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The Effects of Uber Diffusion on the Mental Health of Drivers

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While the spread of digital technologies and the growth of associated atypical forms of work are attracting increasing attention, little is known about the impact of these new forms of work on psychological well-being. This paper examines the effect of Uber diffusion on several dimensions of the mental health of drivers, taking advantage of the rollout of Uber across UK regions. We match individual-level information on health and sociodemographic characteristics from the UK Household Longitudinal Study (Understanding Society) between 2009 and 2019 with data on the diffusion of Uber across the country. We first show that Uber diffusion is positively associated with mental health, as measured by the General Health Questionnaire, in the population group of self-employed drivers. We argue that this positive correlation captures a selection effect (of comparatively healthier individuals into the category of self-employed drivers after Uber entry) and the omission of unobserved factors, rather than a causal effect. Indeed, we do not observe any improvement in mental health for workers who were already self-employed drivers before Uber entry. In parallel with this, among individuals who remained salaried drivers over time, our results suggest there may be a decline in mental health after Uber's introduction, probably because they feel the competition from Uber drivers.

Keywords: Mental health; Self-employment; Gig economy; Uber.

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Ethical Approval Statement
The University of Essex Ethics Committee has approved all data collection on Understanding Society main study and innovation panel waves, including asking consent for all data linkages except to health records. Requesting consent for health record linkage was approved at Wave 1 by the National Research Ethics Service (NRES) Oxfordshire REC A (08/H0604/124), at BHPS Wave 18 by the NRES Royal Free Hospital & Medical School (08/H0720/60) and at Wave 4 by NRES Southampton REC A (11/SC/0274). Approval for the collection of biosocial data by trained nurses in Waves 2 and 3 of the main survey was obtained from the National Research Ethics Service (Understanding Society - UK Household Longitudinal Study: A Biosocial Component, Oxfordshire A REC, Reference: 10/H0604/2).

Data Availability
The data that support the findings of this study are available from the UK Data Service. Restrictions apply to the availability of these data, which were used under license for this study. Data are available authors with the permission of the UK Data Service.

1. Introduction

Several studies have documented that “work” defined as the type, tenure, and precariousness of employment has been changing substantially since the early 1980s (OECD, 2019). Whether through globalization, automation, changing bargaining power or other influences, the rate of precarious employment, turnover, and alternate forms of work has been increasing. In particular, gig economy type jobs,[1] enabled by online technology, are rapidly developing. In Europe, 9% of the population in the UK or Germany and 22% of the population in Italy report having done some work in the gig economy.[2] Coincident with these changes in employment, rates of mental health disorders, such as depression and other chronic mental health problems, have been growing over the past 25 years (McManus et al., 2016). In this paper, we focus on Uber (i.e. a gig economy company which connects drivers and customers seeking a ride through a platform/application[3]) and explore the effect of the spatial diffusion of Uber on the mental health of drivers in the UK.

The relationship between mental health and gig economy work, which is characterized by self-employment,[4] flexibility, and precarity, is not a priori obvious (Apouey et al., 2020; Stabile et al., 2020). Historically, most empirical studies show that self-employment is positively

[1] The Department for Business, Energy and Industrial Strategy in the UK (2018a) uses the following definition of the gig economy: “the gig economy involves the exchange of labour for money between individuals or companies via digital platforms that actively facilitate matching between providers and customers, on a short-term and payment-by-task basis” (page 8).
[2] See http://researchprofiles.herts.ac.uk/portal/files/13124212/Huws_U._Spencer_N.H._Syrdal_D.S._Holt_K._2017_.pdf
[3] We note that Uber does not own vehicles and that drivers are independent contractors who are paid for each ride they deliver, rather than Uber’s employees. Passengers do not connect directly with a driver but instead through the Uber application. The company’s website is the following: uber.com.
[4] For our period of interest in our data, gig work was codified as “self-employment” in the UK. However, in February 2021, the UK Supreme Court upheld that Uber drivers would be classified as “workers” instead of “self-employed.” See https://www.jdsupra.com/legalnews/uk-supreme-court-ruling-uber-drivers-5251635/#:~:text=On%2019%20February%202021%2C%20the,and%20are%20not%20self%2Demployed.

associated with health, while precarious employment is negatively correlated with it (Benavides et al., 2000). Importantly, self- and precarious employment can take various forms in various contexts depending on the social safety net, alternative options, and the nature of work opportunities.

The correlation between gig work and health may be interpreted in three different ways. First, this association may reflect a causal effect of this employment type on health. The sign of the effect is unclear though: while greater uncertainty about employment and earnings may contribute to stress and mental health issues, it is also entirely possible that some characteristics of gig economy jobs have a positive effect on mental health. For instance, gig work (such as Uber and Deliveroo) may provide flexibility, earnings potential for a given education level, or levels of autonomy that positively contribute to mental health. Second, it is entirely possible that health status also has an influence on employment type (reverse causation and selection). In other words, there may be a selection in who decides to be a gig worker. Third, there are likely hidden common factors that affect both gig work and health. In this case, gig work and health will be correlated, but not in any causal way.

While the growth of the gig economy creates controversy, there have been only few attempts to estimate its influence on worker health (Berger et al., 2019). In this paper, we explore this impact through the lens of Uber in the UK. We focus on the population group of "taxi, cab drivers and chauffeurs" (and to a lesser extent on the broader group of "transport drivers and operatives" that includes "taxi, cab drivers and chauffeurs"). Exploiting the spatial and temporal diffusion of the Uber platform across the country, we study the effect of Uber work on several dimensions of mental health for this population group. We employ individual-level data on health from Understanding Society, i.e. the UK household longitudinal study, between 2009 and 2019. To overcome identification concerns (reverse causation and selection), we use information on the diffusion of Uber at the area level and we exploit the longitudinal nature of Understanding Society (by comparing individual health before and after Uber introduction and including individual fixed effects).

We first show that in the population group of self-employed drivers (i.e. self-employed "taxi, cab drivers and chauffeurs"), mental health, as measured by the General Health Questionnaire (GHQ), is greater after Uber introduction. This positive correlation between Uber and GHQ is explained by greater decision-making capabilities, a decrease in psychological strain, a greater ability to overcome difficulties, greater enjoyment of day-to-day activities, and higher confidence and self-worth. We argue that the positive association between Uber and mental health among self-employed drivers captures a selection effect (of comparatively healthier individuals into the category of self-employed drivers after Uber entry) and the omission of third factors, rather than a causal effect on individuals who were already self-employed drivers before Uber entry. Indeed, we do not find any significant causal effect for these individuals who were already self-employed drivers before Uber introduction. In addition, we provide suggestive evidence of a decrease in mental health after Uber entry for salaried drivers. These results obtained for the population group of "taxi, cab drivers and chauffeurs" are supported by those found for the broader group of "transport drivers and operatives."

This paper contributes to the large literature on the effect of employment types on health. It offers a detailed look at the effects of the diffusion of a new source of self-employment -- Uber -- on drivers' mental health and some insight as to which workers might suffer or benefit from this diffusion. It also incorporates additional data on gig economy activity, which is not yet well-measured in national surveys.

The rest of the paper proceeds as follows. Section 2 provides background information on the gig economy in the UK and reviews the literature on employment types and health. Sections 3 and 4 contain the presentations of the data and of the empirical strategy. Our results are presented in Section 5, while Section 6 offers some concluding remarks.

2. Background

Background on Employment and Gig Economy in the UK

Several features of the UK labor market over our period of interest (2009-2019) are worth mentioning. First, the unemployment rate remained low over the period (7.6% in 2009 and 4.9% in 2016, with a peak at 8.1% in 2011).[5] Moreover, self-employment has been rapidly growing since the turn of the century (12% of the labor force in 2001, versus 15.1% in 2017).[6]

While general population surveys do not include questions on the gig economy directly, two recent reports for the Department for Business, Energy and Industrial Strategy (BEIS) describe the characteristics (BEIS, 2018a) and experiences (BEIS, 2018b) of workers in the gig economy. While acknowledging that there is no single accepted definition of the gig economy, they use the following working definition: "The gig economy involves the exchange of labour for money between individuals or companies via digital platforms that actively facilitate matching between providers and customers, on a short-term and payment-by-task basis" (BEIS,

[5] See https://www.ons.gov.uk/employmentandlabourmarket/peoplenotinwork/unemployment/timeseries/mgsx/lms.

[6] See https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/articles/trendsinselfemploymentintheuk/2018-02-07

2018a, p. 8). Exploiting quantitative data collected in 2017 in Great Britain, the report on characteristics provides descriptive statistics on these workers. Findings show that 4.4% of the population had worked in the gig economy in the 12 months preceding the survey. Importantly, providing services through Uber is the most common type of gig economy activity (18%). The income from the gig economy reflects a small share of total income and workers generally see "the income from the gig economy as an extra source of income on top of their regular income (32%)." Overall, workers are satisfied with their gig economy work (53%), mainly because of the independence and flexibility aspects of their job. Finally, workers in the gig economy have a similar gender profile and educational attainment to the rest of the population, but they are younger and most commonly live in the London area than the general population.

Moreover, in a recent paper, Berger et al. (2019) specifically focus on Uber drivers in the London area. The authors surveyed Uber "driver-partners" in 2018, i.e. six years after Uber's first day in 2012 in London, and match these data with administrative data from Uber and official surveys on London workers. The study provides detailed information on subjective motives: for instance, the flexibility of working hours is a strong motivation to work for Uber. Moreover, descriptive comparisons between population groups reveal that Uber drivers report both higher levels of life satisfaction and higher levels of anxiety than other workers. Authors hypothesize that this may be due to a trade-off between evaluative and emotional well-being (the former reflects an assessment of well-being in the longer term, while the latter refers to day-to-day experiences).

In contrast with this article, we focus on the diffusion of Uber in the whole country starting 2012. While Berger et al. (2019) study is mainly descriptive, we try to estimate the effect of

Uber by following people over time and comparing health levels before and after Uber introduction.[7]

Causal and Selection Effects

A substantial literature in the social sciences explores the correlation between types of employment and health indicators. While this correlation may mean that the type of employment has a causal effect on health (contextual effect), it could also capture the impact of health on the type of employment (selection effect) (Rietveld et al., 2015).

To understand the contextual effect, theoretical insights from the Job Demands-Control model (Karasek, 1979; Karasek and Theorell, 1990; Theorell and Karasek, 1996) may be useful. In this approach, occupational stress depends on two factors: (1) job requirements (job demands) and (2) autonomy or decision-making authority (job control). The imbalance between job demands and job control results in different levels of stress. Experiencing both high job demands and low job control is the most stressful situation.

Compared with typical wage workers, self-employed drivers (including "Uber partners") may have a higher job control level, because they have more control over the organization of their working life (they chose their number of hours for instance). In particular, the studies cited above note some potential autonomy benefits of working in the gig economy. However, self-employment (including Uber work) may also be associated with greater uncertainty of pay and time of work. Finally, while self-employed drivers may be more able to achieve work-life

[7] Berger et al. (2018) examine the impact of Uber's introduction on labor market outcomes (earnings, etc.), for conventional taxi services in the US. Their paper does not study health outcomes. Like our strategy, their method compares outcomes before and after Uber's introduction.

balance (which has beneficial health effects), this type of work may also blur work-life boundaries (and thus have detrimental health effects) (Rosenblat and Stark, 2016).

Compared with traditional self-employment as a taxi driver, while not necessarily increasing autonomy, Uber work may be associated with different levels of job demands and controls. For instance, Uber drivers do not need to find customers, which could improve mental well-being. However, Uber drivers must take any customer when they are logged into the system (which is not the case for traditional self-employed taxi drivers), which may have a negative impact on their well-being.

Self-Employment and Precarious Jobs

Our study relates to the literature on the impact of self-employment and precarious work on health. First, research highlights that the self-employed are healthier than wage workers. For instance, using cross-sectional data from the German National Health Survey 1998, Stephan and Roesler (2010) show that entrepreneurs exhibit better health (lower mental and somatic morbidity and higher life satisfaction, among others) as compared to employees. However, the interpretation of this association between self-employment and health is not obvious: it may mean that self-employment improves health or it may reflect the selection of healthier individuals into self-employment. Using longitudinal data from the Health and Retirement Study (HRS), Rietveld et al. (2015) try to gauge the plausibility of the two interpretations. By estimating several models (a dynamic model, a fixed effect model, and a bivariate probit model), they conclude that the cross-sectional association between self-employment and health is due to a selection effect, and that self-employment does not have any health benefit.

A very substantial literature studies the correlation between precarious work and health. While studies generally find that precarious employment is negatively associated with health, the relationship depends on the context and the type of precarious work in question. For example, in their very recent literature review for Europe, Hünefeld et al. (2019) conclude that temporary agency work is associated with higher levels of depression and fatigue. Moreover, in their review of 27 studies, Virtanen et al. (2005) find higher psychological morbidity for temporary workers compared to permanent workers. However, this association depends on instability of temporary employment and on national contextual factors -- the negative effect is found in countries in which the number of temporary and unemployed workers is low. In addition, a number of articles report mixed findings, depending on the choice of health outcomes. For instance, Benavides et al. (2000) exploit data from 15 European countries and show that precarious employment is negatively associated with stress (in comparison with full time permanent workers), but positively associated with fatigue, backache, and muscular pain. Virtanen et al. (2002) employ data from eight Finnish towns and also highlight that contractual employment security and perceived security in employment have different effects on health. While fixed term workers report better self-assessed health (SAH) compared with permanent employees (for both sexes), psychological distress is associated with low perceived security (for both sexes) and with low contractual security (for women).

