0 \phi_{i0} H_{i0}^{\omega_0 - 1}}{\omega_1 \phi_{i1} H_{i1}^{\omega_1 - 1}} = \frac{W_0}{W_1 - d_{i1}} \Leftrightarrow \frac{H_{i0}^{\omega_0 - 1}}{H_{i1}^{\omega_1 - 1}} = \frac{\omega_1 \phi_{i1} W_0}{\omega_0 \phi_{i0}(W_1 - d_{i1})}.$$

Without trying to simplify this expression further, it is already apparent that the hours differential across low and high minority areas for driver i will be related to the wage difference across areas, the distaste for the high minority area by driver i, the intertemporal elasticity, as well as any driver-specific tastes that are not related to discrimination. I can impose the simplifying assumptions that non-discriminatory, driver-specific tastes do not differ across areas ($\phi_{i0} = \phi_{i1}$), and that the parameter related to the intertemporal elasticity also does not differ across areas ($\omega_0 = \omega_1 = \omega$), resulting in:

$$\ln\left(\frac{H_{i0}}{H_{i1}}\right) = \beta \ln\left(\frac{W_0}{W_1 - d_{i1}}\right),$$

where the log hours differential across areas for driver i is a function of the log differential in wages across areas net of any driver-area-specific discriminatory tastes, scaled by the intertemporal, net-of-discrimination wage elasticity, $\beta = 1/(\omega - 1)$. In the absence of discrimination ($d_{i1} = 0$), differences in hours across areas are fully explained by differences in wages, and $\beta = \beta_0$ is the observed wage elasticity. In this case, while there may be an intercept difference in driver labor supply across areas, there will not be a slope difference, as β_0 will be the same regardless of minority representation in an area.[67]

However, with discrimination present ($d_{i1} \neq 0$), now a slope difference across areas is expected, as higher values of wages in the minority area, W_1, are now required to obtain the same work hours as before, H_{i1}. In other words, β_0 is no longer the observed wage elasticity in this case since β now incorporates the unobserved wage net of discrimination in the minority area, $\widetilde{W}_{i1} = W_1 - d_{i1}$. The observed elasticity, β_1, which summarizes the

[67] While technically not identifying a disparity in labor supply at the x-axis, I nevertheless refer to a "level" disparity in hours at a given set of wages as the intercept difference. Similarly, while specifically identifying an elasticity difference in labor supply, I refer to a "change" disparity in hours across various sets of wages as the slope difference. The signs of the slope and elasticity parameters will be the same.

relationship between observed wages (W_0, W_1) and hours (H_{i0}, H_{i1}) with discrimination present, is smaller than β_0, reflecting diminished wage sensitivity in the minority area due to discrimination.

A.1.2 Statistical Discrimination

Let $j = 0, 1$ serve to index demographic group concentration, where 0 is a low minority share and 1 is a high minority share, $p = 0, 1$ indexes large geographic places, and $i = 1, ..., N$ indicates cab drivers. Once again, places have no demographic profile unless paired with groups to form "areas" (group-place pairings).

Define a_{pj} as the component of the log wage anticipated by *all* drivers (the log wage is demand-driven and varies by place p and group j, not driver i), w_{ipj} is the realized ("measured") log wage faced by driver i (an imperfect indicator of a_{pj}), and u_{ipj} is the component of the log wage unanticipated by driver i ("errors," driven by both demand and supply). Let $w_{ipj} = a_{pj} + u_{ipj}$, with $E(u_{ipj}|a_{pj}, j, p) = 0$. Thus, u_{ipj} is uncorrelated with: 1) anticipated wage a_{pj} (classical measurement error), 2) minority share j ("errors" are unbiased, that is, no distaste is present), and 3) place p (no spatial component to "errors").[68]

Regarding the extensive margin hours choice, I can define r_i as the reservation log wage, constant across place-groups, while H_{ipj} is hours driven by driver i in place-group pj. Let $H_{ipj} = 0$ if $E(a_{pj}|w_{ipj}) < r_i$, while $H_{ipj} > 0$ if $E(a_{pj}|w_{ipj}) \geq r_i$. Focusing on the intensive margin hours choice, h_{ipj} is log hours driven, defined for $H > 0$. Thus, $h_{ipj} = ln(H_{ipj}) = \beta E(a_{pj}|w_{ipj})$, where β is the "expected wage" elasticity of labor supply.

Assuming the minority share j is observable in each area (that is, each pj pairing), I can define the expected conditional anticipated wage as:

$$E(a_{pj}|w_{ipj}, j) = (1 - \psi_{ij})\overline{a}_j + \psi_{ij}(w_{ipj}),$$

where $\psi_{ij} = \frac{\sigma^2_{a,j}}{\sigma^2_{w,ij}} = \frac{\sigma^2_{a,j}}{\sigma^2_{a,j}+\sigma^2_{u,ij}} \in [0, 1]$. Define ψ_{ij} as the "reliability ratio" (that is, the signal to total variance ratio) displaying the reliability of driver i's place-specific realized wage, in terms of indicating the anticipated component of wages, in areas with a given minority share j (and, thus, the weight placed on those observations).

Examining extreme cases offers some intuition on how the reliability ratio affects labor supply. If $\psi_{ij} = 1$, then $h_{ipj} = \beta(w_{ipj})$, showing that the minority share does not affect driver i's hours decision in any place(s) p with minority share j (that is, there are no variables indexed only by j). Conversely, if $\psi_{ij} = 0$, then $h_{ipj} = \beta\overline{a}_j$, showing that the minority share is the only factor that matters for driver i's hours decision in any place(s) p with minority share j (that is, there are only variables that are solely indexed by j). Here, a driver's hours decision for a place-minority share pairing will be identical for all places with a given minority share. Note that $\partial\psi_{ij}/\partial\sigma^2_{a,j} > 0$, pushing results closer to the $\psi_{ij} = 1$ case, while $\partial\psi_{ij}/\partial\sigma^2_{u,ij} < 0$, pushing results closer to the $\psi_{ij} = 0$ case.

[68] Alternatively, one could model how well the anticipated wage proxies for the realized wage given potential errors from the unanticipated wage. I use the given approach instead because: a) the classical measurement error assumption would not hold with the alternative approach (unanticipated wages are correlated with realized wages by definition); and b) for both approaches, the focus is on how closely the variation in realized wages corresponds to the variation in anticipated wages.

To derive more general results than these extreme cases, assume that by minority share, there are: i) different anticipated wage means $\overline{a}_j$, and ii) the same reliability of ψ_{ij}. More specifically, I assume $\overline{a}_0 > \overline{a}_1$ and $\psi_{i0} = \psi_{i1} = \psi_i < 1$. Given this, I can write down the expectation for the low minority place anticipated wage:

$$E(a_{p0}|w_{ip0}, j = 0) = (1 - \psi_{i0})\overline{a}_0 + \psi_{i0}(w_{ip0}),$$

as well as the expectation for the high minority place anticipated wage:

$$E(a_{p1}|w_{ip1}, j = 1) = (1 - \psi_{i1})\overline{a}_1 + \psi_{i1}(w_{ip1}).$$

The log hours differential between low and high minority share places with the same realized wage for driver i ($w_{ip0} = w_{ip1}$) is $\beta(1 - \psi_i)(\overline{a}_0 - \overline{a}_1) > 0$. Thus, for an equivalent set of realized wages, a driver will still spend more hours driving in the low minority place than the high minority place. Here, by construction, the wage elasticity β does not differ by minority group, and so the hours disparity reflects an intercept difference in driver labor supply across areas. However, if the elasticity is allowed to vary by minority group, the log hours differential for driver i is $(1 - \psi_i)(\beta_0\overline{a}_0 - \beta_1\overline{a}_1) > 0$ given a sufficient assumption that $\beta_0 \geq \beta_1$ (labor supply is weakly more elastic in the low minority place). In this case, the log hours differential gets larger as β_0 gets more elastic or as β_1 gets more inelastic, introducing the possibility of a slope difference in driver labor supply across areas.

Lastly, it can also be shown that at each level of the *anticipated* wage, low minority places are serviced more compared to high minority places. The *expected* log hours differential for driver i between low and high minority share places with the same anticipated wage ($a_{p0} = a_{p1}$) is $\beta(1 - \psi_i)(\overline{a}_0 - \overline{a}_1) > 0$, which is the same expression obtained earlier when conditioning on realized wages. In summary, the result regarding the log hours differential across low and high minority places, conditional on driver realized wages, as well as the result regarding the expected log hours differential across low and high minority places, conditional on anticipated wages, both reflect supply-side discrimination.

A.2 Spatial Analysis: Additional Empirics

A.2.1 Wage Threshold Determination

Average hourly earnings of an area-specific shift can sometimes be quite high and may be due to measurement error. In order to retain as much of the sample as possible while still removing shifts fraught with measurement error, I would like to impose a wage threshold for area-specific average hourly earnings. As a guide for choosing the threshold value, I use the neoclassical intertemporal model of labor supply. This model predicts that intertemporal labor supply elasticities will be unambiguously positive when wage changes are anticipated, as noted by Farber (2015). Thus, any negative ordinary least squares (OLS) elasticities observed when focusing on anticipated wage variation are presumably due to measurement error. Using anticipated log area-specific average hourly earnings, I estimate equation (1) without controls and with the addition of $\mathbf{M}_a$ as a regressor (since area fixed effects are excluded, equivalent to Appendix equation (3) without controls), as well as estimate an even more basic specification that only includes anticipated log area average hourly earnings and a constant as regressors.[69] Starting with a one-half sample of 9,172,588 area-specific shifts, if I obtain a negative coefficient on wage elasticity β, I then drop any shifts above some wage threshold, re-estimate the wage elasticities, and iterate (successively lowering the wage threshold by \$5 in each iteration) until only positive elasticities are estimated.[70] Implementing this procedure, I obtain a threshold for area-specific average hourly earnings of \$25, in equation (1) both without controls and with the addition of $\mathbf{M}_a$, as well as the simpler analog of that specification. Thus, I drop 5,428,531 shifts where average hourly area earnings exceed \$25 (59.18 percent of 9,172,588 area-specific shifts), resulting in a dataset of 3,744,057 area-specific shifts from 2,984 drivers.

