**Early Draft**

# Occupational Licensing of Uber Drivers

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*Occupational Licensing of Uber Drivers*


***Abstract***

Two of the most rapidly growing segments of the labor market are the workers in the gig economy and occupational licensing. One potential barrier to entry for ride-sharing companies is the requirement that drivers be licensed by state or local governments. These requirements are typically justified by regulators as ensuring a minimum level of safety and quality. We examine the influence of these regulations using data from the ride-sharing firm Uber, state and local statutes and other administrative sources. More specifically, we analyze the influence of occupational licensing of Uber drivers on their workforce composition, pricing, and the satisfaction and safety of consumers. In order to examine a variety of cities operating under different licensing regimes, we focus on New York City, New Jersey, and Seattle. Depending on the city or other political jurisdictions and changes in the regulatory regime, we implement difference in difference and quasi-random assignment approaches. We find that occupational licensing of Uber ride-sharing reduces the number of Uber drivers, raises base prices, but has little influence on consumer satisfaction or measures of health and safety.

***Occupational Licensing of Uber Drivers***

*1. Introduction*

Two of the most rapidly growing segments of the labor market are the expansion of employment in the gig economy and occupational regulations by government in the labor market (Katz and Krueger, 2016, Kleiner and Krueger, 2013). The ride-sharing firm Uber is faced with both issues as part of its business model. The firm has come to exemplify the technology "revolution" and labor market outcomes embodied in the gig economy by providing ride-sharing services. The firm had more than 80 percent of the total ride-sharing (cab-substitute market) in the U.S. in 2016 (DMR Statistics 2017). The creation of a sophisticated app allowed this process of matching to be done in an efficient and profitable manner for the company. By 2017 the company had more than 734,000 active drivers in the U.S. and more than 1,500,000 drivers worldwide. The economic value of the company was estimated to be almost $70b in 2017 according to the *Wall Street Journal* (June, 2, 2017).

Occupational licensure is the legal process by which governments (mostly U.S states but also local governments and the federal government) identify the legal qualifications required to work in a trade or profession, after which only regulated practitioners are allowed by law to receive pay for doing tasks in the occupation. This form of labor market regulation has rapidly become one of the most significant factors affecting labor markets in the United States (Kleiner and Krueger 2010, 2013). Over the past several decades, the share of U.S. workers holding an occupational license has grown sharply. Estimates from a recent White House report suggest that over 1,100 occupations are regulated in at least one state, but fewer than 60 are licensed in all 50 states, showing substantial differences in which occupations states and local governments choose to regulate (U.S. Executive Office of the President 2015). As of 2015, about 25 percent of the U.S. workforce had attained an occupational license, with the vast majority doing so at the state level (U.S. Bureau of Labor Statistics 2016, Kleiner and Volotnikov, 2017). In contrast, in 1950 only 5 percent of U.S. workers were licensed at the state level (Kleiner and Krueger 2013). For Uber these regulations may impose constraints on the number of drivers in their system.

In this study, we examine the effect of occupational licensing of Uber drivers on the composition of the workforce, pricing, and the quality and safety of the ride. The paper proceeds as follows. Section 2 provides background on occupational licensing and Uber including recent trends and reviews previous work, and then presents a theoretical model of regulation in the ride-sharing business. Section 3 describes our data and empirical strategy. Section 4 presents our results and their implications, and Section 5 summarizes and concludes.

Our findings show that tougher licensing of Uber drivers results in more intensive use of the Uber app by "partners". In order to examine a variety of cities and other jurisdictions operating under different rules, we focus on the New York/New Jersey, and Seattle. Finally, we examine whether occupational licensing of Uber drivers influences the satisfaction of riders using the Uber service and the safety of the ride, using information derived from the Uber drivers' app devices.

## *2, Background on Occupational Licensing and Uber*

The issue of occupational regulation has been a key element in economics since its modern origins (Smith, 1937). Many economists have viewed such regulation as rent-seeking behavior and have empirically examined the economic effect of occupational licensing within that framework (Friedman and Kuznets, 1945; Friedman, 1962). In contrast, other models have suggested that regulation provides incentives for workers to enhance their human capital through greater investments in their work life by limiting low skilled substitutes (Shapiro, 1986).

Occupational licensing is a form of regulation that requires individuals who want to perform certain types of work for pay to obtain the permission of a governmental or quasi-governmental agency. Over the past several decades, the share of U.S. workers holding an occupational license has grown sharply. About 25 percent of the U.S. workforce is in an occupation licensed (BLS, 2016). One study found that for a subset of low- and medium-skilled jobs, the average license required around 9 months of education and training (Carpenter et. al. 2012). Since taxi drivers are licensed most often by city governments, the focus of our analysis is on the influence of occupational licensing of Uber drivers on the composition of the company's workforce, pricing outcomes, and the quality and safety of the ride for consumers.

One firm that has come to exemplify the recent technology "revolution" and labor market outcomes embodied in the gig economy is the ride-sharing firm Uber. Recent data shows that the firm had between 84 and 87 percent of the total ride-sharing trips (i.e. cab-substitute markets) in 2016, and is active in 450 cities in the U.S. and worldwide (DMR statistics, 2017). Uber began its first rides in 2010 in San Francisco and in New York City in 2011, as a way to match individuals who needed rides to work or recreation with those individuals who were willing to provide those rides for a price. The creation of an app and accompanying software allowed this process of matching to be done in an efficient and profitable manner for the company (Roth and Ockenfels, 2002). The cost to the driver of the matching process is that Uber takes a percentage of the ride price for the company as their fee for the matching process. The drivers anticipate an ample supply of customers, and the waiting times for traditional cabs were reduced and revenues enhanced for those providing rides. Although the company has had more than its share of adverse publicity, it has still been one of the major economic success stories and labor market innovators among high tech startups since 2000.

For Uber, drivers (Uber refers to them as “driver-partners”) provide transportation services to customers requesting rides via Uber’s app on their smartphones or other devices. Uber is one of the best representatives of the gig economy company, responsible for perhaps two-thirds of all activity in the app-based labor market according to Harris and Krueger (2015).

Although the on-demand workforce was growing very rapidly, other more narrowly focused surveys suggest that less than 1 percent of the U.S. workforce participated in the direct on-demand economy in 2015 (Katz and Krueger, 2016). Based on data from Google Trends, Harris and Krueger (2015) infer that Uber is by far the largest on-demand labor platform, which makes an understanding of occupational regulation, and the motivation of Uber’s driver-partners under regulation an important element in understanding the gig economy with occupational regulation.

*Occupational Licensing and Ride-Sharing: A Literature Review*

In our review of the literature we initially examine the results first on the influence of occupational regulation on the workforce, prices and quality. Second, we examine the economic literature on taxi services and hours worked and prices, which is a close substitute for the ride-sharing services that Uber provides to riders. We conclude by explaining the gaps in the current literature and how our analysis plans to address these issues.

As mentioned earlier, occupational licensing has grown to be one of the largest and influential institutions in the U.S. labor market (Kleiner and Krueger, 2013). More specifically, varying estimates find that licensing at the state level confers a wage premium that varies from almost 9 to about 17 percent (Kleiner and Krueger, 2010, Kleiner and Krueger, 2013, Kleiner and Volonikov, 2017 and Gittleman, Kleee and Kleiner, forthcoming). Local licenses by themselves are generally associated with lower wages, and certification has a smaller effect on wages using data from the Survey of Income and Program Participation (Gittleman, Klee, and Kleiner, forthcoming).

The use of other data and methods finds that the wage premium from licensing is heterogeneous and it is often more modest, and sometimes estimated as zero such as the case of licensed engineers (Hur, Kleiner, and Wang, 2017). Moreover, licensing also confers better employment opportunities and health and pension benefits (Gittleman, Klee, and Kleiner, forthcoming). Unlike the minimum wage or unemployment insurance which requires all employers that are covered by the law to pay the new wage or transfer payment immediately, occupational licensing allows individuals who are working in the occupation, but do not meet the current licensing requirements, to continue working (Han and Kleiner, 2016). This practice is called "grandfathering." In addition, the regulated occupation generally has the ability to ratchet up the requirements—that is, raise the requirements for initial entry or movement into the occupation from other political jurisdictions with minimal constraints from policy makers (Wheelan, 1999). A unique aspect of occupational licensing is that individuals who do not meet the current requirements for new entrants are allowed to keep working with permission from the government.

Occupation specific estimates of the influence of the length of licensing statutes on wage determination include results for massage therapists, nurses, lawyers, and barbers (Law and Marks, 2009, Pagliero, 2010, Timmons and Thornton, 2010, Timmons and Thornton, 2013). The main results suggest that for specific occupations such as massage therapists and barbers, the length of time that a licensing statute has been in place enhances the earnings of these practitioners, but little evidence of the influence of duration was found for nurses (Law and Marks, 2013, Han and Kleiner, 2016)). However, the estimates are limited to these occupations over a relatively short time period.

Although not explicitly addressed, the process occurs by allowing current practitioners to avoid the explicit general and specific education requirements, internships, tests, continuing education mandates, and good moral character investigations, assuming that they were in good standing prior to the new licensing laws. To the extent that these requirements raise marginal productivity, they may also raise wages. Also, it takes many years for the individuals who did not meet these requirements to leave the occupation or retire, and as a result, the educational quality of the new entrants is higher, and they dominate the current members of the occupation only after a substantial period of time (Han and Kleiner, 2016). In contrast, the influence of licensing on employment growth is more gradual, but the findings suggest that comparing states that license occupations with those that do not suggest that states that licensed occupations grow more slowly (Kleiner 2006).