A handful of papers use instrumental variables strategies to explore the causal effect of precarious employment. Findings highlight the detrimental influence of precarious jobs. For instance, Moscone et al. (2016) focus on the effect of precarious employment on psychotropic medication prescription. For a given worker who is being employed, they use the firm-level job characteristics -- the percentage of workers having temporary or permanent contracts, the average number of days worked within the year, and the percentage of changes in contract -- as instruments for worker employment instability. Using data on employee residents in the Lombardy region in Italy, authors show that precarious employment is positively associated with psychotropic prescriptions. Given that most mental health problems go untreated, their result may only provide a lower bound of the true effect of instability. In a related study, using data on males from the 2010 European Working Conditions survey (which contains salaried employees and self-employed), Caroli and Godard (2016) focus on the relationship between perceived job insecurity and health. They use the stringency of the employment protection legislation in the country, interacted with the rate of dismissals in the industry, as an instrument for individual perceived insecurity. They find that insecurity increases the probability of suffering from headache or eyestrain and skin problem, but does not have any significant effect on other health outcomes.

Finally, Robone et al. (2011) focus on the effect of contractual and working conditions and address the endogeneity of these conditions using a dynamic model that includes lagged health. Data come from the British and Household Panel Survey (1991/1992-2002/2003) and the authors focus on SAH and psychological well-being (GHQ). Findings indicate that under certain circumstances, adverse conditions have a detrimental effect on health and well-being. They note that while some results hold equally for men and women, there are also interesting differences by gender, particularly in the presence of children.

Compared with this literature, our paper focuses on a fairly recent employment type (Uber work) that combines aspects of self-employment and precarity. Moreover, rather than using an instrumental variable approach or a dynamic model to address the endogeneity of employment type, we exploit exogenous dates of entry of Uber across the UK and fixed effect models to estimate the causal effect of Uber spatial diffusion on individual health for drivers.

3. Data

Understanding Society

Our individual-level data come from Understanding Society, the UK Household Longitudinal study, between 2009 and 2019. This is a panel survey carried out every year. Information is collected during face-to-face interviews and through a self-completion questionnaire.

The data contain rich information on individual health. We measure mental health using the 12-item General Health Questionnaire (GHQ) as well as its subcomponents. This questionnaire identifies minor psychiatric disorders and is widely used by psychologists and epidemiologists. The GHQ comprises 12 questions, each with a four-point Likert scales for responses. The questions capture whether the respondent is able to concentrate, loses much sleep over worry, feels that she is playing a useful role, feels capable of making decisions, feels constantly under strain, feels she cannot overcome difficulties, is able to enjoy her normal day-to-day activities, is able to face up problems, feels unhappy or depressed, loses confidence in herself, thinks of herself as a worthless person, and feels reasonably happy. Each question is converted into a dichotomous variable. We first use the GHQ score which runs from 0 (worst psychological health) to 12 (best psychological health) as our dependent variable. We also use dummies for the various subcomponents, to examine how various inputs to the mental health index perform.

Understanding Society data also contain detailed information in each year on the current economic activity of the respondent. More precisely, workers are classified by their occupation, using the UK Standard Occupation Classification (SOC, 2000 version), for their first and secondary job (if they have one).[8] The rest of the paper will pay particular attention to the SOC 8214 category, i.e. "Taxi, cab drivers and chauffeurs" (and to a lesser extent to the broader SOC 821 category, i.e. "Transport drivers and operatives," that includes SOC 8214). Moreover, the data indicate each year whether the individual is self-employed or salaried.

The data also provide information on sociodemographic characteristics including gender, race, age, education, and income. Table 1 presents summary statistics for health, labor market status, and sociodemographic variables for our full sample and specifically for SOC 8214. We observe that SOC 8214 (drivers) is heavily skewed towards men (only 6% of the drivers in the SOC are women).[9] Hence our findings should be viewed with this gender imbalance in mind. The distribution of the GHQ score is shown in Figure 1. For SOC 8214, the mean is 10.5 out of 12, with the bulk of responses between 10 and 12.

Finally, the data indicate the travel to work area (commuting area), hereafter TTWA, of each household (which we use to merge Understanding Society with aggregate data). A TTWA is meant to capture a geographical area where residents both work and live. The criterion used to define a TTWA is that "generally at least 75% of an area's resident workforce work in the area and at least 75% of the people who work in the area also live in the area" (Office for National Statistics, 2015). TTWAs are calculated using Census data to capture commuting flow data of workers. TTWAs are updated periodically to reflect changes in local labor market areas. In particular, recent changes were made in 2001 and 2011, and the number of TTWAs has decreased over time. There are now 228 TTWAs in the UK (149 in England, 45 in Scotland, 18 in Wales, 10 in Northern Ireland, and 6 cross-borders TTWAs).

[8] The full set of SOC 2000 occupational categories is listed in Appendix A.
[9] We also observe an extreme over-representation of men in SOC 821.

Aggregate Data

We merge the Understanding Society data with aggregate data on employment, self-employment, and population size, from the Official Labour Market Statistics for the UK (Nomis). Aggregate data are defined at the 2011 TTWA level. Depending on waves, the Understanding Society data contain information on either 2001 TTWAs or 2011 TTWAs. We harmonize data at the 2011 TTWA level. More precisely, we employ information on more precise geographic areas of households (2001 lower layer super output areas, LSOAs) and we map these areas into 2011 TTWAs. We lose a limited number of observations.

Uber Diffusion

We create a dummy variable capturing Uber diffusion. This indicator takes the value of 1 if the date of interview of the respondent is on or after the date when Uber arrives in the respondent's TTWA, based on the month and year. In TTWAs in which Uber is not operating at the date of interview, the Uber diffusion variable is coded as zero.

The dates of Uber arrival were gathered from a number of online sources, including Uber UK's Twitter account, local news outlets, and Wikipedia, for each of the 19 locations Uber lists on the UK section of its "cities" webpage. In cases when the date of Uber arrival is ambiguous given the online sources found, the earliest mention of Uber operating in an area is used. The maps on Uber's cities website are then used to map the areas that Uber specifies it operates in to the multiple TTWAs that fall within these operating zones. The dates are then extrapolated to the TTWAs. Figure 2 shows the diffusion of Uber in the UK over time. This type of data on

Uber spatial diffusion has been used before us by Berger et al. (2018) to study the impact of Uber on labor market outcomes (earnings, etc.) in conventional taxi services in the US.

Uber entry may be correlated with factors that explain mental health. To understand the determinants of entry, we regress the year of entry (in the TTWA) on a range of TTWA characteristics measured prior to Uber entry, using OLS, following Berger et al. (2018). More precisely, TTWA characteristics are either measured in 2011, i.e. the year before Uber entry in 2012 in the UK, or averaged over the 2009-2011 period. Table 2 presents the results and shows that Uber is more likely to enter early in TTWAs with greater population size, with a higher share of people less than 40, where there are more drivers as a share of the workforce, and where non-white drivers make up a higher share of the driver population. Uber entry is uncorrelated with average mental health among workers and among drivers (as measured by pre-Uber GHQ scores).

4. Empirical Strategy

Our difference-in-differences approach borrows from the empirical strategy employed by Berger et al. (2018). We first estimate the correlation between Uber diffusion and individual mental health as follows:

$$MH_{ijt} = \alpha + \beta . UberDiffusion_{jt} + \gamma . X_{ijt} + \omega_j + \delta_t + \epsilon_{ijt} \quad (1)$$

where MH_{ijt} denotes individual mental health. We will use the total GHQ score and the twelve questions of the GHQ questionnaire as our mental health indicators.

Because the Uber variable is defined at the TTWA level (rather than an individual-level measure capturing whether the individual works for Uber), reverse causation running from individual health to the Uber indicator is highly unlikely. The coefficient on Uber diffusion compares health before and after Uber introduction, in our samples of interest.

The model often includes individual-level controls as well as TTWA and year fixed effects. In some specifications, we also include time-varying controls related to SOC 8214 (share of workers, women, white drivers, college drivers, self-employed drivers, and mean income in SOC 8214) and TTWA characteristics. These additional control variables are meant to capture the unobserved factors correlated with Uber entry (see results of Table 2). We estimate models that include or exclude household income, as income is a possible mechanism through which Uber may influence health, and as we wish to capture the correlation between Uber and health that is not mediated by income. Standard errors are clustered at the TTWA level to adjust for within-TTWA correlation.

We estimate equation (1) for the sample of self-employed workers in SOC 8214 (hereafter "self-employed drivers") and the sample of salaried (i.e. not self-employed) workers in SOC 8214 (hereafter "salaried drivers") separately. The sample of "self-employed drivers" contains observations of individuals who are currently self-employed drivers. Note that if an individual becomes a self-employed driver at some point, we keep in the sample his observations when he is a self-employed driver, but delete the rest of his observations. The sample of "salaried drivers" is defined in a similar way. We estimate the equation for self-employed and salaried drivers separately, as we expect that the effect of Uber diffusion may be different in these two groups: in particular, salaried drivers, who may work for regular taxi companies or other chauffeur services, may feel the competition from Uber drivers and may thus be negatively affected by Uber entry.

In our initial specification of equation (1), we neither restrict the sample further nor include individual fixed effects. In this case, when we employ the sample of self-employed drivers for instance, the coefficient on Uber diffusion will compare the health of self-employed drivers before Uber introduction, with that of self-employed drivers after the introduction. Note that these are not necessarily the same individuals. Indeed, some workers from other occupational categories may become self-employed drivers at some point, in particular following Uber's introduction. Similarly, some individuals may choose to stop being self-employed drivers at some point. We discuss this selection issue below.

5. Results

Uber Entry and Mental Health among Drivers

We present our estimates of the association between Uber entry and mental health for self-employed drivers (i.e. self-employed workers in the SOC 8214 occupational code) in Table 3. The first column reports results from a specification including only individual-level controls and TTWA and year fixed effects. Uber diffusion is positively and significantly correlated with mental health among self-employed drivers. More precisely, our results suggest a 0.6-point increase (on a scale ranging from 0 to 12) for self-employed drivers, which corresponds to 22% of a standard deviation. In the next columns, we add TTWA- and SOC-level controls. Importantly, the coefficient on Uber remains relatively stable across specifications and is robust to the inclusion of these additional controls, which means that the coefficient on Uber entry was not capturing these omitted factors. The results thus show a positive correlation between Uber and overall mental health, among self-employed drivers in SOC 8214.

When we focus on the sample of self-employed workers in the broader SOC 821 category, we also find a positive and significant association between Uber entry and the GHQ score, but the size of the coefficient is smaller (Table B1 in Appendix B).

In Table 4, we estimate the same models for salaried drivers in SOC 8214, instead of self-employed drivers. These models are presented in column (3) to (6). Moreover, because there are few salaried drivers in our sample, we estimate two additional models with fewer right-hand side variables: the model in column (1) contains only Uber, individual-level variables, and year fixed effects, and the model in column (2) contains only Uber and TTWA and year fixed effects. A priori, we expect that Uber entry could also affect these salaried drivers: indeed, Uber may represent increased competition and uncertainty which could, in turn, affect mental health. In the table, the coefficient on Uber is large and consistently negative in sign. Moreover, in the model with only Uber and TTWA and year fixed effects, the coefficient on Uber is statistically significant (column (2)). For salaried workers in the broader SOC 821 category, the correlation between Uber introduction and GHQ is also consistently negative, but never significant (Table B2).

The recent literature has highlighted concerns with two-way fixed effects difference-in-differences models when treatment groups are treated at different times. To check the robustness of our estimates, we use the estimator proposed by Gardner (2021).[10] This estimator is appropriate for our setting that exploits individual-level data and includes TTWA fixed effects.[11] The results, reported in Table 5, are very consistent with our previous findings: the coefficients have the same signs as our previous coefficients (i.e. a positive sign for self-

[10] We use the DID2S package in STATA.
[11] We also applied the Callaway and Sant'Anna (2021) method, using the CSDID package in STATA (results available upon request). This approach does not allow to include TTWA fixed effects in our individual-level model. Coefficients are insignificant. Because we consider that including TTWA fixed effects is important in our model, the Gardner (2021) estimator is our preferred method here.

employed and a negative sign for salaried drivers) and are statistically significant (moreover, they are greater, in absolute values, than our coefficients).

