Uber Happy? Work and Well-being in the “Gig Economy”[1]

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Summary

We explore the rise of the so-called "gig economy" through the lens of Uber and its drivers in the United Kingdom. Using administrative data from Uber and a new representative survey of London drivers, we explore their backgrounds, earnings, and well-being. We find that the vast majority of Uber's drivers are male immigrants primarily drawn from the bottom half of the London income distribution. Most transitioned out of permanent part- or full-time jobs and about half of drivers' report that their incomes increased after partnering with Uber. After covering vehicle operation costs and Uber's service fee, we estimate that the median London driver earns about £11 per hour spent logged into the app. But while Uber drivers remain at the lower end of the London income distribution, they report higher levels of life satisfaction than other workers. Consistent with a trade-off between evaluative and emotional well-being observed among the self-employed, they also report higher anxiety levels. We hypothesize that the higher life satisfaction among Uber drivers partly reflects their preferences for flexibility and the autonomy that the platform offers. We provide suggestive evidence showing that drivers that emphasize flexibility as an important motivation to join Uber also report higher levels of subjective well-being. Meanwhile, a minority of drivers who report that they would prefer work as an employee report lower levels of life satisfaction and higher levels of anxiety. Overall, our findings highlight the importance of non-monetary factors in shaping the welfare of workers in the gig economy.

JEL: O18, J31, J81, D60
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1. Introduction

Life satisfaction and several other facets of subjective well-being are deeply intertwined with an individual's income, employment, and working conditions.[2] Despite this fact, little is known about how workers fare in alternative work arrangements, which are becoming a prominent feature of 21st-century labour markets. In the United Kingdom, the pronounced increase in self-employment, around the turn of the century, has more recently been accompanied by the rise of so-called 'gig work'.[3] In particular, the spread of Uber—often called the flagship of the gig economy—has given rise to a spirited debate. On the one hand, it has been argued that Uber extends the opportunity to become a 'micro-entrepreneur' to groups often marginalized in the traditional labour market. By giving individuals full autonomy over working time, it allows drivers to achieve work-life balance and provides opportunities to earn additional income when needed, the story goes. On the other, in a report entitled *Sweated Labour: Uber and the Gig Economy*, one influential Labour MP suggests that pay and working conditions for the country's Uber drivers are grim—the term 'sweated labour' was coined in Victorian Britain to describe work involving drudgery, long hours, and low wages. While these narratives provide two diametrically opposed views of gig work, they have one thing in common—they both rely on anecdotal accounts. Regrettably, we have limited systematic evidence on who actually works in the gig economy and how they fare relative to those in traditional work arrangements more broadly.

In this paper, we explore work and well-being of workers in the gig economy through the lens of Uber and its 'driver-partners'.[4] Using administrative data from Uber, official government surveys, and a new independent survey carried out by the polling company ORB of a representative sample of 1,001 active UberX and UberPOOL drivers in London in March 2018, we explore several fundamental questions to help inform the discussion.[5] Who becomes an Uber driver? Are drivers primarily drawn from economically disadvantaged backgrounds? Are they previously unemployed workers who have turned to Uber as a last resort? And how do they fare in terms of income and subjective well-being?

We begin our analysis by exploring who Uber drivers are, comparing the socio-demographic composition of the driver pool with other London workers. We document that drivers overwhelmingly are male immigrants often drawn from Black, Bangladeshi,

[2] See, for example, Freeman (1978), Blanchflower and Oswald (1998), Blanchflower (2000), Blanchflower et al. (2001), Benz and Frey (2008), Frey and Stutzer (2010), De Neve and Ward (2017), and Lindqvist et al. (2018).

[3] Self-employment in the U.K. has seen significant growth in recent years, rising from 12 percent of the labour force in 2001 to over 15 percent in 2017, which partly reflects the expansion of alternative work arrangements such as gig work. Indeed, recent estimates by Balaram et al. (2017) suggest that if the British gig economy was an organization, it would be about as large as the National Health Service (NHS).

[4] For brevity referred to as 'Uber drivers' or simply 'drivers' throughout the paper.

[5] Among the services provided through Uber, its low-cost alternatives UberX and UberPOOL, which provide point-to-point transportation using a standard private hire vehicle, are by far the most popular among drivers. Consequently, we focus on drivers using the UberX and UberPOOL services since they are the most representative of the London driver pool.

and Pakistani ethnic groups. Yet, we find little evidence to suggest that the typical London driver has turned to the gig economy due to the absence of jobs in the conventional labour market. A negligible share of drivers transitioned out of unemployment. Instead, the vast majority held permanent part- or full-time jobs primarily in distribution, transportation, or services prior to joining Uber. Moreover, while driving with Uber is the main source of work for most drivers, about a quarter continue to hold other jobs, or own a business.

Turning to drivers' earnings, we find that Uber drivers are drawn from the bottom half of the London income distribution: the median self-reported gross weekly income (i.e., including income streams other than Uber) among drivers is £460, which is considerably lower than the £596 median gross weekly pay among London workers in the January—March 2018 Labour Force Survey (LFS). Notably, almost three-quarters of Uber drivers thus earn less on a weekly basis than the median London worker. Yet, about half state that their incomes increased after becoming an Uber driver, which reflects that many drivers transitioned out of blue collar or service jobs with presumably low levels of pay. While these findings clearly demonstrate that Uber drivers are drawn from the lower end of the London income distribution, they remain silent about the money that drivers make driving with Uber.

A complicating matter in estimating drivers' earnings from Uber is that they—like most other self-employed black cab and private hire vehicle (PHV) drivers—have to cover the costs of operating their vehicles (e.g., commercial insurance and petrol) that are only observed by the individual driver. Thus, while it is straightforward to show that the median London driver between January—March 2018 received an average hourly payout of £16.50 from Uber (net of its 'service fee') based on data registered in the Uber app, this does not capture their level of earnings after covering their costs. To estimate expenses incurred while driving with Uber, we surveyed drivers on their expenditure on car rental or financing repayments, insurance, and petrol. We complement these data with independent estimates of the cost of car tax, depreciation, and maintenance for the vehicle fleet operated by the drivers in our sample, as well as estimates by Transport for London (TfL) on the costs of becoming a licensed PHV driver, which is a requirement to drive with Uber. Using these different sources of data, we construct estimates of the expenses incurred while driving with Uber.

Our estimates suggest that the median Uber driver in London earns about £11 per hour spent logged into the app, after deducting Uber's service fee and drivers' expenses. While these estimates should be interpreted cautiously, given the challenges involved in estimating the costs that drivers have to bear and the difficulties associated with accurately measuring working time in flexible work arrangements, we reassuringly obtain similar estimates when we instead rely on drivers' self-reported income and hours worked.[6] Interestingly, while these estimates suggest that being an Uber driver is low-paid work, it

[6] See Harris and Krueger (2015) for a discussion of the 'immeasurability of hours' in flexible work arrangements, which may arise in our context if drivers, for example, are engaging in 'multiapping' (i.e., spend time logged into several ridesharing apps simultaneously). However, a very small share of drivers in the ORB survey (less than three percent) report that they use other ridesharing apps in addition to Uber suggesting this is unlikely to affect our estimates. We return to this discussion below.

seemingly provides similar earnings to lower-paying jobs held by many immigrants in the conventional London labour market.[7]

A growing body of work, however, shows how a wide range of job characteristics affect individuals' subjective well-being beyond monetary compensation (e.g., Frey and Stutzer, 2010; De Neve and Ward, 2017). The fact that many Uber drivers may have selected into a flexible work arrangement to gain greater autonomy over their working hours suggests that such dimensions might affect their well-being. Indeed, the majority of surveyed drivers point to autonomy, scheduling flexibility, or improved work-life balance as reasons for joining the Uber platform. Most also state that they would require significant earnings increases to accept working a fixed schedule, which suggests a high willingness to pay for flexibility (Mas and Pallais, 2018). Consistent with these survey responses, administrative data shows that drivers use their discretion over hours to significantly adjust their working time: more than a third of drivers adjust the hours they spend logged into the Uber app by more than 50 percent on a week-to-week basis. Consequently, comparing how Uber drivers fare in relation to workers in traditional jobs in purely monetary terms potentially leaves out important job amenities that are seemingly highly valued by drivers (e.g., Angrist et al., 2017; Chen et al., 2017; Hall and Krueger, 2018).

Bearing this in mind, we proceed to examine Uber drivers subjective well-being using identical survey instruments as the Office of National Statistics (ONS), which allows us to pitch Uber drivers against other London workers in terms of life evaluation (life satisfaction and worthwhileness) and emotional well-being (happiness and anxiety). Strikingly, Uber drivers report higher average levels of life satisfaction and worthwhileness in the ORB survey compared to employed and self-employed London workers in the April 2016—March 2017 Annual Population Survey (APS).[8] The flipside of this is that they also report higher levels of anxiety. An apparent trade-off between life satisfaction and anxiety speaks to a growing body of work demonstrating that while self-employed workers typically state that they are more satisfied with the lives (e.g. Blanchflower and Oswald, 1998; Blanchflower, 2000; Blanchflower, et al., 2001), they also experience higher levels of negative emotional well-being like anxiety and stress (e.g., De Neve and Ward, 2017).

At first glance, the higher life satisfaction and relatively low hourly earnings of Uber drivers is at odds with a large literature documenting that evaluative well-being measures are typically positively correlated with an individual's level of income (e.g., Stevenson and Wolfers, 2008; Kahneman and Deaton, 2010). Yet we find at best a weak link between

[7] While the minimum wage legislation does not apply to self-employed workers, it is also interesting to note that median driver earnings are higher than the National Living Wage for employees aged 25 and over (£7.50 during the period under consideration), as set by the UK government. We also note that our median earnings estimates exceed the London Living Wage (£10.20 in 2017-18), which is voluntary and set by the Living Wage Foundation.

[8] We note that the use of the April 2016—March 2017 APS data may somewhat bias these comparisons, but also emphasize that measures of subjective well-being in the UK have been shown to be stable over time. In the latest statistical bulletin from the ONS (17 May, 2018), for example, it is noted that '[t]here has been no overall change in average ratings of life satisfaction and anxiety' over the year ending in December 2017. Future revisions of the paper will include more recent APS data once it is released in November, 2018.

a variety of alternative income measures and subjective well-being among drivers. However, drivers' perceptions of how their incomes *changed* after partnering with Uber is a key predictor of differences in life satisfaction. Intuitively, drivers that transitioned to Uber from lower-paid work are more satisfied with their lives, as suggested by earlier work documenting how relative income matters in shaping individuals' aspirations and subjective well-being (e.g., Clark and Oswald, 1996; Ferrer-i-Carbonell, 2005; Luttmer, 2005; Clark, Frijters, and Shields, 2008).

A possible explanation for the observed gap in subjective well-being is that it arises due to compositional differences between Uber drivers and the broader London workforce. However, a decomposition exercise that adjusts for factors such as age, educational attainment, ethnicity, and income, suggests that the higher subjective well-being among London's Uber drivers relative to workers in traditional forms of employment is not driven by observable group-level differences. We instead hypothesize that part of this unexplained gap relates to the apparent preferences for flexible work among the majority of drivers. Indeed, we find no link between working time and subjective well-being, which plausibly reflects the fact that drivers can match actual working hours to their individual working time preferences. We also provide suggestive correlations showing that drivers who state that they partnered with Uber to take advantage of the flexibility the platform offers also exhibit substantially higher subjective well-being. Conversely, the minority of drivers that put less emphasis on the role of flexibility, or would prefer to be classified as an employee rather than independent contractor, exhibit relatively lower levels of life satisfaction and higher levels of anxiety.

While these correlations should not be interpreted as causal links, they are suggestive of flexibility playing a role in shaping well-being among individuals in independent work arrangements. Most individuals selecting into such arrangements—at least on the Uber platform—seemingly have strong preferences for autonomy and scheduling flexibility, which enables them to achieve higher levels of subjective well-being than in traditional employment. In our view, this provides one plausible explanation for the fact that a growing share of workers are trading the benefits associated with a traditional nine-to-five job for work in the gig economy, even if the latter oftentimes provides less protection, stability, and lower monetary rewards (e.g., Abraham et al., 2017; Katz and Krueger, 2016; Harris and Krueger, 2015; Hara et al., 2017).[9]

2. Who becomes an Uber driver?

Since its UK launch in 2013, Uber's driver pool has grown exponentially. However, identifying the number of Uber drivers is complicated by the fact that drivers have full discretion over their working hours: the labour supplied by drivers may thus vary significantly at daily, weekly, or monthly frequencies. To circumvent this issue, Hall and

[9] In a broad sense, this is also consistent with the fact that self-employment in general often does not pay more, suggesting that the self-employed are willing to forego income for a higher degree of autonomy and independence at work (Hamilton, 2000).

Krueger (2018) define an 'active' Uber driver as someone who completes at least four trips in a given month. According to this definition, there were almost 50,000 active London drivers registered with Uber as of March 2018. As shown in Figure 2.1, the bulk of UK drivers work in London, which motivates our focus on the capital city. In the subsequent analysis, we rely on a representative sample of 1,001 drivers from the London driver pool that were surveyed by the ORB to elicit information on drivers' individual characteristics and motivations for becoming an Uber driver.[10]

[FIGURE 2.1 HERE]

2.1. The socio-demography of Uber drivers

Table 2.1 presents the demographic composition among the sample of 1,001 Uber drivers based on the ORB survey and three comparison groups: all employed and self-employed London workers, those that report self-employment in their main job, and taxi and cab drivers (i.e., also including Uber drivers) from the January—March 2018 LFS.

[TABLE 2.1 HERE]

A majority of Uber's drivers are in their 30s or 40s and thus overwhelmingly prime-aged relative to the general London workforce.[11] Conversely, a comparison with the broader taxi population suggests that those who partner with Uber tend to be somewhat younger than the typical black cab or PHV driver in London. As drivers are on average older than other London workers, however, it is unsurprising that marriage rates are higher among both Uber drivers and the broader taxi workforce, and that both groups are also more likely to have children in their household. Notably, similar to the general black cab and PHV driver workforce, the Uber driver pool has an extreme underrepresentation of women.

