Platform Driving in Seattle: In Brief

Our Charge

Our charge sounded relatively simple: use very fine-grained data collected by transportation network companies (TNCs) Uber and Lyft to determine how much drivers on these platforms earn per hour in the City of Seattle. We would receive the complete data for all the drivers in Seattle. In principle, our results should be more dependable than those that rely instead on the published averages of the platforms. They should also be more credible than studies based on survey data, because the design of those questionnaires and the driver sampling strategies generally fail to meet the standards for sound organizational research. With this data, we wanted to provide independent third-party analysis for a crucial question of our time: what do platform drivers earn?

This summary begins by providing the earnings estimates that emerged from our data. Readers will see wide variation in earnings estimates for two reasons: (1) we compare implications of different assumptions, and (2) earnings vary widely among drivers. We find that our estimates are very sensitive to various assumptions that we—or anyone working with the data—must make. In addition, unlike a normal service-sector job, where people doing the same work earn roughly the same amount, platforms drivers show extraordinary earnings variation. In our data, during the same week and using the same assumptions, we found some drivers making less than $10/hour while others earned more than $40 dollars/hour. A single number of central tendency (be it the median, mean, or something else) will never represent the range of experiences of TNC drivers. In the larger report, we detail all the factors that made our seemingly simple task far more complicated than one might expect.

We also want to be very clear about what readers will *not* find in this report. Our role is not to serve as defenders or apologists for the TNCs, whose data we analyze here and who, as is typical for university research, paid for the costs of this study (though none of the researchers themselves received any additional compensation, there are additional costs to carrying out research). Accumulated research to date suggests that their business model may be inimical to worker interests, owing to the power TNCs wield in both the labor market and the rides market. Since we were not asked to triangulate our quantitative estimates with worker interviews or surveys, we cannot and do not address those findings here. In providing our quantitative estimates, at minimum, we ask that they *not be taken out of context* by the City of Seattle or others. Furthermore, these findings cannot be generalized to other cities, domestically or internationally. If our findings raise questions about drivers' earnings in other places, the answer is more research rather than speculative leaps. We can also go a step further, for those who might misinterpret our findings as suggesting that all platform drivers are highly compensated. That is not the case. Our various estimates suggest that many drivers earn below the minimum wage. This finding supports the establishment of an earnings floor for rideshare drivers, if not broader policies that would increase drivers' bargaining power vis-à-vis the TNCs.

At the same time, neither is it our role to be critical of TNCs. We are not committed to showing that the ride-share industry is uniquely pernicious in underpaying Seattle workers. Our benchmarking data, for instance, show that many typical service economy jobs—with the protections of employment law—also pay workers below what many might consider a living wage. And, of course, many drivers earn far more through platform driving than they would earn in these other kinds of work.

Our goal is to accurately and truthfully analyze the patterns in the data, using different assumptions that a reasonable reader—whether a critic or defender—would find appropriate. In this study, we present many different ways to approach earnings among drivers, so that informed readers can come to their own conclusions.

Our Key Findings

With those caveats, our *median* hourly wage estimates for Uber and Lyft drivers differ based on different assumptions.

For instance, if you consider only full-time drivers, and count all their wait time, then hourly earnings have a median of $17.40/hour. Even with the most capacious definition of full-time, however, only 15% of drivers are full-time, so this model, while true for that 15%, is not valid for the rest of the drivers.

Consider, instead, all the drivers, and count only their time preceding a ride, and the median hourly earnings rise to $23.25/hour. We highlight this number in the report because this number, $23.25, describes the median driver, who drives about 10 hours per week—not full-time. If you want to understand the average driver, $23.25 is the hourly earnings number you want to use.

These numbers are not a range. One number is not true and the other false. Instead they are the result of different assumptions, which in turn are driven by different questions.

For both numbers, the medians imply that half of drivers earn more than that number, and half earn less. (And as we will see below, significant numbers of drivers have hourly earnings quite different than the medians.)

As noted above, what strikes us about these estimates how widely they vary. With just simple changes in the underlying assumptions, our estimates of hourly earnings increase by almost 35 percent. The lower estimate of $17.40/hour reflects the following assumptions:

- All drivers are full-time.
- All wait time logged into the app counts as paid work, whether followed by a ride or not.
- Drivers incur both marginal and fixed costs.
- Costs include forgone returns to capital.

By contrast, the higher estimate of $23.25/hour depends on these assumptions:

- Drivers may be casual, committed casual, part-time, or full-time.
- Wait time only counts as paid work when followed by a ride.
- Drivers incur only marginal costs.
- Costs exclude forgone returns to capital.

In the report, to explain these differences, we unpack these assumptions to show what they mean. In different contexts, depending on the specific research or policy question one is posing, both results are valid.

Why So Much Variation?

Most people know how to calculate an hourly wage. Sum a driver's total earnings. Add up the total number of hours they worked. Divide total earnings by total hours. Problem solved.

If only it were always that easy. For many jobs, it is, but not for TNC drivers. At least conceptually, we can still begin with *hours worked* and *total earnings*. But, even with those numbers in hand, we must still account for the *costs of doing business*, namely those arising from the purchase, operation, and maintenance of a vehicle. For example, costs are complicated by the fact that while they reduce gross earnings, some of that reduction will be offset by tax deductions. The tax treatment for independent contractors is not the same as that for employees, so if we begin to consider taxes, we need to do it for our employee benchmarking as well. If that were not enough, calculating any one of these four quantities individually for a given worker relies on a wide-range of assumptions.

Hours Worked

For conventional jobs, there is little argument over when work begins and ends. But for TNC drivers, reasonable people can disagree. Does work begin when a driver logs into the app and end when they log out? And, what if they are logged into two apps at once waiting to be offered a fare? What if they are logged into one app while already driving a passenger in the other? Alternatively, should pay start on the driver's way to pick up a fare? Should it start when the driver arrives, and the passenger gets in the car to begin their journey?

For our study, just to make it even more complicated, the City of Seattle wanted to know the hourly earnings of Seattle drivers. Yet important parts of the Seattle metro area are outside the city limits, like the airport.

Total Earnings

Relative to hours worked, earnings are straightforward. At the end of each work week, drivers receive a direct deposit from one or both TNCs, after the platforms take their cut. The itemization includes two categories—gross earnings and tips, the latter of which are passed through the app for the convenience of all parties.

Because the TNCs consider their drivers to be independent contractors rather than employees (a hugely controversial designation increasingly subject to legislative and judicial scrutiny), Uber and Lyft do *not* deduct income taxes from these gross earnings. Instead, drivers receive a Form 1099 at the end of the year and must pay the taxes on their own, including what some refer to as the "self-employment tax." This is essentially the portion of social security and Medicare contributions paid by employers in a conventional employment arrangement. At the same time, because drivers are independent contractors, they have access to tax deductions that regular employees cannot take.

Our study does not address taxes, which is an important limitation that we hope to look at in the future.

Costs of Doing Business

In general, conventional employees need not consider costs of doing business because those are borne by their employer. TNC drivers, though, do have costs of doing business.

But, which costs count, and how should we compute them? In the body of the report, we detail how we attempted to answer this double-barreled question correctly and fairly. Reasonable people can disagree over whether we accomplished this. Much of the difference comes down to how we believe drivers approach their work for Uber and Lyft. Is it a livelihood, or a "side hustle?" Once again, without triangulating our quantitative analysis with interviews, we cannot know with certainty. Unfortunately, the survey estimates we have seen to date are not reliable for this purpose because their samples are not representative.

For TNC drivers, "marginal costs" are those incurred solely by virtue of driving for-hire. On the one hand, to the extent one that TNC drivers use their own car to "pick up a few hours here and there," it seems sensible to include only marginal costs as their costs of doing business. After all, the driver bought the car to use in his or her daily life. That said, these drivers do have additional costs for depreciation and maintenance that they would not incur if they were not driving for Uber or Lyft. We include these costs for all drivers.

On the other hand, certainly some drivers essentially drive full-time for one or both TNCs. Perhaps these drivers purchased their car for the express purpose of for-hire passenger transport. In fact, maybe they would not own a car or drive at all but for their work as an Uber or Lyft driver. These "fixed costs," once borne, are independent of how many hours a driver drives. For full-time drivers, it makes sense to adopt a more inclusive measure of costs.

The costs of doing business, however, are not just expenses, but anticipated returns to investment—the returns to capital. This question is even more complicated. Drivers, like regular workers, supply their labor, for which they are paid a wage or salary. But TNC drivers, unlike normal workers, also "rent out" their own assets—namely, their own personal vehicle. In principle, this amount is already "baked in" to their weekly payment from the company, which is paying for both the drivers' labor and car. The cost of the "returns to capital," some fraction of which may go to the platform, for the driver are in excess of simply the day-to-day cost of the car. A good faith estimate of earnings per hour requires "netting out" the rental cost of capital from gross earnings. For full-time drivers, our cost model includes the cost of capital because rental companies will charge for their capital costs. For non-full-time drivers, we make no adjustment for capital returns in most of our calculations, but provide, in the full report, an easy way for readers to make this adjustment.

Driver Types or Driver Engagement

What the above approach to costing suggests is that our data could and should inform us on how "engaged" drivers are with each of the platforms. That is, how much do they drive for the TNCs? Once again, our data are uniquely equipped to answer this question, since they tell us the total amount of hours worked by a given driver *across both* platforms. Some drivers work relatively few hours per week, which would make us comfortable treating them as more casually engaged, and thus, not expecting or entitled to "full costing." Other drivers, though, appear to be engaged in full-time work, as seen by the number of hours driven they log. For these drivers, a more comprehensive measure of costs seems fair and appropriate.

Drivers have a wide range of experiences. For different kinds of drivers, different cost models are more appropriate.

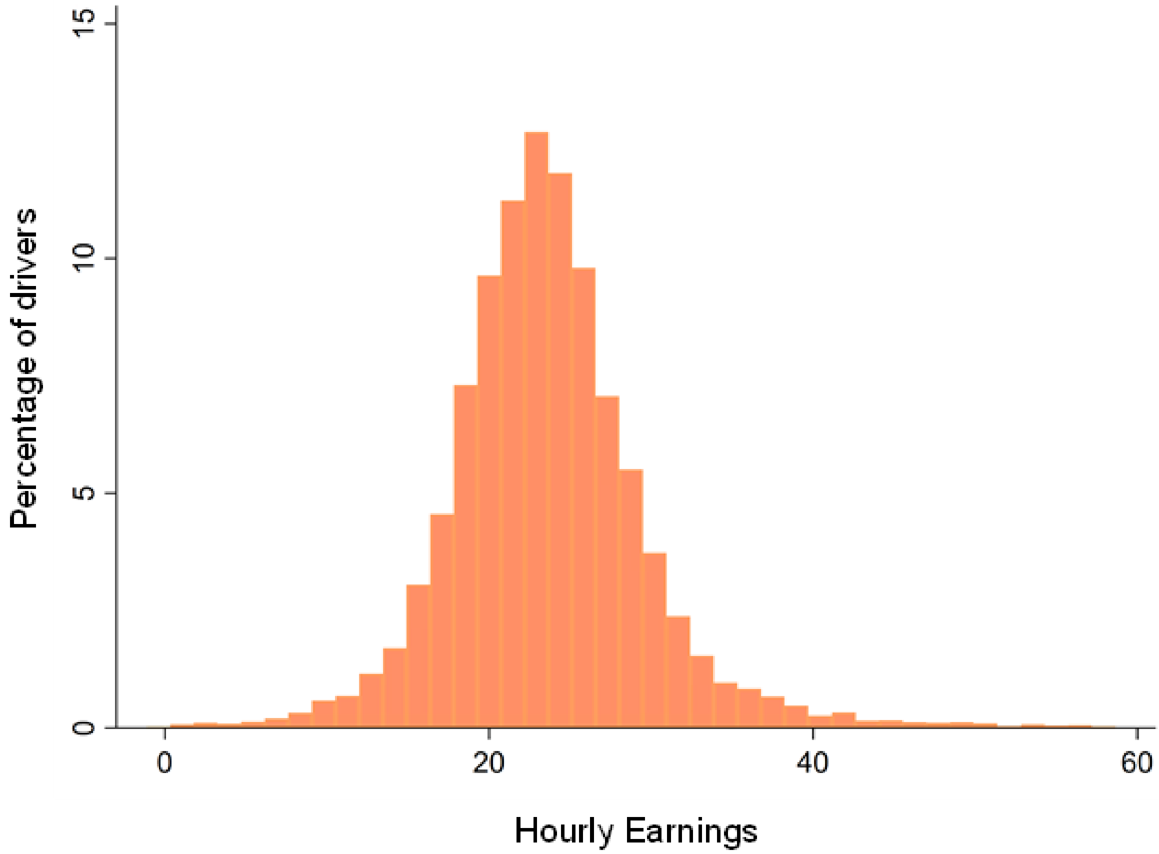
The Variation Is As Important As the Average

In a normal service economy job, at Starbucks, Wal-Mart or McDonald's, the variation in worker earnings is very low. For platform drivers, the opposite is true.

Throughout the full report, we provide graphs known as histograms that show the percentage of drivers earning different amounts per hour. Consider below two histograms from the end of the report., Chart 6.7 and Chart 6.8. These histograms have some assumptions baked into them: only driver wait time that precedes a ride should be considered work time and that costs are limited to marginal costs. The point here is not about the assumptions, or even the average. The story here is about the spread. The way that histograms work is that the higher the bars are, the higher the percentage of drivers who earn that much per hour. Most of the bar height is in the middle, but there are a lot of bars further out.

Here in Chart 6.7, for instance, right in the middle of the curve, is the $23.25 median that we discussed earlier. Simply eyeballing it, you can see that about 13% of drivers make about the median. So the vast majority of drivers (about 87%) earn either more or less than $23.25. Also notice how some drivers are making more than $40 per hour, and some are making less than $10 per hour. That variation is very different from a normal job. Working at a Starbucks cash register, you will not earn $9 an hour while the person next to you earns $41 an hour.

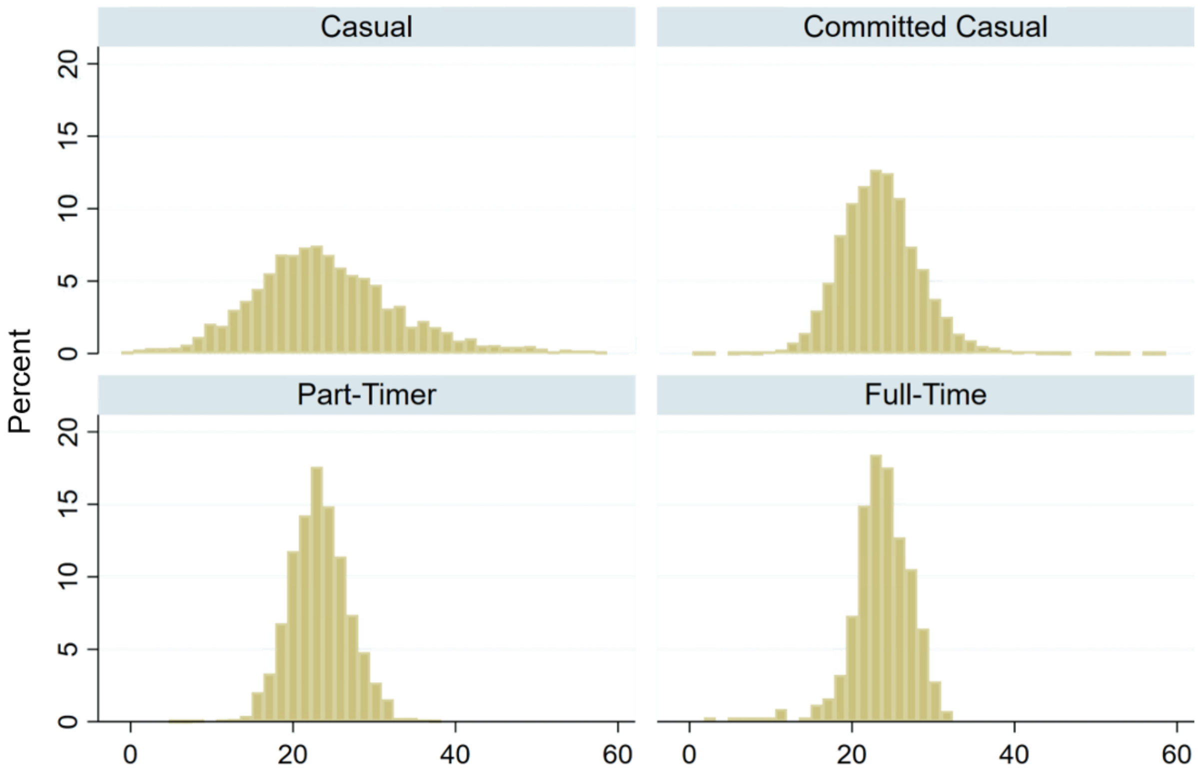
Chart 6.7: Distribution of net hourly earnings (P1 + P2 + P3, net rate)



Now consider Chart 6.8, also from the end of the report. It makes the same histogram again, but sorts it by different kinds of drivers, who are defined by the number of hours they spend on the platform. That grouping of drivers, again, depends on some assumptions. The story here is not just the medians of those different driver types (which don't vary too much), but how different the variation is by driver type. The shapes of those histograms are shockingly different. Notice how spread out the casual drivers are in comparison to the drivers who spend more time on the platform.

One reason why the full report is so long is that we believed it was important to have charts like these that reveal the variety of driver experiences, rather than one simple number. Such complexity makes for worse soundbites, but is necessary to understand driver earnings.

Chart 6.8: Net hourly earnings distribution by type



Where Does This Leave Us?

Our analysis seeks to inform diverse stakeholders whom we expect to disagree with each other on what are reasonable assumptions when calculating the earnings of TNC drivers. We encourage readers and other users of our estimates to seriously consider which assumptions best fit the specific questions they seek to answer. That said, a few specific policy concerns jump out to us:

- Under the worst-case scenario for drivers—the lower estimate above—34% of full-time drivers earn less than the minimum wage. The question for platforms and policymakers is not whether some drivers make less than a minimum wage (in all our models, some do), but what is the best way to compute costs and time. However, that only changes the specific calculation, not the overall justification for a policy-prescribed wage floor. That wage floor should rely on shared definitions between government, drivers, and platforms. Determining those definitions and the associated data will require independent analysis.
- Depending on how one thinks about driver wait time, which is further complicated by the practice of multi-apping, one can reasonably argue that waiting time goes uncompensated.

Driver advocates argue that time should all be considered work, while critics retort that unless that time leads to a ride it is not really work. A fitting answer to this question would require more data and more research.

- Somewhat counterintuitively, hourly earnings are actually *lower* for full-time drivers than they are for casual, committed casual, and part-time drivers.
    - Looking under the hood, it turns out the difference stems entirely from costing assumptions. Yet these "assumptions" are not arbitrary. As drivers commit more hours to platform driving, they must inevitably begin to consider more than marginal costs. Fixed costs and returns to capital accounted for the in the fixed cost model drive down hourly earnings.
    - The incorporation of these additional costs may explain the relatively few full-time platform drivers in Seattle. Even using the most expansive definition of full-time, 32 hours a week and including all wait time, only 15% of drivers would be included. It could be that platform driving simply doesn't make good sense once you include fixed costs, which the more you drive, become a reasonable inclusion.
    - Policymakers and TNCs may want to address this anomaly, which only became apparent with the analysis afforded by the fine-grained administrative data. Again, this finding could also be a result of restricting our analysis to the City of Seattle rather than the larger metro area. More research should be conducted to find out whether this is a result of that spatial restriction or an accurate picture of drivers.
- Since TNC drivers work as independent contractors, they receive no employer-provided benefits. Aside from missing out on tax-advantaged health insurance and retirement savings (which are, it must be pointed out, also generally absent for comparable service economy work), they have no access to sick leave, unemployment insurance, or workers' compensation. Likewise, they are generally left unprotected by labor and employment regulations, including wage and hour laws (though, again, many service sectors workers do not enjoy their full labor rights either). At minimum, this implies that TNC drivers' wages should actually be a bit more than otherwise comparable employed people to account for this difference. More importantly, it suggests that companies like Uber and Lyft should either pay a larger share of the state's social welfare bill and perhaps should advocate for increased taxes in exchange for disconnecting crucial social welfare benefits from employment altogether. Or, alternatively, policymakers may find a new way to address these needs outside of traditional structures, perhaps through a portable benefits model. In the end, however, fairness suggests that drivers need the same kind of security afforded to other workers—if not more.

Platform Driving In Seattle

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Key Findings

- The median driver earned, after expenses, $23.25 per hour, close to the Seattle median hourly earnings of $25.45, and more than the median hourly of taxi drivers ($16.81).
- 9 in 10 drivers made more per hour than the average taxi driver ($16.81), even after expenses.
- 92% of drivers make more than the Seattle minimum wage ($16.39) even after deducting expenses.
- 96% of drivers drove less than 40 hours per week, including driver wait time on the app. 31% less than 5 hours.
- For every ten dollars drivers grossed, they had, on average, one dollar in expenses.
- Only a third of drivers use both Lyft and Uber

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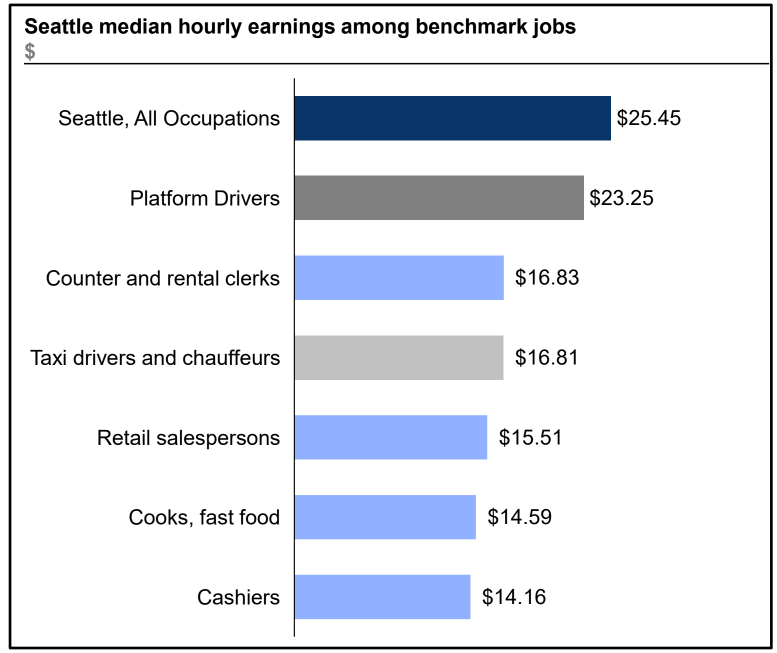
Executive Summary

In this study we use the complete set of ride records for both Lyft and Uber for one week in Seattle to estimate driver earnings and hours. We merge the data from the two companies to understand how drivers' use of two platforms (multi-apping) affected their earnings. We also examine how different definitions of P1— that time after drivers turn on an app, but before they drive to pick up a passenger—affect hourly earnings. With access to such granular platform data, our study moves beyond averages to examine the distribution of drivers' hours and earnings. We place these results in context, by benchmarking the results against other Seattle workers.



The results surprised us.

From anecdotes, interviews, and surveys, we had the impression that the majority of drivers are underpaid and work full-time. We find that while such drivers certainly exist, the vast majority of drivers do not fit that description. For most drivers, platform driving is a side-job, with hourly earnings, while not stellar are about average for Seattle—and above average for comparable service-economy jobs. We acknowledge, however, that our approach through much of this report, does not take into account any return to drivers, their returns to capital, for providing use of their cars in addition to driving services (though we do account for drivers' costs).

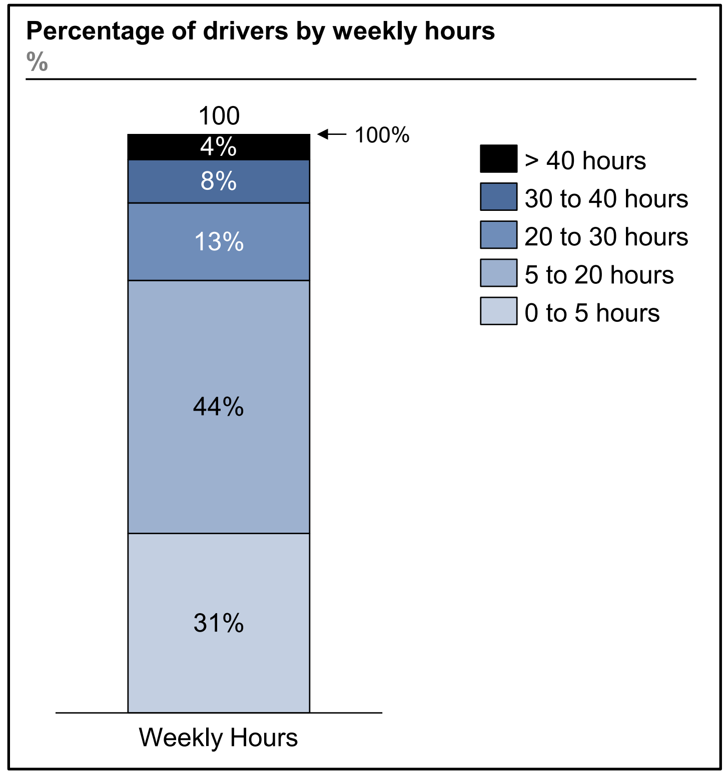
In this report, we discuss different reasonable ways to think about and calculate both time and costs. Yet, even with some expansive definitions of driver time, our data paints a different picture than the conventional wisdom.

$$\frac{\textbf{Earnings - Costs}}{\textbf{Driving time}} = \textbf{Hourly Earnings}$$

Using our preferred estimate, the median driver earned $23.25 per hour after expenses. For some readers, these hourly earnings may seem low, but, even after expenses, nine in ten platform drivers made more per hour than the average employee taxi driver ($16.81). Platform drivers earned, after marginal costs, close to the Seattle median for all occupations ($25.45). Platform drivers, instead of being underpaid, earn about average.

Considering earnings as a full-time driver is useful for comparisons with other workers but is not useful for understanding how drivers actually spend their time. Platform drivers were overwhelmingly not full-time drivers: 96% of drivers drove less than 40 hours per week, including driver wait time on the app. 31% of drivers drove less than 5 hours. Using Washington's definition of full-time, 32 hours a week, only 10% of drivers drove full-time.

Our results suggest that platforms offer drivers a way to make additional money in whatever time they have in their schedule. Their hourly earnings are not exceptional, but neither are they terrible—they are about average for Seattle.



1: Defining Driving in Seattle

Introduction

The purpose of this study is to understand platform drivers' hourly earnings in Seattle. The answer is much more complicated than it might appear at first glance. You might think that to get that number you can simply divide earnings by time, like in a normal workplace. For app-based drivers, however, that workplace is harder to define. Drivers can turn the app on, whether or not they are actually working. To further complicate matters, drivers can have Lyft activated on one phone, while driving through Uber on another phone—or even DoorDash. These apps allow drivers to combine multiple workplaces at once, in a truly novel way. To understand drivers' earnings, and to contrast those earnings with comparable benchmarks, requires us to examine how we think about when work begins and when it ends. As more Americans workers find themselves combining multiple income streams across platforms, this study is an attempt to understand how that combination of platforms affects workers' earnings.

Good policy relies on good analysis. This study should be useful to policymakers and the public, we believe, because the hours and earnings of platform drivers have been analyzed by an independent, reputable third-party with direct access to the lowest-level microdata.[1] The results derive not from a survey or from aggregate statistics, but from data on every driver for the two major platforms in Seattle, taken directly from administrative records. We hope that policymakers, as they move forward, will find this report and subsequent studies on this dataset useful to help understand an important part of the changing nature of work in Seattle.

For the study, both platforms provided time and earnings data about their drivers. Cornell's data repositories at the CRADC (Cornell Restricted Access Data Center) in New York provided data security. Each platform provided a complete record of each driver's logged data for a week, as well as the week's earnings. In these data, each driver has a unique, yet anonymized, identifier that allows researchers to merge time records without being able to identify the drivers personally. These merged data provide a complete time account of every driver in Seattle for that week across the two

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[1] The study entered planning at the end of 2019. Seattle policymakers were interested in learning whether platform drivers were adequately compensated via research conducted independently of in-house independent Uber and Lyft analysis. At the same time, Uber and Lyft sought to protect their sensitive data from public disclosure and to have the analysis performed by a party independent of local policy involvement. Thus, Uber and Lyft approached Louis Hyman, director of the Institute for Workplace Studies at the ILR School of Cornell University, about doing a time and earnings study.

platforms, which neither platform could know. Researchers could know how drivers actually spent their time across two different platforms using internal administrative data. At no time did either platform have access to the merged data set.

The merged microdata makes possible much more accurate analysis than was previously possible.

- **Deduplication**: In previous studies, researchers had to rely on the aggregated statistics of Uber and Lyft, which included the time that drivers waited for a ride (P1). For drivers that used both apps, these waiting periods overlapped. Since each individual platform did not know the state of the other platform, the time reported was the sum of these multiple times. In this report, we have eliminated this overlap.
- **Cost Analysis**: In previous studies, researchers often needed to use approximations for the types of cars, ages of cars, and mileages of cars. In this study we use actual drivers' cars, which allows us to model the actual composition of the platform driving fleet. Driver car microdata matters a great deal because the Seattle platform driver fleet differs significantly from the U.S. as a whole, and that whole U.S. fleet is used to calculate often misused depreciation numbers like the I.R.S. mileage deduction. Because of this specificity, we were able to use the actual prices of cars in Seattle to estimate depreciation. We used the same data source that the state of Washington uses to calculate vehicle taxation.
- **Statistical Weaknesses**: Perhaps most significantly, previous researchers relied on averages of aggregated statistics, like "hours driven" and "weekly earnings" which have implications for errors in subsequent calculations.
    - *Jensen's Inequality*: These numbers, in and of themselves, are not wrong, but every time a researcher computed a ratio with them, like "weekly earnings" divided by "hours driven" in order to calculate what they think is 'earnings per hour', they ran up against a bias problem that can be explained by Jensen's Inequality.[2] As discussed later, Jensen's Inequality is a mathematical property of estimated ratios that *biases* the results downwards. Ratios calculated from averages, like 'earnings per hour', will tend to be lower than reality simply because of the mathematical properties of averages. In our study, since we have actual individual driver data, we can take the averages of the ratios, which has no bias in the estimation.
    - *Means of Skewed Distributions*: It is well known that means are a poor measure of central tendency for right skewed distributions since the large data values pull the estimate upward. The downward

[2] https://en.wikipedia.org/wiki/Ratio_estimator

bias mentioned above is further exacerbated when one divides by a mean calculated from right skewed data since there is additional downward bias.

- *Imputation*: Previous researchers used imputed numbers of hours driving because of complications in determining company-specific working time when a driver uses more than one platform when using aggregated data. Aggregating imputed working time across app platforms by driver likely inflate P1 times. Our analysis with the micro data, rather than aggregated data, uses actual times that can explicitly account for the multiple apps and can deal with the deduplication of the P1 times. Furthermore, the imputed number of hours are means calculated from right skewed data, so the downward bias issues mentioned above cannot be controlled. The biases of the imputation cannot be corrected.

