

Uber down under: The labour market for drivers in Australia*

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May 2021

Abstract

We investigate the labour market for Uber drivers in Australia using administrative and survey data. Uber drivers' total hours of work and driving schedules exhibit substantial heterogeneity and week-to-week variation; which appear to mainly reflect drivers' preferences. We identify several pathways to driving with Uber, associated with different effects on income and job satisfaction. Drivers for whom Uber is a supplemental source of earnings tend to have increased incomes after joining Uber and express above-average levels of job satisfaction; whereas drivers who come to Uber on becoming unemployed have lower incomes and express below-average levels of job satisfaction. Drivers in Australia are relatively more likely to be using Uber to earn supplemental income rather than as their main source of income, similar to the United States, but different from London and France. We find that average earnings (after costs) of Uber drivers in Sydney in 2018 were \$21.00 per hour. Variability in earnings between drivers depends primarily on differences in the number of trips per hour – which in turn is related to job tenure, time and location of driving, and the proportion of offered trips accepted by drivers.

*This paper uses data sources constructed for a research consultancy undertaken by AlphaBeta Australia (now part of Accenture) for Uber Technologies Inc. (see AlphaBeta, 2019). We are grateful to Mitch Cooper and Maggie Lloyd at Uber for assistance with data and valuable input; to Libby Mishkin at Uber for many helpful comments and suggestions which have greatly improved the paper; and to Phil Senior at Accenture whose work on the research consultancy is drawn on in this paper. Jeff Borland has not received payment for preparation of this research paper and has no material financial relationships with entities related to the research. Amit Singh is a former employee of Uber, and as a result, continues to hold stock units that may constitute a material financial position. This paper uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA Project was initiated and is funded by the Australian Government Department of Social Services (DSS) and is managed by the Melbourne Institute of Applied Economic and Social Research (Melbourne Institute). The findings and views reported in this paper are those of the authors and should not be attributed to DSS, the Melbourne Institute or Accenture, nor necessarily to Uber Technologies Inc.

1. Introduction

At the fore of debates on the future of work is how the gig economy might reshape labour markets. The creation of platform-based ‘on-demand’ supply of goods and services has brought a new way of working. Some regard it as a way of working that broadens access to employment and enables better work-life balance by increasing workers’ control over timing of their labour supply. Others express concern that it is a threat to ‘take over’ the labour market; and that being outside the regulatory framework for standard employment brings adverse consequences for workers’ well-being.

Despite the extent of commentary on the gig economy, evidence on its prevalence and impacts remains limited.¹ This lack of evidence has been primarily due to the absence in official national surveys of a category of work that could be interpreted as gig employment.² In Australia, the main evidence on the incidence and impact of gig work is from a special purpose household survey, commissioned for a Victorian government review of gig work, undertaken in early 2019 by McDonald et al. (2020). That survey found 7.1 per cent of the population had offered to work on a digital platform in the past 12 months, although at the time of the survey only about 0.2 per cent were doing full-time gig work and entirely reliant on that source of income. Gig work was concentrated in transport and food delivery (18.6 per cent), professional services (16.9 per cent) and odd jobs (11.6 per cent)³

¹ In a review of issues relating to measurement of the gig economy in the United States, Abraham et al. (2017, p.3) note that ‘different sources of data send conflicting messages regarding the prevalence of non-employee work generally and gig employment specifically...[and]...relatively little is known about the answers to other important questions about the gig economy’. With reference to the United Kingdom, Berger et al. (2018, p.3) state: ‘...we have limited systematic evidence on who actually works in the gig economy and how they fare relative to those in traditional work arrangements...’. For Australia a recent review by Healy et al. (2017, p.10) concluded ‘There are many questions unanswered and much that is not yet known, including exactly who works in the gig economy, why they do so, how much they are paid...’.

² For example, see the discussions in Katz and Krueger (2018) and Abraham (2019, pp.357-58).

³ Measures of the incidence of gig work in the United States have been derived from financial transactions data and tax records. These studies conclude that: (1) About 1.5 per cent of a sample of checking account holders were involved in platform-based gig work in 2018; but a much larger proportion, 4.5 per cent, had been involved at some time in the past 12 months (Farrell et al., 2019a, 2019b); (2) About two-thirds of platform-based gig employment is in the taxi and limousine services industry (Abraham et al., 2019; Collins et al., 2019; Farrell et al., 2019); (3) Growth in participation has been driven by workers for whom the gig economy provides a secondary source of income

In this study, we extend analysis of the impact of the gig economy in Australia by investigating labour market outcomes for a specific group of workers: Uber drivers. Uber first launched in Australia in Sydney in 2012 and has subsequently spread to 36 other cities. The analysis for Australia follows studies describing the labour market for Uber drivers in major cities in the United States (Hall and Krueger, 2017; Hyman et al., 2020), London (Berger et al., 2018), France (Landier et al., 2016) and Egypt (Rizk, 2017).⁴

Our study makes several main contributions. First, it is the only detailed analysis of a gig economy labour market in Australia.⁵ The market for Uber drivers is a valuable place to start such analysis - given evidence that growth in non-employer businesses has been concentrated in the taxi and limousine services sector and the prominence of Uber in that sector (for example, McDonald et al., 2020, p.38 find that 20.8 per cent of individuals who had offered services via a digital platform did that with Uber). Second, a rich set of data - including linked information on drivers' demographic characteristics, their hours of work and earnings, and job satisfaction – allows us to develop new insights on the impact of working with Uber. Third, we integrate findings for Australia with other countries to present a cross-country perspective on the operation of Uber's ridesharing business and labour markets.

Two main data sources are used to study the Uber labour market in Australia: first, administrative data on a one-eighth random sample of drivers who used the Uber platform in Sydney, Melbourne, Brisbane and Perth over a one-year period from late 2017 to 2018; and second, a survey of 824 drivers in Sydney and Melbourne. Using these sources, it is possible to provide a detailed perspective on drivers and their experiences – including drivers' characteristics and motivations for partnering with Uber, their patterns of employment and

(Collins et al., 2019); and (4) Growth in participation in gig work has been the main cause of increased self-employment (Jackson et al., 2017).

⁴ See also Berg and Johnston's (2019) critique of the Hall and Krueger study; and a response by Hall and Krueger (2019). Other studies using Uber data include Angrist et al. (2017), Chen et al. (2017), Cook et al. (2018) and Hall et al. (2019). Studies using alternative data sources that examine the determinants and consequences of gig economy work are Buchak (2018), Berger et al. (2018) and Jackson (2019).

⁵ Previous studies of the market for Uber drivers in Australia have: (1) Undertaken simulations to estimate the net income of Uber drivers using Uber pricing rules and assumptions on driving costs (Stanford, 2018); and (2) Examined job conditions and satisfaction for a sample of 24 current and ex-Uber drivers in Brisbane (Holtum and Marston, 2019).

earnings, and job/life satisfaction. Some aspects of the experiences of Uber drivers are also compared to the general workforce in Australia using the HILDA survey.

Several main themes emerge from our study. First, Uber drivers' hours of work exhibit a high degree of heterogeneity and variability over time – both in total hours worked and the timing of hours worked each week. This feature of the Uber labour market is already well-established from international studies. We add to what is known by evaluating whether the heterogeneity and variability are driven by demand or supply-side influences. Uber drivers to some extent must adapt when they drive to demand conditions. However, preferences over labour supply are also shown to have a substantial influence on variability in driving time and schedule. Flexibility to choose hours appears to cause self-selection in who drives with Uber – for example, a majority of drivers express a preference for flexible hours over a guaranteed minimum wage.⁶

Our second main theme is the diversity of drivers' pathways to Uber. Drivers with very different backgrounds and motivations integrate employment with Uber into their lives and work schedules. Distinguishing between these pathways is therefore essential for understanding the impact on drivers' circumstances and job satisfaction. We identify one group of drivers who were working prior to, and remain in another job after, joining Uber. For these drivers Uber primarily constitutes an extra source of income. Another group of drivers appear to join Uber as a response to moving out of a job they previously held – either voluntarily to commence study or involuntarily via job loss; and for these drivers working with Uber is likely to be their main source of income.

The third theme is job satisfaction of Uber drivers. Overall job satisfaction for Uber drivers is on a par with comparable workers in the occupation group of machinery operators and drivers, but below the average level for all workers in Australia. Job satisfaction of Uber drivers is, however, shown to depend importantly on their pathway to the job. Drivers for whom Uber provides supplementary income express a higher average level of job satisfaction than for workers in similar occupations. Whereas drivers who are looking for other work and experience a decrease in income at the time they join Uber express lower average

⁶ For a similar conclusion regarding gig economy workers in the United States, see Mas and Pallais (2020).

satisfaction. Uber drivers express higher levels of satisfaction regarding job flexibility, hours worked and the work itself than the whole workforce. Satisfaction with pay and job security is lower for Uber drivers than the whole workforce.

The fourth theme is the detailed perspective on the determinants of drivers' earnings we develop. Uber drivers in Sydney had average hourly earnings of \$29.46 net of Uber services fees and \$21.00 after also subtracting average hourly costs of driving. Variation between drivers in earnings per hour are primarily related to differences in their trips per hour (rather than differences in earnings per trip). Trips per hour are related primarily to working time variables such as tenure and hours driven per week; and to variables representing drivers' choices regarding location of driving, timing of driving schedule and whether to accept offered rides.

The rest of the paper is organised as follows. Section 2 describes the data sources, defines key terms and introduces the Uber labour market in Australia. Section 3 describes the data sources used in the study. Section 4 presents descriptive information on demographics, work activities and tenure of Uber drivers. Section 5 provides a variety of perspectives on drivers' motivations for partnering with Uber. Sections 6 and 7 present descriptive information on and analysis of the amount of time spent driving and the weekly schedules of Uber driver-partners. Section 8 considers the extent to which heterogeneity and variability over time in hours of work and weekly schedules of Uber drivers reflect demand or supply forces. Section 9 presents descriptive information on and analysis of the determinants of job satisfaction for Uber drivers. Section 10 presents findings from analysis of correlates of the hourly earnings of Uber drivers. In section 11 the main findings on the labour market for Uber drivers in Australia are compared with other locations as a way of drawing some broader insights on the operation of the market. Concluding remarks in section 12.

2. Background on the Uber labour market

Passengers use the Uber app to set their location and destination; and to request a ride. These trip requests are sent to a nearby driver. The driver can either accept or decline the request during a short time window after seeing the rider's location. If the driver declines the ride, the request is sent to another nearby driver. After the trip, the fare is automatically charged to the

passenger's credit card or payment option. Uber handles all billing, customer support, marketing and lead generation.

Uber drivers choose when and where they work; although of course the amount of work obtained depends on the times and locations at which they choose to drive. For each trip completed, drivers are paid a base fare plus a per-kilometre and per-minute rate. A surge price - which applies a multiplier to standard fares for trips at busy times of the day and in specific locations – may also be paid.⁷ Payments are made to drivers after Uber deducts a service fee of 20 or 25 per cent (depending on when a driver started working with Uber).⁸ Uber also uses other incentive payment mechanisms, for example, to induce drivers to complete higher volumes of trips.

In Australia, an Uber driver must be over 21, have held a non-restricted licence (no P-platers) for at least 12 months in the past two years and not have any disqualifying offences on their driving record. Drivers are required to pass a criminal background check through the National Crime Check. They must also meet local regulations – for example, drivers in Sydney are required to obtain a Passenger Transport Licence Code and undertake driver safety education. Drivers need to have a car less than 10 years old which passes a vehicle inspection test and to be covered by comprehensive or third-party property damage insurance. GST registration and an Australian Business Number are required to access the Uber

⁷ Hall et al. (2019, p.8) characterise price-setting in the United States as follows: 'The price of a trip for a passenger depends on several parameters set by Uber. There is a per-minute time multiplier and per-mile distance multiplier, as well as a fixed initial charge, and service fees in some markets. To calculate the actual fare paid by a passenger, the parameters are multiplied by the realized time and distance of a trip, which is then multiplied by the surge multiplier that was in effect when the trip was taken. The surge multiplier is set algorithmically in response to supply and demand imbalances. During "un-surged" periods, the multiplier is 1.0. There is a minimum charge that applies if the calculated fare is below that minimum.'

⁸ In major Australian cities Uber has upfront pricing for riders. The upfront price is calculated using the expected duration and distance of the trip and local traffic. The upfront price may change if a rider adds stops, alters their destination or the route or time to complete the trip changes materially. More information is available on base rates is available from the rider fare estimator at: <https://www.uber.com/au/en/price-estimate/>.

app.⁹ Drivers are also required to complete safety education modules prior to accessing the app, repeated annually.

3. Data sources

The first main data source used is administrative data on Uber drivers in Australia. A one-eighth anonymous random sample of drivers who used the Uber platform to provide the UberX (peer-to-peer) service in Sydney, Melbourne, Brisbane and Perth between the weeks beginning 16/10/2017 and 15/10/2018 was extracted.¹⁰ This sample amounts to 10,795 drivers. The full set of administrative data is used for analysis of drivers' work hours and schedules; and the sample of drivers from Sydney for analysis of drivers' earnings.

For the purposes of our study, a driver is defined to be working in any week in which they spent time 'online' using the Uber platform. Correspondingly, 'hours worked in a week' are the total time in a week spent by a driver online. Being 'online' includes all time carrying passengers, driving to pick up a passenger, or being online and able to receive dispatch requests.¹¹ Hours worked will therefore be greater than driving time due to the definition of being online. As well, working time can include commuting to the location where a driver plans to work and to pick up passengers, periods of time where drivers are multi-apping but only going offline from Uber if they receive a job from another platform, or time where a driver is online and at home waiting for a request to come through.¹²

'Weeks worked' for a driver is calculated as the sum of weeks during the sample period in which a driver spent any time online using the Uber platform. For some purposes an alternative measure of 'weeks on platform' is calculated: defined as the duration from the

⁹ For further details relating to becoming an Uber driver in Sydney see: <https://www.uber.com/en-AU/drive/sydney/get-started/signupnsw/>; <https://www.uber.com/en-AU/drive/sydney/get-a-license/>; <https://www.uber.com/en-AU/drive/sydney/inspections/>

¹⁰ During this time period the regulatory environment in which Uber operated and Uber's share of the ride-share market were relatively stable. The regions covered by Uber in each city are displayed at: <https://www.uber.com/en-AU/cities/>. An example (Sydney) is shown in Online Appendix 1.