In contrast, immigrants are vastly overrepresented among Uber drivers. Among those with non-missing responses on immigrant status, some 82 percent state they immigrated to the UK, which is more than twice the share observed among the general London workforce. Although immigrants are also overrepresented in the broader black cab and PHV driver population, the share among Uber drivers is slightly higher. Notably, few immigrant drivers are new arrivals: the mean year of immigration is 2001, and almost 90 percent have resided in the UK for more than five years. The large share of immigrants among Uber drivers is also mirrored in an overrepresentation of several ethnic minority

[10] We use additional criteria (e.g., that drivers have worked at least eight distinct weeks in the last year) to define the pool of London drivers from which we draw the sample of 1,001 drivers that were interviewed by the ORB. We describe these criteria and the survey in more detail in the Appendix, and document that the sample of 1,001 drivers is representative of the London driver pool that fulfil the sample selection criteria (approximately 38,000 drivers in total) in observable dimensions such as hours worked, payouts, and tenure on the platform.

[11] We impute the age of approximately 100 Uber drivers that provided a binned age response (aged 18-24, 25-34, etc.) in the ORB survey using the mean age of respondents with numeric responses within each age bin.

groups. In particular, Black, Bangladeshi, and Pakistani groups are all vastly overrepresented compared to the London workforce. Conversely, individuals that identify as White British constitute a much smaller share of Uber drivers than in the labour force, or indeed the full population of London black cab and PHV drivers.[12]

Although Uber drivers overwhelmingly come from immigrant backgrounds, they exhibit high levels of educational attainment. More than half (63 percent) report having at least some college credits or a degree; 22 percent of those reporting educational attainment have at least some college credits but no degree, while 18 and 6 percent of respondents have received a Bachelor's and Master's degree respectively. When reclassifying UK educational qualifications of the London workforce in the LFS to map onto the categories used in the ORB survey, we find that Uber drivers tend to have an educational composition that broadly mirrors the London workforce.[13] In other words, they have substantially higher educational attainment on average when pitched against the broader taxi driver population, suggesting that individuals that partner with Uber tend to be more educated than the average London driver.

In sum, the Uber driver pool closely resembles the composition of the broader black cab and PHV driver workforce, with the main exception of their relatively higher educational attainment. Yet, while demographic characteristics are useful to highlight compositional differences between the pool of Uber drivers and other groups of London workers, they do not shed light on the underlying factors shaping drivers' decision to join the platform. We next examine the employment history of London drivers and discuss the role of income and flexibility in shaping the decision to start driving with Uber.

[TABLE 2.2 HERE]

2.2. Motives for joining the Uber platform

Table 2.2., panel A, tabulates responses from the ORB survey concerning the employment history of drivers. A vast majority of respondents (64 and 23 percent respectively) were employed either full- or part-time prior to partnering with Uber, and most (80 percent) described their previous job as 'a permanent job that would be there until they left it, got fired, or laid off'. A meagre two percent reported being unemployed prior to joining the platform, which suggests that most drivers did not partner with Uber due to a failure to find permanent work in the conventional labour market. Instead, most drivers (43 percent) transitioned out of employment in the transportation sector, while

[12] Note that this conceals significant differences in ethnic composition between black cab and PHV drivers that are clearly evident when breaking down ethnicity by driver status: http://content.tfl.gov.uk/taxi-and-phv-demographic-stats.pdf.

[13] In light of most drivers having immigrant backgrounds, the ORB survey used more widely used classifications of educational attainment (high school, college, etc.) to encompass the fact that drivers are likely to have qualifications from different (non-UK) education systems. See the notes to Table 2.1 for further details on the mapping of educational qualifications.

about one third were previously working in the services sector, including distribution, hotels, and restaurants (see panel B).

A potential motive for partnering with Uber is the possibility of earning additional income. To shed light on where in the London income distribution Uber drivers are drawn from, we begin by examining their self-reported *total* income. Figure 2.2 compares the distribution of gross weekly pay among workers in London based on data from the January—March 2018 LFS and self-reported income of Uber drivers in the ORB survey.[14] Unsurprisingly, Uber drivers are typically drawn from the bottom half of the income distribution: nearly three-quarters (72 percent) of individuals driving with Uber have a lower self-reported gross weekly income than the *median* London worker, while about 90 percent of drivers report a lower income than the *average* gross weekly pay in London. Lower earnings among drivers presumably partly reflects the fact that Uber drivers tend to belong to groups (e.g., immigrants) that exhibit lower average incomes in the London labour market. At the same time, despite the relatively low income levels of drivers, most state that their incomes increased after they started driving with Uber. Almost half (45 percent) of respondents' say that their income increased 'a little' or 'a lot', while less than one in five (19 percent) state that their incomes decreased. An increase in income after partnering with Uber and the fact that most drivers still make substantially less than the typical London worker can potentially be reconciled by noting that most drivers transitioned out of blue collar and services jobs with presumably low levels of pay (see Table 2.2, panel C).

[FIGURE 2.2. HERE]

According to previous survey results of Uber drivers in the United States, one of the main motivations for partnering with Uber is the perceived flexibility that the platform offers (Hall and Kruger, 2018). Indeed, Uber drivers are not committed to drive a specific number of hours, and they are able to go offline at any time. Moreover, drivers are able to take on trips through traditional minicab operators or other ridesharing apps if they like, and they are under no obligation to accept trips when online in the Uber app.[15]

Against that backdrop, flexibility indeed emerges as a seemingly important motivation to become an Uber driver in London. About four-fifths of surveyed drivers 'agree' or 'strongly agree' with the statements 'Being able to choose my own hours is more important than having holiday pay and a guaranteed minimum wage' (82 percent) and 'I don't want to work for a traditional company in case I lose the flexibility I have' (84 percent). Similarly, almost all (93 percent) agree with the statement 'I partnered with Uber

[14] The precise wording of the question in the ORB survey is: 'Thinking about your total average monthly income (before tax), what is your average monthly income?'. For drivers refusing to report numeric earnings, we impute monthly income for the approximately 250 respondents that instead provided a binned response using the mean earnings within each bin among respondents with non-missing numeric responses.

[15] While drivers tend to emphasize the role of flexibility as an important motivation for partnering with Uber, others argue that Uber and other digital platforms leverage considerable control over independent workers. Rosenblat and Stark (2016), for example, suggest that Uber exerts 'soft control, affective labor, and gamified patterns of worker engagement on its drivers'. See Prassl (2018) for a recent overview of this perspective.

to have more flexibility in my schedule and balance my work life and family'. Moreover, 80 percent of drivers' say that they prefer flexible over fixed hours when directly asked. Within this group, the median driver further stated that he would require a 25 percent hourly pay increase to accept working fixed rather than flexible hours.[16] A non-negligible share of drivers' state that they would require an approximate doubling of their hourly pay to accept a fixed schedule. Thus, most drivers emphasize the role of autonomy and having choice over working hours as a motivation to join the Uber platform and have a seemingly high willingness-to-pay for such forms of flexibility. In light of this, it is unsurprising that the majority (81 percent) of respondents' state that they prefer to remain independent contractors rather than be classified as an employee and lose the flexibility of setting their own schedule.[17]

Another way to gauge the role of flexibility and work-life balance is to examine other (work) activities that drivers combine with driving with Uber. A relatively small share of drivers in the ORB survey state that they continue to hold other full-time (10 percent of respondents) or part-time (12 percent) jobs, or that they have their own business (6 percent), in addition to driving with Uber, suggesting that there is complementarity between independent work and more traditional employment, at least for some (e.g., Koustas, 2018). Some drivers also act as caregivers for a relative or friend (7 percent), or are studying to obtain more qualifications (9 percent), which further points to some of the ways independent work may be well suited to those with other commitments.

In sum, these findings suggest that the typical Uber driver in London is not a marginalized worker that has been squeezed out of the conventional labour market, or forced to partner with Uber due to a lack of other options. Most drivers left permanent employment to start driving with Uber and were seemingly attracted to the platform by the flexibility it offers. Moreover, while most Uber drivers report low incomes relative to other London workers, about half at the same time say that their incomes increased after partnering with Uber, which presumably reflects that many drivers transitioned out of low-paid blue collar and service jobs. Yet, while most drivers seem content with their work arrangements, we note that there exists a minority of drivers that would prefer fixed hours and traditional employment arrangements.

[16] Drivers were first asked: 'Would you prefer to work fixed hours rather than the fully flexible hours you have now?'. The 80 percent of drivers that stated that they prefer flexible over fixed hours were subsequently asked: 'Say you were given the opportunity to switch to set hours with Uber, rather than the fully flexible driving hours you have now. How much would your hourly income need to increase for you to accept those set, non-flexible working hours?'

[17] Drivers were asked whether they preferred to '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 (currently £7.50 per hour) and holiday pay' or 'be classified as a worker or employee of Uber so I could be eligible for things like a guaranteed minimum wage (currently £7.50 per hour) 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'.

3. Uber drivers' pay and working hours

Our analysis in the previous section uncovered that Uber drivers tend to be drawn from economically disadvantaged groups with most drivers reporting lower incomes than the typical London worker. An important drawback of these income estimates, however, is that while they shed light on how drivers fare economically, they are silent on drivers' income streams from Uber itself. Thus, in this section we turn to examining drivers' income from driving with Uber. In a first step, we use anonymized administrative data collected through the Uber app to shed light on the distribution of payouts and working time among drivers. We then proceed to estimate the expenses incurred while driving, which allows us to estimate the hourly earnings drivers receive after these costs and Uber's service fee have been deducted.

3.1. A view of payouts and working hours from administrative data

Uber drivers are paid for each trip they drive according to a predetermined formula: in London, drivers on UberX receive a base fare of £2.50, plus £1.25 per mile and £0.15 per minute while on a trip with a minimum fare for any trip of £5. A system of dynamic pricing—referred to as 'surge pricing'—applies a multiplier (e.g., x1.5) to fares in areas of high demand, which induces significant spatial and temporal variation in fares. Payouts are made directly to drivers after Uber deducts its 'service fee', which stands at either 20 or 25 percent depending on when a driver joined the platform.[18]

We begin by examining the distribution of these payouts in the sample of 1,001 London drivers using administrative data collected through the Uber app over the period 1st January—31st March, 2018. Throughout most of the subsequent analysis, we focus on mean hourly payouts that are simply calculated as total payouts net of Uber's service fee divided by the total number of hours spent logged into the Uber app, which constitutes an oft-used definition of hours worked on the platform (e.g., Angrist et al., 2017; Chen et al., 2017; Cook et al., 2018).[19]

[FIGURE 3.1 HERE]

Figure 3.1 graphs the distribution of mean hourly payouts for the London drivers in our sample, which is virtually identical to the distribution of payouts among the full population

[18] In our data, total payouts is the sum of all trip-related payouts (including trip incentives such as surge pricing, tips, etc.), referral bonuses and any other promotions that a driver may have received. However, note that referrals and promos constitute less than 0.25 percent of total payouts among London drivers.

[19] Although hours spent logged into the Uber app constitutes a straightforward measure of hours worked, it comes with a number of potential drawbacks. For example, drivers are not obligated to accept trips and are free to ignore incoming trip requests, which means that drivers in principle can be logged into the app while doing other work or even being at home. At the same time, hours spent logged into the app does not include, for example, time spent cleaning the car etc. and may thus constitute a blunt measure of hours actually 'worked'. Again, this highlights the 'immeasurability of hours' in flexible work arrangements (see Harris and Krueger, 2015).

of drivers (see Figure A.1). The median driver receives an hourly payout of £16.50 net of Uber's service fee, though there is notable variation in mean hourly payouts across drivers, reflected in an interquartile range that spans £14.84 to £18.17.[20] A variation in hourly payouts naturally raises the question of whether this reflects productivity differences between part-time drivers, that spend only a few hours per week driving, and those who drive full time. To understand whether Uber constitutes the main source of work for the typical driver, we next examine the time that drivers spend logged into the app on a weekly basis, and then proceed to analyse if hourly payouts vary with working time.

[FIGURE 3.2 HERE]

Figure 3.2 presents the distribution of mean weekly hours spent logged into the Uber app and time spent 'on trip' (i.e., logged into the app spent en route to pick up a passenger, or with a passenger on board) across the 1,001 drivers in our sample. Most drivers spend substantial hours driving with Uber. About half spend on average 30 hours or more logged into the app (out of which 19 hours are spent on trip) per week, which indicates that Uber constitutes an important source of work for the typical driver. However, a comparison with weekly working hours among other London workers suggests that Uber drivers work less when measured by time spent in the Uber app. In the January—March 2018 LFS, for example, the median London employee and taxi driver reported working 39 and 35 hours in the reference week, respectively. Notably, these differences are evident throughout the working-time distribution. Uber drivers at the 25th and 75th percentile of the hours distribution spend approximately 5-10 hours less logged into the app per week than the reported working hours among the London workforce and taxi drivers at the same percentiles.[21] At the same time, when asked how many hours a respondent used his/her car with the Uber app in an average week, the median response in the ORB survey is 40 hours.[22] Self-reported hours, in other words, suggest that the median driver worked slightly longer hours than those reported by other London workers in the LFS, though Uber drivers clearly overestimate the actual number of hours they spend in the app.

An interesting question is whether hourly payouts vary between part- and full-time drivers, or whether an Uber driver can essentially choose the number of hours to drive without any effect on their (hourly) earnings. To explore whether mean hourly payouts are correlated with hours spent driving, Table 3.1 reports a breakdown of payouts across

[20] It is informative to note that the mean hourly payout of £16.49 across drivers is nearly identical to the mean payout received by the median driver (£16.50) in our sample. Also, note that the mean hourly payout between January—March in our sample is slightly *lower* than the mean hourly payout between June 2017—June 2018 across all active London drivers that fulfil the criteria outlined in section A.1 in the Appendix (see Figure A.2).

[21] One potential explanation is that some Uber drivers combine driving with other types of work activities as discussed above. Indeed, having a business or holding another full- or part-time job is more common among drivers that drive relatively few hours with Uber. Yet, the hours spent logged into the app among drivers that report no additional job or owning a business in the ORB survey is only about one hour less at the median, which indicates that even drivers without other work commitments spend less time logged into the Uber app on a weekly basis than the working hours of a typical London worker.