*Occupational Licensing, Service Quality, and Prices*

A key public policy justification for occupational regulation in general, and licensing in particular, is its ability to protect consumers and the wider public from incompetent and unscrupulous practitioners (Kleiner, 2006). Where the provision of a technical service requires special knowledge and skill is involved, consumers may lack the knowledge or information necessary to assess the quality of the product or service prior to its purchase. Through setting minimum skills standards for entry to occupations, occupational licensing is expected to raise average skills levels in the occupation, since low-quality providers cannot meet the new skill standard and are driven out of the occupation (Pagliero 2013). As a result, consumers should receive a more homogeneous and high quality product while the resulting higher investments in training have the potential to enhance the skills base in the economy (Shapiro 19864). In the model, quality is ensured through the regular monitoring of performance standards, deviations from which can lead to 'punishments' such as financial penalties or exclusion from practicing the occupation (Kleiner and Todd, 2009). Finally, professional associations' activities related to encouraging members to discuss and promote positive aspects of work experiences, disseminate information about how to do the job better, engage in job-specific training, promote ethical standards, or devise methods of adjudicating disputes between consumers and producers all have the potential to positively affect service quality. Other forms of regulation such as minimum skill standards are a key feature of certification. Since such schemes make stipulations regarding competence which could in turn be positively related to human capital characteristics (or propensity to invest in their acquisition), one would expect these schemes to have some impact on quality; although, the extent of this impact would depend on the demand for regulated practitioners in the market (Koumenta et al. 20145).

The effect of regulation on service quality also can be negative. Quality is not only linked to skill but also to quantity supplied. If an increase in quality through better trained practitioners results in a subsequent decrease in their supply (due to aspiring practitioners not meeting the entry requirements), the overall service received by the consumer suffers for the following reasons (Pagliero 2011). First, if a decline in the number of available practitioners leads to an increase in price of the product or service, then some consumers may opt for lower quality services. In the context of licensing, such substitution is confined to 'do-it-yourself' services (Friedman 1962; Kleiner 2006). Price increases also can be driven by consumers themselves.

Regulation can reduce uncertainty or the likelihood of poor quality practitioners in the market. As a consequence, consumers perceive the service to be of higher quality and demand more of the service, thus pushing up the price.

A more extreme unintended consequence of occupational licensing could involve the decision not to consume the service at all, which may pose health and safety risks. Such an outcome is likely to be more pronounced for low-income consumers, meaning that any improvement in quality is only felt by those at the middle and upper quartiles of the income distribution (Shapiro 1986). Overall, the influence of regulation should be analyzed not only in relation to improvements in skill levels, but also in relation to the price and availability of services. For example, while one might receive a better quality service from a licensed pharmacist, such effects cannot be realized if such individuals are in short supply and access to pharmaceutical services is limited. Since licensing restricts competition between practitioners, licensing can reduce the pressure to compete on quality, thus leading to a fall in the overall service quality received by consumers (Caroll and Gaston 1981).

Licensing also can influence prices, if raising the entry requirements via occupational licensing (a) limits the supply of labor to a profession and (b) increases the entry costs for practitioner (e.g. financial investment on education and training), then the influence on the price of the product or service will depend on a number of factors. First, the more price inelastic the good, the more scope there is for licensed producers to increase its price. Price elasticity will depend on the price and availability of substitutes, and whether other labor inputs also are subject to occupational licensing. If there is a strong substitution effect with unlicensed products, then producers will be less inclined to increase price. Further, producers will have more scope to increase prices for services that consumers perceive as necessities rather than luxuries. As such, if the good is highly income inelastic, demand is likely to be relatively unresponsive to price changes. The proportion of income that is devoted to the purchase of the good or service also is an important consideration. The lower the proportion of consumer's income spent on the service, the greater the scope for licensed producers to increase prices without experiencing a proportionate fall in demand. Second, the influence of occupational licensing on prices also will depend on the ability of consumers to switch to unregulated services. Generally speaking, this is more likely to be the case with services are generally non-exportable in nature (e.g. one's ability to import childcare or a haircut from abroad is restricted).

To summarize, the effect of occupational regulation on quality has been promoted as the main justification for its existence. However, as the review has demonstrated, because of the corresponding effects of regulation on labor supply, it is difficult to determine regulations impact on the quality of the service provided. Similarly, any net effect on price will depend on the characteristics of the product and service in question. However, estimates of service quality can either be difficult to measure (e.g. the quality of a visit to a physician) or data might not always be available (e.g. customer satisfaction surveys). The ability of our analysis to obtain firm level data on the provision of ride-sharing services by licensed and unlicensed individuals allow us to estimate the influence of occupational licensing on key outcome measures for the first time.

*A Model of Ride-sharing with Occupational Licensing*

In order to specify a general model of ride-sharing with occupational licensing we specify a model with the following parameters. The model serves as a basis to inform the empirical work, rather than as a fully specified general equilibrium model of ride-sharing production under regulation.

$$Q_r = H = f[P(z),K] \qquad (1)$$

$Q_n = HL = f[P(z), N(z),K]$ (2)

Initially we assume that $Q_r$ is the output produced by the licensed driver, which we will refer to as "high skilled licensed services (HH)." $Q_n$ is the output produced by the unlicensed ride-sharing provider, which we will refer to as "lower skilled driver services (HL)." P(z) represents the high skilled licensed driver, recognizing that output relies on their decision of personal input and N(z) represents the input of the unlicensed provider, recognizing that output relies on her decision of personal effort input. K represents the quantities of capital inputs which in this case is the app provided by the ride-sharing firm and an efficient and clean car.

With full licensing by a jurisdiction, no services are provided without the direction of the licensed workers and taxi/ medallion owners. Licensed drivers and taxi/medallion owners, who are generally in control of the production of these services, can limit lower wage substitutes. The larger empirical question the paper examines is the influence of regulation on the perceived and actual quality and safety of rider-services. To the extent that consumer satisfaction is not improved with more regulation, then these barriers to entry may be largely rents and not consumer surplus.

*Measuring Quality*

One approach to assessing the outcome quality of Uber rides is through driver quality ratings. After completing a trip, riders rate the driver on a scale of one to five stars, with one star associated with the lowest quality and a five with the highest. Quality ratings are highly right skewed, with nearly 86% of trips receiving a five-star rating. In contrast, less than 2% of trips receiving one star. See Figure 1, which includes data for all rated personal transportation trips completed in the US between June 2012 and January 2017, excluding trips taken with uberTaxi, which is less than 2 percent of all Uber rides. The distribution of driver quality ratings is also relatively consistent across locales. See Figure 2, which includes the eight U.S. cities with highest uberX trip volume that were operational with the uberX product as of January 2014.

**Figure 1: Ratings Distribution on US Trips**

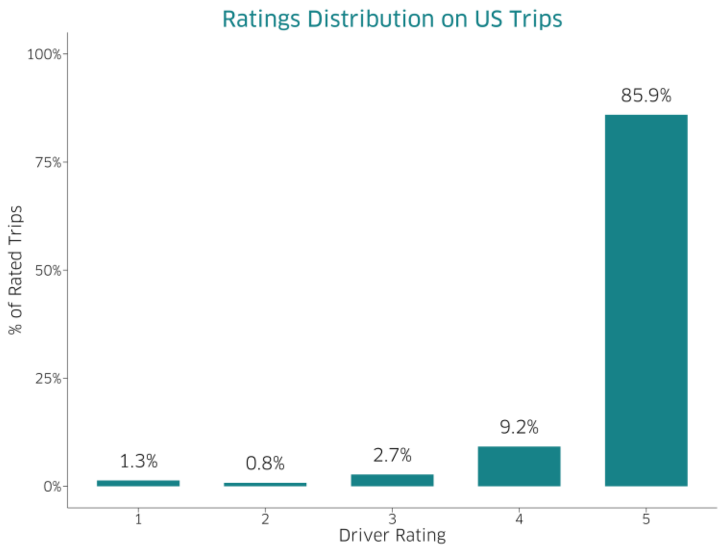
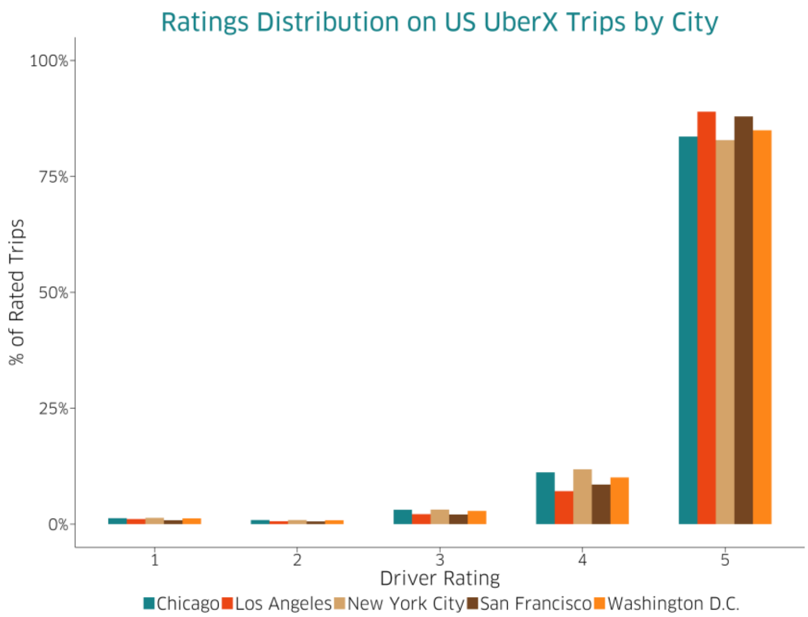


