Regulating The Taxicab Market In The Smartphone Era

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***Abstract*—The development of ridesourcing services like Lyft and Uber has led to calls for regulation by traditional taxi companies. In this paper, I review the old rationale behind the current regulation of the taxicab market in New York City, and how the development of the peer-to-peer services might have weakened it. I then perform one of the first estimations of the difference in the user populations between the two services, showing a growing divergence. This divergence signals the reshaping of this old industry, and the resolution of some market failures. I conclude on the need of a new regulatory framework.**

***Index Terms*—Taxis, Uber, Regulation, Random draws.**

I. Introduction

THE regulation of the taxicab market has long been a staple of Economics textbooks. Since the end of the 1930s, when numerous local governments put in place barriers to entry and fare regulations, the taxicab market has been presented as a classical example of unnecessary government regulation causing a shortage of supply and high prices [1]. After the deregulation movement in the airline industry in the 1980s, several local governments, in Northern America, Europe and Australia have tried to repeal some of this regulation, with mixed benefits [2].

Beyond this age-old debate, the taxicab market has experienced some radical changes in the past few years. The development of smartphone applications to book taxis like Uber, Lyft, or Getty has dramatically shaken up a market unwelcoming to new entrants. The disruption has been so rapid that "Uberization" has become synonym of the reshaping of a sector [3].

As long-time incumbents have been confronted to new competitors, they have urged regulators to extend to those service providers the same constraints enforced on old-school cabs. Uber, as the most prominent figure of those services, is facing numerous lawsuits and political battles: it has been banned in Germany, restricted in France, and the New York City Mayor Bill de Blasio tried (and failed) to cap the number of Uber cars in the summer of 2015.

Fundamentally, the regulatory problem lies in the characterization of those new services, as illustrated by the fluctuating terminology: ridesharing services, ridesourcing services, Transportation Network Companies (for the California Public Utilities Commission [4]). The apps developers claim to be no substitute to old taxis companies, and that they merely connect people with complementary need and resources. The incumbent cab drivers, on the other hand, state that they face an unfair competition, and ask for the enforcement of the existing regulation.

In this back and forth argument, both parties take the existing regulation as an exogenous variable, to be either enforced or avoided. This is probably for strategic reasons: Uber and Lyft would be better off in a world were they do not face any additional regulation, but their competitors still are restricted by those; Old taxi companies know how to maximize their profit under the old regulation, and they would benefit from their incumbent position, were all the players subject to this regulation.

The characterization of those new players and the argument for regulation are however interwoven: if ridesharing companies are indeed competitors to taxis, what does it reveal of the new features of this market? How does that affect the old rationale for regulation? In order to shed light on this question, I first review the old argument (and counter-argument) in favor of taxi regulation, and how new technologies might affect it in section II. In Section III, I use taxi and Uber data in New York City to estimate the overlap between the two user populations, and thus whether they are substitutes or complementary. I finally review the implications in term of regulation in Section IV. Section V concludes.

II. Literature Review

A. The Rationale Behind Taxicab Regulation

In the neoclassical paradigm of economics, government intervention in a market should be justified and never defaulted [5]. In the case of the taxicab market, the regulation is defendable because: *(i)* an unregulated taxicab market does not converge to an efficient equilibrium price; *(ii)* the industry displays several market failures, so that the unregulated outcome does not maximize social utility.

1) An Arbitrary Unregulated Price: According to Frankena and Pautler [6], the current regulation of the cab industry in North America dates back to the late 1930s. Between 1920 and 1937, the industry enjoyed in New York City an unregulated era [7]. Although a number of fare wars started before the Great Depression, the influx of unemployed people in the market as drivers with rented cars led to a decline in taxi fares, occupancy rates, quality, and revenues per cab. The regulation was established after heavy pressure from the suppliers themselves, including the National Association of Taxicab Owners.

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This historic precedent constitutes for Shreiber a proof that the taxicab market cannot reach an equilibrium (even less a desirable one) if let unregulated [8]. According to him, this stems from the impossible synchronization between supply (available cabs) and demand (passengers). In order to ensure a full occupancy rate, customers would have to be much more numerous than taxis, and endure very long waiting times, which he considers unsustainable. So even if the usual conditions for competitive industry are met (atomistic supply side, free entry and exit), customers cannot compare prices and choose the driver offering to the lowest one.

With free entry, Shreiber posits that occupancy rates must decline with price, as more drivers join the market. As the occupancy rate declines and the number of cabs increases, the waiting time must decrease with price. According to Shreiber, a consequence of this feature is that prices will tend to stick at an arbitrarily high level, even when customers prefer a low price/long waiting times combination:

- If the price happens to be low, waiting time will be very long. When a customer encounters a cab, the cost of turning away this cab is very high, and the driver has thus an incentive to increase her price.
- If the price happens to be high, waiting time will be short. Unless the price is high enough so that the waiting time approaches zero, customers cannot threaten to get into another car when one taxi announces the price. Without this power, the customer will probably take the first cab she sees. There is thus no incentive to lower the price.

As the competitive model is irrelevant in the case of the taxicab market, Shreiber argues that a mix of *price* and *entry* regulation is justified in order to achieve the price/waiting time combination preferred by the population (although he recognizes the difficulty to gather information on this preferred combination).

The framework might seem contradictory with the unregulated period in New York City, which failed because of the drop in fares from $1.15 (1920) to 66c (1924), and the low profits associated with them. But Shreiber points out that a decrease in the cost of automobiles and stable fares led to an increase in profits, and a subsequent influx of new cab drivers. The waiting time was then reduced near zero (the only instance where people can actually shop around for prices), and fares dropped . The oversupply of cabs perdured after 1924 without any additional drop in price, supporting the conclusion that "high prices and very short waiting time will stick" [7].