Independence

This study ran through the Office of Sponsored Research at Cornell, which oversees all grant-funded research at the university. The researchers received total academic freedom in the analysis. No member of Uber or Lyft was on the team doing the analysis, unlike the case in some earlier studies. The researchers could publish the results of the study regardless of the results, in both this report and subsequently in peer-reviewed journals. Though Uber and Lyft covered the costs of the study (as is common in academic research), no member of the team received any additional compensation (except the students who were paid out of the grant money). The study was priced as cost-plus, which covered the costs of the research plus overhead to the university. In total, study costs came to $120,000.

Data

Source

Driver earnings for all of our analyses came directly from Lyft and Uber. They provided week-level earnings data, including tips, for every driver in Seattle. The population includes 14,109 unique drivers with over 3.2 million state transitions. Every time a driver transitioned between periods, such as from P1 to P2, we received a time-stamped observation. The time-stamped data consisted of records for all platform logons and rides originating in Seattle on these two platforms for the week of October 7 to October 14, 2019.

This week was chosen because in November 2019 the city of Seattle asked Uber and Lyft for data for the first week of each month. We used this particular week because it was the most recent week when we started this project. It did not have a holiday or a major event. The week was unusually cold, but aside from that, it was a completely normal week.

Privacy
We use hashed driver license numbers to merge records from the two companies, while maintaining the anonymity of the drivers.

Data Validation
Using statistical methods developed for forensic accounting, we checked for fabricated data. We found no evidence of fabricated data.

The week chosen for analysis was not cherry-picked from a year of data but was the most recent week in a long series of weeks supplied to the city of the Seattle.

Method
We then aggregated the period times for each driver and matched the drivers with their weekly earnings from both platforms. We then performed standard statistical analyses. We used median rather than mean in most analyses because we wanted to exclude the extreme outliers in the data set. Some of the regression analyses used means, but generally we used quantile regression to estimate the median.

Definitions

Interpreting Results
Interpretation of the results of this study requires understanding a few statistical terms. For your convenience, a glossary has been provided in the Appendix.

Hours
When we use "hours" in this study, it is always weekly hours, not daily, monthly or annual. The basic unit of analysis for this study is the week.

Earnings and Hourly Earnings
Throughout this study, we refer to earnings and hourly earnings. For this study, we received each driver's earnings and tips from each platform. We then calculated different measurements of how long that driver worked during that week (as discussed below in *Times Periods*). We then divided those earnings by the hours of work to calculate hourly earnings. Hourly earnings are the dollars earned for an hour of work.

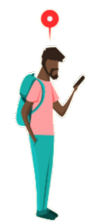
We did not break out tips separately from earnings in every calculation but have provided tip data in tables below.

Time Periods

The ride-sharing industry uses a shorthand convention to talk about time. Driving times include four components, as follows

- P0—when the app is off
- P1—when the app is on, but a ride has not been accepted
- P2—when driving to pick up passengers
- P3—when passengers are in the vehicle

While both platforms know the data for their own platform, they do not know what else drivers are doing at the same time. As is well-known, drivers can have both apps on at the same time, which is known as “multi-homing” or “multi-apping.” The P1 time visible to both platforms then could be actual time drivers wait for a ride, or it could be time when the driver is on the other platform—or doing something else entirely. Drivers cannot be in P3 for both platforms at once, but we do find cases with drivers in P2 for one platform while completing a ride (in P3) for another platform. The intersection of data, especially for the 1/3 of drivers who drive on both platforms, whom we call multi-app drivers, is very important in considering how we think about driver earnings and time. This study then can eliminate the overlap in time periods—deduplication—which is especially important in thinking about P1 time.

Period	Description	Car	App	Passenger
P0	the app is off		✕	✕
P1	the app is on, but no passenger		lyft Uber	✕
P2	driving to pick up passengers		lyft Uber	
P3	passengers are in the vehicle		lyft Uber	

The Unconventional Nature of P1 Time

P1 time is the most controversial of the periods to consider because P1 challenges our conventional notions of work. When does work begin? For a regular job, the answer is easy: when I arrive at the workplace the job begins. For ride-sharing the answer is more complicated because even after the app is on, we don't know what the driver is doing.

The complication emerges because we typical think of work time as exclusive. That is, a person can't perform two tasks at exactly the same time.

P1 time could be spent patiently waiting for a passenger on the app, driving through another platform, working another job, or just watching YouTube. Should that time *not* picking up or driving a passenger be considered work? The driver might simply have the app on while doing something else or wait patiently for hours for a ride that never comes: we simply don't know right now and hope to explore that more in future studies.

Deduplicating P1

As work time is exclusive time, we have deduplicated, unless otherwise noted, the data. Time spent in P2 for Lyft should not, at the same time, count as P1 for Uber, or vice versa. In this study, when we "deduplicate" the data, we do not count P1 on another platform while the driver is in P2 or P3 on the other. Similarly, we do not double-count P1 when a driver has both apps on.

This deduplication of P1 time would not be possible by either Lyft or Uber, since they do not know when drivers are using the other platform. They do not know which drivers use multiple apps, and do not know how long drivers overlap.

Because they are unable to deduplicate P1 time, for anti-trust reasons, any P1 data that platforms have provided in the past necessarily overestimates the total amount of P1 time because of multi-apping by some drivers.

Upper and Lower Bounds on Hours

Reasonable people can disagree on how to think about P1 time, which necessarily determines the how we calculate hourly earnings. In this report, we offer three versions of P1 that represent an upper bound on hourly rates, a lower bound on hourly rates, and what we think is a reasonable middle ground on hourly rates. We provide these separate analyses so that readers can see the impact and choose among the options.

Section 2: No Waiting
If you think that waiting time should not count at all, then you should drop all P1. This view would be held by readers who believe that any time not spent picking up or driving a passenger should not be considered work. In this study, the section called "*P1 No Waiting"* examines hours and earnings from this point of view.

Section 3: Waiting
If you think that any P1 time should be included, regardless of what is happening, then you should count all P1 time (excluding only that time that would be double-counted on two platforms). In this study, we call this version of "*P1 All*". We believe this measure of P1 might be too inclusive for some readers, since it would include commute time or time that might be used in other ways. We include this analysis for readers who consider all time when the app is on to be work time, regardless of whether a spell results in picking a rider up.

Section 4: Preceding Ride
If you think that only P1 time that precedes a ride should be considered work, then you would include only P1 time that is immediately followed by P2 time (driving to get a rider). The concept is that during this time, we have evidence that the driver was clearly waiting to pick someone up. In this case, you should drop any P1 time that did not precede a ride. In this study, we call this version "*P1 Preceding Ride*."

We prefer this measure of P1. In this measurement, we include the first ride of the day, which could easily be commuting time. We do this because unlike conventional work, drivers may hop on or hop off the app throughout the day. Commuting to work is not as a clear for ridesharing as it is for other kinds of work. This inclusion pushes our P1 Preceding Ride hourly earnings lower. Nonetheless, we think this is the right metric to use.

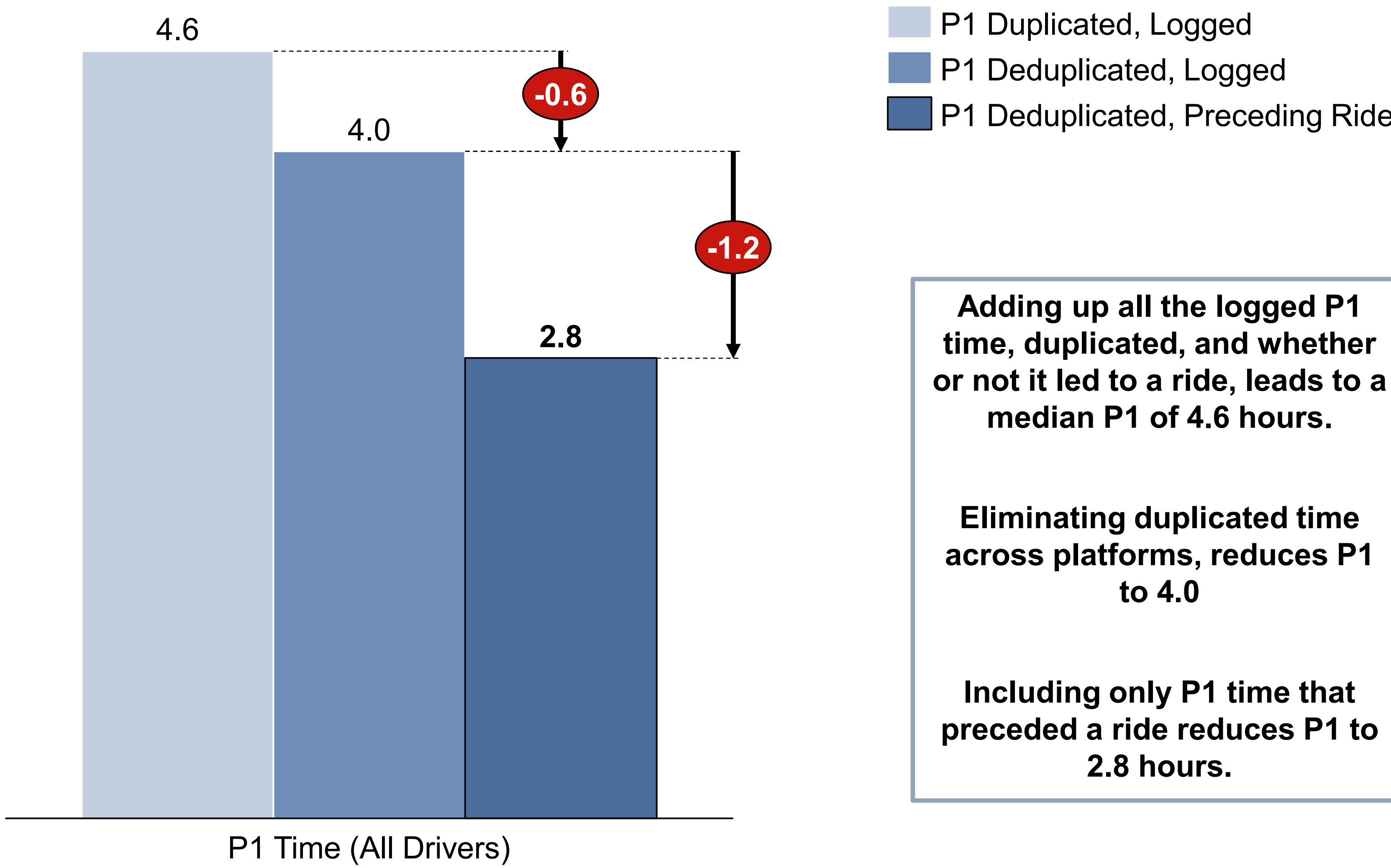
This definition of P1 Preceding Ride is more expansive than how ride-sharing platforms typically define P1, since it could include initial commute time, and makes no allowance for how long the P1 period is before a ride is accepted. It would not however, include commute time to return home if the driver left the app on for the drive.

Period	Description	Periods included	Problem
P1, Logged, Duplicated	All logged P1 time across both platforms	P1:P0, P1:Rejected, P1:P2, P1:P3	Double counts time when driver is in P1 on both platforms
P1, Logged, Deduplicated	All logged P1 time removing double-counted time	P1:P0, P1:Rejected, P1:P2, P1:P3	Includes P1 time that does not lead to a ride (unproductive)
P1, Before Rides, Deduplicated	P1 time before a ride, removing double-counted time	P1:P2, P1:P3	None

Measuring Deduplication

In the following Charts 1.1, 1.2, and 1.3, we show how the elimination of duplicated time across platforms reduces P1. There is no effect, of course, for single-app drivers. Note also that casual drivers disproportionately tend to be single-app users.

Chart 1.1: Median P1 by different definitions of P1
hours



Adding up all the logged P1 time, duplicated, and whether or not it led to a ride, leads to a median P1 of 4.6 hours.

Eliminating duplicated time across platforms, reduces P1 to 4.0

Including only P1 time that preceded a ride reduces P1 to 2.8 hours.

Chart 1.2: Median P1 by different definitions of P1 by app-use
hours

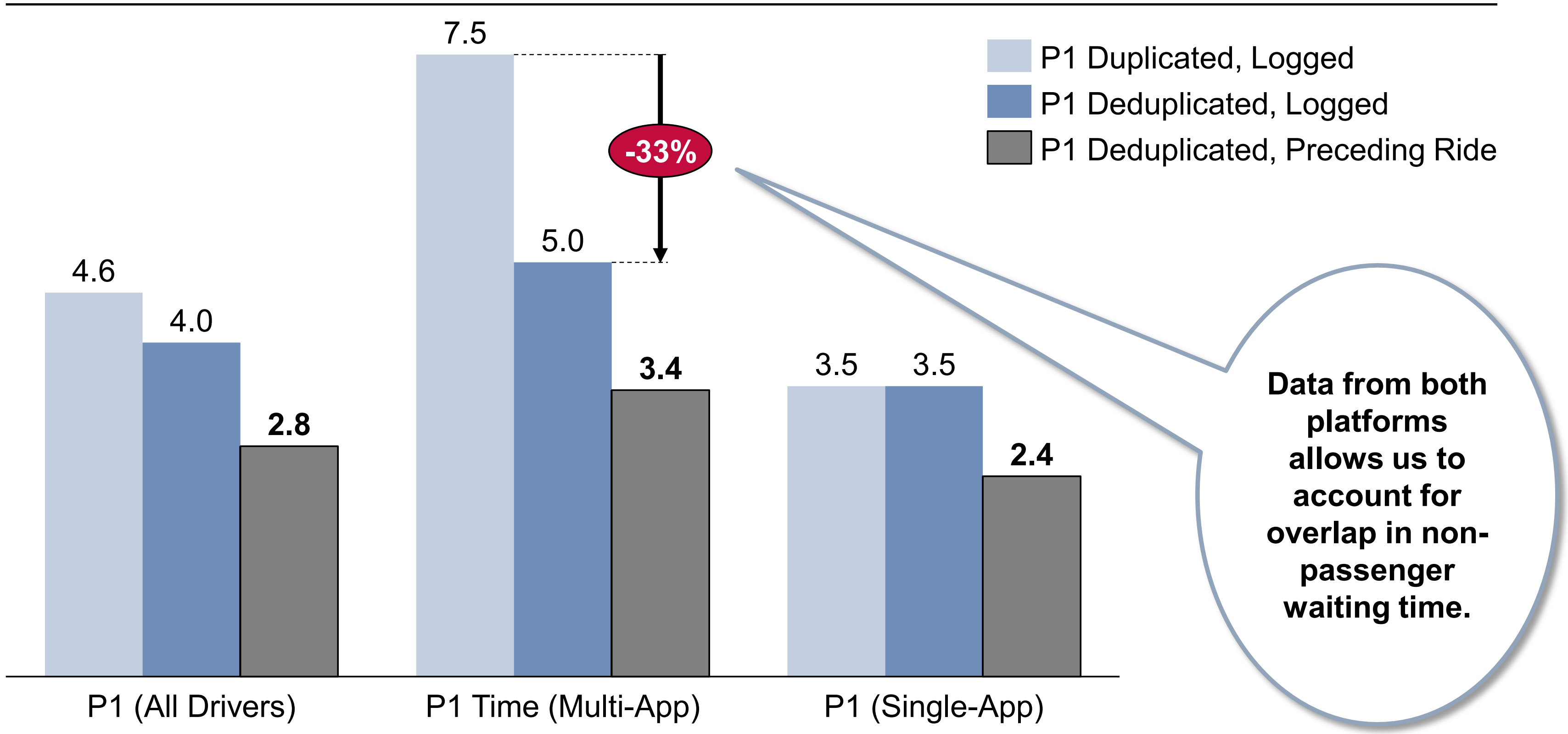
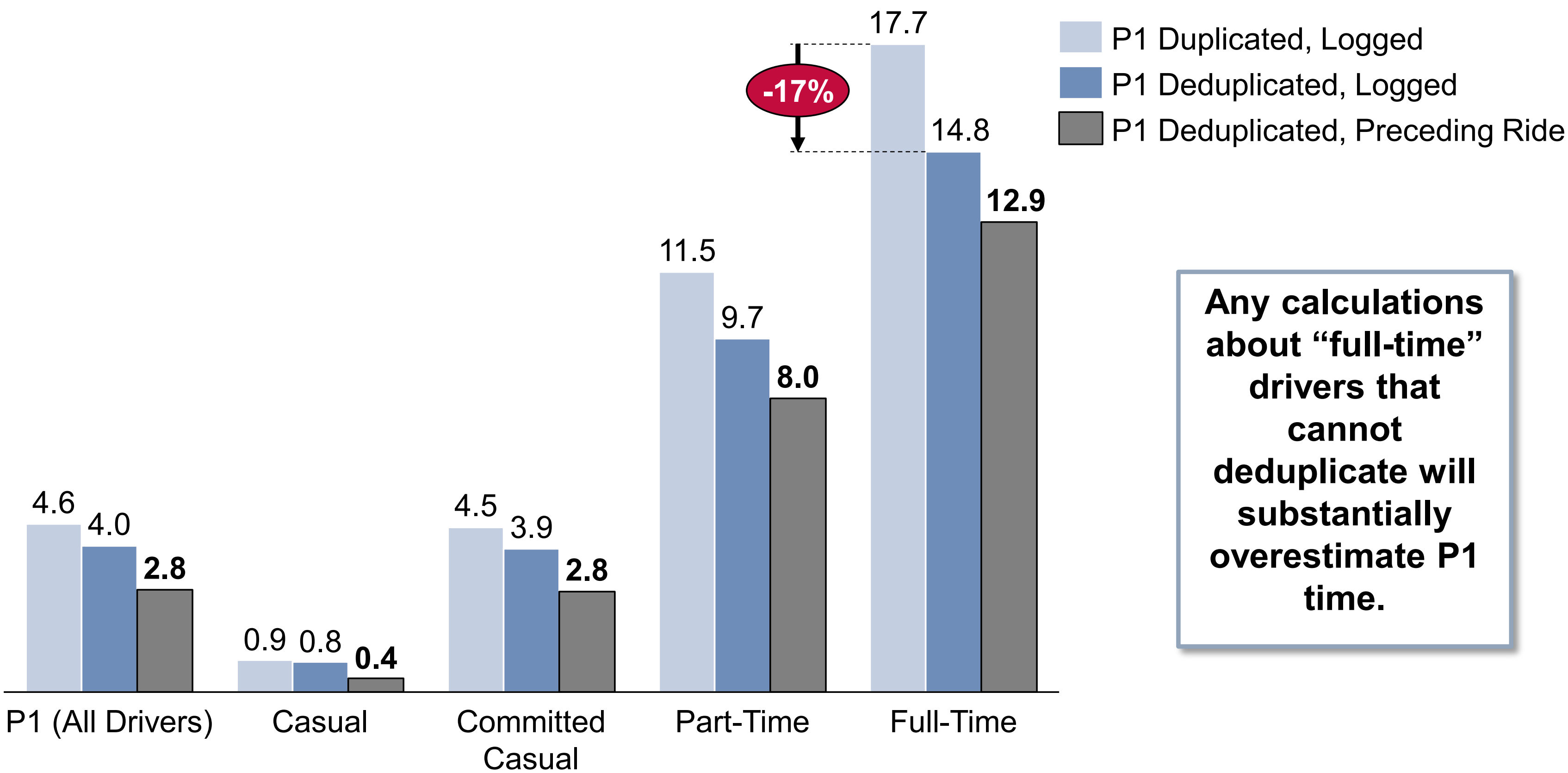


Chart 1.3: Median P1 by different definitions of P1 by driver type
hours



Any calculations about "full-time" drivers that cannot deduplicate will substantially overestimate P1 time.

Drivers

One advantage of this study is our ability to examine driver experiences across platforms. Neither company knew before the study which of its drivers also drove on the other, and still do not. With this information, we can compare drivers' weekly hours, earnings, and platform choice.

Driver Types

In our analysis, we divide the drivers into four categories that reflect different levels of engagement.

Our four categories of drivers, as seen in Chart 1.4 and Table 1.4, are defined by the number of hours that they drove in Seattle, excluding P1 time. That is, we cut the population into four groups by hours driven in P2+P3 time. The percentiles (0-25%, 25-75%, 75-95%, and 95-100%) roughly, but not exactly correspond to conventional definitions of work commitment.

Since we are allowing for different definitions of P1, defining driver categories by including P1 would not allow for easy comparison across definitions. By using P2+P3, which is not controversial, we have a stable definition.

We also know that some readers would prefer to have a sense of the breakdown of driver time by the different definitions of P1 used in this report. In Chart 1.5 and 1.6, below, we show the percentage of drivers in different bins. In Chart 1.7, we illustrate the breakdown of time by driver type. In Chart 1.8, we show a histogram of drivers' weekly hours, broken down in 5 hour increments.

Chart 1.4: Driver types as percentage of all drivers

%

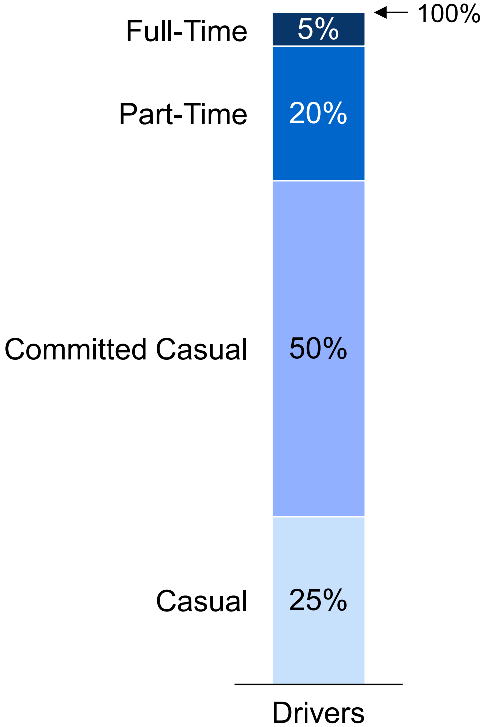


Table 1.4: Hours and earnings by driver type (P2 + P3)

%; hours; $

Type	Driver Percentage	Median Hours (P2+P3)	Median Weekly Pay
Full-Timer	5%	31.0	$1,162.88
Part-Timer	20%	18.7	$689.59
Committed Casual	50%	6.9	$254.28
Casual	25%	1.2	$43.90
All	**100%**	**6.9**	**$254.04**