¹¹ Having the app open without making oneself available to receive dispatch requests does not count in our measure of hours-worked.

¹² Hyman et al. (2020, p.74) find that in Seattle, Uber drivers spent one hour commuting to pick up passengers for every four hours driving with passengers.

first week to the last week in the sample period when a driver is observed using the Uber platform. The two measures will differ where a driver has some weeks not using the Uber platform but subsequently again uses the platform.¹³

A range of information on characteristics of trips completed by drivers is used. First, driver-level data on hours worked each week are available. Weekly hours can be disaggregated between four time periods: weekday daytime; weekday evening; weekend daytime; and weekend evening. Daytime is defined as hours from 6am to 7pm, and evening from 7pm to 6am. Second, it is possible to identify time spent by drivers in ‘core areas’ and in ‘preference mode’. Core areas are defined as the smallest set of geographic areas in a capital city in which two-thirds of rides occur. In preference mode drivers are able twice a day to nominate that they are only available to pick up rides in the direction they are already heading.¹⁴ Third, for the time they spend online, it is possible to calculate each driver’s completion rate, equal to their ratio of rides completed to rides offered. Data are also available on the proportion of trips a driver completed for which surge pricing applied. Our main measure of drivers’ earnings is average hourly earnings; calculated as total earnings (net of the Uber service fee) divided by total hours online on the Uber platform.

The second major data source is a survey of Uber drivers undertaken for Uber by YouGov. The sample frame was a representative sample of 10,000 drivers provided to YouGov. The survey was conducted from late November 2018 to early February 2019. Responses to the survey were made by 1,255 drivers; and after removing surveys with incomplete and inconsistent responses there were 1,155 drivers remaining.

Responses to the driver survey came predominantly from Sydney and Melbourne, and for this reason it was decided to restrict analysis of the survey data to drivers in those cities. A comparison between the administrative data on work hours for all drivers in Sydney and Melbourne and for those drivers who responded to the survey shows differences in the distributions of weeks worked and average hours worked per week. Hence, the survey data have been reweighted using those variables to be representative of driving time for all drivers

¹³ Online Appendix Figure 2.1 shows the distribution of drivers’ weeks worked as a fraction of their weeks on the Uber platform. A majority of drivers work in more than 90 per cent of the weeks in which they are on the Uber platform.

¹⁴ This is to allow drivers to provide rides while returning to their homes.

in Sydney and Melbourne.¹⁵ Even with this reweighting, it is important to recognise that survey respondents may not be representative of the full sample of Uber drivers – for example, in other characteristics we do not observe or in how they interpreted the survey questions.¹⁶

Several other sources of data are used. First, data from the 2016 Census of Population and Housing are used to compare selected characteristics of Uber drivers with other workers in the occupation of automobile drivers. Second, a variety of data sources are combined to construct an estimate of the average costs incurred by an Uber driver in Sydney. Third, data from the 2016 HILDA survey are used to compare perceptions of job satisfaction for Uber drivers with the general Australian workforce.

4. About drivers

Who becomes an Uber driver in Australia? To answer this question, descriptive information on characteristics of drivers – drawing from both administrative and survey data sources - is presented in Table 1 and Figure 1. Where possible, comparisons are made with workers classified in the occupation group of automobile drivers, using data from the 2016 Census.

Uber drivers in Australia are predominantly male, consistent with the occupation group of automobile drivers.¹⁷ They are heavily concentrated in the age range from 25 to 54 years, which makes them somewhat younger on average than all automobile drivers.¹⁸ Drivers in Sydney and Melbourne each account for about one-third of the Uber administrative sample, and Brisbane and Sydney about one-sixth each. This is similar to the distribution of

¹⁵ Online Appendix Table 2.1 shows that the characteristics of drivers from Sydney and Melbourne who responded to the survey (unweighted or weighted) are much the same as for the full sample of drivers who responded. Online Appendix Table 2.2 shows the difference in weeks worked and average hours of work per week between all drivers in the administrative data set and the drivers from Sydney and Melbourne who responded to the survey. Weighting was undertaken by dividing the samples into 25 categories (using five categories for weeks worked and five categories for average hours worked per week (contingent on working)).

¹⁶ The standard YouGov template was used to introduce the survey to drivers – see Appendix 1.

¹⁷ Studies for the US and London show that respectively 13 per cent and 1 per cent of Uber drivers are females (Hall and Krueger, 2016, Table 1; Berger et al., 2018, Table 2.1)

¹⁸ The same finding is made for the United States (Hall and Krueger, 2016, Table 1) and London (Berger et al., 2018, Table 2.1).

automobile drivers across those capital cities. Just over 70 per cent of drivers are married or living with a partner and about one-half have children aged under 18 years living in their household. Uber drivers are relatively highly educated compared to the occupation of automobile drivers and the population of employed persons in Australia. For example, almost 50 per cent of Uber drivers have a Bachelor degree or above as their highest level of education attainment, compared to just over 30 per cent for all employed persons and 25 per cent for automobile drivers. Drivers are doing a range of other activities while working with Uber. About 50 per cent are working full-time or part-time in another job, 10 per cent are studying, 18 per cent running a business and 18 per cent looking for a job.

Length of tenure of Uber drivers is relatively dispersed. About one-half of drivers in the administrative sample had been working with Uber for less than a year, one-quarter for 1 to 2 years and one-quarter for more than 2 years. Underlying the tenure distribution is a pattern of inflows to and exits from Uber by driver-partners. Figure 1 reports two series of survival rates of drivers with Uber, which use alternative lengths of time not driving for Uber to define entry to and exit from working with Uber (4 weeks and 8 weeks).¹⁹ Drivers exit steadily from Uber for the first six months after commencing with the platform - by which time the proportion of drivers remaining is between 50 and 60 percent. After that time, there is very little further exit through to the end of the sample period at 12 months.

5. Motivation for driving

A distinguishing feature of work with Uber is the scope for drivers to choose the times at which they are willing to supply labour. Table 2 present drivers' responses to questions from

¹⁹ The survival rates are constructed in several steps. First, we create a sub-sample of drivers who are observed to commence driving for Uber during sample period. This is defined to occur if a driver is not observed to use the Uber app in the first 4 (8) weeks of the sample period. Second, for the sub-sample we identify whether in the sample period a driver stops driving for 4 (8) weeks and is not subsequently observed to start again. If answer is 'yes' then we define these drivers as stoppers; and if the answer is 'no' we define these drivers as continuers. Third, we calculate the survival rate at one month as the number of drivers who continued to one month divided by the number of drivers who commenced with Uber. (The number of drivers who continue to one month equals the number of drivers who commence during the sample period minus the number of drivers who ceased driving with Uber after one month or less.) This step is repeated for two months, three months, and so on.

the survey relating to preferences over alternative work arrangements.²⁰ A large majority of drivers express a preference for flexible hours over fixed hours; and a slight majority say that they prefer to remain an independent contractor over the alternative of a being an employee.

Previous work for the United States (Mas and Pallais, 2018) found that the average worker does not put a high value on flexibility in scheduling their work times, but that there is a small group of workers who do attach a high value to this job characteristic. Hence, it appears that, to a large degree, Uber drivers are self-selected from that subset of the overall workforce who do attach high value to scheduling flexibility.²¹

An alternative perspective on drivers' motivations can be obtained by linking their main activity prior to joining Uber with information on other current activities (in addition to driving with Uber). Table 3a is a transition table which presents this linked information for drivers who prior to Uber were employed, unemployed or studying (who account for 89.4 per cent of drivers who responded to the survey). Several main patterns are evident.

First, a large proportion of drivers are continuing to do what was their main activity prior to joining Uber – for example, of those drivers who were working full-time or part-time prior to working with Uber, 35 to 40 per cent remain employed in jobs outside Uber. Drivers who are working in another job spend less hours working with Uber than other drivers; and drivers who work full-time in another job have lower average hours than those working part time.²²

Second, some drivers have joined Uber from unemployment or on becoming unemployed – 6.7 per cent state that unemployment was their main activity prior to joining Uber, and 10 to 15 per cent of drivers who were previously employed have responded that looking for another job is their main activity when working with Uber.²³ Of those who were unemployed before

²⁰ Analysis of determinants of preferences for flexibility are in Online Appendix Table 2.3. Not much evidence is found of associations between preferences for flexibility and demographics including gender, age, marital status and number of children.

²¹ For evidence that the majority of Uber drivers in the United States and London place a high value on scheduling flexibility, see Chen et al. (2017) and Berger et al. (2018, Table 4.1).

²² See Online Appendix Table 2.4.

²³ Studies for the United States have found that financial distress is a major motivation for drivers commencing with Uber (Koustas, 2019; Jackson, 2019; Garin et al., 2020). Using gig economy employment to adjust labour supply in response to a temporary decrease in income is also consistent

joining Uber, some had relatively long durations; for example, over 55 percent had been unemployed for more than six months.

Third, some drivers appear to be using Uber to earn income having moved to running their own business (in addition to Uber), studying or being a caregiver. For example, of those drivers whose main activity prior to Uber was working full-time or part-time, about 20 per cent were working in their own business when driving with Uber.

In summary, the transition analysis indicates that drivers arrive at Uber through multiple pathways.²⁴ Diversity in pathways is also evident in how joining Uber correlates with changes to drivers' incomes. Table 3b shows drivers' survey responses on what has happened to their monthly income after joining Uber. Overall, 43 per cent state that their incomes increased and 38 per cent that their incomes decreased. But this story changes considerably when distinguishing between drivers according to their path to joining Uber. Of drivers who were working full-time or part-time prior to joining Uber, and continued working in that category of job after joining Uber, about 65 per cent experienced an increase in income. By contrast, for drivers who had been working full-time or part-time prior, but at the time of driving with Uber were looking for work, only 22 per cent had an increase in income and about 60 per cent experienced a decrease.²⁵

6. Hours worked

Two main dimensions of drivers' hours of work can be distinguished – total hours worked and the timing of work (weekday/weekend and daytime/evening). In this section we present descriptive information on total hours, and in the next section on the timing of hours worked.

with evidence on relatively high rates of worker turnover (see Figure 1; also the discussion in Mas and Pallais, 2020).

²⁴ Surveys of self-employment in the United States, United Kingdom and Italy similarly find that gig economy workers are primarily seeking to earn top-up income or to buffer negative shocks to income (Boeri et al, 2020, p.182).

²⁵ The hypothesis of equal proportions between drivers who followed different pathways to Uber is rejected using a chi-squared test at the 1 per cent significance level.

We report two main types of descriptive information on total hours: first, summary measures for the entire sample period; and second, on week-to-week variation.²⁶

The distribution of total hours of worked by drivers over the twelve months sample period is shown in Figure 2.²⁷ The overwhelming impression is of heterogeneity between drivers. Looking at the distribution for all drivers, about 35 per cent worked for less than 100 hours while almost 20 per cent worked for more than 1000 hours. For the sample of drivers who worked at least eight weeks, the distribution becomes more weighted towards longer total hours driven – but the high degree of heterogeneity remains.²⁸

Descriptive information on weeks worked by drivers and their average hours worked per week is presented in Figures 3a and 3b. The distribution of weeks worked by Uber drivers shows a large proportion who worked for less than 10 weeks (about 40 per cent) and relatively even proportions who worked for higher numbers of weeks.²⁹ The majority of drivers average relatively few hours per week in those weeks in which they are working. About one-third work for less than 10 hours per week and only about 13.5 per cent meet the standard definition of full-time employment (35 hours and above) based on their average weekly hours.³⁰

²⁶ While on the Uber platform or at other times, drivers may be making themselves available to other services. In the survey of Uber drivers, about 25 per cent reported using a ride-sharing app in addition to Uber, with the main other services used being Ola and Didi. See Online Appendix Table 2.5.

²⁷ An overall perspective on hours worked by Uber drivers is provided in Online Appendix Figures 2.2a and 2.2b. Total hours worked showed a slight upward trend over the sample period. The exception to this pattern was during the summer holiday period. Hours fell sharply during the last week of December and first week of January, and then took until mid-February to recover to their previous level. The proportions of hours worked each week at weekends and at evenings were relatively stable across the sample period at about 40 per cent. The percentage of trips with surge payment averaged 11 per cent, with some variation over time.

²⁸ Driver-level heterogeneity in total hours worked could be due to variation in weeks worked or in average hours per week worked (or both). Online Appendix Table 2.6 presents the results from simple regressions with log(total hours) as the dependent variable and log(weeks worked) or log(average hours per week) as the explanatory variable. Variation in weeks worked and average hours per week appear equally influential in explaining driver-level variation in annual hours.

²⁹ The incidence of short spells may reflect both drivers who commenced and stopped driving with Uber during the sample period, but also drivers who only commenced at the end of the sample period (and hence have censored spells).

³⁰ For drivers who worked for at least 8 weeks the distribution of average hours worked per week shifts towards higher average weekly hours. However, the proportion of drivers whose average hours are 35 or more is similar to the full sample of drivers. See Online Appendix Figure 2.3.

Descriptive information on week-to-week variation in drivers' hours worked is reported in Table 4. Drivers are classified into categories based on their average hours of work per week, for weeks in which they were on the Uber platform. For each category of average hours, the table shows the proportion of weeks in which drivers' hours worked were in that category compared to alternative categories of weekly hours. For example, the top left-hand element in Table 4 shows that of those drivers whose average weekly hours of work were between zero and nine hours, on average, in 66.1 per cent of the weeks in which they were on the Uber platform, they had weekly hours of work which fell into that interval.