As a further robustness check to the estimates presented in Table 3 above, we perform similar analyses to Table 3 for all other occupational categories (SOCs), that is, we test whether Uber significantly correlates with the mental health of self-employed workers in all the occupational categories that do not relate to driving. This is a placebo test to confirm that the positive result we find for self-employed drivers is not due to some unobserved trend or event that would have happened at the same time as Uber entry and would have had a positive effect on mental health. In the absence of such a broad unobserved trend, we should not find any positive correlation between Uber and mental health for self-employed workers in other SOCs. The results for the 24 SOC occupational categories, as well as for self-employed drivers in SOC 8214 and salaried drivers in SOC 8214, are presented in Figure 3. In addition to the significant effect of Uber on mental health for self-employed drivers in SOC 8214, we find a significant effect in five cases out of 24. While five cases are not negligeable, the coefficients on Uber for these cases are smaller (in absolute value) than the coefficient on Uber for self-employed drivers in SOC 8214 and salaried drivers in SOC 8214. These two categories stand out in the figure, which we believe lends support to our results above. We take this evidence as suggestive that that there was no uniform shock to mental health that occurred at the same time as Uber entry.

Decomposition of the Correlation with the General Health Questionnaire Score

The GHQ-12 score is composed of 12 individual questions. While the variable is best used as an aggregate of the entire set of questions in order to capture minor psychiatric disorders, the individual components can provide some insight into the components of mental health which are most affected by the diffusion of the gig economy. We therefore estimate the correlation between Uber diffusion and the mental health of self-employed drivers in SOC 8214, for each element of the GHQ. We report the results in Table 6 (each column contains the results of a regression in which a component of the GHQ score is used as the dependent variable). The correlation with mental health appears to be concentrated in six areas: decision making capabilities, less under strain, less problems overcoming difficulties, greater enjoyment of day-to-day activities, confidence, and self-worth. When we focus on the larger sample of self-employed drivers in SOC 821, the effects are significant for three domains: less under strain, greater enjoyment of day-to-day activities, and greater ability to face problems (Table B3).

Confounding Factors, Causal Effect, and Selection Effect into Uber Employment

Our results above suggest that after Uber entry, overall mental health was greater among self-employed drivers in SOC 8214. While it is possible that Uber introduction improved the mental health of individuals who were already self-employed drivers before Uber entry (causal effect), it is also possible that important confounding factors were omitted in the models (omitted factors), or that it was new entrants into the Uber labor market, and/or leavers, that caused mental health to improve among self-employed drivers (selection effect).

To further understand what is driving our results, we estimate three additional sets of models. First, we re-estimate our models from Tables 3 and 4 (for self-employed and salaried drivers in SOC 8214), but including linear time trends to better capture unobserved confounding factors. Second, we re-estimate the OLS model but restricting the sample to individuals who were self-employed drivers in SOC 8214 both before and after Uber entry, to explore whether there is any observed change in health for these individuals. In this approach, there is no selection effect (because individuals who became self-employed drivers in SOC 8214 after Uber entry are dropped, as well as individuals who stopped being self-employed drivers in SOC 8214 before Uber entry). Third, to address selection, we also estimate models that include individual fixed effects, which control for unobserved individual-level characteristics that are fixed over time. This type of models looks at within person changes in mental health: in particular, the coefficient on Uber in this regression will compare the health of the same individuals before and after Uber introduction.

We present the results of these additional models in Table 7. In column (1), when we include the linear time trends in our regression for self-employed drivers, the coefficient on Uber remains positive and significant, but is slightly smaller (than in Table 3).

In column (2), we restrict the sample to drivers who were self-employed both before and after Uber entry. The coefficient on Uber is smaller and no longer significant. This implies that the positive association in Table 3 is partly due to a selection effect of comparatively healthier individuals (in the category of self-employed drivers in SOC 8214 after Uber introduction).

Columns (3) and (4) contain fixed effects models for the sample of self-employed drivers. We note again that these models focus on the within person change in mental health and control for unobservable fixed characteristics. Including these fixed effects leaves the coefficient on Uber entry both smaller and insignificant, suggesting that the positive correlation between Uber and GHQ in Table 3 is not driven by improvements in mental health for individuals who were self-employed drivers pre-Uber entry. This is perhaps not surprising, in that if a driver was already self-employed before Uber entry, he was already enjoying many of the benefits and suffering from most of the drawbacks of this type of work on mental health.

Column (5) contains results of the OLS model that includes time trends, for the sample of salaried drivers. The correlation between Uber entry and GHQ remains negative and insignificant. We do not estimate the model with individual fixed effect for this sample, given the small sample size. Note that for the larger sample of salaried workers in SOC 821, a fixed-effect model indicates a detrimental and significant association between Uber entry and mental health (Table B4, column (7)). We thus find a clear negative impact of Uber entry on mental health for individuals who were salaried at baseline and remained salaried over time. This result is consistent with increased stress and unhappiness caused by the additional competition created by Uber.

Mental Health Before and After Uber Entry

A central assumption to ensure the validity of our difference-in-differences models is that in the absence of treatment, trends in mental health would have been parallel in the treatment and comparison groups. In other words, our model relies on the hypothesis that Uber did not target locations with differential trends in mental health. We test this parallel trend assumption by re-estimating our baseline model including leads, i.e. allowing the “effect” of Uber to vary over the years prior to Uber entry. We estimate several models, including different sets of right-hand side variables. Given the very small number of salaried drivers in SOC 8214, we do not estimate a model with individual fixed effects for this sample. As shown in Tables 8 (OLS models for self-employed drivers in SOC 8214), 9 (OLS models for salaried drivers in SOC 8214), and 10 (models with individual fixed effects for self-employed drivers in SOC 8214), there is no significant difference in the evolution of mental health before Uber introduction in the treatment and comparison groups, which provides support for the parallel trend assumption.

We also include lags in the models reported in Tables 8, 9, and 10 to assess the dynamic effect of Uber entry on mental health, since this influence may take time to materialize. Findings are consistent with our previous results. For self-employed drivers, in the OLS models, the positive effect of Uber on mental health emerges the year of Uber introduction and remains significant in the following years (compared to the pre-Uber period) (Table 8, columns (5) and (6)). However, in the fixed effects models, the coefficients after Uber introduction are always positive but never significant (Table 8). These findings for self-employed drivers are consistent with the results reported in Tables 3 and 7.

For salaried drivers, in Table 4, the coefficient on Uber was negative in all specifications, and significant in one specification. For this population group, we now find in Table 9 (columns (5) and (6)) a detrimental and significant effect of Uber expansion starting one year after Uber introduction (compared to the pre-Uber period). This result is obtained for a small sample though.

Our results for the larger sample of workers in SOC 821 also provide evidence for the parallel trend assumption, both in the OLS and fixed effect models (Tables B5 through B8). In all cases, the lead effects are insignificant.

For self-employed workers, in the OLS model, we find evidence of lagged effects of Uber entry on mental health from the year of entry, with the stronger effects at two or more years after entry (Table B5). However, in the fixed effect model, the corresponding coefficients are no longer significant for this population group (Table B7), which is consistent with the previous results from fixed effect models (Table B4).

For salaried workers, we find a negative and significant lagged effects in the OLS model (Table B6). While remaining negative, this effect becomes insignificant in the fixed effect model (Table B8). However, we should keep in mind that for salaried workers, when we do not include different lagged effects, the impact of Uber on mental health is significant in a fixed effect specification (Table B4, last column).

6. Conclusion

The rise of the gig economy and the growth of atypical forms of work are attracting increasing attention. However, their impact on health is largely unknown. The aim of our paper is to investigate how the spatial and temporal diffusion of Uber over the UK has affected several dimensions of the mental health of drivers. Our analysis thus complements the article by Berger et al. (2019) which studies well-being of Uber drivers in London. We notice the extreme over-representation of men in the driver occupation, and our results mainly apply to this population group. We find that Uber introduction is positively correlated with mental health, as measured by the GHQ score, in the population group of self-employed drivers. This positive association is driven by greater decision-making capabilities, a decrease in psychological strain, a greater ability to overcome difficulties, greater enjoyment of day-to-day activities, and higher confidence and self-worth. We then show that this positive correlation is not due to improvements over time in mental health for existing self-employed drivers, but to a selection effect (i.e. new entrants into self-employed driving post Uber entry, or leavers) and to the omission of confounding factors. The role of the selection effect (to explain the correlation between some job types and health) has already been emphasized in the previous literature: in particular, Rietveld et al. (2014) show, using US data, that the selection of comparatively healthier individuals into self-employment explains the positive correlation between self-employment and health in cross-sectional data. Our finding on the absence of a causal effect of Uber on mental health for self-employed drivers may mean that Uber expansion did not affect the balance between the advantages (e.g. flexibility and autonomy) and drawbacks (e.g. variation in the amount of work and in pay levels) for self-employed workers already engaged in this occupation.

Our analysis also provides suggestive evidence of a decline in mental health for salaried drivers, which means that Uber entry in the market may have generated negative spillover effects. However, because the number of salaried drivers (in SOC 8214) is small in our data, further research with higher-quality data is needed to better understand our result. A detrimental effect on mental health for salaried drivers could be due to increased competition and uncertainty. On a related matter, Berger et al. (2018) show that Uber diffusion reduced the earnings potential of drivers in conventional taxi services in the US.[12]

To the extent that changes in the labor market are towards offering more flexible forms of self-employment, our results suggest that these jobs may have negative impacts on some dimensions of mental health for some workers. Exploring the exact mechanism driving these results, or other organizational factors that may affect worker psychological well-being, is a topic for future research.

[12] Note that in some models we control for household income.

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Table 1: Summary Statistics for All Workers and for Drivers in SOC 8214 Occupation

	All workers					SOC 8214				
	N	Mean	SD	Min	Max	N	Mean	SD	Min	Max
Mental health outcomes										
GHQ (0-12 scale)	188663	10.447	2.761	0	12	1405	10.496	2.729	0	12
GHQ: Concentration	188663	2.115	0.477	1	4	1405	0.875	0.330	0	1
GHQ: Loss of sleep	188663	1.818	0.760	1	4	1405	0.846	0.362	0	1
GHQ: Playing a useful role	188663	2.008	0.506	1	4	1405	0.877	0.329	0	1
GHQ: Capable of making decisions	188663	1.989	0.431	1	4	1405	0.907	0.290	0	1
GHQ: Constantly under strain	188663	2.033	0.748	1	4	1405	0.819	0.386	0	1
GHQ: Problem overcoming difficulties	188663	1.748	0.711	1	4	1405	0.872	0.334	0	1
GHQ: Enjoy day-to-day activities	188663	2.094	0.494	1	4	1405	0.854	0.353	0	1
GHQ: Ability to face problems	188663	2.022	0.438	1	4	1405	0.892	0.311	0	1
GHQ: Unhappy or depressed	188663	1.805	0.785	1	4	1405	0.842	0.365	0	1
GHQ: Losing confidence	188663	1.671	0.761	1	4	1405	0.893	0.310	0	1
GHQ: Believe in self-worth	188663	1.368	0.651	1	4	1405	0.927	0.261	0	1
GHQ: General happiness	188663	2.016	0.546	1	4	1405	0.893	0.309	0	1
Explanatory variables										
Self-employed	188578	0.126	0.332	0	1	1405	0.826	0.379	0	1
Age	188663	41.611	12.029	18	64	1405	46.621	9.884	20	64
Female	188661	0.532	0.499	0	1	1405	0.060	0.238	0	1
White	187019	0.847	0.360	0	1	1405	0.498	0.500	0	1
College	186827	0.462	0.499	0	1	1324	0.192	0.394	0	1
Household income (/1000)	187467	4.573	2.811	-52.285	89.487	1398	2.981	1.965	-0.765	15.566

Notes: Pooled data over time (wave 1-9). “All workers” is defined by an observation listing a SOC 2000 code for primary occupation.