A.2.2 Alternative Estimation Strategy

To examine the impact of area demographic composition on cab driver labor supply while incorporating local earnings opportunities, rather than estimating equation (1) with area fixed effects, I could alternatively estimate the following equation:

$$lnH_{kidcta} = \mu + \mathbf{M}_a'\zeta + \beta lnW_{kidcta} + (lnW_{kidcta} \times \mathbf{M}_a)'\eta + \phi_d + \gamma_c + \theta_t + \pi_{dct} + \mathbf{X}_a'\lambda + \varepsilon_{kidcta}, \quad (3)$$

where, for shift k, driver i, day of the week d, calendar week of the year c, year t, and area a, H is the area-specific duration of a shift in hours, $\mathbf{M}$ is a vector of "minority"/demographic population shares (that is, black, Asian, Hispanic, female, and 65 years of age and older, all as measured in the 2010 Census), W is the area-specific average hourly earnings on a shift, and ε is an error term, with standard errors clustered at the driver level.

This specification also includes controls that either help to account for supply differences within areas, non-discriminatory supply differences across areas, or differences in demand across areas. First, $\mathbf{X}$ is a vector of area-specific characteristics potentially relevant to demand by individuals or non-discriminatory supply by drivers across areas, all as measured in the 2006–2010 five-year American Community Survey (Minnesota Population Center 2010). Namely, $\mathbf{X}$ includes the area share of workers 16 years of age and older who use a taxicab for transportation to work, the area share of workers 16 years of age and older who use a motorized vehicle for transportation to work, the log of area median household income, the log of area median gross rent (all intended to capture resident taxi demand), and three area shares of the population 25 years of age and older whose educational attainment is less than a high school diploma or GED, a high school diploma, or else some college or an associate's degree (intended to capture non-discriminatory driver supply, if resident education is correlated with area amenities that drivers might care about).

Also, ϕ controls for day-of-week fixed effects, γ controls for week-of-year fixed effects, θ

[69] To obtain anticipated log area-specific wages, I run a regression of log area-specific wages on all of the fixed effects and controls listed in Appendix equation (3) — namely, $\phi_d, \gamma_c, \theta_t, \pi_{dct}$, and $\mathbf{X}_a$. I then generate predicted values from this regression to capture anticipated log area-specific wages, using this variable as the wage regressor when running equation (1) without controls and adding $\mathbf{M}_a$, as well as the more basic variant of that equation. Because the focus of this procedure is on coefficient signs rather than inference, I do not take further steps to adjust standard errors given the presence of a generated regressor.

[70] This one-half sample of 9,172,588 area-specific shifts is smaller than the one-half sample of 9,890,638 area-specific shifts noted in the text because not all areas have non-missing demographic shares; also, the inclusion of various fixed effects requires having enough data to estimate the fixed effects and parameters.

controls for year fixed effects, and π controls for major holidays. Similar to Farber (2015) and equation (1), these additional controls help account for the anticipated variation in wages, which likely contributes to driver supply differences within areas, as well as passenger demand and non-discriminatory driver supply across areas. The ζ coefficients in equation (3) cannot be identified in equation (1) with area fixed effects, as these coefficients reflect differences in shift hours by the demographic population shares of an area *conditional* on the market wage (that is, these are the intercept differences at a given wage). Meanwhile, as in equation (1), the η coefficients reflect differences in wage elasticities by area demographic shares. If there is discrimination, I expect $\zeta < 0$ and/or $\eta < 0$.

While equation (3) accounts for local earnings opportunities via area-specific wages, I may nevertheless remain concerned that the limited controls in $\mathbf{X}$ do not sufficiently account for demand-relevant or non-discriminatory supply-relevant characteristics across areas that are correlated with $\mathbf{M}$, thus resulting in inconsistent estimates of the ζ and η coefficients. Indeed, in estimating equation (3), I observe signs on some of the controls that do not align with a priori reasoning (for example, a negative sign on the area share of workers 16 years of age and older who use a taxicab for transportation to work), perhaps indicating biased estimation.

One possible solution to this concern is the inclusion of fixed effects at the regional level or the region-year level (for example, large neighborhoods) if the correlation of $\mathbf{M}_a$ with ε_{kidcta} occurs at this larger geographic level rather than at the area a level. For instance, perhaps non-discriminatory driver supply decisions are affected by criminal activity at a larger geographic boundary but not at the block group boundary, and such crime is correlated with block group demographics. Thus, with region or region $\times$ year effects, the estimation occurs only within regions or region-years, respectively, rather than across them.[71] However, the signs on control variables from such specifications still raise doubts about whether consistent estimation has been achieved, as region or region-year effects may not fully account for all differences in demand or non-discriminatory supply across areas. Thus, rather than pursue equation (3) and estimating both ζ and η, I focus on equation (1) and estimating η only.

A.2.3 Discrimination Variance Decomposition

I first identify driver-area-experience bins that are observed for a large number of area shifts (50 or more). As discussed in Farber (2015) and the Appendix, I focus on "new" drivers whose first shift in the data does not occur for at least one year, starting in January 2011.

[71] Regions are large Boston neighborhoods or Massachusetts counties. They are specified as 25 Boston neighborhoods inside of Boston (largely following neighborhood boundaries and underlying 2010 Census tracts from the Boston Planning & Development Agency (2010), except that "Downtown" is split into Chinatown (tract 702) and the remainder of Downtown, and "Dorchester" is split into North Dorchester (tracts 914, 915, 910.01, and all other Dorchester tracts located north of those) and South Dorchester (tracts 903, 916, 918, 921.01, and all other Dorchester tracts located south of those)), with another region being the balance of Suffolk County outside of Boston, and the remaining 13 regions being the rest of the 13 counties in Massachusetts apart from Suffolk County, for a total of 39 regions. Thus, the implication for identification is that demand-relevant or non-discriminatory supply-relevant characteristics vary at a smaller geographic boundary within Boston than in the rest of Suffolk County or Massachusetts. For instance, in the case of non-discriminatory supply choices motivated by area crime rates, this assumption is consistent with cab drivers from the Boston area having more detailed knowledge of how crime varies across areas within Boston than outside of Boston.

I then define driver experience "periods" as occurring every six weeks, with a week defined as seven non-spatial shifts.[72] I use this definition so that experience periods are defined broadly enough to obtain a sufficient number of area shift observations within periods for estimation but also are defined narrowly enough so that I can observe driver-area variation in discrimination across periods, if such changes occur (for example, due to driver learning with on-the-job experience).[73] Finally, to further ensure a sufficient number of area (that is, block group) shifts for the estimation, I broaden the definition of bin areas to be regions (large Boston neighborhoods or Massachusetts counties, as described earlier) rather than block groups. The estimation sample contains 4,182 driver-region-experience bins for a total of 274,519 area shifts, comprised of 658 drivers and 16 regions, and where the number of experience periods ranges from 1 to 35.

I estimate the analog of equation (1) for each driver-region-experience group of shifts to obtain IV estimates of η.[74] Once the 4,182 IV driver-region-experience $\hat{\eta}_{ire}$ terms are estimated, where e is experience, I then run OLS estimation of $\hat{\eta}_{ire}$ on driver $\times$ region fixed effects. The residual variation from this regression represents how much of the gross variation in the $\hat{\eta}_{ire}$ discrimination terms occurs within driver $\times$ region cells over time/experience. Meanwhile, the predicted variation in $\hat{\eta}_{ire}$ arising from driver $\times$ region fixed effects, $\hat{\eta}_{ir}$, accounts for how much of the gross variation in the $\hat{\eta}_{ire}$ discrimination terms occurs across driver $\times$ region cells and can be further decomposed by running OLS estimation of $\hat{\eta}_{ir}$ on driver fixed effects. The residuals from this additional regression pick up variation in discrimination within driver but across regions, while the predicted values from this regression, $\hat{\eta}_i$, account for discrimination variation across drivers that is region-invariant.

In addition to analysis in the paper, Figure A1 plots some of the $\hat{\eta}$ distributions in order to illustrate the heterogeneity in discrimination. For instance, the top plot of Figure A1 displays the distribution of $\hat{\eta}_{ir}$ across drivers conditional on region, for the three regions with the least variation in $\hat{\eta}_{ir}$ for the female share (that is, Brighton, Middlesex County, and the North End).[75] Similarly, the bottom plot of Figure A1 displays the distribution of $\hat{\eta}_{ir}$ across regions conditional on driver, for the 5 percent of drivers with the least variation in

[72] One to six non-spatial shifts are rounded up to a week.

[73] For instance, as Appendix Figure A11 shows regarding changes in taxi driver wage elasticities over time, much learning occurs within the first six months of a driver's on-the-job experience. Any driver-area-experience bin is dropped if it reflects fewer than a full 42 non-spatial shifts. I also drop any driver-area-experience bin with fewer than 50 spatial shift (that is, block group shift) observations. This restriction, intended to assist in precise estimation, may nevertheless result in some bias toward zero when estimating baseline wage elasticity β or discrimination parameter η if wages or the demographic composition in a block group sufficiently influences driver spatial labor supply behavior on the extensive margin. Thus, in terms of magnitudes, I obtain lower bound estimates of these parameters in the current stratified analysis.

[74] As before, in the non-overlapping sample, the average across drivers of log average hourly earnings of shifts k on day of week d, calendar week c, year t, and in area a ($\overline{lnW}_{kdcta}$) serves as the instrument for the log of average hourly earnings in the estimation sample for driver i with shifts k that start on day of week d, calendar week c, year t, and in area a (lnW_{kidcta}).

[75] The three regions with the most variation in $\hat{\eta}_{ir}$ for the female share are Charlestown, the South End, and Downtown. The regions with the least variation in $\hat{\eta}_{ir}$ for the black share are Mattapan, South Dorchester, and the South End, while the regions with the most variation are the Back Bay, the North End, and Allston. Lastly, the regions with the least variation in $\hat{\eta}_{ir}$ for the Asian share are Jamaica Plain, Middlesex County, and Brighton, while the regions with the most variation are Downtown, Fenway, and the Back Bay.