The assumption that customers cannot compare prices does not hold if a fleet operator can differentiate his cabs in order to signal a lower fare [7]. Shreiber points out however that, as long as the market share of the operator is small, the knowledge of the existence of those low-fare cabs will not influence the choice of a customer to turn down a high-fare cab. This commitment is thus likely to happen only in an oligopolistic setting [9], which is not a feature of the New York City taxicab market [10]. Other frameworks modeling the taxicab market with features similar to job search lead to the same conclusion [11].

2) A Set of Market Failures: Beyond the question of the equilibrium price, a taxicab market with free entry displays several market failures which justify in themselves some regulation. They are manifestations of three classical types of markets failures: *(i)* information asymmetry; *(ii)* unequal access; *(iii)* externalities.

First of all, it is a market riddled with information asymmetries. A customer does not have any information on the driver who is providing a service to him. The same reasons which prevent a customer to shop around to find the lowest price also prevent him to compare him to compare the potential "dangerosity" of different drivers before going with the (perceived) safest one.

Beside some extreme cases, when the danger is obvious, the customer thus has to assess *before* taking a cab whether or not she is willing to take the risk associated with the uncertainty about the driver. This then becomes a classic problem of information asymmetry [12], and only the share of the population which has the highest tolerance towards this risk will remain on the demand side of the market. In this case, the intervention of the state to establish *entry* regulations such as mandatory background checks (enforced by the regulator or by operators) is a way to reduce the uncertainty of the consumers on the safety of a taxi ride. Moreover, the medallion system can be seen as a bond between the regulator and the driver, ensuring good conduct from the latter [11].

Second, consider low-demand periods, such as late nights (the argument works as well for isolated areas). There may be a social benefit associated with the presence of the service at this time of day [11]. Given the small number of cabs around, the cost to search for an alternative once a taxi is found can be so high that the situation is approximated by a bargaining with no opportunity to search for alternative. In such a situation, no equilibrium is simultatenously individually rational, incentive-compatible and efficient [13].

If the regulator considers that there is a social necessity to have service during those hours, fixing the price and forcing the drivers to operate during those hours will *de facto* result in a cross-subsidy between high- and low-activity operation hours. This might be the only way to provide a necessary service.

Finally, taxis, as private cars, generate negative externalities which are not included in the costs that the drivers or the consumers are facing. Those externalities are of different kinds: air pollution, congestion, crashes. Coffman considers that, as the taxicab market is not the only one subject to those negative externalities, regulation is not justified as long as it targets this specific industry, without consideration of the most cost-efficient way to reduce the externality [7]. But a political economy counter-argument can be made, as efficiency in policy should be sought both in costs but also in political feasibility.

B. The Impact of New Technologies

If the taxicab market is considered as a traditional market where supply and demand meet, it seems that government regulation is just unnecessary, will produce higher cost and shortage. Moreover, as in any regulation framework, the School of Public Choice posits that there is a risk of "capture of the regulator by the regulated [14]. Though still officially in charge of enacting and enforcing regulation, a captured regulator becomes the protector of rent-seekers charged to keep barriers to entry high and competition mild.

The disagreement over taxi regulation usually comes with a critique of the justifications stated previously, especially Shreiber's framework and his conclusion that the market price will be arbitrarily and inefficiently high. But the main argument *against* regulation comes from the Public Choice Theory: even if there are imperfections, it must be possible to state very clearly the goals and tools of regulation, so that it does not turn into a rent-protecting commission. The taxi industry is not seen as one where regulation is obvious and well stated enough [15].

One does not however have to consider that regulation was unjustified twenty years ago to argue that it is superfluous today. Many aspects of the taxicab market have changed, and some critical assumptions supporting the rationale behind the regulation are weaker. The main culprit is the spread of telecommunication devices, and especially smartphones, as they have the ability of *(i)* enabling fare competition without over supply of cars; *(ii)* reducing the information asymmetry; *(iii)* facilitating the service of low-activity areas/hours.

1) Fare competition: A critical assumption of Shreiber's framework is indeed that "cruising" is the principal mode of operation [7] [10]. As the model was based on New York City, the assumption was not outlandish: in a high-density area like Manhattan, cruising can indeed be the main if not unique mode of operation.

But the fact is that many critiques of the framework have been dismissed by Shreiber himself because they held only for rides booked through a telephone. In those rides, as customers have to choose first a phone number to call, advertisement can create prior knowledge about lower fares and capture through it a higher share of the market [9]. There is then an incentive for cabs to lower their prices. The possibility to book a cab from a cellphone and not only from a landline has increased the appeal of telephone orders everywhere.

Moreover, the new telecommunication devices enable to get rapidly a cost estimation of a trip through different services. In the world of Getty, Lyft, and Uber, instead of having to call someone to book a ride and know the price, a quick glance on a mobile will give all the information. The customer now has the ability to "shop around" before making her choice. The abundance of cabs in a location is not anymore the necessary condition to choose the cheapest cab.

2) Provision of information: The reason why taxicab markets suffer from information asymmetry between customers and drivers is the quasi total absence of repeated transactions, which reduce the cost associated with bad behavior: a rude or racist taxi driver will not suffer from the refusal of the customer to ride with him again in the future, as it is very unlikely that they will "match" again.

As such, booking a cab through a telephone call or app presents a substantial improvement: the dispatch center or the app company have some control on their drivers, and they know which one has made which ride. They can thus pool the feedback from many different users to rate their drivers. In the case of a call center, the user then have to trust that the drivers with low ratings are punished. And in the case of an application, as they see the rating before accepting the ride, the customers have to believe that the company does not drop the bad reviews. The systematic rating of the drivers after a ride enable the customers to have some *a priori* knowledge of the quality of their future driver [16].