Table 2: Determinants of Uber Entry (Aggregate Level)

	Outcome: year of Uber entry		
	(1)	(2)	(3)
Share of workers in SOC 8214	-0.659	-24.385***	-26.356***
	(3.510)	(8.512)	(7.018)
Mean GHQ in SOC 8214	-0.027	-0.025	-0.035
	(0.024)	(0.022)	(0.030)
Share of female drivers in SOC 8214	0.194	0.287	0.294
	(0.388)	(0.281)	(0.353)
Share of low-educated drivers in SOC 8214	-0.457	-0.132	-0.007
	(0.383)	(0.422)	(0.396)
Share of white drivers in SOC 8214	0.796***	0.146	-0.246
	(0.273)	(0.298)	(0.264)
Share of self-employed drivers in SOC 8214	0.159	0.520*	0.257
	(0.284)	(0.307)	(0.310)
Mean income in SOC 8214	-0.002	0.035	0.000
	(0.033)	(0.029)	(0.000)
TTWA characteristics			
Mean GHQ		0.077	0.151
		(0.146)	(0.199)
Population (ln)		-0.463**	-0.378**
		(0.175)	(0.153)
Mean earnings		0.084	0.023
		(0.200)	(0.182)
College share		-1.667	-1.358
		(1.485)	(1.407)
Share aged < 40		-1.481	-3.586**
		(1.851)	(1.477)
Characteristics measured in	2011	2011	2009-11
N	47	47	50
R^2	0.185	0.510	0.513

Notes: In column (3), the average is taken over the three years preceding Uber's first entry.
Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Correlation between Uber and the GHQ Score
for Self-Employed Drivers in SOC 8214 (OLS Models)

	(1)	(2)	(3)	(4)
Uber	0.640**	0.706**	0.666**	0.651**
	(0.271)	(0.272)	(0.288)	(0.282)
25-39	-0.024	-0.113	-0.341	-0.223
	(0.872)	(0.917)	(0.859)	(1.007)
40-54	0.564	0.474	0.272	0.353
	(0.724)	(0.780)	(0.729)	(0.870)
55-64	0.739	0.687	0.549	0.562
	(0.873)	(0.925)	(0.868)	(1.007)
Female	-1.331	-1.388	-1.301	-1.257
	(1.660)	(1.776)	(1.765)	(1.763)
College	-0.434	-0.394	-0.327	-0.324
	(0.431)	(0.419)	(0.417)	(0.416)
White	0.624*	0.653**	0.797***	0.742**
	(0.318)	(0.313)	(0.293)	(0.294)
Household income (/1000)	0.106	0.107		0.121
	(0.078)	(0.077)		(0.098)
Share of workers in SOC 8214			10.364	10.073
			(6.668)	(6.924)
Share of females in SOC 8214			-1.154	-1.220
			(1.626)	(1.678)
Share of college drivers in SOC 8214			-0.705	-0.710
			(0.883)	(0.868)
Share of white drivers in SOC 8241			-0.989	-0.931
			(0.821)	(0.840)
Share of self-employed drivers in SOC 8214			-0.207	-0.261
			(0.742)	(0.745)
Mean income in SOC 8214			0.046	-0.071
			(0.083)	(0.129)
Share of female workers		-4.441	-2.747	-2.626
		(3.635)	(3.404)	(3.369)
Share of college educated workers		-1.480	0.546	0.425
		(2.276)	(2.107)	(2.123)
Share of workers 25-39		0.555	-0.468	-0.540
		(4.208)	(4.444)	(4.474)

Share of workers 40-54		-0.939	-1.344	-1.314
		(5.435)	(5.296)	(5.385)
Share of workers 55-64		-1.199	-3.240	-3.115
		(3.282)	(3.882)	(3.952)
Mean income of workers		0.119	0.120	0.120
		(0.338)	(0.324)	(0.322)
TTWA population (ln)		-2.409	-2.668	-2.464
		(3.361)	(3.217)	(3.303)
Constant	9.193***	44.090	47.826	45.006
	(0.823)	(46.033)	(43.723)	(45.131)
TTWA FE & year FE	Y	Y	Y	Y
Linear time trend	N	N	N	N
N	1080	1080	1080	1080
R-sq	0.165	0.168	0.167	0.171

Notes: Standard errors clustered at the TTWA level in parentheses.
* p < 0.10, ** p < 0.05, *** p < 0.01.

Table 4: Correlation between Uber and the GHQ Score
for Salaried Drivers in SOC 8214 (OLS Models)

	(1) Fewer right-hand side variables	(2) Fewer right-hand side variables	(3) Same right-hand side variables as in Table 3 column (1)	(4) Same right-hand side variables as in Table 3 column (2)	(5) Same right-hand side variables as in Table 3 column (3)	(6) Same right-hand side variables as in Table 3 column (4)
Uber	-1.349	-2.007**	-1.902	-1.881	-1.542	-1.717
	(0.853)	(0.840)	(1.173)	(1.225)	(1.292)	(1.285)
25-39	-0.308		-0.254	-0.242	-0.704	-0.332
	(0.663)		(1.053)	(1.139)	(1.525)	(1.193)
40-54	-0.643		0.023	0.033	-0.343	-0.150
	(0.683)		(0.975)	(1.024)	(1.343)	(1.055)
55-64	0.241		0.959	1.013	0.668	0.697
	(0.704)		(1.215)	(1.303)	(1.623)	(1.304)
Female	-0.032		-1.668**	-1.592**	-1.404	-1.225*
	(0.439)		(0.682)	(0.694)	(0.888)	(0.721)
College	1.105**		2.007***	1.934**	2.121**	2.245**
	(0.455)		(0.663)	(0.762)	(0.955)	(0.856)
White	1.195**		1.312	1.128	0.882	1.344
	(0.493)		(0.792)	(0.811)	(0.736)	(0.851)
Household income (/1000)	0.130		0.157	0.144		0.280
	(0.125)		(0.195)	(0.206)		(0.225)
Share of workers in SOC 8214					-4.046	-6.259
					(21.459)	(20.941)
Share of females in SOC 8214					-2.326	-2.383
					(2.151)	(2.019)
Share of college drivers in SOC 8214					-2.341	-2.064
					(3.365)	(3.395)
Share of white drivers in SOC 8241					-0.087	-0.523
					(3.711)	(3.837)
Share of self-employed drivers in SOC 8214					-1.979	-2.014
					(2.130)	(2.093)
Mean income in SOC 8214					-0.144	-0.411
					(0.322)	(0.360)
Share of female workers				-3.900	-2.291	-2.311
				(6.717)	(6.593)	(6.565)
Share of college educated workers				6.741	8.174	7.740
				(6.825)	(7.397)	(7.245)
Share of workers 25-39				2.004	3.824	3.726
				(7.240)	(8.294)	(8.364)

Share of workers 40-54				1.070	3.548	3.630
				(5.833)	(7.201)	(7.131)
Share of workers 55-64				5.932	7.631	7.468
				(7.750)	(9.285)	(9.129)
Mean income of workers				-0.059	-0.269	-0.335
				(1.201)	(1.216)	(1.234)
TTWA population (ln)				-3.399	-4.061	-3.629
				(7.968)	(7.934)	(8.180)
Constant	9.700***	11.624***	9.271***	51.577	60.195	54.881
	(1.004)	(0.447)	(1.099)	(104.194)	(104.986)	(108.383)
Year FE	Y	Y	Y	Y	Y	Y
TTWA FE	N	Y	Y	Y	Y	Y
Linear time trend	N	N	N	N	N	N
Household income	Y	N	Y	Y	N	Y
TTWA controls	N	N	N	Y	Y	Y
SOC controls	N	N	N	N	Y	Y
N	238	244	238	238	238	238
N ind.	-	-	-	-	-	-
R-sq	0.125	0.374	0.451	0.458	0.467	0.477

Notes: Standard errors clustered at the TTWA level in parentheses.
* p < 0.10, ** p < 0.05, *** p < 0.01

Table 5: Correlation between Uber and the GHQ Score
for Self-Employed and Salaried Drivers in SOC 8214

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\hat{\beta}_{fe}$	$\hat{\beta}_{fe}$	Gardner (2021)	Gardner (2021)	$\hat{\beta}_{fe}$	$\hat{\beta}_{fe}$	Gardner (2021)	Gardner (2021)
Sample	Self-Employed	Self-Employed	Self-Employed	Self-Employed	Salaried	Salaried	Salaried	Salaried
Uber	0.577**	0.640**	0.661*	0.705*	-2.007**	-1.902	-2.773***	-2.915***
	(0.281)	(0.271)	(0.387)	(0.395)	(0.840)	(1.173)	(0.671)	(0.749)
p-value	0.043	0.020	0.087	0.074	0.020	0.110	0.000	0.000
N	1161	1080	1161	1080	244	238	244	238
TTWA FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
TTWA controls	N	Y	N	Y	N	Y	N	Y

Notes: Columns (1), (2), (5), and (6) show OLS coefficients for a two-way FE regression (with no TTWA controls and TTWA controls respectively). Column (2) here is similar to Column (1) in Table 3. Column (6) here is similar to Column (3) in Table 4.
Columns (3), (4), (7), and (8) show the Gardner (2021) estimator.
Standard errors in parentheses.

Table 6: Decomposition of the GHQ Score for Self-Employed Drivers in SOC 8214 (OLS Models)

	Outcomes: GHQ Components											
	(1) Concen-tration	(2) Loss of sleep	(3) Playing a useful role	(4) Capable of making decisions	(5) Constantly under strain	(6) Problem overcoming difficulties	(7) Enjoy day-to-day activities	(8) Ability to face problems	(9) Unhappy or depressed	(10) Losing confidence	(11) Believe in self-worth	(12) General happiness
Uber	0.062	0.052	0.044	0.079***	0.114***	0.085*	0.078*	0.030	-0.006	0.064**	0.051**	0.022
	(0.047)	(0.044)	(0.035)	(0.027)	(0.037)	(0.044)	(0.040)	(0.029)	(0.034)	(0.030)	(0.021)	(0.032)
25-39	0.275	-0.286***	0.217	0.261	0.194	0.215	-0.271***	-0.238***	0.185	-0.260***	-0.171**	-0.228***
	(0.382)	(0.075)	(0.436)	(0.466)	(0.259)	(0.279)	(0.102)	(0.081)	(0.295)	(0.053)	(0.065)	(0.064)
40-54	0.310	-0.238***	0.296	0.342	0.196	0.247	-0.231**	-0.236***	0.255	-0.192***	-0.103*	-0.164***
	(0.392)	(0.058)	(0.401)	(0.446)	(0.280)	(0.278)	(0.094)	(0.083)	(0.306)	(0.041)	(0.057)	(0.050)
55-64	0.336	-0.178*	0.311	0.360	0.243	0.258	-0.234**	-0.235***	0.261	-0.202***	-0.093	-0.177***
	(0.390)	(0.090)	(0.414)	(0.436)	(0.262)	(0.269)	(0.107)	(0.077)	(0.298)	(0.071)	(0.063)	(0.052)
Female	-0.041	-0.230*	-0.082	-0.103	-0.125	-0.147	-0.125	-0.077	-0.243*	-0.115	-0.111	-0.169
	(0.160)	(0.116)	(0.159)	(0.150)	(0.113)	(0.118)	(0.187)	(0.136)	(0.123)	(0.186)	(0.185)	(0.163)
College	-0.031	-0.005	-0.060	-0.004	-0.074	-0.043	0.012	-0.060	-0.043	-0.057	-0.039	-0.009
	(0.032)	(0.047)	(0.041)	(0.034)	(0.052)	(0.051)	(0.054)	(0.050)	(0.043)	(0.036)	(0.035)	(0.040)
White	0.042	0.066	0.054**	0.063	0.045	0.090**	0.119***	0.080*	0.068*	0.055*	-0.025	0.031
	(0.037)	(0.050)	(0.025)	(0.040)	(0.041)	(0.040)	(0.043)	(0.043)	(0.038)	(0.030)	(0.035)	(0.044)
Household income (/1000)	0.007	0.012	-0.002	0.005	0.014*	0.012	0.009	0.013	0.012*	0.004	0.003	0.009
	(0.008)	(0.009)	(0.008)	(0.005)	(0.009)	(0.009)	(0.010)	(0.008)	(0.007)	(0.006)	(0.004)	(0.006)
Share of female workers	-0.234	0.461	-0.086	-0.144	-0.498	-0.913*	-0.370	-0.830*	-0.037	-0.541	-0.399	-0.401
	(0.473)	(0.566)	(0.442)	(0.269)	(0.539)	(0.493)	(0.411)	(0.424)	(0.530)	(0.471)	(0.343)	(0.510)
Share of college educated workers	0.196	0.060	0.439	-0.119	-0.666	-0.089	-0.522	-0.371	-0.062	-0.078	-0.144	0.026
	(0.306)	(0.350)	(0.284)	(0.204)	(0.414)	(0.301)	(0.345)	(0.283)	(0.371)	(0.303)	(0.262)	(0.265)

Share of workers 25-39	0.077	-0.164	0.348	0.159	0.289	0.451	0.105	0.047	-0.255	0.086	-0.029	-0.252
	(0.470)	(0.459)	(0.464)	(0.428)	(0.624)	(0.449)	(0.552)	(0.428)	(0.620)	(0.503)	(0.477)	(0.414)
Share of workers 40-54	-0.131	-0.412	0.215	0.120	0.070	-0.163	0.128	0.339	0.026	-0.007	0.012	-0.620
	(0.561)	(0.654)	(0.505)	(0.492)	(0.721)	(0.576)	(0.585)	(0.507)	(0.729)	(0.611)	(0.503)	(0.441)
Share of workers 55-64	0.259	-0.889*	0.409	0.215	0.062	0.050	-0.118	0.034	-0.126	-0.363	-0.225	-0.372
	(0.431)	(0.527)	(0.356)	(0.337)	(0.538)	(0.419)	(0.368)	(0.353)	(0.449)	(0.540)	(0.405)	(0.314)
Mean income of workers	-0.018	0.044	-0.063	0.017	-0.022	-0.041	0.006	0.009	0.005	0.062*	0.025	0.028
	(0.040)	(0.060)	(0.041)	(0.024)	(0.053)	(0.036)	(0.043)	(0.038)	(0.054)	(0.034)	(0.025)	(0.038)
TTWA population (ln)	-0.411	0.132	-0.146	-0.288	-0.080	-0.216	-0.492	0.133	0.099	0.040	-0.241	-0.329
	(0.403)	(0.488)	(0.418)	(0.256)	(0.405)	(0.326)	(0.464)	(0.384)	(0.444)	(0.387)	(0.295)	(0.346)
Constant	6.130	-0.796	2.486	4.341	1.940	3.989	7.865	-0.454	-0.711	0.566	4.414	5.861
	(5.562)	(6.538)	(5.625)	(3.654)	(5.485)	(4.415)	(6.353)	(5.204)	(5.959)	(5.218)	(4.011)	(4.525)
TTWA FE & year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Linear time trend	N	N	N	N	N	N	N	N	N	N	N	N
N	1095	1096	1092	1096	1092	1096	1096	1095	1095	1094	1092	1091
R-sq	0.105	0.132	0.143	0.121	0.146	0.129	0.138	0.121	0.131	0.133	0.120	0.130

