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The Effects of Uber Diffusion on Mental Health

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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 well-being. This paper examines the effect of Uber diffusion on several dimensions of mental health among UK workers, 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 self-employment expands in the "transportation" occupational category after Uber's introduction. We then find 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 (generated by individuals who become self-employed drivers after Uber introduction) 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 workers who remained wage-employed drivers over time, we find a decline in mental health after Uber 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).

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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] are rapidly developing, due to technology growth. 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 explore the effect of the spatial diffusion of Uber -- the pioneer of gig economy work -- on mental health in the UK.

The relationship between mental health and gig economy work, which is characterized by self-employment,[3] flexibility, and precarity, is not a priori obvious. Historically, most empirical studies show that self-employment is positively 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.

[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] 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.

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., 2018b). In this paper, we explore this impact through the lens of Uber in the UK. Specifically, 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. 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 verify that Uber's diffusion has a direct effect on self-employment in the transportation sector, but not elsewhere. We then show that within this sector, there are accompanying changes in well-being. We find that in the population group of self-employed drivers, mental health, as measured by the General Health Questionnaire (GHQ), is greater after Uber's introduction. This positive correlation between Uber and GHQ is explained by a greater enjoyment of daily activities, a decrease in psychological strain, and a greater ability to face problems after Uber introduction. In contrast, among employed drivers, GHQ worsens after Uber entry. We argue that the positive association between Uber and mental health among self-employed drivers captures a selection effect (generated by individuals who become self-employed drivers after Uber introduction) 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 individuals who were already self-employed drivers before Uber entry. In addition, we observe a decrease in mental health after Uber entry for workers who remain wage-employed drivers over time.

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 one major source of new self-employment – Uber – on worker 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, section 3 presents our data, section 4 contains our methodology and results, and section 5 concludes.

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).[4] Self-employment has been rapidly growing since the turn of the century (12% of the labor force in 2001, versus 15.1% in 2017).[5] Meanwhile, the labor market has become increasingly precarious.

While general population surveys do not include questions on the gig economy, 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. In particular, 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 "saw 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

[4] See https://www.ons.gov.uk/employmentandlabourmarket/peoplenotinwork/unemployment/timeseries/mgsx/lms.
[5] See https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/articles/trendsinselfemploymentintheuk/2018-02-07

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. (2018b) 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.

In contrast with this article, we focus on the diffusion of Uber in the whole country starting 2012. While Berger et al. (2018b) 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's introduction.[6]

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).

[6] Berger et al. (2018a) 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.

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 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. First, 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 generate anxiety and have a negative impact on health.

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 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.

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 individuals report better self-assessed health (SAH) compared with permanent employees, low perceived security has a deleterious impact on SAH, chronic diseases, and psychological distress.

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.

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.

3. Data

Understanding Society

Our individual-level data come from Understanding Society, the UK Household Longitudinal study, between 2009 and 2019. Information is collected during face-to-face interviews and through a self-completion questionnaire. The data contain rich information on different types of health measures.

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.

In addition, we examine worker anxiety using the anxiety subscale from Warr's (1990) job-related affective well-being scale. This subscale measures job "anxiety-contentment." The measure is only available on waves 2, 4, and 6, and runs from 3 to 15, where higher values represent lower levels of anxiety (15 being the least anxious).

Understanding Society data also contain detailed information in each year on current economic activity of the respondent, and in particular on whether the individual is self-employed or employed (i.e. wage-employed, not self-employed). 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).[7] The rest of the paper will pay particular attention to the SOC 821 category, i.e. "Transport drivers and operatives."

[7] The full set of SOC 2000 occupational categories is listed in the appendix.

The data also provide information on sociodemographic characteristics including gender, race, age, household size, and income. Table 1 presents summary statistics for health, labor market status, and sociodemographic control variables for our full sample and specifically for SOC 821. The distribution of the GHQ score is shown in Figure 1. For SOC 821, the mean is 10.8 out of 12, with the bulk of responses between 10 and 12. Finally, the data indicate the travel to work area (commuting area), or TTWA, of each household, which we use to merge Understanding Society with aggregate data.

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. 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).

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, or where Uber is still yet to arrive, the Uber diffusion variable is coded as zero.