**Figure 2: Ratings Distribution on US uberX Trips by City**




Although licensed taxi drivers are assumed to operate in different markets than ride-sharing drivers, we examine how regulations may influence the number of hours licensed and unlicensed drivers allocate to work (Farber, 2014 and Crawford and Meng, 2011). For example, the standard employment arrangement of New York City cab drivers, who do not own their own cabs/medallions is that a driver leases a cab for a fixed period, usually a 12-hour shift. The driver pays a fixed fee for the cab plus fuel, and they keep 100 percent of the fare, income plus tips. The driver is free to work as few or as many hours as they wish within a 12-hour shift (Farber, 2014, Crawford and Meng, 2011). Since New York City requires that all drivers be licensed to pick up a fare, all Uber ride-sharing partners also must have a license equivalent to that required for taxi drivers. We will examine if the rides of “higher quality” New York City licensed drivers and those in New Jersey, where there is no requirement that drivers obtain a taxi license.

The likelihood that an individual continues to operate on the Uber app over time varies considerably across cities. Figure 3 displays the percentage of drivers remaining active during their first 40 days on the app for the cities with the largest number of drivers who become active between January 2015 and July 2015. New York City has the highest barriers to entry among U.S. cities, and it has very low quit rates within the first 40 days relative to other U.S. cities. In contrast, Houston has relatively high quit rates, and requires drivers to complete a fingerprint background check within 30 days of beginning to operate on the Uber platform.

**Figure 3: Likelihood of Driver-Partners Remaining Active by City**

3. *Data and Empirical Strategy*

Trip level data provided by Uber were used to conduct all of our analyses. We conducted several preliminary analyses to explore the potential impact of occupational licensing regulation on the quality and safety outcomes of rides provided by drivers operating on the Uber platform. We present an initial attempt at generating causal estimates of the impact of occupational licensing on quality and safety outcomes for New York City and adjacent New Jersey drivers and the Seattle / Tacoma, Washington drivers.

*Comparison of Trip Ratings of Licensed and Unlicensed Drivers: New York City v. New Jersey*

We compared the ratings received by drivers who have gone through the licensing process with the ratings received by drivers on the same Uber app service who have never gone through the licensing process. We determined whether a driver is currently or were licensed by observing whether a given driver had previously completed trips on an Uber product that requires a driver to have an occupational license (e.g., UBER BLACK). This analysis is limited to cities with greatest number of "switchers" from licensed to unlicensed products, which included San Francisco, Seattle, Chicago, and Washington, D.C. Data are from rated trips on varying services (uberX (basic service) and Select (a higher end service) completed by accounts associated with current or formerly licensed drivers (licensed) and accounts never associated with current or formerly licensed drivers (unlicensed). Licensed accounts are restricted to accounts associated with drivers who were licensed prior to driving on unlicensed Uber products.

We used a linear probability model (LPM) to estimate the probability that a driver who was never licensed would receive a one, two, three, four, or five star rating on a ride. We controlled for base fare (USD), surge multiplier, trip distance (miles), trip duration (seconds), the number of trips a driver conducted in their lifetime, and the number of trips the rider who issued the rating has rated. Additionally, we included city and time fixed effects in our model.

*Comparison of Licensed and Unlicensed Drivers on UberSELECT Trips*

We compared ratings received by licensed drivers on UberSELECT and Plus trips (unlicensed products), to ratings received by unlicensed drivers on the UberSELECT and Plus products. We identify drivers who have an occupational license by filtering for drivers who have completed one or more rated trips in the same vehicle and city on both a licensed and unlicensed product. Our dataset is comprised of rated trips on UberSELECT, Plus, BLACK, SUV, and LUX services from January 2013 through December 10, 2016.

We used a LPM to estimate the probability that a driver who *only* operates on the UberSELECT or Plus (unlicensed) would receive a one, two, three, four, or five star rating on a ride. We controlled for base fare (USD), surge multiplier, trip distance (miles), trip duration (seconds), the number of trips a driver conducted in their lifetime, and the number of trips the rider who issued the rating has rated. We also included city and time fixed effects in our model.

*Quasi-Random Assignment of Rides to Licensed and Unlicensed Drivers*

In New York City, individuals seeking to drive on the Uber platform as a for-hire vehicle driver must complete an intensive array of requirements and training to receive an occupational license, including completion of a Department of Motor-Vehicle approved defensive driving course/exam, a Wheelchair Accessible Vehicle class, and a 24-hour Driver Education course/exam, among other requirements. In stark contrast, drivers operating on the UberX service in neighboring New Jersey are not required to obtain an occupational license or fulfill any of these requirements. Both licensed drivers from New York City and unlicensed drivers from New Jersey and can pick-up Uber riders in New Jersey. We use a quasi-random assignment approach along with the geographic overlap in pick-up capability to exploit this border discontinuity in licensing requirements and estimate the effect of requiring a driver to obtain an occupational license on the quality and safety outcomes of rides.

The quasi-random assignment of rides occurs because Uber's dispatch algorithm, which determines the driver for a particular ride request, is based on factors other than licensing for certain combinations of geography and product type requested. While the dispatch algorithm has evolved over time, it is mainly based on a driver's proximity to a rider's location (based on distance and time). Thus, a ride is essentially randomly assigned to a licensed driver from New York City or an unlicensed driver from New Jersey. The data set is only comprised of rides that full the quasi-random assignment criteria described above.

Our model was specified as follows:

$$Q_{it}, HA_{it}, HB20_{it} = \beta_0 + \beta_1 Geography_{it} + \beta_2 X' + \delta_1 Licensed_t + \eta_h + \epsilon_{it}$$

$Q$= Quality rating
*HA* = Fraction of hard accelerations
*HB20* = Fraction of hard brakes on a trips is > 20%
*i* = individual driver
*t* = an individual trip

$Geography$controls for the pickup location (PU) and the destination location (DO) using TripMatchR, which algorithmically implements a geography-based clustering approach

$X'$ is a vector of covariates controlling for observable characteristics that may impact the dependent variable for drivers on a particular ride, which includes overall fare amount (USD), predicted estimated time of arrival (ETA), driver experience (previous number of trips), rider experience (previous number of trips), trip distance (miles), trip duration (seconds), gender, and age

$Licensed$ is whether a particular ride is performed by a driver with an occupational license (1 = the driver has an occupational license; 0 = the driver does not have an occupational license)

$\eta_h$ are "time" fixed effects, which includes hour of the day, day of the week, and month of the year fixed effects.

For our examination of the quality effect of licensing in New York and New Jersey, we used the program TripMatchR, which was designed by John Horton at New York University, to separate trips that were performed in New Jersey into "regions" or "clusters" by partitioning the trips into iso-count regions (equal number of pickups per region). We identified regions where greater than 10% of the pickups were performed by NYC drivers, and we identified pickups performed at Newark International Airport. We conducted separate analyses for each samples. The greater than 10% of pickups performed by NYC drivers dataset also contains pickups performed at Newark International Airport.

We only present the results for the Newark Airport analysis because they are qualitatively similar to those where greater than 10% pickups analysis and the allocation of rides is potentially closer random assignment than are other pickups in New Jersey. At Newark International Airport, Uber drivers are placed in a ranked queue when they arrive at the airport and are given the pickup request that occurs when they are at the top of the queue. Drivers do not know where they are located in the queue, or the individual pickup request they are going to receive.