Chart 1.5: Percentage of drivers by hours, by measurement metric

%

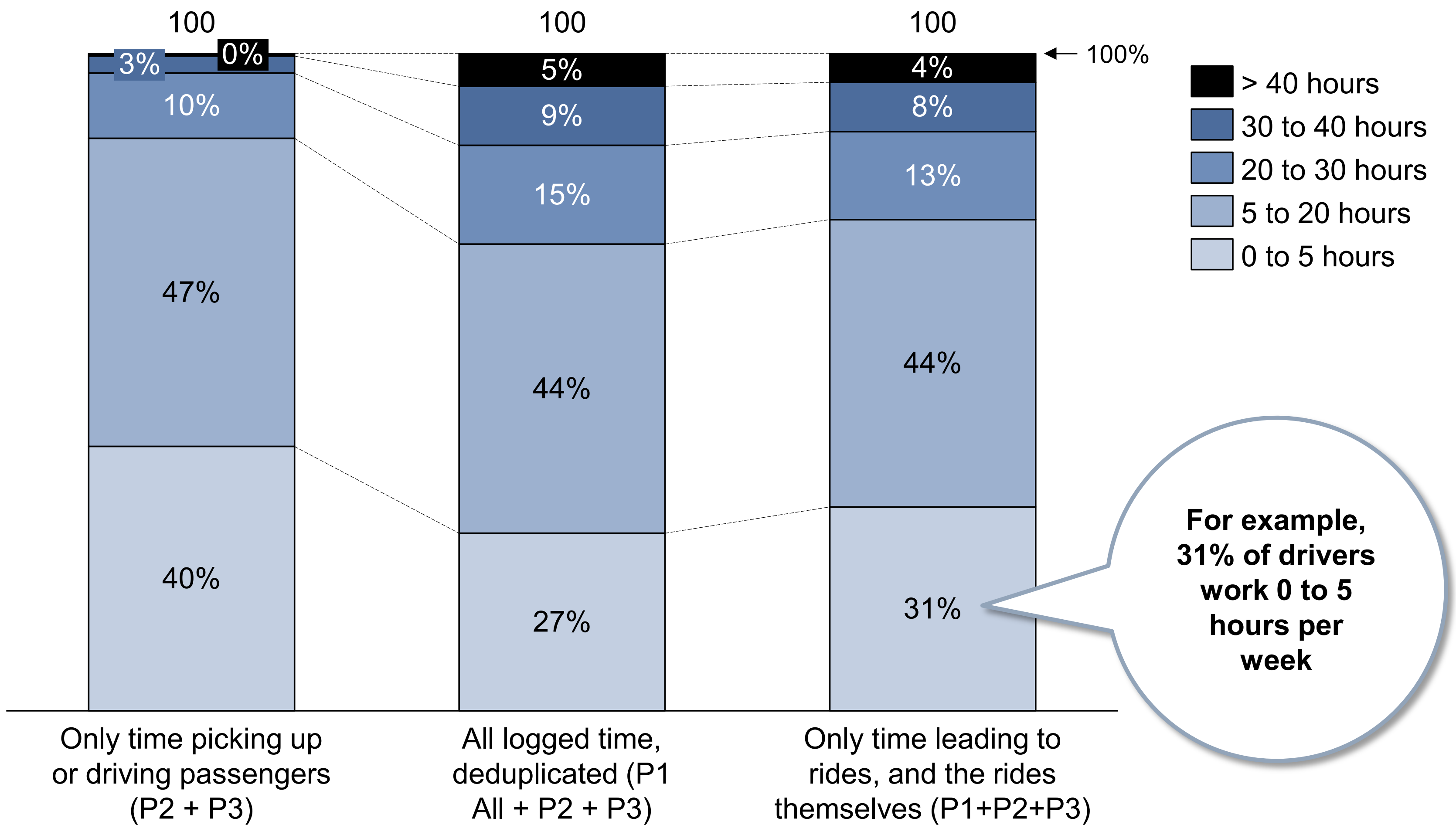


Chart 1.6: Percentage of drivers by hours, by measurement metric

%

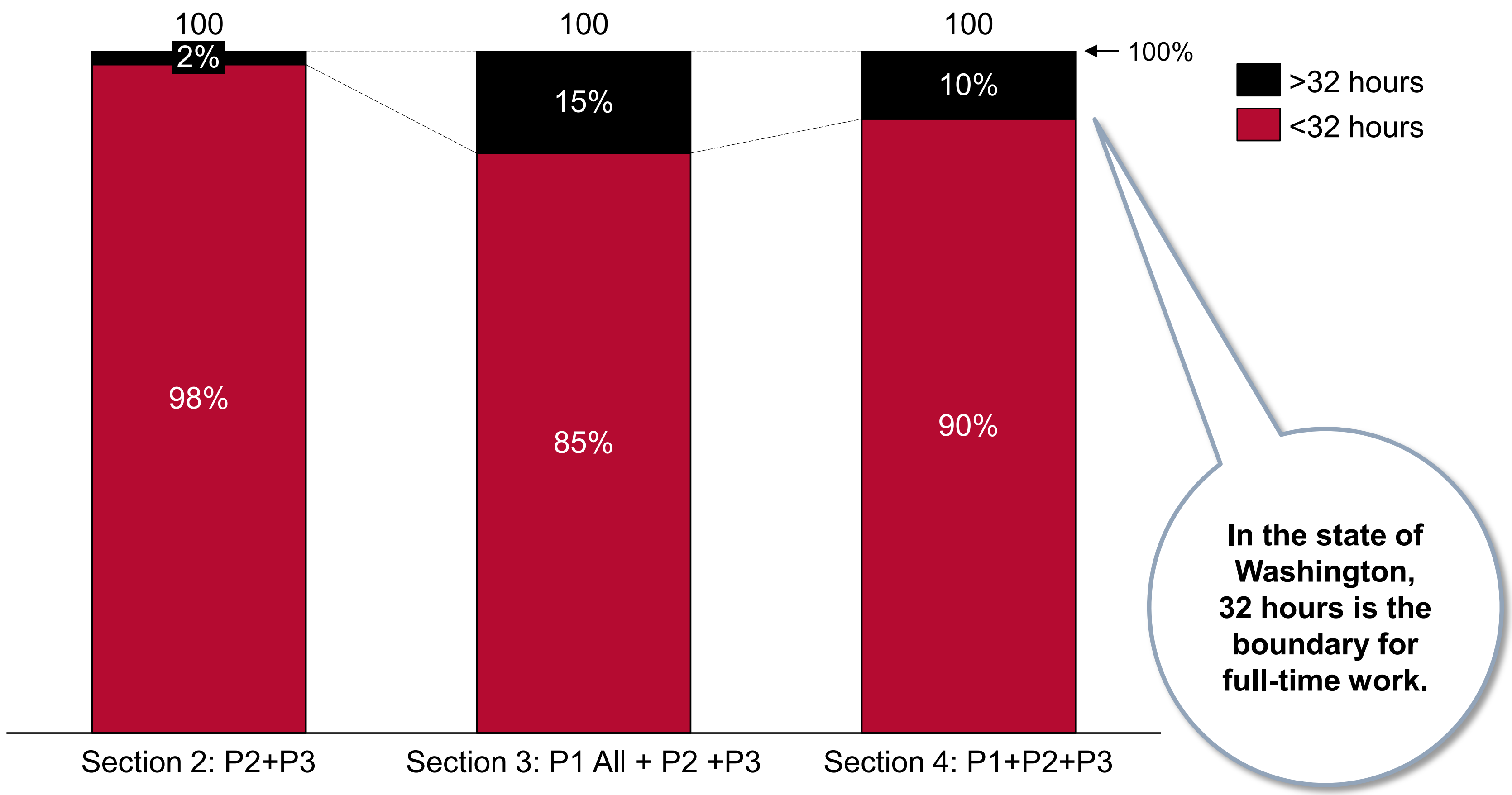


Chart 1.7: Median weekly hours by period by driver type

#

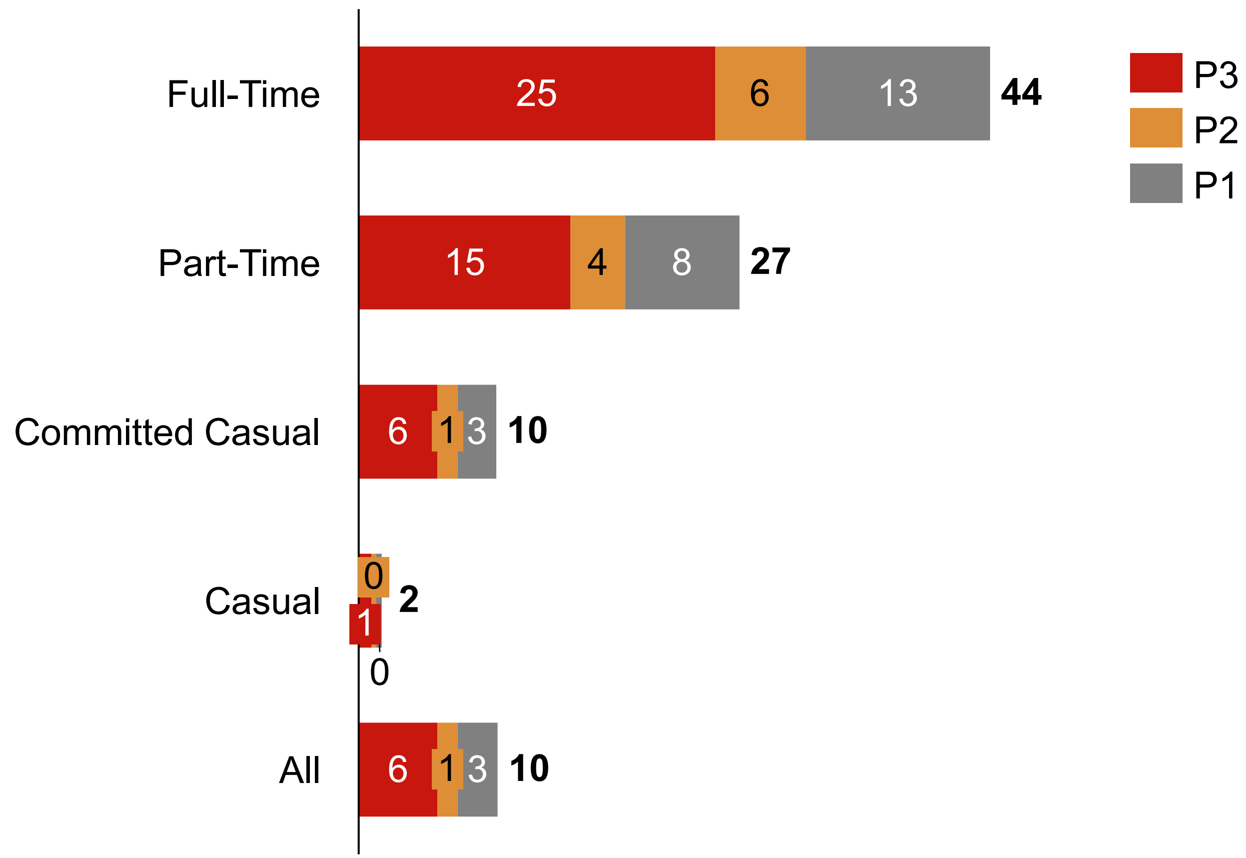
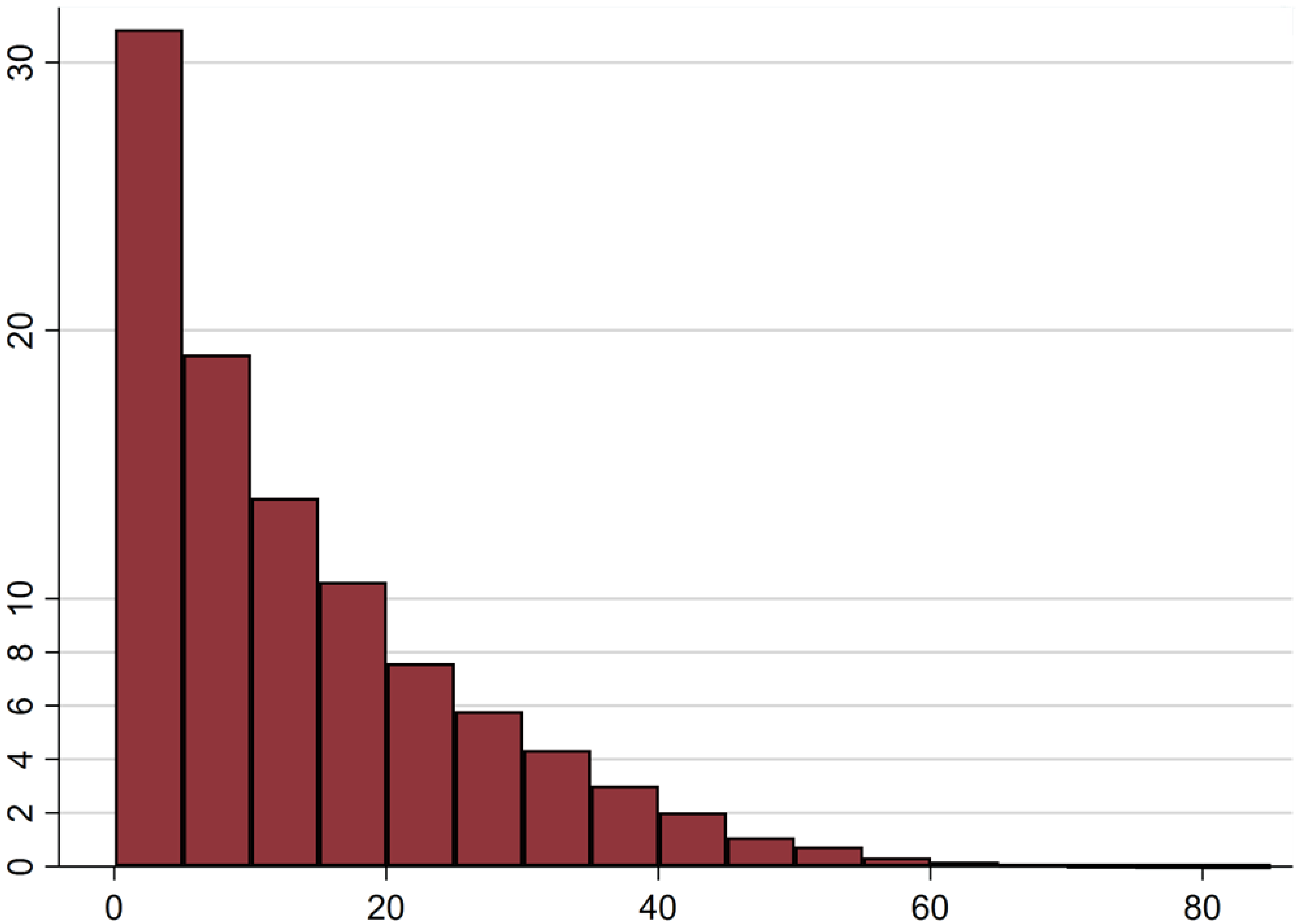


Chart 1.8: Percent of drivers with hours driven (P1+P2+P3)

hours



Earnings
Throughout the study we have added together drivers' earnings from tips and from platforms, except where otherwise noted. All earnings are for one week in Seattle.

Regardless of the different measurements of time, the weekly earnings necessarily remain the same.

The median share of platform earnings that came from was 8 percent, as seen in Table 1.9.

Table 1.9: Platform earnings, tip earnings (one week)
$, %

Type	Platform Earnings (median)	Tip Earnings (median)	Tip Ratio (median)
Casual	$43.90	$3.00	7.7%
Committed Casual	$254.28	$20.71	8.3%
Part-Timer	$689.59	$56.33	8.1%
Full-Timer	$1162.88	$93.87	8.0%
All	**$254.04**	**$20.64**	**8.1%**

Multi-apping and Single-apping
The mix of drivers across platforms, as seen in Chart 1.10, is also an important policy question, since it might be the case if one platform were significantly different in earnings, hours, or market share from the other. For anti-trust reasons, this report has not commented on platform-level earnings data.

In Seattle, the app-use of drivers is ⅔ single-app and ⅓ multi-app. Drivers that drove only for Lyft or Uber, as seen in Table 1.11, were roughly evenly divided.

Chart 1.10: Driver app use by driver type

%

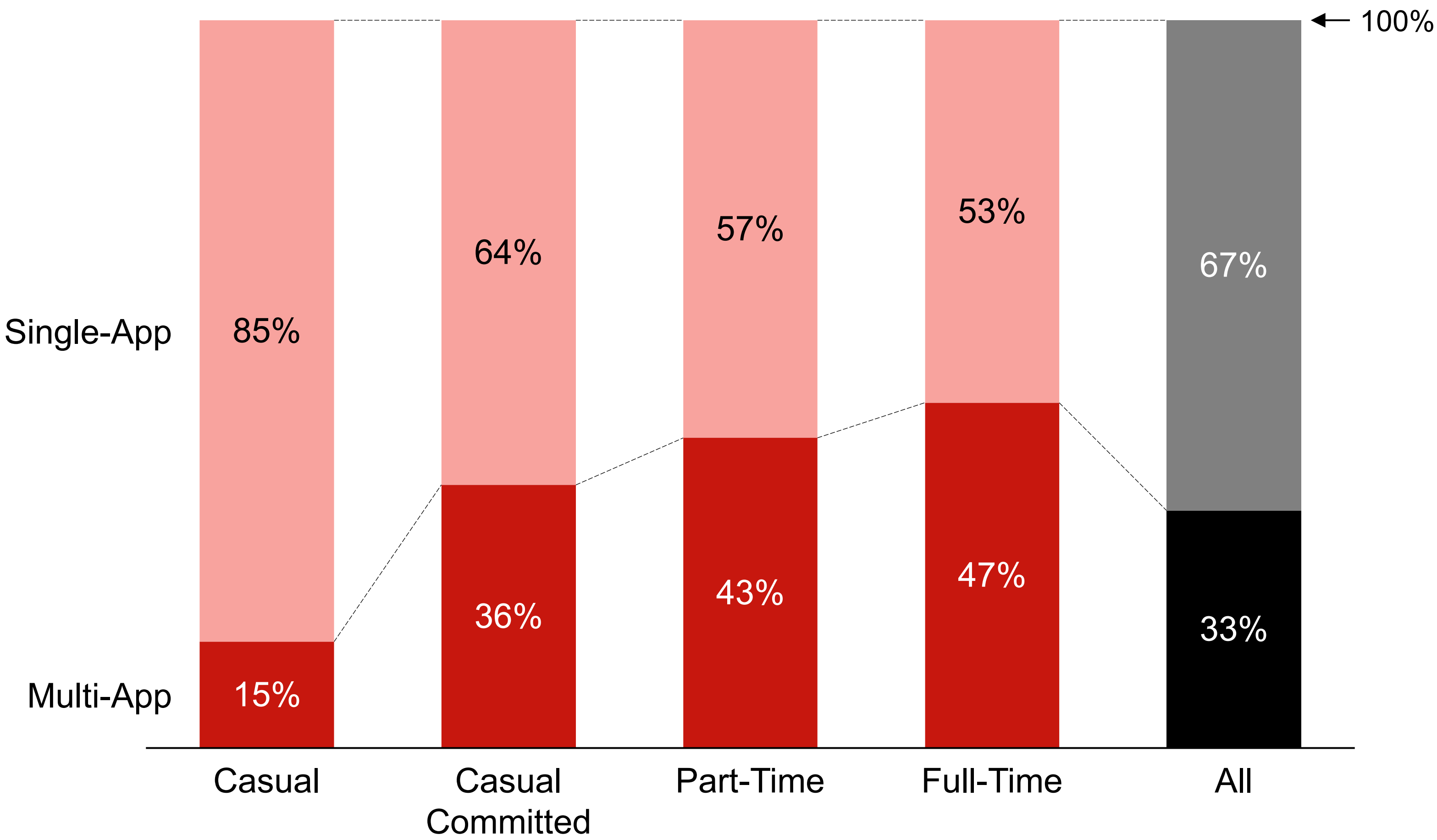


Table 1.11: Platform mix of drivers

Type	Count	Percentage
Only Uber	5,215	37%
Only Lyft	4,291	30%
Both Uber and Lyft	4,603	33%

Weighting by Drivers vs. Weighting by Hours
In this study we emphasize the driver as the basic unit of analysis. Other studies emphasize hours driving or miles driven. In doing so, they deemphasize the experience of drivers who spend less time on the platform. We do not discount the different experiences of more committed drivers, but also believe that drivers who participate less also matter, especially as they make up the vast majority of drivers.

For readers who wonder if our results would differ if they were weighted by hours driving (emphasizing more committed drivers over more casual drivers), we recalculate some key statistics. The answer is no. The results do not change.

These reveal that such weights do not meaningfully alter the medians. For instance, the median gross hourly earnings of drivers (only using P2+P3) is $36.31. If we instead weight that calculation by hours, using P1+P2+P3, emphasizing the hourly earnings of more committed drivers, the median changes to $36.71, which is a negligible rise of 1.1%. Using another hour weight, P1 All + P2 + P3, produces a similar result of $36.76, or a rise of 1.2%. In this study we do not general use means (since the distributions are so skewed) but we found the same effect on means. We also find only small shifts in other keys statistics using hour weights. Since hours are proportional to miles, we see the same effect if we reweight by miles.

Costs: Marginal Costs, Fixed Costs and Asset Rental

Another challenging area for estimating drivers' earnings are costs. Drivers supply two services through the platform: their labor as drivers, and their car as an asset. Drivers can own the car, but they can also rent the car (though car rental on a regular basis is more expensive than ownership). These distinctions matter because as drivers earning a return on their labor, they can be easily compared to normal wage-earners. As car owners, however, they are also renting access to their capital (or renting a car, and then rerenting it). As drivers, the marginal costs matter. As owners, the fixed costs matter.

Conceptually, the two components of costs are marginal costs and fixed costs, but in this case fixed costs should be seen as the cost for on-going access to the car itself, not the operation of the car (marginal costs). To that end, we use car rental as the fixed cost, which incorporates both the on-going cost of a fixed asset (maintenance, financing, depreciation, etc.) as well as the market rate for a return to capital (since the rental car agency demands a profit on every car rented). In other studies that used "average costs," we believe this was an indirect way to approximate the return on capital. With access to the actual cars, we can more directly differentiate the driver component of costs (marginal costs) and the owner component of costs (fixed costs).

We begin by considering marginal costs. As is standard in economic analysis, we see platform drivers as earning additional dollars for their work, or as economists usually say, marginal revenue. Similarly, for drivers' direct costs, a marginal perspective is appropriate. Nearly all drivers (96%) drive less than what is conventionally understood as full-time (40 hours). Our marginal cost model starts from the premise that driving in Seattle is a mostly side job, as the data confirm.[3]

For marginal costs we include additional costs associated with driving for the platforms. The question we ask about any car-related cost is, "does this cost increase because the driver drives on the platform?" If the answer is no, then the cost is not marginal to driving for a platform. Instead it is as incurred a fixed cost of car ownership. If the answer is yes, then the cost should be considered a marginal cost. The benefit to the driver on a platform is the difference between the marginal revenue from driving minus the marginal costs they incur.

As drivers spend more time on the platforms, their sense of costs becomes less like a driver focused on marginal cost, and more like an owner, focused on fixed costs. For the casual driver, car ownership is just a sunk cost. They already own the car. They already pay the fixed costs. For the full-time driver, who is making a choice to drive full-time, they are making a choice to incur the fixed costs through the platform.

As a particularly germane, example consider platform drivers in New York City compared to those in Seattle. Relatively few New Yorker City families (45 percent) own cars, compared to Seattle where 81 percent own.[4] Furthermore, 60 percent of New York City platform drivers drive 32 hours per week or more, according to the Parrot & Reich study. In our Seattle data set, only 12 percent drive 30 hours or more. That is, many more Seattle drivers drive casually and have family cars already.

These two factors (high rates of car ownership and casual drivership) suggest that it is important to focus on which car-related costs are truly marginal costs for platform drivers in Seattle. These will be different from the additional costs

[3] Studies of New York City reveal that drivers there tend to be overwhelmingly full-time (Parrot & Reich: 2018). The story in Seattle appears to be different.
[4] https://www.seattletimes.com/seattle-news/data/seattles-rate-of-car-ownership-saw-the-biggest-drop-among-big-u-s-cities-by-far/; https://edc.nyc/article/new-yorkers-and-their-cars; In NYC that ownership is heavily concentrated on Staten Island and the far outer boroughs.

incurred by a typical platform driver in places like New York City. If the drivers are as full-time as Parrot & Reich estimate, then car ownership is not a sunk cost, but a necessary additional cost.

In Seattle, we consider the following as marginal costs for most platform drivers: fuel costs, depreciation due to mileage, maintenance due to mileage, and insurance. Both platforms include insurance, even in P1, for drivers while they are driving through the platform, so the cost for that insurance is zero.[5] Previous studies generally include insurance, but Seattle's regulations, since 2014, require platforms to maintain insurance on behalf of drivers.[6] If drivers chose to get supplementary insurance, that would be their prerogative—and many drivers do— but it is not strictly necessary for driving on the platform, and we did not include that cost.[7] This approach excludes fixed costs that would be incurred regardless of platform driving activity. The fixed costs we exclude are include purchasing the car, personal insurance, car financing costs, registration costs, and annual depreciation.

We excluded a few fees for simplicity's sake. For instance, we excluded the for-hire permit required in the City of Seattle. Total annual costs are $145.25.[8] The per week cost of that would be $2.78, which would not change any of the results in any meaningful fashion.

Returns to capital and imputed rent

Drivers earnings are different than an employee's in a particularly way: they either own or rent the cars that they are driving, which means they are supplying production assets. These assets have an implicit value, what economists call imputed rent. In other studies, researchers have emphasized drivers' average costs, rather than differentiating between marginal and fixed costs. For casual drivers, using average costs neglects the ways that car ownership is already a sunk cost. Yet that car usage still has a value. Particularly for the very casual driver, these costs can be hard to identify, and

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[5] https://www.uber.com/us/en/drive/insurance/

[6] The quality of this insurance during P2 and P3 seems to be more than most personal insurance policies, but less than a typical insurance policy during P1.

[7] In our research into rideshare insurance, it seems that while some drivers have a marginal increase in premiums ($10-20 per month) others found, like our research assistant, that their premiums actually would fall.

[8] https://www.kingcounty.gov/depts/records-licensing/licensing/taxi-for-hire-transportation-networks/driver/application-fees.aspx; https://www.seattle.gov/business-regulations/taxis-for-hires-and-tncs/transportation-network-companies/tnc-drivers#penaltiesandappeals

easy to ignore. As drivers drive longer hours, it becomes evident that drivers are in some sense renting out their car as well as their labor.

If the asset is otherwise idle, it could be thought as having a zero opportunity cost, but as soon as it is driven, the asset has value made possible by both the driver and the platform.

If the driver only earned the opportunity cost of their labor, such as a minimum wage or a taxi driver wage, then all the returns to capital would go to the platforms. If the drivers earn more than that wage, as we show in this report, then the returns to capital, the imputed rent, are being shared between the driver and the platform.

Full-time drivers might be considered differently, and we incorporate this perspective on imputed rents in our fixed-cost model.[9] For the small number of drivers who do drive full-time, including fixed costs might be appropriate. That is, they may buy and maintain a specific car that is used mostly for work. In the section on costs and net income, we include in a model for full-time drivers that accounts for the cost of full-time access to a car. We base this estimate on the weekly rental cost of a car.[10] This model is the maximum possible cost for the minimum possible car. This max-min allows us to estimate not the actual costs for full-time drivers (as we do with marginal costs for everyone else) but the highest possible costs for full-time drivers. This estimate, then, includes total replacement costs, which critics might argue should be included for drivers. Our results from the fixed, full-time model, then, should be read as the lower bound on full-time earnings, but completely incorporating the returns to asset ownership.

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[9] Early report readers, who wished to remain anonymous, offered us several objections. An objection that we have heard is that drivers choose more expensive cars than they otherwise would have bought. Our analysis is only for the entry-level drivers (like UberX) not the larger cars. If a driver bought a more expensive car than is necessary to drive on the platform, reasonably, those additional costs should not be included. Other early readers also suggested that we include “full replacement cost” for every car, pro-rated by the time spent on the platform. Incorporating “replacement cost”, they argued, would allow for a sustainable long-term platform engagement. Incorporating fixed costs are not how, we believe, casual drivers do think or should think about costs. Moreover, depreciation costs due to mileage account for the loss of value in a car due to driving. At the end of a car’s life, there would be a recouped price that would be the difference between the total depreciation and the original value. Replacement costs, then, would be any cost in excess of the total depreciation + the recoup price, like transaction costs. In usual circumstances, businesses realize their depreciation costs during the replacement. In our accounting, and in tax filings, such depreciation costs can be accounted for over time. If, still, you believe that the total cost of car should be replaced, we still account for those costs in the full-time fixed cost model.

[10] https://www.uber.com/us/en/drive/vehicle-solutions/hertz/

As expected, the lower bound of the median net hourly rate for full-time drivers falls when more costs are included. Instead of earning a median net rate of $23.70, full-time drivers using the fixed cost model earn a median lower-bound net rate of $18.06. One of the surprising findings for us in this study was the relatively low share of full-time drivers. We note that the low share of full-time drivers could well reflect the low net earnings they receive when accounting for all the fixed costs of investing in and operating a car.

This leads to the second consideration: returns for the use of cars. All drivers, whether full-time or casual, use their car (or perhaps a rented one) to provide services to the platforms' riders. Thus, policy intended to regulate the terms and conditions of work by platform drivers should consider now to account for the value of cars' services. Using only marginal costs omits that component.

Incorporating imputed rent for more casual drivers can be done as well, but again, it remakes the hourly earnings numbers from their actual averages into lower bounds on their averages. Again we can use rental cost as a first approximation for this adjustment. In many comparable cities, but not Seattle, it is possible to rent a car to drive on a platform for $4 per hour.[11] Hourly rentals are the highest possible rental price, and includes fixed costs (insurance, maintenance, depreciation, replacement, returns on capital, etc.)

If a reader would like to adjust for imputed rent, it is not as simple as deducting $4 from hourly earnings. As fully compensated asset owners, like the rental car company, the costs of assets would then need to be remove, or there would be double counting. We would need to add back in the cost of maintenance and depreciation as in the fixed cost model. Maintenance and depreciation costs per mile are about $0.10. Using median percentages spent in P1, P2, and P3, we get a maintenance and depreciation per hour of $1.41. As we subtract $4 per hour, we must then add back in $1.41 per hour, for a total of $2.59. If you would like to compensate for the imputed rent, subtract $2.59 from each cost estimate, except for the fixed cost model for the full-time drivers.

We would like to further explore these returns to capital in a future paper. More research is needed, though, to establish a more precise measure of the appropriate return to drivers for use of their cars.

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[11] https://www.uber.com/us/en/drive/vehicle-solutions/getaround/

Table 1.12: Distinguishing fixed and marginal costs

	Fixed Costs	Marginal Costs
Definition	• Costs incurred regardless of production, like owning a car.	• Additional cost for one more unit of production (like driving a passenger)
What if?	• If the driver did not drive through the platform, then the costs would still be incurred, like car ownership.	• If the driver did not drive through the platform, then the cost would not be incurred, like gas costs.
So What?	• No additional fixed cost for any additional driving. • Really big costs included in other models, like car ownership, should be considered fixed costs.	• Cost only occurs if a driver uses platform • Economists agree that decisions are made by the comparison of marginal revenue vs marginal cost (not average cost which includes fixed costs).
Implication	• Fixed costs should only be included if the cost would not have occurred unless the driver was committed to platform driving. • That is, fixed costs should not be included unless a full-time driver.	• Marginal costs should be included for all drivers.
Example Costs	• Car Financing • Annual depreciation • Car registration • Personal Insurance	• Mileage depreciation • Maintenance per mile • Fuel per mile • Platform driving insurance (which is free for all drivers in P1, P2, or P3)

Benchmarking

Platform drivers choose that form of work (at least temporarily) over their other labor market opportunities.

To put these earnings in context, a reasonable starting point would be comparing the earnings of platform drivers to taxi drivers (and perhaps chauffeurs), to other typical service-economy jobs, and as well as to average earners in Seattle.

In this report, we use median taxi driver hourly earnings ($16.81) and the Seattle minimum wage ($16.39) as yardsticks against which to compare platform drivers' hourly earnings. The taxi driver data we use, as discussed below, is for taxi drivers and chauffeurs in Seattle. We used these numbers as a point of comparison because we know that one of the critiques of the platform economy is that the drivers are categorized as independent contractors and not employees. We find, calculated many different ways, that platform drivers' net earnings are higher than these employee taxi drivers.

Taxi drivers, as employees do have some benefits, like unemployment insurance and workers' compensation, that platform drivers do not. However, as far as we can tell, these taxi drivers do not have retirement plans or health insurance provided by their companies. Moreover, our analysis is pre-tax, so all of our figures on platform drivers do not take account of the ways in which independent contractors can deduct their expenses, and take advantage of other small business tax opportunities —which of course, employees cannot.

For readers concerned with the relationship of earnings and tips, please see Chart 1.9 above.

OES

Taxi Drivers and Chauffeurs Earnings

Unfortunately, the 2019 earnings numbers for taxi drivers are no longer available from the Bureau of Labor Statistics.

The 2019 OES survey, released in May 2020, combined Taxi Drivers and Chauffeurs in a new category: "Passenger Vehicle Drivers, Except Bus Drivers, Transit and Intercity" that combines Taxi Drivers and Chauffeurs with School Bus Drivers (despite the name). If we used the new 2019 category, the earnings of taxi drivers would be outweighed by those earnings of bus drivers. In Seattle, bus drivers number almost twice (6,200) that of taxi drivers and chauffeurs (3,160). Bus drivers had 2018 median hourly earnings of $21.81 compared to taxi drivers, who had a 2018 median hourly earnings of $16.15. Using the 2019 OES category of “Passenger Vehicle Drivers” we believe, would incorrectly suggest a massive increase in taxi driver earnings.

Since we actually want to compare the platform drivers against taxi drivers and chauffeurs, not school bus drivers, we adjusted the 2018 earnings numbers by the Employment Cost Index.

In order to adjust for a year’s wage inflation, we apply adjustment factor of 4.1% in the second column. This adjustment is the change in the Employment Cost Index for private employees in Seattle-Tacoma for the 12 months ending in September 2019 (2.4%) plus the national private sector difference in the ECI increase for transportation and moving occupations compared to all employees (1.7 percentage points).

After this adjustment, the median taxi hourly earnings are $16.81 in 2019, and the median annual earnings are $34,957.

Taxi Drivers and Chauffeurs Population
Chart 1.15 also shows that there are relatively few taxi and limousine drivers in Seattle, compared to the number of platform drivers.

In our study, we found over 14,000 platform drivers in just one week, while the OES data shows about 3,000 taxi and limousine drivers—or about one-fifth the number of platform drivers. In Charts 1.13, 1.14, and 1.15, we show the relative population of employed taxi drivers in Seattle, as well as their relative hourly earnings compared to other service-economy jobs.