The dates of Uber's 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's 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. (2018a) to study the impact of Uber on labor market outcomes (earnings, etc.) in conventional taxi services in the US.

Uber's 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's entry in 2012 in the UK, or averaged over the 2009-2011 period. Table 2 presents these results and shows that Uber is more likely to enter early in TTWAs with greater population size, with a higher level of education, where there are more drivers as a share of the workforce, and where low-educated and 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 and results

Effect of Uber Rollout on Self-Employment

We begin by examining the effect of the diffusion of Uber on self-employment across occupational categories in the UK. To do so, we run regressions of the following form, for each of the 25 occupational categories separately:

$$SelfEmployment_{ijt} = \alpha_i + \beta.UberDiffusion_{jt} + \gamma.X_{it} + \psi.V_{jt} + \omega_j + \delta_t + \epsilon_{ijt} \quad (1)$$

where $SelfEmployment_{ijt}$ is a dummy for whether a person i, who lives in TTWA j, is self-employed in year t. Moreover, $UberDiffusion_{jt}$ is the indicator for Uber being present in TTWA j at time t. In addition, X is a vector of individual-level, time-varying characteristics, that includes a female dummy, age group dummies, a white dummy, a college education dummy, and household income (/1,000). Moreover, V is a vector of TTWA-level characteristics, that includes the shares of workers who are female, are in each age group, and have a college degree, the mean household income of workers in the TTWA-year, and population size in the TTWA-year. The regressions include TTWA fixed effects (ω_j) and time fixed effects (δ_t). Standard errors are clustered at the TTWA level.

The results are displayed graphically in Figure 3. The diffusion of Uber has almost no effect on self-employment in the different occupational categories, with the notable exceptions of SOC 821 (which is “Transport drivers and operatives”), SOC 21 (“Science and technology professionals”), and SOC 24 (“Business and public service professionals”). In other words, Uber diffusion increased the probability of drivers being self-employed (and increased the share of self-employed people in science and technology professions and decreased this share in business and public service professions), but did not have significant effects on self-employment rates for other workers. This suggests that an interesting place to study the effect of Uber entry on worker health is within the “Transport drivers and operatives” category (where we find significant changes in self-employment).

Uber Entry and Mental Health among Drivers

Based on the results from Figure 3 presented above, we begin our analysis of the impact of Uber diffusion on mental health by focusing on workers within the “Transport drivers and operatives” occupational category (SOC 821). We first estimate the correlation between Uber diffusion and worker mental health as follows:

$$MH_{ijt} = \alpha + \beta . UberDiffusion_{jt} + \gamma . X_{ijt} + \omega_j + \delta_t + \epsilon_{ijt} \quad (2)$$

where MH_{ijt} denotes individual mental health. 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’s introduction, in our samples of interest.

The model systematically includes individual-level controls as well as TTWA and year fixed effects. In some specifications, we also include time-varying controls related to SOC 821 (share of workers, women, white, and college drivers in SOC 821) 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. We also tried clustering at the individual level which resulted in slightly larger standard errors.

We estimate equation (2) for the sample of self-employed workers in SOC 821 (hereafter "self-employed drivers") and the sample of employed (i.e. not self-employed) workers in SOC 821 (hereafter "employed 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 "employed drivers" is defined in a similar way. We estimate the equation for self-employed and employed drivers separately, as we expect that the effect of Uber diffusion may be different in these two groups: in particular, employed drivers, who may work for regular taxi companies, may feel the competition from Uber drivers and may thus be negatively affected by Uber entry.

In our initial specification of equation (2), 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 workers may choose to stop being self-employed drivers at some point. We discuss this selection issue below.

We estimate equation (2) using, as dependent variables, the total GHQ score, but also the twelve questions of the GHQ questionnaire and a measure of anxiety. In a heterogeneity analysis, we test whether effects depend on gender, education, and income.

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 821 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 0.4-point increase (on a scale ranging from 0 to 12) for self-employed workers, which corresponds to 16% of a standard deviation. In the next columns, we add TTWA- and SOC-level controls. Importantly, the coefficient on Uber remains 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 workers in SOC 821.

In Table 4, we estimate the same models but for employed workers instead of self-employed workers. A priori we expect that Uber's entry could also affect these workers: indeed, Uber may represent increased competition and uncertainty which could, in turn, affect mental health.