Notes: Standard errors clustered at the TTWA level in parentheses. Worker shares by demographic characteristics are for all workers.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Understanding the Correlation between Uber Entry and the GHQ Score in SOC 8214 (OLS and Fixed-Effect Models)

	(1)	(2)	(3)	(4)	(5)
Sample	Self-Employed	Self-Employed Before and After	Self-Employed	Self-Employed	Salaried
Model	OLS with time trend	OLS	FE	FE	OLS with time trend
Uber	0.515*	0.443	0.311	0.269	-0.564
	(0.308)	(0.371)	(0.291)	(0.294)	(1.590)
25-39	-0.442		1.803***	1.699***	0.097
	(1.209)		(0.330)	(0.341)	(1.642)
40-54	0.071	0.540	2.599***	2.472***	-0.507
	(1.082)	(0.630)	(0.593)	(0.627)	(1.277)
55-64	0.465	0.698	2.258**	2.067**	1.327
	(1.205)	(0.602)	(0.908)	(0.900)	(1.617)
Female	-1.311	-0.794***			-1.160
	(1.943)	(0.273)			(1.051)
College	-0.298	-0.901	2.257	2.406	2.692**
	(0.430)	(0.884)	(3.836)	(4.022)	(1.294)
White	0.714**	1.353***			1.100
	(0.290)	(0.445)			(1.060)
Household income (/1000)	0.119	0.037	-0.006	0.027	0.375
	(0.102)	(0.100)	(0.073)	(0.084)	(0.306)
Share of workers in SOC 8214	2.445	45.681***		12.505**	-26.839
	(7.493)	(15.694)		(5.898)	(59.276)
Share of females in SOC 8214	-3.629	-6.088***		-2.965*	-4.453
	(2.399)	(1.165)		(1.664)	(3.231)
Share of college drivers in SOC 8214	0.488	-2.057		-0.975	-0.770
	(0.929)	(1.321)		(0.857)	(10.014)
Share of white drivers in SOC 8241	0.170	-0.723		-0.191	3.272
	(1.246)	(0.842)		(0.717)	(8.911)
Share of self-employed drivers in	0.166	0.774		-0.040	-3.011
	(1.008)	(1.029)		(0.841)	(4.461)

SOC 8214					
Mean income in SOC 8214	-0.000 (0.146)	-0.162 (0.152)		-0.099 (0.101)	0.085 (0.805)
Share of female workers	2.250 (6.066)	-3.912 (4.551)	-0.798 (3.539)	0.203 (3.316)	-14.944 (16.557)
Share of college educated workers	-1.484 (4.121)	1.115 (4.431)	-1.344 (2.481)	0.460 (2.659)	16.757 (14.188)
Share of workers 25-39	-0.415 (5.252)	4.079 (6.453)	-0.410 (3.769)	-2.224 (3.982)	-2.992 (14.546)
Share of workers 40-54	-1.150 (7.498)	-1.642 (7.099)	-1.975 (3.344)	-3.008 (3.351)	12.241 (11.599)
Share of workers 55-64	-0.647 (5.204)	0.045 (6.337)	-3.381 (2.992)	-5.989* (3.589)	14.059 (14.086)
Mean income of workers	0.334 (0.398)	0.616 (0.442)	0.620** (0.258)	0.630** (0.262)	-0.145 (1.516)
TTWA population (ln)	-3.529 (4.096)	-2.058 (4.358)	1.492** (0.598)	1.494*** (0.550)	-4.053 (16.907)
Constant	-864.471 (832.617)	35.559 (60.590)	-12.995 (8.870)	-12.366 (8.234)	1686.626 (2097.966)
Year FE	Y	Y	Y	Y	Y
TTWA FE	Y	Y	N	N	Y
Linear time trend	Y	N	N	N	Y
Individual FE	N	N	Y	Y	N
N	1080	563	1080	1080	238
N ind.	-	-	357	357	-
R-sq	0.240	0.280	0.042	0.050	0.616

Notes: Standard errors (clustered at the TTWA level in columns (1), (2), and (5)) in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: The GHQ Score Before and After Uber Entry
for Self-Employed Drivers in SOC 8214 (OLS Models)

	(1)	(2)	(3)	(4)	(5)	(6)
1-2 Years Before Uber	-0.119	-0.151				
	(0.259)	(0.238)				
Year Uber arrives	0.491	0.485				
	(0.348)	(0.348)				
Post-Uber	0.601	0.614				
	(0.465)	(0.464)				
1-2 Years Before Uber			-0.092	-0.116		
			(0.279)	(0.246)		
Year Uber arrives			0.535	0.546		
			(0.388)	(0.365)		
1 Year After Uber			0.571	0.576		
			(0.446)	(0.455)		
2 or more Years After Uber			0.767	0.866		
			(0.660)	(0.622)		
Year Uber arrives					0.611^{**}	0.641^{**}
					(0.267)	(0.273)
1 Year After Uber					0.655^{*}	0.680^{*}
					(0.351)	(0.392)
2 or more Years After Uber					0.866^{*}	0.987^{*}
					(0.484)	(0.512)
TTWA & year FE	Y	Y	Y	Y	Y	Y
Linear time trend	N	N	N	N	N	N
Individual controls	Y	Y	Y	Y	Y	Y
Household income control	Y	N	Y	N	Y	N
TTWA & SOC controls	N	Y	N	Y	N	Y
N	1080	1080	1080	1080	1080	1080
R-sq	0.166	0.167	0.166	0.168	0.166	0.167

Notes: The reference categories are 3 years or more before Uber entry (columns (1) to (4)) and before Uber entry (columns (5) and (6)).
Standard errors clustered at the TTWA level in parentheses.
* p < 0.10, ** p < 0.05, *** p < 0.01.

Table 9: The GHQ Score Before and After Uber Entry
for Salaried Drivers in SOC 8214 (OLS Models)

	(1)	(2)	(3)	(4)	(5)	(6)
1-2 Years Before Uber	0.514	0.216				
	(0.792)	(0.871)				
Year Uber arrives	-0.909	-0.987				
	(1.482)	(1.604)				
Post-Uber	-2.707	-2.710				
	(1.657)	(1.722)				
1-2 Years Before Uber			0.535	0.265		
			(0.860)	(0.919)		
Year Uber arrives			-0.873	-0.898		
			(1.521)	(1.638)		
1 Year After Uber			-2.696	-2.675		
			(1.660)	(1.733)		
2 or more Years After Uber			-2.603	-2.447		
			(2.050)	(2.104)		
Year Uber arrives					-1.401	-1.158
					(1.170)	(1.268)
1 Year After Uber					-3.317**	-2.981**
					(1.348)	(1.383)
2 or more Years After Uber					-3.363**	-2.817*
					(1.457)	(1.570)
TTWA & year FE	Y	Y	Y	Y	Y	Y
Linear time trend	N	N	N	N	N	N
Individual controls	Y	Y	Y	Y	Y	Y
Household income control	Y	N	Y	N	Y	N
TTWA & SOC controls	N	Y	N	Y	N	Y
N	238	238	238	238	238	238
R-sq	0.468	0.479	0.468	0.479	0.466	0.478

Notes: The reference categories are 3 years or more before Uber entry (columns (1) to (4)) and before Uber entry (columns (5) and (6)).
Standard errors clustered at the TTWA level in parentheses.
* p < 0.10, ** p < 0.05, *** p < 0.01.

Table 10: The GHQ Score Before and After Uber Entry
for Self-Employed Drivers in SOC 8214 (Fixed Effect Models)

	(1)	(2)	(3)	(4)	(5)	(6)
1-2 Years Before Uber	-0.001	0.021				
	(0.352)	(0.349)				
Year Uber arrives	0.205	0.195				
	(0.419)	(0.424)				
Post-Uber	0.507	0.470				
	(0.534)	(0.532)				
1-2 Years Before Uber			0.004	0.032		
			(0.359)	(0.355)		
Year Uber arrives			0.214	0.215		
			(0.428)	(0.432)		
1 Year After Uber			0.503	0.461		
			(0.531)	(0.529)		
2 or more Years After Uber			0.548	0.559		
			(0.636)	(0.636)		
Year Uber arrives					0.211	0.186
					(0.276)	(0.280)
1 Year After Uber					0.499	0.430
					(0.398)	(0.401)
2 or more Years After Uber					0.544	0.523
					(0.478)	(0.483)
Year FE	Y	Y	Y	Y	Y	Y
TTWA FE	N	N	N	N	N	N
Linear time trend	N	N	N	N	N	N
Individual FE	Y	Y	Y	Y	Y	Y
Individual controls	Y	Y	Y	Y	Y	Y
Household income control	Y	Y	Y	Y	Y	Y
TTWA controls	Y	Y	Y	Y	Y	Y
SOC controls	N	Y	N	Y	N	Y
N	1080	1080	1080	1080	1080	1080
N ind.	357	357	357	357	357	357
R-sq	0.043	0.051	0.043	0.051	0.043	0.051

Notes: The reference categories are 3 years or more before Uber entry (columns (1) to (4)) and before Uber entry (columns (5) and (6)).
Standard errors in parentheses.
* p < 0.10, ** p < 0.05, *** p < 0.01