Chart 1.13: Taxi driver hourly earnings and employment
#;$nominal

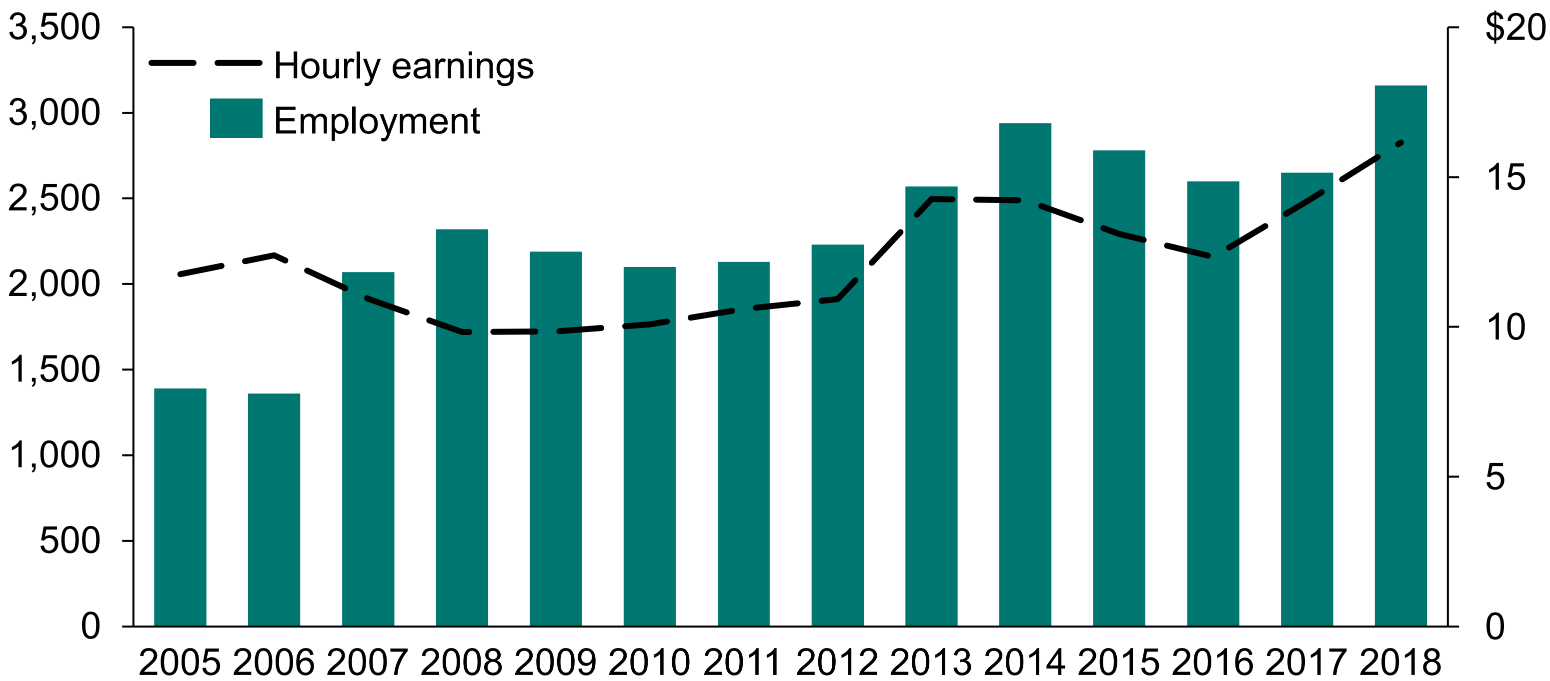

Chart 1.14: Seattle hourly earnings among benchmark jobs
$nominal

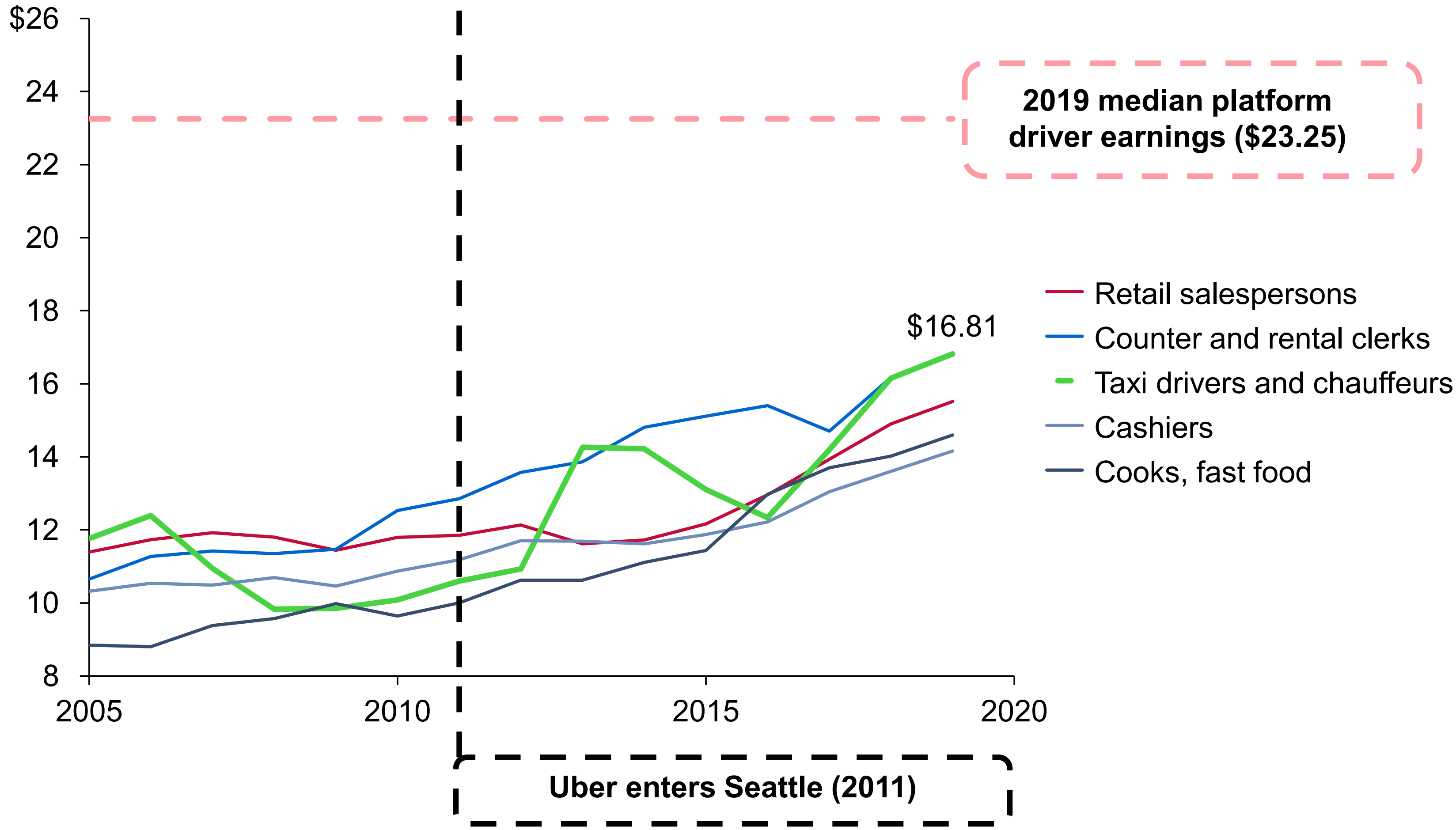

Chart 1.15: Seattle benchmark worker count

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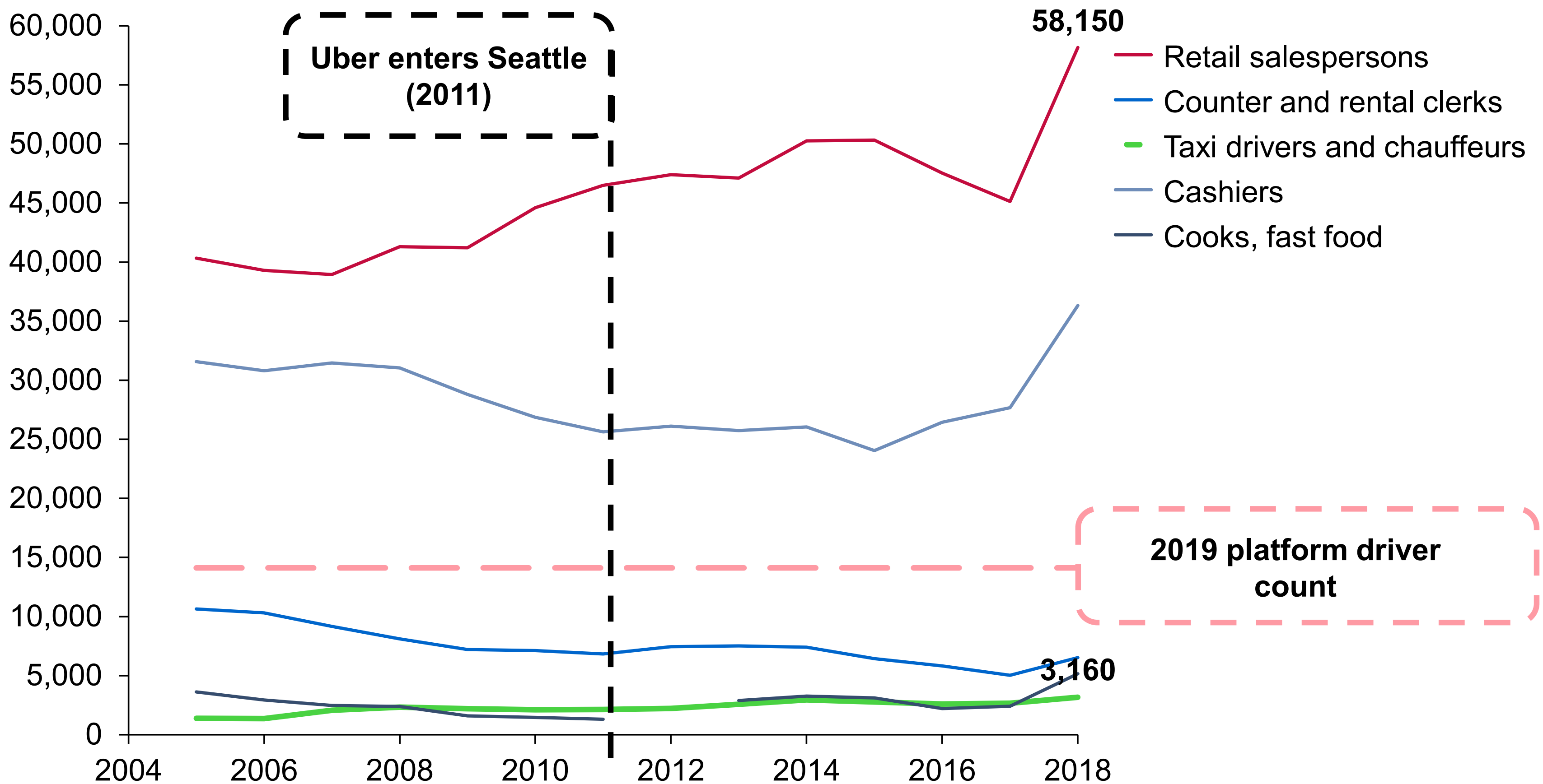

Critique of OES

Hall and Krueger (2016) are suspicious of the OES data because OES is survey data sent from employers. Thus the data included in OES is related only to employees, not independent contractors. The category is also broad and does not pertain exclusively to taxi drivers. Rather, it includes chauffeurs, limo drivers, etc, whose hourly earnings are probably higher than taxi drivers.

If anything, these OES numbers overestimate the hourly earnings of taxi drivers because limousine drivers are better paid (we believe).

Hall/Krueger believe the hourly earnings comparison between platform drivers and taxi drivers is not accurate since employees "probably" do not bear the same expenses that Uber/Lyft drivers do: gas, maintenance, depreciation, health insurance, employer taxes. They do note that these expenses can be deducted from income taxes but do not include tax deductions in their analysis. They concede that this overestimates driver costs in their study.

We believe that independent contractors, after subtracting their costs, could reasonably compare their pre-tax earnings with those of drivers who are employees. Taxes are particularly controversial in comparing employees and independent contractors, but we think starting with pre-tax income is a necessary first step.

Despite these difficulties, therefore, we still think the OES is the most reasonable benchmark. If anything, the OES wage numbers are *higher* than the actual taxi driver earnings. For most policymakers, the relevant question is: are platform drivers, as independent contractors, paid more or less than taxi drivers who are employees? The answer, as we will see below, is ‘more’—for nearly all drivers.

Taxi Driver Costs

An inevitable question is whether taxi drivers’ earnings include their costs or not. Survey level data from OES, and QCEW provide data on wages only and with respect to employees. As such, we conclude that these data sources do not include costs. The data on self-employed taxi drivers, however, is less clear. The survey questions asked pertain only to earnings and do not ask respondents to account for expenses. Self-employed taxi drivers, however, do incur expenses, including the leasing of medallions.

The OES survey reports on the earnings of employees, not the self-employed.[12] OES wages are gross pay before taxes. Tips are included. It does not report on whether costs are included or not. As employees, we assume that these taxi drivers are reimbursed for their expenses.

Seattle and the Nation

For all occupations in Seattle, we performed a similar adjustment as for taxi drivers, in order to remain consistent. The median annual earnings for all occupations in Seattle in 2019 was $52,945. The hourly median was $25.45. At the national level, we would not have used the same numbers from the Employment Cost Index, and decided to use the actual OES estimates for median earnings in 2019, which was $39,810.

Quarterly Census of Employment and Wages

The BLS offers another measurement of taxi and limousine services, the Quarterly Census of Employment and Wages (QCEW). The QCEW is based on employer administrative data, not employer survey data, which should make it more objective. Yet, it seems based on a very small sample that inflates the earnings data.

For the fourth quarter of 2019, the QCEW estimated an average weekly wage in King County, where Seattle is located, at $2,109 or $52.73 per hour.[13] For King County, the QCEW listed only 385 drivers in 26 establishments. These hourly earnings seem much higher and the employment much lower than in OES.

We find these numbers, because of their small sample size and high hourly earnings (more than twice the median hourly earnings in Seattle, about the same as an industrial engineer or an optometrist), dubious.

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[12] https://www.bls.gov/oes/2017/may/oes_tec.htm

[13] NAICS 4853 Taxi and Limousine Service;
https://data.bls.gov/cew/apps/Table_maker/v4/Table_maker.htm#type=1&year=2019&qtr=4&own=5&ind=4853&supp=0

Existing Literature

We consider several studies that have set the pace for analysis of the driver app labor market: Hall and Krueger (2018), Parrott and Reich (2018), Mishel (2018), and Zoepf et al (2018). Each of these studies touch on several controversies in the field that warrant further consideration and comparison. We evaluate these studies in light of expense estimates, working hour estimates, and demographic data. Our comprehensive use of Seattle microdata leads us to different conclusions than these earlier studies.

Each of the aforementioned studies takes a slightly different approach to estimating expenses.

Local, National

Hall and Krueger analyze their study at a national scale and draw out conclusions based on major metropolitan areas. This comes with analytical costs. Critics have pointed to Hall and Krueger's insufficient attention to the particularities of place. Municipal governance is not universal. Each city has its own licensing regimes, costs, and spatial driving patterns. Without sufficient attention to these idiosyncrasies, Hall and Krueger are unable to account for the full weight of driver costs and expenses.

Vehicles

Further, Hall and Krueger concede that without knowledge of specific car models and other driving information that their model is at best a rough approximation.[14] This should not be taken as a criticism of Hall and Krueger's analysis. They simply lacked the data to make more granular estimations of costs.

Parrott and Reich improve on the assumptions of Hall and Krueger by isolating the Toyota Camry as the most popular car utilized by New York City drivers. Our study, by contrast, considers the range of car make and models used in Seattle. We consider cars of standard and expensive trim specifications. This allows us to take a close look at the variation of expenses incurred by Seattle drivers. Zoepf et al similarly base their expense modelling off the most popularly used cars by Uber drivers but again rely on national car statistics for their analysis.[15]

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[14] Jonathan V. Hall and Alan B. Krueger, "An Analysis of the Labor Market for Uber's Driver-Partners in the United States," *ILR Review* 71, no. 3 (May 2018): 726.

[15] Stephen Zoepf, Stella Chen, Paa Adu, Pozo Gonzalo, "The Economics of Ride Hailing: Driver Revenue, Expenses, and Taxes," Unpublished paper, MIT. While other parts of their study were heavily criticized, expense estimates were not challenged.

Expense Categories

Parrott and Reich (2018) provide very careful and detailed of analysis in their study of New York drivers. Their study groups costs in certain categories: one-time (amortized over five years), recurring, and operating. One-time costs include examinations, licenses, and training required as part of New York City regulatory codes. Recurring costs include further licensing and renewals, vehicle registration, and inspection fees. Operating costs include gas, car payments, commercial insurance, and vehicle maintenance. These costs reflect the particular New York regulatory environment in which drivers work. Parrott and Reich acknowledge that the New York driving environment is particularly cost heavy and this drives up their expense estimates.

Many of our assumptions reflect similar logic in estimating expenses but are tailored to the local environment in Seattle. Like Parrott and Reich we consider in detail the local conditions that shape a driver's experiences.[16] Our study takes into account driver costs that are unique to Seattle. We account for local gas prices, car values, driving patterns, and tax policies that might impact Seattle app drivers. We similarly estimate fuel economy based on city driving. Seattle drivers do not face the intense regulatory environment of New York.

Furthermore, Parrott and Reich assume a full-time driver averages 35,000 additional miles over the course of a year. When calculating per mile values, the authors utilize this value as a denominator. In some ways, this approach is similar to considering the returns to the asset value of the cars as a part of driver costs.

Where we differ is in our starting assumptions about drivers. According to the data set that we have, very few drivers are on the road in Seattle more than 40 hours per week. We treat costs as marginal expenses, except for the small percentage of full-time drivers. These differences are discussed in more detail in Section 5: Expenses. A recent study by AlphaBeta in Sydney, Australia similarly used an incremental approach to evaluate expenses.[17] We acknowledge that the marginal cost approach does not take into account any return to drivers for the use of their car.

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[16] James A. Parrott and Michael Reich, "An Earnings Standard for New York City's App-Based Drivers: Economic and Policy Assessment," *New York: The new School, Center for New York City Affairs* (July 2018). A Report for the New York City Taxi and Limousine Commission.

[17] AlphaBeta, "Flexibility and fairness," news release, March 2019, accessed June 25, 2019, https://ubernewsroomapi.10upcdn.com/wp-content/uploads/2019/03/Alphabeta-Report_Flexibility-and-fairness_-what-matters-to-workers-in-the-new-economy.pdf

Mishel (2019) follows Zoepf et al (2018) in his expense analysis. However, Mishel also develops a cost model that considers the tax implications of app driver's expense and earnings.[18] While we do not consider it here, we believe tax analysis is worth further study in a subsequent paper.

Demographic Data:
Parrot and Reich along with Hall and Krueger, and more recently AlphaBeta, pay careful attention to driver characteristics. With their survey level data, they are able to account for a demographic representation of drivers in their studies: education levels, familial status, etc. We do not have the ability to link our data set to those demographic variables.

Demographic data may impact the policy implications and the sociological context in which drivers make decisions. It also impacts the expenses incurred by drivers. Parrott and Reich argue that many New York City drivers are young immigrants and thus face higher than average insurance fees. They further argue that most drivers are full-time and would otherwise work as taxi drivers. With this information, they argue that full time drivers are most likely to purchase another vehicle for their app driving. Accordingly, car payments and leases are included as major expenses in their study. Given the regulatory environment and driver demographic information, Parrott and Reich argue that flexibility claims about the nature of app driving work are exaggerated.[19]

Our study does not utilize demographic data and thus we make no assumptions about the demographic makeup of a typical driver. This makes it difficult to fully engage with Hall and Krueger, Parrot and Reich, and Alphabeta's claims regarding the value and costs of flexibility in the app driver labor market. We have accounted for alternative job options and wage potential. However, it would be difficult to say what alternative is indeed an appropriate job for drivers of different demographics. We can however compare taxi drivers with similar low-wage jobs in Seattle, which we do in Chart 1.14 above.

Working Hours
In their 2018 study, Parrott and Reich use a four-part scheme to organize the distribution of working hours on a weekly basis. Drivers are grouped according to numbers of hours worked: 1-15, 16-34, 35-39, and over 50. Like the IRS, Parrott

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[18] Lawrence Mishel, "Uber and the Labor Market: Uber Drivers' Compensation, Wages, and the Scale of Uber and the Gig Economy," Economic Policy Institute, 2018.
[19] James A. Parrott and Michael Reich, "An Earnings Standard for New York City's App-Based Drivers: Economic and Policy Assessment," *New York: The new School, Center for New York City Affairs* (July 2018). A Report for the New York City Taxi and Limousine Commission.

and Reich consider work times in excess of 30 hours as full-time work. Drivers who work less than 20 hours are considered part-time. In New York City, Parrott and Reich estimate that approximately 60 percent of drivers are full-time and 16 percent are slightly above part-time classification, with the remaining drivers classified as part-time.[20] This is in stark contrast to the data we have found in Seattle where only a small number of drivers are full-time. We also posit a novel imputation of part-time and full-time status in our study.

Without log-on and log-off time, Parrot and Reich calculate working hours based off trip starting and ending times: from the beginning of the first trip to the end of the last trip. They consider working hours only when a driver takes on a passenger ride. This, as they acknowledge, slightly underestimates working time as drivers often spend time on the app waiting for a ride to come up. Because their data is aggregated across platforms and they lack log-on and log-off, Parrott and Reich estimate working hours by summing the total trip durations and dividing this sum by the proportion of total working time that a driver has a passenger. This allows them to account for multi-platform drivers who might move between apps during their "shift." Our measurement of hours aligns with this logic, but with access to more granular data we are able to offer a more fine-tuned picture of working time.

Faulty Statistics

Aggregated data, such as made available to other researchers in Seattle and in other previous studies, contains very important, yet not obvious limitations.

Consider estimating "hourly earnings" as the ratio of $\frac{earnings}{hours}$. For an individual driver, we would simply divide earnings by hours. Naively, we might use the provided aggregated statistics for a similar calculation, and compute $\frac{mean\ earnings}{mean\ hours}$. Many previous studies, drawing on the published aggregated statistics of Lyft and Uber have done so.

While this division seems intuitively correct, it is nonetheless mathematically misleading. The number $\frac{mean\ earnings}{mean\ hours}$. is *not* equivalent to $mean\left(\frac{earnings}{hours}\right)$. In fact, $\frac{mean\ earnings}{mean\ hours}$ can be shown to be always equal to or less than $mean\left(\frac{earnings}{hours}\right)$, a well-known mathematical result called Jensen's inequality.

[20] James A. Parrott and Michael Reich, "An Earnings Standard for New York City's App-Based Drivers: Economic and Policy Assessment," *New York: The new School, Center for New York City Affairs* (July 2018). A Report for the New York City Taxi and Limousine Commission.

As an example consider Table 1.16, using numbers made up simply for illustrative purposes, the $mean\left(\frac{A}{B}\right)$ is greater than $\frac{mean\ (A)}{mean\ (B)}$. Using A and B (which could be earnings, hours, or anything), we compute $\left(\frac{A}{B}\right)$. Here the $mean\left(\frac{A}{B}\right)$ is 1.3, while the $\frac{mean\ (A)}{mean\ (B)}$ is 0.7. To simply take a mean and divide it by another mean does not actually give the true number desired, even though the calculation looks very similar to the proper calculation. Only with the underlying data can the proper $mean\left(\frac{A}{B}\right)$ be calculated. Any similarity between $mean\left(\frac{A}{B}\right)$ and $\frac{mean\ (A)}{mean\ (B)}$ is coincidental. In this example, in Table A.2, the actual average is almost double the 'average' calculated by dividing means.

Any ratio computed from means should be considered an estimation that is biased downward.

Table 1.16: Illustrative example of the distinction in the calculation of means

Observation	**A**	**B**	$\left(\frac{\boldsymbol{A}}{\boldsymbol{B}}\right)$
Alpha	2.0	20.0	0.1
Bravo	4.0	4.0	1.0
Charlie	6.0	9.0	0.7
Delta	8.0	6.0	1.3
Echo	10.0	3.0	3.3
	Mean: 6.0	Mean: 8.4	Mean: 1.3

$mean\left(\frac{A}{B}\right)$ = 1.3

$\frac{mean\ (A)}{mean\ (B)}$ = $\frac{6.0}{8.4}$ = 0.7

Earlier we discussed statistical problems in earlier studies. In Parrott and Reich, for instance, the researchers computed a ratio estimate with “weekly earnings” divided by “hours driven” in order to calculate what they think is ‘earnings per hour’. This estimate has a downward bias. Furthermore, as can be seen in Chart 1.6, the distribution of hours driven is right skewed so using a mean to estimate hours driven leads to an even greater downward bias in the estimated earnings per hour.

Parrott and Reich use imputed numbers of hours driving because of complications in determining company-specific working time when a driver uses more than one platform when using their aggregated data. In our microdata we found a third of the drivers used multiple apps. Using imputed driver working time to estimate hourly earnings for each driver on a given platform would give an error in about a third of the drivers. We take great care to deduplicate the microdata P1 times and calculate the correct the P1 times. Aggregating imputed driver working times across app platforms inflates P1 times which further compounds the downward bias in the Parrott and Reich estimated earnings per hour.

Anticipated Objections to Comparing Taxi Drivers and Platform Drivers

The ride-sharing and taxi industries compete for some of the same passengers, so it might be believed that the rise of ride-sharing has decreased taxi earnings and employment, and therefore the benchmark for taxi driver earnings would be decreased because of Uber and Lyft drivers. We did not find evidence of this decrease.

As seen in the Chart 1.17, we can see that after Uber’s entry into Seattle in 2011, the number of taxi drivers actually grew at compounded annual growth rate (CAGR) of 5.8%. Similarly median taxi hourly earnings also grew, at a CAGR of 6.2%. As shown in Table 1.18, we show the percentiles of taxi driver earnings for 2018, the last year for which there is reputable data. Taxi drivers had considerable variation in earnings, and many earned below the minimum wage.

The taxi driver hourly earnings are far more volatile than other low-wage jobs, but that volatility occurred before Uber’s entry into the Seattle market. We suspect that the mix of taxi drivers and limousine drivers, as well as the increase in the supply of taxi and limousine drivers is behind the variation in these hourly earnings, but have no evidence to support that claim. We do not, however, see any relationship between the timing of Uber’s market entry and a change in the number of taxi drivers or their median earnings.

Chart 1.17: Taxi employment, median hourly earnings
#, $nominal

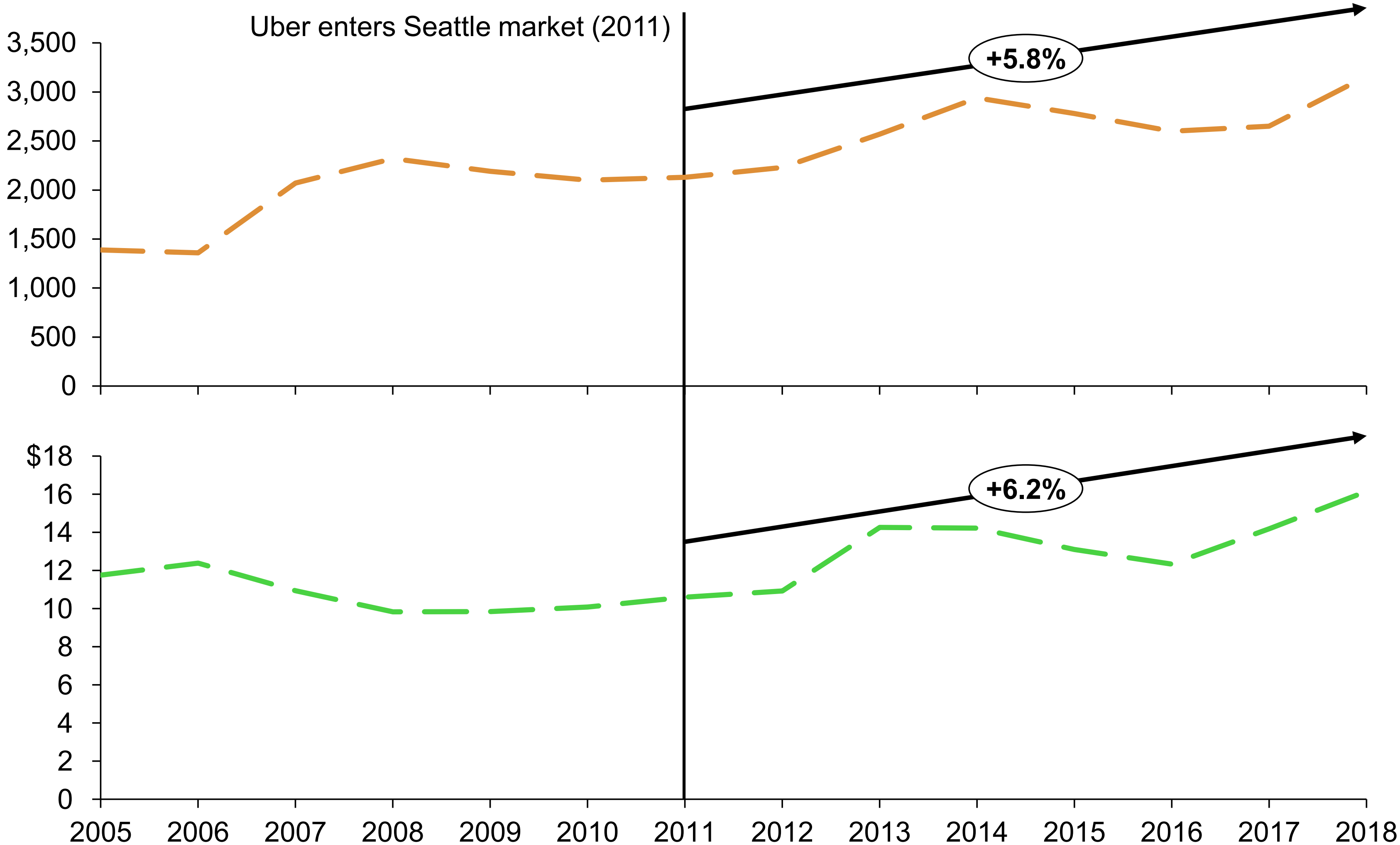


Table 1.18: Taxi driver hourly and annual earnings in Seattle
$nominal

	2018
Number	3,160
10th	$ 12.08
25th	$ 13.53
Median	$ 16.15
75th	$ 18.47
90th	$ 21.79
Annual Median	$33,580

Limits of the Study

As hopefully useful as these findings are, the study has limits that need to be highlighted:

Place: These findings reflect the drivers in Seattle. Hours, hourly earnings, and platform mix might vary outside the city limits of Seattle.

Time: These findings reflect a particular week in October of 2019. While we believe there was nothing particularly special about that week, further studies would be necessary to detect weekly, monthly, or annual patterns.

Source: We received the data for the total population, not a random sampling under our control.

Costs: We may not have considered additional hidden costs that drivers incur when driving. In our regression analyses to differentiate marginal costs from fixed costs, we used the majority of car models driven by Uber and Lyft drivers. Some uncommon car models might have different marginal costs.

Categories: We divide drivers into four groups, the names of which may be slightly misleading since they are grouped by percentiles not hour cutoffs. We also define that percentile by P2+P3 time, not P1+P2+P3 time. Full-timers, for instance, are defined as the most committed 5% of drivers, not drivers above 40 hours a week. Yet once their P1 time is included, their median time is actually more than 40 hours per week, so these categories do roughly accord with common sense. Having the driver categories defined by percentile rather than hour cut-offs allows us to allow the hours to fluctuate across definitions.

Decomposition of P1: We would have liked to have spent more time handling the subtleties of P1 across time of day, but because of COVID, we found ourselves constrained. We plan to explore this topic in a subsequent report.

Taxes: We would like to have examined the tax implications for drivers, but decided that would be better explored, more fully, in a subsequent report.

Driver Tenure: We did not have a variable on how long drivers had been using either app, so we could not test "experience" against hourly earnings.

Bonuses: Our earnings data did not include "streak bonuses" or similar kinds of incentive earnings for drivers. For drivers that participated in these programs, their earnings would have been higher.

Car Size: We examined only cars in the UberX and LyftDF, not UberXL, UberSelect, LyftXL, Lyft Lux, or similar programs. We also did not examine shared rides, like Lyft Shared or Uber Pool.

Airport: Seattle is unlike many other cities in that its major airport, Seattle-Tacoma International Airport, is outside the city limits and therefore out the scope of this study. Unlike studies of New York City, where two of three major airports are in the city limits, our study would not account for the wait time of drivers at the airport.

2: No Waiting (P2+P3)

Introduction

In Section 2, we look at the P2 and P3 time of drivers excluding P1. In this section, when we refer to “hours” or “driving hours” we intend P2 + P3 time.

If drivers did not have to wait for a ride, they would still need to drive to pick someone up (P2) and then drive that person somewhere else (P3). This Section can be thought of as a thought experiment if the apps were 100% efficient in connecting passengers to drivers with no wait time. If that were the case (which it is not), drivers would have median hourly earnings, as shown below in Table 2.2, of $36.31. That figure, $36.31, should be thought of as the median upper limit on earnings.

In a world where drivers never waited for a ride, the median driver would earn $36.31 an hour.

Hours

Examination of the distribution of driving hours reveals the variety of driver behavior in Seattle. The mean driver drove about 9 hours in that week. The median driver only drove 7 hours, which implies that some drivers drove exceptionally longer hours than the median driver. Yet very few drivers drive what we would consider full-time, when excluding P1. Even with a conservative minimum, 26 hours, only 5 percent of drivers were full-time. Overall, only 0.3 percent of drivers drove 40 hours or more a week in P2 + P3.

Earnings

It is easy to imagine different stories for the relationship between hours driven and earnings, some of which have contradictory predictions. A full-time driver, for instance, could have more tactical knowledge to maximize earnings: deciding on the best fares to take, the choicest locations, or estimating the most profitable routes. On the other hand, the casual driver might cleverly only come on the app during peak surge demand, driving up their hourly rate.

We expected that drivers’ hourly earnings rate would go up as drivers’ hours went up, reflecting the experience of a more committed driver. Our regression analysis, however, did not support this hypothesis. The hourly rate did not depend on the number of hours. The P2+P3 hours, of course, is not the same as driver tenure. We did not have access to the length of time a driver had been using the app. Further studies might reveal a connection between hours driven over a long period of time that more meaningfully predicts hourly earnings.

Instead, as we see in Table 2.1, hourly earnings, when only accounting for P2+P3 time, were markedly stable across the majority of drivers, regardless of how long they drove in a week. Also, regardless of whether a driver drove only for Lyft, only for Uber, or for a mix of the two, their hourly earnings were statistically equivalent (again, when only considering P2+P3 time).

Using P2+P3 hours, the difference in average hourly pay between the most casual and the most full-time drivers is a little under two dollars an hour. Put another way, the median casual driver earns 95% of the full-time driver's hourly earnings. Regardless of time spent, drivers still took home roughly the same hourly pay rate.