Generally, what is apparent is a high incidence of week-to-week variation in drivers' weekly hours of work. For example, for drivers whose average weekly hours of work were from 20 to 34 hours, in any given week on average only about 40 per cent of those drivers were working that number of hours. Switching of hours by drivers is however primarily to the adjacent hours categories.³¹

7. Driving schedule

We now turn attention to driver-level weekly schedules. Table 5 summarises drivers' schedules using the four time periods into which hours of work can be classified. Drivers are defined to have a *weekday evening* schedule when they spend more than 5 percentage points above the average time spent by all drivers working on weekdays (53 per cent) and more than 5 percentage points above average time spent by all drivers working on evenings (44 per cent). Similarly, drivers are defined to have a *weekend daytime* schedule when they spend more than 5 percentage points above the average time spent by all drivers working on weekends and more than 5 percentage points above the average time spent by all drivers working at daytime hours. *Weekday daytime* and *weekend evening* schedules are defined

³¹ Table 4 excludes the summer holiday period (where drivers might have been constrained to drive zero hours due to lack of demand) in order to more closely represent changes in weekly hours that can be attributed to choices made by drivers. Online Appendix Table 2.7 shows a similarly high degree of variability when week-to-week transitions in hours worked by drivers across the whole sample period are considered.

analogously. Altogether, drivers with these four schedules account for 83.3 per cent of the administrative sample.³²

Table 5 shows that there is substantial heterogeneity between drivers in their ‘average’ weekly schedules. The most common schedule is weekday daytime, accounting for about one-third of drivers. Drivers in this category have relatively high average hours worked per week. Weekend evening and weekend daytime schedules each account for about one-fifth of all drivers. Drivers with weekend evening schedules tend to work relatively few hours each week and are not likely to spend a large amount of time driving in core areas. Drivers with weekend daytime schedules on the other hand spend a large fraction of their time working in core areas. Weekday evening schedules account for only a small proportion of drivers.

Week-to-week variation in drivers’ schedules is described in Table 6. Each element in the table shows the proportion of drivers who worked during a time period who also worked in that time period in the next week, for the sample of episodes where drivers worked positive hours in adjacent weeks. Given the breadth of the time periods and the restriction to drivers who worked positive hours in adjacent weeks, it seems reasonable to interpret the table as showing that there is a high degree of variability in driving schedules. For example, although the weekday daytime period encompasses about one-third of hours worked each week, still one-quarter of drivers who worked in that period in a given week did not work at all in the weekday daytime period in the subsequent week.³³

8. What explains variation in driving time and schedules?

Drivers’ hours of work and weekly schedules exhibit two main features. First, there is considerable heterogeneity between drivers in ‘average behaviour’ – both in their weekly

³² The remaining drivers are within a 5 per cent band of average hours spent by all drivers working either at daytime or at evenings.

³³ Online Appendix Tables 2.8 and 2.9 show respectively variation in driver-level schedules between weekday/weekend and daytime/evening across all weeks. Drivers are classified based on their ‘average’ schedule across the whole sample period; and for each category, the proportion of weeks in which drivers worked that ‘average’ schedule is shown. The dominant feature is again the variability in drivers’ schedules. For example, for drivers who spent an average of 40 to 59 per cent of their time working on weekdays, in only about 40 per cent of their weeks working did they spend that amount of time driving on weekdays.

hours worked and schedules. Second, individual drivers exhibit a high degree of week-to-week variability in their hours worked and schedules.

Heterogeneity between drivers and variation across weeks in their hours worked and schedules could be driven by supply or demand factors, or by some combination. Where hours worked and schedule are determined solely by drivers' preferences, heterogeneity between drivers in hours worked and schedules then reveals that drivers differ in their preferences and circumstances; and week-to-week variability that drivers' circumstances change over time. Where hours worked and timing of work reflect passengers' demand for ride sharing services, heterogeneity in time worked or differences in schedules between drivers would then imply rationing of available rides between drivers. Variation over the sample period in driving time and schedules would be due to week-to-week changes in demand for ride sharing services.

Early studies of labour markets for Uber drivers interpret variability in hours worked and schedules as revealing the influence of labour supply - drivers exercising the flexibility offered by the job to choose work hours.³⁴ Some recent commentary, however, has suggested that it is the demand-side that mainly accounts for the variability in hours worked and schedules of Uber drivers. For example, Berg and Johnston (2019, p.53) argue that: '...workers' schedules are highly dictated by the availability of work and their financial dependence on income from Uber.'

The demand-side of the ride-sharing market is undoubtedly an important determinant of hours worked and the weekly schedule of Uber drivers. The volume, timing and location of demand for ride-sharing services directly affects the amount of work drivers can obtain, and when and where they need to drive to obtain the most work. As well, through practices such as surge pricing, Uber seeks to tailor the available supply of drivers to demand conditions.

None of this, however, precludes the supply-side of the ride sharing market being a major influence on the amount and timing of hours worked by individual Uber drivers. In what follows, we present evidence on role of the supply-side in determining hours of work. First, we show that differences between drivers in average weekly hours worked are related to

³⁴ See for example Hall and Krueger (2017) and Chen et al. (2017).

characteristics likely to reflect their work preferences. Second, we demonstrate that week-to-week variation in drivers' hours worked and schedules appear to primarily reflect preferences of individual drivers.

To examine the relation between drivers' preferences and their average hours worked, we estimate a regression model for the determinants of drivers' average weekly hours worked including a set of explanatory variables that can be interpreted to proxy for drivers' preferences about work hours. The analysis is done for the sample of drivers who responded to the Uber survey, as this is the group for whom there is the richest set of information on characteristics. The findings are reported in Table 7. Overall, the regression model has relatively low explanatory power. Nevertheless, variables that are significantly related to average hours worked do appear consistent with an influence deriving from drivers' preferences. Drivers who have a part-time job at the same time as driving for Uber work about 3.5 extra hours per week more than drivers with a full-time job. As well, drivers with three or more children at home, likely to have higher household expenses, drive for 5.5 hours more each week on average than a driver with no children.

Our method to investigate how drivers' preferences affect week-to-week variability in work hours is to examine correlations between weekly variation in aggregate hours worked by all drivers and weekly variation in hours worked by individual drivers. The distribution of correlations can be used to make inferences on the effect of drivers' preferences on work hours.

The correlation analysis is undertaken as follows. First, we calculate a demeaned series of weekly aggregate hours worked. Second, the same exercise is repeated for every individual driver for each week in which a driver was on the platform; and restricting the sample to drivers who were on the platform for at least eight weeks.³⁵ Third, the correlation coefficient between the demeaned series of aggregate hours worked and the demeaned series for every individual driver is calculated (for the weeks in which each driver worked). These steps are undertaken separately for the four capital cities; and then pooled to report the set of correlation coefficients for all drivers.

³⁵ Most of the omitted observations display close to perfect negative or positive correlation with total weekly hours by all drivers.

We interpret a higher correlation between week-to-week variation in a driver's hours and aggregate hours as showing a stronger influence of demand on the driver's hours worked. For example, if the correlation coefficients for all drivers were equal to one, this would be interpreted as the week-to-week variation in hours worked by individual drivers being mainly due to variation in aggregate hours demanded by passengers – on the basis that few drivers would be likely to have preferences exactly matching the pattern of variation in aggregate hours; whereas if the correlation coefficients for all drivers were equal to zero, it would be taken to imply that the week-to-week variation in hours worked by individual drivers is mainly explained by their preferences.

Figure 4 presents the findings from the correlation analysis for weekly hours. Only for a small proportion of drivers is there a strong positive correlation with week-to-week variation in aggregate hours worked; for example, for only 5.3 per cent of drivers is the correlation greater than 0.5. Hence, we conclude that week-to-week variation in work hours appears to primarily be associated with drivers' supply preferences. A similar analysis of week-to-week variation in the percentage of time each week spent working on weekdays also finds that drivers' preferences are the main explanation for variation between weeks.³⁶

9. Job satisfaction

It has become increasingly common to evaluate workers' overall job satisfaction (for example, De Neve and Ward, 2017). In this section, findings on the job satisfaction of Uber drivers are reported. We begin with summary information on Uber drivers' satisfaction ratings, both for overall job and specific job attributes, presented in Figure 5.³⁷ The ratings are based on questions with 11-point response scales where a response of zero was designated as 'totally dissatisfied' and 10 as 'totally satisfied'. In Figure 5 we have defined low satisfaction as 0 to 3; medium satisfaction as 4 to 6; and high satisfaction as 7 to 10.³⁸ Generally, Uber drivers appear satisfied with their work. A high level of overall satisfaction with their job is expressed by about 60 per cent of drivers. A majority of drivers express high

³⁶ Online Appendix Figure 2.4 reports the correlation coefficients from this analysis.

³⁷ These questions were asked at the beginning of the driver survey to avoid ordering effects – see for example the discussion in Berger et al. (2018, pp.19-20).

³⁸ Full responses in Online Appendix Table 2.10.

levels of satisfaction with work hours, flexibility, job security and the work itself. Satisfaction with pay is more evenly distributed across the categories.³⁹

The job satisfaction ratings of Uber drivers and general populations of workers (all workers and the subset of workers in the occupation category of machinery operators and driver) are compared in Table 8. Data on the general populations of workers are from the HILDA survey.⁴⁰ Overall job satisfaction for Uber drivers (6.8) is lower than for all workers (7.6); but similar to the occupation group of machinery operators and drivers (7.0). Job satisfaction is higher for Uber drivers who expressed a preference for flexibility in their work.⁴¹ On specific job attributes, Uber drivers have higher average levels of satisfaction than all workers regarding flexibility to balance work and non-work commitments; and similar average levels of satisfaction for hours of work and the work itself. On the attributes of total pay and job security, however, Uber drivers have lower average levels of satisfaction than all workers.⁴²

A further interesting perspective on job satisfaction is to compare between drivers who experience different changes in income after joining Uber. This is done in Table 9. Satisfaction levels are strongly ordered by the direction of income change. Drivers whose income increased after joining Uber have a relatively higher average level of overall job satisfaction, above other workers in similar occupations. But drivers whose incomes decreased express much lower levels of satisfaction. Similar results are found for life satisfaction. Drivers' feelings of satisfaction about financial stress and employment opportunities are also positively correlated with the change in income they have experienced after joining Uber.

³⁹ These findings are consistent with information on drivers' perceptions of selected job attributes which is presented in Online Appendix Figure 2.5. These perceptions are derived from questions with 7-point response scales where a response of 1 was designated as disagree and 7 as agree. In reporting responses we have defined disagree as 1-2; neutral as 3-5; and agree as 6-7. Drivers overwhelmingly agree that their job has flexibility and that they are able to control their working time. They are mainly neutral on fairness of pay and job security; and disagree that the job is unexpectedly stressful.

⁴⁰ Responses are from employed persons aged greater than 18 years who answered questions on gender, age and income. Observations are reweighted by age and gender to match the sample of Uber drivers from Sydney and Melbourne who responded to the survey.

⁴¹ The hypotheses of equal distributions of overall job satisfaction ratings for drivers who (i) did and did not partner with Uber for flexibility and (ii) prefer/do not prefer to remain an independent contractor are rejected at the 1 per cent level of significance.

⁴² Similar findings on satisfaction from gig work in Australia are reported in McDonald et al. (2020).

As a final step to investigate job satisfaction of Uber drivers, we have estimated regression models for the determinants of overall job satisfaction, with a focus on the impact of preferences for flexible working hours. Table 10 reports the main findings from an OLS analysis of drivers' job satisfaction ratings (0 to 10 scale).⁴³ For variables relating to driving with Uber for flexibility and being able to choose one's own work hours, the comparison is between drivers who agree/strongly agree and who disagree/strongly disagree (rows 1 and 2). For variables relating to preferring to remain an independent contractor and fixed hours, the comparison is between drivers who agree and disagree (rows 3 and 4). Columns (1) and (2) are models with only demographic variables and with demographic variables plus a set of indicators for drivers' main activity apart from working for Uber. Columns (3) to (6) add dummy variables representing drivers' preferences for flexibility one at a time. Column (7) includes the full set of dummy variables representing preferences for flexibility.

Drivers' preferences for flexibility are strongly associated with their level of job satisfaction. Drivers who partnered with Uber to have more flexibility, who value being able to choose their own hours or who prefer to remain an independent contractor express levels of job satisfaction about 0.8 to 1 point higher (on the 11-point scale); whereas drivers who prefer fixed hours express levels of satisfaction that are lower by about the same amount. Effect sizes are reduced, but for the most part remain significant, when the four variables representing drivers' preferences for flexibility are included together.⁴⁴

An important additional finding is that drivers who are looking for work express job satisfaction levels that are 1.1 to 1.4 points lower than other drivers. Matched with the result from Table 9 – that drivers who experience a decrease in income on joining Uber express lower job satisfaction – this finding suggests that drivers' pathways to Uber have a major impact on their job satisfaction. Drivers who are working in another job while working for

⁴³ A variety of studies have shown that the findings from OLS models of ordinal response items are typically very similar to using ordered models (see the discussion in Berger et al., 2018, p.20). Full results are reported in Online Appendix Table 2.11.

⁴⁴ Given that the job attributes of driving for Uber are well-known it seems likely that this association mainly reflects the impact of drivers with an exogenous preference for flexibility deriving higher job satisfaction from working with Uber. But the association may also to some degree reflect drivers rationalising the benefits of what they discover to be the main job characteristics of working with Uber.

Uber tend to have higher total earnings after joining Uber, and express higher job and life satisfaction than an average worker. But drivers who have become unemployed and who are looking for work while driving for Uber tend to have had decreases in income, and express lower job and life satisfaction than an average worker.

The association between a driver's pathway and job satisfaction could reflect two influences. The first potential influence is the closeness of match between a driver's preferred job characteristics and driving with Uber. Drivers who are using Uber to earn supplementary income may value characteristics such as flexibility more highly due to already having another job; and are in a position where they have some discretion over whether to take on the job of driving with Uber. By contrast, drivers for whom Uber is an alternative to being without an income may feel they need to take the job, even where it does not match well with their preferred job characteristics. The second potential influence is that drivers' responses on job satisfaction may be reflecting their more general circumstances (such as being unemployed) – and not just how they regard the job of driving with Uber.

Some other variables are related to drivers' job satisfaction. First, drivers' education attainment affects job satisfaction. Drivers with any level of qualification at or above high school completion express job satisfaction that is lower by about 1 point than drivers who had not completed high school. This result may be explained by mismatch between the jobs that Uber drivers with higher levels of qualification have trained for and believe themselves capable of doing compared to driving with Uber. Second, some aspects of family background are significantly related to job satisfaction. Drivers who are single express levels of job satisfaction that are lower by about one-half of a point compared those who are married/cohabiting. As well, drivers who have three or more children express job satisfaction levels that are about 1 point below those of drivers with no children.