$\hat{\eta}_{ir}$ for the female share.[76] Figure A1 shows that even in regions of Boston with the least heterogeneity in $\hat{\eta}_{ir}$ for the female share, there are still substantial differences in the amount of estimated discrimination, with a large mass of $\hat{\eta}_{ir}$ values between –20 and 20. The many cases of positive $\hat{\eta}_{ir}$ estimates reflect *greater* wage sensitivity of cab drivers' block group shift hours as the block group female population share increases. Figure A1 also shows that even for drivers with the least variance in $\hat{\eta}_{ir}$ estimates based on an area's female share, these drivers still display considerable heterogeneity in how sensitive their area shift hours are to the area wage as the local female population share rises. Here, I observe a large mass of $\hat{\eta}_{ir}$ values between –10 and 10. Heterogeneity similar to the pattern displayed in Figure A1 is present when examining corresponding estimate distributions across drivers for the black and Asian population shares.

A.3 Non-Spatial Analysis: Comparison to Farber (2015)

A.3.1 Data Sample

The final dataset of 1,788,470 shift-level observations used for estimation was constructed from an initial, raw dataset of 54,596,409 trip-level observations by running several quality checks and making data adjustments or sample restrictions accordingly.

In terms of sample restrictions, the raw dataset of 54,596,409 trips was reduced to 54,580,528 trips by dropping all observations for which the:

1. Driver ID is not available (7,962 trips; 0.01 percent);
2. Trip starts or ends before May 1, 2009 (7,182 trips; 0.01 percent);
3. Trip starts or ends after December 31, 2015 (737 trips; 0.001 percent).

In terms of additional data adjustments, this sample-restricted dataset of 54,580,528 trips was refined further to an intermediate dataset (with the same number of observations) by making the following changes or confirmations:

1. *Trips that start before the previous trip ends (overlapping trips)*: I assume that the start time is correct and adjust the previous trip's end time match the subsequent trip start time.
2. *Trips with negative distance*: I adjust the distance to be equal to zero if and only if the trip start location is the same as the trip end location. If these locations are not the same, I set the trip distance equal to the smallest positive trip distance in the data (one-tenth of a mile).
3. *Trips with zero distance*: I keep the distance equal to zero if and only if the trip start location is the same as the trip end location. If those locations are not the same, I set trip distance equal to the smallest positive trip distance in the data (one-tenth of a mile).

[76] Each density plot is weighted by the inverse sampling variance of $\hat{\eta}$ estimates. In the upper plot, I examine three regions rather than one in order to ensure a sufficient number of $\hat{\eta}_{ir}$ estimates underlying the plot given an uneven count of $\hat{\eta}$ estimates across regions. In the lower plot, I focus on a 5-percent grouping of drivers so as to not display the results obtained by isolating an individual driver.

4. *Trips with negative fares*: I adjust the fare to be equal to zero.
5. *Trips with zero fares*: I keep the fare as zero, noting that over 95 percent of these trips have a trip distance of zero.
6. *Trips with very long, positive durations*: I truncate trips longer than 24 hours to be equal to 24 hours.
7. *Trips with negative durations (trip end time occurs before the start time)*: I assume that the start time is correct. I then adjust the duration to equal 1 minute by setting the end time equal to the start time plus 1 minute.
8. *Trips with zero durations (trip end time is the same as the start time)*: I assume that the start time is correct. I then adjust the duration to equal 1 minute by setting the end time equal to the start time plus 1 minute, noting that over 95 percent of these trips have a trip distance of zero.

This intermediate dataset of 54,580,528 trips was then further stripped of any duplicate observations based on driver ID and trip start time. Specifically, I make the following changes:

- *Trips that are duplicates based on the driver ID and start time*:
  1. If the trips' end times differ, I assume that the trip end times are correct. I then adjust the trip start time for the trip with the later end time to be the same as the end time of the earlier trip.
  2. If the trips' end times are the same, I assume that the trip with the largest fare is the correct one. I then keep the trip with the largest fare and delete the other trip(s).
  3. If the trips' end times are the same and the trips also have the same, largest fare:
     (a) If all such trips have the same start and end locations, whether non-missing or missing, I keep any one (and only one) of these trips.
     (b) If just one such trip has a non-missing start location, and a different such trip has a non-missing end location, I first replace the missing location information in each trip with the non-missing location information from the other trip. I then keep just one (and only one) of these complete trips.
     (c) If multiple such trips have non-missing locations but differ by the start and/or end location, I then keep whichever trip (only one) has the greater number of non-missing values for the remaining variables in the data (for example, medallion ID, tip, tolls).
     (d) If multiple such trips have non-missing locations but differ by the start and/or end location, and have the same number of non-missing values for the remaining variables in the data, I then keep just one (and only one) of these trips.

Adjusting for duplicates as described above leads to 10,706 trips being dropped (0.02 percent of the raw data). As mentioned in the paper, the resulting cleaned sample of 54,569,822 trips was then constructed into a dataset of 3,828,897 shift-level observations, following Farber (2015). He reasons a priori that a gap between trips of six hours or more determines the end of one shift and the start of another. To examine this assumption further, I construct a variable for the gap between every pair of trips in the data and examine the distribution of this gap variable, conditional on the gap being greater than one hour and less than or equal to 24 hours. As Figure A2 shows, a large mass of this gap distribution occurs at small gap values (for example, two hours or less) that would likely often falsely indicate the true end of a shift. Such a low gap threshold would lead to a large number of type I errors (false positives, with trips being designated as parts of different shifts that are actually part of the same shift). Conversely, a large portion of the gap distribution also occurs at very large gap values (for example, 14 hours or more) that would likely often fail to indicate the true end of a shift. This situation would result in a large number of type II errors (false negatives, with trips being designated as part of the same shift that are actually parts of different shifts). To choose the appropriate shift gap "threshold" — because the probability of type I error declines as the threshold value is raised, but the probability of type II error increases — I select the trough of the trip gap distribution in order to balance these two sources of error. This trough actually occurs at six hours, thus aligning with Farber (2015).[77] I truncate shifts longer than 24 hours to be equal to 24 hours.

In some cases, the average hourly earnings for a shift are quite high and may be the result of measurement error. In order to retain as many shifts as possible, conditional on those shifts likely being sufficiently free of measurement error, I need to determine and then apply some criteria for "likely being sufficiently free of measurement error." As a guide, I use the reference-dependent model of choice applied to the daily labor supply decisions of taxi drivers, as detailed by Farber (2015). A prediction of this model is that negative intertemporal labor supply elasticities, consistent with target earnings behavior, may occur only when the realized wages are sufficiently close to expectations, as defined by a range of wage deviations from such expectations. Outside of that range of wage deviations, the theory predicts that labor supply elasticities will be unambiguously positive. Thus, any negative elasticities observed during a sample of shifts that occur on calendar days when the realized wages were sufficiently far from expected wages are presumably due to measurement error.[78] If I estimate such negative elasticities, I then drop any shifts above some wage threshold, re-estimate the wage elasticities, and iterate (successively lowering the wage threshold by $5 in each iteration) until only positive elasticities are estimated.[79] Implementing this test,

[77] A study by Nelson\Nygaard Consulting Associates (2013) discusses how shifts are divided over the course of a day for some of Boston's fleet companies. However, because I cannot determine which anonymized medallion IDs and associated trips match to particular fleet companies, I am unable to identify any shifts in this manner. While the method for shift identification used in this paper will inevitably have some error, such noise should be reduced by shifts being identified using trip gaps for a given driver rather than across drivers, assuming that drivers do not frequently move between fleet companies with different rules for when shifts start and end.

[78] Conservatively, I use the narrow bounds on deviations from wage expectations derived by Farber (2015), ranging from –0.15 to +0.12, since this allows more shifts to be predicted to exhibit unambiguously positive wage elasticities.

[79] More specifically, as informed by Farber (2015), I follow these steps: 1) for all shift data (estimation and non-overlapping samples), use the shift start date to indicate the calendar day for all shifts, across all calendar days; 2) now focusing on the non-overlapping sample, within a calendar day across all shifts

I obtain a threshold for average hourly earnings of $45 (in specifications with controls, to isolate unanticipated transitory wage variation, but excluding driver fixed effects). Thus, I drop 218,289 shifts where average hourly earnings exceed $45 (comprising 784,270 trips, 1.44 percent of the raw data).[80] The impact on labor supply of retaining these shifts will be discussed.

This results in a data sample of 3,610,608 shifts (comprising 53,785,552 underlying trips) that contains 8,170 drivers and includes zero wage shifts. With zero wage shifts excluded (since the log wage is undefined in such cases), the resulting final data sample contains 3,608,721 shifts (comprising 53,782,015 individual trips) and 8,128 drivers.[81] However, most of the estimation is run on a random one-half sample of drivers, resulting in 1,788,470 shifts and 4,052 drivers.[82] The median shift is 9.3 hours in length, with an average hourly wage at the median of about $22.

As in Farber (2015), Figures A3–A5 provide additional descriptive data further sup-

and drivers, calculate the expected log average hourly earnings (call this the "expected wage"). It is the predicted wage from an OLS regression of the within-day average of log average hourly earnings (call this the "average wage"), on indicators for day of week, week of year, year, and major holiday; 3) for each calendar day, calculate the difference between the average wage and expected wage, which is the deviation of the average daily log wage from its expectation (call this the "wage deviation"). By construction, the average wage deviation is 0; 4) for each calendar day, calculate the absolute value of the wage deviation; 5) using the narrow wage deviation bounds for target earnings behavior from –0.15 to +0.12 that Farber (2015) derives, note the subset of calendar days in both the non-overlapping and estimation samples where the wage deviation is either below the lower bound or above the upper bound; 6) now focusing on the estimation sample, run the OLS elasticity regression(s) in Table A3, restricting to only shifts that fall on the calendar days indicated in step 5; 7) if a positive elasticity is obtained, the test has concluded. If a negative elasticity is found, drop the shift observations where log average hourly earnings are above the wage threshold being examined (that is, either the initial threshold, or else 5 dollars lower than the previous iteration's wage threshold); 8) repeat steps 6 and 7 as needed.