The P2 + P3 hourly earnings had a median of $36.31 per hour. The middle of the distribution is relatively concentrated, with the 25th percentile earnings $32.85 and the 75th percentile earning $40.21 per hour. The extremes were a bit more extreme in this case, with the top 1 percent earning $66.12 and the bottom 1 percent earning $21.36. In Chart 2.2, we show a histogram of drivers' hourly earnings. In Table 2.3, we show the percentiles of drivers' hourly earnings by type. As is common in this data set, the casual drivers exhibit far greater variation than more committed drivers.

Considering only P2+P3 time, only a vanishingly small number of drivers earned less than the minimum wage of $16.39 an hour — 0.3 percent.

Table 2.1: Hours and earnings by driver type (P2 + P3)

Type	Driver Percentage	Minimum Hours	Maximum Hours	Mean Hours	Median Hours	Median Hourly Pay	Median Weekly Pay
Casual	25%	0.0	2.7	1.3	1.2	$35.53	$43.90
Committed Casual	50%	2.7	14.0	7.4	6.9	$36.19	$254.28
Part-Timer	20%	14.0	26.6	19.2	18.7	$36.63	$689.59
Full-Timer	5%	26.7	58.1	32.3	31.0	$37.22	$1,162.88
All	**100%**	**0.0**	**58.1**	**9.5**	**6.9**	**$36.31**	**$254.04**

Chart 2.2: Hourly earnings of drivers (P2+P3)

%, hourly earnings

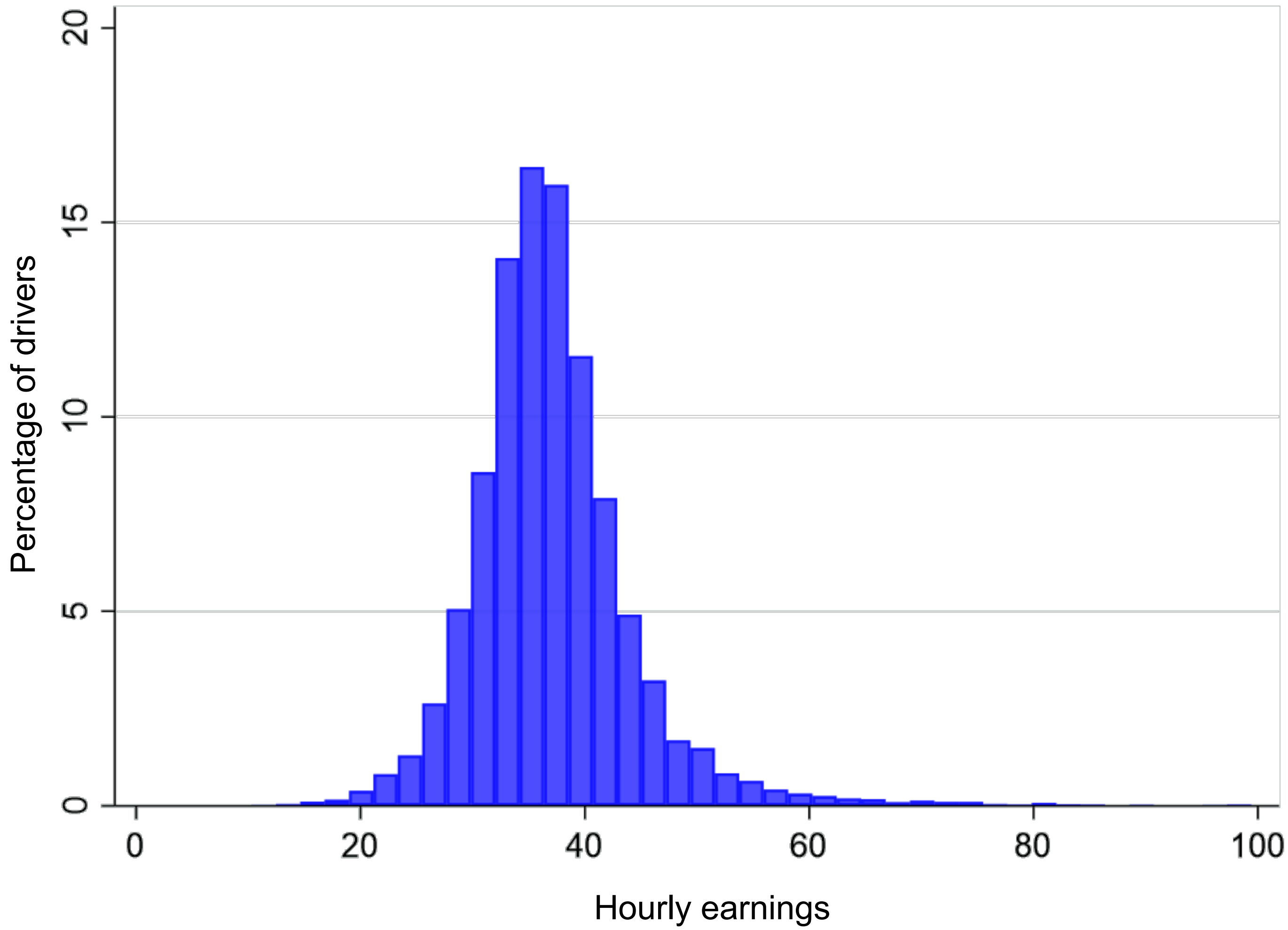


Table 2.3: Hourly earnings by driver type (P2 + P3)

Type	25th Percentile	Median	75th Percentile
Casual	$29.64	$35.53	$42.68
Committed Casual	$33.02	$36.19	$39.86
Part-Timer	$34.17	$36.63	$39.53
Full-Timer	$34.68	$37.22	$39.94
All	**$32.85**	**$36.31**	**$40.21**

Platforms, Multi-Apping and Earnings

We do find that drivers who multi-apped had P2+P3 earnings $0.77 per hour higher than single-app drivers. Again, while this was statistically meaningful, the model overall had an R^2 of approximately zero (0.18%), suggesting that almost none of the difference in the hourly earnings between the drivers could be explained by whether they single-apped or multi-apped, when looking only at the P2+P3 time.

Share of Passengers
Two of the main questions, as well, for policymakers is how much time drivers spend conveying passengers (P3) versus driving to get the passengers (P2), and what kinds of drivers are moving people around the city.

The P3:P2 ratio is the ratio of the amount of time driving a customer to driving to pick up a customer. In Seattle, as seen in Table 2.3, the median ratio of P3 to P2 time was four hours—or for every hour driven to pick someone up, drivers spent 4 hours actually transporting passengers/fares. Another way of thinking about this time is in percent of time in P2 and P3. We see very little variation in the ratio of time spent picking up to driving passengers across driver types as seen in Table 2.4. Yet drivers, overall, vary in their P3:P2 ratios, as seen in the histogram in Chart 2.5.

As policymakers consider who is actually driving passengers around Seattle, it is important to notice that most passenger hours (80%) are driven by Committed Casual and Part-Time drivers, as shown in Chart 2.6. Full-time drivers account for only 17% of passenger hours. Casual drivers, despite being 25% of the driver population, account for only 3% of passenger hours, as seen in Chart 2.6.

Table 2.4: Time drive to pick up passengers, to drive passengers by driver type (P2 + P3)

Type	Median P3:P2 Ratio	Median P2 Percentage	Median P3 Percentage
Casual	3.6	22%	78%
Committed Casual	3.8	21%	79%
Part-Timer	3.9	20%	80%
Full-Timer	4.0	20%	80%
All	**3.9**	**21%**	**79%**

Chart 2.5: Percentage of drivers' P3:P2 ratios

%, hours

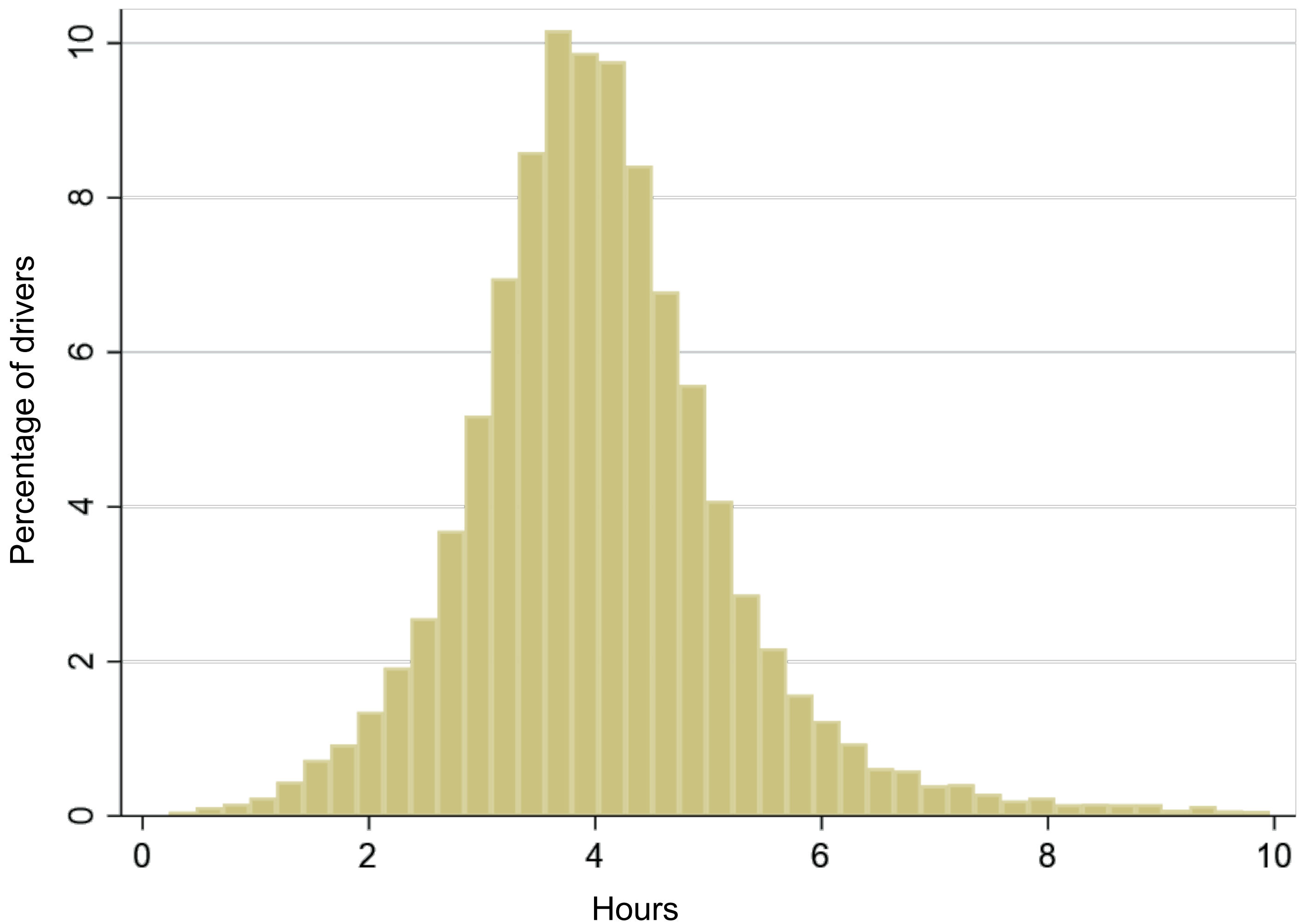
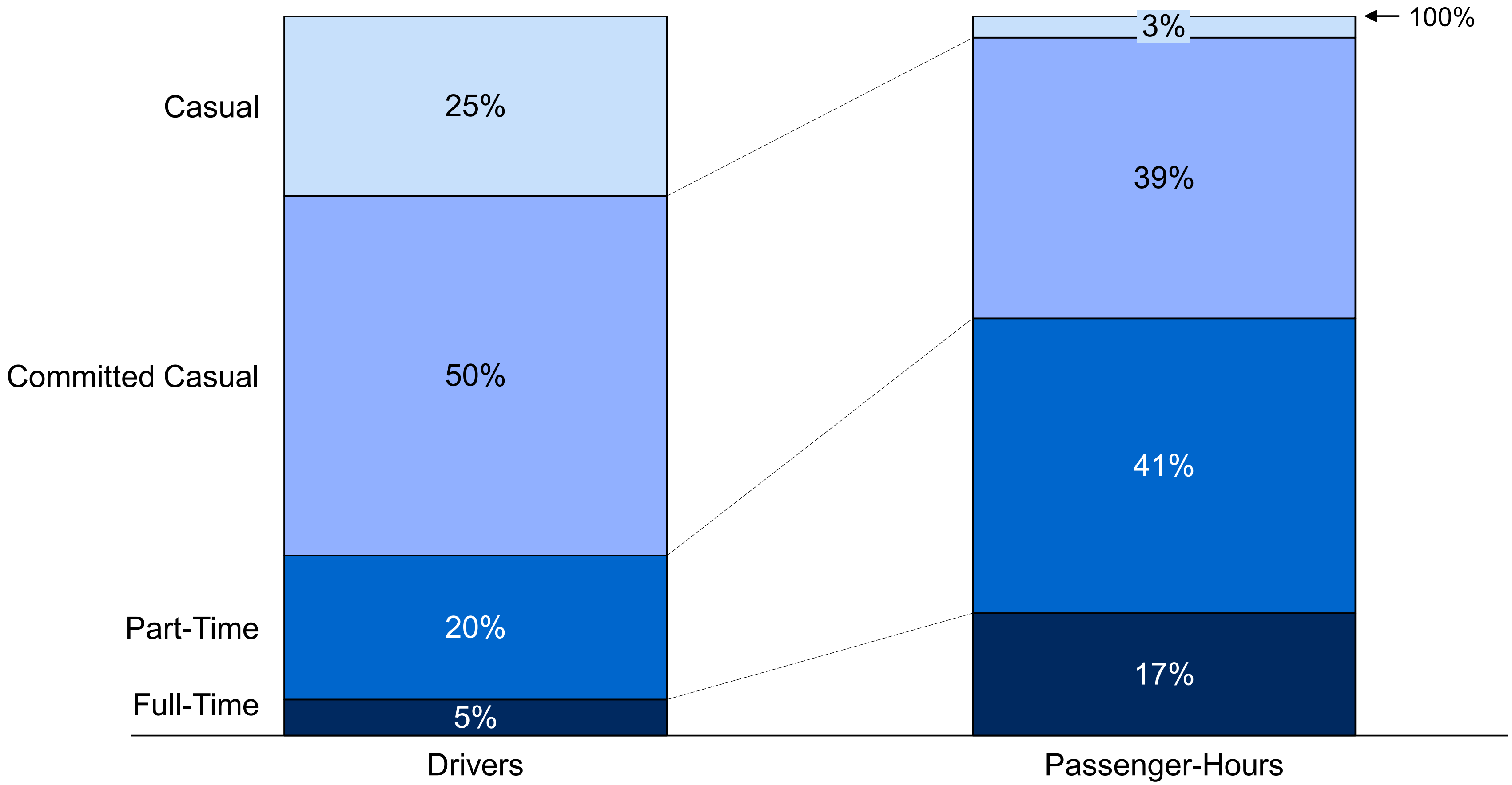


Chart 2.6: Driver Share of Passenger-Hours
%



3: Waiting (All Logged P1+P2+P3)

Introduction

In this Section, when we refer to P1 time it is all the logged P1 time, except for P1 double counted across platforms. This deduplicated P1 time includes P1 time that preceded rides, but also P1 time that preceded rejections and logoffs.

In this Section, P1 or P1 All, unless otherwise noted, refers to this most-expansive definition of P1.

Hours

The hours are longer once P1 is added, with 11.2 median weekly hours. Even with this expansive definition of P1, only 5.4% of drivers exceeded 40 hours per week.

The median driver spent 36% of his or her time in P1 All, but this median conceals vast differences. More committed drivers spend much less time (32%) in P1 All than more casual drivers (42%).

Table 3.1: Time percentage in P1 All
%

	P1 Percentage
Casual	42%
Committed Casual	36%
Part-Timer	34%
Full-Time	32%
All	**36%**

Table 3.2: Time percentage in P1 All
%

	P1 Percentage
25^{th} Percentile	29%
Median	36%
75^{th} Percentile	43%

Earnings

The gross median hourly earnings for drivers, when including expansive P1, was $23.20, as seen in Table 3.1 and Chart 3.2. This number is earnings before costs.

The earnings had considerable variation, unlike the hourly earnings when only considering P2+P3 time. The 25th percentile was $19.68 and the 75th percentile was $26.46. The median pay varies more as more P1 time is added, as seen in Table 3.3. While the time to pick up passengers and the time to drive passengers does not vary much across the categories of drivers, P1 time does, which drives considerable variation in hourly earnings, as seen in the histogram in Chart 3.4. Overall, 13% of drivers earn less per hour than the average taxi driver ($16.81) and 12% less than the minimum wage ($16.39).

Such averages can be very misleading, however. Consider that 12% of drivers earn less than $16.39, but that is largely driven by the large number of casual drivers, 32% of whom earn less than the minimum wage, as seen in Chart 3.5. Only 3% of the full-time drivers — just 20 drivers out of more than 14,000 — earn less than the minimum wage.

As seen in Chart 3.6, while casual drivers make up 25% of the driver population, they are 54% of all drivers who earn less than minimum wage. While there are fewer part-time and full-time drivers, there are also very few of those drivers (4% and 1% respectively) earning less than the minimum wage.

Drivers who multi-apped earned, on average, $2.01 more per hour. Regression analysis showed a weak, but extant, R^2 of 2%.

Table 3.3: Hours and earnings by driver type (P1 All + P2 +P3)

Type	Driver Percentage	Median Hours	Median Hourly Pay	Median Weekly Pay
Casual	25%	2.2	$20.18	$43.90
Committed Casual	50%	11.1	$23.15	$254.28
Part-Timer	20%	28.9	$24.32	$689.59
Full-Timer	5%	46.5	$25.32	$1,162.88
All	**100%**	**11.2**	**$23.20**	**$254.04**

Chart 3.4: Distribution of hourly earnings (P1 All + P2 + P3)

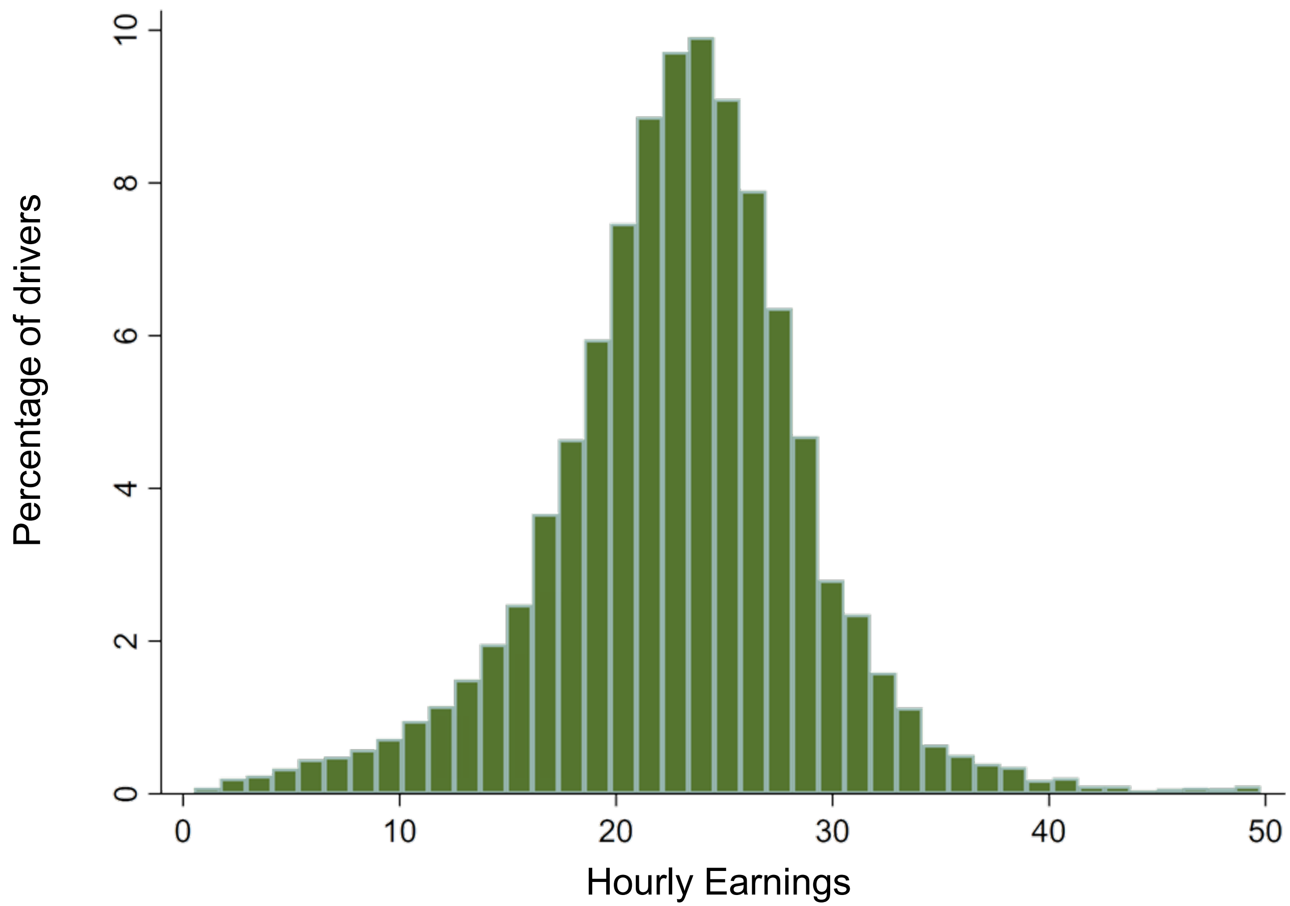


Chart 3.5: Below minimum wage drivers by category (P1 All + P2 + P3)

%

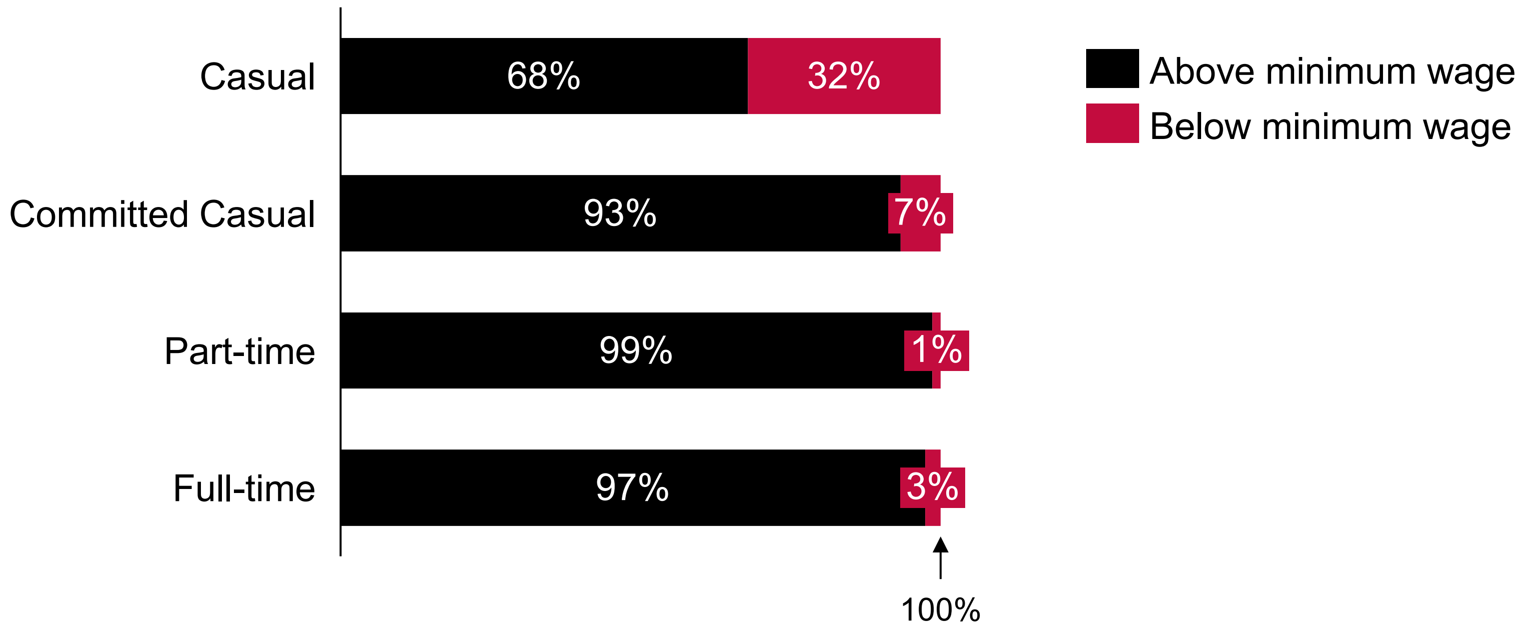
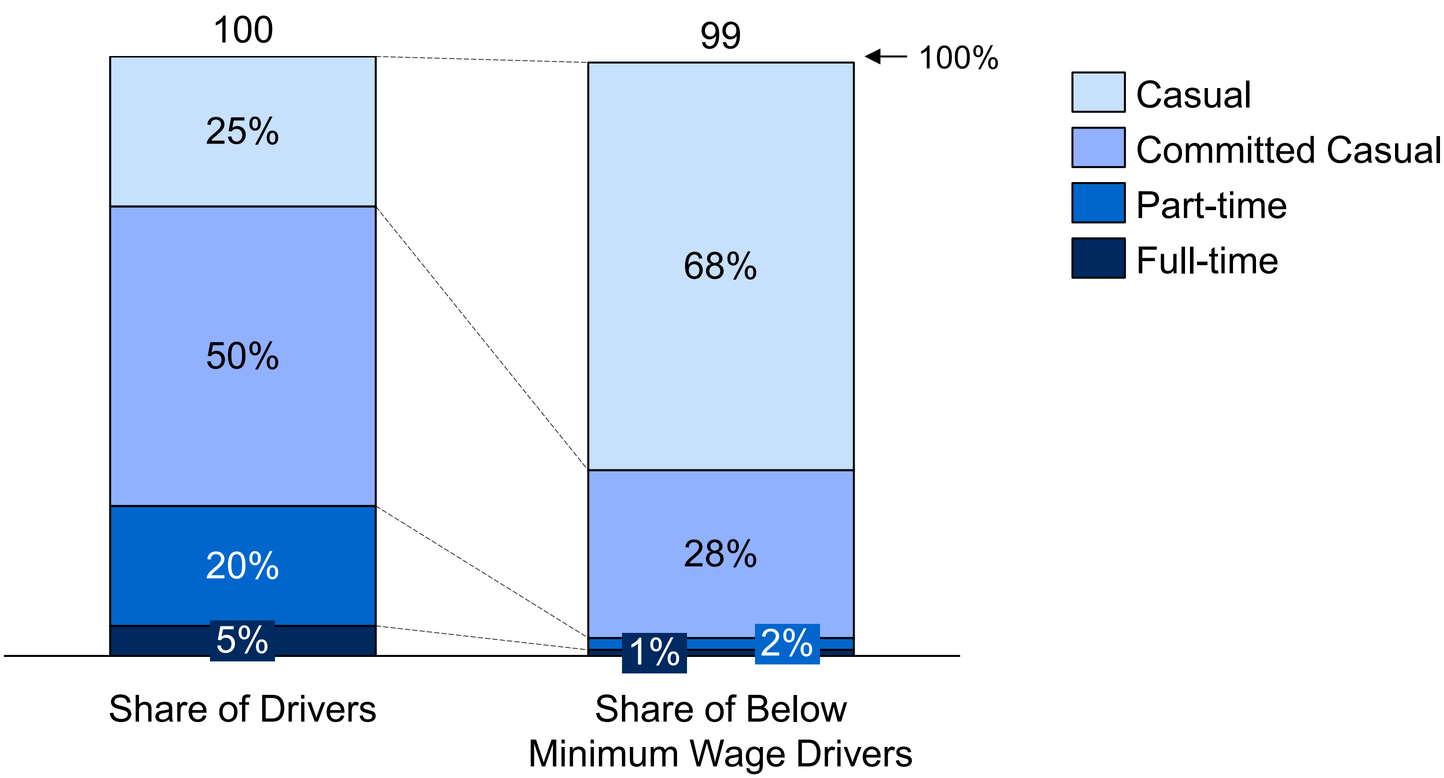


Chart 3.6: Share of Drivers Earning Below Minimum Wage by category (P1 All + P2 + P3)

%



4: Waiting For A Ride (P1 Preceding Ride+P2+P3)

Introduction

In this Section we only include P1 that preceded a ride. If a driver rejected a ride or logged off, we have excluded that P1 time. We believe this is a reasonable estimate for P1, in that it considers time that lead to work as work, and time that did not lead to work not as work.

In this Section, whenever we refer to P1, we are using that definition which we think is a reasonable middle ground between no P1 and all P1.

Hours

Once the app is on, the median driver spends about 29% of his or her time waiting for a ride, as seen in Table 4.1. Casual drivers, again, have had different experiences than the rest of the drivers, but the gap here is not as large as in Section 3. The elimination of P1 time leading to P0 or rejected rides, reduces the differences in between more and less committed drivers.

P1 time is more variable than either P2 or P3 time. As seen in Table 4.2, drivers in the top 25% spend about 22% of their time waiting for a ride, while drivers in the bottom 25% spend at least 35% of their time waiting for a ride.

As show in Table 4.3, multi-app drivers reduce their P1 time, allowing them to spend more time picking up passengers.

Table 4.1: Time percentage in P1 by driver type
%

	P1 Percentage
Casual	27%
Committed Casual	29%
Part-Timer	30%
Full-Time	29%
All	**28%**

Table 4.2: Time percentage in P1 for all drivers
%

	P1 Percentage
25th Percentile	22%
Median	28%
75th Percentile	35%

Table 4.3: P1 percentage by driver type and app-use
%

	Casual	Committed Casual	Part-Time	Full-Time	All
Multi-app	22%	25%	27%	26%	26%
Single-app	25%	30%	32%	31%	30%

Earnings

For drivers who concentrated on just one platform (about 2/3 of all drivers) we find that regardless of the platform, they earned the same rate. Including P1 in the rate, we find that the medians simply shifted lower. The distribution of hourly earnings remained roughly the same.

As seen on Tables 4.4 and 4.5, the top 10 percent earned at least $33 per hour. The 25th and 75th percentiles were, respectively, about $23 and $29. The bottom 10% of drivers earned slightly under $20 per hour. As in other sections of this study, casual drivers had a greater variation than the other categories of drivers.

When P1 is included, 2.5 percent drivers earn less than $15 per hour, which is ten times the percentage than when just considering P2+P3, but still a very small fraction of drivers.

As seen in Charts 4.6 only 3.8 percent of drivers make less than the current Seattle minimum wage of $16.39 per hour. Perhaps most tellingly, 96 percent of all drivers earned more than the median hourly earnings for Seattle taxi drivers and chauffeurs—$16.81. And as we look closer, we see that, again, casual drivers disproportionately made up those drivers earning less than the minimum wage. While casual drivers were only ¼ of all drivers, they made up ¾ of all drivers making less than the minimum wage.