[22] The precise wording of the question in the ORB survey is: 'In an average week, how many hours do you use your car for [using the Uber app]?'.

drivers by their mean weekly hours logged into the Uber app. Payouts are relatively stable across the working time distribution, which suggests that the variation in payouts does not mainly reflect differences in productivity between part- and full-time drivers. At the same time, there is significant intra-group variation, which manifests itself in a relatively wide interquartile range of hourly payouts and a notable dispersion across drivers, as well as ‘within’ drivers from week to week. Notably, while hourly payouts are slightly lower for drivers that drive at least 40 hours per week on average compared to those driving fewer hours, the dispersion of payouts generally tends to decrease with hours spent driving per week.

We provide a preliminary exploration of the underlying determinants of the cross-driver variation in hourly payouts by presenting simple OLS regressions in the Appendix showing that the key correlate is tenure on the platform, while other driver characteristics such as educational attainment are seemingly unrelated to payouts (see Table A.2).[23] Another key determinant is capacity utilization, or the share of time spent logged into the Uber app that is spent on trip. Indeed, a simple bivariate regression reveals that slightly less than half of the variation in hourly payouts is accounted for by differences in capacity utilization. Notably, there is a non-negligible number of drivers with very low capacity utilization rates, which are also overrepresented in the left tail of the payout distribution in Figure 3.1. Understanding what drives the variation in capacity utilization and whether it is related to drivers’ choices of when and where to drive, or that some drivers are logged into the app but not ‘working’ is an interesting question. Yet, while ongoing and recent work is using administrative Uber data to explore factors such as gender or compensating wage differentials (e.g., for night-shift driving) in shaping the variation in hourly payouts and capacity utilization among Uber drivers (e.g., Cramer and Krueger, 2016; Chen et al., 2017; Cook et al., 2018), we leave a detailed analysis of the determinants of individual productivity among London drivers for future work.

[TABLE 3.1 HERE]

A relative stability of hourly payouts across the working-time distribution as evident in Table 3.1 suggests that drivers can shift their hours spent driving from week to week without a significant impact on their hourly pay. Yet, while the vast majority of drivers emphasize this choice over working hours as an important motivation to become an independent contractor with Uber (see section 2.2), it remains unclear whether drivers actually use this option. We next examine the extent to which drivers adjust their working time by drawing on administrative data for the 1,001 London drivers to examine week-to-week variation in hours spent logged into the Uber app.

[23] While the positive link between tenure and hourly payouts is suggestive of learning by doing, its interpretation is complicated by the potential selective exit of less productive drivers from the platform and the fact that Uber’s service fee varies across drivers, which mechanically inflates the mean hourly payouts of drivers with longer tenure. As an alternative proxy for tenure, Table A.3 presents OLS regressions of hourly payouts and the total number of trips a driver has completed. Total trips are also a significant correlate of mean payouts, again suggesting that driver productivity increases with time spent on the platform.

[FIGURE 3.3 HERE]
[FIGURE 3.4 HERE]

Figure 3.3 graphs the distribution of changes in weekly hours spent logged in to the Uber app relative to the hours in the previous week across 9,797 week-pairs for the sample of London drivers. Evidently, drivers are adjusting the quantity of hours driving significantly from week to week by either increasing or decreasing hours spent in the Uber app. About three-quarters of all weeks driven on the platform between January—March deviate at least 10 percent from hours worked in the previous week, while about a quarter of weeks' exhibit either positive or negative deviations of 50 percent or more. Figure 3.4 sheds further light on the substantial hours' variation by plotting percentage changes in hours spent logged into the Uber app relative to the previous week for each *individual* week-pair. Solid red dots correspond to week-pairs for part-time drivers, while solid navy dots denote week-pairs for full-time drivers that on average spend more than 40 hours per week logged into the app. Even though the relative variation mechanically is highest for weeks with a low baseline number of hours worked, there is evidently still substantial hours' variation also among full-time drivers that spend substantial hours per week logged into the app.

To enable a categorization of drivers by the extent to which they adjust their working time, we average absolute percentage changes in hours spent logged into the Uber app from week to week for each individual driver. More than a third of all drivers on average adjust their weekly hours logged into the Uber app by 50 percent or more on a weekly basis.[24] Uber drivers are thus extensively using their choice over working time to adjust the quantity of hours worked. Notably, consistent with the results reported in Table 3.1, this seemingly has little effect on their mean hourly payouts: the raw week-pair correlation between percentage changes in mean hourly payouts and hours spent logged into the Uber app is a relatively low 0.11. London drivers, in other words, are able to adjust the quantity of hours worked without much impact on their hourly payouts.

3.2. How much does it pay to be an Uber driver?

Administrative data provides an extremely accurate account of the payouts that Uber drivers receive. However, it does not take vehicle operation costs into account. It therefore inevitably overstates driver earnings since expenses incurred while driving have not been deducted. Expenses are only observed by the individual driver and we therefore proceed to approximate hourly earnings net of these costs using two distinct approaches. First, we draw on administrative data from Uber on mean hourly payouts for each of the 1,001 individual drivers in our sample between January—March 2018, which we link to self-

[24] Among full-time drivers, nearly one in five (16 percent) adjust their hours logged into the app by more than a 50 percent on a weekly basis.

reported estimates of driver-level costs from the ORB survey, independent vehicle-level estimates of costs such as car taxes and depreciation, and TfL's estimates of the costs involved in becoming a licensed PHV driver. Second, we use self-reported information on income and hours worked from the ORB survey where drivers presumably deduct the expenses they have to bear. We describe in detail how we construct our cost estimates in the next section and return to presenting our results below in section 3.2.2.

3.2.1. Estimating the expenses of Uber drivers

Our cost estimates are based on three different sources: (i) self-reported driver-level estimates on insurance, petrol, and rental or repayment costs; (ii) independent vehicle-level estimates of car tax, depreciation, and servicing and maintenance costs; and (iii) estimates provided by TfL on the costs involved in becoming a licensed PHV driver.

As a starting point, we draw on self-reported estimates of driver-level costs from the ORB survey.[25] To obtain an estimate of the per-hour cost of driving that we can match to administrative data on hourly payouts, we first use information on each driver's reported weekly expenditure. Weekly expenditure includes car repayments and rental costs for drivers that finance or rent their car, as well as insurance and petrol for all drivers. We allocate the total weekly expenditure between driving with Uber and other use based on weekly hours driving with Uber as a share of total hours of any purpose driving.[26] We then scale the total expenditure to the hour level by dividing with the reported number of weekly hours driving with Uber.[27] Across the drivers in our sample, the mean hourly cost including car rental or repayments, insurance, and petrol for those renting or financing their car is £5.73 and £6.34 respectively. Among drivers that own their vehicle, the mean hourly cost is £4.27 covering insurance and petrol.[28]

We approximate car tax, depreciation, and servicing costs based on information on the vehicle used by each individual driver in our sample, which is drawn from anonymized administrative Uber data. For each individual make-model-year combination, we obtain information from a government-funded car cost aggregator—*the Money Advice Service*—that provides estimates of annual car tax, depreciation, and servicing costs.[29] We linearly

[25] As part of the ORB survey, drivers were asked to gauge the costs incurred from driving, including the cost of petrol in an average week, car insurance, as well as car rental payments or financing/leasing repayments. All cost items were summed to a weekly costing and respondents were offered the opportunity to revise the total figure. In addition to driving with Uber, respondents were also asked about the hours they were using their car for driving family or friends, leisure activities, practical personal use (e.g., shopping) in an average week: the median driver reported that they drive a total of 50 hours per week, out of which 40 hours are spent using the Uber app.

[26] While some drivers would potentially not own a car if not being an Uber driver, it is informative to note that only 15 percent of respondents in the ORB survey said they would 'not have a car at all' if they were not driving with Uber.

[27] We exclude drivers that report zero hours driving with Uber in an average week in the ORB survey.

[28] 'Owners' are defined as respondents in the ORB survey that state 'I paid for my car outright and do not make any repayments'. 'Financers' correspond to respondents that state 'I paid for my car using finance and make weekly or monthly payments and will own my car after all my payments are complete' or 'I paid for my car using lease finance and make weekly or monthly payments towards it and will have to return my car after all my payments are complete'. Renters correspond to respondents that state 'I rent my car for as long as I need it'.

[29] See: https://www.moneyadviceservice.org.uk. We extract costs for each make-model-year combination based on a total miles driven per year of 15,000 and expected ownership of one year. We impute the costs for

scale these costs by drivers' annual miles of any-purpose driving, and then divide it by the total annual number of hours of driving based on responses from the ORB survey. If a driver uses more than one vehicle, we calculate the cost for each individual vehicle and then calculate an average cost weighted by the driver's trip mileage using each respective vehicle. Based on this data, drivers that own their vehicle incur an additional average hourly cost of depreciation and servicing of £1.91, as well as £0.06 in car taxes. For drivers financing their vehicle, we include the cost of car taxes (on average £0.06 per hour among those financing their vehicle), maintenance and servicing (£0.33 per hour), and the cost of repayments rather than depreciation, as described above. We do not include car taxes, depreciation, or servicing costs for those renting their vehicles, as these costs are typically included in rental deals.

All Uber drivers are required to obtain a private hire driver licence that lasts three years which according to the TfL costs £310 (including the licence application fee and grant of licence fee), while a PHV licence requires annual renewal at a cost of £140 per year (we exclude the PHV license cost for those renting their vehicles, as this is typically covered by the rental cost). In addition, a driver has to pass a criminal background check (£56.85), medical examination (approximately £120), and a topographical test (approximately £75).[30] We convert the licensing cost to the hour level by summing each respective cost item and divide it by the reported number of hours driving with Uber per week scaled to a three-year period. Across the drivers in our sample, the mean estimated hourly cost of the license procedure is £0.24 per hour (£0.10 for those renting their vehicle) spent logged into the Uber app.

We aggregate these costs for each individual driver in our sample, which results in a mean total hourly cost of £6.51 across all drivers, while the cost for the median driver is £5.19. Since information on all individual vehicles used by drivers is not available, we present earnings estimates using both driver-level costs for the subset of drivers where all cost data is available, as well as estimates for all 1,001 drivers using a fixed cost corresponding to that which the median driver incur while driving for one hour.

3.2.2. Estimates of Uber drivers pay net of expenses

Table 3.2, panel A, presents estimates of hourly earnings net of expenses calculated as the difference between the average hourly payout net of Uber's service fee between January—March 2018 and the hourly cost estimates defined in the previous section.

Column 1 shows that among the 854 London drivers for which we observe driver-level costs, the median driver earns about £11.07 per hour logged into the Uber app after deducting costs incurred while driving. Column 2 restricts the sample to full-time drivers that report having no other part- or full-time job, or having their own business, and spend on average at least 40 hours logged into the Uber app each week. Estimated earnings are

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make-model-year combinations that lack information by averaging the cost estimates for identical make and model (but different year) combinations.

[30] English qualifications tests were not in effect during our study period, although they are a requirement from April 2019 and onwards (see: https://tfl.gov.uk/info-for/taxis-and-private-hire/english-language-requirement).

slightly reduced for drivers in the top half of the earnings distribution, which mainly reflects the lower average hourly payouts among this driver group.

We next explore the extent to which measurement error or misallocation of individual costs may influence our estimates. To that end, columns 3 and 4 deduct a fixed hourly cost for all (full-time) drivers corresponding to the median hourly expenses within the three groups of drivers that own, finance, and rent their car respectively. We interpret these estimates as the *earnings potential* of drivers calibrated to the vehicle optimization of the median driver. After deducting expenses and Uber's service fee, the median driver can expect to earn about £11.30 per hour. Notably, earnings levels increase particularly among drivers in the bottom half of the distribution in columns 3 and 4, which indicates an important role of operational costs in shaping earnings among drivers.

[TABLE 3.2 HERE]

As an alternative way to approximate hourly earnings levels net of expenses, we use information on self-reported income from the ORB survey where each driver was asked about their average pre-tax monthly income and hours driving with Uber.[31] A potential caveat with this data is that it may also include other income streams. To isolate drivers that are more likely to obtain the majority of their income from driving with Uber, we exclude drivers that reported working part- or full-time, or owned a business, in addition to being an Uber driver. We also restrict the sample to drivers that on average spend at least 40 hours per week logged into the Uber app to isolate full-time drivers, which are less likely to have other major income streams. We convert the monthly self-reported pre-tax income to a weekly income and divide it by the reported hours driving with Uber in an average week to obtain comparable estimates of hourly earnings.

Table 3.2, column 5, presents the implied hourly earnings level of £11.51, based on self-reported income and hours spent driving with Uber. It is reassuring that estimated hourly earnings levels drawing on this alternative source of data are broadly of a similar magnitude to the median estimates for full-time drivers of £10.72 and £11.09 in columns 2 and 4, which are derived from administrative data and estimated hourly expenses. A slightly higher level of earnings when relying on self-reported data can potentially be reconciled with our estimates by noting that the former may include other income streams than Uber despite our sample restrictions, or that drivers are not accurately deducting expenses.

A natural question is to ask how these pay rates compare to those of other groups of London workers. An important caveat in making such comparisons, however, is that many conventional workers may have additional benefits (e.g., holiday pay) that are not included in their reported pay rates, which complicates direct comparisons. Such complications notwithstanding, an interesting implication of the estimates in Table 3.2 is that the vast majority of Uber drivers earn above the National Living Wage standing at £7.50 prior to

[31] Again, the precise wording of the question in the ORB survey is: 'Thinking about your total average monthly income (before tax), what is your average monthly income?'

April 2018. Yet, as shown in panel B of Table 3.2, the estimated hourly earnings among the median Uber driver is lower than reported hourly pay rate of the median worker in London. A similar result is obtained in a comparison with the median hourly pay among workers in distribution, transport, and other services, or male immigrants that should both be relevant comparison groups in light of results discussed in section 2. At the same time, the estimated earnings for Uber drivers are broadly similar, or somewhat higher, compared to the reported hourly pay among London workers at the lower end of the pay distribution.