3) Equal access: The failure of the bargaining between a customer and a driver in a low-activity area/time relies on the assumption that the customer has no possibility to find a taxi other than hoping to encounter one. But if cruising is not the only mode of operation, then low-activity areas/time can get access to the service without having to rely on an exogenous price setting by the regulator. If a customer can call (or use a smartphone) to book a ride whose price he will know beforehand, the bargaining situation will not happen. Of course, the driver could try to renegotiate the price once he meets the customer, but the threat of a low rating should prevent this from happening.

A downside of regulation is that it takes the features of an imperfect market as static. In New York City in the 1980s, the important feature was the small share of rides booked by telephone [10]. But given the spread of telecommunication devices, several critical assumptions may not hold anymore, requiring a reevaluation of the rationale behind regulation.

Judging by the amount of headlines, the development of smartphone-based apps is more threatening than the spread of simple cellphones. In 2010, 20% of New York City rides on the taxicab market were in Private Hire Vehicles already [17], without any public debate of a magnitude similar to the current one. It is then possible that simple cellphone booking, although theoretically able to solve the market failures of the taxicab market, still presented too many downsides to disrupt the market like the ridesourcing apps.

This ability of the telecommunication devices to solve the market failures and thus to render regulation obsolete is nevertheless theoretical. Given that a yellow cab trip is still cheaper than an Uber trip (something quite specific to New York City) [2], it might be that the growth of ridesourcing services is only the manifestation of a new market, distinct from the taxicab market. This is in some way what Uber is saying when it claims that its cars are servicing outer Boroughs. If there is no overlap between the areas and users of the taxis and ridesourcing apps, then Lyft and Getty are not solving old market failures of the taxicab market, but creating a new service. They should thus be regulated specifically, and the taxicab regulation should not be simply expanded to them.

The critical question to be answered becomes then to what extent the ridesourcing companies are creating a new market. This does not have an obvious answer, as it entails many parameters (length and purposes of rides, time of the day, area services), but I attempt to provide new information by estimating the characteristics of the users of taxis and ridesourcing services.

III. Data & Methods

A. Known Facts on Ridesourcing Services

On December 31, 2014, the Taxi and Limousine Commission (TLC) in New York City voted to require all For Hire Vehicles (FHV) bases to submit trip records data, in order to "better understand the FHV industry and ensure that passengers who want rides can get them safely and reliably" [18]. Although the measure has been fought by Uber, claiming that it would be an attack on its drivers privacy, the rule has not been struck down yet.

In the Summer of 2015, the website Five-Thirty-Eight filed a Freedom of Information Law (FOIL) request to the TLC, and received trip records of rides from ten FHV companies in New York City. The data covers two periods, from April to September 2014, and from January to June 2015. The three months gap is due, according to the TLC, to a formatting problem that prevents the publication of the data without compromising the drivers' privacy.

After analyzing the data, the website has made it publicly available online [1]. Along with the open data policy of the TLC, New York City is now the only city where a comparison between the services of the old taxicabs and the new FHV companies is possible. As Uber is much bigger than any other FHV company, the rest of the paper focuses on Uber.

Several facts have been laid out, answering partially the question of competition between the services:

(i) Taxi trips are at least partially replaced by Uber trips: between April-June 2014 and April-June 2015, the sum of cabs and Uber trips has increased from 48 millions to 51 millions, while the number of yellow cabs trips decreased from 42 millions to 38 millions [19].

(ii) Uber is serving the outer Boroughs of New York more than Taxis are: between April and September 2014, 22% of Uber trips started outside of Manhattan, compared to 14% of Yellow and Green cabs [20].

This seem to point in two opposite directions. First, Uber and traditional cabs seem to be in competition on the same market. Second, Uber seems to be partly servicing a different market by going more in the outer Boroughs. But this contradiction is the product of the division of traditional cabs between yellow and green cabs, as green cabs are forbidden to service the core of Manhattan (South of 110th Street on the West Side, south of 96th Street on the East Side). As the number of green cabs trips has increased over the same period, most of the second fact might just be an effect of the move of wealthy New Yorkers from Manhattan to certain neighborhoods in Queens and Brooklyn (like Williamsburg).

[1]Github Repository: https://github.com/fivethirtyeight/uber-tlc-foil-response

We cannot therefore say from those facts how distinct the markets for Uber (and more largely for smartphone-based FHV services) and cabs are. A characterization of the use and the population of users is necessary, but not much exist on the topic. Some surveys have been realized in San Francisco [4] and Toronto [21], showing that FHV users are likely to be younger than taxi users. Unfortunately, those studies do not offer a comparison in terms of income and education, as the figures for taxi users are not known. Moreover, the small size of the samples (around 300 respondents) should inspire caution.

B. Proposed Method

As deep as the lack of knowledge on the different characteristics of traditional cabs and Uber users is, the common publicly available information on both taxis and Uber trips is poor: the dataset handed over by the TLC contains, for Uber trips, only the date and time at which the trip started, and the location where it started.

With this data, the estimation strategy that I propose is to find a time at which it can be reasonably assumed that trips start not too far from the users' home. The location of the trip start is then an indication of where the user lives. Moreover, the American Community Survey (ACS) dataset contains data on the distribution of age, income, and education at the Census Tract level. Combining this information with the difference in spatial distribution between Uber and traditional cabs will thus provide a first picture of the two populations.