10. Earnings

a. Descriptive

Summary information on average hourly earnings and driver costs in Sydney is presented in Table 11. Average hourly earnings for drivers over the sample period, calculated as earnings per hour online excluding Uber's service fee, were \$29.46.⁴⁵ The average total incremental cost of driving for Uber in Sydney is estimated to be \$8.46 per hour. This accounts for GST, fuel, maintenance, vehicle depreciation, and the additional cost for comprehensive insurance for Uber drivers.⁴⁶ Hence, the average hourly earnings of a driver, net of costs, was \$21.00.

How do earnings of Uber drivers compare with other workers in Australia?⁴⁷ We find that average earnings of Uber drivers are close to the 40th percentile of the distribution of hourly earnings for casual employees. Average hourly earnings at the 30th and 40th percentile points in the distribution for casual employees are respectively \$18.70 and \$21.31.

b. Decomposition of sources of driver-level variation in earnings

A driver's earnings per hour can be thought of as the multiple of their trips per hour and earnings per trip.⁴⁸ **Trips per hour** is the volume of work. It depends on: (i) rides offered per hour and (ii) the acceptance rate by drivers. Rides offered depends on influences such as location and times worked. The acceptance rate reflects driver preferences and strategy –

⁴⁵ Over the sample period, average weekly earnings ranged from about \$26 to \$35 per hour. See Online Appendix Figure 2.6.

⁴⁶ This estimate is from detailed analysis undertaken by AlphaBeta (2019). For more details on AlphaBeta's calculation of the average total incremental cost, see Appendix 2.

⁴⁷ A direct comparison of earnings of Uber drivers with casual employees is possible, as neither group receives leave entitlements. We use the HILDA survey for 2016 to calculate the distribution of average hourly earnings for casual employees in Australia; and apply the WPI to adjust to 2018 dollars. Average hourly earnings are calculated as Usual Gross Weekly Wage in Main Job divided by Usual Weekly Hours in Main Job for employees aged 15-69 years with hourly earnings between \$5.87 and \$195.95 (following Lass and Wooden, 2019, p.14). The adjustment for wage growth is made using the private sector WPI index from 2016 to 2018 (September) from ABS, Wage Price Index, catalogue no.6345.0, Table 1.

⁴⁸ Cook et al. (2018, p.8) provide a more detailed decomposition of the hourly earnings of a Uber driver into: wait time; distance to pick up passenger; distance on trip(s); driving speed; surge multiplier; and incentive payments earned.

such as selectiveness about trips and dual-apping. **Earnings per trip** depends on (i) distance travelled and (ii) the rate of pay. Distance travelled reflects the purpose of the passenger's trip and is likely to vary by location and times worked. The rate of pay is determined by whether a driver is working at a time where standard pricing or surge pricing applies and incorporating any promotions or additional bonus offers.⁴⁹

A simple decomposition can be applied to determine the relative influence of variation in trips per hour and earnings per trip on drivers' earnings per hour. This is done by estimating a regression with $\ln(\text{earnings per hour})$ as the dependent variable and $\ln(\text{trips per hour})$ or $\ln(\text{earnings per trip})$ as the explanatory variable. Both variables are shown to be important determinants, but trips per hour explains much more of the variation in earnings per hour than earnings per trip. A one per cent increase in trips per hour is associated with a 0.80 per cent increase in earnings per hour; and about 63 per cent of the variation in earning per hour is explained by trips per hour alone. A one per cent increase in earnings per trip is associated with a 0.57 per cent increase in earnings per hour; but only about 13 per cent of the variation in earnings per hour can be explained by earnings per trip.⁵⁰

c. Correlates of earnings

To investigate further the correlates of drivers' earnings, we have estimated regression models for $\ln(\text{earnings per hour})$, $\ln(\text{driver-level trips per hour})$ and $\ln(\text{earnings per trip})$. The findings are reported in Table 12. All regressions are estimated weighted by drivers' total hours of work. Three sets of explanatory variables are included in each model: first, variables representing contemporaneous and accumulated working time (tenure on Uber platform; weeks worked in sample period; average hours worked per week during sample period); second, variables representing driving behaviour (distribution of work by time period; per cent of time worked in core geographies or preference mode; per cent of trips driven when surge pricing applied; completion rate); and third, demographics (gender; age).⁵¹

⁴⁹ These aspects of the payment system are not dealt with directly in this paper.

⁵⁰ See Online Appendix Table 2.12.

⁵¹ Descriptive information on explanatory variables is in Online Appendix Table 2.13.

Findings from the regression analysis should be regarded as showing associations between the variables rather than necessarily causal relations. For example, it is possible that the results reflect reverse causality – such as if drivers choose the amount of time they work and their driving schedules with a view to optimising their earnings per hour.

The strongest associations exist between earnings per hour and the driving behaviour variables.⁵² First, the driving schedule matters. For example, on average a driver who switches 10 per cent of driving time from weekday daytime to weekend evening will experience an increase in earnings per hour of 5.1 per cent; with that effect coming from increases in both trips per hour and earnings per rise. Second, the impacts on earnings per hour of the choice variables – completion rate, time spent in core areas and preference mode – are significant. The direction of effect of those variables reflects a trade-off between their impact on trips per hour and earnings per trip. A higher completion rate and a larger fraction of time spent time driving in core areas are associated with an increase in trips per hour but decrease in earnings per trip. For both these variables the former effect outweighs the latter so that there is a positive relation with earnings per hour. By contrast, a larger fraction of time spent driving in preference mode is associated with less trips per hour but higher earnings per trip – and the former effect dominates so that there is a negative relation with earnings per hour. Third, surge pricing is significantly related to earnings per trip. A driver who switched from no trips with surge pricing to the average number of trips (about 10 per cent) would experience an increase in earnings per hour of 7.2 per cent. The associations found between the driving behaviour variables and earnings suggests that drivers are able – to some degree – influence their earnings through choices about timing and location of work.⁵³

Evidence on the relation between the working time variables and trips per hour or earnings per trip is mixed – and in any case the effect sizes are relatively small. The strongest evidence of a relation is with average hours worked per week. An increase in hours per week from 10 to 30 hours raises earnings per hour by 3.4 per cent. Effect sizes for tenure are also

⁵² Evidence on the relation between pay and the working time variables is mixed – and in any case the effects sizes are relatively small.

⁵³ From the demographic variables tested, it appears that drivers 25 years and above drive less trips per hour than younger drivers; and for females, there is a significant negative association with earnings per trip, but no apparent relation with trips per hour.

small. Going from tenure of 26 weeks to 78 weeks raises earnings per hour by 2.9 per cent. There is little evidence of a significant association between weeks worked and earnings.⁵⁴

11. Cross-country comparison

Some additional perspectives on how drivers use Uber work can be drawn from cross-country comparisons – bringing together the findings for Australia with previous studies for the United States, London and France. In this section we use cross-country comparisons to further investigate drivers' pathways to working with Uber and the determinants of drivers' earnings.

A main finding from analysis of the Uber labour market in Australia is the diverse pathways into working with Uber. The same diversity of pathways exists in Uber labour markets in other countries. What is noteworthy is how the relative importance of the pathways appears to vary between countries. In Australia and the United States, the role of Uber as a supplementary source of income predominates, whereas in London and France Uber appears to constitute a main source of income for a larger share of drivers.⁵⁵ This difference in balance is evident in several ways. First, in Australia and the United States, much larger proportions of drivers are doing other jobs at the same time as driving with Uber compared to London (50 to 60 per cent compared with 20 per cent).⁵⁶ Second, weekly hours worked also appear to be higher for drivers in London and France than Australia or the United States (about one-half averaging more than 30 hours per week in London compared to 10 to 15 per cent working 35 hours or more in Australia).⁵⁷ Third, there is a variety of direct evidence that in the United States driving for Uber mainly provides a supplemental source of income (often in response to financial distress); whereas in France 71 per cent of drivers report working

⁵⁴ The estimated relation between working time and trips per hour could reflect reverse causality – with drivers who are able to receive more jobs per hour choosing to drive for longer hours. Similarly, the result on the relation between tenure and earnings per trip could also reflect a selection effect – with drivers who are able to achieve higher earnings choosing to work at Uber for longer spells. However, analysis of Uber drivers in the United States by Cook et al. (2018, p.22) concludes that selection bias is not a major influence on the observed relation between tenure and earnings per hour.

⁵⁵ The market for Uber drivers in Egypt encompasses features of both model – see Rizk (2017).

⁵⁶ Australia – Table 1; United States – Hall and Krueger (2018, p.713); London – Berger et al. (2018, p.10); France – Landier et al. (2016, Table 4).

⁵⁷ London – Berger et al. (2018, p.12); United States – Hall and Krueger (2018, Table 3); Australia – Figure 3b.

with Uber as their main source of income.⁵⁸ Uber drivers in France must obtain a professional VTC license, which involves studying for and passing a written exam as well as a practical, on-the-road exam. This entry requirement may cause a selection effect: only for those potential drivers who expect to earn a relatively high income from driving for Uber is it worth qualifying for the VTC licence. Fourth, while similar proportions of Uber drivers in the three locations come to Uber from full-time or part-time work, a much larger proportion in London transit from work in the transportation sector and in France from unemployment.⁵⁹

Another valuable cross-country perspective comes from inspecting the determinants of drivers' earnings. Some variables have a common effect on drivers' earnings across all locations. A major example is the findings of a positive relation between tenure as an Uber driver and earnings per hour.⁶⁰ Cook et al. (2018, p.21) suggest that: '...there is much to learn being a driver on Uber. Uber pays according to a fixed formula, but many of the parameters of the formula...are within the driver's control. For example, drivers can indirectly affect the surge multiplier and wait times by choosing where and when to work and directly affect their driving speed by simply driving faster. As drivers work more, they can begin to learn optimal driving behaviors to maximize earnings.' Other examples of common findings are how driver preferences for location and driving time affect their earnings⁶¹; and lower earnings for female drivers – although the effect appears to be smaller in Australia than the United States (Chicago).⁶²

12. Conclusion

This study has reviewed the labour market for Uber drivers in Australia. It reinforces the central role of flexibility in gig economy markets evident from previous research; such as in the heterogeneity and variation across time in hours worked. To this has been added an additional perspective – the diversity of pathways by which drivers come to work with Uber,

⁵⁸ Farrell et al. (2019, p.366); Abraham et al. (2018, p.36); Koustas (2019); Landier et al. (2016, p.6).

⁵⁹ London – Berger et al. (2018, pp.8-9); France – Landier et al. (2016, Figures 5, 7); Australia – Table 3a; United States – Hall and Krueger (2018, p.712).

⁶⁰ London – Berger et al. (2018) – Tables A2 and A3; Australia – Table 12; United States – Hall and Krueger (2018, Table 7); Cook et al. (2018, pp.2-3).

⁶¹ Australia – Table 12; United States – Cook et al., (2018, p.19).

⁶² Australia – Table 12; United States – Cook et al. (2018).

and the implications of that pathway for income and job satisfaction. We also use the findings for Australia to describe how the use of gig economy work varies between countries.

There are many extra topics that could be pursued in further work on the gig economy and Uber labour market in Australia. Determinants of tenure as an Uber driver; the effect of participation in the gig economy or driving with Uber on subsequent labour market outcomes; and the effect of competition from the gig economy work on standard labour markets – are just several examples of interesting questions.

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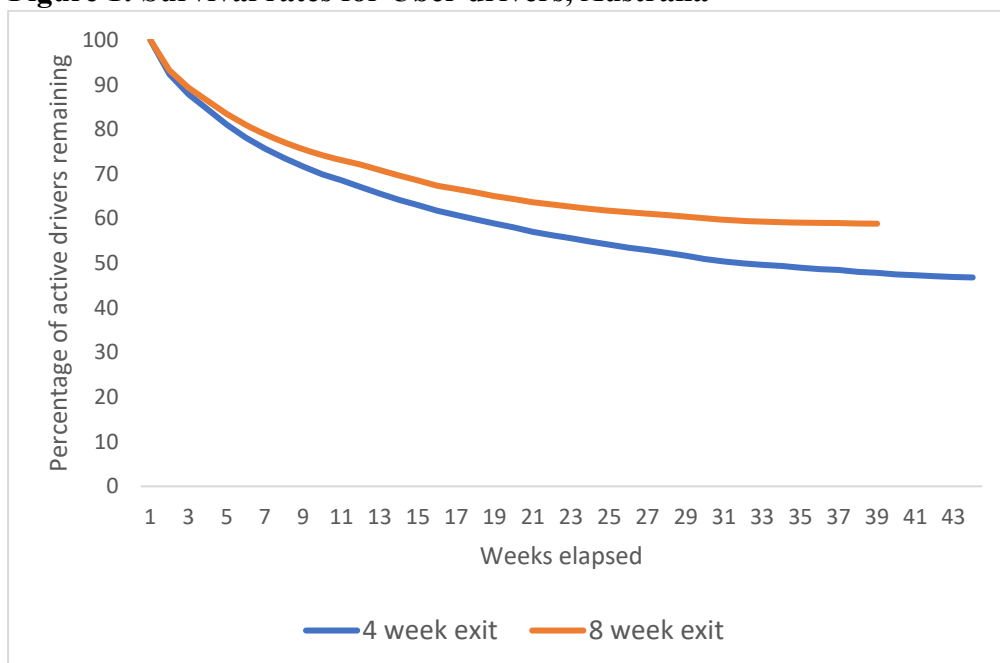
Table 1: Characteristics of Uber drivers, Australia

Variable	Uber driver-partners (%)	Auto drivers (Census, 2016)	All employed persons (Census, 2016)
Uber administrative data (Sydney, Melbourne, Brisbane, Perth)			
1] Gender			
Male	92.8	94.2	52.5
2] Age			
18-24 years	5.5	2.9	14.5
25-34 years	38.7	24.3	23.1
35-54 years	44.2	40.7	43.7
55 plus years	11.6	30.1	18.7
3] Capital cities		Accounts for 54.7 per cent of Australian sample of auto drivers	Accounts for 60.0 per cent of Australian sample of all employed persons
Sydney	36.4	40.9	35.6
Melbourne	38.4	30.7	33.1
Perth	10.7	15.5	16.8
Brisbane	14.5	12.8	14.5
4] Tenure			
Up to 6 months	32.5		
6 months to 1 year	16.3		
1 to 2 years	26.6		
2 years plus	24.6		
Uber driver survey (Sydney and Melbourne)			
5] Current status – In addition to driving with Uber are you...			
Working in another full-time job	30.6		
Working in another part-time job	18.3		
Caregiving	4.3		
Studying to obtain more qualifications	10.6		
Have your own business	16.2		
Looking for another job	18.0		
Retired	2.9		
Other	15.1		
6] Highest education qualification			
Postgraduate degree/Professional qualification	25.0	9.2	10.2
Diploma or VET	31.7	30.2	32.8
Bachelor degree	24.9	17.3	22.0

Senior secondary school	11.6	38.4	31.7
Junior secondary school	6.9	4.9	3.3
7] Marital status			
Single and never married	13.8		
Single and been married	14.6		
Married/Living with partner	71.6	71.4	63.5
8] Children under 18 living in household			
Zero	51.8		
1	17.7		
2	23.0		
3 or more	7.4		
9] Description of job prior to working with Uber (Occupation)			
White-collar professional or managerial	40.2		
White-collar administrative or clerical	11.7		
Blue-collar	13.8		
Service Job	16.3		
Other	18.0		

Sources: Uber administrative data and driver survey; ABS, Commonwealth Census 2016, Tablebuilder.