A perhaps intuitive, but important, finding is that the lower the percentage of time spent in P1, the higher the hourly rate. One could easily imagine a strategy where drivers waited longer for possibly better paying rides. The data, however, contradicts this hypothesis. For every one percent point increase in P1 time, a driver's hourly rate of pay falls about $0.31. So, a 10 percentage point increase in P1 time implies a $3.10 drop in hourly earnings rate. Waiting for a ride does not lead to higher hourly earnings.

About 30% of the differences in drivers' hourly earnings comes from the variation in the percentage of time in P1, which is the strongest effect we found in the data.

Drivers who mix platforms tend to have higher hourly earnings than drivers who do not mix platforms, but there is considerable distribution within single-appers and multi-appers, as seen in Table 4.4 and Chart 4.7. In Table 4.5 and Chart 4.6, we can see the different earnings distributions for the different types of drivers. Full-time drivers have less variation in their earnings than casual drivers.

Table 4.4: Hourly earnings percentiles by app-use (P1+P2+P3)
$

	10th Percentile	25th	50th	75th	90th Percentile
Single-App	$18.79	$21.78	$24.99	$28.58	$33.06
Multi-App	$22.30	$24.62	$27.24	$30.06	$33.12
Total	**$19.67**	**$22.69**	**$25.82**	**$29.19**	**$33.08**

Table 4.5: Hourly earnings percentiles by driver type (P1+P2+P3)
$

	10th Percentile	25th	50th	75th	90th Percentile
Casual	$15.90	$20.77	$25.90	$32.25	$39.53
Committed Casual	$20.27	$22.80	$25.83	$28.93	$32.27
Part-Timer	$21.40	$23.32	$25.64	$28.06	$30.57
Full-Time	$22.21	$24.34	$26.30	$28.58	$30.61
All	**$19.67**	**$22.69**	**$25.82**	**$29.19**	**$33.08**

Chart 4.6: Below minimum wage drivers by category (P1 + P2 + P3)
%

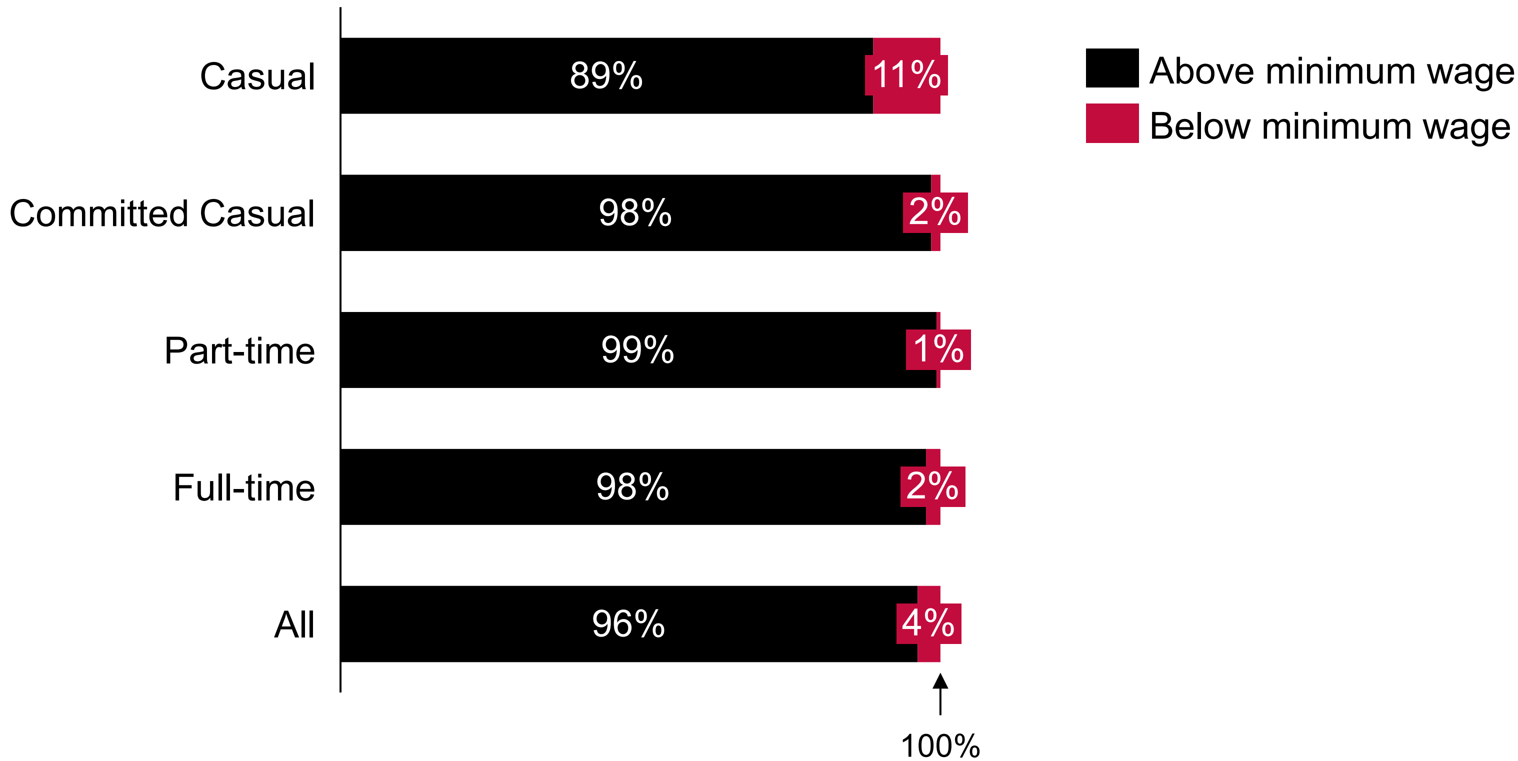


Chart 4.7: Share of Drivers Earning Below Minimum Wage by category (P1 + P2 + P3)
%

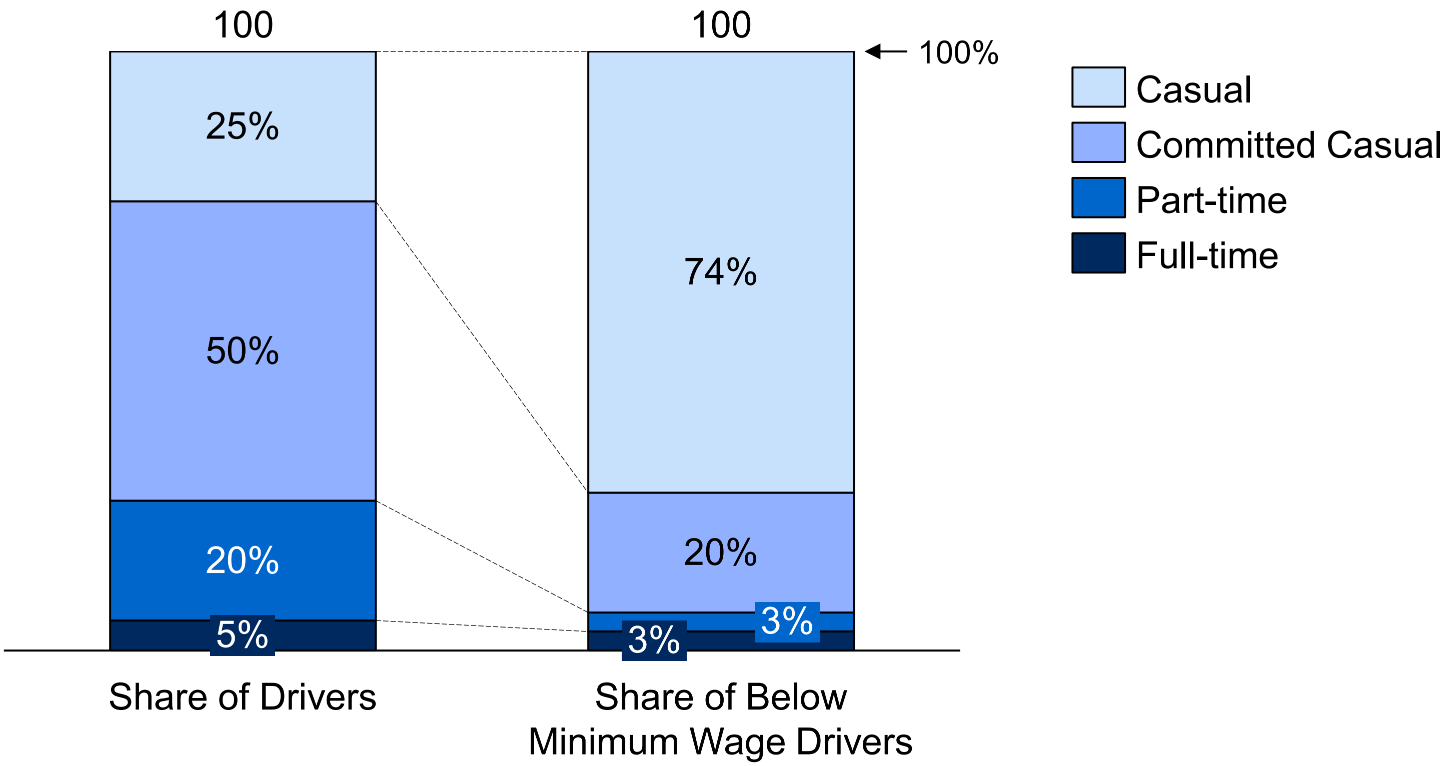


Chart 4.8: Distribution of hourly earnings (P1 + P2 + P3)

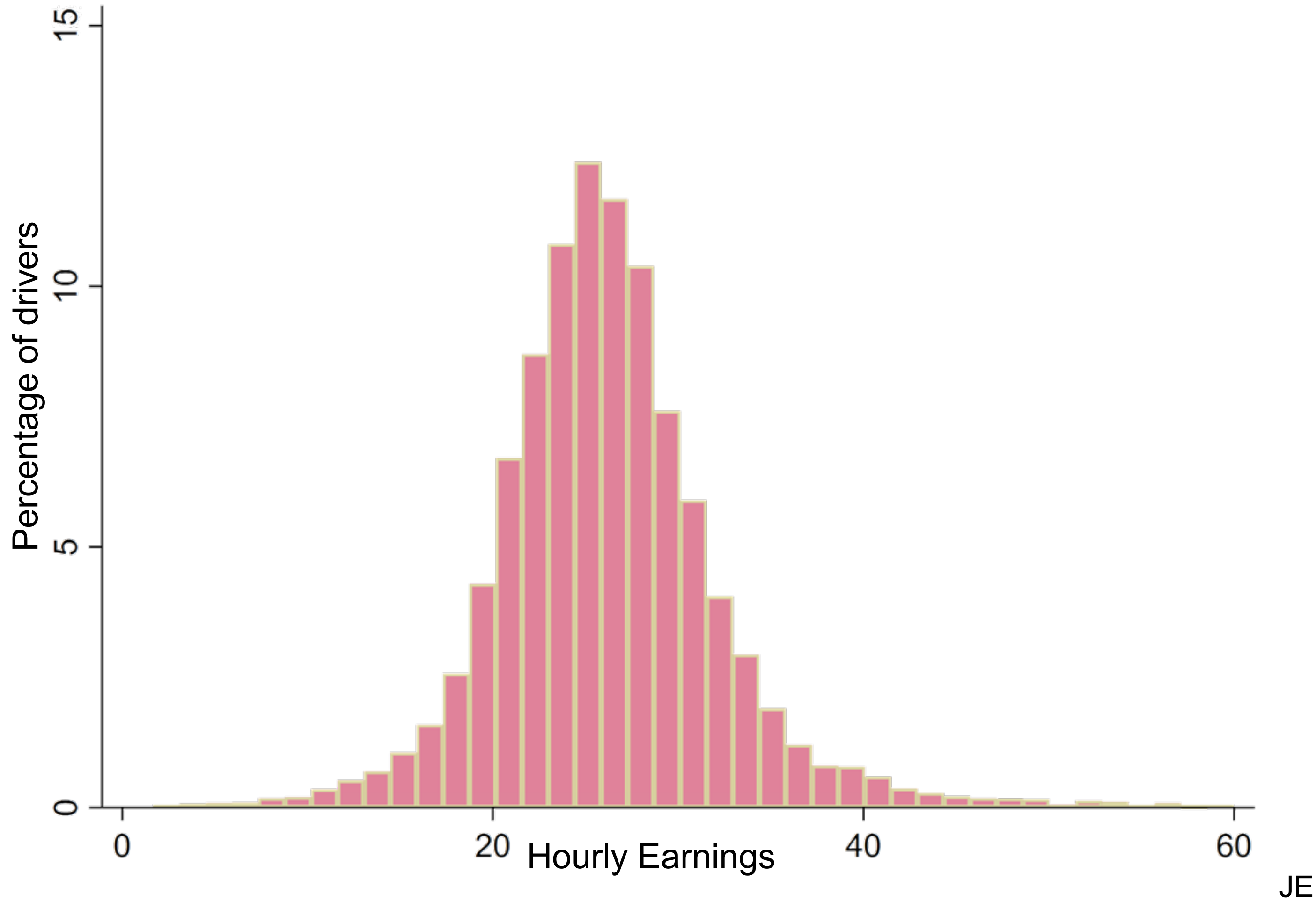
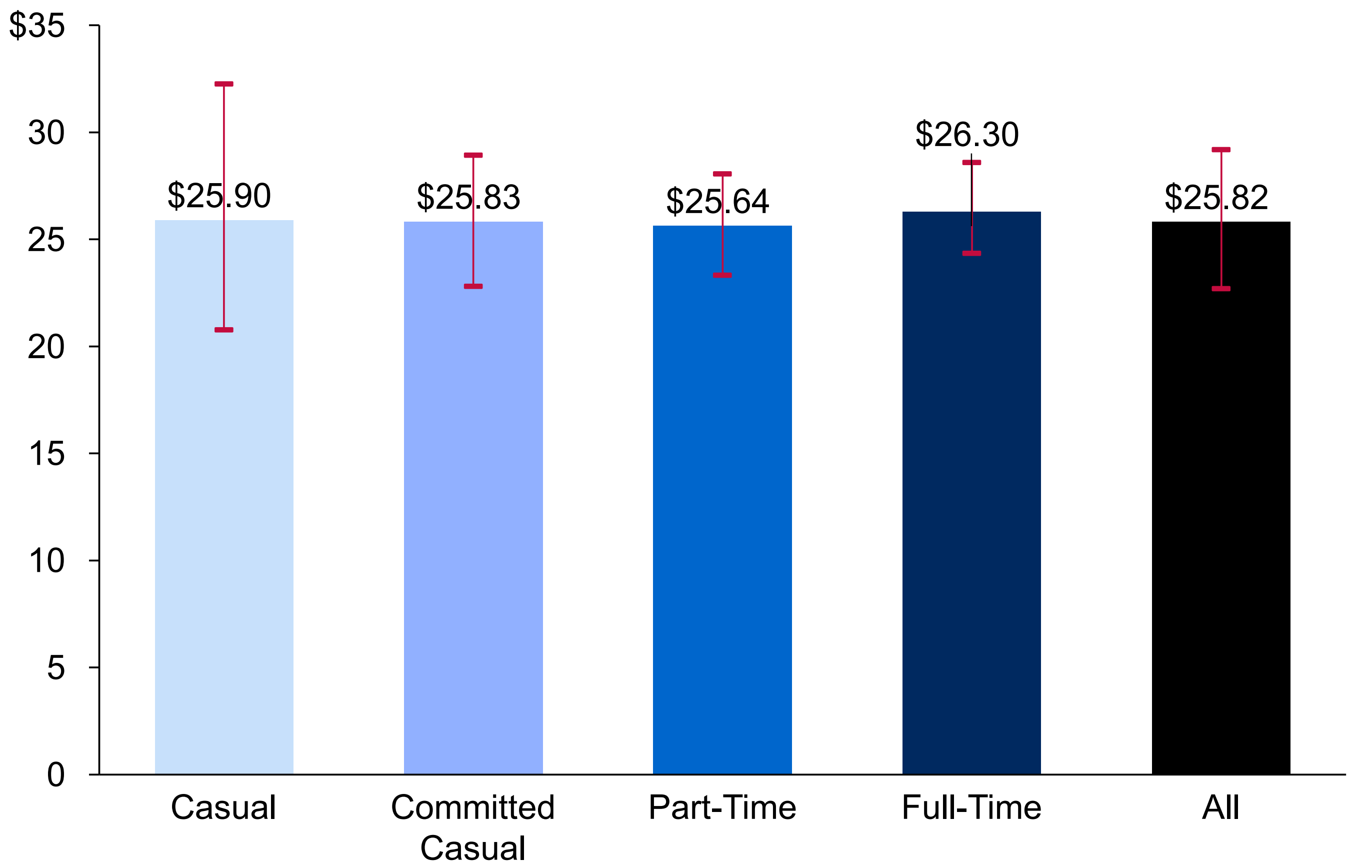


Chart 4.9: Hourly earnings (75th percentile, median, 25th percentile) by driver type (P1+P2+P3)
$



Drivers made about the same per hour, regardless of weekly hours

Chart 4.10: Driver percentage of hourly earnings by platform usage (P1+P2+P3)

$

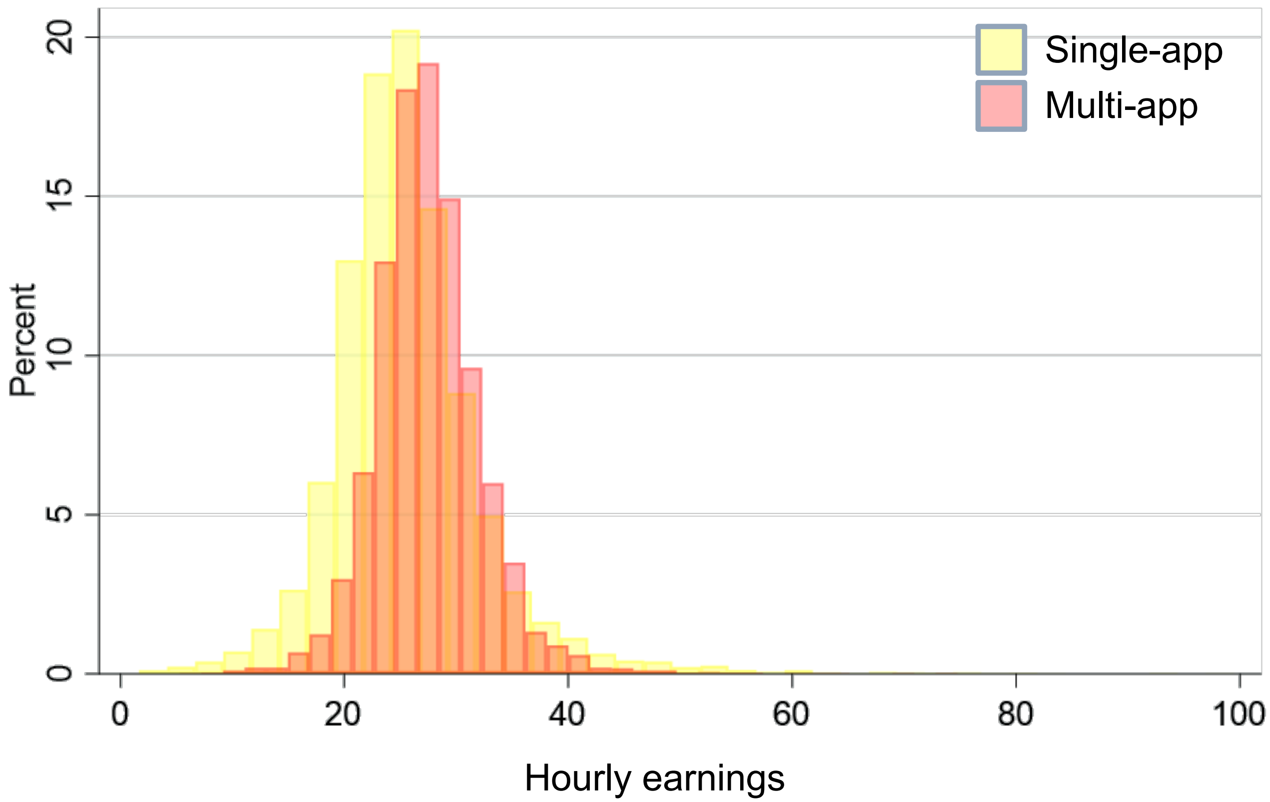
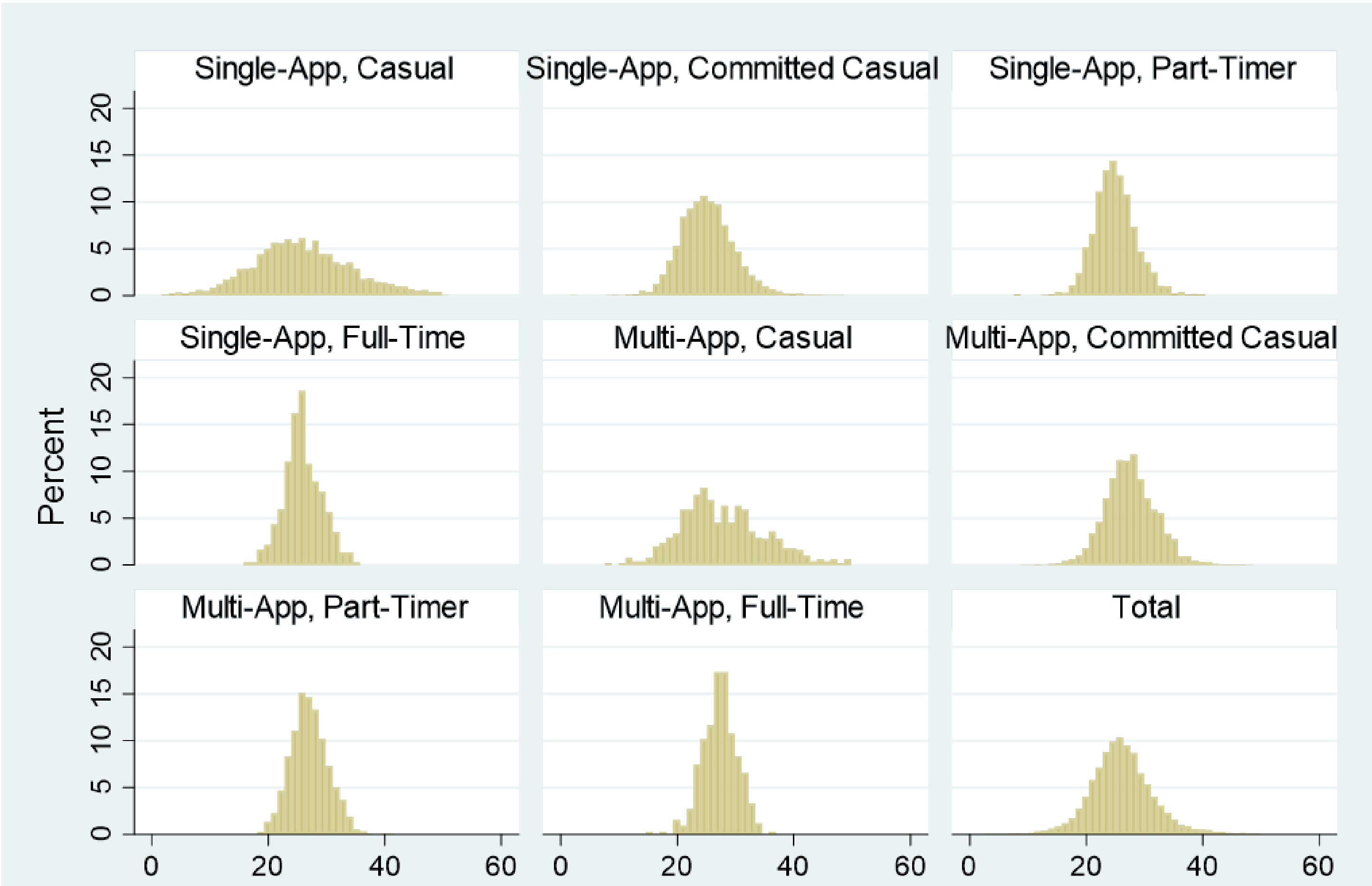


Chart 4.11: Driver percentage of hourly earnings by platform usage, driver type (P1+P2+P3)
$



5: Expenses

Introduction

Drivers incur costs while driving on Lyft and Uber. For every additional dollar earned, there is some additional cost. We include only additional costs that the drivers otherwise would not have incurred. Costs that a car owner would have regardless of driving on Lyft or Uber are not included (like finance charges, registration fees, personal insurance, etc.) The variable costs we consider important are depreciation, maintenance, and fuel. Since both platforms provide insurance while the app is on, there are no additional insurance costs.

A reader might object that some drivers might purchase or lease an additional or more expensive car because they intend to drive on Uber or Lyft. We imagine that this might be the case for some full-time drivers (who are 5% of all drivers), but it is hard to believe that would be the case for the rest of the drivers. For those full-time drivers, a subsequent study would be needed to address the incremental cost of the car they would have otherwise purchased and the one that they bought to drive on Uber or Lyft.

Similarly, a reader might object that we should include other forms of benefits, such as health insurance. Again, this kind of insurance is not marginal and should not be considered part of the additional costs. Moreover, it is not clear that most job alternatives available to platform drivers offer such benefits.

We have calculated the costs on a per mile basis, in keeping with established methods of the IRS and AAA.

We estimate that drivers have, on average, marginal costs of $0.19 per mile. Because in this study we calculate only pre-tax earnings, it should be noted that the difference between the IRS mileage deduction rate ($0.58) and the actual per mile cost ($0.19) represents a significant tax deduction opportunity for drivers.

Finally, as noted in the general section on marginal costs and asset rental, our marginal cost approach does not account for any return to capital for drivers who provide the service of their car. This issue requires more research and the attention of policymakers who seek to regulate the terms and conditions under which platform drivers work.

	Value	Calculation
IRS cost estimate	• Fixed $0.58 per mile 	• Uses average U.S. fleet to calculate average depreciation and then divides by average miles • Uses average U.S. gas prices and mileage to calculate fuel costs • Uses average maintenance cost per mile
Our cost estimate	• Median $0.19 per mile • 25th percentile: $0.14 • 75th percentile: $0.22	• Uses actual platform driver fleet to calculate marginal depreciation and then multiplies by actual miles driven. • Uses actual Seattle gas prices in October to calculate fuel costs. • Uses AAA categorical estimates for maintenance cost per mile.

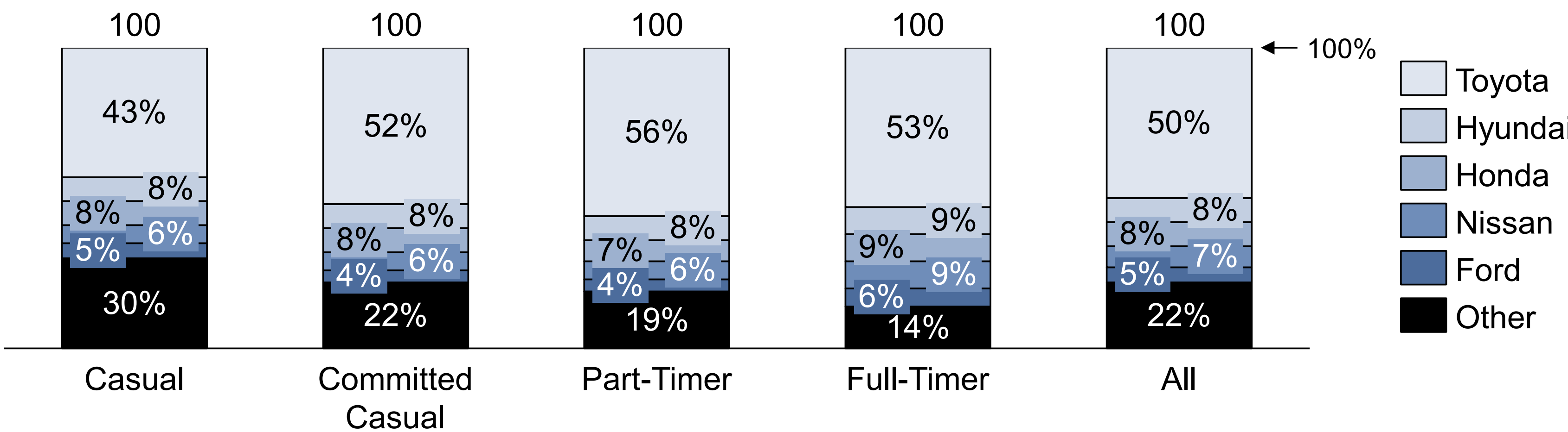
Car Types

Drivers tend to use similar makes of cars across driver engagement. We see a smaller range of models for full-time drivers, but even among the casual drivers, most are using the same makes of cars.

Table 5.1:	Top Car U.S.		Top Car Seattle		Top Car Platform Drivers	
1	Ford F-150		Ford F-150		Toyota Prius	
2	Chevrolet Silverado		Honda CR-V		Toyota Camry	
3	Ram 1500		Subaru Outback		Toyota Corolla	

Make of drivers' cars by driver type

%



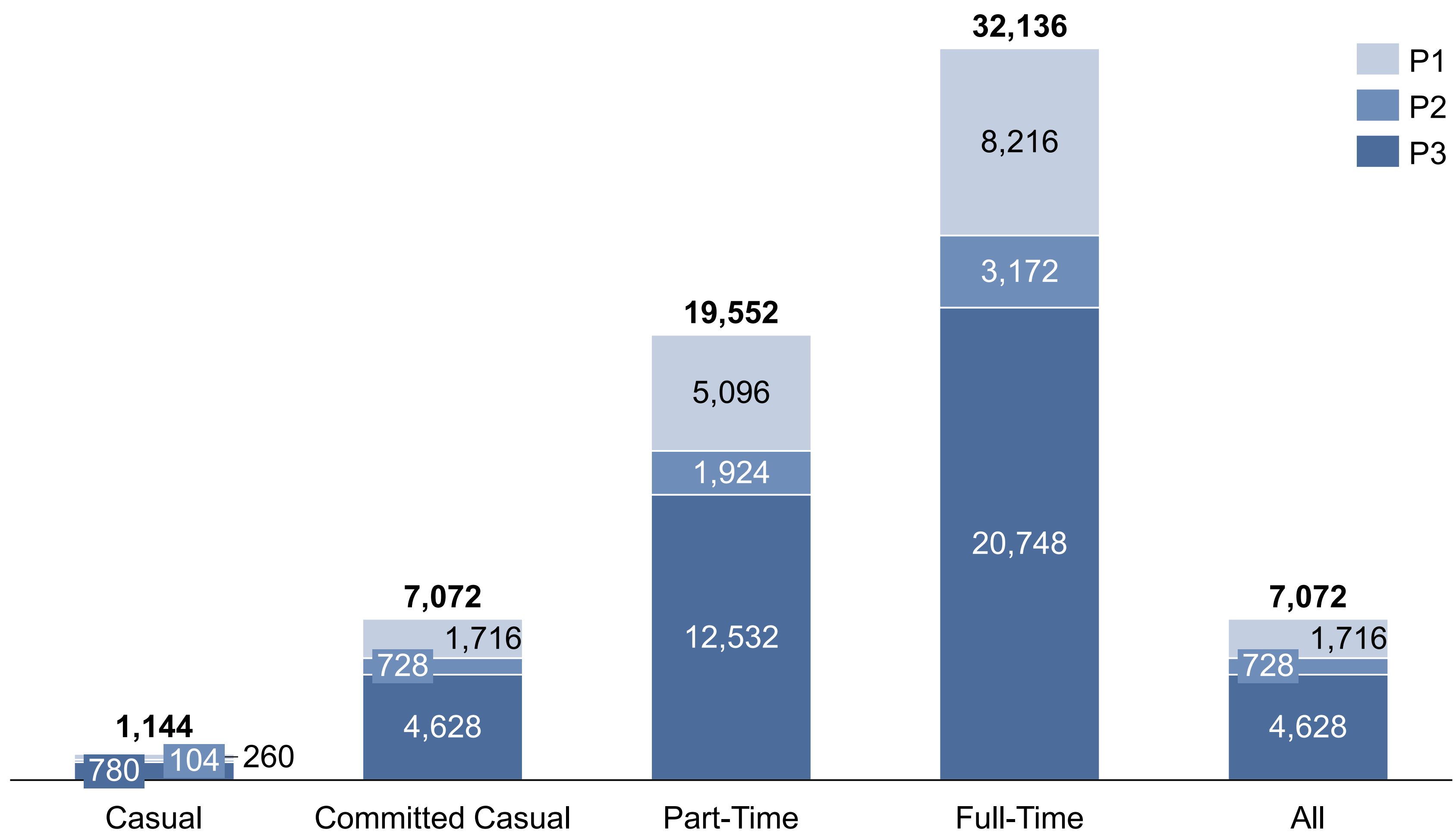
Mileage

Understandably, drivers who drove longer hours, drove longer distances.