[80] In addition to using behavioral theory, I also tried using the official rules on how taxi fares in Boston are calculated for a trip, as discussed in section 2, to generate reasonable predictions on average hourly earnings. Based on two thought experiments, I obtain predictions of $40 and $47, which align closely with the $45 threshold based on behavioral theory. Specifically, for thought experiment 1, the miles per hour driving speed (based on the average distance traveled per hour across each of the 58,464 clock hours in the taxi data from May 1, 2009 to December 31, 2015) at the 99th percentile is 17.65 miles per hour with a passenger, while the amount of time with a passenger per hour (on average, across each of the 58,464 clock hours in the data) is 46.28 minutes at the 99th percentile. Taken together, this corresponds to 13.61 miles driven in an hour with a passenger which, based on fare rules regarding distanced traveled, results in a driver earning approximately $40 per hour. Alternatively, for thought experiment 2, assuming approximately four trips over the 46.28 minutes spent with passengers (since at the 99th percentile of 58,464 clock hour averages, a driver takes five trips per hour), this corresponds to a new trip of distance 3.4 miles (13.61 miles divided by four trips) every 11.5 minutes (46.28 minutes divided by four trips). For each of these four trips, again based on fare rules regarding distance traveled, earnings would be $11.73, resulting in earnings of approximately $47 per hour.

[81] Thus, shifts that are dropped due to exceeding the wage threshold have on average 3.6 underlying trips, whereas the shifts that are kept in the final sample have on average 14.9 underlying trips. This aligns with the reasonable expectation that measurement error is more likely to occur in shifts comprised of fewer trips.

[82] Including zero wage shifts, the random one-half estimation sample contains 1,789,418 shifts and 4,070 drivers. Meanwhile, excluding zero wage shifts, the non-overlapping sample contains 1,820,251 shifts and 4,076 drivers. Including zero wage shifts, the non-overlapping sample contains 1,821,190 shifts and 4,100 drivers.

porting that shifts are reasonably characterized in the analysis.[83] Figure A3 shows the distribution of shift length in hours (truncated, so that 8.5 hours is shown as 8 hours, for instance) and closely resembles the analogous figure in Farber (2015), with the modal shift duration similarly being in the ninth hour. Figure A4 displays the fraction of shifts that start in each clock hour and once again closely resembles the same figure in Farber's paper, as both are bimodal distributions with spikes for shifts starting in the early morning and late afternoon/early evening. Lastly, Figure A5 shows the average shift duration in hours by the clock hour of the shift start. Similar to Farber, these results find that shifts starting in the very early morning last longer on average (more than 10 hours) than shifts that begin later in the day.

Following Farber (2015), these shifts are further stratified into day, night, and other shifts based on their start times. Specifically, I define shifts that start between 4AM and 9:59AM as day shifts (757,866 shifts, or 42.38 percent of all shifts) and shifts that start between 2PM and 7:59PM as night shifts (651,712 shifts, or 36.44 percent of all shifts). The remaining 378,892 shifts (21.19 percent of all shifts), starting between 10AM and 1:59PM or between 8PM and 3:59AM, are unclassified (neither day nor night) and are designated as other shifts. For example, as Farber points out, drivers who start their shifts in the late morning or early afternoon could be day shift drivers who are getting a late start or night shift drivers who are getting an early start.

Figure A6 plots the average shift length by the day of week for day and night shifts, finding that day shift drivers work longest on Sundays and Saturdays (the latter differs from Farber (2015)), while night shift drivers work longest on Fridays and Saturdays but generally a bit less than day shift drivers (which also differs somewhat from Farber (2015)). Figure A7 displays shift income by day of week for day and night shifts. While the observed patterns are not completely disparate with Farber (2015), Boston cab drivers in my data appear to take home less income on average than NYC drivers in Farber's data (the difference ranges from a few dollars less to more than $50 less, depending on the day and shift), but the income for day and night shift drivers is more similar in my data than in Farber's. Finally, Figure A8 shows average hourly earnings by day of week for day and night shifts. Although cab driver wages appear to be lower by about $4–6 in my Boston data compared to Farber's NYC data, night shift drivers in both settings appear to earn a few dollars more on average than day shift drivers.[84] Additionally, like Farber (2015), I perform a variance decomposition for the average log wage and log hacks (that is, drivers) by hour for all 58,464 clock hours in the taxi data from May 1, 2009 to December 31, 2015.[85] I find that 24.4 percent of the variation in the average log wage by hour is transitory unanticipated variation, as is 23.2 percent of

[83]Data in the figures corresponds to the random one-half sample used for estimation, reflecting 1,788,470 shifts and 4,052 drivers.

[84]Given stable fare rates over the estimation period, shift earnings and average hourly earnings remain in nominal terms. Nevertheless, to the extent that annual inflation affects shift-level labor supply decisions, usage in my analysis of fixed effects or stratification at the year level will account for this.

[85]As in Farber (2015), the decomposition has two stages. In stage 1, I regress clock-hour average log hourly earnings on year indicators (6). The predicted values from this regression are my measure of permanent anticipated wage variation. In stage 2, I regress the residuals from the stage 1 regression on a set of indicators for hour $\times$ day of week (167), week of year (51), and holiday (1) (defined in section 5.1). The predicted values from this regression capture transitory anticipated wage variation, while the residuals capture transitory unanticipated wage variation.

variation in log hacks by hour, compared to 12.1 percent and 12.4 percent, respectively, in Farber (2015).[86] Thus, as Farber likewise notes, reference dependence in this context, which results from unanticipated wage variation, is not capable of explaining broad patterns of variation in labor supply, which largely result from anticipated wage variation. Only about one-quarter of the total variation in wages and labor supply could possibly be influenced by target earnings behavior due to reference dependence, although this scope for targeting behavior is much greater than in Farber's NYC data.

A.3.2 Findings

Like Farber (2015), I run the following OLS estimation:

$$lnH_{kidct} = \mu + \beta lnW_{kidct} + \phi_d + \gamma_c + \theta_t + \pi_{dct} + \kappa_i + \varepsilon_{kidct}, \tag{4}$$

where, for shift k, driver i, day of the week d, calendar week of the year c, and year t, H is the duration of a shift in hours, W is the average hourly earnings on a shift, ϕ are day-of-week fixed effects, γ are week-of-year fixed effects, θ are year fixed effects, π controls for major holidays, κ are driver fixed effects, and ε is an error term. The β coefficient estimates the intertemporal wage elasticity of labor supply. As in Farber (2015), driver fixed effects are omitted in some specifications, and all other controls are also omitted in other specifications.

The main findings from this analysis are shown in Table A3 and are quite closely aligned with Farber (2015), despite the change in geographic market and my smaller number of shifts and drivers. OLS results reveal small elasticities that are often positive and sometimes negative (particularly once driver fixed effects are included), but never approaching –1 as in Camerer et al. (1997). These OLS elasticities are also not always significant. Like Farber, I also observe night shift elasticities that are larger in magnitude than day shift elasticities, likely reflecting night shift drivers' greater capacity or ability to adjust to information about unanticipated transitory earnings opportunities. In contrast to Farber, however, the elasticities of other shift drivers in Boston seem closer to those of night shift drivers, whereas the elasticities of other shift drivers in NYC appeared more similar to those of day shift drivers. Focusing on "all shifts" across the three models in Table A3, the OLS elasticities in Farber (2015) range from –0.100 to 0.016, whereas in this paper, they range from –0.279 to 0.023.

The OLS estimates in Table A3 may be biased because the log of average hourly earnings, lnW_{kidct}, might not be solely driven by passenger demand, and rather could be influenced by driver supply-side factors that also affect area shift hours. Additionally, due to shift hours appearing as the dependent variable and in the denominator of the independent wage variable, measurement error may bias the wage elasticity estimate toward –1 (that is, division bias). To address these issues, following Farber (2015) and inspired by Camerer et al. (1997), I instrument for lnW_{kidct} with the log of area-specific average hourly earnings averaged across other drivers in a non-overlapping, randomly selected one-half sample of drivers used to construct the instrument.[87] The average across drivers of log average hourly earnings of

[86] Meanwhile, for the average log wage by hour, 11.2 percent of the variation is permanent anticipated and 64.4 percent is transitory anticipated. For log hacks by hour, 13.6 percent of the variation is permanent anticipated and 63.2 percent is transitory anticipated.

[87] As proposed in Angrist and Krueger (1995) and discussed in section 5, unlike typical IV estimation, this

shifts k on day of week d, calendar week c, and year t ($\overline{lnW}_{kdct}$) in the non-overlapping sample serves as the instrument for the log of average hourly earnings for driver i with shifts k that start on day of week d, calendar week c, and year t (lnW_{kidct}) in the estimation sample.

Like the OLS results, my IV results are very similar to those of Farber (2015), both qualitatively and quantitatively across shifts.[88] All IV elasticities are large, positive, and significant, with magnitudes that are generally largest for other shift drivers, followed by night shift drivers, and with the smallest elasticities associated with day shift drivers. Also similar to Farber's results, the inclusion of driver fixed effects no longer has much of an impact on the IV elasticities, unlike what I observe with the OLS results, perhaps suggesting that much of the measurement error that the IV analysis addresses is present in the within-driver wage variation. However, unlike Farber (2015), inclusion of controls in my sample reduces the magnitude of the elasticities rather than increasing it, suggesting that the controls are positively correlated with labor supply among Boston drivers but negatively correlated with labor supply among NYC drivers. Focusing again on "all shifts" across the three models, the IV elasticities in Farber (2015) range from 0.229 to 0.589, whereas in this paper, the IV elasticities range from 0.365 to 0.475. In both cases, these elasticity magnitudes are consistent with other microeconometric estimates of the Frisch labor supply elasticity based on more general populations, which tend to range from 0 to 0.5 (Altonji 1986; MaCurdy 1981; Peterman 2016).

Figure A9 and Table A4, via binned scatterplots and analogous IV regressions, respectively, display the impact on labor supply of dropping observations due to measurement error considerations.[89] Figure A9 reveals that labor supply in the full sample is non-linear and "bends" at sufficiently high wages, resulting in a negative elasticity when estimated by linear IV. Thus, the sample restriction at \$45 wages, motivated by measurement error (which IV itself could also address), helps to uncover this wage-hours relationship. However, as Table A4 shows, the results are not qualitatively affected by the specific choice of a \$45 wage threshold which, it should be recalled, only results in 1.4 percent of the raw trip data being dropped. For lower or higher thresholds (for example, \$25 or \$10,000, respectively), linear IV estimation still results in significantly positive elasticities. This suggests that negative elasticities reflecting income targeting behavior are only observed for very high wage outliers (for example, \$100,000).