More formally, I define:

- For a passenger $i \in [1, N_j]$, where N_j is the total number of cabs/Uber trips
- $j = c$ if it is a cab trip, $j = u$ if it is an Uber
- $A_{i,j}, E_{i,j}$ and $I_{i,j}$ are the age, education, and income level of passenger i
- $C_{i,j}$ is the Census Tract where passenger i starts her trip
- $\Omega_A, \Omega_E, \Omega_I$, and Ω_C the range of possible values for age, education, income, and Census Tracts

Bayes theorem yields then, $\forall k \in \Omega_A$:

$$\begin{aligned} P(A_{i,j} = k) &= \sum_{n \in \Omega_C} P\big[(A_{i,j} = k) \ \cap (C_{i,j} = n)\big] \\ &= \sum_{n \in \Omega_C} \big[P(A_{i,j} = k \ | C_{i,j} = n) \times P(C_{i,j} = n)\big] \end{aligned} \tag{1}$$

Equation (1) is derived from the law of total probabilities, as a trip cannot start simultaneously from two different Census Tracts. I then substitute the terms with known quantities:

- $P(C_{i,j} = n)$ is the probability that a trip starts from a given Census Tract. This is the percentage of trips starting from said Census Tract.
- $P(A_{i,j} = k \ | C_{i,j} = n)$ is the probability that a passenger has a certain age, knowing that his trip is starting from a given Census Tract. This is the share of residents aged k years in this specific Census Tract.

Several parameters need to be set in this process. First is the time range during which it is reasonable to assume that the trip starts from home. Given that, according to the ACS, the median hour of arrival to work in New York City is 8:24 am, I consider only trips which started between 6:30 and 9:30 am [22]. Although the same percentage of people (25% each) arrive to work before 7:30 and after 9:30 am, I do not extend the boundary after 9:30 am because of the high number of trips after this hour that might not start near homes, on the contrary to trips between 6:30 and 7:30 am.

Second, I need to define the range of values Ω_A, Ω_E, and Ω_I. The conditional probability assumes that passenger i is randomly drawn from the population of the Census Tract, but maybe that this assumption is only reasonable for a subset of the Census Tract. This becomes problematic in the (very unlikely) situation where a rich passenger living in a very poor neighborhood makes regular trips, leading to a positive bias in the estimate of the share of low-income customers. It is however non-trivial to decide which population to exclude: 11% of the taxi customers in 2012-2013 reported an income lower than $10,000, 35% of them reported being less than 20 years old, and 12% reported being older than 71. Moreover, the use of Uber to send kids to school makes the exclusion of the lowest age categories problematic. I thus do not exclude any category from the age, education, or income distribution, and I estimate separately the characteristics of taxi users for 2013, in order to compare them with the figures presented by the TLC.

Finally, there is a choice between using the bins of the ACS dataset (in which case the levels k are categories), or fitting densities to the histograms before combining them (in which case equation (1) needs to be slightly modified to accommodate continuous random variables). I do not exclude either approach, and carry both of them before comparing the results.

C. Sources and Cleaning

The scope of the study is limited by the FHVs data publicly available. I use the trip records of 4.5 millions Uber rides from April to September 2014, and 14.3 millions Uber rides from January to June 2015.

In order to control for seasonality and other exogenous events (similar to the visit of the Pope in September 2015), I use the same discontinuous 12 months for TLC data, both for green and yellow cabs. This amounts to 92 millions taxi rides between April and September 2014, and 86 millions rides between January and June 2015.

The assumption that the ride starts near the passenger's home requires to focus only on the weekday rides from 6:30 to 9:30 am (the rides on Saturday and Sunday morning have to be excluded because of the late-night party people going home). This reduces substantially the size of the sample: overall, I estimate the characteristics over 1.8 millions Uber trips (9.5%), and 16.5 milliions taxi trips (9.3%). Although the percentage of total trips used for the estimation fluctuates between 8.5% and 11.5%, it is relatively stable (Figure 1).

Once the trips are subsetted, I spatially join them with the boundaries of Census Tracts, so that each trip is associated with the Census Tract in which it started. I then get the number of trips which started in each Census Tract, by month. Finally I compute, for the whole 12 months and for each month separately, the share of trips which started in each Census Tract. Although the taxi data has the number of passengers per trip, it is lacking in the Uber trips records, so I only use the number of trips for both.

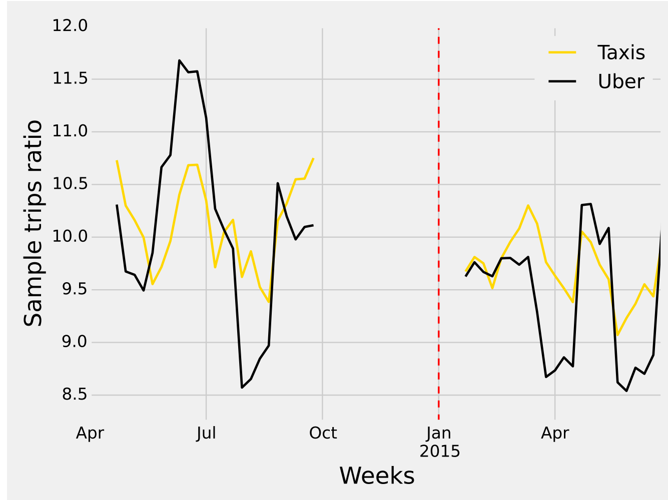

Fig. 1. Rolling mean (over a month) of the percentage of the total number of trips included in the estimation, by week. The subsample contains trips starting in a weekday between 6:30 and 9:30 am.

The ACS data comes from the 2014 5-years rolling estimates. For the three variables age, education, and income, the dataset contains the number of people in each category, per Census Tract. There are 18 age categories (plus the number of males and females), 22 education categories, and 16 income categories (see Appendix A for the detail of the categories). In order to plot the distributions (and estimate the densities), I assign to each category the value of its mean: if in a Census Tract, 200 persons are between 10 and 14 years old, I consider that 200 persons are 12 years old. I then compute the share of each category in each Census Tract.

Unfortunately, the location information for Uber trips is much more precise for the April-September 2014 period (latitude and longitude), than for the January-June 2015 period, where only a "location id" is available. They can be approximated by the Neighborhood Tabulation Areas (NTA)[2] As my goal is not to present an absolutely accurate estimate of the populations characteristics, but rather to compare the imperfect estimations for taxis and Uber users, I estimate also the distribution for taxi users in 2015 at the NTA level. They are agglomerations of Census Tracts, so there is no difficulty in aggregating the ACS data at this level.