[FIGURE 3.5 HERE]

We next examine the earnings distribution of Uber drivers relative to the above-mentioned groups in the London labour market. Figure 3.5 plots the distribution of our earnings estimates for full-time drivers from Table 3.2, column 2, and the distribution of pay among full-time workers in distribution, transport, and other services, as well as male immigrants, in London with hourly pay rates below £25. As evident in the figure, there is a large share of workers in distribution, transport, and other services, as well as male immigrants, in London holding jobs with hourly pay rates similar to our estimates for Uber drivers. Although earnings are not directly comparable, these patterns are suggestive of labour market equilibration where the hourly earnings of Uber drivers are broadly similar to the pay levels in jobs that presumably reflect their outside options. Such an interpretation is also consistent with the results described in section 2 showing that most drivers reported leaving permanent jobs—often from the sectors depicted in Figure 3.5—to start driving with Uber. While the left tail of the distribution indicates that a small number of Uber drivers exhibit very low earnings, this is largely explained by drivers with very low capacity utilization rates, which drives down their mean hourly payouts as discussed above. Thus, while the patterns in Figure 3.5 are suggestive, we emphasize that the distribution of earnings should be interpreted cautiously given the challenges involved in accurately defining costs and working time for drivers in the tails of the distribution and, as noted above, we leave a detailed analysis of the individual determinants of drivers' capacity utilization, earnings, and payouts for future work.

A more conceptually challenging issue in making inferences about the relative welfare of drivers based on these estimates is that Uber drivers may put a high value on non-monetary benefits associated with being an independent worker, such as choice over working hours. Indeed, it is interesting to note that Mas and Pallais (2018) find that the *average* worker seemingly does not put a high value on scheduling flexibility, while they find that there exists a small group of workers with a high willingness-to-pay for flexibility. Indeed, a growing body of evidence suggests that Uber drivers tend to be drawn from groups that put a high premium on flexibility (e.g., Angrist et al., 2017; Chen et al., 2017; Hall and Krueger, 2018). As discussed above in section 2.2, flexibility is also a seemingly important motivation for joining Uber in London and most drivers would require substantially higher hourly pay rates to work on a fixed schedule. An important implication is thus that making inferences about the welfare of Uber drivers based on earnings alone may significantly underestimate their well-being if such job amenities are priced into their pay.

4. Are Uber drivers 'uber happy'?

Against the backdrop of a rich literature documenting how a range of job characteristics beyond monetary compensation shapes individuals' subjective well-being, we turn to examining well-being among Uber drivers in London. In our analysis, we explore two distinct domains of subjective well-being: life evaluation measures, which are based on an individual's assessment of his or her life over a longer time horizon, and emotional well-being, which measures the quality of an individual's everyday experience through the lens of emotions such as anxiety or happiness (see Kahneman and Krueger, 2006, and Kahneman and Deaton, 2010). An increased interest in alternative metrics to elicit information about individual well-being has fortunately not been limited to academic research. Official government surveys in the UK have in past decades increasingly followed suit in measuring subjective well-being, to aid the monitoring of national well-being, facilitate international comparisons, and help citizens to make informed decisions about their lives, such as choosing a place to live and work. In the analysis below, we rely on ONS data for the London workforce matched with a new dataset on subjective well-being among our sample of 1,001 Uber drivers from the ORB survey. In the next subsection, we describe the measurement of different dimensions of subjective well-being and in the subsequent two subsections we compare the well-being of Uber drivers with other London workers, and explore the determinants of their well-being.

4.1. Measuring subjective well-being

As part of the ORB survey, we included several questions to elicit measures of life evaluation and emotional well-being among Uber drivers following an identical survey methodology to that of the ONS. A first-order concern is that individuals may be reluctant to answer questions that probe their well-being. Yet, questions relating to an individual's happiness or well-being typically have higher response rates than, for example, questions relating to an individual's earnings (Kahneman and Krueger, 2006, p.6). Indeed, while almost a third of the drivers in the ORB survey refused to report their precise monthly income, not a single individual refused to answer any of the questions relating to their subjective well-being.[32] As is well-known from the literature on subjective well-being, the survey structure may give rise to ordering effects (e.g., Bertrand and Mullainathan, 2001). In particular, questions relating to potentially sensitive topics such as family situation or

[32] An additional concern is that respondents may respond differently to interviews carried out face-to-face vs. interviews carried out by telephone. According to the ONS, testing has shown that respondents tend to give more positive answers when interviewed by telephone, as compared to face-to-face interviews. Although this may affect reported levels of subjective well-being, the available versions of the APS datasets do not allow for a distinction between well-being measures derived from telephone vs. face-to-face interviews, which precludes any direct examination of how the mode of interviewing affects well-being measures.

income, for example, may affect levels of self-reported well-being. In the ORB survey, the well-being questions were therefore placed directly after an introductory set of neutral questions and the ordering of questions was identical as in the ONS surveys underlying the APS dataset. Each individual driver was asked the following four questions:

1. Overall, how satisfied are you with your life nowadays?
2. Overall, to what extent do you feel that the things you do in your life are worthwhile?
3. Overall, how happy did you feel yesterday?
4. Overall, how anxious did you feel yesterday?

and were asked to give their answer on an 11-point scale ranging from 0-10, where 0 is 'not at all' and 10 is 'completely'. An empirical concern is that imposing a cardinal interpretation of subjective well-being measures may be problematic, as it assumes that respondents are accurately converting verbal labels such as 'not at all' and 'completely' and divides the response space into equal parts when giving their numerical answer (Clark, Frijters, and Shields, 2008). Yet, there is extensive evidence based on a variety of datasets showing that the assumption of cardinality of responses and the use of linear models typically yields very similar results to using ordered models, and that the debate over whether subjective well-being measures are ordinal or cardinal has limited empirical relevance (e.g., Helliwell, 2003; Ferrer-i-Carbonell and Frijters, 2004; Kahneman and Krueger, 2006).

4.2. Subjective well-being among Uber drivers and London workers

Table 4.1 reports the average responses to the four well-being questions among Uber drivers based on the ORB survey and similar estimates for other employed and self-employed workers aged 18 and above residing in London drawn from the April 2016—March 2017 APS dataset. Although average differences in subjective well-being are informative, they potentially conceal a great deal of within-group variation. As a complementary approach, we therefore also present results in Figure 4.1 using the thresholds defined by the ONS to convert the numerical responses to each subjective well-being question into four categories ranging from 'low' to 'very high'.[33]

[TABLE 4.1 HERE]

[33] Answers to the life satisfaction, worthwhileness, and happiness questions are here classified on a scale from low (rating 0-4), medium (5-6), high (7-8), to very high (9-10). Answers to the anxiety question is similarly classified on a scale ranging from very low (0-1), low (2-3), medium (4-5), to high (6-10). For more information, see: https://www.ons.gov.uk/peoplepopulationandcommunity/well-being/methodologies/personalwell-beingintheukqmi

Table 4.1 shows that Uber drivers report the highest average levels of evaluative well-being, while self-employed workers report higher levels than those in traditional work arrangements. Notably, a comparison with road transport drivers (that includes black cab and PHV drivers) also suggests that Uber drivers exhibit higher levels of evaluative well-being than the broader pool of conventional drivers.[34] At the same time, while Uber drivers report higher levels of happiness than employed London workers, the level is slightly lower than among the self-employed. A similar picture arises from Figure 4.1. Using both measures of evaluative well-being (life satisfaction and worthwhileness) and happiness, the share of individuals that report 'very high' is highest among Uber drivers. At the same time, although the differences are smaller in magnitude, there is also a higher share that report 'low' subjective well-being, which indicates that the distribution of subjective well-being is more polarized among Uber drivers. One should, however, be cautious in attaching a causal interpretation to these differences since it is plausible that individuals with a brighter outlook on life, or with personality traits correlated with higher well-being select into self-employment, or driving with Uber. Yet these results are consistent with a growing body of work showing that the self-employed generally tend to exhibit higher levels of subjective well-being in most countries, also when controlling for a range of potentially omitted (observable) characteristics (e.g., De Neve and Ward, 2017).

[FIGURE 4.1 HERE]

As shown in Table 4.1 and Figure 4.1, however, Uber drivers also report substantially higher average levels of anxiety relative to both self- and wage-employed workers. One potential explanation—presumably intuitive to anyone who has been driving in London—is that higher anxiety levels may arise from driving *per se*. Yet, the reported anxiety levels among Uber drivers is considerably higher also compared to road transport drivers (with an average anxiety rating of 3.05) suggesting that the higher stress levels are not simply a function of driving in London. While the ongoing public debate regarding Uber's fate in the capital city may serve to fuel a higher anxiety among drivers also relative to other London drivers, there is some additional evidence suggesting that the higher anxiety levels are more likely related to Uber drivers' work arrangements. Indeed, a more granular look at the subjective well-being among the self-employed in London suggests that anxiety levels are also higher among freelance workers (the average self-reported anxiety is 3.49) with similar work arrangements as Uber drivers. In our view, a plausible hypothesis based on these patterns is therefore that having more autonomy at work simultaneously leads to higher levels of life satisfaction *and* anxiety among Uber drivers. More broadly, this is consistent with the fact that while self-employed workers tend to report higher average levels of life evaluation, working for oneself or owning a business is also generally associated with a heightened experience of negative emotions such as anxiety, stress, or worry (De Neve and Ward, 2017).

[34] In the APS, the average life satisfaction, for example, among employed and self-employed road transport drivers is 7.42, which is lower than among the broader London workforce.

[TABLE 4.2 HERE]

A potential explanation for these observed differences in subjective well-being is that they arise due to compositional differences. If groups that on average are more satisfied with their lives become Uber drivers, the observed differences in evaluative well-being may simply reflect such underlying compositional differences. To explore whether this is the case, we perform a simple Blinder-Oaxaca decomposition to examine whether compositional differences in terms of demographics or income can account for the gap in well-being between Uber drivers and other London workers.[35] Table 4.2 presents the results from such a decomposition exercise where we control for a quartic in age, educational attainment, ten major ethnic groups, immigrant status, marital status, sex, as well as (*ln*) gross weekly income. As evident from Table 4.2, the 'unexplained' gap is even larger than the raw gap when comparing life satisfaction, worthwhileness, and anxiety. Thus, compositional differences are, if anything, biasing the relative subjective well-being of Uber drivers downwards.[36] Naturally, this puts further emphasis on the question: why do individuals driving with Uber exhibit higher levels of life satisfaction, despite primarily being drawn from disadvantaged low-income groups in the labour market?

4.3. What explains the subjective well-being of Uber drivers?

As a first step to understand why Uber drivers exhibit higher levels of life satisfaction and worthwhileness than the general London workforce, we proceed to disentangle the underlying determinants of differences in subjective well-being among drivers. Against the backdrop of Uber drivers being drawn from low-income groups in the London labour market, the fact that they on average exhibit higher life evaluation scores is at odds with absolute income levels being an important determinant of their subjective well-being. To explore the role of income, we first estimate simple OLS regressions comparing a variety of income measures and subjective well-being among London drivers. We control for a set of baseline demographic controls, (*ln*) mean hours logged into the Uber app per week, a set of indicators capturing whether a driver holds another job or has a business, as well as a full set of ethnic group fixed effects.[37] An important concern is that attrition from the Uber platform of less satisfied drivers may mechanically lead to higher subjective well-being among the driver pool that we observe. Therefore, we always also include tenure

[35] We restrict our comparisons to employed London workers because the self-employed are not reporting income in the APS dataset. We have experimented with alternative decompositions excluding income as a covariate and including self-employed workers, which yields similar results (not reported).

[36] We obtain similar results when estimating differences in life satisfaction between Uber drivers and London workers using propensity score matching techniques based on the same set of covariates as in the Blinder-Oaxaca decomposition. Using one nearest neighbour and imposing common support (leading to the exclusion of 20 drivers in the sample), we find a gap in life satisfaction of 0.473 (*t*-stat = 3.42) that is larger than the gap observed between Uber drivers and London workers in the unmatched sample.

[37] We limit our sample in the subsequent analysis to the subset of drivers with non-missing data on all controls such as age, educational attainment, and ethnicity.

(number of years since first trip on the Uber platform) as a control though we find no link between tenure and any the four subjective well-being measures (see Table A.4).

[TABLE 4.3 HERE]

Table 4.3 show that there exists no apparent relationship between life satisfaction and absolute income among Uber drivers in London.[38] Column 1 documents that the link between life satisfaction and (*ln*) gross weekly income, while positive, is small in magnitude and not statistically significant. Columns 2 and 3 reports similar non-significant relationships between life satisfaction and mean hourly payouts (net of expenses) where the estimated link is *negative* though again small in magnitude.[39] Reassuringly, we obtain similar results in columns 5-7 when examining the link between gross weekly income and other measures of evaluative and emotional well-being. Thus, absolute income is seemingly unrelated to subjective well-being among the pool of Uber drivers.

A growing body of work, however, argues that subjective well-being is rather shaped by *changes* in income. Intuitively, this literature documents that individuals tend to evaluate their income in relation to their own past income and that increases tend to correlate positively with subjective well-being (e.g., Clark and Oswald, 1996; Ferrer-i-Carbonell, 2005; Luttmer, 2005; Clark, Frijters, and Shields, 2008). As a first test of this hypothesis, Figure 4.2 plots life satisfaction scores among Uber drivers and whether they perceive that their income has increased, stayed the same, or decreased after partnering with Uber based on responses in the ORB survey. The share reporting 'very high' life satisfaction is substantially higher among respondents that perceive their income to have increased 'a lot' and decreases monotonically with lower increases in income.[40] In other words, while drivers' absolute level of income seemingly has a limited explanatory role, Figure 4.2 is suggestive of a positive link between relative changes in income and their overall life satisfaction.

[FIGURE 4.2 HERE]

To bolster our interpretation of these patterns, column 4 of Table 4.3 presents OLS regressions that confirm a significant link between changes in income after joining the

[38] We present the full regression output in the Appendix (see Table A.4).

[39] Note that the number of observations is reduced in column 3 mainly due to missing data on hourly expenses. As an alternative earnings measure, we have also estimated Mincer earnings regressions using the LFS to estimate the predicted pay in traditional work for each individual Uber driver based on the full set of demographic covariates. However, we find no link between subjective well-being and the *difference* between a driver's hourly payout (net of expenses) and the predicted hourly pay in other employment based on a driver's characteristics (not reported).

[40] It is interesting to note that the mean hourly payout net of Uber's service fee is relatively stable across the distribution of perceived changes in income: drivers who state that their income decreased 'a lot' after partnering with Uber have a mean hourly payout of £16.15, while drivers who state that their income increased 'a lot' have a mean hourly payout of £16.49. A stable distribution of hourly payouts suggests that the variation in perceived income changes is driven mainly by income levels prior to driving Uber, rather than variation in hourly earnings on the Uber platform.