Figure 1: Survival rates for Uber drivers, Australia



Source: Uber administrative data.

Table 2: Uber drivers' preference for flexibility versus security, Sydney and Melbourne

	Proportion
1] Preference for:	
Remain an independent contractor for Uber so I can keep the flexibility to choose when and where I drive and set my own schedule, but not be eligible for things like a guaranteed minimum wage and holiday pay	55.9
Be classified as a worker or employee of Uber so I could be eligible for things like a guaranteed minimum wage and holiday pay, even if that means having less flexibility to set my own schedule or being told when and where to drive and which trips to accept.	44.1
2] Would you prefer to work fixed hours rather than the fully flexible hours you have now?	
Yes	31.0
No	69.0

Source: Uber driver survey.

Table 3a: Transitions of Uber drivers, Sydney and Melbourne

		Status now							
		Studying	Caregiver	Working FT	Working PT	Retired/ Pensioner	Looking for another job	Own business	Other
Prior to Uber									
Working PT	19.1	6.5	4.4	21.9	35.8	0.6	11.9	9.9	8.8
Working FT	60.0	4.5	2.6	37.4	7.9	1.7	15.5	12.0	18.3
Unemployed	6.7	7.7	0	7.7	0	6.2	25.0	15.5	35.9
Studying	3.6	63.3	3.4	0.4	19.1	0	3.9	2.8	7.1

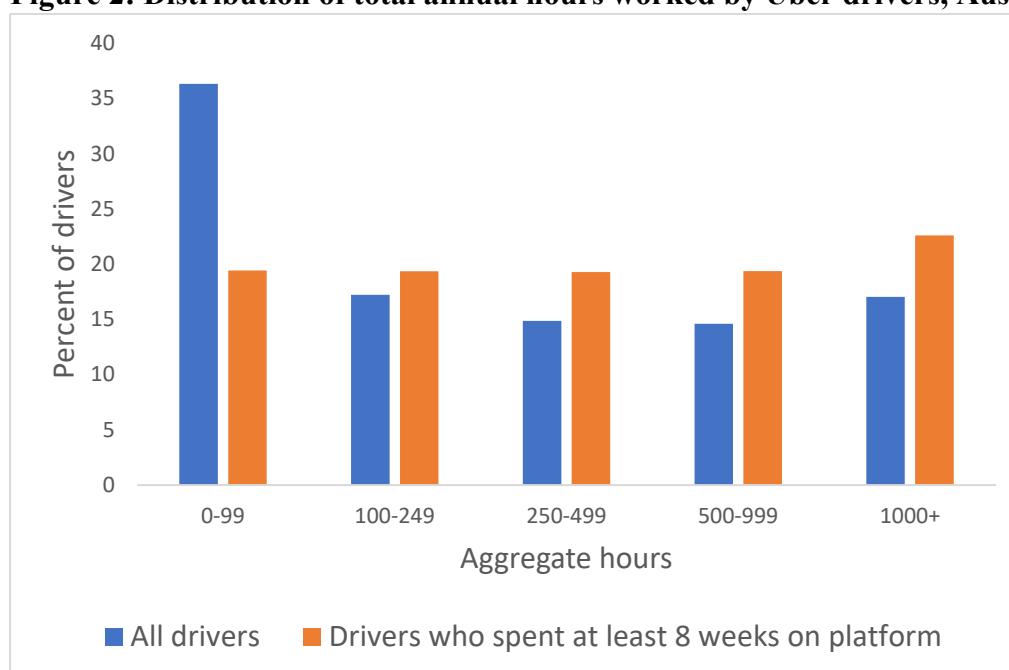
Source: Uber driver survey. Note: 1] The list of drivers' activities prior to joining Uber is not exhaustive. Hence the proportions do not add to 100 per cent; 2] Multiple responses could be given to the question on 'Status now'. Where a driver gave one status now it is given a weight of one; where a driver gave two current statuses each is given a weight of 0.5 etc.

Table 3b: Drivers' changes in incomes since commencing driving with Uber, Sydney and Melbourne

Since driving with Uber, do you think your average monthly income has:	All responses	Worked FT prior to and while driving for Uber	Worked PT prior to and while driving for Uber	Worked FT or PT prior to driving for Uber and currently looking for work
Increased a lot	4.9	3.3	2.8	3.3
Increased a little	38.2	63.7	57.3	22.3
Stayed the same	18.3	10.3	20.6	17.7
Decreased a little	19.8	17.6	12.2	15.7
Decreased a lot	18.8	5.1	7.1	41.0

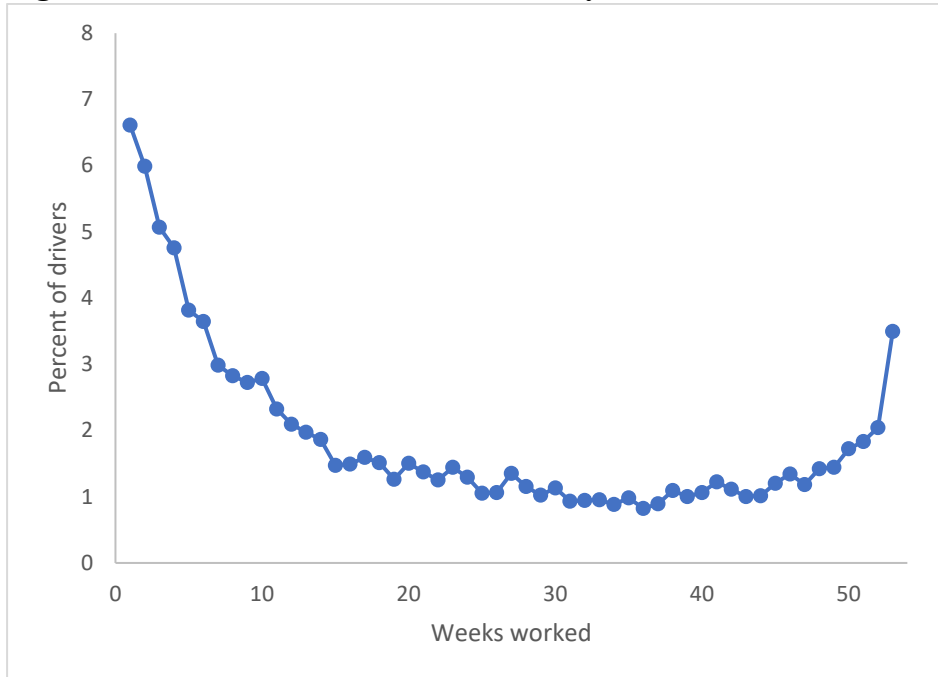
Note: Worked FT prior to survey includes drivers doing multiple jobs prior to survey.

Source: Uber driver survey.

Figure 2: Distribution of total annual hours worked by Uber drivers, Australia

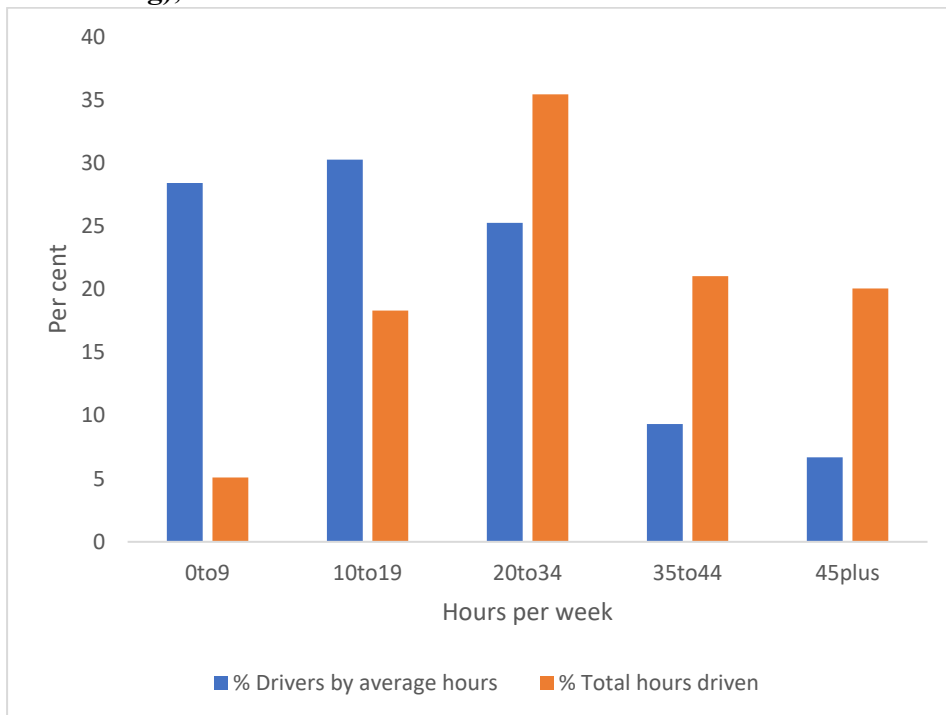
Source: Uber administrative data.

Figure 3a: Distribution of weeks worked by Uber drivers, Australia



Source: Uber administrative data.

Figure 3b: Distribution of average hours worked per week by Uber drivers (Contingent on working), Australia



Source: Uber administrative data.

Table 4: Variation over year in weekly hours worked by Uber drivers, Weeks on platform, Without summer holidays, Australia

Average weekly hours band	% of drivers	Distribution of hours worked by average hours band (%)				
		0-9	10-19	20-34	35-44	45+
0-9	46.7	66.1	25.4	6.6	1.1	0.9
10-19	17.3	27.6	39.9	26.5	4.2	1.9
20-34	16.7	9.9	18.7	42.3	19.0	10.1
35-44	6.7	4.2	7.4	22.3	29.6	36.5
45+	12.7	6.5	8.2	15.0	15.0	55.3

Source: Uber administrative data.

Table 5: Distribution of ‘average’ weekly schedules of Uber drivers, Australia

	Percent of sample	Percent with average hours worked below 10 hours	Percent spending high amount of time driving in core location
Weekday evening	8.2	32.4	44.3
Weekend evening	21.7	45.8	16.7
Weekday daytime	33.4	29.6	42.7
Weekend daytime	20.0	36.4	71.2

Source: Uber administrative data.

Table 6: Week-to-week variation in Uber drivers’ schedules, Australia

Whether worked any time in week t during:	% of drivers	Whether worked same period of week in week (t+1)
Weekday daytime	83.9	77.1
Weekday evening	67.1	56.0
Weekend daytime	75.6	63.0
Weekend evening	80.5	71.5

Source: Uber administrative data.

Note: Sample restricted to episodes where drivers worked positive hours two weeks in a row.

Table 7: Correlates of average weekly hours worked, Uber drivers who responded to survey

Intercept	16.56 (13.02)
25-34 years	2.55 (8.87)
35-54 years	4.17 (8.85)
55 years plus	7.22 (8.87)
Married or living with partner	2.35 (1.71)
Divorced	0.38 (2.53)
Single	2.77 (2.07)
1 child	0.47 (1.42)
2 children	-1.09 (1.36)
3 + children	5.49** (1.92)
Studying	-2.91 (1.55)
Caring	0.27 (2.32)
PT work	3.58** (1.23)
Retired	-3.31 (2.97)
Looking for another job	-1.05 (1.23)
Own business	0.70 (1.30)
Observations	824
Adjusted R-squared	0.025

Note: Omitted categories are: Age = 18-24 years; In a relationship but not living with Partner/Separated/Widowed; Zero children; Other activity = FT work. **=Significant at 1% level; *=Significant at 5% level.