In the last part of the process, I gather the trips and the ACS data. Following Equation (1), I multiply the percentage of people in each age, education, and income category for each Census Tract by the percentage of trips which started in this Census Tract.

[2]GitHub Repository: https://github.com/toddwschneider/nyc-taxi-data

IV. Results & Implications

A. Bias Check

The strategy proposed in this paper obviously suffers from different biases. The main bias is that it estimates the characteristics of only a subset of the population of Uber and taxi users, namely the subset which makes trips in the morning in weekdays. This population is likely to be older and richer than the whole population of users. But this bias goes in the same direction for both Uber and taxi users. It is therefore fair to assume that the *differences* between the two populations are largely preserved. And more than the actual distribution of age among Uber users, the goal here is to measure the gap between the two distributions.

In order to test the robustness of the estimation method, and to better understand to which direction the bias is tilting the estimation, I use the figures from the Taxicab Factbook to benchmark my results [23]. As the metrics from the Factbook were collected during in-car surveys in 2012 and 2013, I use the trip records from March to April 2013 to compute the "test" estimation, along with ACS estimates for 2013.

As expected, the subset analyzed seems to be older and richer than the whole population:

TABLE I
Estimation Bias

Category	Factbook	Estimates	Bias
$\leq$ 20 years old	35%	13.5%	21.5
51-70 years old	5%	22%	-17
$\leq$ \$10,000	11%	6.7%	4.3
$\geq$ \$100,000	42%	49%	-7

Table I: I use the proposed method to estimate the characteristics of taxi users in 2013, and compare the result with the 2014 Taxicab Factbook.

Beside those expected differences, the estimated figures are relatively close to the surveys (see Appendix B for the full comparison). Moreover, the survey may have some biases as well, as it was performed over several months, was voluntary, and has some No answer" categories absent from the ACS data. Sticking to it as the "ground truth" would thus be problematic as well.

B. Results: Two Divergent Populations

The first result is that the distributions of age, income and education for taxis and Uber users are strikingly similar: when comparing the average distribution over a six months period (2014 or 2015), the estimated kernel densities are nearly indistinguishable. It therefore seems that, in terms of those variables, the users are not really different between the two services. They are richer, younger, and more educated than the overall population of New York. Given that a taxi or Uber ride is still substantially more expensive than public transportation, given the coverage of public transportation in New York, and given the fact that most of those rides are concentrated in Manhattan, the richest borough, this result is not surprising.

This similarity is confirmed by a Kolmogorov-Smirnov (KS) test, which fails to reject at the 5% confidence interval the Null

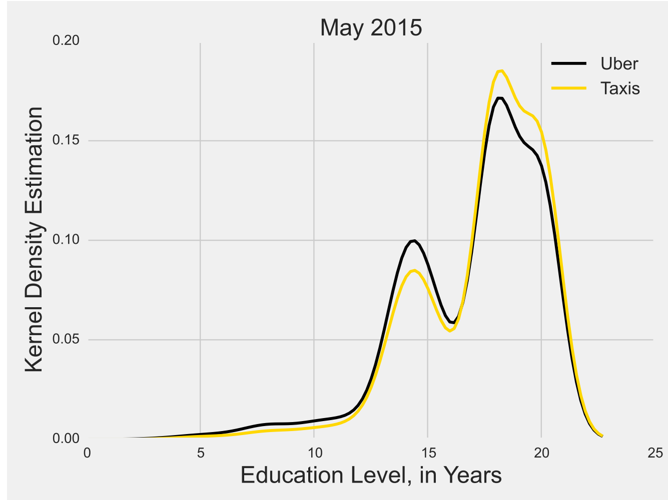

Fig. 2. Kernel density estimations for the distributions of Education levels of Uber and taxi users, in May 2015. The bandwidth is selected through cross-validation, and set at a value of 0.9, and the method of estimation of the density is gaussian.

Hypothesis that the pair of variables (Uber/taxis) are drawn from the same underlying distribution. This test is however not considered totally robust [24]. Moreover, between April 2014 and June 2015, the spatial distribution of Uber trips has significantly changed, as the share of trips (in the morning in weekdays) starting outside Manhattan has increased from 20% to 30%. Averages can thus be misleading, which leads me to comparing the distributions month by month.

A first glance at the distribution of education for Uber and taxis trips estimated separately for the months of April 2014 and May 2015 points to an evolution over the months: while the curves were indistinguishable in April 2014, this is not the case anymore in May 2015 (Figure 2). An estimated 60.4% of the Uber users in May 2015 had more than 18 years of education, compared to 68.1% for the taxi users. In April 2014, those figures were of 67.6% and 69.6% respectively. The difference has thus increased from 2 to 7.7 percentage points for this education bracket.

In order to compare the distributions month by month more systematically, I compute the Residual Sum of Squares as a metric. The aim is less to set a threshold under which I would conclude that the distributions are similar, than to track the evolution of this metric. With this metric, the trends are clear: the distributions of Income and Education for Uber and taxi users over the months are increasingly dissimilar, but not the distribution of Age (Figure 3).

What then, is driving this divergence? In order to draw conclusions from the data at hand only, I look at the difference between the distributions of Income and Education between Uber and taxi users, for April 2014 and May 2015. I look at the difference in the distributions drawn from the ACS brackets, and not at kernel density estimates, as those tend to smoothen the distributions, and thus might wash away some results.