Table 1: Descriptive Statistics: New York and New Jersey

| | | Observations | Mean | SD | Min | Max |
|---|---|---|---|---|---|---|
| **Total Fares ($)** | New Jersey | 712,390 | 31.72 | 18.18 | 4.84 | 678.13 |
| | New York City | 166,901 | 49.72 | 16.41 | 5.6 | 348.46 |
| **Predicted ETA (min)** | New Jersey | 712,390 | 2.34 | 2.37 | 0.02 | 236.67 |
| | New York City | 166,901 | 2.57 | 2.35 | 0.02 | 212.68 |
| **Trip Duration (min)** | New Jersey | 712,390 | 30.93 | 11.55 | 0.03 | 1,214.57 |
| | New York City | 166,901 | 41.67 | 17.90 | 0.05 | 339.25 |
| **Trip Distance (mi)** | New Jersey | 712,390 | 18.96 | 11.87 | 3.82E-07 | 445.50 |
| | New York City | 166,901 | 19.61 | 9.58 | 2.40E-06 | 334.51 |
| **Driver Experience** | New Jersey | 712,390 | 1662.38 | 1543.30 | 1 | 13140 |
| | New York City | 166,900 | 2065.60 | 2026.28 | 1 | 15872 |
| **Gender** | New Jersey | 712,390 | 0.92 | 0.28 | 0 | 1 |
| | New York City | 166,901 | 0.98 | 0.13 | 0 | 1 |
| **Age** | New Jersey | 712,390 | 41.79 | 11.51 | 21 | 84 |
| | New York City | 166,901 | 39.47 | 11.16 | 21 | 84 |

| | | Observations | Mean | SD | Min | Max |
|---|---|---|---|---|---|---|
| **Star (Quality) Ratings** | New Jersey | 364,044 | 4.789 | 0.639 | 1 | 5 |
| | New York City | 90,488 | 4.797 | 0.621 | 1 | 5 |
| **Fraction Hard Brakes** | New Jersey | 500,786 | 0.100 | 0.111 | 0 | 1 |
| | New York City | 118,187 | 0.084 | 0.093 | 0 | 1 |
| **Fraction Hard Accelerations** | New Jersey | 439,654 | 0.073 | 0.101 | 0 | 1 |
| | New York City | 106,187 | 0.065 | 0.085 | 0 | 1 |
| **Fraction of Trips with > 20% Hard Brakes** | New Jersey | 500,786 | 0.167 | 0.373 | 0 | 1 |
| | New York City | 118,187 | 0.115 | 0.319 | 0 | 1 |
| **Fraction of Trips with > 20% Hard Accelerations** | New Jersey | 439,654 | 0.105 | 0.307 | 0 | 1 |
| | New York City | 106,187 | 0.079 | 0.270 | 0 | 1 |
| **Fraction of Safety Incidents** | New Jersey | 712,390 | 0.001 | 0.031 | 0 | 1 |
| | New York City | 166,901 | 0.001 | 0.034 | 0 | 1 |

In the table2 below we show the estimates of the influence of licensing coverage on measures of customer satisfaction with controls for the type of ride and the human capital characteristics of the drivers. The estimates show that licensing does not have much influence on the quality of the rides based on customer satisfaction in the New York and New Jersey areas.

Table 2: Results: Star (Quality) Rating

| Variables | (1) Star (Quality) Rating | (2) Star (Quality) Rating | (3) Star (Quality) Rating | (4) Star (Quality) Rating |
|---|---|---|---|---|
| **Licensing Coverage** | **-0.0435*** ** | **-0.0503*** ** | **-0.0457** ** | **-0.0457** ** |
| | (0.0000) | (0.00223) | (0.00259) | (0.00264) |
| Constant | 4.766*** | 5.035*** | 5.142** | 5.149** |
| | (0.0000) | (0.724) | (0.0961) | (0.0824) |
| Observations | 749,765 | 744,868 | 744,868 | 744,868 |
| R-squared | 0.001 | 0.009 | 0.014 | 0.014 |
| Controls[1] | | X | X | X |
| Geography FE | | | X | X |
| DOW & TOD FE | | | | X |

*** p<0.01, ** p<0.05, * p<0.1

[1] trip duration (s), trip distance(mi), client fare, trip predicted, trip predicted eta, driver experience, driver surge multiplier, gender, age, vehicle model & year

Robust standard errors clustered by partner-driver locale

The estimates show results with the star (quality ratings) as the dependent variable. In the first specification (1) contains only the licensing coverage variable. In the second column we show the licensing coverage variable as well as a series of control variables that includes including total fare, estimated eta, trip duration, trip distance, driver experience (the number trips a driver performed before a particular trip), rider experience (the number trips a rider has taken before a particular trip), gender, age, vehicle make and year, and rider most frequent city (which is the city where a rider most frequently takes trips). In the third specification our estimates also include geography controls for the beginning and end location of a trip. In the fourth column we also include the type of trip, driver, rider, and geography level controls, contains time fixed effects (month of the year, day of the week, and hour of the day).

Beyond just satisfaction we also estimate the influence of occupational licensing on the quality of the trip, which includes the fraction of hard breaking, the number of trips where hard braking was greater than 20 percent of the trips. We estimate the same model for the fraction of hard accelerations and where those accelerations are greater than 20 percent of the trips.

Table 3:Results: Fraction of Hard Brakes

| Variables | (1) Frac(Hard Brakes) | (2) Frac(HB) | (3) Frac(HB) | (4) Frac(HB) | (1) Frac(Trips > 20% HB) | (2) Frac(Trips > 20% HB) | (3) Frac(Trips > 20% HB) | (4) Frac(Trips > 20% HB) |
|---|---|---|---|---|---|---|---|---|
| **Licensing Coverage** | **-0.00299***** | **-0.00367** | **-0.00395*** | **-0.00400*** | **-0.00665***** | **-0.00639** | **-0.00735*** | **-0.00740*** |
| | (0.0001) | (0.000714) | (0.000502) | (0.000468) | (0.0001) | (0.00132) | (0.00113) | (0.00102) |
| Constant | 0.0721*** | 0.0618* | 0.0443 | 0.0372 | 0.139*** | -0.105 | -0.0972* | -0.114* |
| | (0.0001) | (0.00847) | (0.00932) | (0.00981) | (0.0001) | (0.0236) | (0.0120) | (0.0118) |
| Observations | 1,451,661 | 1,373,570 | 1,373,570 | 1,373,570 | 1,464,588 | 1,386,130 | 1,386,130 | 1,386,130 |
| R-squared | 0.001 | 0.074 | 0.082 | 0.086 | 0.001 | 0.049 | 0.053 | 0.055 |
| Controls[1] | | X | X | X | | X | X | X |
| Geography FE | | | X | X | | | X | X |
| DOW & TOD FE | | | | X | | | | X |

*** p<0.01, ** p<0.05, * p<0.1

[1] trip duration (seconds), trip distance (miles), driver experience, gender, age, device iOS, vehicle solutions, vehicle model & year, driver surge

Robust standard errors are clustered by partner-driver locale

The magnitude of the licensing coverage coefficients is small across all of the specifications. .

Finally we estimate the influence of licensing on the number of safety incidents using the same model in the Table below. The results show no influence of occupations licensing using a linear probability model.

Table 4: Results: Fraction of Hard Accelerations

| Variables | (1) Frac(Hard Accels) | (2) Frac(HA) | (3) Frac(HA) | (4) Frac(HA) | (1) Frac(Trips > 20% HA) | (2) Frac(Trips > 20% HA) | (3) Frac(Trips > 20% HA) | (4) Frac(Trips > 20% HA) |
|---|---|---|---|---|---|---|---|---|
| **Licensing Coverage** | **-0.00319***** | **-0.00409**** | **-0.00462**** | **-0.00465**** | **-0.00558***** | **-0.00554***** | **-0.00711**** | **-0.00710***** |
| | (0.0000) | (0.000310) | (0.000240) | (0.000219) | (0.0000) | (0.0000) | (0.000184) | (0.000108) |
| Constant | 0.0576*** | 0.216** | 0.204** | 0.202** | 0.106*** | 0.923*** | 0.944*** | 0.938*** |
| | (0.0000) | (0.00623) | (0.00894) | (0.00920) | (0.0000) | (0.0118) | (0.00383) | (0.00358) |
| Observations | 1,451,902 | 1,373,797 | 1,373,797 | 1,373,797 | 1,464,588 | 1,386,130 | 1,386,130 | 1,386,130 |
| R-squared | 0.001 | 0.082 | 0.087 | 0.089 | 0.001 | 0.041 | 0.044 | 0.045 |
| Controls[1] | | X | X | X | | X | X | X |
| Geography FE | | | X | X | | | X | X |
| DOW & TOD FE | | | | X | | | | X |

*** p<0.01, ** p<0.05, * p<0.1

[1] trip duration (seconds), trip distance (miles), driver experience, gender, age, device iOS, vehicle solutions, vehicle model & year, driver surge

Robust standard errors are clustered by partner-driver locale

**Comparison of UberBLACK & UberSELECT**

We compare the outcomes of individuals who UberSelect is a mid-upper tier car and ride experience while sharing lots of overlap in vehicle makes, models, and years. Select also has less luxurious models/makes such as Volkswagon, Kia, Toyota, Acura, and Ford. The basic descriptive data is presented in Table 5 below.