Table A5 mirrors additional analysis in Farber (2015) and shows that I observe smaller elasticities on days with small deviations in realized wages from expectations, compared with days exhibiting large deviations. While this finding once again suggests the presence of some reference-dependent behavior by Boston cab drivers, even on such "small deviation" days, the estimated elasticities remain significantly positive. In terms of driver heterogeneity in the observed wage elasticities, my results also mirror those of Farber. Figure A10 shows that

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split-sample IV estimation is biased toward zero rather than the probability limit of the OLS estimate and is thus preferred.

[88]Like Farber, although I do not present first stage results, the instrument is similarly very strong in my estimation. The first stage F-statistic is always greater than 2,000, and the coefficient on the instrument in the first stage is generally close to 1, ranging from 0.88 to 1.09, depending on the specification.

[89]Absent an IV estimation routine in Stata's `binscatter` command, I plot log area shift hours on fitted values of the log area shift wage (from a first stage regression), controlling for the indicators and driver fixed effects in Table A3, model (3).

very few drivers display the large negative labor supply elasticities predicted by reference dependence; this is especially true for night shift drivers. Only 0.24 percent of day shift drivers and 0.1 percent of night shift drivers have elasticities less than –0.5, and less than 1.1 percent of day shift drivers and 0.7 percent of night shift drivers have elasticities less than –0.25.[90]

Finally and again similar to Farber (2015), I observe that drivers learn to optimize their labor supply behavior over time, and that more inefficient drivers tend to quit driving cabs. Figure A11 shows that labor supply elasticities grow with experience and that such growth does not appear driven by changes in the sample composition of drivers.[91] However, it is worth noting that the elasticity growth for Boston drivers is less steep than the growth for NYC drivers, leveling out around months 4–6 of driver experience for Boston drivers. This difference in learning could perhaps be because the smaller Boston market requires less experience to understand and take advantage of unanticipated earnings opportunities and maximize earnings compared to the larger NYC market. Haggag, McManus, and Paci (2017) find that some of this driver learning occurs across neighborhoods as drivers acquire location-specific experience.[92] Meanwhile, as in Farber (2015), Table A6 shows that within their first shifts, the drivers with the smallest elasticities are significantly more likely to quit than drivers who have larger wage elasticities.[93] Thus, market exit is not random with respect to profit-earning.[94]

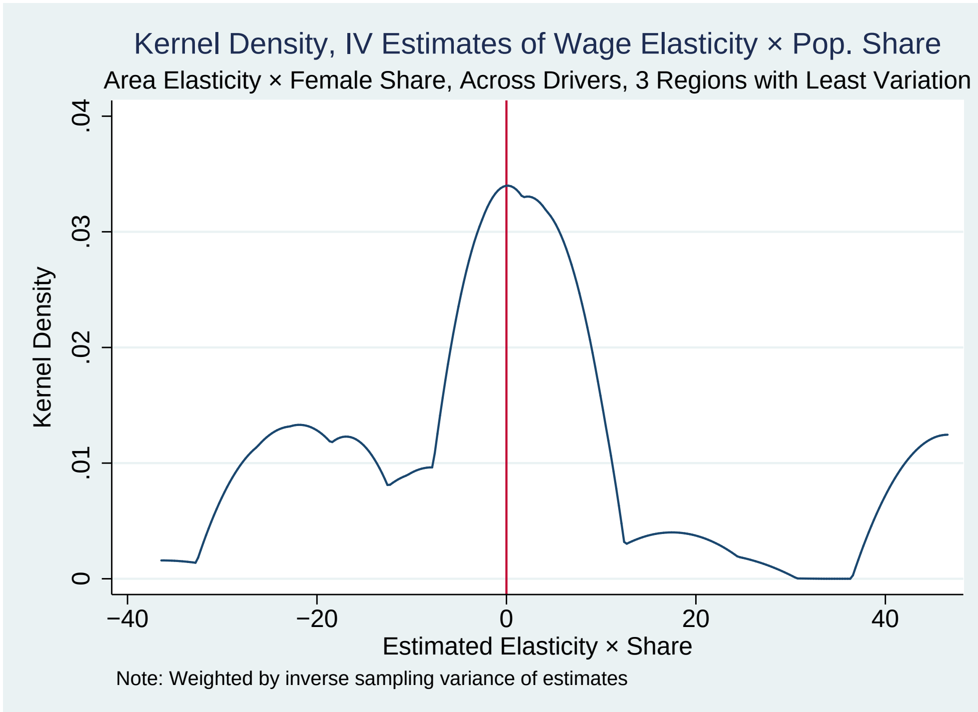
[90]All driver elasticities are weighted by the inverse sampling variance of estimates.

[91]Like Farber, I define "new" drivers to be those not observed driving for a full year at the start of my data. Since my estimation data starts in May 2009, I thus focus on drivers only observed from May 2010 through December 2015. In the estimation sample, I observe various patterns of entry, exit, and reentry. Specifically, about 41 percent of drivers did not drive for at least one three-month period and then returned to driving. Roughly 29 percent did not drive for six months before returning, 16 percent returned after a one-year absence, 10 percent returned after 18 months without driving, and 6 percent did not drive for two years before returning. To balance retaining a sufficiently large sample with accurately identifying new drivers, I follow Farber (2015) in choosing a one-year absence to designate such drivers, although in his data, only 5 percent of drivers return to the industry after one year without driving, and 14 percent return after a six-month absence. I thus accept the fact that about 16 percent of the drivers that I classify as new are actually misclassified experienced drivers.

[92]In this paper, as Figure 5 shows, I cannot precisely determine whether learning by Boston drivers is related to area-specific discrimination.

[93]Like Farber (2015), to better ensure that a (new) driver has truly left the taxi industry, I require a full year of observation following the final shift in order to classify a driver as having exited. Since my data ends in December 2015, I therefore focus on drivers observed from May 2010 through December 2014. I drop new drivers who are observed only for a single shift. Drivers who are observed for fewer than 12 shifts necessarily have fewer than 12 observations, and likewise, drivers observed for fewer than 30 shifts necessarily have fewer than 30 observations.

[94]In this paper, based on the close similarity of the plots in Figure 5 with the same plots for all new drivers rather than only those with more than 28 non-spatial shifts, I find that exit is not particularly related with how much a driver discriminates.



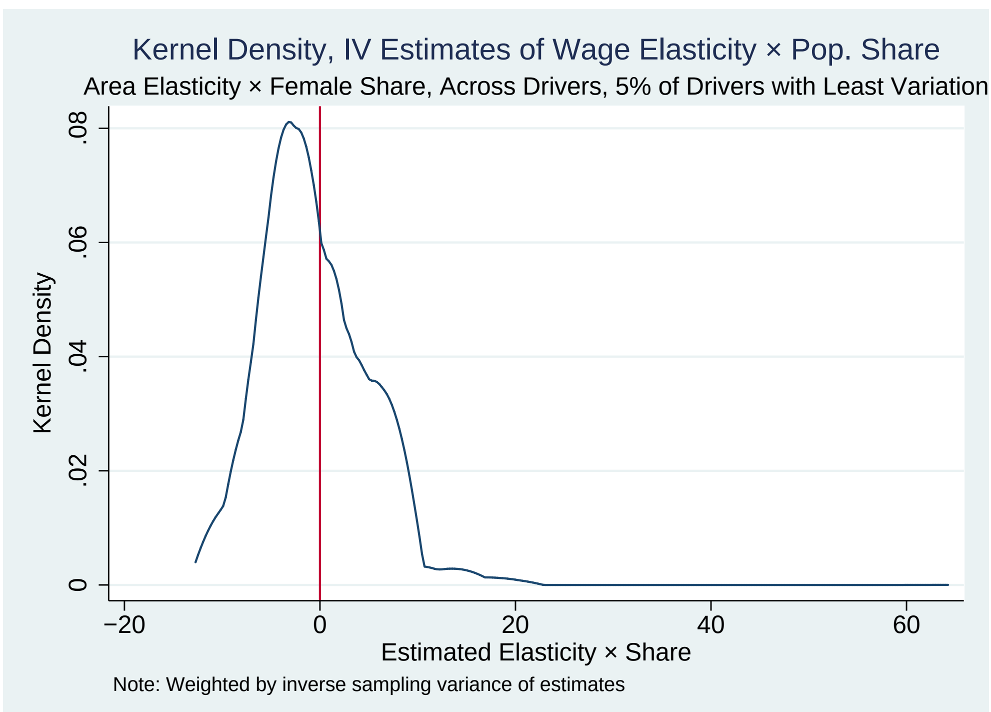


Figure A1: Variation By Region and Driver in Area Wage Elasticity x Area Female Population Shares, IV Estimates By Driver-Region-Experience

Source: Boston taxi data, 2010 U.S. Census, and author's calculations.