Figure 4: Distribution of correlations between weekly variation in driver hours and aggregate hours, Administrative sample of drivers

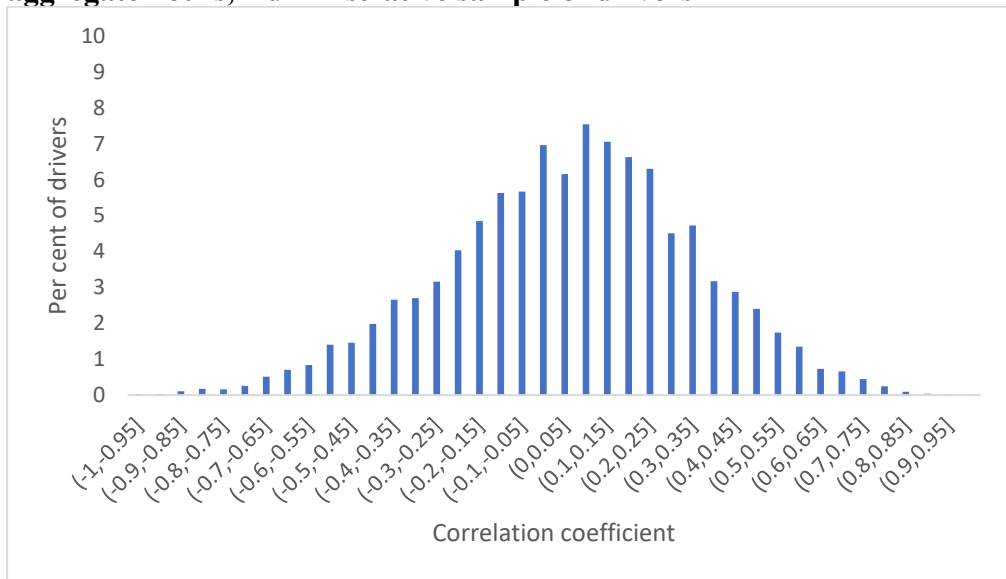
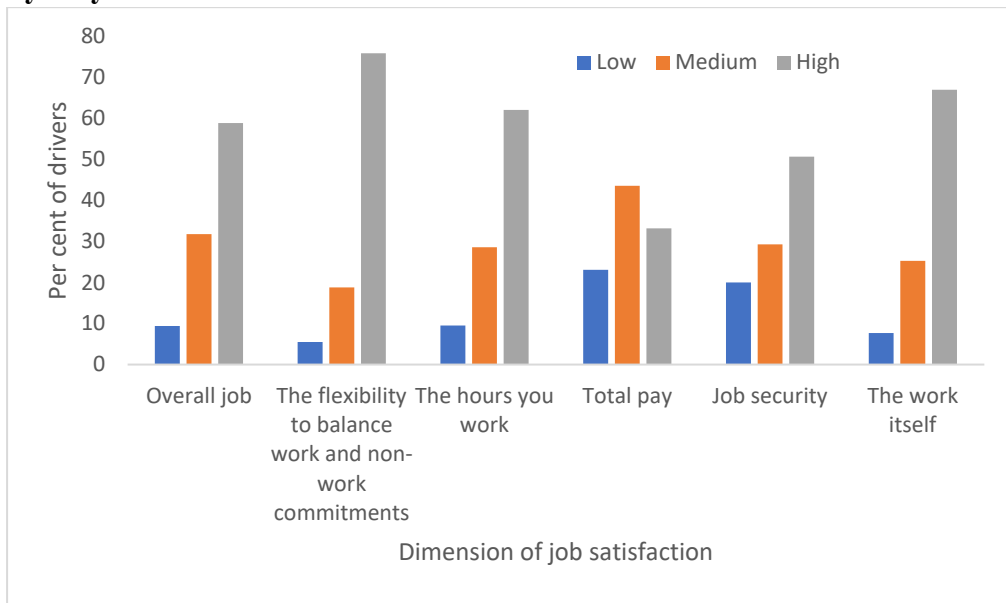


Figure 5: Satisfaction with aspects of working on the Uber platform, Uber drivers, Sydney and Melbourne



Source: Uber driver survey.

Table 8: Job satisfaction of Uber drivers (Sydney and Melbourne) and all workers

	Uber drivers			General population of workers	
	All drivers	Prefer to remain independent	Partnered for flexibility	All workers	Occupation = Drivers etc.
1] Overall job	6.8	7.3	7.1	7.6	7.0
2] The flexibility to balance work and non-work commitments	7.8	8.4	8.0	7.5	6.8
3] The hours you work	7.0	7.6	7.3	7.3	6.7
4] Total pay	5.3	5.9	5.6	7.1	6.6
5] Job security	6.1	6.7	6.3	7.7	7.0
6] Work itself	7.2	7.6	7.2	7.6	7.2

Sources: Uber driver survey; HILDA survey.

Notes: Uber drivers are classified as preferring to remain independent and partnering for flexibility if they agreed or strongly agreed with these statements – see Table 3.

Table 9: Job satisfaction of Uber drivers, Sydney and Melbourne

Income when join Uber	Proportion of drivers	Job satisfaction	Financial stress	Employment opportunities
Increased a lot	4.9	8.3	7.4	8.3
Increased a little	38.2	7.2	6.2	7.1
Stayed the same	18.3	6.9	6.2	6.8
Decreased a little	19.8	6.8	5.9	6.7
Decreased a lot	18.8	5.5	4.8	5.3

Source: Uber driver survey.

Table 10: Correlates of overall job satisfaction of Uber drivers, Sydney and Melbourne

	Model						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1] Partnered with Uber to have more flexibility... (0=Strongly Disagree/Disagree; 1=Agree/Strongly Agree)			0.841*** (0.080)				0.503*** (0.090)
2] Being able to choose my own hours... (0=Strongly Disagree/Disagree; 1=Agree/Strongly Agree)				0.789*** (0.074)			0.485*** (0.084)
3] Prefer to remain an independent contractor (cf. Be classified as worker...) (1=0; 2=1)					1.044*** (0.158)		0.258 (0.170)
4] Prefer fixed hours rather than fully flexible hours... (1=0; 2=1)						-0.941*** (0.166)	-0.455*** (0.169)
Demographic variables	YES	YES	YES	YES	YES	YES	YES
Current status		YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.074	0.134	0.238	0.239	0.177	0.166	0.286
Number of observations	824	824	824	824	824	824	824

Source: Uber driver survey.

Table 11: Average earnings and costs per hour of Uber drivers, Sydney

	\$
Average hourly earnings (excluding Uber's service fee)	29.46
Average hourly incremental cost	\$8.46
Average hourly earnings net of costs	\$21.00

Source: Uber administrative data; AlphaBeta analysis of costs of Uber drivers.

Table 12: Correlates of earnings (pre-cost) of Uber drivers per hour worked, Sydney

	(2)	(3)	(4)
	ln(Earnings per hour)	ln(Trips per hour)	ln(Earnings per ride)
Weeks worked	0.0015* (0.009)	0.0004 (0.010)	0.0012* (0.0007)
Weeks worked squared	0.000018 (0.000013)	0.0000016 (0.000015)	-0.000019* (0.00001)
Hours per week	0.0031*** (0.0007)	0.00030*** (0.0001)	0.000045 (0.00005)
Hours per week squared	-0.00003*** (0.00001)	-0.00005*** (0.0001)	0.000024*** (0.000007)
% Driving weekday night	0.095*** (0.022)	0.051** (0.025)	0.0231* (0.016)
% Driving weekend day	0.25 (0.023)	0.165*** (0.026)	0.101*** (0.017)
% Driving weekend night	0.510*** (0.016)	0.472*** (0.018)	0.052*** (0.012)
% Time driving in preference mode	-0.150*** (0.017)	-0.222*** (0.019)	0.085*** (0.012)
Completion rate	0.740*** (0.068)	2.286*** (0.077)	-1.613*** (0.051)
Age – 25 to 34 years	-0.018 (0.014)	-0.034** (0.016)	0.017 (0.010)
Age – 35 to 54 years	-0.025 (0.014)	-0.052** (0.016)	0.025** (0.010)
Age – 55 plus years	-0.020 (0.015)	-0.033** (0.017)	0.009 (0.011)
Female	-0.015 (0.012)	0.018 (0.014)	-0.033** (0.009)
Tenure (Weeks worked)	0.00049** (0.00022)	0.00004 (0.0002)	0.00005 (0.001)
Tenure (Weeks worked) squared	0.00000065 (0.0000010)	-0.000002* (0.000001)	0.000028*** (0.000005)

% hours in core areas	0.280** (0.012)	0.436*** (0.012)	-0.131*** (0.009)
% trips in November or December	0.18*** (0.020)	0.198*** (0.022)	0.0004 (0.015)
% trips when surge pricing applies	0.720*** (0.048)		0.515*** (0.036)
Constant	2.15*** (0.067)	1.851*** (0.076)	4.067*** (0.050)
R-squared	0.495	0.436	0.437
Number of observations	3,668	3,668	3,668

Source: Uber administrative data.

Note: Omitted categories are: i] Driving time: Weekday daytime; ii] Age: 15-24 years.

Paper appendices

Appendix 1: Introductory statement to survey of Uber drivers

Appendix 2: Estimation of costs of driving

Appendix 1: Introductory statement to survey of Uber drivers

Dear xxxx,

Uber has commissioned the research company YouGov to conduct a survey amongst its partner drivers. We would really appreciate it if you could complete this short survey (about 10 minutes) so we can continue to learn & improve.

If you cannot view or click on the button above, please copy and paste this link into your browser: yyyy

If you would prefer not to receive such emails please unsubscribe.

If you need more details about the survey, please email us with the code AUS158 at supportap@yougov.com after completion of the survey, or feel free to visit our website at <https://au.yougov.com> to know more about YouGov.

Thank you so much

zzzz

YouGov

Appendix 2: Calculation of costs for an Uber driver in Sydney (AlphaBeta, 2019, p.20)

Type of cost	Estimated incremental cost per hour (\$)	Assumptions
Fuel	2.57	Fuel efficiency is assumed to be 13.25 kilometres per litre – Based on estimate for top 10 car models used by Uber drivers. Fuel cost assumed to be \$1.41 per litre – Based on AIP data for sample period.
GST	2.05	GST payable to government based on actual fares minus estimated GST deductibles
Maintenance	1.94	Estimated as \$0.08 per kilometre
Insurance	1.27	Monthly policy cost for comprehensive cover for ride share drivers of c.\$189 (c.\$2266 per annum). Incremental cost vs. private car is c.50% of this value
Depreciation	0.64	Vehicle value of \$34,500 (based on weighted average of top 10 models). Estimate reflects calculation approach based on developing a depreciation model based on real vehicle price data to determine the impact of additional kilometres. Treat car values as equal to: $Car\ value_{itd} = f(X_i, t, d)$ where X_i is a vector of unique car features, and t and d are respectively age of the car and distance driven in the car. Incremental cost associated with driving for Uber is estimated as $Car\ value_{itd(Uber)} - Car\ value_{itd(No\ Uber)}$. To estimate this cost data were obtained on price, make, model, age, distance driven and engine using a web-crawler from over 100,000 advertisements on carsales.com; and those data were applied to estimate a statistical model for the relationship between prices of cars and those characteristics of cars.
Total	8.46	

Notes:

1] Based on average hours per week and average kilometres driven (excluding drivers whose driving time was less than 50 hours over the sample period).

2] Costs per hour are calculated using all hours spent online by drivers.

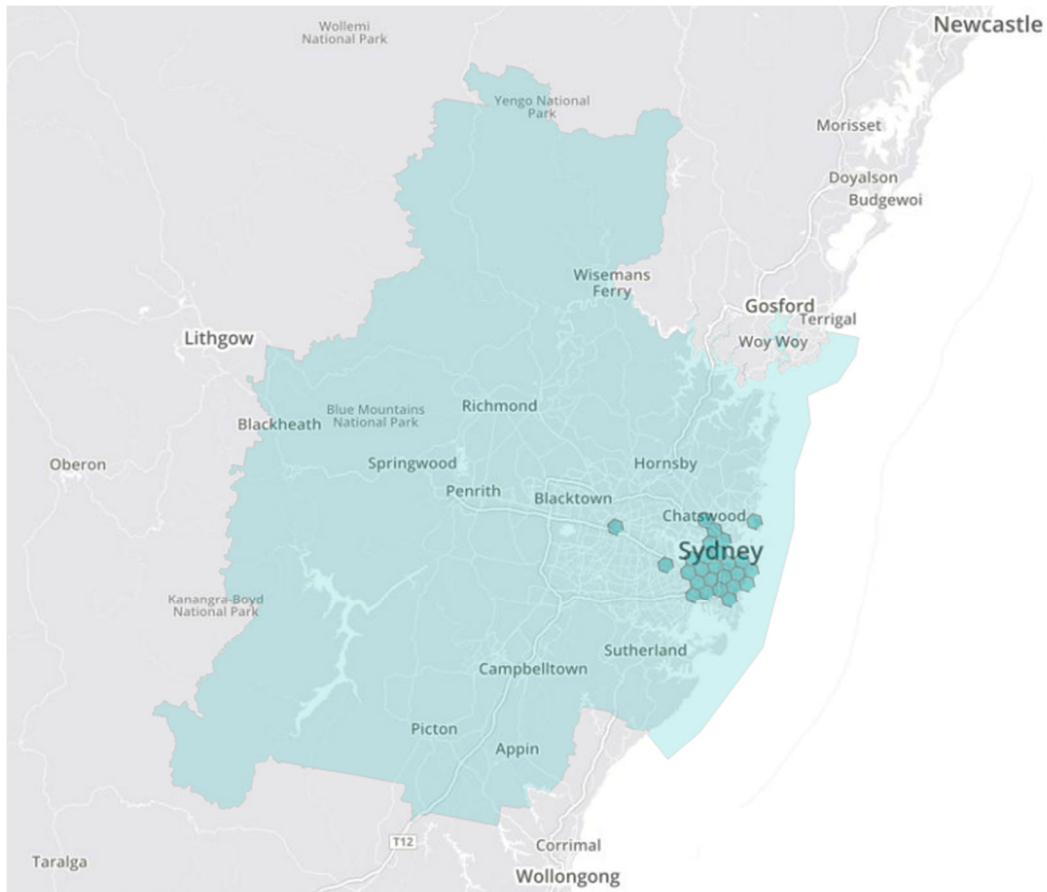
3] Financing, registration and CTP are not included.