The gap between the distributions for education shows that, compared to taxi users, Uber users are more likely to have 13

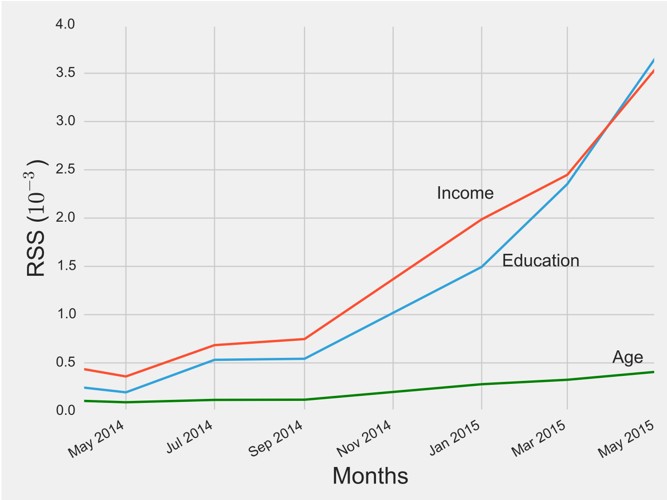

Fig. 3. Evolution of Residual Sum of Squares (RSS) over the months, for each variable. The RSS is computed between the distributions of each variable for Uber and taxi users, by month.

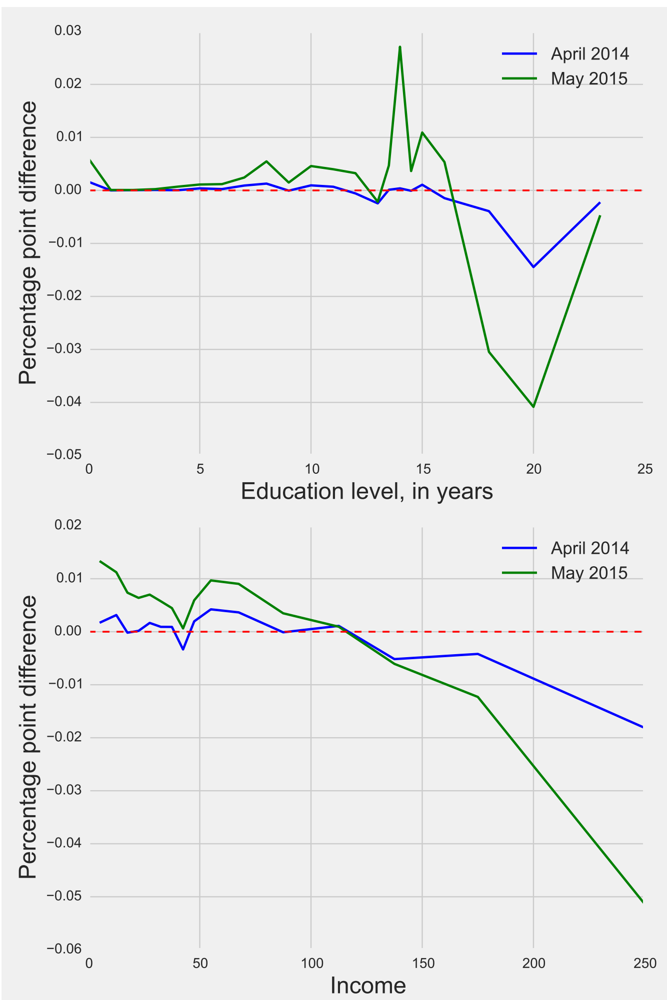

Fig. 4. Difference between the distributions of education and income of Uber and taxi users, in April 2014 and May 2015. A positive value indicates that the share of the users in this category is higher among Uber than taxi users. The categories are from the American Community Survey.

to 16 years of education, and less likely to have 16 to 22 years of education, and increasingly so. It thus seems that people with at least a bachelor degree are overrepresented among taxi users, compared to Uber users.

Similarly, the widening gap in the income distributions is driven by the higher share of people earning less than \$100,000 among Uber users, and the lower share of people earning more than \$100,000 among Uber users.

Uber operates through a smartphone app, and its success relies on the trust of its customers on its ability to control the safety and the quality of the rides it sells. This is what economist call a credence good, whose quality is known only after its consumption. As the trust is built on online ratings, a system ubiquitous on internet, it is relatively surprising to see that the Uber customers are not significantly younger than the taxi users. This is however in line with results showing that people under 35 years old are less likely to think that ratings are a fair representation of the quality of a service [25].

Overall, the picture painted by this estimation is a tale of two increasingly different populations. One thing to notice is that the distribution of those variables for taxi users has not changed substantially between April 2014 and May 2015. The widening gap has then been driven by a change in the characteristics of the Uber customers. And it seems that they increasingly do not hold a bachelor degree, and earn relatively less than taxis customers (but still significantly more than the average New Yorker).

This fact implies that the higher share of Uber trips started outside of Manhattan have not been solely to get customers identical to those in Manhattan, but who tend to move in the gentrifying parts of Brooklyn. A tentative explanation of this evolution is the introduction, in December 2014, of UberPool, a service which allows customers to share a cab and split the bill, if they are willing to modify slightly their itinerary[3]. In the absence of trip records between October and December 2014 however, it is impossible to identify a “break” due to the introduction of this service.

C. *Market Creation And Regulation*

The puzzle that I set to answer was whether the smartphone-based ridesourcing applications are competitors solving market failures in an old industry (the taxicab market) or simply new businesses creating their own market.

The near-perfect identity between the profile of Uber and Taxis customers in terms of Age, Education, and Income at the beginning of the period studied (Spring-Summer 2014) suggests that, during those months, Uber was simply a competitor to the yellow and green cabs, operating with different processes, but nevertheless targeting the same audience. Obviously, one could argue that the similar profile of users does not immediately mean that the two markets are the same, but I believe that the service proposed is too similar to be artificially distinguished, given the identical typical customer.

The profile of those Uber customers is however evolving. Among the new users that Uber is attracting every month, a significant share comes from a population different than the

[3]Uber announcement: https://newsroom.uber.com/announcing-uberpool/

one who already uses yellow and green cabs. Although there is no definitive evidence, it is possible that the ability of Uber to make people trust the service enough to share a cab has accelerated the expansion of the market on which it operates.