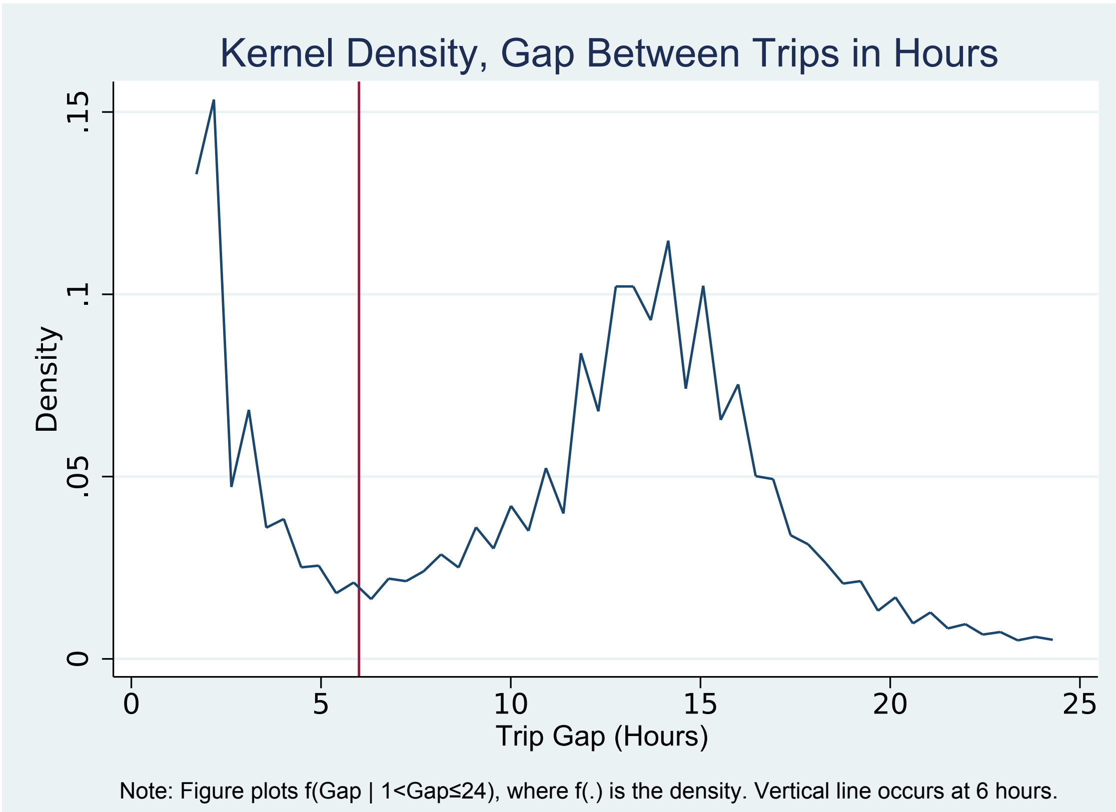


Figure A2: Distribution of Trip Gap in Hours
Source: Boston taxi data and author's calculations.

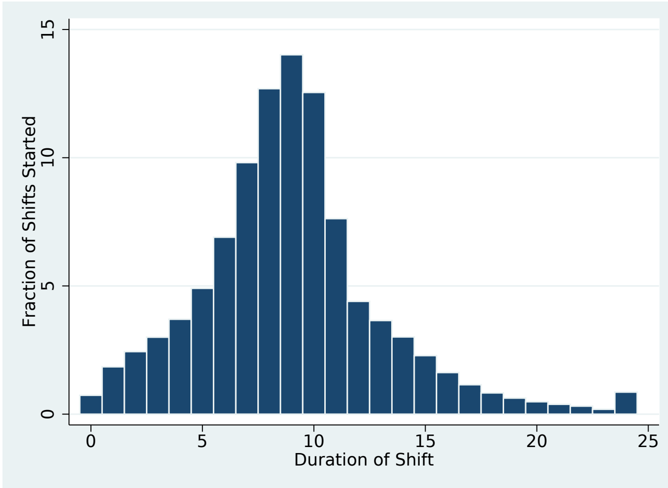


Figure A3: Distribution of Shift Length in Hours

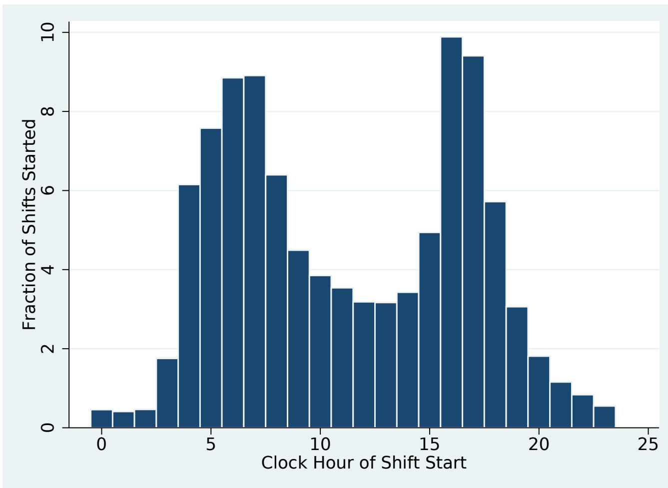


Figure A4: Distribution of Shift Start Time, by Clock Hour

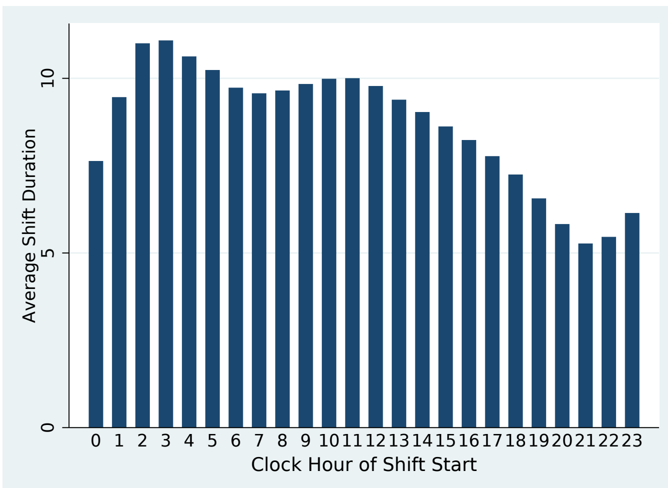


Figure A5: Average Duration of Shift, by Clock Hour of Start
Source: Boston taxi data and author's calculations (Figures A3–A5).

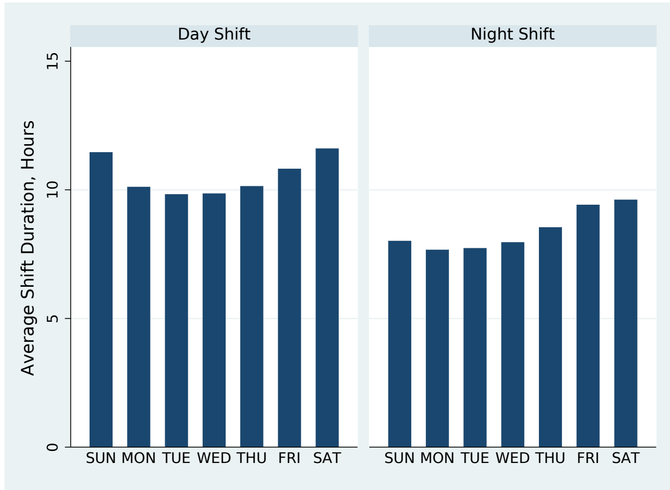


Figure A6: Average Shift Length in Hours, by Day of Week and Shift Type

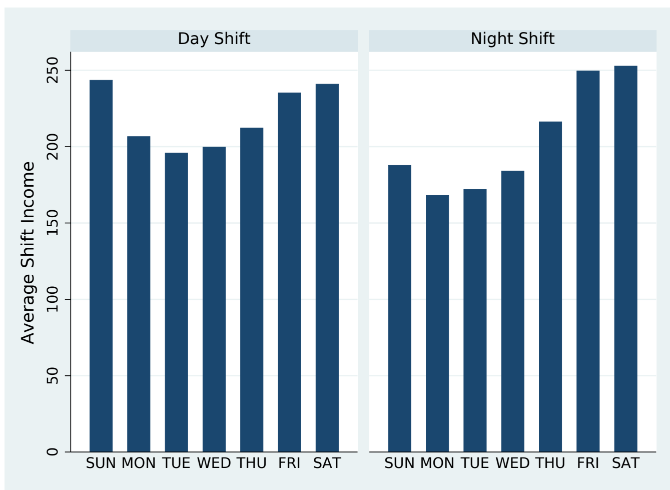


Figure A7: Average Shift Income, by Day of Week and Shift Type

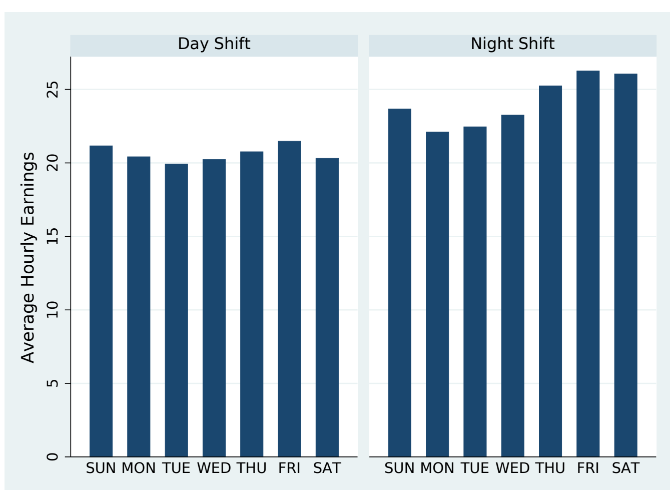


Figure A8: Average Hourly Earnings, by Day of Week and Shift Type
Source: Boston taxi data and author's calculations (Figures A6–A8).