Uber platform and life satisfaction, where the omitted group is respondents stating that their income has 'stayed the same'. Notably, the pattern visualized in Figure 4.2 thus remains broadly unaffected when controlling for an individual's self-reported weekly income and the baseline set of controls. Moreover, the overall weaker link between relative income and emotional well-being (i.e., happiness and anxiety) in columns 6 and 7 is also consistent with the argument that income mainly affects evaluative, rather than emotional, well-being (Kahneman and Deaton, 2010). Thus, while these correlations should not be interpreted as causal links, they suggest that relative income is seemingly important in explaining the variation in evaluative well-being among Uber drivers. In other words, drivers that left lower-paid work to partner with Uber report being more satisfied with their lives, while those that saw their incomes decrease report relatively lower levels of evaluative well-being.

An emerging literature also shows that subjective well-being is strongly associated with job characteristics: the level of individual autonomy, control over how the workday is organized or the pace of work, as well as work-life balance all emerge as particularly strong predictors (De Neve and Ward, 2017). In light of this, an interesting hypothesis is that the flexibility offered by the Uber platform and the fact that drivers use this extensively to shift their hours worked from week to week might help explain the relatively high levels of life satisfaction among drivers. Indeed, as shown in Table 4.4, there is no evidence of a direct link between the (*ln*) mean hours spent logged into the Uber app per week and either evaluative or emotional well-being.[41] Although these estimates may differ for part- and full-time drivers, the link between hours spent logged into the app and evaluative well-being is *positive* among full-time drivers, further suggesting that there exists no negative effect of long hours, though the smaller sample of full-time drivers should caution the interpretation of these correlations.[42]

A non-existent link between hours spent logged into the Uber app and life satisfaction among drivers is interesting in light of a substantial debate over whether working long hours has a causal negative effect on subjective well-being, or whether it simply reflects a mismatch between actual and preferred working time (e.g., Wooden et al 2009; Angrave and Charlwood 2015; Hamermesh et al., 2017). Since an Uber driver is free to drive as many hours as he or she wants, it should reduce mismatch between actual hours worked and working time preferences.[43] Thus, a suggestive interpretation of these results is that improving choice over working hours diminishes the negative relationship between working hours and well-being observed among workers in traditional employment arrangements, suggesting it is mainly driven by mismatch and the lack of scheduling flexibility.

[41] Instead, using self-reported hours driving with Uber in an average week from the ORB survey yields a weak negative relationship that is not statistically significant and small in magnitude.

[42] A similar regression as that in column 1 in a sample restricted to full-time drivers yields an OLS estimate (s.e.) of the coefficient for (*ln*) mean weekly hours spent logged into the Uber app of 1.76 (1.01), which implies that a one standard deviation increase in hours spent logged into the app is associated with an *increase* in life satisfaction of about 0.12 standard deviations.

[43] However, since January 2018 there is an upper limit of 10 hours after which a driver cannot access the app for the next six-hour block to prevent 'drowsy driving' thus marginally reducing drivers' discretion over hours.

[TABLE 4.4 HERE]

As described in more detail in section 2.2, the vast majority of drivers tend to emphasize the role of flexibility as an important motivation to start driving with Uber. To more directly explore the potential role of drivers' preferences over flexibility in shaping subjective well-being, we present simple OLS regressions in Table 4.4 where we correlate the four subjective well-being measures with responses from the ORB survey indicating the extent to which a respondent's decision to partner with Uber was motivated by flexibility.

Columns 1 and 3 show that drivers who 'agree' or 'strongly agree' with the statement 'I partnered with Uber to have more flexibility in my schedule and balance my work life and family' or 'Being able to choose my own hours is more important than having holiday pay and a guaranteed minimum wage' exhibit substantially higher levels of life satisfaction on average, conditional on an extensive set of controls including income and weekly hours spent logged into the Uber app. Similarly, column 2 shows that drivers who state that they prefer to work flexible rather than fixed hours report higher levels of life satisfaction relative to the minority of drivers that prefer a fixed schedule. While drivers who 'agree' or 'strongly agree' with the statement 'I don't want to work for a traditional company in case I lose the flexibility I have' are slightly more satisfied with their lives relative to those that disagree, the estimated difference is small in magnitude and not statistically significant (column 4). As shown in columns 7 and 8, the majority of drivers that tend to emphasize flexibility as a motivation to drive with Uber also generally exhibit higher levels of worthwhileness and happiness. Although direct comparisons should be interpreted with caution, it is interesting to note that the relative differences in subjective well-being between drivers that emphasize flexibility and those that do not are similar in magnitude as the gap in well-being between drivers that say that their income increased after partnering with Uber and those that say it stayed the same (see Table 4.3).

Against the backdrop of these correlations, it is not surprising that the majority of drivers that state that they prefer to remain independent contractors, rather than to be classified as employees or workers and thus lose their scheduling flexibility, also report higher levels of life satisfaction (column 5).[44] As shown in column 9, these drivers also exhibit substantially lower levels of anxiety relative to those that state they would prefer to be employees or workers. Interestingly, the subset of drivers that state that they prefer not to work on a fixed schedule exhibit both significantly higher levels of evaluative well-being *and* anxiety, which is consistent with a trade-off between evaluative and emotional well-being observed among other self-employed workers discussed above.

[44] An alternative interpretation of these correlations is that drivers that put a higher value on the flexibility offered by the Uber platform or prefer to remain independent contractors also have stronger 'work identity', which in turn may partly explain the positive relationship with subjective well-being (Bryan and Nandi, 2015). An informal test of the work-identity hypothesis is to examine whether drivers who, in the ORB survey, state that they would continue driving (with another app, or as a black cab, minicab, or PHV driver) if Uber was no longer available in their area exhibit higher levels of life satisfaction. While the correlation is positive, it is small in magnitude and not statistically significant (not reported).

In our view, these correlations constitute suggestive evidence that at least part of the higher evaluative well-being among London's Uber drivers stems from their preferences for flexibility and the autonomy that the platform offers.[45] However, while we can rule out that the gap in subjective well-being reflects observable group-level differences between Uber drivers and other London workers, it may still be the case that drivers are selected based on unobservables that are potentially correlated with drivers' emphasis on flexibility as a motivation to become an Uber driver. While we cannot fully rule out such alternative explanations, the fact that the variation in subjective well-being within the group of Uber drivers is polarized and tightly linked to drivers' emphasis on flexibility is highly suggestive. In particular, drivers that are less content with their work arrangements tend to report significantly lower levels of subjective well-being than other Uber drivers. Moreover, the mean reported life satisfaction among the minority of drivers that would prefer to be classified as employees or workers, rather than independent contractors, even if it means losing their scheduling flexibility is similar to that reported by other drivers in London.[46] Thus, while the majority of Uber drivers report being more satisfied with their lives than other London workers, those drivers that place less value on the flexibility that the platform offers are seemingly no better off than other drivers in traditional work arrangements.

5. Concluding discussion

Though the gig economy is still a small percentage of total employment, it is by most accounts becoming an increasingly prominent feature of work in the 21st century (e.g., Katz and Krueger, 2016; Abraham et al., 2017). While some see this as a shift toward increasingly precarious employment, others put more emphasis on the opportunities offered to people with a preference for flexible work. For policy makers interested in the well-being of the working population, it thus seems critical to understand how workers fare as labour markets evolve. Yet, a lack of systematic measurement limits our knowledge of workers' well-being in the gig economy.

In this paper, we provide the first comprehensive statistical evaluation of work and well-being in the gig economy through the lens of Uber and its drivers in London. Drawing upon new survey data, administrative data from Uber, and newly collected data on vehicle costs, we shed light on the background, income, and subjective well-being of the gig workforce. Our findings suggest that the typical Uber driver did not sign up to the platform as a last resort. A meagre two percent of drivers were previously unemployed, and the vast

[45] In light of the fact that the majority of drivers are immigrants, a potential alternative explanation for the higher levels of life satisfaction is lower levels of discrimination on the Uber platform relative to the conventional cab and taxi sector. Yet, as shown in Table A.4 there are no statistically significant differences in life satisfaction between immigrant and native drivers, which suggests that this is a less relevant explanation. However, further work on how digital matching platforms may affect levels of ethnic and racial discrimination constitutes, in our view, an important area for future research.

[46] Among the minority of Uber drivers that would prefer traditional working arrangements, the mean life satisfaction score is 7.34, which is close to the average reported life satisfaction of 7.42 among other road transport drivers in London discussed above.

majority left permanent part- or full-time jobs to start driving with Uber. Most were seemingly attracted by the flexibility that the platform offers, and use their discretion over working time to significantly adjust hours worked from week to week. It is also noteworthy that London's Uber drivers overwhelmingly come from economically disadvantaged backgrounds. About four-fifths of drivers are first-generation male immigrants, mainly drawn from the bottom half of the London income distribution, suggesting that Uber provides work for groups that are often marginalized in the labour market.

While about half of drivers' report that their earnings increased after partnering with Uber, we estimate that they have firmly remained at the lower end of the London pay distribution: the median driver earns about £11 per hour spent logged into the app after both Uber's service fee and the costs incurred by driving have been deducted. Yet while being an Uber driver is relatively low-paid work, the London drivers' report higher average levels of life satisfaction than other workers. A gap in subjective well-being persists when compositional differences are accounted for, and is seemingly unrelated to absolute income levels and working time among Uber drivers. Instead, we provide suggestive evidence that their higher subjective well-being partly can be explained by strong preferences for flexible work among the majority of Uber drivers, and the fact that they have full discretion over working hours.

The flipside of being an Uber driver, it seems, is higher levels of anxiety. Uber drivers report substantially higher average levels of anxiety than the remainder of the London working population. This finding mirrors those of past studies showing that while self-employed workers report higher average levels of life satisfaction, working for oneself or owning a business is also generally associated with a heightened experience of negative emotions such as anxiety and stress. However, the anxiety levels across the pool of Uber drivers are highly polarized, which seemingly reflects divergent preferences for flexibility: drivers who want to remain independent contractors exhibit lower levels of anxiety, whereas roughly a fifth of the Uber driver pool, which attaches less value to flexibility, and would prefer to be classified as an employee, exhibit lower levels of life satisfaction and higher levels of anxiety. Thus, the polarization of well-being among Uber drivers' highlights a well-known challenge for policy makers. As recently put by the Taylor review on modern working practices:

> *'Hearing one person describe a job as the best they have had followed by another person describing the same job as highly stressful or exploitative highlights the challenge for policy makers in seeking to promote better work for all.'*[47]

An important question is to what extent our findings are generalizable to other forms of flexible work arrangements, or Uber drivers in other countries. While our study provides

[47] See: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/627671/good-work-taylor-review-modern-working-practices-rg.pdf

a first step in shedding light on work and well-being in the gig economy, we caution against interpreting our findings as applicable across geographies and digital platforms for several reasons. First, the gig economy—like the conventional labour market—consists of a broad range of segments, of which many are seemingly not comparable. For example, recent estimates suggest that median hourly earnings on Amazon Mechanical Turk are as low as ~$2 (Hara et al., 2017). In contrast, our findings suggest that the majority of Uber drivers earn above the UK minimum wage. Though direct comparisons are complicated by mandated benefits in conventional jobs, earnings on the Uber platform are seemingly similar to other low-paid jobs held by large groups of male immigrants in London. While this highlights differences in pay across two platforms, more work is surely needed to more fully understand the variation in income across countries and gig platforms, and the extent to which it is shaped by country-, platform-, and worker-specific factors.

Second, the relative attractiveness of gig work likely differs across countries, depending on labour-market institutions and prevalent economic conditions. For example, that few London drivers were unemployed prior to joining Uber is consistent with previous studies of Uber drivers in Egypt and the United States (Hall and Krueger, 2018; Rizk, 2017). In France, however, a quarter of drivers were previously unemployed (Landier et al., 2016), which possibly reflates to extremely high rates of youth unemployment (Cahuc et al., 2013). Similarly, entry barriers (e.g., in terms of costs and licensing requirements) also shape individual selection patterns. While London's Uber drivers in most dimensions resemble the broader taxi driver workforce, the demographic makeup of US drivers mirrors the general workforce rather than taxi driver population, presumably reflecting lower barriers to entry (Hall and Krueger, 2018). Thus, understanding the extent to which transitions into gig work differs across countries and how it relates to national labour-market institutions is an important area for future research.

Still, our findings have important general implications for future work on the gig economy. The preference for flexible work expressed by Uber drivers, which we find to be strongly correlated with their subjective well-being, suggests that evaluations of the gig economy preferably should go beyond monetary metrics. Notably, an important role of non-monetary factors also extends to more traditional work arrangements. Indeed, the latest British Social Attitudes survey shows that less than half feel that work is only about monetary compensation, and the importance people attach to income has been falling in recent years. Thus, happiness economics seemingly has an important role to play in the context of evaluating workers' welfare in the future of work.

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A. APPENDIX

A.1 Survey design and sample selection

At the request of Uber, ORB, a polling company and member of the British Polling Council, were commissioned to run an independent survey of a representative sample of Uber drivers in London. To ensure that we are surveying current drivers that are active in London mainly driving with UberX or UberPOOL, we limited the pool of drivers to those that fulfilled the following criteria:

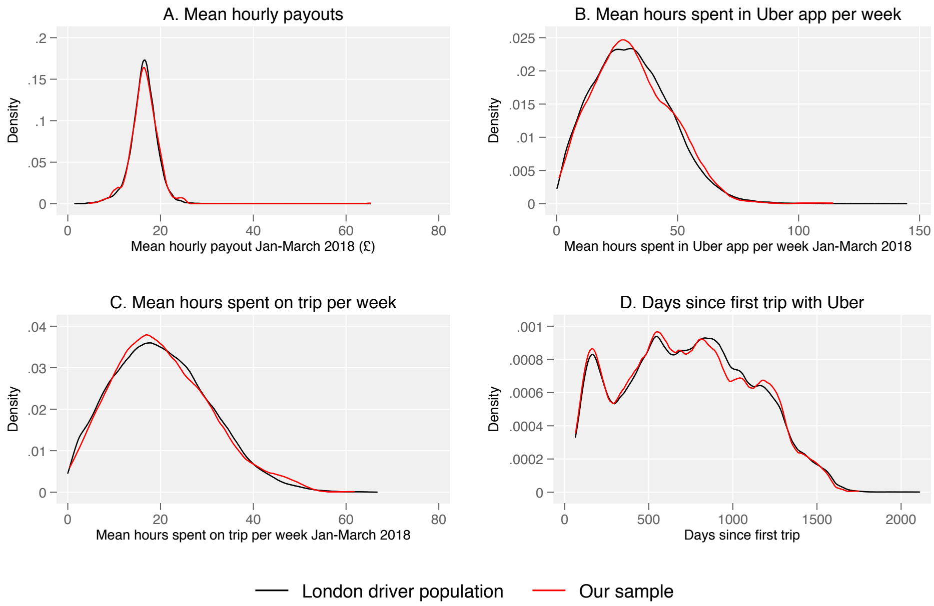
- *Spatial:* Drivers had completed at least 80 percent of their trips in London, identified using Uber's 'geofence' which broadly overlaps with the Greater London area.
- *Temporal:* Drivers had completed at least one trip in the last four weeks.
- *Total weeks worked:* Drivers were required to have worked at least eight distinct weeks in the last year (52 weeks from week starting 2017-02-27).
- *Mean trips per week:* Drivers were required to have on average (over all weeks in the last year) completed one or more trips per week.
- *Product type:* Drivers were required to have done at least 90 percent of their trips on UberX or UberPOOL to exclude drivers providing high-end services.