Two facts have thus been laid out: *(i)* Uber operates on the same market as traditional taxis; *(ii)* Uber is expanding the scope of the taxicab market demand side.

Ironically, the consequences in terms of regulation are in opposition with what both of the actors are supporting up to now. On the one hand, Uber is operating on the same market as taxicabs, and thus cannot claim to be so different that the call for regulation of its activity is unjustified. On the other hand, its ability to service a portion of the population up to now excluded from the taxicab market, without being substantially cheaper, suggests that it is avoiding the market failures that justified the regulation of the taxicab market in the first place.

A new regulation is thus necessary. The old market failures which supported the regulation of the taxicab market have apparently no impact on the business of those new unregulated ridesourcing services. If booking a cab through a smartphone is the future of the service, one needs to incorporate the features of the "sharing economy" in the formulation of new regulation.

If the taxicab market becomes dominated by peer-to-peer services between drivers and customers, the companies facilitating those transactions can be seen as playing a role of brokers. This role is not unseen in the taxicab market outside New York City, as telephone dispatch systems have been organized through cooperatives acting as brokers [11]. Considering Lyft, Getty and others as brokers would inform the regulation of their role, and especially their liability and how their share of the surplus is determined.

Sundararajan and Cohen moreover suggest that the ridesourcing companies, as other actors of the sharing economy, should be subject to self-regulation [16]. This concept does not amount to a blind trust in the goodwill of each company, but rather takes into account the tremendous importance of trust building in their business. As such, a collegial authority, recognized as legitimate by the companies, but independent enough to enforce rules, could be in charge of regulating the market. One of main roles would be to issue quality standards, and to enforce them. The authors consider that the ridesourcing companies, as "bottlenecks" between the drivers and the customers, have the power to monitor those standards. This self-regulation would be a constraint for companies like Uber who claim to be non-liable in case of misconduct by their drivers, without just maintaining a decades old regulation on a rapidly evolving market.

D. *Limits*

The analysis presented in this paper suffers from several limitations, that may or may not hinder on the robustness of the conclusions.

First, the user profile estimations suffer from a significant bias. Only around 9-10% of the whole population of Taxi and Uber users is considered here, and this subset is probably significantly different than the true whole population. I have carried on with this strategy by relying on the assumption that the bias is the same for Uber and Taxis, and so that the comparison between the two is still meaningful.

I have also assumed that the evolution over time of the difference between the two populations of morning users gives more general information about the difference between the two whole populations. But it might be that only the morning users of Uber have gotten comparatively poorer and less educated than taxi users. Maybe that the other Uber users are still extremely similar to taxi users, such that the difference between the two whole populations can actually not be inferred from those results.

Second, I have used Uber as a representative ridesourcing service , drawing conclusions for the regulation of this service and all its direct competitors. This was motivated by the weight of Uber in New York City: in September 2014, Uber supplied on its own 63.5% of the rides offered by all ten For Hire Vehicles companies monitored by the TLC. And among those companies are some regular FHVs relying on phone booking and not on smartphone applications.

Despite this domination, the conclusion drawn on the regulation of the market might be weaker if it happens that Uber is not representative of the ridesourcing actors. It happens that Lyft, Ubers main competitor, is concentrated in New York City on late-night rides [26] This specialization has however only been reported for New York City, where Uber is particularly dominant.

Finally, the estimation strategy inherently suffers from two sources of measurement errors. 2015 Uber trips are geocoded far less granularly than 2014 trips, only at a neighborhood level. Instead of relying on more than 2,000 Census Tracts, the estimation then relies on 200 Neighborhood Tabulation Areas (NTA). Once again, as the goal was to compare two population, I also estimated the Taxi users profile in 2015 at the NTA level, in order to have the same bias.

The second measurement error comes from the ACS. I am using 2014 5-years estimate for both 2014 and 2015 trips, assuming that the evolution of the characteristics of the population in a Census Tract is slow enough to be used for the next year. But the ACS estimates can have relatively high margins of error. This is the reason why I did not use the Block Group estimates for 2014 trips. The margins are smaller at the Census Tract level, but can still be substantial. Both Taxis and Uber users estimations suffer from the same bias, but it might well be that the increasing difference between the two population is just driven by noise. Unfortunately, combining the margin of errors over trips and Census Tracts is not trivial, and so I could not report any confidence interval in the final estimations.

V. Conclusion

Given that ridesourcing companies have been able to thrive on the taxicab market without being subject to regulation (especially in terms of servicing low-activity areas), one could conclude that technological change has modified the features of the taxicab market.

This however assumes that ridesourcing companies such as Lyft, Getty, and Uber are operating on the same market than traditional taxis. As those companies are claiming that this is not the case, I performed in this paper an analysis of the competition between Uber and yellow and green cabs in New York City.

The method takes advantage of the differential spatial distribution of rides from the two services to estimate the characteristics of their users in terms of age, income, and education. This is possible thanks to the release of Uber trips records (including location) for April-September 2014 and January-June 2015 by the Taxi and Limousing Commission, and the granularity of the socio-demographic data from the American Community Survey.

I draw from this estimation two facts: *(i)* The users of Uber and traditional taxis services were indistinguishable at the beginning of the period; *(ii)* With the development of the service, the profile of Uber users has shifted to include less wealthy and less well-educated people than the typical cab customer. The combination of those two findings suggests that ridesourcing services are operating on the old taxicab market, but that they are changing the rules, and expanding the customer base.

The results give weight to the decades-old critiques of regulation on the taxicab market, who predicted that the development of phone booking would weaken the rationale behind entry and prices regulation. Although the cellphone booking services have not been able to change the status quo, it seems that the smartphone-based services are. An update of the regulation is long overdue.