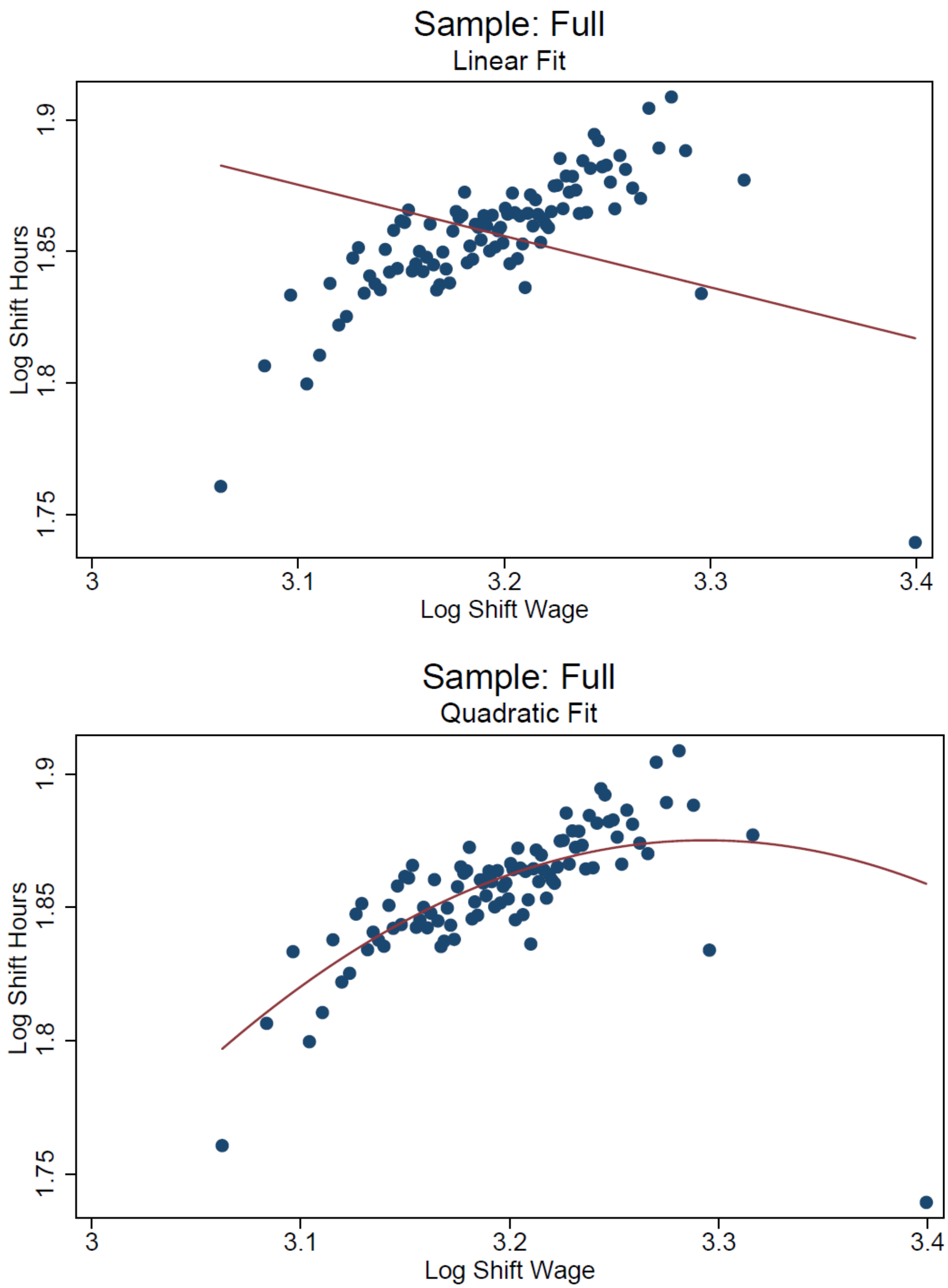
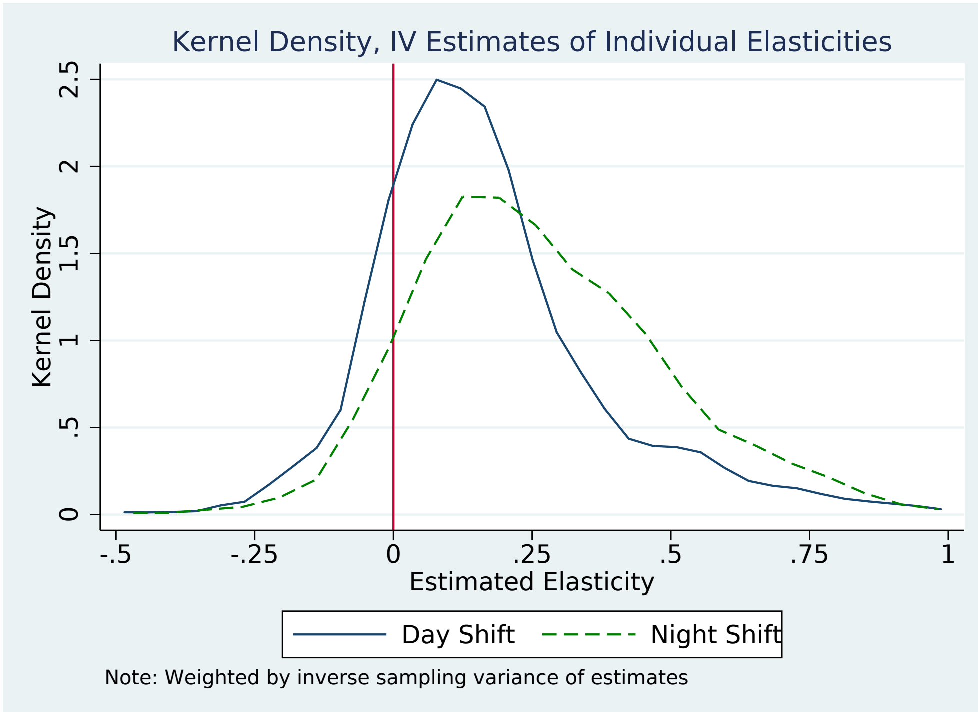


Figure A9: Driver Labor Supply, IV Estimate for Full Sample
Source: Boston taxi data and author's calculations.



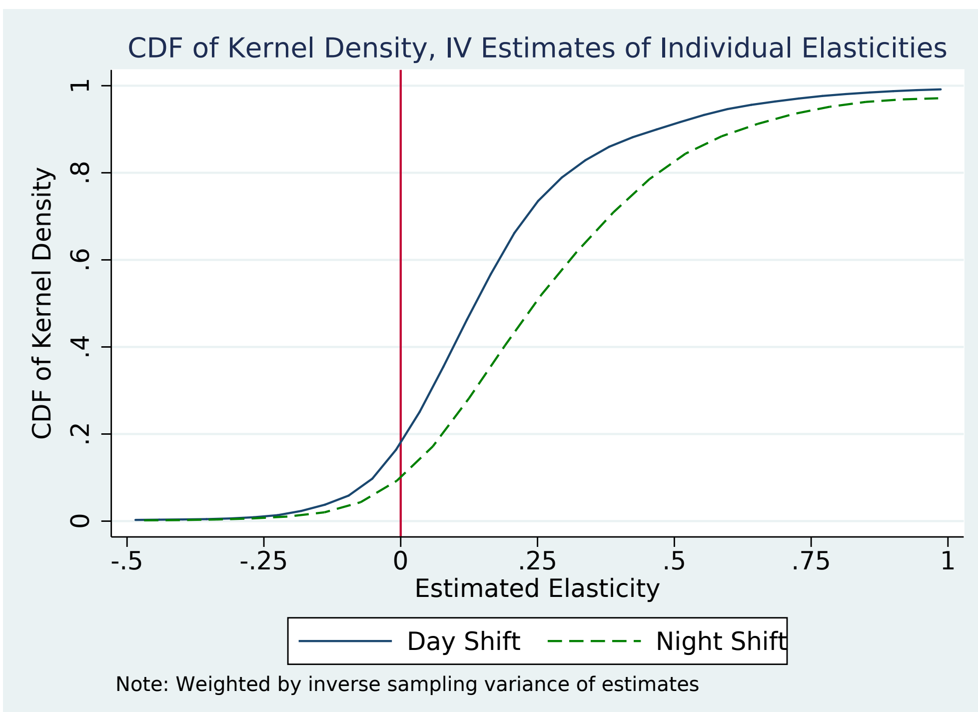


Figure A10: Kernel Density Estimates of Distribution of Estimated Elasticities Over Individual Drivers, Separately for Day Shift and Night Shift Drivers

Source: Boston taxi data and author's calculations.

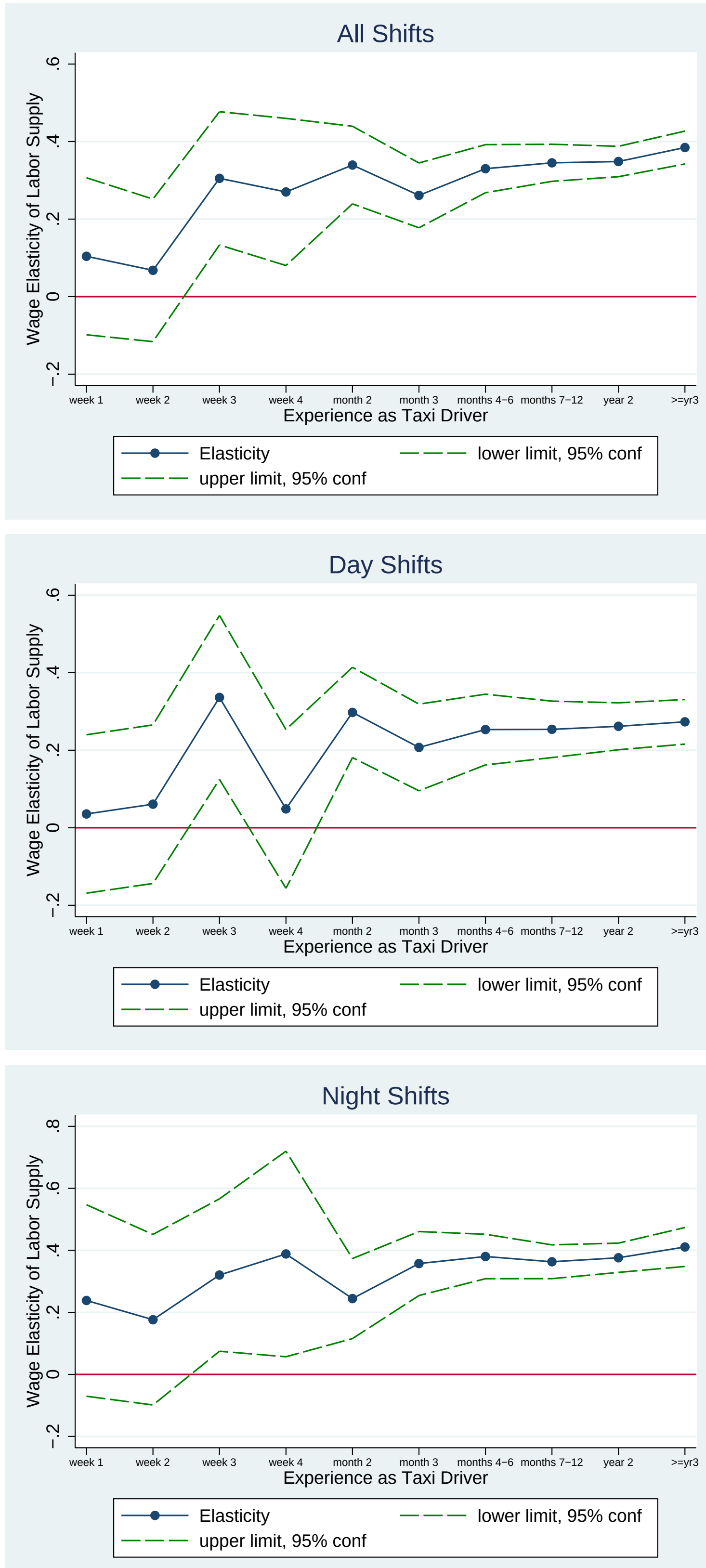


Figure A11: Wage Elasticity of Labor Supply, IV Estimates by Experience (New Drivers with More than 28 Shifts)

Source: Boston taxi data and author's calculations.