Table 5: **Descriptive Statistics – Driver & Rider Variables**

| Variables | Product | N | Mean | SD | Min | Max |
|---|---|---|---|---|---|---|
| Gender | BLACK | 178,811 | 0.98 | 0.15 | 0 | 1 |
| | SELECT | 427,419 | 0.92 | 0.27 | 0 | 1 |
| Age | BLACK | 252,618 | 40.10 | 8.13 | 21 | 50 |
| | SELECT | 433,268 | 38.89 | 8.45 | 21 | 63 |
| Driver Experience | BLACK | 334,850 | 4,029 | 3,054 | 1 | 19,942 |
| | SELECT | 434,603 | 2,467 | 2,632 | 1 | 21,462 |
| Rider Experience | BLACK | 334,850 | 229.2 | 324.3 | 1 | 4,562 |
| | SELECT | 434,603 | 224.7 | 333.8 | 1 | 4,918 |

Panel B

| Variables | Product | N | Mean | SD | Min | Max |
|---|---|---|---|---|---|---|
| Predicted etimated time of arrival (eta; minutes) | BLACK | 334,850 | 3.76 | 4.97 | 0.42 | 12.82 |
| | SELECT | 434,603 | 3.96 | 3.93 | 0.43 | 13.42 |
| Eta difference (1st driver in queue - 2nd driver in queue) | BLACK | 334,850 | 1.263 | 1.416 | 0.00 | 8 |
| | SELECT | 434,603 | 1.29 | 1.45 | 0.00 | 8 |
| Trip distance (miles) | BLACK | 334,850 | 6.978 | 8.016 | 0.318 | 315.1 |
| | SELECT | 434,603 | 7.172 | 8.473 | 0.343 | 352.2 |
| Trip duration (minutes) | BLACK | 334,850 | 17.05 | 12.57 | 2.37 | 320.23 |
| | SELECT | 434,603 | 17.42 | 13.19 | 2.37 | 482.02 |
| Driver surge muliplier | BLACK | 334,850 | 1.025 | 0.151 | 1 | 7.600 |
| | SELECT | 434,603 | 1.032 | 0.158 | 1 | 8 |

Panel C

| Variables | Product | N | Mean | SD |
|---|---|---|---|---|
| Star (Quality) Rating | Black | 158,291 | 4.845 | 0.558 |
| | P2P | 211,301 | 4.829 | 0.599 |
| Fraction of Hard Brakes | Black | 329,435 | 0.0606 | 0.0993 |
| | P2P | 427,917 | 0.0677 | 0.106 |
| Fraction of Hard Accelerations | Black | 329,466 | 0.0527 | 0.0938 |
| | P2P | 427,935 | 0.0607 | 0.102 |
| Fraction of Trips w/ > 20% Hard Brakes | Black | 329,435 | 0.104 | 0.306 |
| | P2P | 427,917 | 0.119 | 0.324 |
| Fraction of Trips w/ > 20% Hard Accelerations | Black | 329,466 | 0.0876 | 0.283 |
| | P2P | 427,935 | 0.105 | 0.307 |

Figure 4: Star Quality Ratings

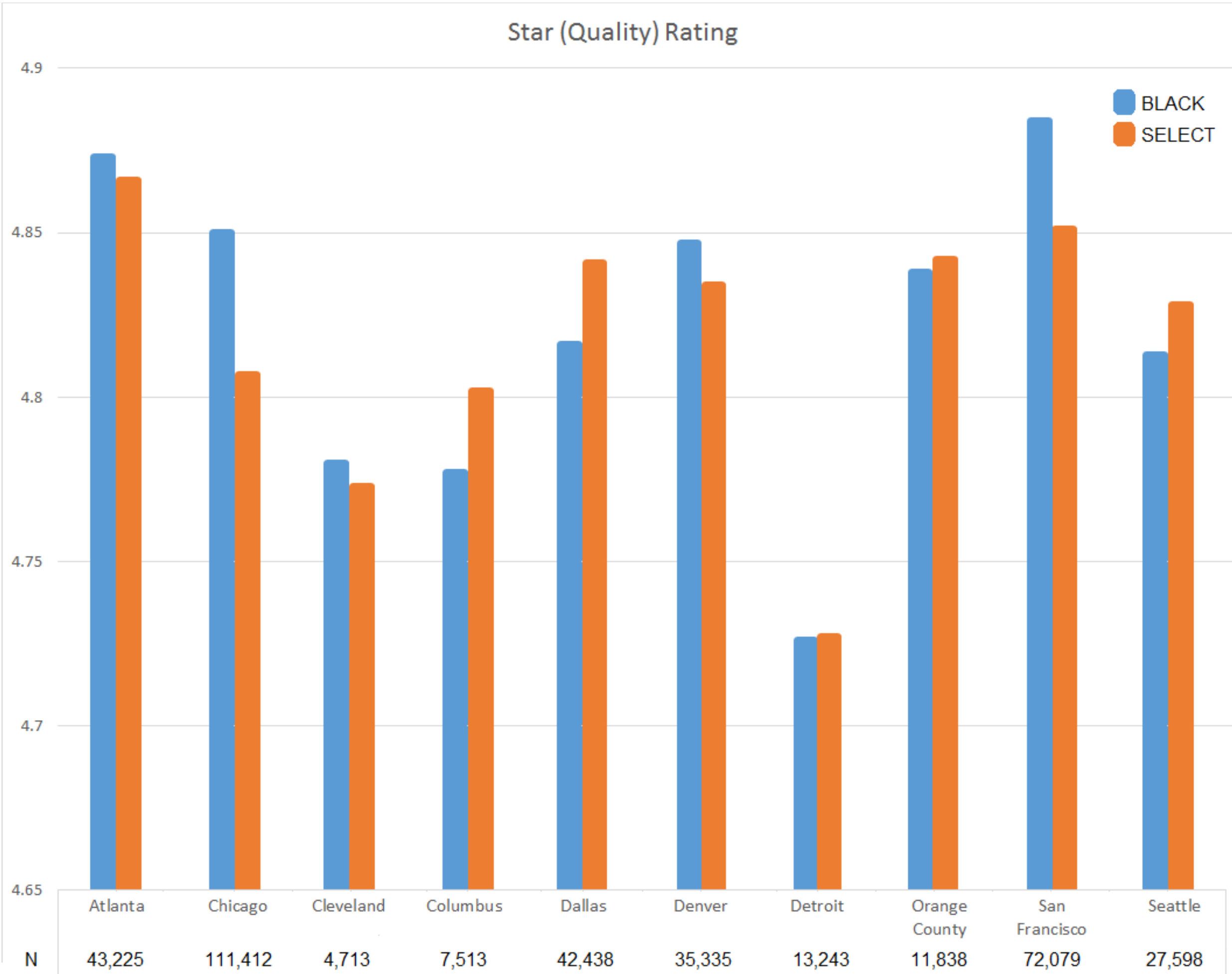

Star (Quality) Rating
4.9
4.85
4.8
4.75
4.7
4.65
BLACK
SELECT
Atlanta
Chicago
Cleveland
Columbus
Dallas
Denver
Detroit
Orange County
San Francisco
Seattle
N
43,225
111,412
4,713
7,513
42,438
35,335
13,243
11,838
72,079
27,598

Table 6: **BLACK/SELECT Results: Star (Quality)**

| Variables | (1) Rating | (2) Rating | (3) Rating | (4) Rating |
|---|---|---|---|---|
| **Commercial Driver** | **0.0166** | **0.0158** | **0.0159** | **0.0156** |
| | (0.0109) | (0.00965) | (0.00974) | (0.00977) |
| Constant | 4.857*** | 4.894*** | 4.862*** | 4.856*** |
| | (0.00374) | (0.0293) | (0.0293) | (0.0305) |
| Observations | 369,592 | 291,215 | 291,215 | 291,215 |
| R-squared | 0.003 | 0.008 | 0.009 | 0.010 |
| City FE | X | X | X | X |
| Controls[1] | | X | X | X |
| Geography FE | | | X | X |
| DOW & TOD FE | | | | X |

*** p<0.01, ** p<0.05, * p<0.1

[1] trip duration (s), trip distance(mi), client fare, trip predicted, trip predicted eta, driver experience, driver surge multiplier, gender, age, vehicle model & year

Robust standard errors clustered by partner-driver locale

Table 7 Fraction of Hard Brakes

| Variables | (1) Frac(Hard Brakes) | (2) Frac(HB) | (3) Frac(HB) | (4) Frac(HB) | (1) Frac(Trips > 20% HB) | (2) Frac(Trips > 20% HB) | (3) Frac(Trips > 20% HB) | (4) Frac(Trips > 20% HB) |
|---|---|---|---|---|---|---|---|---|
| **Commercial Driver** | **-0.00687***** | **-0.00360***** | **-0.00393***** | **-0.00386***** | **-0.0146***** | **-0.00608**** | **-0.00800***** | **-0.00781***** |
| | (0.00120) | (0.000609) | (0.000666) | (0.000655) | (0.00365) | (0.00264) | (0.00193) | (0.00193) |
| Constant | 0.0565*** | 0.0520*** | 0.0714*** | 0.0655*** | 0.0880*** | 0.0423 | 0.135*** | 0.119*** |
| | (0.000418) | (0.0160) | (0.0160) | (0.0155) | (0.00127) | (0.0320) | (0.0308) | (0.0282) |
| Observations | 757,352 | 596,869 | 596,869 | 596,869 | 757,352 | 596,869 | 596,869 | 596,869 |
| R-squared | 0.014 | 0.047 | 0.053 | 0.055 | 0.011 | 0.042 | 0.045 | 0.046 |
| City FE | X | X | X | X | X | X | X | X |
| Controls[1] | | X | X | X | | X | X | X |
| Geography FE | | | X | X | | | X | X |
| DOW & TOD FE | | | | X | | | | X |

*** p<0.01, ** p<0.05, * p<0.1

[1] trip duration (seconds), trip distance (miles), driver experience, gender, age, device iOS, vehicle solutions, vehicle model & year, driver surge