This paper focuses on the features of the taxicab market, and the theoretical justification for regulation. It does not take into account the other policy issues brought by the development of ridesourcing companies, such as the relationship between the drivers and the companies (challenged in a class-action in California[4]), the compensation for the loss in value of taxis medallions [27] [28], or the impact of those services on traffic congestion (which might be positive, if ridesharing services like UberPool catch on [29]).

Finally, this paper does not provide a political economics analysis of the incentives to push for a change in regulation. A regulated market usually avoids deregulation because the incumbents (who have to lose with deregulation) are organized and influential, while the outsiders are scattered and unorganized [30]. But if anything, the numerous lawsuits initiated by traditional taxis companies all over the world suggest that the ridesourcing companies are anything but powerless.

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APPENDIX A
DISTRIBUTIONS ESTIMATIONS

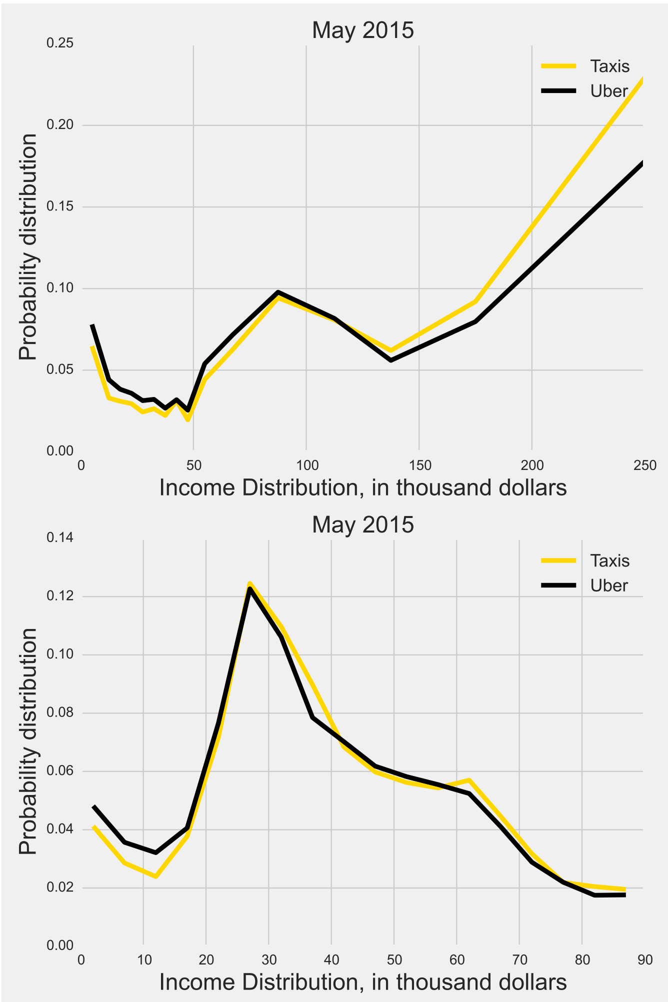

Fig. 5.

APPENDIX B
AMERICAN COMMUNITY SURVEY CATEGORIES

For Age, the bins are simply 5-years brackets: people aged 0-4 years old, people aged 5-9 years old, people aged 10-14 years old, and so forth.

TABLE II
ACS INCOME BRACKETS

Income	
$<$ \$10k	\$10-\$14.9
\$15-\$19.9	\$20-\$24.9
\$25-\$29.9	\$30-\$34.9
\$35-\$39.9	\$40-\$44.9
\$45-\$49.9	\$50-\$59.9
\$60-\$74.9	\$75-\$99.9
\$100-\$124.9	\$125-\$149.9
\$150-\$199.9	$>$ \$200

TABLE III
ACS EDUCATION LEVELS

Years	Education	Years	Education
0	No schooling	1	Nursery school
2	Kindergarten	3	1st grade
4	2nd grade	5	3rd grade
6	4th grade	7	5th grade
8	6th grade	9	7th grade
10	8th grade	11	9th grade
12	10th grade	13	11th grade
13.5	12th grade, no diploma	14	High school diploma
14	GED or alternative	14.5	Some college, $< 1y$
15	$> 1y$ of college, no degree	16	Associate's degree
18	Bachelor's degree	20	Master's degree
20	Professional school degree	23	Doctorate degree

APPENDIX C
2013 ESTIMATES VS. TLC SURVEY

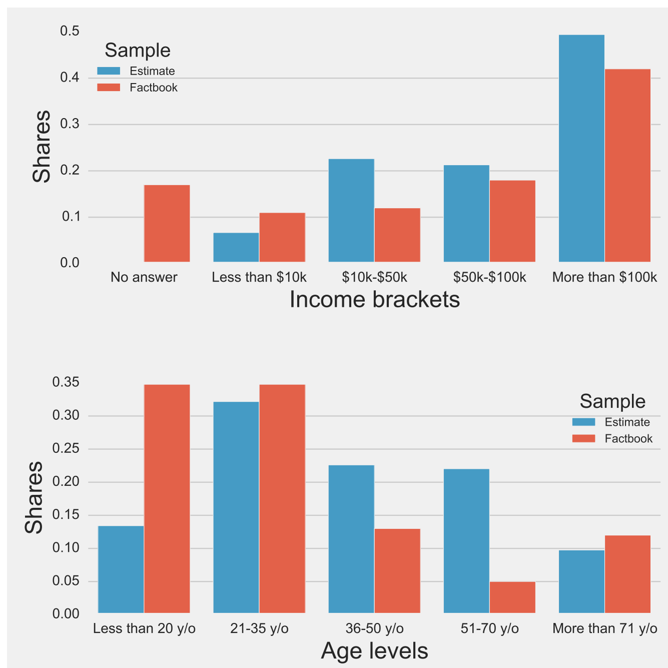

Fig. 6. Difference between the estimations with the proposed methods and the figures from the Taxicab Factbook survey. The estimation is computed on March-May 2013, and the survey figures are from 2012-2013 in-cab surveys