Figure 1: Distribution of the GHQ Score

Figure 1a: Distribution of the GHQ Score Across All Workers

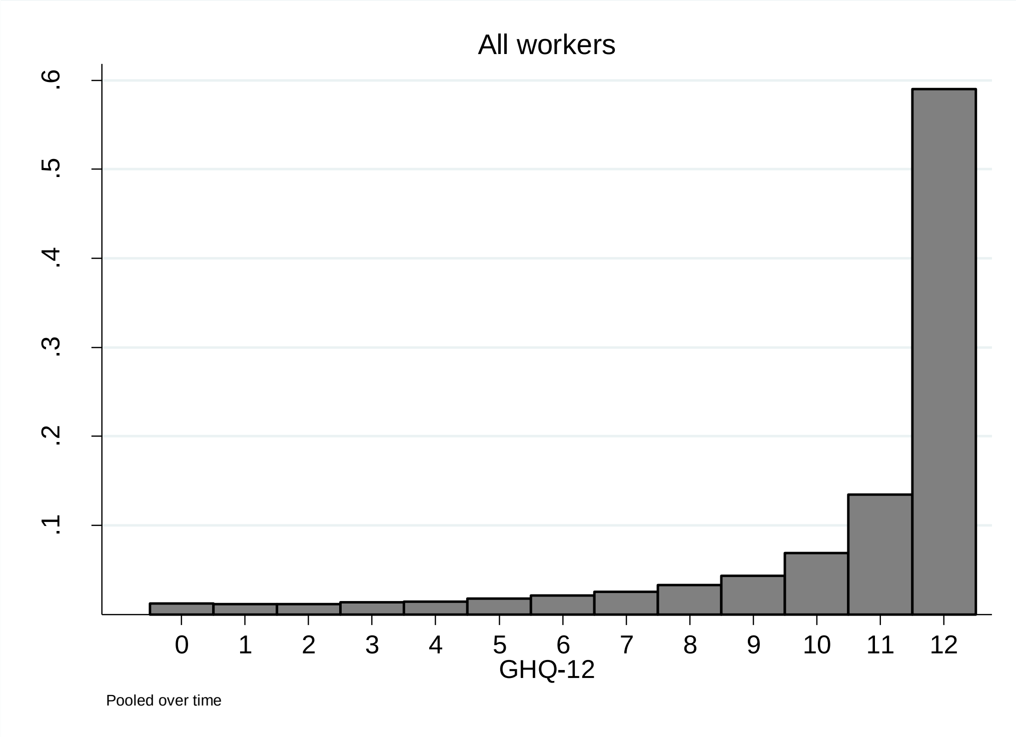


Figure 1b: Distribution of the GHQ Score in the SOC 8214 Category

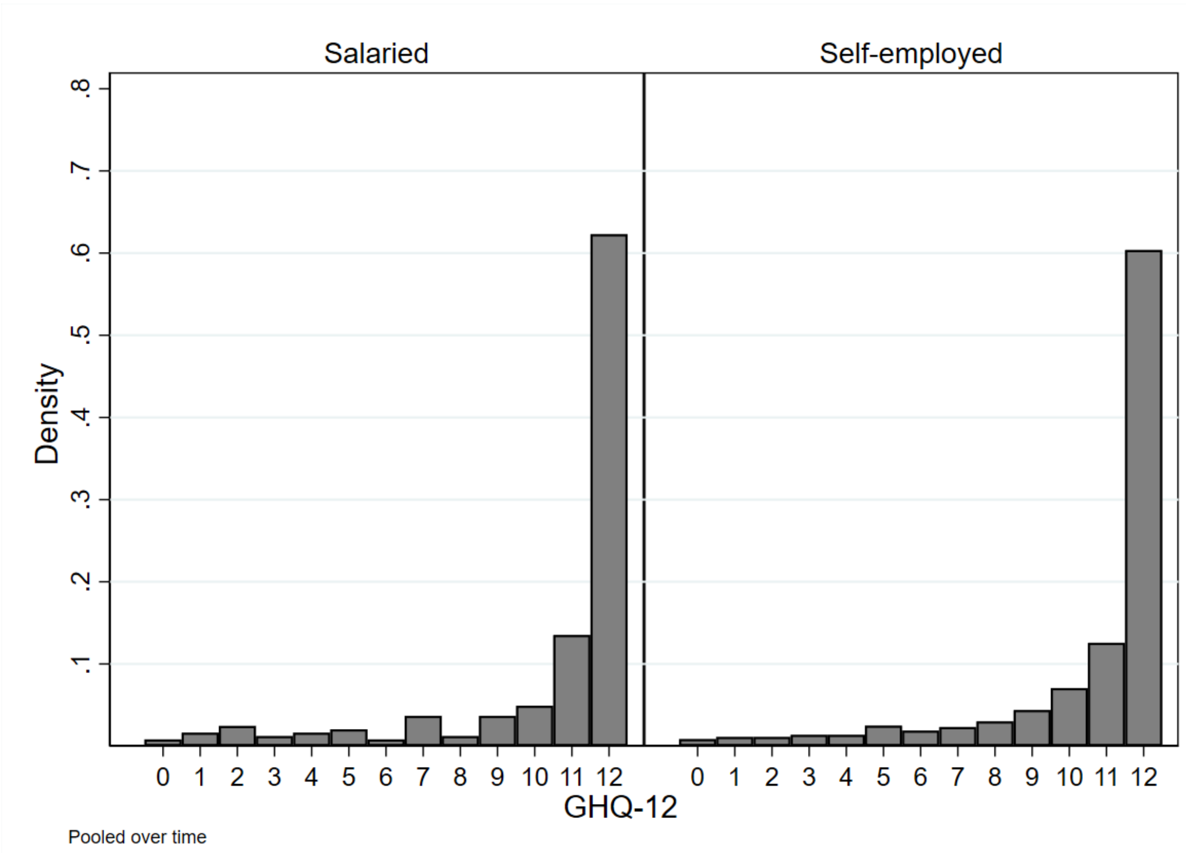


Figure 2: Uber UK Entry Date by Area

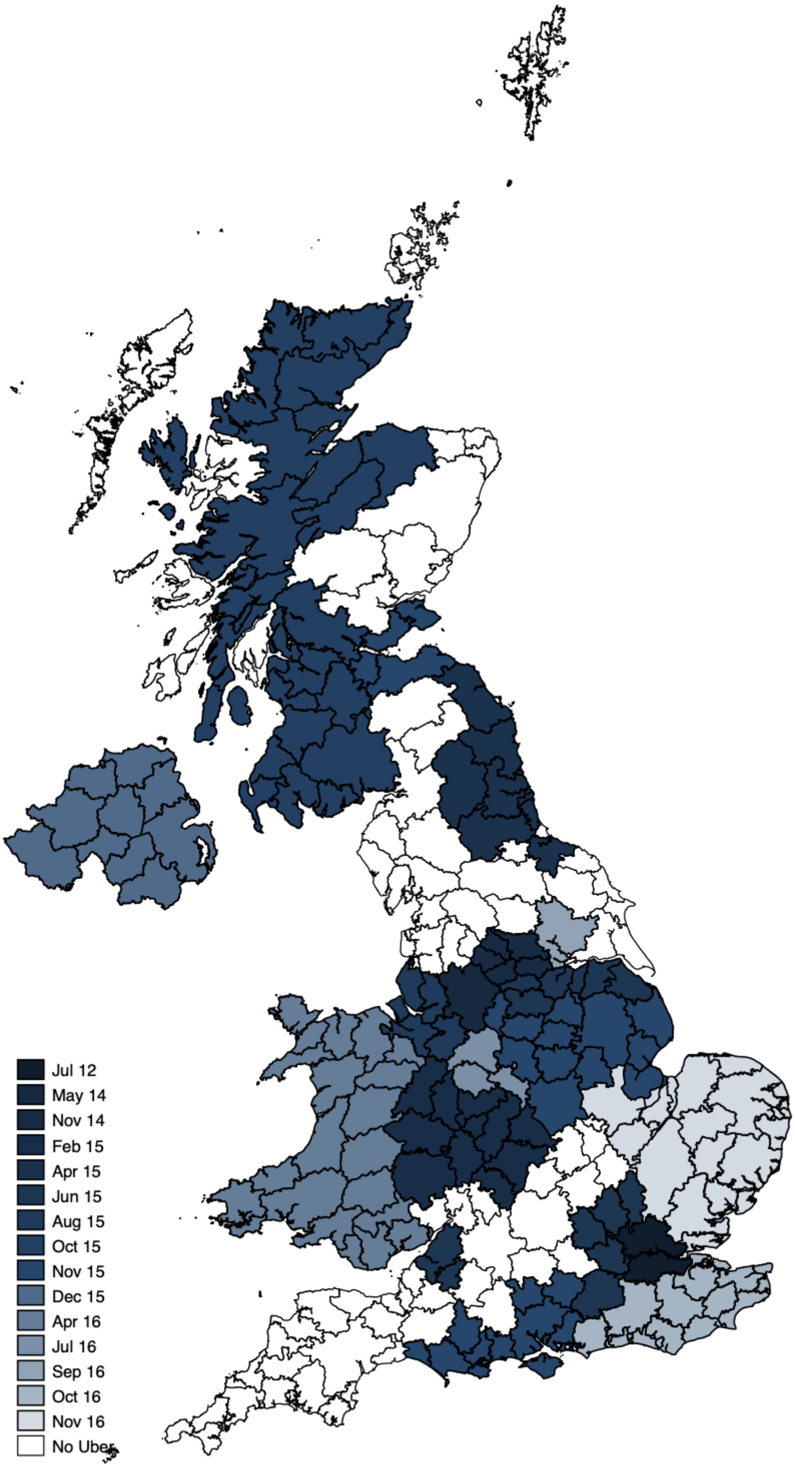
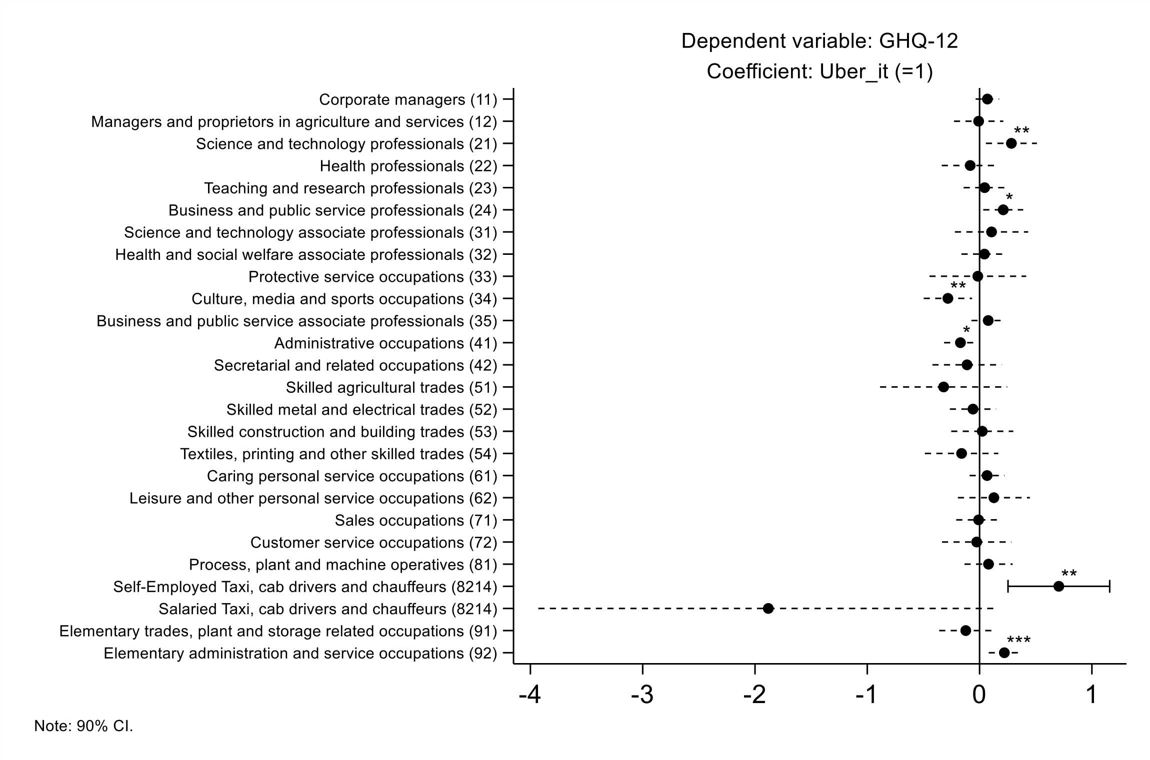


Figure 3: Correlation between Uber Diffusion and the GHQ Score



Notes: The figure presents the coefficients on Uber diffusion from a set of regressions (for each SOC) of the GHQ score on a dummy for Uber diffusion, controlling for female, white, age, college, household income (/1000), share of workers who are female / have a college degree / are in each age group, the mean household income of workers in the TTWA-year, population (ln) in the TTWA-year, and year and TTWA fixed effects. The 2-digit SOC codes are used, and in addition, we distinguish between self-employed and salaried drivers in SOC 8214.
Standard errors are clustered at the TTWA level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix A: SOC 2000 Job Classification Codes

Major Group	Sub-Major Group	Minor Group
1 Managers and Senior Officials	11 Corporate managers	111 Corporate managers and senior officials
		112 Production managers
		113 Functional managers
		114 Quality and customer care managers
		115 Financial institution and office managers
		116 Managers in distribution, storage and retailing
		117 Protective service officers
		118 Health and social services managers
	12 Managers and proprietors in agriculture and services	121 Managers in farming, horticulture, forestry and fishing
		122 Managers and proprietors in hospitality and leisure services
		123 Managers and proprietors in other service industries
2 Professional Occupations	21 Science and technology professionals	211 Science professionals
		212 Engineering professionals
		213 Information and communication technology professionals
	22 Health professionals	221 Health professionals
	23 Teaching and research professionals	231 Teaching professionals
		232 Research professionals
	24 Business and public service professionals	241 Legal professionals
		242 Business and statistical professionals
		243 Architects, town planners, surveyors
		244 Public service professionals
		245 Librarians and related professionals
3 Associate Professional and Technical Occupations	31 Science and technology associate professionals	311 Science and engineering technicians
		312 Draughtspersons and building inspectors
		313 IT service delivery occupations
	32 Health and social welfare associate professionals	321 Health associate professionals
		322 Therapists
		323 Social welfare associate professionals
	33 Protective service occupations	331 Protective service occupations
	34 Culture, media and sports occupations	341 Artistic and literary occupations
		342 Design associate professionals
		343 Media associate professionals
		344 Sports and fitness occupations

	35 Business and public service associate professionals	351 Transport associate professionals 352 Legal associate professionals 353 Business and finance associate professionals 354 Sales and related associate professionals 355 Conservation associate professionals 356 Public service and other associate professionals
4 Administrative and Secretarial Occupations	41 Administrative occupations	411 Administrative occupations: Government and related organisations 412 Administrative occupations: Finance 413 Administrative occupations: Records 414 Administrative occupations: Communications 415 Administrative occupations: General
	42 Secretarial and related occupations	421 Secretarial and related occupations
5 Skilled Trades Occupations	51 Skilled agricultural trades	511 Agricultural trades
	52 Skilled metal and electrical trades	521 Metal forming, welding and related trades 522 Metal machining, fitting and instrument making trades 523 Vehicle trades 524 Electrical trades
	53 Skilled construction and building trades	531 Construction trades 532 Building trades
	54 Textiles, printing and other skilled trades	541 Textiles and garments trades 542 Printing trades 543 Food preparation trades 549 Skilled trades N.E.C.
6 Personal Service Occupations	61 Caring personal service occupations	611 Healthcare and related personal services 612 Childcare and related personal services 613 Animal care services
	62 Leisure and other personal service occupations	621 Leisure and travel service occupations 622 Hairdressers and related occupations 623 Housekeeping occupations 629 Personal services occupations N.E.C.
7 Sales and Customer Service Occupations	71 Sales occupations	711 Sales assistants and retail cashiers 712 Sales related occupations
	72 Customer service occupations	721 Customer service occupations
8 Process, Plant and Machine Operatives	81 Process, plant and	811 Process operatives 812 Plant and machine operatives

	machine operatives	813 Assemblers and routine operatives 814 Construction operatives
	82 Transport and mobile machine drivers and operatives	821 Transport drivers and operatives *8211 Heavy goods vehicle drivers* *8212 Van drivers* *8213 Bus and coach drivers* *8214 Taxi, cab drivers and chauffeurs* *8215 Driving instructors* *8216 Rail transport operatives* *8217 Seafarers (merchant navy); barge, lighter and boat operatives* *8218 Air transport operatives* *8219 Transport operatives n.e.c* 822 Mobile machine drivers and operatives
9 Elementary Occupations	91 Elementary trades, plant and storage related occupations	911 Elementary agricultural occupations 912 Elementary construction occupations 913 Elementary process plant occupations 914 Elementary goods storage occupations
	92 Elementary administration and service occupations	921 Elementary administration occupations 922 Elementary personal services occupations 923 Elementary cleaning occupations 924 Elementary security occupations 925 Elementary sales occupations