The coefficient on Uber is consistently negative in sign but not significant. Once again, the coefficient is relatively stable across a variety of different specifications.

As a 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 generally find for self-employed drivers is not due to some unobserved trend or event that would have happened at the same time as Uber's 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. We present the results in Figure 4 for 25 other SOC occupational categories, and find a significant effect in only 6 cases out of 25. In all these cases, the coefficients are smaller (in absolute value) than the coefficient on Uber for self-employed workers in SOC 821, suggesting that there was no uniform shock to mental health that occurred at the same time as Uber entry. We interpret the combination of evidence in Figures 3 and 4 to suggest that both the "effects" of Uber entry on (a) self-employment and (b) mental health are concentrated in the areas where Uber should, a priori, have had the greatest impact, and not in other random occupational categories.

We investigate whether the correlation between Uber and health is heterogeneous in regards to gender, race, and education. In each case, we interact the Uber diffusion variable with a dummy for either being female or white or having pursued college education. The results (available upon request) suggest no differences along these dimensions.

Decomposition of the Correlation with the General Health Questionnaire Score

The GHQ-12 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 elements of mental health which are most affected by the diffusion of the gig economy. We therefore estimate our main specification on the correlation between Uber diffusion and the mental health of self-employed workers in SOC 821, for each element of the GHQ. We report the results in Table 5 (each column contains the results of a regression in which a sub-component of the GHQ score is used as the dependent variable). The correlation with mental health appears to be concentrated in three areas: less under strain, greater enjoyment of daily activities, and greater ability to face problems.

Anxiety

We also estimate models using a measure of job anxiety (constructed from an Understanding Society anxiety subscale, as noted above) as the dependent variable. In this case, higher values of the scale represent lower levels of anxiety. The results are reported in Table 6.[8] As with the main results discussed above, the sample consists of self-employed workers in SOC 821 and each column represents a regression with different controls. While coefficients are positive in each specification, and fairly stable across specifications, they are never statistically significant. We note that given the limited data availability on anxiety, our sample sizes are much smaller, which may account, in part, for the absence of significance here.

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

[8] Because the anxiety variable in available in three waves only, the sample size is smaller.

Our results above suggest that after Uber entry, self-employment became more frequent among drivers (which could be due to workers moving to become self-employed drivers), and that overall mental health improved at the same time among self-employed workers in SOC 821. 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 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 employed workers in SOC 821), but including linear time trends to better capture unobserved confounding factors. Second, we re-estimate the model in Table 3 but restricting the sample to individuals who were self-employed workers in SOC 821 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 workers in SOC 821 after Uber entry are dropped, as well as individuals who stopped being self-employed workers in SOC 821 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 entry. We do this for both self-employed drivers and employed drivers.

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, but is smaller (than in Table 3) and no longer significant. This suggests that the positive correlation between Uber entry and GHQ in Table 3 is partly driven by omitted factors.

In column (2), we restrict the sample to drivers who were self-employed both before and after Uber entry. The coefficient on Uber remains large, but is not significant. This implies that the positive association in Table 3 is also partly due to a selection effect (in particular, new entrants who are in better health).

Columns (3) and (4) contain fixed effects models for the sample of self-employed workers in SOC 821. 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 very small and insignificant, suggesting that the positive correlation between Uber and GHQ in Table 3 is not driven by improvements in mental health for self-employed drivers. 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.

Columns (5) to (7) report results for the sample of employed drivers, and highlight that the correlation between Uber entry and GHQ is negative and statistically significant for this population group, in these more reliable models. First, column (5) shows that when a linear time trend is included, the coefficient on Uber is negative and statistically significant (note that in contrast, Table 4 showed a negative but insignificant effect). Results from the fixed effect models in Table 7, columns (6) and (7), also highlight a detrimental impact. In contrast with results for self-employed drivers, when we include individual fixed effects, the coefficient on

Uber becomes larger (than in Table 4) and more significant, in the sample of employed drivers. We thus find a strong negative impact of Uber entry on mental health for individuals who were employed drivers at baseline and who remained employed drivers over time. This result is consistent with increased stress and unhappiness caused by the additional competition created by Uber.