Extra online appendices

Appendix 1: Example of coverage of Uber in a capital city region – Sydney

Appendix 2: Extra results

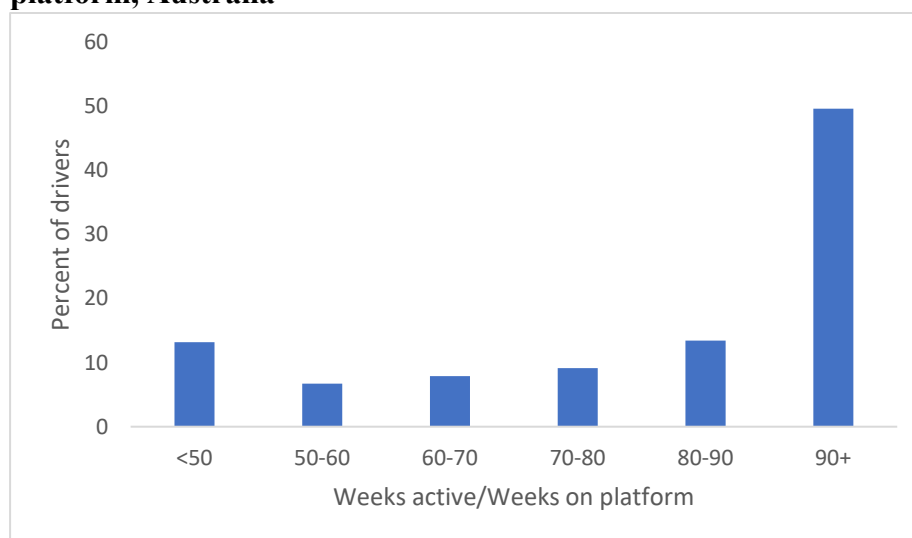
Appendix 1: Example of coverage of Uber in a capital city region – Sydney



Source: Uber administrative data.

Appendix 2: Extra results

Appendix Figure 2.1: Uber drivers, Weeks worked as a percentage of weeks on platform, Australia



Source: Uber administrative data.

Appendix Table 2.1: Sample of drivers in Uber driver survey

	All driver survey responses - Unweighted	Sydney/Melbourne driver survey responses - Unweighted	Sydney/Melbourne driver survey responses - Weighted
1] Highest education qualification			
Diploma or VET	31.6	31.2	31.7
Bachelor degree	22.9	23.6	24.9
Senior secondary school	15.6	15.5	11.6
Junior secondary school	7.2	6.9	6.9
Postgraduate degree	17.5	17.8	19.5
Professional qualification	5.3	5.0	5.5
2] Marital status			
Single and never married	65.5	73.9	71.6
Single and been married	9.0	13.1	13.8
Married/Living with partner	13.3	13.0	14.6
3] Children under 18 living in household			
Zero	52.4	51.8	51.8
1	18.2	19.2	17.7
2	21.1	20.5	23.0
3	6.2	5.9	4.6
4 or more	2.2	2.6	2.8
4] Current status			

Working in another full-time job	26.4	26.3	30.6
Working in another part-time job	16.2	16.4	18.3
Caregiving	5.1	4.6	4.3
Studying to obtain more qualifications	10.2	10.1	10.6
Have your own business	14.7	15.2	16.2
Looking for another job	17.0	17.2	18.0
Retired	5.5	4.5	2.9
Other	19.8	20.4	15.1

Source: Uber driver survey.

Appendix Table 2.2: Work time characteristics of Uber drivers, Alternative samples

	All drivers (Sydney, Melbourne, Perth, Brisbane)	All drivers (Sydney, Melbourne)	Sydney/Melbourne linked sample
Average weeks			
1] On platform	26.9	26.6	39.8
2] Worked	20.3	20.3	33.2
Hours worked per week			
3] Average hours per week on platform	18.0	17.6	20.1
4] Average hours per week worked	23.5	23.1	24.1
5] % drivers by average hours worked per week			
0-10	36.3	37.5	21.1
10-20	28.1	28.1	31.2
20-30	15.8	15.6	17.7
30-40	10.6	10.2	16.3
40plus	9.3	8.7	13.7
6] Share of total hours by average hours worked per week			
0-10	5.4	5.7	4.5
10-20	18.5	18.7	18.8
20-30	22.5	22.3	20.7
30-40	23.8	23.8	25.5
40plus	29.9	28.4	30.6

Source: Uber administrative data.

Appendix Table 2.3: Determinants of preferences for flexibility expressed by Uber drivers, Sydney and Melbourne

	Prefer fixed hours	Prefer to remain an independent contractor
Constant	0.563* (0.324)	0.355 (0.340)
Female	-0.161*** (0.064)	0.083 (0.067)
25-34 years	-0.093 (0.323)	-0.012 (0.339)
35-44 years	-0.198 (0.323)	0.112 (0.339)
45-54 years	-0.215 (0.323)	0.188 (0.339)
55-64 years	-0.344 (0.322)	0.251 (0.338)
65 years plus	-0.350 (0.327)	0.366 (0.343)
Married/Living with partner	-0.063 (0.048)	0.144*** (0.051)
Single	0.041 (0.065)	0.019 (0.068)
1 child	0.089 (0.046)	-0.031 (0.049)
2 children	0.022 (0.048)	-0.016 (0.050)
3 plus children	0.049 (0.063)	-0.180*** (0.066)
Adjusted R-squared	0.047	0.063
Number of observations	824	824

Source: Uber driver survey.

Appendix Table 2.4: Hours worked per week by Uber drivers, By whether have other full-time or part-time job, Sydney and Melbourne

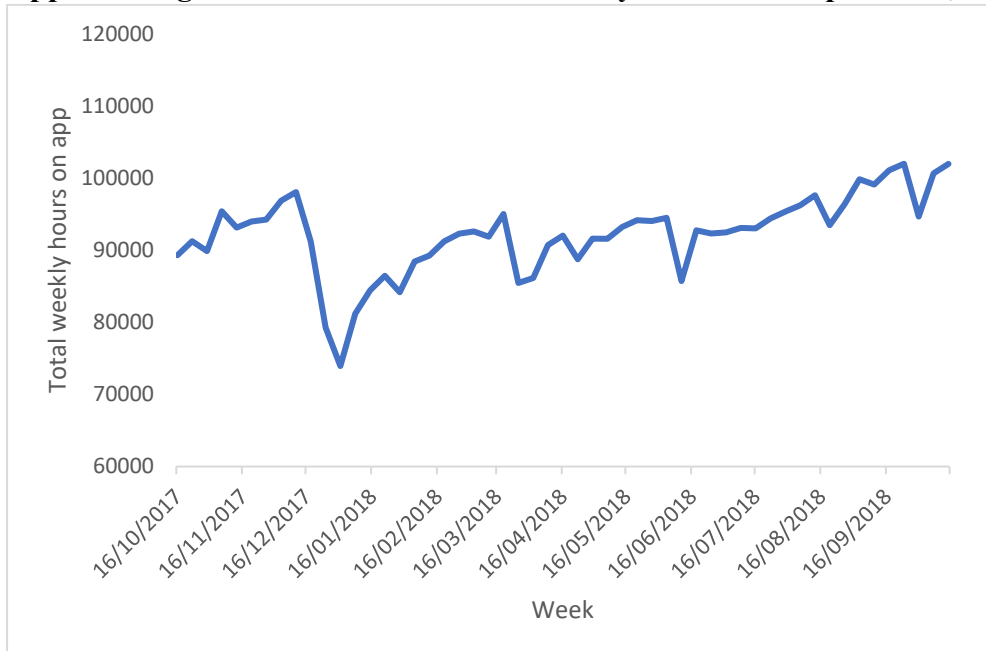
	Number	Average hours per week	Hours worked per week			
			0-9	10-19	20-29	30+
All drivers	824	22.5	37.4	28.0	13.6	21.0
Working PT in another job	135	18.3	46.6	30.2	8.9	14.3
Working FT in another job	217	15.4	51.2	33.2	7.6	8.0

Source: Uber driver survey.

Appendix Table 2.5: Usage of ride-sharing apps by Uber drivers in the past 3 months

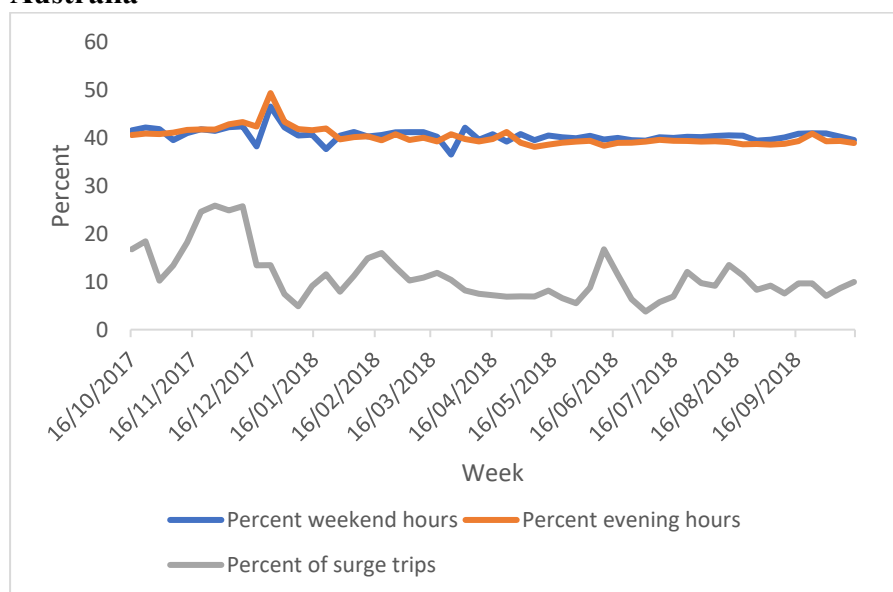
1] App	Percentage
Didi	10.5
GoCatch	3.3
Ola	17.7
Taxify	9.4
Other	1.3
Uber	100.0
2] Number of apps used	Percentage
1	74.6
2	13.5
3	7.3
4 plus	4.6

Source: Uber driver survey.

Appendix Figure 2.2a: Total hours worked by Uber drivers per week, Australia

Source: Uber administrative data.

Appendix Figure 2.2b: Composition of work hours and trips by week for Uber drivers, Australia



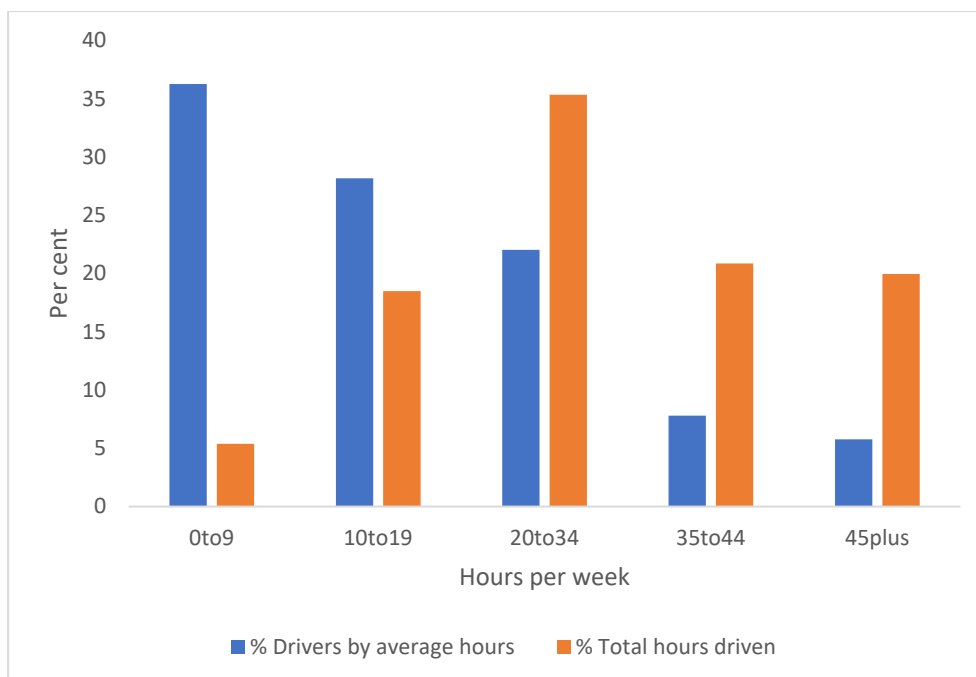
Source: Uber administrative data.

Appendix Table 2.6: Determinants of total annual hours worked by Uber drivers, Australia

	(1)	(2)
Log(Total weeks worked)	1.415*** (0.01)	
Log(Average hours per week)		1.713*** (0.11)
Constant	1.530*** (0.97)	0.667*** (0.29)
R-squared	0.830	0.709
Number of observations	10,795	10,795

Source: Uber administrative data.

Appendix Figure 2.3: Uber drivers, Average hours per week driven (Contingent on working, Drivers who spent at least 8 weeks on platform), Australia



Source: Uber administrative data.

Appendix Table 2.7: Uber drivers, Week-to-week variation in driver-level weekly hours (All weeks on platform), Australia

Hours in week t	Per cent of drivers	Distribution of hours worked in week (t+1) (Per cent)					
			0	1-9	10-19	20-34	35-44
0	27.0	64.8	16.8	7.2	4.4	1.5	1.5
1-9	20.3	35.9	38.5	17.3	6.3	1.1	0.9
10-19	16.9	18.3	21.9	34.8	19.7	3.3	2.0
20-34	17.5	12.0	7.7	19.2	41.4	13.5	6.2
35-44	8.4	8.6	3.3	6.8	28.3	31.6	21.4
45+	9.9	8.7	2.0	3.1	10.7	18.1	57.4

Source: Uber administrative data.