Approximately 38,000 drivers fulfilled these criteria, which can be compared to the approximately 50,000 drivers that completed at least four trips in London during March 2018 (see Figure 2.1 above). Uber provided ORB with a random sample of 16,000 driver records from the population of 38,000 drivers, that solely contained unique identifiers and telephone numbers of London drivers. ORB conducted 1,001 telephone interviews between 18th—28th March 2018 by randomly selecting interviewees from the sample of 16,000 drivers that fulfilled the criteria through a computer-aided random digit dialer. In the case of non-response from a selected respondent, or a respondent answering but being unavailable at that particular time, a call-back was scheduled. ORB provided Berger and Frey with the raw data from the interviews, and Uber with non-identifiable aggregated data tables.

A.2 Balance tests

An empirical concern is that the 1,001 interviewed drivers are not representative of the broader London pool of Uber drivers, for example, due to non-response bias. To explore the representativeness of the final sample of 1,001 drivers, Figure A1 depicts the distribution of four central driver characteristics for this sample and the 38,000 London drivers that fulfilled the four criteria outlined in the previous section and thus constituted the underlying population. Reassuringly, the distribution of mean hourly payouts, hours spent in the Uber app per week, and mean hours spent on trip is virtually identical. In the bottom-right panel, we also show that the distribution of tenure (days since first trip with Uber) is very similar. Additional balance tests reported in Table A1 lend further support to these ocular inspections, showing that there are no statistically significant differences in group means between our sample and the full population of London drivers in these four dimensions. In our view, this evidence strongly suggests that our sample of 1,001 drivers is representative of the population of London drivers.

Figure A.1: Sample representativeness.



Notes: These figures plot the kernel density distribution of four key variables (mean hourly payouts net of Uber's service fee, mean hours spent logged into the Uber app per week, mean hours spent on trip per week, and the number of days since a driver's first trip with Uber) among the 1,001 drivers in our sample and the London population of drivers in January—March 2018.

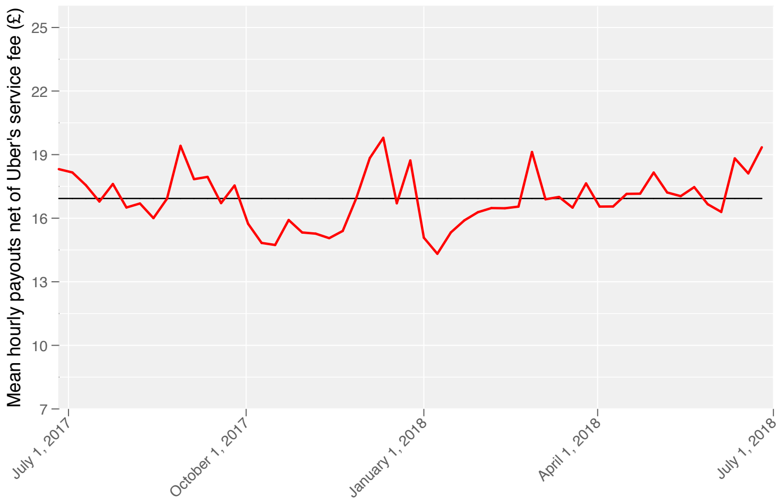
Table A.1: Balance tests.

	Our sample (1)		London drivers (2)		Difference (t-test) (3)
	N	Mean/SE	N	Mean/SE	(1)-(2)
Mean hourly payout	1001	16.486	38041	16.405	0.081
		[0.104]		[0.015]	
Mean hours spent in Uber app per week	1001	31.386	38041	31.101	0.284
		[0.508]		[0.082]	
Mean hours spent on trip per week	1001	20.277	38041	20.215	0.062
		[0.332]		[0.054]	
Days since first trip	1001	719.735	38041	728.470	-8.734
		[11.963]		[1.936]	

Notes: This table reports balance tests of four key characteristics of drivers (mean hourly payouts net of Uber's service fee, mean hours spent logged into the Uber app per week, mean hours spent on trip per week, and the number of days since a driver's first trip with Uber) in our sample and the full population of London drivers. Values displayed for t-tests are the differences in the means across the groups and ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

A.3 Additional figures and tables

Figure A.2: Mean hourly payouts net of Uber's service fee among London drivers, 2017-2018.



Notes: This figure displays weekly mean hourly payouts net of Uber's service fee in London for drivers that fulfil the sample selection criteria outlined in section A.1. Mean hourly payouts is calculated for each week as the unweighted average of mean hourly payouts across all active drivers in that week. A solid horizontal line denotes the mean hourly payout over the period.

Table A.2: Hourly payouts and driver characteristics.

Outcome:	Mean hourly payout (ln)		Mean hourly payout net of expenses (ln)	
	(1)	(2)	(3)	(4)
Age	-0.002**	(0.001)	-0.002	(0.002)
Female (=1)	0.017	(0.064)	0.158*	(0.084)
Immigrant (=1)	0.009	(0.022)	-0.025	(0.053)
Married (=1)	-0.013	(0.016)	0.036	(0.044)
High school degree (=1)	-0.020	(0.023)	-0.091	(0.059)
Some college (=1)	0.007	(0.021)	0.001	(0.051)
College (=1)	0.001	(0.022)	-0.051	(0.054)
Asia (=1)	0.001	(0.038)	0.068	(0.114)
Bangladeshi (=1)	0.082**	(0.036)	0.187*	(0.105)
Chinese (=1)	0.011	(0.044)	0.248**	(0.110)
Black (=1)	0.014	(0.033)	0.063	(0.107)
Indian (=1)	-0.030	(0.044)	-0.137	(0.150)
Mixed/multiple (=1)	0.058	(0.058)	0.190	(0.117)
Other (=1)	-0.039	(0.038)	0.019	(0.120)
Pakistani (=1)	0.000	(0.038)	0.029	(0.110)
Other White (=1)	-0.069*	(0.038)	-0.026	(0.116)
White British (=1)	.	(.)	.	(.)
Additional full-time job (=1)	-0.018	(0.026)	-0.005	(0.054)
Additional part-time job (=1)	-0.026	(0.025)	-0.048	(0.059)
Additional business (=1)	0.019	(0.027)	-0.009	(0.099)
Tenure (years since first trip)	0.021***	(0.007)	0.048**	(0.019)
Mean weekly hours spent in Uber app (*ln*)	-0.010	(0.019)	0.006	(0.036)
Constant	2.857***	(0.082)	2.261***	(0.167)
Observations	822		687	
R-squared	0.072		0.049	

Notes: This table reports OLS estimates from driver-level regressions where the outcome is the natural log of the mean hourly payout net of Uber's service fee, or the mean hourly payout net of expenses. Robust standard errors are reported in parentheses. Statistical significance is denoted by: *** p<0.01, ** p<0.05, * p<0.1.

Table A.3: Hourly payouts and driver characteristics including total trips.

Outcome:	Mean hourly payout (*ln*)		Mean hourly payout net of expenses (*ln*)	
	(1)	(2)	(3)	(4)
Age	-0.002**	(0.001)	-0.002	(0.002)
Female (=1)	-0.006	(0.051)	0.122*	(0.067)
Immigrant (=1)	0.005	(0.020)	-0.030	(0.053)
Married (=1)	-0.004	(0.015)	0.049	(0.043)
High school degree (=1)	-0.022	(0.022)	-0.099*	(0.058)
Some college (=1)	0.004	(0.020)	-0.006	(0.050)
College (=1)	-0.000	(0.020)	-0.054	(0.052)
Asia (=1)	0.005	(0.034)	0.092	(0.107)
Bangladeshi (=1)	0.087***	(0.033)	0.203**	(0.099)
Chinese (=1)	0.015	(0.037)	0.258***	(0.098)
Black (=1)	0.016	(0.030)	0.081	(0.100)
Indian (=1)	-0.028	(0.042)	-0.130	(0.152)
Mixed/multiple (=1)	0.013	(0.061)	0.118	(0.108)
Other (=1)	-0.031	(0.034)	0.046	(0.113)
Pakistani (=1)	0.003	(0.035)	0.048	(0.105)
Other White (=1)	-0.062*	(0.034)	-0.008	(0.110)
White British (=1)	.	(.)	.	(.)
Additional full-time job (=1)	-0.013	(0.025)	0.008	(0.054)
Additional part-time job (=1)	-0.032	(0.024)	-0.065	(0.058)
Additional business (=1)	0.026	(0.025)	0.005	(0.091)
Total no. of completed trips (100s)	0.026***	(0.004)	0.044***	(0.010)
Mean weekly hours spent in Uber app (*ln*)	-0.122***	(0.033)	-0.190***	(0.064)
Constant	3.111***	(0.099)	2.722***	(0.185)
Observations	822		687	
R-squared	0.135		0.076	

Notes: This table reports OLS estimates from driver-level regressions where the outcome is the natural log of the mean hourly payout net of Uber's service fee, or the mean hourly payout net of expenses. Robust standard errors are reported in parentheses. Statistical significance is denoted by: *** p<0.01, ** p<0.05, * p<0.1.

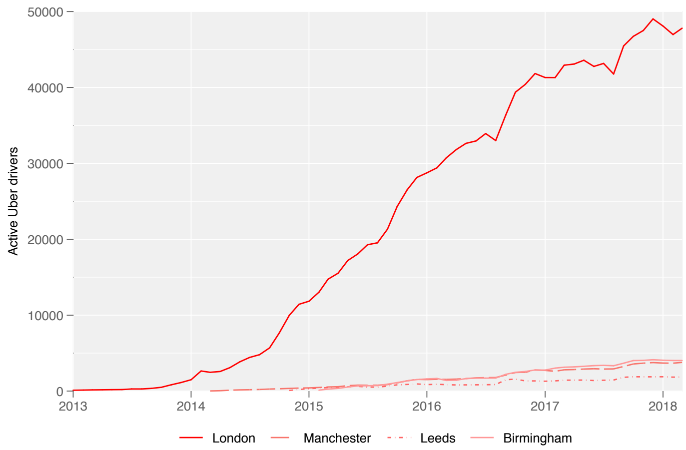
Table A.4: Subjective well-being and driver characteristics.

	Outcome: Subjective well-being (0-10)							
	Life satisfaction		Worthwhileness		Happiness		Anxiety	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gross weekly income (*ln*)	0.093	(0.134)	0.066	(0.123)	0.164	(0.171)	-0.150	(0.224)
Income change after partnering with Uber								
Increased a lot (=1)	0.982***	(0.223)	0.670***	(0.197)	-0.460	(0.368)	0.220	(0.466)
Increased (=1)	0.485***	(0.178)	0.187	(0.168)	0.455**	(0.227)	-0.472	(0.318)
Stayed the same (=1)	.	(.)	.	(.)	.	(.)	.	(.)
Decreased (=1)	-0.880***	(0.265)	-0.718***	(0.245)	-0.999***	(0.368)	-0.726*	(0.426)
Decreased a lot (=1)	-1.669***	(0.447)	-1.273***	(0.399)	-1.571***	(0.514)	0.507	(0.570)
Don't know (=1)	0.022	(0.445)	-0.171	(0.406)	-0.096	(0.513)	-1.428**	(0.583)
Mean weekly hours spent in Uber app (*ln*)	-0.122	(0.134)	-0.018	(0.124)	-0.014	(0.154)	0.076	(0.225)
Age	0.020**	(0.008)	-0.004	(0.008)	0.007	(0.011)	-0.006	(0.015)
Female (=1)	0.227	(0.773)	0.182	(0.816)	0.201	(0.808)	-0.298	(0.705)
Immigrant (=1)	0.383	(0.238)	0.297	(0.215)	0.396	(0.280)	0.610*	(0.348)
Married (=1)	0.265	(0.194)	0.077	(0.166)	-0.030	(0.234)	0.428	(0.302)
High school degree (=1)	-0.483*	(0.276)	-0.481**	(0.243)	-0.478	(0.340)	-0.442	(0.447)
Some college (=1)	-0.296	(0.261)	-0.255	(0.222)	-0.345	(0.317)	-0.096	(0.433)
College degree (=1)	-0.479*	(0.260)	-0.516**	(0.231)	-0.221	(0.322)	0.155	(0.429)
Asian (=1)	-0.128	(0.402)	-0.110	(0.377)	-1.133**	(0.504)	0.013	(0.660)
Bangladeshi (=1)	-0.277	(0.393)	0.076	(0.354)	-0.307	(0.431)	0.253	(0.612)
Chinese (=1)	-0.363	(1.234)	-0.830	(0.915)	-1.386**	(0.582)	3.727***	(1.010)
Black (=1)	0.431	(0.358)	0.497	(0.341)	-0.184	(0.411)	-0.275	(0.602)
Indian (=1)	-0.428	(0.515)	0.062	(0.456)	-0.230	(0.547)	0.824	(0.839)
Mixed/multiple (=1)	-1.482	(1.238)	1.028	(0.751)	0.416	(0.764)	-0.732	(1.525)
Other (=1)	-0.189	(0.412)	-0.176	(0.386)	-0.391	(0.453)	-0.024	(0.657)
Pakistani (=1)	-0.226	(0.390)	0.014	(0.356)	-0.396	(0.435)	-0.115	(0.625)
Other White (=1)	0.113	(0.396)	-0.085	(0.370)	-0.789*	(0.470)	0.463	(0.641)
White British (=1)	.	(.)	.	(.)	.	(.)	.	(.)
Additional full-time job (=1)	-0.301	(0.290)	-0.021	(0.262)	0.375	(0.317)	0.665	(0.455)
Additional part-time job (=1)	-0.449	(0.279)	-0.547**	(0.255)	-0.648*	(0.336)	0.780*	(0.410)
Additional business (=1)	-0.458	(0.288)	-0.437*	(0.255)	-0.720*	(0.416)	0.415	(0.506)
Tenure (years since first trip)	0.012	(0.077)	-0.064	(0.074)	-0.106	(0.099)	-0.016	(0.124)
Constant	6.881***	(0.976)	8.033***	(0.925)	7.113***	(1.228)	4.107**	(1.668)
Observations	822		822		822		822	
R-squared	0.133		0.094		0.074		0.040	

Notes: This table reports OLS estimates from driver-level regressions where the outcome is one of four measures of subjective well-being measured on a 0-10 scale. Robust standard errors are reported in parentheses. Statistical significance is denoted by: *** p<0.01, ** p<0.05, * p<0.1.