Table A2: Characteristics of Taxi Drivers and Population

	Boston (Means)		United States (Means)	
Variable	Drivers	Population	Drivers	Population
Wage Income (2010 USD)	20,298	48,233	19,267	40,961
Usual Hours Worked (Weekly)	42.0	38.4	40.7	39.0
Share, Population (%)	0.3	100.0	0.1	100.0
Age (Years)	48.7	35.4	49.2	37.8
Share, Age 65+ (%)	12.7	10.3	15.6	13.9
Share, Female (%)	8.4	52.2	14.6	50.8
Share, White Non-Hispanic (%)	22.1	46.0	45.4	62.6
Share, Black Non-Hispanic (%)	61.5	22.7	23.8	12.3
Share, Asian Non-Hispanic (%)	1.8	9.2	11.4	5.1
Share, Hispanic (%)	10.7	18.5	16.5	17.0
Share, Other Non-Hispanic (%)	3.9	3.7	2.9	3.0
Share, Foreign-Born (%)	75.6	30.5	42.8	14.5
Person Count	108	38,174	23,816	18,699,149
Weighted Person Count	12,258	3,856,005	2,669,182	1,891,260,364

Notes: 2010–2015 American Community Survey and author's calculations. Person weights applied to means. Wage income and usual hours worked restricted to employed persons only. "Drivers" are from occupation code 9140: taxi drivers and chauffeurs.

Table A3: Wage Elasticity, Regressions of Log Shift Duration in Hours, By Shift Type

OLS Regressions

Model	Controls	Driver F.E.'s	Elasticity All Shifts	Elasticity Day Shifts	Elasticity Night Shifts	Elasticity Other Shifts
(1)	No	No	0.023**	0.089***	0.065***	0.002
			(0.010)	(0.015)	(0.008)	(0.016)
(2)	Yes	No	0.001	0.080***	0.024**	–0.022
			(0.010)	(0.015)	(0.009)	(0.017)
(3)	Yes	Yes	–0.279***	–0.217***	–0.180***	–0.385***
			(0.011)	(0.014)	(0.012)	(0.014)

IV Regressions

Model	Controls	Driver F.E.'s	Elasticity All Shifts	Elasticity Day Shifts	Elasticity Night Shifts	Elasticity Other Shifts
(1)	No	No	0.475***	0.354***	0.559***	0.553***
			(0.013)	(0.020)	(0.017)	(0.030)
(2)	Yes	No	0.365***	0.259***	0.403***	0.485***
			(0.011)	(0.015)	(0.016)	(0.027)
(3)	Yes	Yes	0.400***	0.272***	0.415***	0.508***
			(0.011)	(0.014)	(0.015)	(0.023)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Author's calculations using Boston taxi data. Each estimated elasticity is from a separate OLS or IV regression, as noted. "Elasticity" is the estimated coefficient of log average hourly earnings from a regression of log shift duration. In IV regressions, the instrument for log average hourly earnings is the log average across drivers of average hourly earnings for a non-overlapping sample of drivers on the same day. "Controls" include indicators for day of week (6), calendar week (51), year (6), and major holiday (1). Estimated using a sample of 1,788,470 shifts for 4,052 drivers from 2009–2015, comprised of 757,866 day shifts, 651,712 night shifts, and 378,892 unassigned shifts. Standard errors clustered by driver are in parentheses.

Table A4: Wage Elasticity, IV Regressions of Log Shift Duration in Hours, By Sample

Model	Controls	Driver F.E.'s	Full	Wages>$45	Wages≤$45	Wages≤$25
(1)	No	No	0.170***	–1.071**	0.475***	0.472***
			(0.047)	(0.028)	(0.013)	(0.026)
(2)	Yes	No	–0.320***	–1.188***	0.365***	0.616***
			(0.033)	(0.021)	(0.011)	(0.024)
(3)	Yes	Yes	–0.195***	–1.084***	0.400***	0.627***
			(0.034)	(0.021)	(0.011)	(0.019)

Model	Controls	Driver F.E.'s	Wages≤ $100	Wages≤ $1,000	Wages≤ $10,000	Wages≤ $100,000
(1)	No	No	0.582***	0.610***	0.415***	0.249***
			(0.018)	(0.031)	(0.049)	(0.048)
(2)	Yes	No	0.440***	0.303***	0.075**	–0.199***
			(0.016)	(0.027)	(0.037)	(0.034)
(3)	Yes	Yes	0.481***	0.430***	0.306***	–0.045
			(0.017)	(0.023)	(0.029)	(0.033)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Author's calculations using Boston taxi data. Each estimated elasticity is from a separate IV regression, as noted. "Elasticity" is the estimated coefficient of log average hourly earnings from a regression of log shift duration. The instrument for log average hourly earnings is the log average across drivers of average hourly earnings for a non-overlapping sample of drivers on the same day. "Controls" include indicators for day of week (6), calendar week (51), year (6), and major holiday (1). Estimated using varying samples of shifts and drivers from 2009–2015, as indicated. Sample sizes are: "Full" (1,901,467 shifts, 4,447 drivers), "Wages $>$ \$45" (112,997 shifts, 3,607 drivers), "Wages $\leq$ \$45" (1,788,470 shifts, 4,052 drivers), "Wages $\leq$ \$25" (1,168,985 shifts, 3,811 drivers), "Wages $\leq$ \$100" (1,831,211 shifts, 4,245 drivers), "Wages $\leq$ \$1,000" (1,872,139 shifts, 4,375 drivers), "Wages $\leq$ \$10,000" (1,898,795 shifts, 4,440 drivers), "Wages $\leq$ \$100,000" (1,901,145 shifts, 4,446 drivers). Standard errors clustered by driver are in parentheses.

Table A5: Wage Elasticity, IV Regressions of Log Shift Duration in Hours, By Shift Type, Subsamples of Absolute Deviation of Average Log Daily Wage from Expected Value

Sample	Absolute Deviation Percentile	Elasticity All Shifts	Elasticity Day Shifts	Elasticity Night Shifts
(1)	0–25	0.265***	0.137	0.285***
	$(N = 455,516)$	(0.079)	(0.111)	(0.095)
(2)	25–50	0.368***	0.211***	0.417***
	$(N = 454,812)$	(0.034)	(0.048)	(0.043)
(3)	50–100	0.363***	0.264***	0.402***
	$(N = 878,142)$	(0.011)	(0.016)	(0.016)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Author's calculations using Boston taxi data. Subsamples by absolute deviation of average log daily wage from expected value. The 25th percentile and median across days of the absolute deviation of the average log daily wage from its expected value are 0.0190148 and 0.0411258, respectively. The expected value for a given calendar day (across all shifts and drivers) is the predicted value from an OLS regression of the within-day average of log average hourly earnings on indicators for day of week, week of year, year, and major holiday. Each estimated elasticity is from a separate IV regression. The instrument for log average hourly earnings is the log average across drivers of average hourly earnings for a non-overlapping sample of drivers on the same day. "Elasticity" is the estimated coefficient of log average hourly earnings from a regression of log shift duration and additionally includes a set of controls for day of week (6), calendar week (51), year (6), and major holiday (1). The listed sample sizes for the "All Shifts" samples are based on the underlying sample of 1,788,470 shifts for 4,052 drivers from 2009–2015, comprised of 757,866 day shifts and 651,712 night shifts. Standard errors clustered by driver are in parentheses.

Table A6: Wage Elasticity, IV Regressions of Log Shift Duration in Hours, By Longevity (Total Number of Shifts as Taxi Driver)

	First 12 Shifts			First 30 Shifts		
Longevity (Total Shifts)	All Shifts	Day Shifts	Night Shifts	All Shifts	Day Shifts	Night Shifts
2–12	–0.015	–0.048	0.094	0.090*	0.087	0.109
	(0.082)	(0.083)	(0.131)	(0.054)	(0.057)	(0.086)
13–30	0.063	–0.016	0.173	0.157***	0.111*	0.172**
	(0.080)	(0.082)	(0.126)	(0.054)	(0.057)	(0.083)
31–60	0.047	–0.015	0.160	0.156***	0.122**	0.176**
	(0.083)	(0.084)	(0.135)	(0.055)	(0.057)	(0.087)
61–90	0.073	–0.010	0.192	0.179***	0.124**	0.205**
	(0.081)	(0.083)	(0.125)	(0.054)	(0.057)	(0.082)
91–150	0.067	–0.023	0.186	0.175***	0.116**	0.200**
	(0.082)	(0.085)	(0.129)	(0.054)	(0.058)	(0.084)
151–300	0.085	–0.007	0.188	0.194***	0.129**	0.209***
	(0.080)	(0.082)	(0.124)	(0.052)	(0.056)	(0.081)
$\geq$ 301	0.104	0.004	0.208*	0.212***	0.144***	0.228***
	(0.080)	(0.082)	(0.122)	(0.051)	(0.055)	(0.079)
Number of Drivers	3,825	2,856	2,422	3,825	3,013	2,720
Number of Shifts	41,886	20,153	13,721	98,161	46,556	33,004

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Author's calculations using Boston taxi data. Each column represents elasticities from a single IV regression. The elasticities are the coefficients of the interaction of log average hourly earnings with a set of indicators for total shifts observed for each driver. The instrument set is the log average across drivers of average hourly earnings for a non-overlapping sample of drivers on the same day, interacted with the set of indicators for total shifts observed for each driver. All models include a set of indicators for day of week (6), calendar week (51), year (5), and major holiday (1). Standard errors clustered by driver are in parentheses.