Robust standard errors are clustered by partner-driver locale

Table 8: **BLACK/SELECT Results: Fraction of Hard Accelerations**

| VARIABLES | (1) Frac(Hard Accel) | (2) Frac(HA) | (3) Frac(HA) | (4) Frac(HA) | (1) Frac(Trips > 20% HA) | (2) Frac(Trips > 20% HA) | (3) Frac(Trips > 20% HA) | (4) Frac(Trips > 20% HA) |
|---|---|---|---|---|---|---|---|---|
| **Commercial Driver** | **-0.00761***** | **-0.00363**** | **-0.00421**** | **-0.00415**** | **-0.0167***** | **-0.00799*** | **-0.00930**** | **-0.00910**** |
| | (0.00165) | (0.00152) | (0.00135) | (0.00136) | (0.00423) | (0.00371) | (0.00329) | (0.00334) |
| Constant | 0.0557*** | -0.00210 | 0.0582*** | 0.0544** | 0.0924*** | 0.0188 | 0.117*** | 0.105*** |
| | (0.000572) | (0.0162) | (0.0164) | (0.0168) | (0.00147) | (0.0279) | (0.0284) | (0.0283) |
| Observations | 757,401 | 596,906 | 596,906 | 596,906 | 757,401 | 596,906 | 596,906 | 596,906 |
| R-squared | 0.008 | 0.041 | 0.043 | 0.044 | 0.006 | 0.033 | 0.034 | 0.035 |
| City FE | X | X | X | X | X | X | X | X |
| Controls[1] | | X | X | X | | X | X | X |
| Geography FE | | | X | X | | | X | X |
| DOW & TOD FE | | | | X | | | | X |

*** p<0.01, ** p<0.05, * p<0.1

[1] trip duration (seconds), trip distance (miles), driver experience, gender, age, device iOS, vehicle solutions, vehicle model & year, driver surge

Robust standard errors are clustered by partner-driver locale

*Training Effects: Seattle*

We examined the effects on quality and safety outcomes of the requirement in King County (Seattle, WA) and Pierce County (Tacoma, WA) that drivers operating on the Uber platform must complete a defensive driving course (DDC). The DDC is a four-hour National Safety Council online course that "...presents real-life driving situations and hazards and motivates drivers to change their driving habits and behaviors to avoid collisions and traffic violations." According to King and Pierce County regulations, the DDC must be completed by drivers (uberX, XL, and SELECT) within sixty days of a driver beginning to operate in Seattle or Tacoma. Thus, many uberX drivers legally operate in Seattle and Tacoma before completing the test. We use a multi-period difference-in-differences (DID) estimator to utilize the variation in completion dates of the DDC in Seattle and Tacoma and estimate the effect of the DDC on quality and safety outcomes of rides. Portland and Minneapolis/St. Paul and serves as our comparison group, and our identifying assumption is that safety and quality outcomes in the treatment group (rides performed by Seattle and Tacoma drivers) would be the same as those in the comparison group (Portland, OR) in the absence of treatment.

We used four different dependent variables (quality ratings, fraction of hard accelerations, fraction of hard brakes, and the occurrence of a safety incident) to assess the impact of the completion of the DDC on quality and safety. The fraction of hard brakes is defined as the fraction of hard braking events on a trip with a high force. The occurrence of a "safety incident" on a trip is based on Uber communications with riders and drivers as well as insurance data.

Our model was specified as follows:

$$\boldsymbol{Q_{ilt}, HA_{ilt}, HB_{ilt}, SI_{ilt} = \beta_0 + \beta_1 X' + \delta_1 DDC_{il}\, x\, BeginTrip_{t=t^0} + \gamma_l + \eta_d + \epsilon_{ilt}}$$

$Q$ = Quality ratings
HA = Fraction of hard accelerations
HB = Fraction of hard brakes
SI = Safety incidences

*t* = date and time the trip began (March 1, 2016 to present)
*i* = driver who began operating on the uberX platform between March 1, 2016 to present
*l* = locales

*Treatment* locales (in which new P2P drivers are required to take an online defensive driving course/test) include King County and Pierce County.

*Control* locales (in which new P2P drivers are *not* required to take an online defensive driving course/test) include Portland, OR

$X'$ is a vector of covariates controlling for observable characteristics that may impact the dependent variable on a particular ride, which includes base fare (USD), surge multiplier, predicted estimated time of arrival (ETA), trip distance (miles), trip duration (seconds), and driver tenure.

$DDC_{il}\ x\ Begin\ Trip_{t=t^0}$ is the interaction of a driver being in the treatment group (required completion of the defensive driving course/test) and when completion of the DDC occurred.

$\gamma_l$ are locale-fixed effects, which control for locale specific characteristics that are time invariant.

$\eta_d$ are "time-fixed effects" effects, including hour of the day, day of the week, and month of the year fixed effects, which control for factors that vary through time but do not vary across locales.

$\epsilon_{ilt}$ is the stochastic error term.

*Comparison of Trip Ratings of Licensed and Unlicensed Drivers*

Table 9 reveals that a driver operating on the UberX platform that has never held an occupational license is, on average, 0.4 percentage points more likely to receive a five star rating on trip than drivers who are or were licensed, controlling for the suite of covariates we have included in the model. Alternatively, for every 1,000 UberX trips that an unlicensed partner takes, the partner receives four more five star ratings, on average, than licensed drivers. However, an unlicensed driver is also 0.4 percentage points less likely to receive a four star rating on a trip and is 0.1 percentage points more likely to receive a one star rating on a trip. All "Never Licensed UberX driver" coefficients are significant at the 5% level with the exception of the three star rating. The inclusion of covariates has only a small positive effect on the probability of receiving a five star rating.

**Table 9 Likelihood of Trip Ratings of Formerly or Currently Licensed Drivers and Unlicensed Drivers**

**Likelihood of Trip Ratings of Formerly or Currently Licensed Drivers and Unlicensed Drivers on uberX Trips**

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | Rating = 1 | Rating = 2 | Rating = 3 | Rating = 4 | Rating = 5 | |
| | | | | | a | b |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Never Licensed uberX Driver | $0.001^{***}$ (0.0002) | $0.0003^{**}$ (0.0001) | 0.00004 (0.0004) | $-0.004^{***}$ (0.001) | $0.003^{**}$ (0.001) | $0.004^{***}$ (0.001) |
| Base Fare (USD) | | | | | | 0.001 (0.001) |
| Surge Multiplier | | | | | | $-0.022^{***}$ (0.001) |
| Trip Distance (Miles) | | | | | | $-0.0003^{***}$ (0.00004) |
| Trip Duration (Seconds) | | | | | | -0.00000 (0.00000) |
| Driver's Lifetime Rated Trips | | | | | | 0.00000 (0.00000) |
| Rider Lifetime Trips | | | | | | $0.0001^{***}$ (0.00000) |
| City Fixed Effects | X | X | X | X | X | X |
| Time Fixed Effects | X | X | X | X | X | X |
| Observations | 11,531,896 | 11,531,896 | 11,531,896 | 11,531,896 | 11,531,896 | 11,492,364 |
| $R^2$ | 0.001 | 0.001 | 0.002 | 0.008 | 0.010 | 0.018 |
| Adjusted $R^2$ | 0.001 | 0.0005 | 0.002 | 0.008 | 0.010 | 0.018 |
| Residual Std. Error | 0.102 (df = 11530304) | 0.085 (df = 11530304) | 0.160 (df = 11530304) | 0.300 (df = 11530304) | 0.350 (df = 11530304) | 0.349 (df = 11490766) |

*Note:* $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

Custered standard errors by driver: 18,420 drivers in sample.

*Comparison of Licensed and Unlicensed Drivers on UberSELECT Trips*

Table 9 indicates that an unlicensed UberSELECT driver is 0.8 percentage points less likely, on average, to receive a five star rating on a trip than licensed UberSELECT drivers when including our control variables in the model. Alternatively, for every 1,000 trips that an unlicensed UberSELECT partner takes, the partner receives eight fewer five than a licensed UberSELECT driver. In contrast, unlicensed UberSELECT drivers are less likely to receive all other star values on a trip than licensed UberSELECT drivers. All “unlicensed UberSELECT Driver” coefficients are significant at the 5% level with the exception of the four star rating.

**Table 10: Likelihood of Trip Ratings of Licensed and Unlicensed Drivers on Uber Select Trips**

**Likelihood of Trip Ratings of Licensed and Unlicensed Drivers on Uber SELECT Trips**

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | Rating = 1 | Rating = 2 | Rating = 3 | Rating = 4 | Rating = 5 | |
| | | | | | a | b |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Unlicensed Uber SELECT Driver | 0.004$^{***}$ (0.0002) | 0.001$^{***}$ (0.0001) | 0.003$^{***}$ (0.0003) | 0.001 (0.001) | -0.009$^{***}$ (0.001) | -0.008$^{***}$ (0.001) |
| Base Fare (USD) | | | | | | 0.009 (0.009) |
| Surge Multiplier | | | | | | -0.047$^{***}$ (0.002) |
| Trip Distance (Miles) | | | | | | 0.001$^{***}$ (0.0001) |
| Trip Duration (Seconds) | | | | | | -0.00001$^{***}$ (0.00000) |
| Driver's Lifetime Rated Trips | | | | | | 0.00000 (0.00000) |
| Rider Lifetime Trips | | | | | | 0.0001$^{***}$ (0.00000) |
| City Fixed Effects | X | X | X | X | X | X |
| Time Fixed Effects | X | X | X | X | X | X |
| Observations | 8,761,338 | 8,761,338 | 8,761,338 | 8,761,338 | 8,761,338 | 8,761,133 |
| $R^2$ | 0.004 | 0.001 | 0.002 | 0.004 | 0.007 | 0.017 |
| Adjusted $R^2$ | 0.004 | 0.001 | 0.002 | 0.004 | 0.007 | 0.017 |
| Residual Std. Error | 0.123 (df = 8760494) | 0.086 (df = 8760494) | 0.151 (df = 8760494) | 0.277 (df = 8760494) | 0.335 (df = 8760494) | 0.334 (df = 8760283) |