Appendix B: Results for the Broader SOC 821 Category

Table B1: Correlation between Uber and the GHQ Score for Self-Employed Workers in SOC 821 (OLS Models)

	(1)	(2)	(3)	(4)
Uber	0.402**	0.435**	0.413**	0.421**
	(0.183)	(0.198)	(0.203)	(0.201)
25-39	-0.278	-0.262	-0.340	-0.305
	(0.404)	(0.413)	(0.400)	(0.394)
40-54	0.047	0.061	-0.034	-0.008
	(0.379)	(0.394)	(0.400)	(0.392)
55-64	0.239	0.268	0.242	0.221
	(0.451)	(0.449)	(0.445)	(0.443)
Female	-0.442	-0.464	-0.297	-0.342
	(0.484)	(0.482)	(0.498)	(0.499)
College	-0.119	-0.092	-0.049	-0.061
	(0.286)	(0.278)	(0.269)	(0.270)
White	0.260	0.276	0.392*	0.366*
	(0.204)	(0.202)	(0.200)	(0.197)
Household income (/1000)	0.093**	0.095**		0.099*
	(0.046)	(0.045)		(0.053)
Share of workers in SOC 821			4.130	4.031
			(3.186)	(3.249)
Share of females in SOC 821			-1.510	-1.501
			(0.948)	(0.939)
Share of college drivers in SOC 821			-1.162	-1.153*
			(0.704)	(0.679)
Share of white drivers in SOC 821			-1.625**	-1.559**
			(0.704)	(0.699)
Share of self-employed drivers in SOC 821			0.023	-0.057
			(0.444)	(0.449)
Mean income in SOC 821			0.053	-0.050
			(0.081)	(0.109)
Share of female workers		-4.731	-2.898	-2.961
		(3.032)	(2.887)	(2.875)
Share of college educated workers		-1.227	-0.207	-0.298
		(1.750)	(1.717)	(1.728)
Share of workers 25-39		0.759	-0.024	-0.135
		(2.656)	(2.591)	(2.599)
Share of workers 40-54		0.745	0.669	0.741
		(3.060)	(2.944)	(2.988)

Share of workers 55-64		0.146	-0.665	-0.526
		(2.159)	(2.043)	(2.052)
Mean income of workers		-0.039	0.019	0.030
		(0.247)	(0.246)	(0.247)
TTWA population (ln)		-1.263	-1.705	-1.979
		(1.616)	(1.442)	(1.444)
Constant	10.021***	29.060	35.118*	38.811**
	(0.530)	(22.030)	(19.434)	(19.432)
TTWA FE & year FE	Y	Y	Y	Y
Linear time trend	N	N	N	N
N	1688	1688	1688	1688
R-sq	0.172	0.174	0.175	0.179

Notes: Standard errors clustered at the TTWA level in parentheses.
* p < 0.10, ** p < 0.05, *** p < 0.01.

Table B2: Correlation between Uber and the GHQ Score for Salaried Workers in SOC 821 (OLS Models)

	(1)	(2)	(3)	(4)
Uber	-0.207	-0.214	-0.219	-0.233
	(0.149)	(0.148)	(0.152)	(0.154)
25-39	-0.073	-0.041	-0.094	-0.055
	(0.317)	(0.318)	(0.316)	(0.317)
40-54	-0.051	-0.027	-0.066	-0.035
	(0.316)	(0.318)	(0.313)	(0.317)
55-64	0.191	0.196	0.148	0.182
	(0.334)	(0.337)	(0.332)	(0.336)
Female	-0.271	-0.270	-0.229	-0.219
	(0.204)	(0.206)	(0.197)	(0.200)
College	-0.017	-0.009	0.038	0.043
	(0.187)	(0.187)	(0.189)	(0.190)
White	0.350**	0.354**	0.387**	0.344**
	(0.159)	(0.161)	(0.156)	(0.162)
Household income (/1000)	0.102***	0.103***		0.104***
	(0.026)	(0.026)		(0.028)
Share of workers in SOC 821			-0.516	-0.520
			(2.113)	(2.119)
Share of females in SOC 821			-0.439	-0.438
			(0.475)	(0.474)
Share of college drivers in SOC 821			-0.830*	-0.823*
			(0.447)	(0.447)
Share of white drivers in SOC 821			0.267	0.330
			(0.497)	(0.505)
Share of self-employed drivers in SOC 821			0.398	0.376
			(0.311)	(0.305)
Mean income in SOC 821			0.084	-0.006
			(0.061)	(0.064)
Share of female workers		-1.931*	-1.695	-1.725
		(1.050)	(1.087)	(1.096)
Share of college educated workers		0.980	1.310	1.297
		(0.987)	(1.019)	(1.027)
Share of workers 25-39		-3.192**	-3.130**	-3.226**
		(1.330)	(1.316)	(1.321)
Share of workers 40-54		-2.274*	-2.204*	-2.304*
		(1.248)	(1.233)	(1.239)
Share of workers 55-64		-0.000	0.175	0.084
		(1.461)	(1.435)	(1.438)

Mean income of workers		-0.055	-0.067	-0.071
		(0.139)	(0.144)	(0.144)
TTWA population (ln)		0.525	0.273	0.377
		(1.341)	(1.370)	(1.378)
Constant	10.094***	6.307	9.183	7.870
	(0.366)	(17.742)	(18.076)	(18.206)
TTWA FE & year FE	Y	Y	Y	Y
Linear time trend	N	N	N	N
N	3772	3772	3772	3772
R-sq	0.107	0.109	0.106	0.110

Notes: Standard errors clustered at the TTWA level in parentheses.
* p < 0.10, ** p < 0.05, *** p < 0.01.

Table B3: Decomposition of the GHQ Score for Self-Employed Workers in SOC 821 (OLS Models)

	Outcome: GHQ Components											
	(1) Concen-tration	(2) Loss of sleep	(3) Playing a useful role	(4) Capable of making decisions	(5) Constantly under strain	(6) Problem overcoming difficulties	(7) Enjoy day-to-day activities	(8) Ability to face problems	(9) Unhappy or depressed	(10) Losing confidence	(11) Believe in self-worth	(12) General happiness
Uber	0.031	0.041	0.033	0.034	0.061**	0.043	0.049*	0.044*	-0.000	0.033	0.004	0.020
	(0.030)	(0.027)	(0.027)	(0.021)	(0.025)	(0.030)	(0.027)	(0.023)	(0.027)	(0.029)	(0.018)	(0.023)
25-39	-0.050	0.035	-0.152	-0.053	0.188*	-0.035	-0.174***	-0.105***	0.110	-0.062	-0.033	-0.004
	(0.079)	(0.126)	(0.102)	(0.095)	(0.107)	(0.088)	(0.047)	(0.038)	(0.112)	(0.089)	(0.071)	(0.107)
40-54	-0.016	0.061	-0.102	-0.006	0.185	-0.027	-0.149***	-0.121***	0.161	-0.023	0.022	0.017
	(0.089)	(0.123)	(0.088)	(0.088)	(0.115)	(0.087)	(0.040)	(0.041)	(0.117)	(0.085)	(0.084)	(0.109)
55-64	0.014	0.099	-0.095	-0.003	0.220*	-0.011	-0.142***	-0.110**	0.181	-0.047	0.022	0.012
	(0.088)	(0.132)	(0.091)	(0.079)	(0.118)	(0.084)	(0.047)	(0.043)	(0.111)	(0.088)	(0.072)	(0.113)
Female	-0.031	-0.076	-0.005	-0.050	-0.081	-0.052	-0.085	-0.023	-0.009	-0.065	-0.012	0.009
	(0.045)	(0.058)	(0.047)	(0.062)	(0.052)	(0.053)	(0.067)	(0.047)	(0.042)	(0.054)	(0.046)	(0.033)
College	-0.012	0.011	-0.046*	0.014	-0.027	0.006	0.010	-0.029	-0.011	-0.014	-0.008	0.015
	(0.032)	(0.029)	(0.026)	(0.023)	(0.038)	(0.030)	(0.037)	(0.031)	(0.031)	(0.026)	(0.023)	(0.026)
White	0.008	0.038	0.040*	0.052**	0.005	0.052**	0.037	0.050*	-0.001	0.031	-0.037	-0.006
	(0.028)	(0.039)	(0.022)	(0.026)	(0.035)	(0.022)	(0.030)	(0.026)	(0.025)	(0.023)	(0.026)	(0.024)
Household income (/1000)	0.010***	0.007	0.003	0.008**	0.011*	0.008*	0.011**	0.010**	0.008*	0.007	0.005*	0.006*
	(0.003)	(0.006)	(0.005)	(0.004)	(0.006)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.003)	(0.004)
Share of female workers	-0.224	0.017	-0.284	-0.301	-0.373	-0.677*	-0.538	-0.794**	-0.362	-0.299	-0.104	-0.442
	(0.370)	(0.444)	(0.335)	(0.219)	(0.449)	(0.398)	(0.352)	(0.325)	(0.460)	(0.402)	(0.261)	(0.414)
Share of college	0.187	-0.070	0.310	-0.160	-0.508	-0.130	-0.252	-0.453**	-0.088	0.153	0.011	0.045
	(0.243)	(0.285)	(0.222)	(0.155)	(0.346)	(0.200)	(0.274)	(0.196)	(0.270)	(0.248)	(0.182)	(0.225)

educated workers												
Share of workers 25-39	0.210 (0.385)	0.166 (0.339)	0.087 (0.329)	0.096 (0.251)	0.218 (0.418)	0.073 (0.307)	0.056 (0.344)	0.180 (0.286)	-0.031 (0.435)	-0.014 (0.366)	0.025 (0.273)	-0.077 (0.352)
Share of workers 40-54	0.034 (0.450)	0.084 (0.408)	0.091 (0.353)	0.163 (0.300)	0.182 (0.461)	-0.280 (0.361)	0.147 (0.369)	0.468 (0.299)	0.385 (0.487)	-0.004 (0.366)	0.086 (0.253)	-0.205 (0.322)
Share of workers 55-64	0.130 (0.426)	-0.369 (0.366)	0.253 (0.276)	0.134 (0.210)	0.317 (0.365)	-0.096 (0.273)	-0.081 (0.259)	0.129 (0.240)	0.148 (0.305)	-0.070 (0.341)	-0.123 (0.252)	-0.051 (0.259)
Mean income of workers	-0.006 (0.036)	-0.002 (0.043)	-0.054* (0.031)	0.003 (0.018)	-0.023 (0.041)	-0.027 (0.029)	-0.018 (0.032)	0.005 (0.028)	0.012 (0.040)	0.016 (0.030)	-0.010 (0.018)	0.012 (0.029)
TTWA population (ln)	-0.372 (0.343)	0.347 (0.284)	-0.129 (0.186)	-0.102 (0.113)	0.265 (0.283)	-0.265 (0.232)	-0.458* (0.260)	-0.104 (0.211)	0.465* (0.256)	-0.226 (0.336)	0.011 (0.100)	-0.388 (0.297)
Constant	5.746 (4.625)	-3.822 (3.751)	2.886 (2.468)	2.333 (1.556)	-2.730 (3.756)	4.956 (3.163)	7.337** (3.434)	2.566 (2.820)	-5.502 (3.444)	3.927 (4.452)	0.835 (1.369)	6.274 (3.915)
TTWA FE & year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Linear time trend	N	N	N	N	N	N	N	N	N	N	N	N
N	1706	1707	1703	1706	1702	1706	1706	1705	1705	1703	1702	1700
R-sq	0.112	0.130	0.142	0.133	0.159	0.132	0.133	0.118	0.129	0.126	0.123	0.136

Notes: Standard errors clustered at the TTWA level in parentheses. Worker shares by demographic characteristics are for all workers.
* p < 0.10, ** p < 0.05, *** p < 0.01.