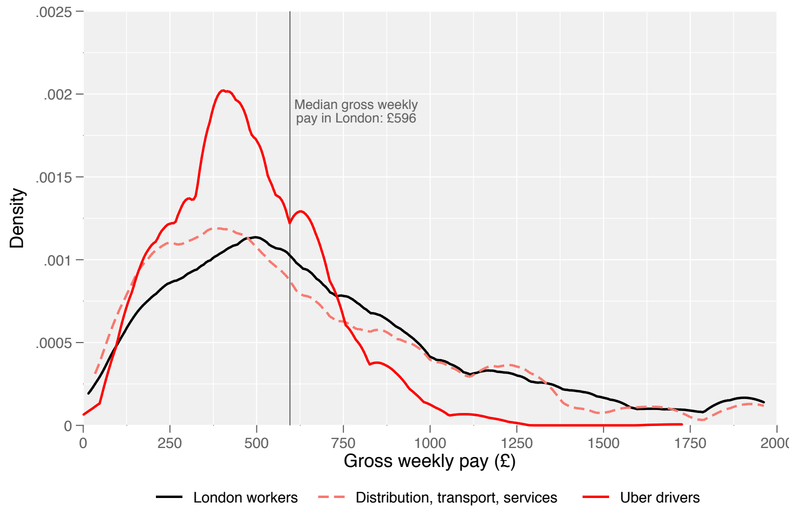
FIGURES AND TABLES

Figure 2.1: Uber's expansion in UK cities, 2013-2018.



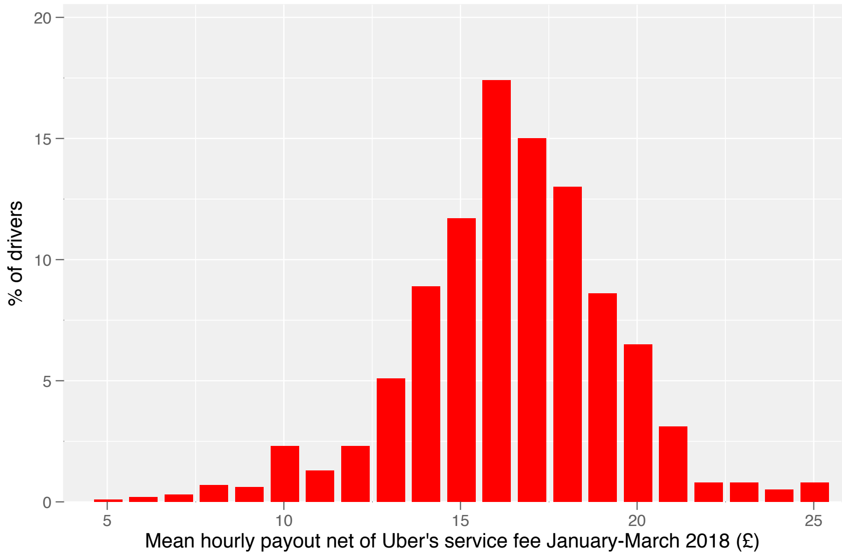
Notes: This figure displays the monthly number of active drivers in Birmingham, Leeds, London, and Manchester based on internal aggregated administrative data from Uber. Active drivers are defined as those providing at least four trips in each respective month.

Figure 2.2: Gross weekly pay among Uber drivers and London workers, 2018.



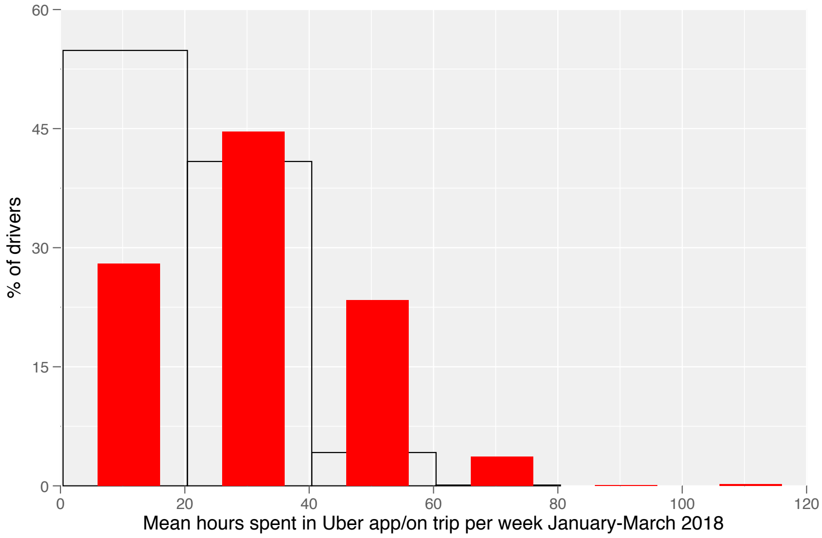
Notes: This figure plots kernel density distributions of self-reported average weekly earnings among Uber drivers in London based on data from the ORB survey and the distribution of weekly pay for all respondents aged 18 and above that report Central, Inner, or Outer London as their region of place of work in the January—March 2018 LFS weighted by the supplied income weights. We present data both for all employed workers, as well as for workers employed in distribution, hotels, and restaurants; transport and communication; and other services, respectively. Weekly earnings for Uber drivers are calculated based on the self-reported average monthly total pre-tax income (i.e., also including income streams other than Uber) scaled to a weekly level. We limit all samples to respondents with gross weekly earnings below £2,000 for presentational purposes.

Figure 3.1: Mean hourly payouts for Uber drivers, 2018.



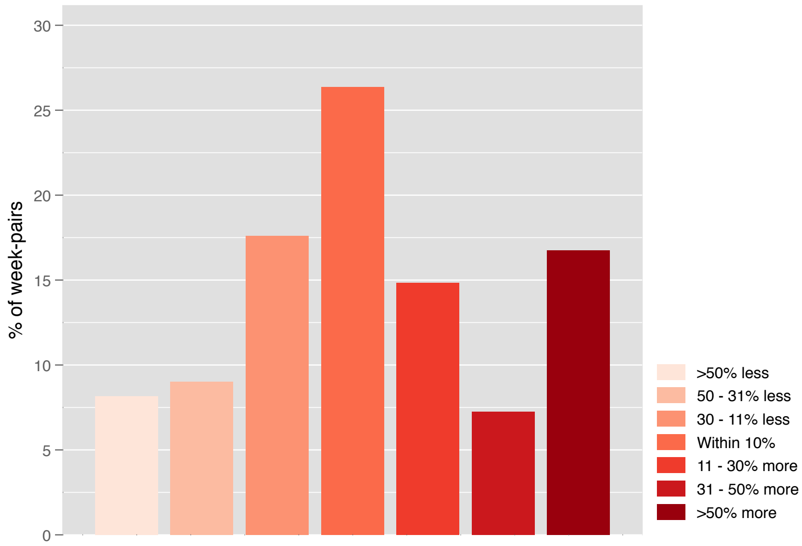
Notes: This figure displays the distribution of mean hourly payouts net of Uber's service fee between January—March 2018 for the sample of 1,001 Uber drivers in London based on anonymized internal administrative data from Uber. For presentational purposes, we exclude one driver with an exceptionally high mean hourly payout (£65) over the sample period.

Figure 3.2: Weekly hours driving with Uber, 2018.



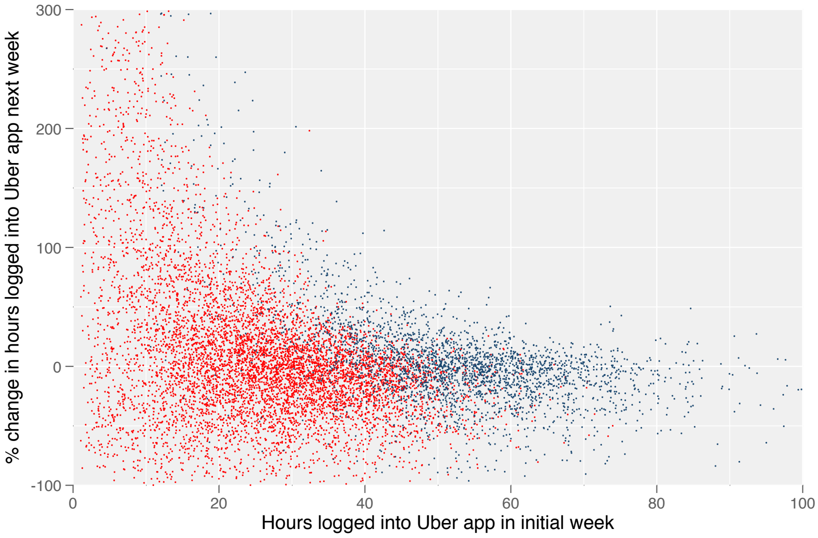
Notes: This figure displays the distribution of mean hours spent logged into the Uber app (solid bars) and the mean hours spent on trip (hollow bars) per week between January—March 2018 for the sample of 1,001 Uber drivers in London based on anonymized internal administrative data from Uber.

Figure 3.3: Week-to-week changes in hours logged into Uber app, 2018.



Notes: This figure displays the distribution of percentage changes in hours spent logged into the Uber app per week relative to the previous week across 9,797 week-pairs based on anonymized internal administrative data from Uber. Individual week-pairs are drawn from 989 (out of the 1,001) London drivers that spent at least one hour logged into the Uber app in two consecutive weeks between January—March 2018.

Figure 3.4: Week-pair changes in hours logged into Uber app, 2018.

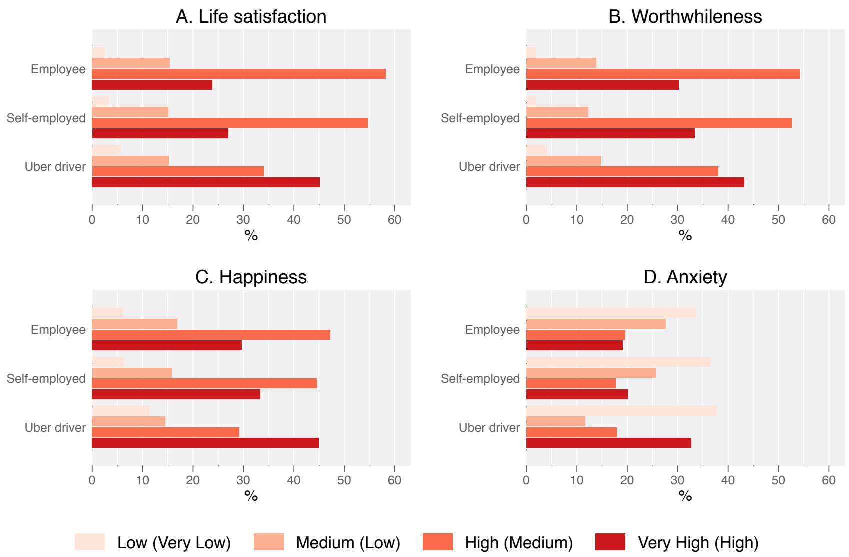


Notes: This figure displays week-to-week percentage changes in hours spent logged into the Uber app and hours in the initial (previous) week based on anonymized internal administrative data from Uber. Navy solid dots denote week-pairs for full-time drivers (i.e., drivers that spend on average at least 40 hours logged into the Uber app each week), while red solid dots correspond to week-pairs for part-time drivers (i.e., drivers that spend less than 40 hours logged into the Uber app per week on average). We include data for 989 (out of the 1,001) London drivers that spent at least one hour logged into the Uber app in two consecutive weeks between January—March 2018. For presentational purposes, we further limit the sample to week-pairs with <300 percent increases in hours worked and <100 hours spent in the Uber app in the baseline week.

Figure 3.5: Hourly earnings for full-time Uber drivers and low-pay workers in London, 2018.

Notes: This figure plots the distribution of estimated mean hourly earnings net of expenses as defined in Table 3.2, column 2, for full-time Uber drivers. Also shown is the kernel density distribution of hourly pay among for London workers employed in distribution, hotels, and restaurants; transport and communication; and other services, as well as male immigrants aged 18 and above with hourly pay below £25 that work at least 40 hours per week based on the January—March 2018 LFS weighted using the supplied income weights.

Figure 4.1: Subjective well-being among London workers, 2016-2018.



Notes: Each panel displays the share of respondents that report 'low' ('very low') to 'very high' ('high') life satisfaction, worthwhileness, and happiness (anxiety), based on data from the ORB survey of 1,001 Uber drivers, as well as wage-employed and self-employed London workers based on the April 2016—March 2017 APS data restricted to respondents aged 18 and above with non-missing responses to each well-being question respectively. All responses in the APS are weighted using the supplied 2017 well-being weights.

Figure 4.2: Life satisfaction and income before and after becoming an Uber driver.

Notes: This figure displays the share of respondents in the ORB survey of 1,001 Uber drivers that report 'low' to 'very high' life satisfaction by drivers' responses to the question: 'Since driving with Uber, do you think your average monthly income has stayed the same, increased or decreased?'. For presentational purposes, we omit the group responding 'Don't know'.