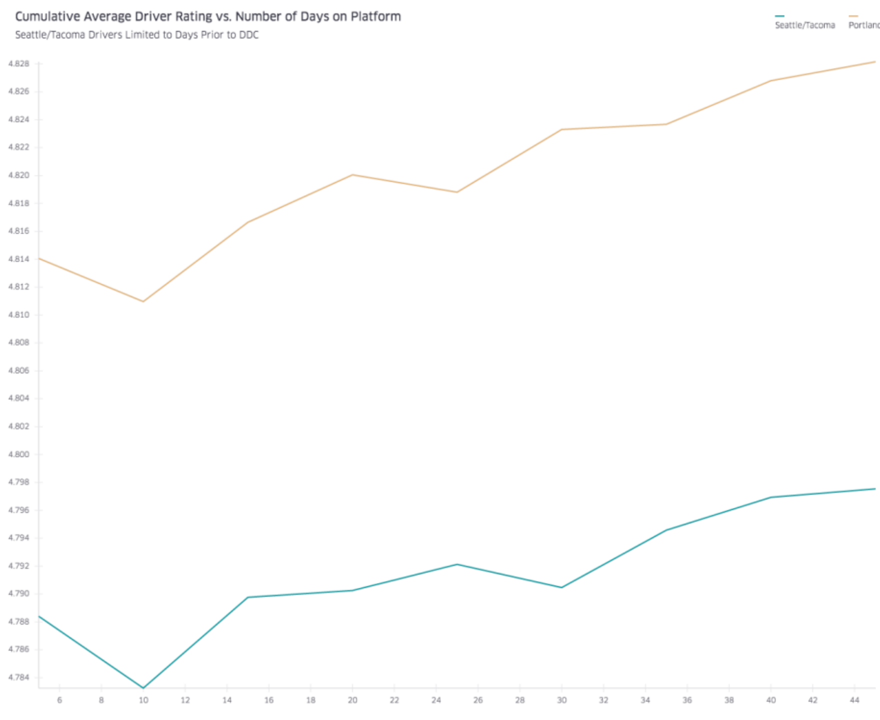
*Note:* $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

Custered standard errors by driver: 59,945 drivers in sample.

Seattle and Tacoma, WA Defensive Driving Course Analysis

To partially assess the validity of the identifying assumption of parallel trends in quality ratings of the comparison group (drivers in Portland, OR) and treatment group (drivers in Seattle, WA and Tacoma, WA), we examined the average ratings given to drivers operating on the Uber platform during our study period based on the drivers tenure, which is measured as time between becoming active on the platform and the time of a particular trip request. We selected 45 days as the maximum day threshold because all Seattle and Tacoma drivers should have completed the DDC by this time. Figure 4 reveals that drivers in the comparison and treatment group follow nearly identical trends in quality ratings during their first 45 days on the platform (the pre-treatment period).

**Figure 5 Cumulative Average Rating vs. Number of Days on Platform**



The DID estimate in the full specified LPM quality ratings model (Table 3), which includes city and time fixed effects and control variables, indicates that, on average, completing the DDC results in higher quality ratings for drivers operating on the UberX platform. The DID coefficients are also consistent across most model specifications. However, the basic DID estimate with controls or fixed effects is negative, indicating a negative relationship between completion of the DDC and quality ratings. Inclusion of city fixed effects switches the sign on the DID coefficient from negative to positive.

**Table 11 LPM Driver Ratings DID Model**

| | Driver Ratings | | | |
|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) |
| DID | **-0.0176*** ** | **0.0616*** ** | **0.0532*** ** | **0.0537*** ** |
| | (0.00246) | (0.00707) | (0.00705) | (0.00703) |
| Base Fare ($) | | | -0.00689 | -0.00908 |
| | | | (0.00815) | (0.00815) |
| Surge Multiplier | | | -0.0307*** | -0.0298*** |
| | | | (0.00186) | (0.00190) |
| Predicted ETA | | | -2.86e-06 | -3.00e-06 |
| | | | (2.87e-06) | (3.00e-06) |
| Trip Distance (miles) | | | 0.00387*** | 0.00404*** |
| | | | (0.000165) | (0.000165) |
| Trip Duration (seconds) | | | -6.01e-05*** | -6.25e-05*** |
| | | | (1.88e-06) | (1.90e-06) |
| Driver Tenure | | | -0.000147*** | -0.000146*** |
| | | | (1.81e-05) | (1.80e-05) |
| Constant | 1.755*** | 1.555*** | 2.830*** | 22.33 |
| | (0.249) | (0.252) | (0.348) | (42.18) |
| City Fixed Effects | | X | X | X |
| Day Fixed Effects | | | | X |
| Observations | 3,037,061 | 2,918,712 | 2,918,708 | 2,918,708 |
| R-squared | 0.001 | 0.001 | 0.003 | 0.003 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results from the LPM for each rating level indicate that individuals who complete the DDC have a higher probability of receiving a five star rating and a lower probability or receiving a one star rating than drivers who did not complete the DDC (Table 4).

**Table 12 LPM Driver Ratings (Each Rating Level) DID Model**

| | Linear Probability Models (Driver Ratings) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| VARIABLES | 5 rating | 5 rating | 4 rating | 3 rating | 2 rating | 1 rating |
| DID | **0.0163***** | **0.0195***** | **-0.00302***** | **-0.00392***** | **-0.00236***** | **-0.00384***** |
| | (0.00251) | (0.00250) | (0.000854) | (0.000572) | (0.000304) | (0.000444) |
| Base Fare ($) | | -0.0229*** | | | | |
| | | (0.00443) | | | | |
| Surge Multiplier | | -0.0288*** | | | | |
| | | (0.000914) | | | | |
| Predicted ETA | | 3.53e-06 | | | | |
| | | (2.67e-06) | | | | |
| Trip Distance (miles) | | -0.00488*** | | | | |
| | | (8.27e-05) | | | | |
| Trip Duration (seconds) | | -3.68e-06*** | | | | |
| | | (7.84e-07) | | | | |
| Driver Tenure | | 2.33e-05*** | | | | |
| | | (7.55e-06) | | | | |
| Constant | -287.9*** | -99.19*** | -73.29*** | -20.73*** | -8.966*** | 10.01*** |
| | (23.28) | (23.26) | (9.014) | (4.871) | (2.408) | (3.376) |
| Observations | 4,693,240 | 4,693,232 | 4,693,240 | 4,693,240 | 4,693,240 | 4,693,240 |
| R-squared | 0.070 | 0.075 | 0.005 | 0.002 | 0.000 | 0.001 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The DID model with fractions of hard accelerations as a dependent variable indicates that drivers who complete the DDC course will have more hard accelerations on trip than drivers who don't complete course; however, in the fully specified model the DID coefficient is not significant at the 10% level (Table 5).

**Table 13Fraction of Hard Accelerations DID Model**

| | Fraction of Hard Accelerations | | | |
|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) |
| DID | **0.00686*****| **0.00362** | **0.00119** | **0.00147** |
| | (0.00138) | (0.00266) | (0.00270) | (0.00270) |
| Base Fare ($) | | | -0.00860*** | -0.00997*** |
| | | | (0.00212) | (0.00214) |
| Surge Multiplier | | | -0.00856*** | -0.00847*** |
| | | | (0.000418) | (0.000412) |
| Predicted ETA | | | 2.65e-05*** | 2.60e-05*** |
| | | | (1.07e-06) | (1.07e-06) |
| Trip Distance (miles) | | | 0.00100*** | 0.000886*** |
| | | | (6.46e-05) | (6.38e-05) |
| Trip Duration (seconds) | | | -1.22e-05*** | -1.10e-05*** |
| | | | (5.03e-07) | (4.92e-07) |
| Driver Tenure | | | -3.55e-05*** | -3.46e-05*** |
| | | | (1.04e-05) | (1.04e-05) |
| Constant | 2.349*** | 2.277*** | 2.743*** | 149.6*** |
| | (0.142) | (0.144) | (0.190) | (20.21) |
| City Fixed Effects | | X | X | X |
| Day Fixed Effects | | | | X |
| Observations | 3,845,599 | 3,690,601 | 3,690,601 | 3,690,601 |
| R-squared | 0.003 | 0.005 | 0.008 | 0.009 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The DID model with fractions of hard brakes as a dependent variable indicates that drivers who complete the DDC course will have more hard breaks on a trip than drivers who don’t complete course; however, in the fully specified model the DID coefficient is not significant at the 10% level (Table 6).