Appendix Table 2.8: Variation in schedules of Uber drivers over sample period (Contingent on working), Australia

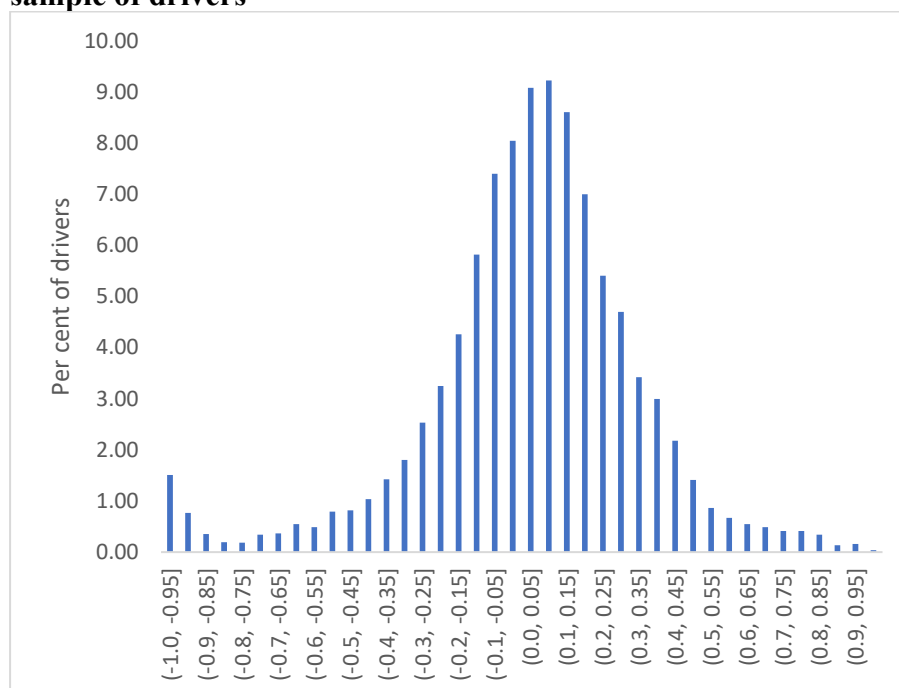
Average percent of hours worked on weekdays	Per cent of drivers	Percent of weeks in which worked specified percentage of hours on weekdays (%)				
			0-19	20-39	40-59	60-79
0-19	14.2	83.7	9.1	3.6	1.1	2.5
20-39	15.4	43.6	27.1	17.8	5.0	6.5
40-59	27.7	15.5	16.2	38.5	18.8	11.0
60-79	26.7	5.2	4.2	17.6	46.5	26.5
80+	15.9	1.9	0.8	2.6	14.7	80.0

Source: Uber administrative data.

Appendix Table 2.9: Uber drivers, Variation over year in driver-level schedule by per cent of time worked in evening (Contingent on working), Australia

Average percent of hours worked on evenings	Per cent of drivers	Percent of weeks in which worked specified percentage of hours on evenings				
			0-19	20-39	40-59	60-79
0-19	27.4	87.9	9.8	1.6	0.4	0.4
20-39	20.3	32.3	42.6	17.2	4.8	3.1
40-59	20.0	10.2	19.9	38.1	21.4	10.4
60-79	17.9	3.9	4.9	17.6	39.7	33.9
80+	14.4	1.1	0.8	2.8	13.1	82.2

Appendix Figure 2.4: Distribution of correlations between weekly variation in proportion of hours driven on weekdays by drivers and in aggregate, Administrative sample of drivers



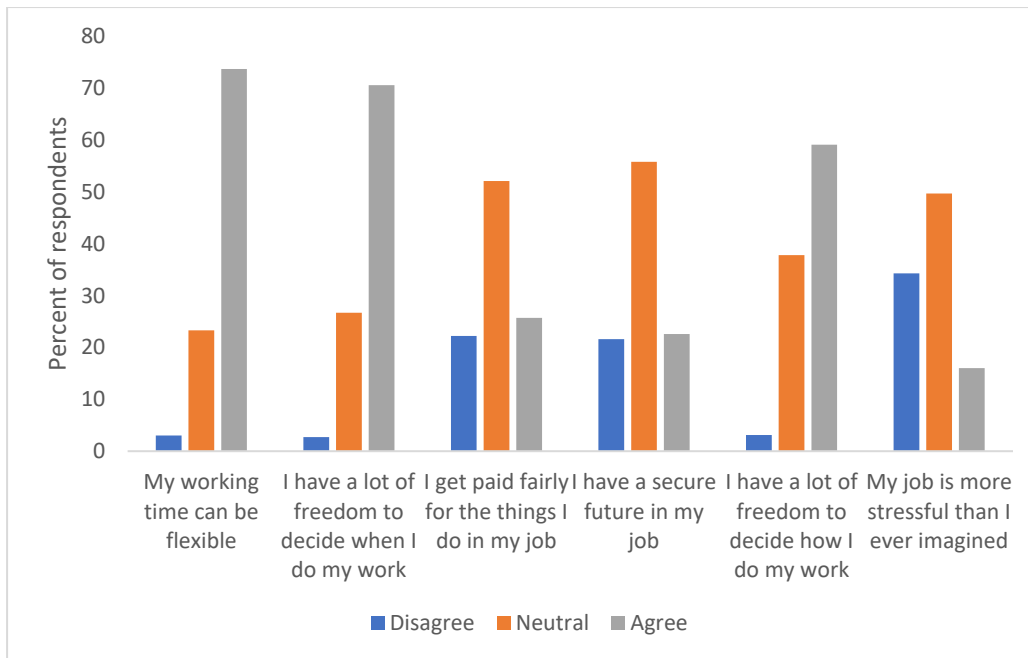
Appendix Table 2.10: Job satisfaction of Uber drivers, Sydney and Melbourne, Percentage of responses

	0	1	2	3	4	5	6	7	8	9	10
1] Overall job	1.0	0.7	2.2	5.5	3.6	13.7	14.5	19.9	15.7	9.1	14.2
2] The flexibility to balance work and non-work commitments	1.7	0.8	1.6	1.4	1.4	11.0	6.4	12.3	16.8	11.2	35.6
3] The hours you work	2.0	1.2	3.6	2.7	5.6	11.4	11.6	14.0	19.0	7.9	21.2
4] Total pay	5.9	4.5	5.7	7.0	10.2	19.9	13.5	11.8	9.2	5.1	7.1
5] Job security	7.1	3.6	4.3	5.0	4.4	15.3	9.6	11.6	13.5	9.5	16.1
6] Work itself	1.0	1.2	1.8	3.7	2.1	10.3	12.5	17.5	19.5	13.2	16.8

Source: Uber driver survey.

Note: 0 = Totally dissatisfied and 10 = Totally satisfied.

Appendix Figure 2.5: Uber drivers, Perceptions of job attributes, Sydney and Melbourne



Source: Uber driver survey.

Appendix Table 2.11: Determinants of job satisfaction of Uber drivers, Sydney and Melbourne

	Model						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	7.123*** (2.72)	7.699*** (2.66)	5.744** (2.50)	6.598*** (2.49)	7.133*** (2.59)	8.197*** (2.61)	5.954** (2.42)
25-34 years	0.115 (2.71)	-0.759 (2.65)	-0.610 (2.47)	-0.701 (2.46)	-0.493 (2.56)	-0.551 (2.58)	-0.468 (2.39)
35-54 years	0.811 (2.71)	-0.016 (2.63)	0.057 (2.46)	-0.218 (2.46)	0.066 (2.56)	0.067 (2.58)	-0.035 (2.39)
55 plus years	0.958 (2.71)	-0.080 (2.63)	0.053 (2.46)	-0.289 (2.46)	-0.082 (2.56)	-0.135 (2.58)	-0.155 (2.39)
Single	-0.745** (0.31)	-0.675** (0.51)	-0.612** (0.29)	-0.671** (0.29)	-0.680** (0.30)	-0.706** (0.30)	-0.651** (0.28)
Married/Living with partner	0.202 (0.23)	0.158 (0.22)	0.195 (0.21)	0.108 (0.21)	0.052 (0.22)	0.088 (0.22)	0.090 (0.020)
1 child	0.206 (0.22)	0.181 (0.22)	0.058 (0.20)	0.038 (0.02)	0.176 (0.21)	0.224 (0.21)	0.039 (0.20)
2 children	-0.264 (0.24)	-0.244 (0.23)	-0.400 (0.22)	-0.321 (0.22)	-0.243 (0.29)	-0.208 (0.23)	-0.366 (0.21)
3 plus children	-0.848*** (0.29)	-1.062*** (0.29)	-0.969*** (0.27)	-0.832*** (0.27)	-0.892*** (0.28)	-1.086*** (0.28)	-0.835*** (0.26)
Professional qualification	-1.386*** (0.43)	-1.294*** (0.42)	-0.997*** (0.39)	-0.977*** (0.39)	-1.264*** (0.41)	-1.433*** (0.41)	-0.981** (0.38)
Postgraduate degree	-0.917*** (0.32)	-0.822*** (0.31)	-0.880*** (0.29)	-0.706*** (0.29)	-0.662** (0.30)	-0.892*** (0.31)	-0.779*** (0.28)
Diploma/VET	-1.570*** (0.29)	-1.303*** (0.28)	-0.941*** (0.25)	-0.832*** (0.25)	-0.886*** (0.26)	-1.190*** (0.26)	-0.892*** (0.24)
Bachelor degree	-1.270*** (0.29)	-1.116*** (0.28)	-1.156*** (0.26)	-1.184*** (0.26)	-1.192*** (0.28)	-1.475*** (0.28)	-1.198*** (0.26)

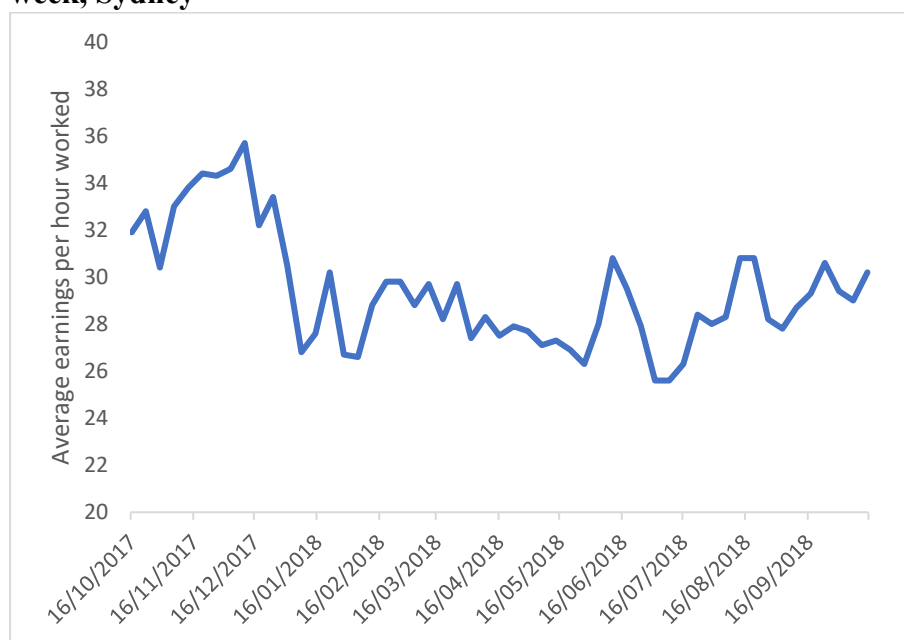
Senior secondary school	-1.297*** (0.27)	-1.035*** (0.26)	-0.965*** (0.26)	-0.918*** (0.26)	-0.952*** (0.27)	-1.223*** (0.27)	-0.916*** (0.26)
Studying	0.039 (0.27)	-0.400 (0.28)	-0.443* (0.26)	-0.266 (0.26)	-0.418 (0.27)	-0.502 (0.28)	-0.397 (0.25)
Working PT		0.039 (0.27)	-0.023 (0.26)	0.060 (0.26)	0.056 (0.27)	0.056 (0.27)	0.026 (0.25)
Working FT		-0.260 (0.28)	-0.150 (0.26)	-0.258 (0.26)	-0.313 (0.27)	-0.282 (0.28)	-0.217 (0.26)
Retired		0.184 (0.42)	0.154 (0.40)	0.227 (0.40)	0.209 (0.41)	0.172 (0.41)	0.193 (0.38)
Looking for work		-1.664*** (0.26)	-1.427*** (0.24)	-1.393*** (0.24)	-1.145*** (0.25)	-1.411*** (0.26)	-1.172*** (0.24)
Own business		-0.103 (0.27)	0.020 (0.25)	0.048 (0.25)	-0.059 (0.26)	-0.125 (0.26)	0.039 (0.24)
Other		0.347 (0.27)	0.357 (0.25)	0.221 (0.25)	0.203 (0.26)	0.283 (0.27)	0.209 (0.25)
Partnered with Uber to have more flexibility... (0=Strongly Disagree/Disagree; 1=Agree/Strongly Agree)			0.841*** (0.080)				0.503*** (0.090)
Being able to choose my own hours... (0=Strongly Disagree/Disagree; 1=Agree/Strongly Agree)				0.789*** (0.074)			0.485*** (0.084)
Prefer to remain an independent contractor (cf. Be classified as worker...)					1.044*** (0.158)		0.258 (0.170)

Prefer fixed hours rather than fully flexible hours...(1=0; 2=1)						-0.941*** (0.166)	-0.455*** (0.169)
Demographic variables	YES	YES	YES	YES	YES	YES	YES
Current status		YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.074	0.134	0.238	0.239	0.177	0.166	0.286
Number of observations	824	824	824	824	824	824	824

Source: Uber driver survey.

Note: Omitted categories are age = 18-24 years; marital status = not stated; number of children = zero; and education = no schooling/some high school.

Appendix Figure 2.6: Average (pre-cost) earnings of Uber drivers per hour worked by week, Sydney



Source: Uber administrative data.

Appendix Table 2.12: Determinants of log earnings (pre-cost) of Uber drivers per hour worked, Sydney

	(1)	(2)
Log(Revenue per ride)	0.271*** (0.022)	
Log(Trips per hour)		0.693*** (0.009)
Constant	2.592*** (0.062)	2.923*** (0.006)
R-squared	0.038	0.595
Number of observations	3,668	3,668

Source: Uber administrative data.

Appendix Table 2.13: Regression analysis of earnings of Uber drivers, Sydney – Sample information, Weighted

	Mean	SD
Weeks worked	39.1	13.9
Weeks worked squared	1723.1	926.7
Hours per week	31.2	14.2
Hours per week squared	1176.6	991.5
% Driving weekday night	16.3	13.6

% Driving weekend day	16.8	12.2
% Driving weekend night	22.9	18.9
% Time driving in preference mode	21.8	15.1
Completion rate	90.8	3.9
Age – 25 to 34 years	26.2	44.0
Age – 35 to 54 years	50.7	50.0
Age – 55 plus years	19.7	39.8
Female	4.1	19.8
Tenure (Weeks worked)	94.6	50.2
Tenure (Weeks worked) squared	11470	10244.3
% hours in core areas	51.5	24.0
% trips in November or December	15.4	13.1
% trips when surge pricing applies	10.5	6.6

Source: Uber administrative data.