Table 2.1: A snapshot of the London labour force, 2018.

	Uber (1)	London workers (2)	Self-employed (3)	Taxi drivers (4)
Aged 18-29	12%	23%	13%	0%
Aged 30-39	40%	30%	25%	26%
Aged 40-49	32%	23%	26%	33%
Aged 50-64	16%	22%	29%	35%
Aged >65	0%	3%	8%	6%
Female	1%	44%	34%	3%
Married	70%	51%	57%	81%
Children in household	64%	42%	42%	63%
Less than high school	13%	24%	28%	66%
High school degree	24%	15%	13%	18%
Some college	31%	7%	7%	4%
College degree	32%	54%	51%	12%
In education or training	9%	18%	12%	3%
Immigrant	82%	40%	47%	72%
Asian (any other)	10%	3%	2%	5%
Bangladeshi	14%	2%	2%	14%
Black	23%	9%	7%	18%
Chinese	0%	1%	1%	0%
Indian	5%	7%	6%	3%
Mixed/multiple	1%	2%	2%	2%
Other ethnic group	11%	4%	5%	6%
Pakistani	15%	2%	2%	17%
White British	6%	51%	48%	21%
Other White	16%	18%	24%	13%
Observations	1,001	5,610	989	56

Notes: Characteristics of Uber drivers are calculated based on the ORB survey of 1,001 drivers and data for other London workers is drawn from the January—March 2018 LFS restricted to employed and self-employed respondents aged 18 and above that report Central, Inner, or Outer London as their region of place of work. We exclude respondents in the ORB and LFS survey with missing responses on a question-by-question basis and weight all responses from the LFS using person weights. 'Children in household' is based on children below the age of 18 in the ORB survey and below the age of 19 in the LFS. 'In education or training' corresponds to drivers stating that they are 'Studying to obtain more qualifications' in the ORB survey and respondents that report being 'in education/training′ in the LFS. Immigrant status is based on the question 'Did you immigrate to the United Kingdom?' in the ORB survey, and country of birth as recorded in the LFS data. As described in the main text, the ORB survey used more widely used educational classifications (e.g., 'college') to reflect the fact that most drivers are unlikely to have UK qualifications. We aggregate responses in the ORB survey to less than high school (no schooling complemented, nursery school, some high school), high school degree (high school graduate), some college (some college credit, no degree; trade/technical/vocational training), and college degree (associate, bachelor's, master's, professional, and doctorate degree). In the LFS data, we classify 'GCSE grades A*-C or equivalent', 'Other qualification', and 'No qualification' as 'less than high school'; 'GCE A level or equivalent' as 'high school degree'; while 'Higher education' and 'Degree or equivalent' is classified as 'some college' and 'college degree' respectively. 'Black' corresponds to 'African/Caribbean/Black British' and 'Other White' also includes those identifying as 'White Irish'.

Table 2.2: What were drivers doing before Uber?

A. What were drivers doing prior to becoming an Uber driver?

Working full time	64%	A caregiver	1%
Working part time	23%	A student	5%
Working multiple jobs	4%	Retired/pensioned	0%
Unemployed	2%	Other	4%

B. Which sectors were Uber drivers previously employed in?

Agriculture, forestry and fishing	1%	Manufacturing	3%
Banking and finance	3%	Other services	23%
Construction	6%	Public admin, education and health	8%
Distribution, hotels and restaurants	12%	Transport and communication	43%
Energy and water	1%		

C. What type of occupation did Uber drivers previously hold?

White-collar (professional or managerial)	19%	Blue-collar	27%
White-collar (administrative or clerical)	6%	Service job (e.g., cashier, waiter)	37%

Notes: Panel A tabulates the responses to the question 'Prior to driving with Uber were you …?' based on the ORB survey of 1,001 Uber drivers in London. Note that a respondent could give multiple answers. Panels B and C tabulates responses to the questions 'And in which industry were you employed?' and 'And would you describe that job as ...' among drivers that were working prior to becoming an Uber driver.

Table 3.1: Mean hourly payouts from Uber, 2018.

	Mean hourly payout in £ for drivers working:					
	>0 h/week	<10 h/week	10-19 h/week	20-29 h/week	30-39 h/week	>40 h/week
	(1)	(2)	(3)	(4)	(5)	(6)
Median driver	16.50	16.00	17.20	16.55	16.57	16.13
(25^{th}, 75^{th} percentile)	(14.84, 18.17)	(12.79, 19.59)	(15.56, 19.13)	(15.14, 18.49)	(14.92, 18.08)	(14.66, 17.43)
Dispersion of hourly payouts						
Across drivers	0.20	0.43	0.17	0.16	0.16	0.16
Within drivers	0.17	0.29	0.18	0.19	0.15	0.12
Share of drivers	100%	8%	17%	25%	20%	29%

Notes: This table reports mean hourly payouts from Uber net of its service fee for the sample of 1,001 London drivers between January—March 2018 based on anonymized internal administrative data from Uber. We present estimates for all drivers in column 1 and break down hourly payouts by the mean number of weekly hours spent in the Uber app over the sample period in subsequent columns. Across-driver dispersion of hourly payouts is calculated as the cross-driver standard deviation of mean hourly payouts divided by mean hourly payouts among drivers in each group. Within-driver dispersion is calculated as the cross-week standard deviation of mean hourly payouts for drivers divided by the mean hourly payout for each individual driver, which are then averaged across drivers in each group.

Table 3.2: Hourly earnings among Uber drivers and London workers.

	Uber drivers hourly earnings in £ after covering expenses and hourly pay for London workers							
	A. Uber drivers					B. London workers		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Median hourly earnings	11.07	10.72	11.30	11.09	11.51	16.00	13.80	15.07
(25th, 75th percentile)	(8.62, 13.12)	(8.63, 12.85)	(9.64, 13.00)	(9.61, 12.42)	(8.89, 14.83)	(10.42, 25.32)	(9.17, 24.05)	(9.93, 29.80)
Expenses	Individual	Individual	Fixed	Fixed	-	-	-	-
Sample	All	Full-time	All	Full-time	Full-time	All	Distribution, transport, services	Male immigrants
Observations	854	194	1,001	217	179	1,280	411	224

Notes: Panel A reports estimates of hourly earnings net of expenses and Uber's service fee among Uber drivers. See the main text for a detailed description of how expenses are estimated and allocated. Panel B reports estimates of hourly pay among employed London workers drawing on data from the January—March 2018 LFS. All responses in the LFS are weighted using the supplied income weights.

Table 4.1: Subjective well-being among Uber drivers and London workers, 2016-2018.

	Uber drivers (1)	Employees (2)	Self-employed (3)
Overall, how satisfied are you with your life nowadays?	7.89	7.62	7.65
	(2.27)	(1.49)	(1.58)
Overall, to what extent do you feel that the things you do in your life are worthwhile?	7.97	7.80	7.91
	(2.08)	(1.46)	(1.47)
Overall, how happy did you feel yesterday?	7.58	7.51	7.60
	(2.77)	(1.86)	(1.91)
Overall, how anxious did you feel yesterday?	3.98	3.05	2.99
	(3.65)	(2.63)	(2.70)
Respondents	1,001	5,715	1,523

Notes: This table reports average subjective well-being measures among three groups of London workers: Uber drivers, employees, and those reporting self-employment in their main job. All responses to each well-being question are rated on a 11-step scale where 0 is 'not at all' and 10 is 'completely'. Data is drawn from the ORB survey of 1,001 Uber drivers in London and the April 2016—March 2017 APS for (self-)employed London workers restricted to respondents aged 18 and above with non-missing responses to all four well-being questions. All responses based on the APS data are weighted using the supplied well-being weights. Standard deviations are reported in parentheses.

Table 4.2: Decomposing differences in subjective well-being: Uber drivers vs. London workers.

		Life satisfaction	Worthwhileness	Happiness	Anxiety
(1)	Uber drivers	7.923***	7.996***	7.502***	3.900***
		(0.079)	(0.071)	(0.100)	(0.126)
(2)	London workers	7.632***	7.810***	7.518***	3.054***
		(0.001)	(0.001)	(0.001)	(0.001)
(3)	Difference (1) - (2)	0.291***	0.186***	-0.016	0.846***
		(0.079)	(0.071)	(0.100)	(0.126)
(4)	'Explained'	-0.083***	-0.157***	0.019**	-0.368***
		(0.009)	(0.006)	(0.008)	(0.012)
(5)	'Unexplained'	0.374***	0.343***	-0.035	1.214***
		(0.079)	(0.072)	(0.100)	(0.127)
(6)	Observations	5,656	5,656	5,656	5,656

Notes: This table presents a Blinder-Oaxaca decomposition of differences in evaluative and emotional well-being between employed workers aged 18 and above in London based on the April 2016—March 2017 APS dataset and Uber drivers based on the ORB survey. We include controls for a quartic in age, a set of educational attainment indicators (less than high school, high school, some college, and college degree), (*ln*) gross weekly income, immigrant status, marital status, a set of indicators for ten major ethnic groups, and sex. Standard errors derived as outlined by Jann (2008) are reported in parentheses and statistical significance is denoted by: *** p<0.01, ** p<0.05, * p<0.1.

Table 4.3: Subjective well-being among Uber drivers: the role of income and working time.

	Outcome: Subjective well-being (0-10)						
	Life satisfaction				Worthwhileness	Happiness	Anxiety
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Gross weekly income (*ln*)	0.151			0.093	0.066	0.164	-0.150
	(0.151)			(0.134)	(0.123)	(0.171)	(0.224)
Mean hourly payout (*ln*)		-0.224					
		(0.464)					
Mean hourly earnings (*ln*)			-0.041				
			(0.175)				
Income change after partnering with Uber:							
Increased a lot (=1)				0.982***	0.670***	-0.460	0.220
				(0.223)	(0.197)	(0.368)	(0.466)
Increased (=1)				0.485***	0.187	0.455**	-0.472
				(0.178)	(0.168)	(0.227)	(0.318)
Stayed the same (=1)				.	.	.	.
				(.)	(.)	(.)	(.)
Decreased (=1)				-0.880***	-0.718***	-0.999***	-0.726*
				(0.265)	(0.245)	(0.368)	(0.426)
Decreased a lot (=1)				-1.669***	-1.273***	-1.571***	0.507
				(0.447)	(0.399)	(0.514)	(0.570)
Don't know (=1)				0.022	-0.171	-0.096	-1.428**
				(0.445)	(0.406)	(0.513)	(0.583)
Mean weekly hours spent in Uber app (*ln*)	-0.066	-0.030	-0.105	-0.122	-0.018	-0.014	0.076
	(0.137)	(0.127)	(0.138)	(0.134)	(0.124)	(0.154)	(0.225)
Demographic controls?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Uber controls?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	822	822	687	822	822	822	822
R-squared	0.047	0.046	0.048	0.133	0.094	0.074	0.040

Notes: This table reports OLS estimates from driver-level regressions where the outcome is one of four measures of subjective well-being measured on a 0-10 scale. ‘Demographic controls’ include age, a set of educational attainment indicators (less than high school, high school, some college, and college degree), immigrant status, sex, marital status, and a set of ten indicators for self-reported ethnic groups. ‘Additional Uber controls’ include a set of indicators reflecting whether a driver reports having another full- or part-time job, or having a business, in addition to driving with Uber, and tenure. Robust standard errors are reported in parentheses. Statistical significance is denoted by: *** p<0.01, ** p<0.05, * p<0.1.

Table 4.4: Subjective well-being among Uber drivers: the role of flexibility.

	Outcome: Subjective well-being (0-10)								
	Life satisfaction						Worthwhileness	Happiness	Anxiety
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Flexibility (=1)	1.146***					0.919**	0.658*	0.965**	0.036
	(0.374)					(0.385)	(0.372)	(0.474)	(0.546)
Flexible hours (=1)		0.453**				0.251	0.317	1.682***	0.809**
		(0.210)				(0.206)	(0.202)	(0.327)	(0.361)
Choose hours (=1)			0.534**			0.357*	0.404**	0.161	0.089
			(0.207)			(0.212)	(0.189)	(0.271)	(0.359)
No traditional company (=1)				0.156		-0.203	0.177	-0.296	-0.120
				(0.234)		(0.229)	(0.216)	(0.280)	(0.390)
Independent contractor (=1)					0.770***	0.517**	-0.032	-0.345	-1.092***
					(0.226)	(0.233)	(0.194)	(0.294)	(0.377)
Demographic controls?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Uber controls?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income controls?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Working hours?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	822	822	822	822	822	822	822	822	822
R-squared	0.147	0.139	0.140	0.133	0.149	0.162	0.114	0.129	0.054

Notes: This table reports OLS estimates from driver-level regressions where the outcome is one of four measures of subjective well-being measured on a 0-10 scale. Each main right-hand-side variable is derived from the ORB survey: ‘Flexibility’ takes the value 1 if a driver ‘agreed’ or ‘strongly agreed’ with the statement ‘I partnered with Uber to have more flexibility in my schedule and balance my work life and family’; ‘Flexible hours’ takes the value 1 for drivers stating they do not prefer to work fixed hours; ‘Choose hours’ takes the value 1 if a driver ‘agreed’ or ‘strongly agreed’ with the statement ‘Being able to choose my own hours is more important than having holiday pay and a guaranteed minimum wage’; ‘No traditional company’ takes the value 1 if a driver ‘agreed’ or ‘strongly agreed’ with the statement ‘I don't want to work for a traditional company in case I lose the flexibility I have’; ‘Independent contractor’ takes the value 1 if a driver stated that he or she preferred to remain an independent contractor rather than be classified as an employee or worker, as described in further detail in section 2. ‘Demographic controls’ include age, a set of educational attainment indicators (less than high school, high school, some college, and college degree), immigrant status, sex, marital status, and a set of ten indicators for self-reported ethnic groups. ‘Additional Uber controls’ controls include a set of indicators reflecting whether a driver reports having another full- or part-time job, or having a business, in addition to driving with Uber, and tenure. ‘Income controls’ include (*ln*) gross weekly earnings and perceived changes in income after partnering with Uber. ‘Working hours’ includes (*ln*) mean hours spent in the Uber app per week. Robust standard errors are reported in parentheses. Statistical significance is denoted by: *** p<0.01, ** p<0.05, * p<0.1.