Table B4: Understanding the Correlation between Uber Entry and the GHQ Score in SOC 821 (OLS and Fixed-Effect Models)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample	Self-Employed	Self-Employed Before and After	Self-Employed	Self-Employed	Salaried	Salaried	Salaried
Model	OLS with time trend	OLS	FE	FE	OLS with time trend	FE	FE
Uber	0.290	0.217	0.029	0.024	-0.323*	-0.254	-0.276*
	(0.254)	(0.293)	(0.221)	(0.222)	(0.190)	(0.162)	(0.163)
25-39	-0.469		-0.860	-0.806	-0.043	0.068	0.062
	(0.430)		(0.928)	(0.943)	(0.332)	(0.616)	(0.608)
40-54	-0.146	0.400	-0.349	-0.315	-0.040	0.194	0.192
	(0.408)	(0.440)	(1.014)	(1.017)	(0.332)	(0.659)	(0.653)
55-64	0.167	0.752	-0.595	-0.529	0.162	0.212	0.203
	(0.459)	(0.503)	(1.084)	(1.085)	(0.357)	(0.711)	(0.706)
Female	-0.365	0.316			-0.204		
	(0.532)	(0.407)			(0.200)		
College	0.022	-0.345	2.428	2.398	-0.030	0.115	0.236
	(0.280)	(0.604)	(3.941)	(3.876)	(0.208)	(0.208)	(0.221)
White	0.308	0.473			0.369**		
	(0.213)	(0.373)			(0.165)		
Household income (/1000)	0.097*	0.034	-0.048	-0.069	0.107***	0.046	0.027
	(0.057)	(0.085)	(0.046)	(0.053)	(0.029)	(0.036)	(0.038)
Share of workers in SOC 821	1.488	12.219*		-0.085	0.717		1.273
	(3.765)	(6.762)		(2.753)	(1.905)		(1.894)
Share of females in SOC 821	-1.613	-3.134**		-1.966**	-0.647		-0.031
	(1.096)	(1.175)		(0.845)	(0.492)		(0.456)
Share of college drivers in SOC 821	0.404	-0.243		-0.028	-1.273**		-0.678
	(0.881)	(1.025)		(0.585)	(0.546)		(0.447)
Share of white drivers in SOC 821	-0.463	0.183		-0.230	-0.088		0.290
	(0.973)	(1.164)		(0.746)	(0.584)		(0.540)
Share of self-employed drivers in SOC 821	-0.351	0.304		0.447	0.422		0.543*
	(0.490)	(0.727)		(0.404)	(0.367)		(0.279)
Mean	-0.052	-0.007		0.070	-0.037		0.068

income in SOC 821	(0.116)	(0.231)		(0.069)	(0.071)		(0.063)
Share of female workers	4.059 (4.515)	-4.522 (4.028)	-0.063 (2.665)	-0.021 (2.620)	-2.205* (1.328)	-0.545 (0.990)	-0.438 (1.032)
Share of college educated workers	-2.061 (3.225)	-1.965 (2.445)	-0.852 (1.805)	-0.562 (1.882)	3.699*** (1.260)	2.496** (1.094)	2.930** (1.158)
Share of workers 25-39	2.378 (2.807)	5.292 (4.076)	0.033 (2.618)	-0.008 (2.732)	-2.879* (1.597)	-2.878* (1.621)	-3.116* (1.650)
Share of workers 40-54	2.573 (3.987)	-1.821 (4.051)	-1.626 (2.432)	-1.621 (2.413)	-2.220 (1.507)	-1.420 (1.553)	-1.625 (1.583)
Share of workers 55-64	2.455 (2.461)	2.829 (4.010)	-1.497 (1.987)	-2.019 (2.152)	0.639 (1.613)	0.779 (1.633)	0.493 (1.674)
Mean income of workers	-0.082 (0.330)	0.244 (0.360)	0.389** (0.189)	0.377** (0.187)	-0.065 (0.162)	-0.157 (0.137)	-0.180 (0.141)
TTWA population (ln)	-2.123 (1.997)	-3.965** (1.865)	1.163* (0.674)	1.274* (0.664)	-1.948 (1.973)	-0.379 (0.498)	-0.379 (0.514)
Constant	4.804 (90.475)	63.009** (25.527)	-5.226 (9.379)	-6.793 (9.185)	-51.778 (135.848)	17.037*** (6.541)	16.619** (6.803)
Year FE	Y	Y	Y	Y	Y	Y	Y
TTWA FE	Y	Y	N	N	Y	N	N
Linear time trend	Y	N	N	N	Y	N	N
Individual FE	N	N	Y	Y	N	Y	Y
N	1688	838	1688	1688	3772	3789	3772
N ind.	-	-	569	569	-	1241	1232
R-sq	0.234	0.280	0.024	0.028	0.152	0.010	0.012

Notes: Standard errors (clustered at the TTWA level in columns (1), (2), and (5)) in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B5: The GHQ Score Before and After Uber Entry
for Self-Employed Workers in SOC 821 (OLS Models)

	(1)	(2)	(3)	(4)	(5)	(6)
1-2 years before Uber	-0.0307	-0.0808				
	(0.252)	(0.247)				
Year Uber arrives	0.271	0.242				
	(0.258)	(0.259)				
Post Uber	0.533	0.513				
	(0.417)	(0.402)				
1-2 years before Uber			0.0199	-0.0261		
			(0.264)	(0.255)		
Year Uber arrives			0.344	0.327		
			(0.276)	(0.271)		
1 year after Uber			0.469	0.439		
			(0.411)	(0.408)		
2 or more years after Uber			0.841	0.912*		
			(0.536)	(0.468)		
Year Uber arrives					0.328*	0.349*
					(0.186)	(0.204)
1 year after Uber					0.451*	0.462
					(0.269)	(0.299)
2 or more years after Uber					0.820**	0.940***
					(0.349)	(0.316)
TTWA FE & year FE	Y	Y	Y	Y	Y	Y
Linear time trend	N	N	N	N	N	N
Individual controls	Y	Y	Y	Y	Y	Y
Household income control	Y	N	Y	N	Y	N
TTWA & SOC controls	N	Y	N	Y	N	Y
N	1,688	1,688	1,688	1,688	1,688	1,688
R-sq	0.172	0.175	0.173	0.176	0.173	0.176

Notes: The reference categories are 3 years or more before Uber entry (columns (1) to (4)) and before Uber entry (columns (5) and (6)).
Standard errors clustered at the TTWA level in parentheses.
* p < 0.10, ** p < 0.05, *** p < 0.01.

Table B6: The GHQ Score Before and After Uber Entry
for Salaried Workers in SOC 821 (OLS Models)

	(1)	(2)	(3)	(4)	(5)	(6)
1-2 years before Uber	0.154	0.107				
	(0.124)	(0.123)				
Year Uber arrives	-0.186	-0.233				
	(0.194)	(0.195)				
Post Uber	0.0928	0.0524				
	(0.238)	(0.242)				
1-2 years before Uber			0.168	0.124		
			(0.127)	(0.127)		
Year Uber arrives			-0.167	-0.207		
			(0.207)	(0.209)		
1 year after Uber			0.0501	0.00140		
			(0.235)	(0.241)		
2 or more years after Uber			0.202	0.201		
			(0.283)	(0.287)		
Year Uber arrives					-0.296*	-0.303*
					(0.159)	(0.163)
1 year after Uber					-0.0893	-0.102
					(0.175)	(0.183)
2 or more years after Uber					0.0349	0.0785
					(0.204)	(0.209)
TTWA FE & year FE	Y	Y	Y	Y	Y	Y
Linear time trend	N	N	N	N	N	N
Individual controls	Y	Y	Y	Y	Y	Y
Household income control	Y	N	Y	N	Y	N
TTWA & SOC controls	N	Y	N	Y	N	Y
N	3,772	3,772	3,772	3,772	3,772	3,772
R-sq	0.107	0.107	0.108	0.107	0.107	0.107

Notes: The reference categories are 3 years or more before Uber entry (columns (1) to (4)) and before Uber entry (columns (5) and (6)).
Standard errors clustered at the TTWA level in parentheses.
* p < 0.10, ** p < 0.05, *** p < 0.01.

Table B7: The GHQ Score Before and After Uber Entry
for Self-Employed Workers in SOC 821 (Fixed Effect Models)

	(1)	(2)	(3)	(4)	(5)	(6)
1-2 years before Uber	0.0699	0.0756				
	(0.252)	(0.252)				
Year Uber arrives	0.0210	0.0286				
	(0.324)	(0.325)				
Post Uber	0.249	0.234				
	(0.387)	(0.389)				
1-2 years before Uber			0.0958	0.101		
			(0.256)	(0.255)		
Year Uber arrives			0.0646	0.0725		
			(0.326)	(0.326)		
1 year after Uber			0.220	0.202		
			(0.384)	(0.386)		
2 or more years after Uber			0.502	0.506		
			(0.464)	(0.465)		
Year Uber arrives					-0.0204	-0.0172
					(0.222)	(0.222)
1 year after Uber					0.126	0.103
					(0.291)	(0.294)
2 or more years after Uber					0.396	0.396
					(0.358)	(0.360)
Year FE	Y	Y	Y	Y	Y	Y
TTWA FE	N	N	N	N	N	N
Linear time trend	N	N	N	N	N	N
Individual FE	Y	Y	Y	Y	Y	Y
Individual controls	Y	Y	Y	Y	Y	Y
Household income control	Y	Y	Y	Y	Y	Y
TTWA controls	Y	Y	Y	Y	Y	Y
SOC controls	N	Y	N	Y	N	Y
N	1,688	1,688	1,688	1,688	1,688	1,688
N ind.	569	569	569	569	569	569
R-sq	0.024	0.029	0.025	0.030	0.025	0.030

Notes: The reference categories are 3 years or more before Uber entry (columns (1) to (4)) and before Uber entry (columns (5) and (6)).
Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B8: The GHQ Score Before and After Uber Entry
for Salaried Workers in SOC 821 (Fixed Effect Models)

	(1)	(2)	(3)	(4)	(5)	(6)
1-2 years before Uber	0.0779	0.0710				
	(0.138)	(0.139)				
Year Uber arrives	-0.187	-0.210				
	(0.199)	(0.201)				
Post Uber	-0.102	-0.134				
	(0.251)	(0.253)				
1-2 years before Uber			0.0923	0.0858		
			(0.137)	(0.138)		
Year Uber arrives			-0.161	-0.184		
			(0.205)	(0.207)		
1 year after Uber			-0.126	-0.158		
			(0.254)	(0.255)		
2 or more years after Uber			0.0476	0.0253		
			(0.305)	(0.307)		
Year Uber arrives					-0.243	-0.261
					(0.170)	(0.171)
1 year after Uber					-0.215	-0.241
					(0.219)	(0.220)
2 or more years after Uber					-0.0566	-0.0712
					(0.275)	(0.278)
Year FE	Y	Y	Y	Y	Y	Y
TTWA FE	N	N	N	N	N	N
Linear time trend	N	N	N	N	N	N
Individual FE	Y	Y	Y	Y	Y	Y
Individual controls	Y	Y	Y	Y	Y	Y
Household income control	Y	Y	Y	Y	Y	Y
TTWA controls	Y	Y	Y	Y	Y	Y
SOC controls	N	Y	N	Y	N	Y
N	3,789	3,772	3,789	3,772	3,789	3,772
N ind.	1,241	1,232	1,241	1,232	1,241	1,232
R-sq	0.011	0.014	0.012	0.014	0.011	0.014

Notes: The reference categories are 3 years or more before Uber entry (columns (1) to (4)) and before Uber entry (columns (5) and (6)).
Standard errors in parentheses.
* p < 0.10, ** p < 0.05, *** p < 0.01.

Figure B1a: Distribution of the GHQ Score
Across All Individuals

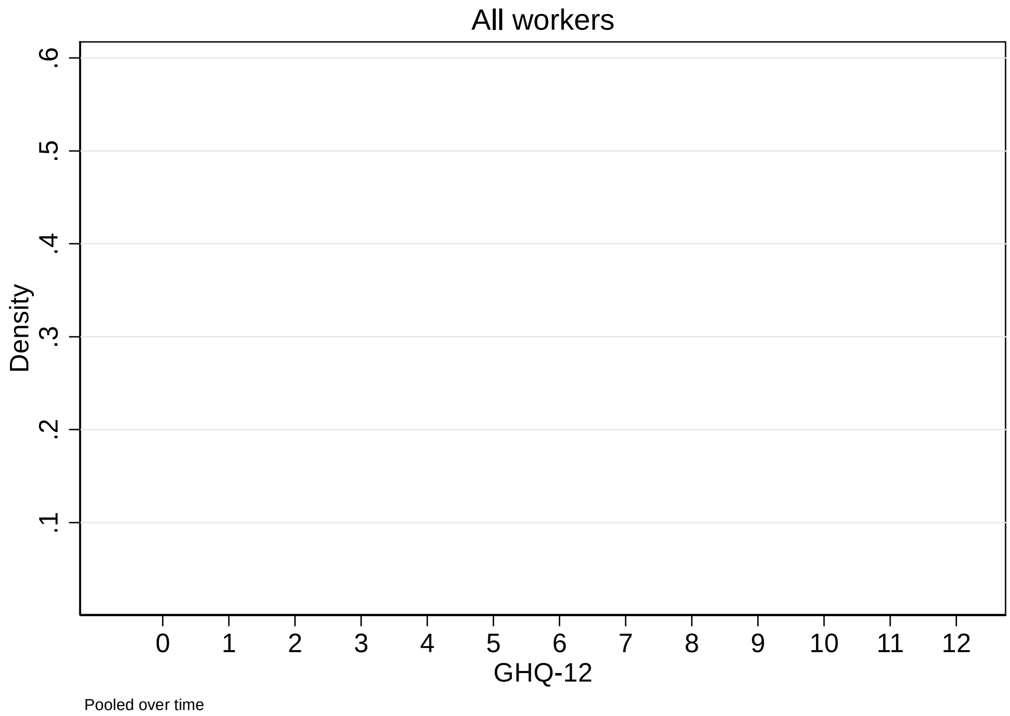


Figure B1b: Distribution of the GHQ Score
in the SOC 821 Category