**Table 14Fraction of Hard Brakes DID Model**

| | Fraction of Hard Brakes | | | |
|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) |
| DID | **0.00375*** ** | **0.00189** | **-2.18e-05** | **0.000281** |
| | (0.00132) | (0.00265) | (0.00268) | (0.00268) |
| Base Fare ($) | | | -0.00668*** | -0.00858*** |
| | | | (0.00204) | (0.00205) |
| Surge Multiplier | | | -0.0107*** | -0.0105*** |
| | | | (0.000439) | (0.000431) |
| Predicted ETA | | | 3.70e-05*** | 3.64e-05*** |
| | | | (1.03e-06) | (1.03e-06) |
| Trip Distance (miles) | | | 0.00161*** | 0.00142*** |
| | | | (6.24e-05) | (6.16e-05) |
| Trip Duration (seconds) | | | -1.50e-05*** | -1.32e-05*** |
| | | | (4.92e-07) | (4.79e-07) |
| Driver Tenure | | | -2.61e-05*** | -2.45e-05** |
| | | | (9.77e-06) | (9.77e-06) |
| Constant | 3.964*** | 3.871*** | 4.297*** | 252.6*** |
| | (0.138) | (0.140) | (0.182) | (19.01) |
| City Fixed Effects | | X | X | X |
| Day Fixed Effects | | | | X |
| Observations | 3,844,669 | 3,689,717 | 3,689,717 | 3,689,717 |
| R-squared | 0.006 | 0.007 | 0.013 | 0.015 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The DID model with the probability of safety incident as a dependent variable indicates that drivers who complete the DDC course are less likely to have a safety incident on a trip than drivers who don’t complete course, and the DID coefficient is significant the most fully specified model (Table 7).

**Table 15: Probability of a Safety Incident DID Model**

| | Probability of an Incident | | | |
|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) |
| DID | **4.93e-05** | **-0.000759*** ** | **-0.000663*** ** | **-0.000435*** ** |
| | (4.31e-05) | (0.000141) | (0.000143) | (0.000138) |
| Base Fare ($) | | | -0.000488** | -7.40e-06 |
| | | | (0.000212) | (0.000212) |
| Surge Multiplier | | | 0.000509*** | 0.000403*** |
| | | | (7.47e-05) | (7.69e-05) |
| Predicted ETA | | | -2.91e-08 | -3.82e-08 |
| | | | (2.69e-08) | (3.43e-08) |
| Trip Distance (miles) | | | -7.42e-05*** | -7.78e-05*** |
| | | | (7.48e-06) | (7.60e-06) |
| Trip Duration (seconds) | | | 1.51e-06*** | 1.56e-06*** |
| | | | (9.26e-08) | (9.42e-08) |
| Driver Tenure | | | 1.62e-06*** | 1.87e-06*** |
| | | | (2.61e-07) | (2.55e-07) |
| Constant | 0.248*** | 0.257*** | 0.243*** | 0.0190 |
| | (0.00863) | (0.00893) | (0.00935) | (1.299) |
| City Fixed Effects | | X | X | X |
| Day Fixed Effects | | | | X |
| Observations | 4,894,365 | 4,693,240 | 4,693,232 | 4,693,232 |
| R-squared | 0.001 | 0.001 | 0.001 | 0.001 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results from the quasi-random assignment analysis in New Jersey and New York City indicate that having an occupational license decreases quality ratings and increases the fraction of hard accelerations and hard brakes on a trip, and the results are significant in each model.

*Future work*

In order to answer the many question raised regarding the effect of occupational licensing on the gig economy, we are expanding our quasi-random assignment analyses to include Washington, D.C. and the Houston metropolitan area. Further, within a variety of the largest metropolitan areas in the U.S., including, Atlanta, Chicago, Cleveland, Columbus, Dallas, Denver, Detroit, Indianapolis, Miami, Minneapolis, Milwaukee, Nashville, San Francisco, and St. Louis, we will use the quasi-random assignment approach to exploit the fact that some drivers operating on the UberBLACK platform, who have an occupational license, also operate on the UberSELECT platform, which does *not* require an occupational license. Lastly, we will examine the effect of the New York Taxi and Limousine Commission (NYC TLC) introducing a 24 hour Driver Education Course and associated exam on labor supply, prices, and quality and safety outcomes.

In Washington, D.C., individuals who want to perform pick-ups on the UberBLACK or UberSUV platforms must obtain an occupational license in either Maryland, Virginia, or Washington, D.C. Each of these locales has different levels of stringency for obtaining an occupational license with Virginia only requiring licensing on the vehicle (not an individual occupational license) and Maryland having far less stringent licensing requirements for individual drivers than Washington, D.C. We will exploit this variation in occupational licensing stringency to compare safety and quality outcomes for rides performed in Washington, D.C. For example, when an UberBLACK/SUV driver licensed in Washington, D.C. (heavy licensing stringency) rejects a ride request or allows the request to expire and the request is accepted and conducted by a driver licensed in Maryland (immediate licensing stringency) with rides in which an UberBLACK/SUV driver licensed in Maryland rejects a ride request or allows the request to expire and the request is accepted and conducted by a driver licensed in Washington, D.C. We will make the same cross comparison between UberBLACK/SUV drivers licensed in Washington, D.C. and Virginia (no licensing requirements) and drivers licensed in Virginia and Maryland.

In the Houston metropolitan area (Greater Houston), drivers operating on the uberX platform within Houston city limits must complete a fingerprint background check within 30 days of being granted a conditional license to continue operating in the city of Houston, which is in addition to the standard background check that Uber requires before a driver can begin operating on their platform. However, UberX drivers who do not operate in the city of Houston and instead operate in the suburbs of Greater Houston, and  they do not have to have an occupation license (i.e., do not have to complete the fingerprint background check). We intend use our quasi-random assignment approach to exploit this regulatory variance and compare safety and quality outcomes for rides performed in the suburbs of Houston. We will compare rides in which a conditionally licensed driver from the city of Houston, who is operating on the Uber platform but has not completed the fingerprint background check, rejects a ride request or allows the request to expire and the request is accepted and conducted by an unlicensed driver from the suburbs of Houston with rides in which an an unlicensed driver from the suburbs of Houston rejects a ride request or allows the request to expire and the request is accepted and conducted by a conditionally licensed driver from the city of Houston. We will make the same cross comparison between conditionally licensed drivers from the city of Houston and fully licensed drivers from the city of Houston, who have completed the fingerprint background check, and fully licensed drivers from the city of Houston and unlicensed drivers from the suburbs of Houston.

We also intend to exploit similarities and overlap in vehicle makes and models between the UberSELECT and UberBLACK/SUV products that exist within cities using our quasi-random assignment approach. Drivers that only operate on the UberSELECT platform do not have to have an occupational license, whereas drivers who operate on the UberBLACK/SUV platform are universally required to have an occupational license. Frequently drivers who are licensed and operate on the UberBLACK/SUV platforms are cross dispatched to conduct pick-ups on the UberSELECT platform. As a result, we can directly compare safety and quality outcomes for rides in which an UberBLACK or SUV driver rejects a UberSELECT ride request or allows the request to expire and the request is accepted and conducted by an UberSELECT driver with rides in which an UberSELECT driver rejects an UberSELECT ride request and allows the request to expire and the request is accepted and conducted by an UberBLACK or SUV driver.

Finally, we intend to use DID and regression discontinuity (RD) approaches to examine the effects of the NYC TLC's newly required 24-hour Driver Education Course on employment levels and hours worked by drivers operating on the Uber platform, the incidence of surge prices, and quality and safety outcomes. The Driver Education Course costs $375, is comprised of eight hours of class over three days, and covers NYC TLC rules and regulations, geography, safe driving skills, traffic rules, and customer service. To receive credit for completing the course, individuals must pass an 80 question multiple choice exam with a score of 70% or higher. All potential Uber drivers who applied for a TLC-license after December 19, 2015 had to successfully complete the course before they could begin operating as a driver on the Uber platform in NYC. We will use a DID estimator, using New Jersey, where Uber drivers are not required to obtain an occupational license, and potentially other locales with similar pre-treatment trends in the outcome variables, to examine the effects of this new course requirement on the number of drivers employed by Uber, the number of hours worked by drivers operating on the Uber platform, surge pricing levels, and safety and quality outcomes.

Additionally, the NYC TLC announced on October 20, 2015 that all Uber drivers who applied for and were granted a “conditional” TLC licence between March 20, 2015 and December 19, 2015 would have to retroactively complete the Driver Education Course and exam when it became available on December 20, 2015. Conditionally licensed drivers had to complete the Driver Education Course before they renewed their initial license, which expired one year after their license was first issued. Because October 20, 2015 was the first time that the retroactive completion date was announced, NYC drivers who applied for their TLC-licenses immediately *before* and *on or after* March 20, 2015 should be identical with the exception of drivers applying for a TLC-license on or after March 20, 2015 having to retroactively complete the TLC Driver Education Course and exam. Thus, we will use an RD approach to directly compare safety and quality outcomes for drivers applying for their TLC-license immediately before and on or after March 20, 2015 for rides performed after each driver’s year one license renewal date.

*IV. Conclusions*

We examine information from one of the most visible company in the gig economy—Uber-- to determine if there are substantial benefits of occupational licensing on labor supply, prices, and consumer satisfaction and safety. Our preliminary results show that number of drivers and turnover of Uber drivers are lower in cities that require licenses of Uber drivers. Using a quasi-experiment in New York and New Jersey we find that there is little relationship between requiring a relatively expensive taxi license and consumer satisfaction or measures of consumer satisfaction and safety.  Occupational licensing of ride-sharing does not seem to deliver on greater consumer satisfaction and safety for the Uber firm. Future examination of the gig economy and occupational licensing should help provide researchers and policy makers with more information on additional firms, nations, and even more comprehensive data on the influence of regulation on technology, regulation, and consumer and labor market outcomes.

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