Usually miles are discussed in annual terms, so we multiplied the weekly numbers by 52 to get annual numbers, as shown in Chart 5.2. This annual number is, almost certainly, an overestimate since it assumes someone drives every week of the year. Nonetheless, it will help us understand the relative scale of the driving compared to what is usually considered the average American's annual mileage—15,000 miles per year (though the U.S. Department of Transportation puts it at 13,476 miles per year).

Additionally, we found it useful to think about earnings per mile, especially when considering tax deductions. The median driver earned $1.83 per mile, which varied from $1.62 at the 25th percentile to $2.05 at the 75th percentile. Those numbers were stable across driver types.

Chart 5.2: Overestimated annualized median mileage by driver type
miles



Depreciation

Depreciation is the decrease in value of an asset over time. For cars that is both the wear and tear on the car (as reflected in mileage) as well as simply becoming older (as reflected in its model year). For each car in the sample, we have the make and model, but do not have the initial mileage.

The typical ways of calculating depreciation are either the IRS method, which is used for tax purposes, or the market (real-world) value of the car.

For taxes, we would use government numbers (which are actually supplied to the IRS by a third-party consultancy). For depreciation, we use data from a trusted third-party source and calculate the change in value ourselves. We attempted to purchase data from Kelley Blue Book (KBB), which is the most well-known third party. However, KBB doesn't sell its data to researchers. We located another provider of car values: Price Digests.

Price Digests is a nationally-recognized data tool that aggregates retail values for cars. Washington state, for instance, uses Price Digests data to compute fair market value for cars for its tax purposes.[21] If these data are good enough for Washington to use for taxation, we felt like they were good enough for us to use to calculate depreciation in Seattle.

We obtained a customized dataset from Price Digests that captures prices for the most used vehicles, by make and model, at the beginning and at the end of 2019. With these data, we know how prices for different makes, models, and mileages of cars changed over the course of a year. With these data, we can estimate how mileage and model year independently affect the change in a car's value. Most other depreciation models lump together the depreciation due to aging and the depreciation due to mileage. Even when they report depreciation per mile, they are adding together the depreciation due to aging and the depreciation due to mileage and then dividing by mileage.

Since we are interested in understanding the costs that drivers face, we are not interested in depreciation due to aging. That depreciation would happen whether or not the driver drove for Lyft or Uber. We want to know the depreciation for the additional miles.

[21] https://www.dol.wa.gov/vehicleregistration/usetax.html

IRS Depreciation Estimates
The IRS outsources its depreciation modelling to a firm called Motus. Motus estimates that depreciation accounts for approximately 37% of a car's "cost to own." Other factors of "cost to own" include fuel costs, insurance, lease payments, registration, maintenance which has increased markedly with the computerization of vehicles and general depreciation. General depreciation is the simple change in value of a car—the difference between a car's initial cost and the price it would receive on the market at a given point in time. General deprecation, thus, is reflective of a range of factors: demand for particular cars, appearance, mileage, and model among other factors. These factors are often location-specific. It is difficult to determine which factor—mileage or model, for example—drives depreciation rates in these estimates.

When the IRS/Motus considers general depreciation, its model takes a national approach in estimating deprecation for a "typical" car, which doesn't reflect the cars driven on platforms. In the United States, the top three best-selling vehicles, according to Edmunds, are the Ford F-150, Chevrolet Silverado, and the Ram 1500. In Seattle in 2019, the top three were Ford F-150, Honda CR-V, and Subaru Outback.[22] For Seattle platform drivers, the top three cars are the Toyota Prius, the Toyota Camry, and the Toyota Corolla. Toyota, Hyundai, Honda, and Nissan account for 72% of all cars on the platforms in Seattle. The percentage of these makes increases with drivers' weekly hours. In Seattle, Ford (4.8%), Chevrolet (4%), and Ram (0.01%) are not represented among platform drivers as in the typical U.S. fleet.

Calculating depreciation per mile assumes that a "typical" car gains 15,000 miles per year.

Ultimately, the IRS/Motus concludes for 2018 that depreciation per mile is $0.25 for a 2018 or 2017 car, $0.24 for a 2016 or 2015 car, and $0.22 for a 2014 car.

The IRS tax deduction, $0.58 per mile, is much more than even the IRS estimates for depreciation, and again, these depreciation averages are for the US fleet, which does not resemble the platform fleet.

AAA Depreciation Estimates
AAA, on the other hand, provides slightly more granular estimates. AAA groups cars in five general categories: small sedan, medium sedan, large sedan, small SUV, and large SUV. For small sedans, for example, AAA estimates that depreciation costs in 2018 totaled $2,268. Thus, depreciation per mile for a small sedan is estimated at $0.15.

[22] https://www.seattlepi.com/seattlenews/article/These-were-the-most-popular-new-and-used-vehicles-14916850.php#item-85307-tbla-13

Cornell Depreciation Estimates

With these two general models we can already see that depreciation calculations vary markedly. Our depreciation calculations are based on data unique to Uber and Lyft in Seattle. It considers the nature of the fleet used on both platforms in the Seattle area, overwhelmingly small, eco-friendly sedans, on average, of the 2015 model year.

Fortunately for our calculations (since we do not have the numbers) initial mileage appears to have no statistical effect on depreciation.

The AAA and IRS models take an average approach, simply dividing annual depreciation by average miles driven. This approach does not differentiate the marginal depreciation of additional miles.

Our modelling accounts for the differential rate the mileage or model of a car might have on depreciation levels.

We used the cars models that account for the majority of the Seattle Uber and Lyft fleet (Toyota Prius, Toyota Camry, Toyota Corolla, Nissan Altima, Toyota Prius V, Hyundai Elantra, Toyota Camry Hybrid, Honda Civic, Hyundai Sonata, Nissan Sentra). While our model is correct for the majority of cars driven, it might over- or under-estimate for the less common models of car.

Using regression analysis, as shown in Table 5.3 below, we differentiated between the depreciation due to additional miles and the depreciation due to car aging. We replicated the analysis with both the least expensive and most expensive trims for each model. The depreciation per additional mile averaged to about $0.02 per mile. We can see that depreciation, even for a car sitting idle, is still quite high. By taking the ratio of the year and the additional mileage, we can calculate that every year, a car loses the equivalent in value to 11,481 miles without driving a single mile. In Table 5.4, we compare the annual depreciation due to aging and the annual depreciation due to driving, by different driver types. On a weekly basis, these numbers are not particularly high.

Table 5.3: Effect of additional miles, initial mileage, and car year on car value in one year
$

	Additional Miles	Additional Miles + Initial Miles	Additional Miles + Initial Miles + Model Year
Additional Miles	-.019***	-.019***	-.019***
Initial Miles		0.001	0.001
Model Year			-218.139***
Constant	-1705.411***	-1747.184***	437,901.746***
R^2	0.053	0.053	0.168

Depreciation = (-$0.019)**Mileage* + (-$218.139)**Model Year of Car* + *Constant*

Every mile costs about two cents.

Every year costs about $218.

Table 5.4: Overestimated annualized mileage, annual mileage depreciation, and annual aging depreciation
miles, $

	Casual	Committed Casual	Part-Timer	Full-Timer	All
Overestimated mileage	1,144	7,072	19,552	32,136	7,072
Mileage Depreciation	$ 21.74	$134.37	$371.49	$610.58	$134.37
Aging Depreciation	$218.14	$218.14	$218.14	$218.14	$218.14

Maintenance Estimates

For general maintenance costs, AAA includes retail parts and labor for routine maintenance as noted by the vehicle manufacturer, comprehensive extended warranty, and “wear and tear” that requires service over five years of operation. In addition, AAA includes one set of replacement tires similar to those included in a car’s original purchase as part of their maintenance estimates.

AAA methodology is standardized to assume a new personal car, owned for five years with 75,000 miles of ownership. These are national estimates that reflect a broad national fleet.

We used the AAA estimates for maintenance, but not fuel.

The maintenance per mile varied little, between \$0.08 at the 25th percentile to \$0.09 at the 75th percentile, with a median \$0.08.

	Value	Calculation
Fuel	• Median: $0.089 per mile • 25th percentile: $0.043 • 75th percentile: $0.108	• Uses actual Seattle gas prices, $3.255, in October to calculate fuel costs. • Uses EPA ratings for city driving for actual car models (unlike IRS and AAA which assume a large fraction of highway driving)
Maintenance	• Median $0.08 per mile • 25th percentile: $0.08 • 75th percentile: $0.09	• Uses AAA categorical estimates for maintenance cost per mile.

Fuel

Over the course of a year, AAA calculates an average of national gas prices, both diesel and regular unleaded, on a daily basis. In their depreciation calculations, AAA estimates a 12-month average for fuel costs. In 2019, AAA estimated fuel costs at $2.679 per gallon. Fuel economy rates, in the AAA estimates, are based on Environmental Protection Agency (EPA) ratings that estimate 55 percent city and 45 percent highway driving.

In our estimates, we used the actual Seattle-area fuel prices from the Bureau of Labor Statistics. We used the Bureau of Labor Statistics numbers for October 2019, $3.255, which was higher than the U.S. average of $2.741.

Our fuel price, then, was higher than the AAA fuel price.

We also used the actual EPA mileage numbers for city driving (which are lower than highway numbers) for every make and model to calculate actual fuel usage, rather than an approximation. The fuel cost varied between $0.043 for the 25th percentile to $0.108 per mile for the 75th percentile. Median fuel cost per mile was $0.089.

Driver Costs

Marginal

We estimate that the median driver has $0.19 per mile in total costs, by combining fuel cost, maintenance, and mileage depreciation. The 25th and 75th percentiles are $0.14 and $0.22 per mile, respectively. The official IRS mileage deduction, again, is $0.58 per mile. So real costs would need to almost triple to exceed the tax deduction.

For every ten dollars a driver grossed, they had, on average, one dollar in expenses. The percentage of costs per dollar of earnings, on average, was about 10%, but varied from 8% at the 25th percentile up to 12% at the 75th percentile.

In Chart 5.5, we show a histogram of the distribution of those costs as a percentage of earnings.

Fixed

For full-time drivers, fixed costs, like the cost of the car should be incorporated.

While more complicated, specific calculations can be made for each specific car (financing, resale recoup, etc), a more accessible yardstick would be the highest possible cost for an actual full-time car.[23] By taking the highest possible cost, we know that drivers would have, almost certainly, lower costs. So the hourly earnings number we calculate will be the lower bound on what a full-time driver could earn. Drivers in Seattle can rent cars from Hertz and Avis with a base rate of $214 per week, excluding taxes and fees.[24]

Auto insurance is included in such a rental.[25] We have also included additional personal insurance. Such insurance costs vary widely, but in downtown Seattle an average seems to be $77 per month or $19.25 a week, which is considerably cheaper than buying insurance through the rental car company.[26] We have used this $19.25 as the cost of insurance for a week in Seattle.

Every car rental comes with fees. We have estimated $50 in fees.

In Seattle combined sales tax (city, county, state) is 10.1%.

The highest possible cost would be a driver renting a car ($290.66) and getting private personal insurance ($19.25) for $309.91 per week. That ~$310 would include car registration, insurance, depreciation, and maintenance all included.

If drivers' cars are more expensive than that price, they are spending more than they need to spend. If their cars are less expensive, which they most likely are, then they are minimizing their costs. So that rental car is the maximum cost of the minimum car needed for platform driving.

For full-time drivers, then, we should include a fixed cost of $309.91, but remove the marginal costs of depreciation and maintenance, which would be included in the rental price. We would still include fuel.

Such a model increases the median cost for full-time drivers from $116 a week to $362 a week. Such costs are perhaps why there are fewer full-time drivers than less committed drivers. We also think that at that cost for a month of rental, many full-time drivers would find a car payment less expensive. Nonetheless, we have estimated this cost as the high end of possible full-time drivers. On a per mile basis, the fixed cost model has a median of $0.58 per mile.

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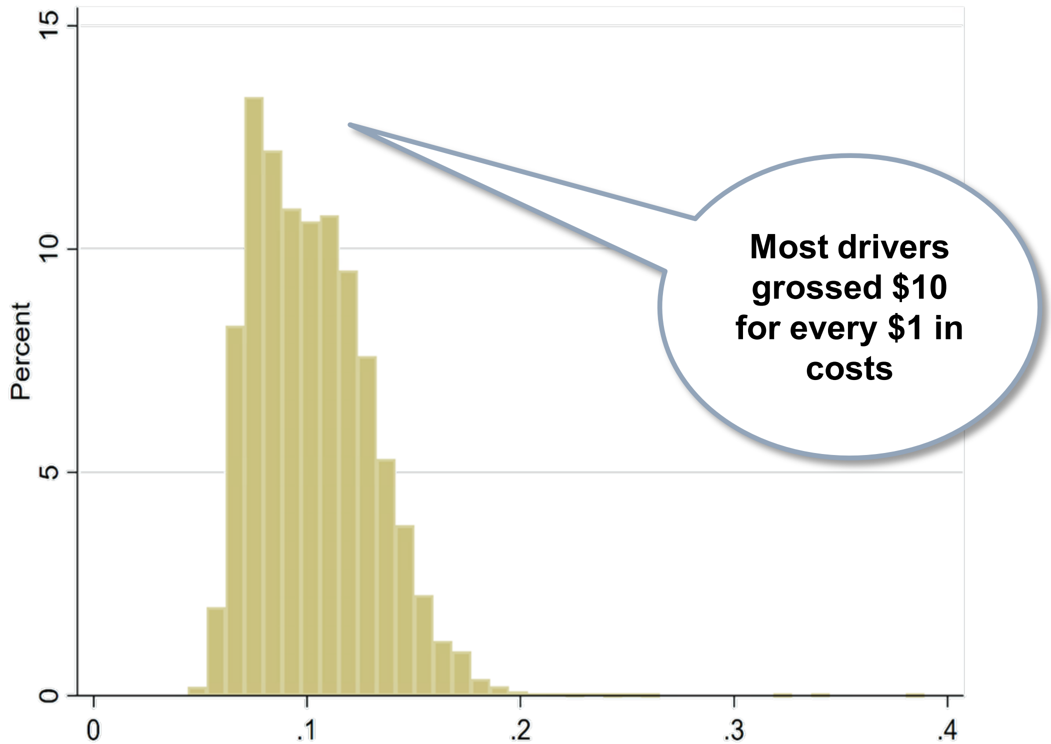
[23] Here we mean, in more economic terms, the maximum cost of the minimum car.
[24] https://www.hertz.com/rentacar/misc/index.jsp?targetPage=uber_landing_page.jsp&LinkType=HZLK; https://bonjour.uber.com/marketplace/
[25] https://www.hertz.com/rentacar/misc/index.jsp?targetPage=uber_landing_page.jsp
[26] https://quotewizard.com/auto-insurance/seattle-washington

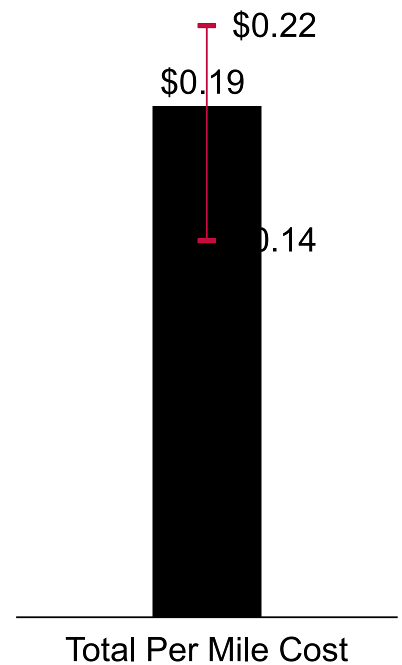
Chart 5.5: Distribution of cost as percentage of earnings

%



Median total per mile cost

$



6: Net Earnings

Introduction

In this section we examine how gross earnings (the amount made before taxes and expenses) is changed by including marginal taxes and expenses.

The pre-tax net earnings calculations do not account for taxes. We plan to release a follow-up report on the tax implications of worker classification. As platform drivers are independent contractors, all of their costs are deductible. Moreover, because the IRS mileage deduction is so much higher ($0.58) than the actual per mile costs ($0.19), the tax consequences will be significant. In a future report, we will examine the tax implications for drivers. The Pre-Tax Net Earnings should not be understood as the final measure of driver earnings, but as the *lowest* possible value.

Pre-Tax Net Earnings

After calculating the costs per mile, we subtract those costs from the earnings. As seen in Table 6.1, the median driver netted $23.25 per hour. For comparison, note that using the (inflated) AAA numbers, the median driver still nets $22.24 per hour. As seen in Chart 6.6, the distribution of net hourly earnings looks similar to the earlier distributions, only with a lower median.

Comparing the net earnings to key thresholds, 5% of drivers make less than $15 per hour, 8% make less than the Seattle minimum wage ($16.39), and 9% make less than the median taxi driver earnings ($16.81). Even after expenses, 9 in 10 drivers made more than the average taxi driver as illustrated in Table 6.1. About 80% of drivers earn more than the best paid 25% of taxi drivers.

In Table 6.3, we can see the way in which P1 affects the overall earnings through the report.

Incorporating fixed costs for full-time drivers, of course, lowers their hourly earnings. As discussed earlier, this fixed cost model is not the actual costs for drivers (as in the marginal model) but the *maximum* possible fixed cost. Actual drivers would have lower costs. Nonetheless, it is a useful estimate for the lower-bound of full-time driver earnings, if you want to consider fixed costs. In Table 6.2 and Chart 6.4, we see that the median hourly earnings, calculated in this way, are $18.06 per hour.

Examining the relative proportions of drivers earning less than the minimum wage, we see the same pattern as earlier. A large fraction of casual drivers earns less than the minimum wage (18%) but relatively few other drivers do. Incorporating the fixed cost model, creates a *maximum* of 26% of full-time drivers earning less than the minimum wage (after expenses). The earnings experience of full-time drivers is quite different, if they incorporate fixed costs. This different in net rate might explain why there are so many more committed casual and part-time drivers than full-time drivers. Yet, even for this estimate of earnings, we still see 38% of full-time drivers making more than the 75th percentile of taxi drivers. Full-time platform drivers, even using the maximal costs, earn slightly more than taxi drivers.

In Charts 6.7, 6.8, and 6.9, we can see the distribution of earnings. As drivers are more engaged with the platforms, the variation in their net hourly earnings lessens, which probably accounts for the concentration of the multi-app drivers' earnings (since multi-app use increases alongside driver commitment.)

Chart 6.1: Gross hourly earnings and net hourly earnings (75th percentile, median, 25th percentile) by driver type

$

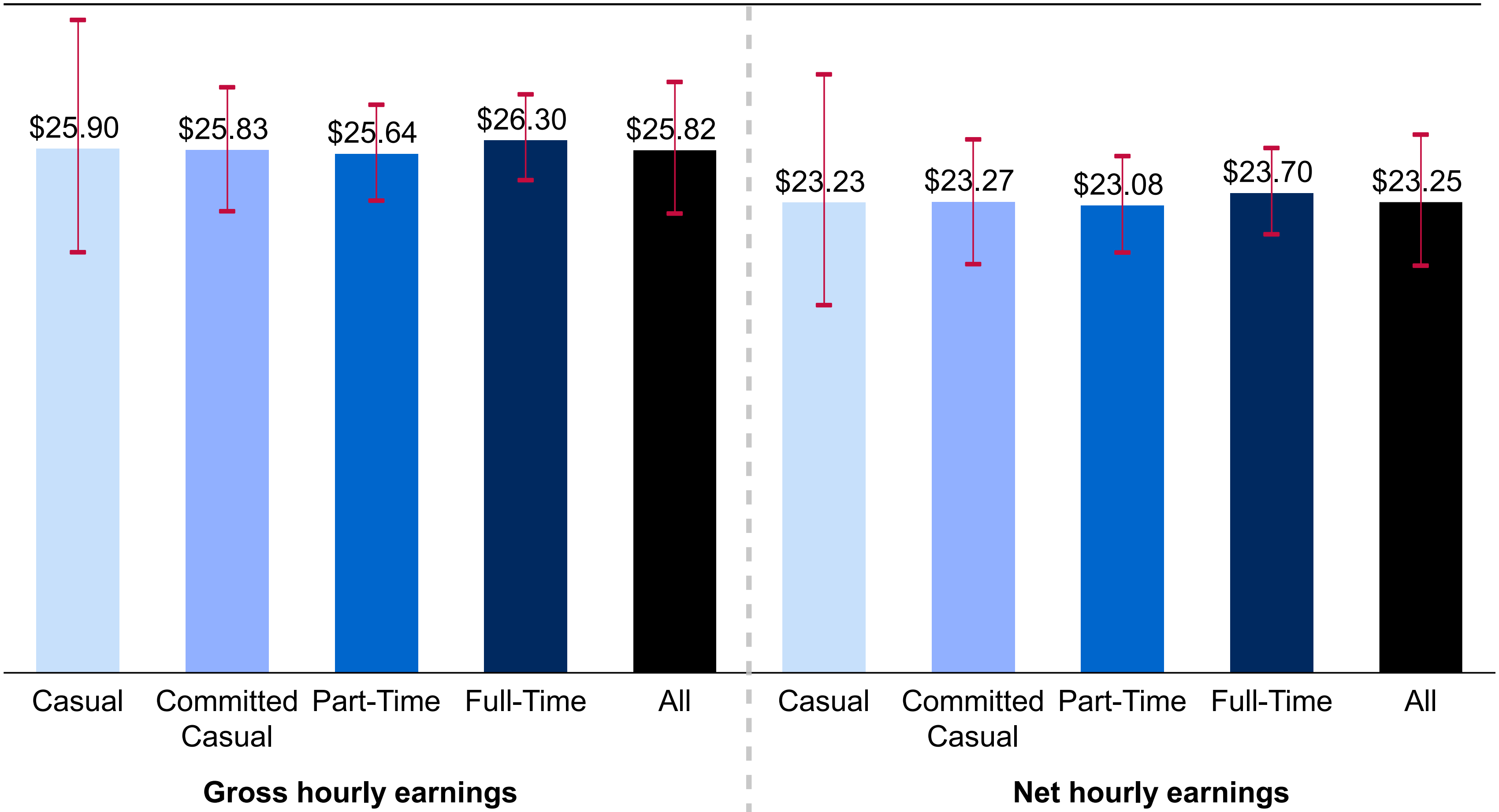


Table 6.2: Net hourly earnings by driver type (P1+P2+P3)

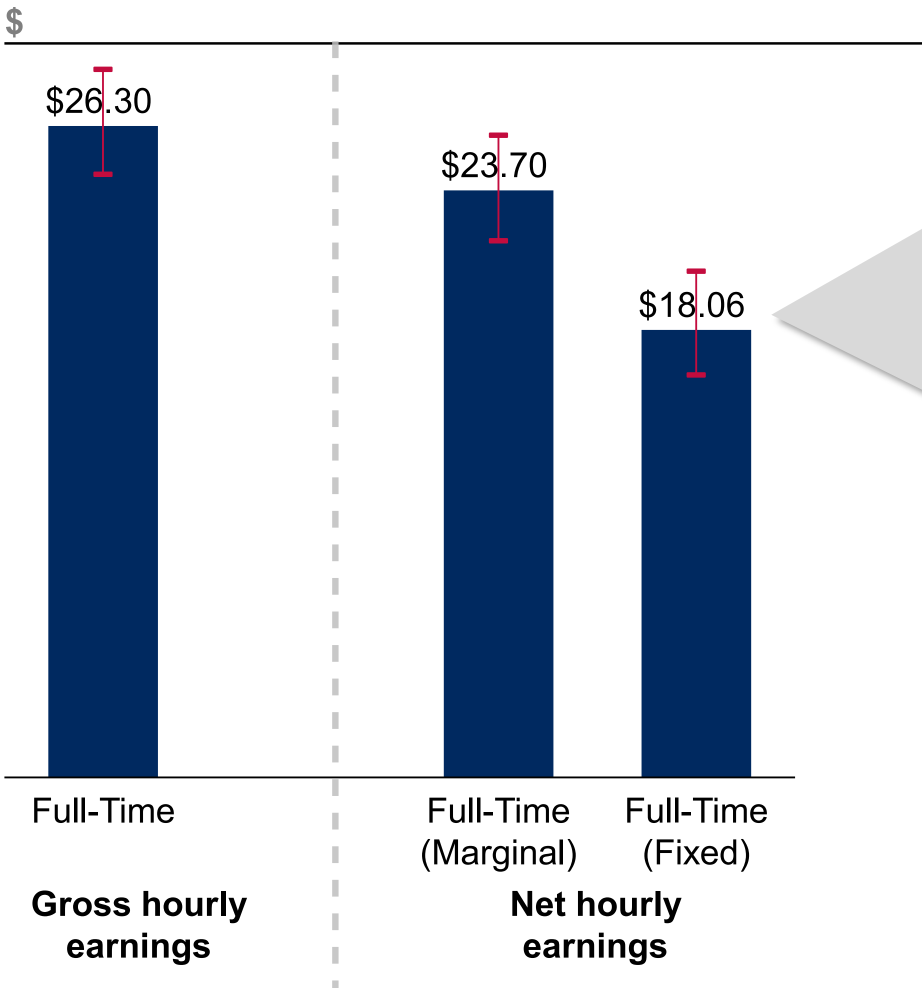
Type	25th Percentile	Median	75th Percentile	More than minimum wage	More than mean taxi driver	More than 75th percentile taxi driver
Casual	$18.16	$23.23	$29.56	82%	81%	70%
Committed Casual	$20.18	$23.27	$26.35	94%	93%	82%
Part-Time	$20.76	$23.08	$25.52	97%	96%	87%
Full-Time (Marginal Costs)	$21.66	$23.70	$25.92	96%	96%	92%
Full-Time (Fixed Costs)*	$16.24	$18.06	$20.43	73%	69%	38%
All	$20.11	$23.25	$26.58	92%	91%	80%

* The fixed cost model incorporates the highest possible costs. Actual driver costs are probably lower. This model is not included in the **All** calculations.

Table 6.3: Comparison of hours, hourly earnings by measurement
hours, $

Type	Driver Percentage	Median Driving Hours (P2+P3)	Median Driving Hours (P1 All + P2 + P3)	Median Driving Hours (P1+P2+P3)	Median Hourly Earnings (P2+P3)	Median Hourly Earnings (P1+P2+P3)	Median Hourly Net Earnings (P1 All + P2 + P3	Median Hourly Net Earnings (P1+P2+P3)
Casual	25%	1.2	2.2	1.7	$35.53	$25.90	$17.95	$23.23
Committed Casual	50%	6.9	11.1	9.9	$36.19	$25.83	$20.76	$23.27
Part-Time	20%	18.7	28.9	27.1	$36.63	$25.64	$21.80	$23.08
Full-Time	5%	31.0	46.5	44.2	$37.22	$26.30	$22.85	$23.70
All	**100%**	**6.9**	**11.2**	**9.9**	**$36.31**	**$25.82**	**$20.83**	**$23.25**

Chart 6.4: Full-time gross hourly earnings and net hourly earnings



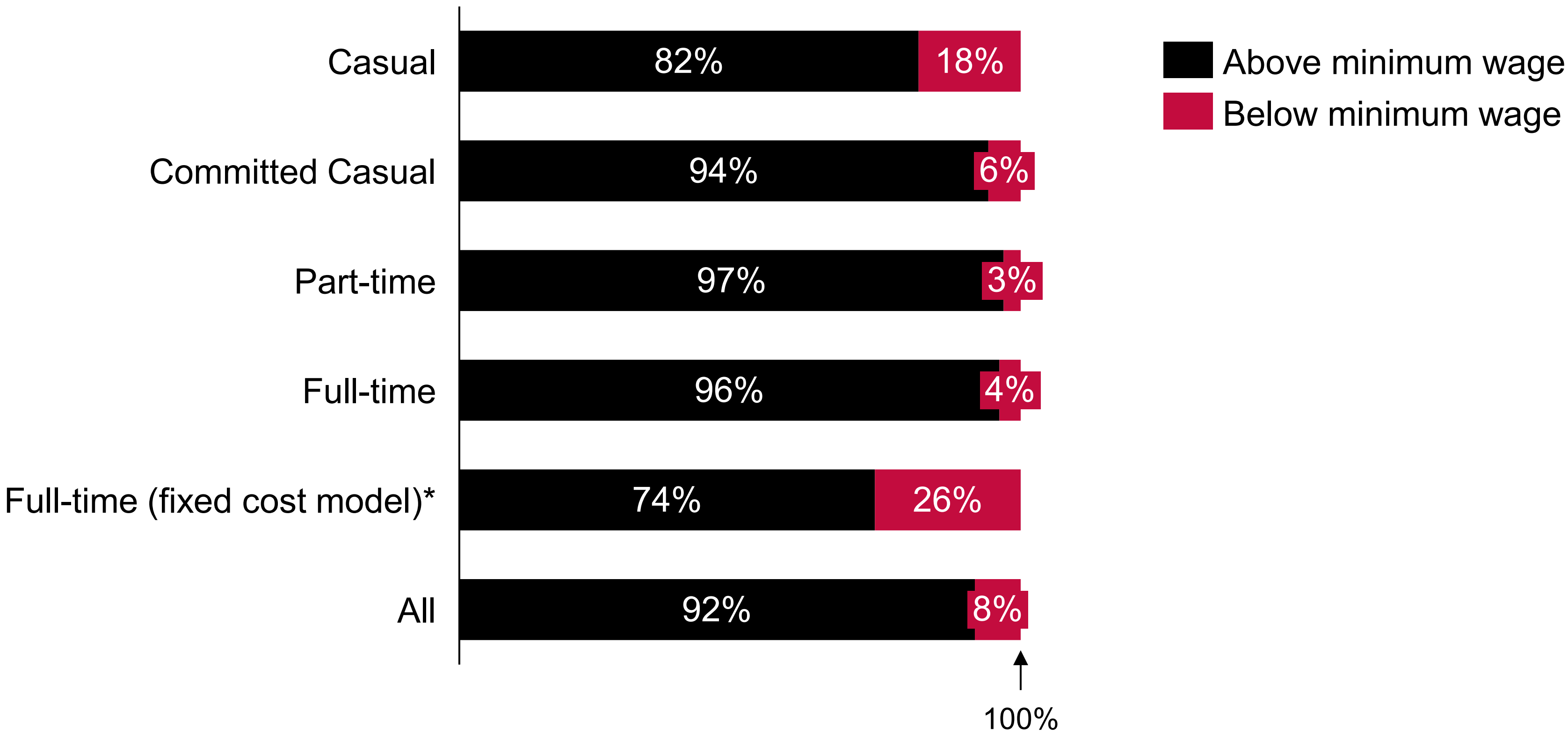
The fixed cost model is almost certainly *more expensive* than full-time drivers' actual costs.

For the full-time cost, we used the most expensive full-time option: a weekly rental.

The weekly rental is more expensive than owning a car, but includes all fixed costs, except personal insurance, which we calculated separately (even though it is not required for platform driving).

$18.06 should be considered the lower bound for median full-time hourly earnings.

Chart 6.5: Below minimum wage drivers by category (P1 + P2 + P3, net rate)
%



* The fixed cost model incorporates the highest possible costs. Actual driver costs are probably lower. This model is not included in the **All** calculations.

Chart 6.6: Share of Drivers Earning Below Minimum Wage by category (P1 + P2 + P3, net rate)

%

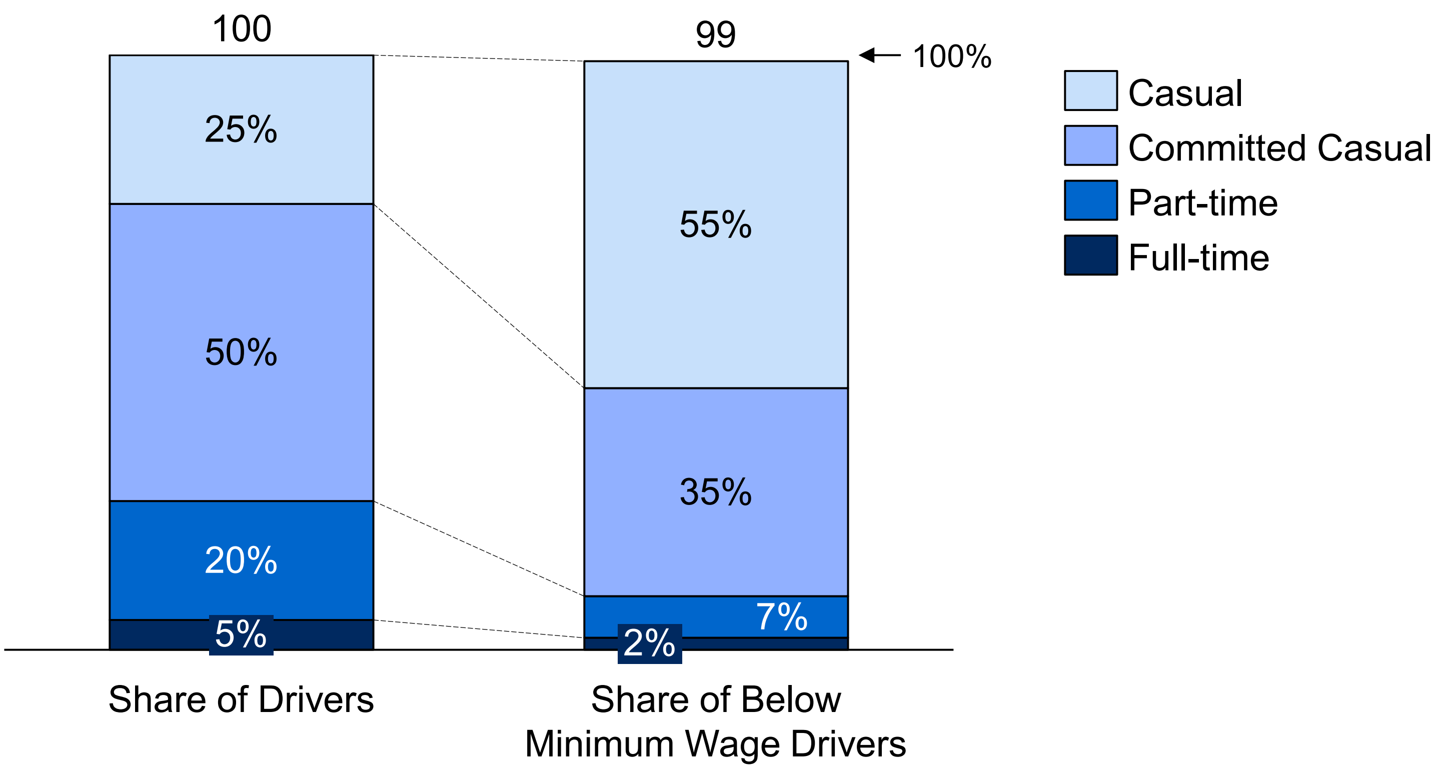


Chart 6.7: Distribution of net hourly earnings (P1 + P2 + P3, net rate)

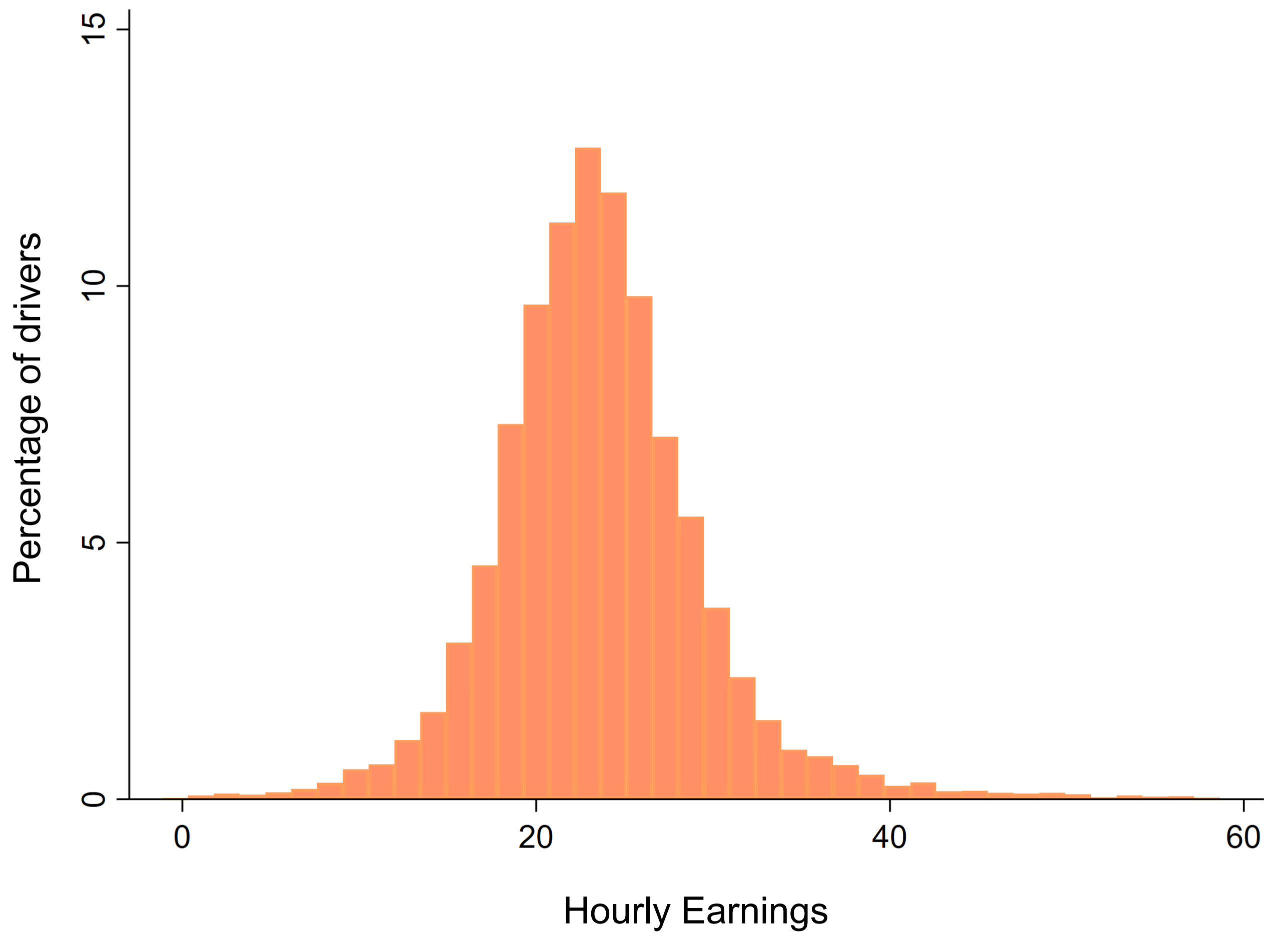


Chart 6.8: Net hourly earnings distribution by type

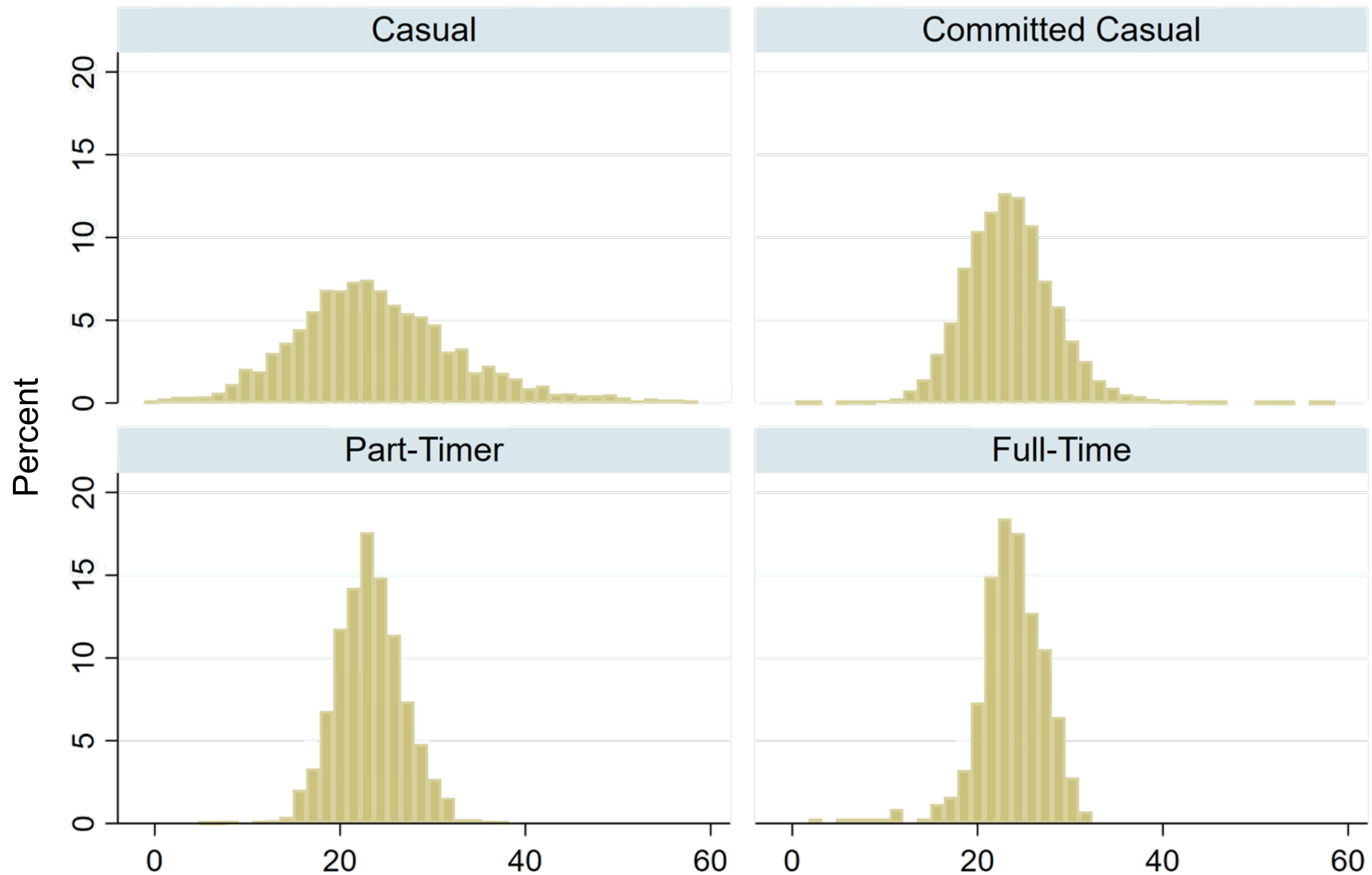
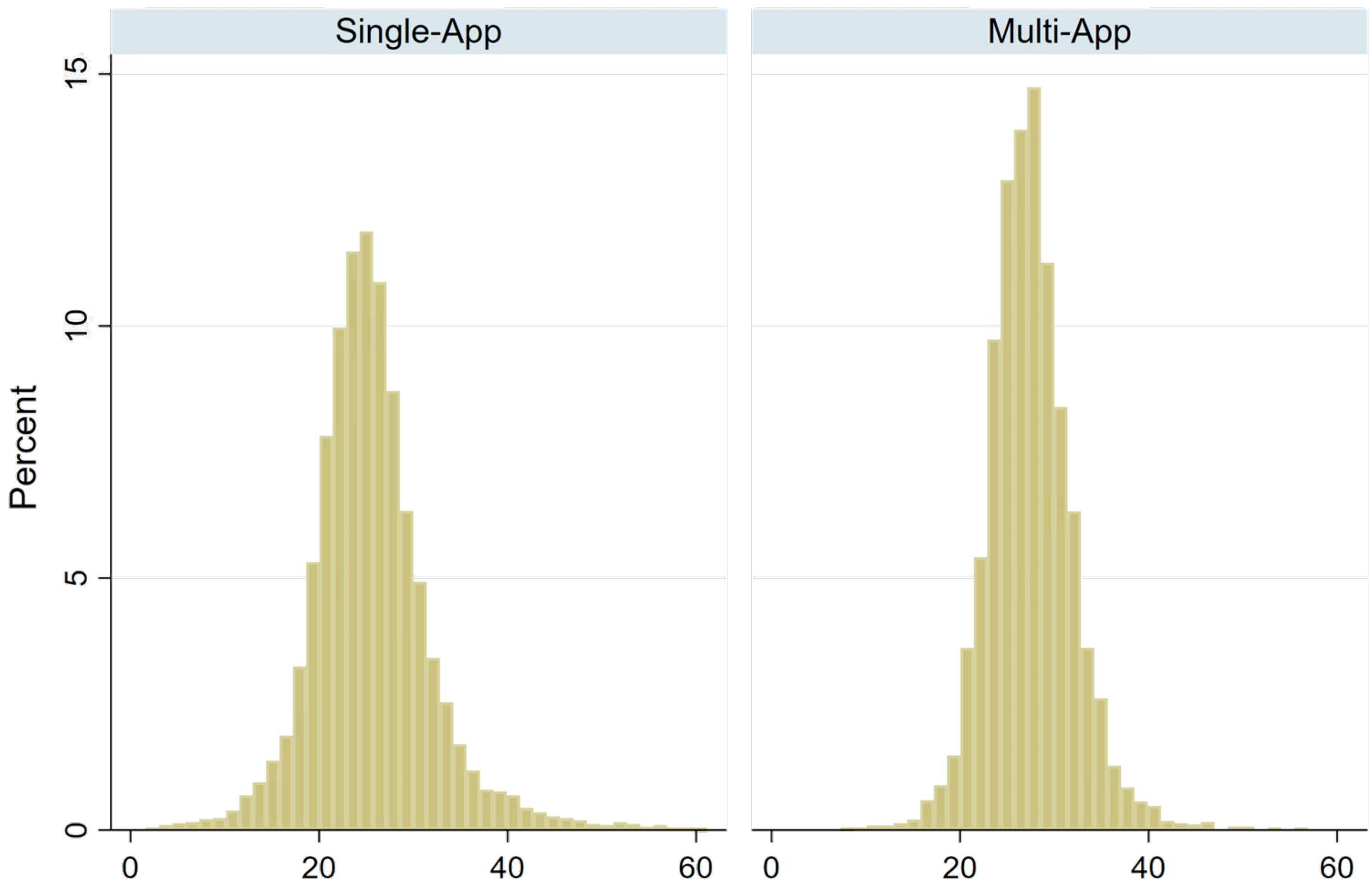


Chart 6.9: Distribution of net hourly earnings by app-use



7: Conclusion

In this study, we have examined hours and earnings for platform drivers in Seattle for one week. These findings suggest the following:

- Platform driving is primarily a side-gig. Very few drivers approach anything like a full-time work week.
- Platform drivers' hourly earnings net of marginal costs are higher than the minimum wage and comparable kinds of work, like taxi driving and chauffeuring. These earnings do not, however, include any returns to drivers for providing the use of their cars.
- Multi-apping increases drivers' earnings, but most drivers do not multi-app.

Future studies could expand the time period and the geographic scope, as well as integrate data that would allow examination of the impact of demographic factors—like race, gender, and national origin—on drivers' hours and earnings. They could also examine, in more detail, the more granular patterns of P1, P2, and P3. Finally, they could consider the most appropriate way to account for drivers' provision of their cars' services.

Appendix

Glossary

Central tendency—the number that is the expected value of a variable. There exist multiple ways to define and measure this central tendency, most commonly mean and median. Conventional this is what people suggest when they say “average.”

Dispersion—if the central tendency is the expect value of a variable, then the dispersion is how far values are from that central tendency. Multiple measures of dispersion exist, but the most common is standard deviation.

Mean—A measure of central tendency which is the arithmetic average of the values. For skewed distributions, the mean is not necessarily the same as the median.

Median—A measure of central tendency, to find the median, arrange the observations in order from smallest to largest value. If there is an odd number of observations, the median is the middle value. If there is an even number of observations, the median is the average of the two middle values.

Range—A measure of dispersion (how spread out a data set is) which is the difference between the lowest and highest values of a data set.

Standard Deviation and Variance—A measure of dispersion which is calculated as the average squared deviation of each number from the mean of a data set. A measure of dispersion which is the square root of the variance.

Percentile —A measure indicating the value below which a given percentage of observations in a group of observations falls. For example, the 95th percentile is the value below which 95% of the observations may be found. The median is the 50% percentile.

Quantile—Point in a distribution that relate to the rank order of values in that distribution, we find any quantile by sorting the sample. Percentiles are descriptions of quantiles relative to 100.

Regression Analysis—A statistical method that allows one to examine the relationship between two or more variables of interest. While there are many types of regression analysis, at their core they all examine the influence of one or more independent variables on a dependent variable. Traditional regression analysis models a relationship between the mean of a dependent variable and one or more independent variables. Quantile regression analysis models a relationship between particular quantiles of a dependent variable and one or more independent variables.

R^2 —The proportion of the variance in the dependent variable that is explained by the independent variable(s) in a regression analysis.

Regression Coefficient—An estimate of the slope of a straight line that is assumed be the relationship between the dependent variable and at least one independent variable. A regression coefficient equal (or nearly) to zero indicates no relationship between the dependent and independent variables. For indicator (dummy) independent variables, this can show up as a parallel shift in the estimated line or even a change in the slope of the line through an interaction with another independent variable.

P-value—A statistical measure that indicates how incompatible the data are with a specified statistical model. In the case of “null hypothesis” testing, a lower p-value indicates the belief that there is no difference between two tested groups. The lower the p-value, the less compatible the data are with the null hypothesis. P-values do not measure the probability that the studied hypothesis is true, or the probability that the data were produced by random chance alone. Scientific conclusions and business or policy decisions should not be based only on whether a p-value passes a specific threshold. A p-value, does not measure the size of an effect or the importance of a result.

Fraudulent Data

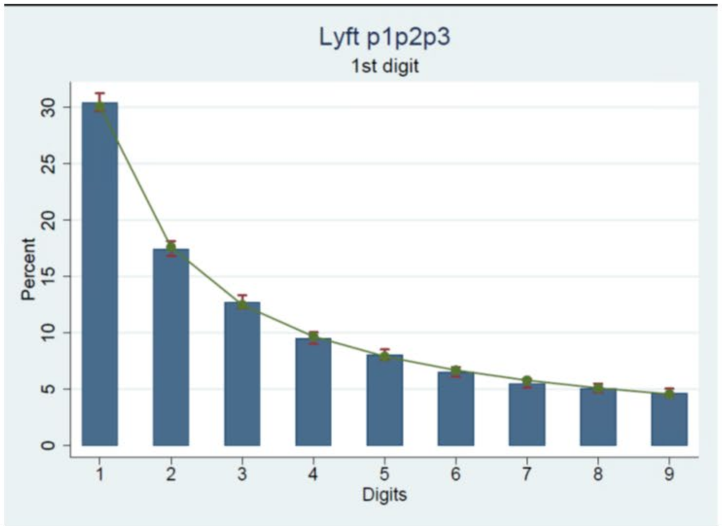
Given that we did not collect the data ourselves, we used standard techniques to detect any irregularities in the data. The results strongly suggest that the data are not fabricated.

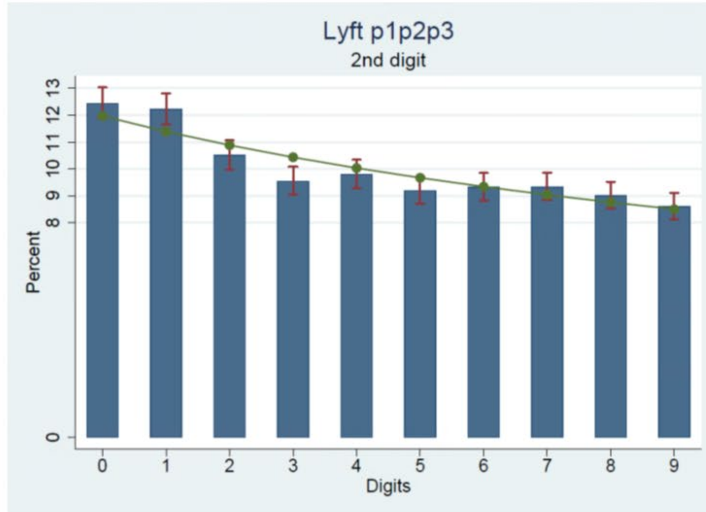
To assess the fidelity of the time-stamped data supplied by Lyft and Uber we applied methods that are routinely used in forensic accounting. The Benford's Law technique, also known as the law of the leading digit, is widely applied to detect anomalous patterns in a variety of data settings. The law suggests that the leading digit of certain types of data entries appear with a certain relative frequency: 1 (30%), 2 (17.6%), 3(9.7%), 4 (7.9%), etc.

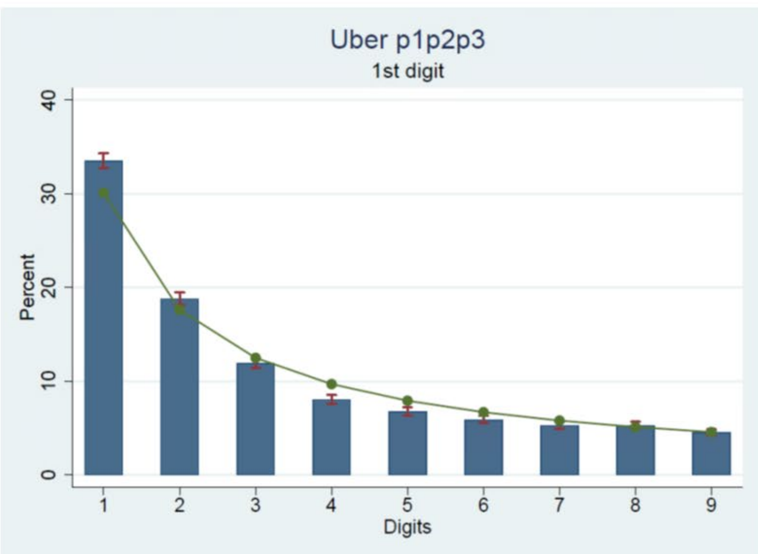
The plots below give the 1st and 2nd digit frequencies for the sum of P1, P2, P3 times measured in second from the data supplied by Lyft and Uber.

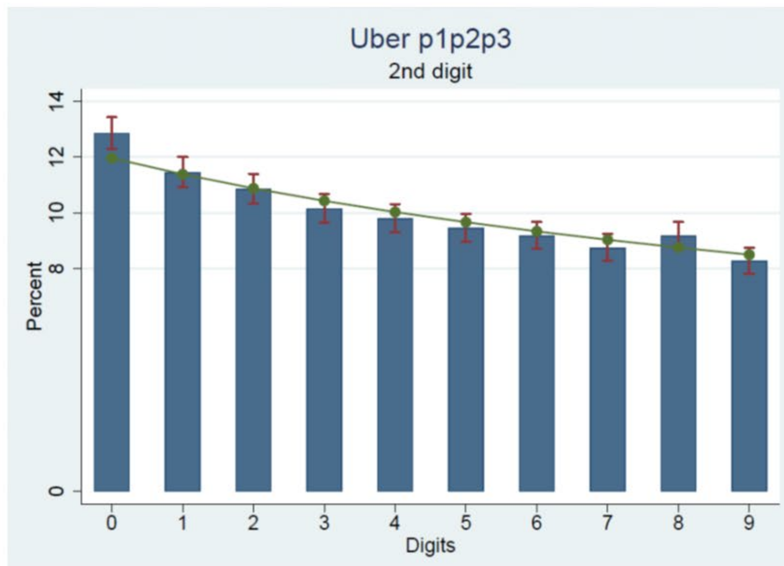
The bars give the relative frequencies in the driver data and the solid line give the expected Benford's Law frequencies. The vertical bars give the 95% confidence intervals.

In all cases the plots suggest a good agreement with Benford's law; therefore we do not believe the data to be fraudulent.


Lyft p1p2p3
1st digit
Percent
Digits


Lyft p1p2p3
2nd digit
Percent
Digits


Uber p1p2p3
1st digit
Percent
Digits


Uber p1p2p3
2nd digit
Percent
Digits

Replication Study: Lyft and Uber Hours and Earnings (P2, P3)

An important part of this study is the ability to examine P1 time across platforms. At the same time, of course, we examined the P2 and P3 time. To confirm that we were calculating P2 and P3 time correctly, we performed similar calculations on the P2 and P3 times used internally by the companies for billing purposes.

Since the two data sets come from different reporting systems at the companies, we expected minor, insubstantial discrepancies, which is what we found.

This replication of the P2 and P3 time is important because neither company knows how their drivers' P1 (or P2 or P3) times intersect. The replication also provides reassurance that the P1 time is correct as well.

Earnings Comparisons

The 2019 Occupational Employment Statistics survey from the Bureau of Labor Statistics recategorized taxi drivers. We had a choice to use the 2019 numbers or the 2018 numbers and adjust them for inflation. We chose to use the 2018 numbers because, as noted above, the weight of that new category skewed the comparison. For emphasis, we repeat the text from earlier in the next three paragraphs.

To put these earnings in context, a reasonable starting point would be comparing the earnings of platform drivers and taxi drivers (and perhaps chauffeurs). Unfortunately the 2019 earnings numbers for taxi drivers are no longer available from the Bureau of Labor Statistics.

The 2019 OES survey, released in May, combined Taxi Drivers and Chauffeurs in a new category: “Passenger Vehicle Drivers, Except Bus Drivers, Transit and Intercity” that combines Taxi Drivers and Chauffeurs with School Bus Drivers (despite the name). Since we actually want to compare the platform drivers against taxi drivers and chauffeurs, not school bus drivers, we adjusted the 2018 earnings numbers by the Employment Cost Index. Including the bus drivers, who number almost twice (6,200) as many as taxi drivers and chauffeurs (3,160), with a 2018 median hourly earnings of $21.81, would incorrectly weight the earnings for taxi drivers, who had 2018 median hourly earnings of $16.15.

The left column of the Table shows the published data for 2018. In order to adjust for a year’s wage inflation, we apply adjustment factor of 4.1% in the second column. This adjustment is the change in the Employment Cost index for private employees in Seattle-Tacoma for the 12 months ending in September 2019 (2.4%) plus the national private sector difference in the ECI increase for transportation and moving occupations compared to all employees (1.7 percentage points).

Because we were already using the 2018 numbers, we decided to continue that analysis at the city and national level, adjusting the earnings in the same way. For the other Seattle numbers, this adjustment is completely sound, but for the national level, 4.1% would be not correct, since that 4.1% comes from local conditions. Instead, for that national all occupations median earnings we used the actual 2019 data.

Summary table for comparison with other studies

Earnings Type	Statistic	This Study
Weekly earnings (including tips)	mean	$350.33
	median	$254.04
	10th percentile	$35.10
Hourly earnings without P1 time (i.e., assuming no waiting time ever) (Section 2) $\frac{\boldsymbol{Earnings}}{\boldsymbol{P2+P3}}$	mean	$37.23
	median	$36.31
	10th percentile	$29.46
Hourly earnings with duplicated and expansive P1 time* $\frac{\boldsymbol{Earnings}}{\boldsymbol{P1\ (All\ Logged, Duplicated)+P2+P3}}$	mean	$19.42
	median	$19.68
	10th percentile	$11.13
Hourly earnings with duplicated, but restricted P1 time (i.e., P1 that leads to a ride).* $\frac{\boldsymbol{Earnings}}{\boldsymbol{P1\ (Only\ Preceding\ Ride, Duplicated)+P2+P3}}$	mean	$26.14
	median	$25.62
	10th percentile	$19.44
Hourly earnings with de-duplicated but expansive P1 time (Section 3) $\frac{\boldsymbol{Earnings}}{\boldsymbol{P1\ (All\ Logged, De-duplicated)+P2+P3}}$	mean	$23.03
	median	$23.20
	10th percentile	$15.72

Hourly earnings with de-duplicated but restricted P1 time (i.e., P1 that leads to a ride) (Section 4) $\frac{\boldsymbol{Earnings}}{\boldsymbol{P1\ (Only\ Preceding\ Ride, De - duplicated) + P2 + P3}}$	mean	$26.37
	median	$25.82
	10th percentile	$19.67

* These findings were not reported elsewhere in this report because duplicated time should not be included. The hourly earnings that results from using duplicated time are included here for comparison purposes with other studies.

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