5. 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 has affected several dimensions of worker mental health. We find that Uber introduction is positively correlated with mental health, as measured by the GHQ score, in the group of self-employed workers in driving occupations. This positive association is driven by greater enjoyment of daily activities, a decrease in psychological strain, and greater ability to face problems. This correlation is not due to improvements in mental health for existing self-employed drivers, but to a selection effect (i.e. new entrants into self-employed driving) post Uber entry, and to the omission of confounding factors. Finally, we provide evidence of a decline in health for drivers who were wage-employed (as opposed to self-employed) before Uber entry, and remained employed drivers, suggesting some negative spillover effects of Uber entering the market.

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.

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Table 1: Summary Statistics for the Full Sample and the SOC 821 Sample

	All Workers					SOC 821				
	N	Mean	SD	Min	Max	N	Mean	SD	Min	Max
Mental Health Outcomes										
GHQ (0-12 scale)	188663	10.447	2.761	0	12	5634	10.812	2.441	0	12
GHQ: Concentration	188663	2.115	0.477	1	4	5634	0.898	0.302	0	1
GHQ: Loss of sleep	188663	1.818	0.760	1	4	5634	0.881	0.324	0	1
GHQ: Playing a useful role	188663	2.008	0.506	1	4	5634	0.910	0.286	0	1
GHQ: Capable of making decisions	188663	1.989	0.431	1	4	5634	0.939	0.239	0	1
GHQ: Constantly under strain	188663	2.033	0.748	1	4	5634	0.849	0.358	0	1
GHQ: Problem overcoming difficulties	188663	1.748	0.711	1	4	5634	0.902	0.298	0	1
GHQ: Enjoy day-to-day activities	188663	2.094	0.494	1	4	5634	0.887	0.316	0	1
GHQ: Ability to face problems	188663	2.022	0.438	1	4	5634	0.924	0.265	0	1
GHQ: Unhappy or depressed	188663	1.805	0.785	1	4	5634	0.863	0.344	0	1
GHQ: Losing confidence	188663	1.671	0.761	1	4	5634	0.908	0.288	0	1
GHQ: Believe in self-worth	188663	1.368	0.651	1	4	5634	0.941	0.235	0	1
GHQ: General happiness	188663	2.016	0.546	1	4	5634	0.909	0.288	0	1
Job-related well-being scale: Anxiety subscale	83587	11.996	2.623	3	15	2489	12.298	2.639	3	15
Explanatory Variables										
Uber	188663	0.276	0.447	0	1	5634	0.303	0.460	0	1
Self-Employed	188578	0.126	0.332	0	1	5631	0.317	0.465	0	1
Age	188663	41.611	12.029	18	64	5634	45.863	10.626	18	64
Female	188661	0.532	0.499	0	1	5634	0.077	0.267	0	1
White	187019	0.847	0.360	0	1	5613	0.765	0.424	0	1
College	186827	0.462	0.499	0	1	5508	0.162	0.368	0	1
Household income (/1000)	187467	4.573	2.811	-52.285	89.487	5607	3.510	1.876	-0.765	21.116

Notes: Pooled 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 in Transport Drivers and Operatives (of workers)	-5.264	-14.211**	-8.370*
	(3.140)	(6.015)	(4.747)
Mean GHQ (of drivers)	-0.002	-0.025	-0.047
	(0.034)	(0.037)	(0.066)
Share female drivers (of drivers)	0.638	-0.030	-0.316
	(1.067)	(1.053)	(1.104)
Share low-educated drivers (of drivers)	-0.324	-1.096*	-1.409*
	(0.606)	(0.601)	(0.803)
Share white drivers (of drivers)	1.576**	1.052**	0.951*
	(0.587)	(0.445)	(0.495)
Share self-employed drivers (of drivers)	0.047	0.450	0.027
	(0.372)	(0.415)	(0.550)
Mean earnings (of drivers)	0.176	0.180*	0.079
	(0.131)	(0.105)	(0.217)
TTWA characteristics			
Mean GHQ		0.234	0.031
		(0.187)	(0.212)
Population (ln)		-0.374**	-0.359**
		(0.172)	(0.172)
Mean earnings		0.183	0.363
		(0.200)	(0.300)
College share		-4.582***	-3.406**
		(1.647)	(1.631)
Share aged < 40		0.384	-2.266
		(2.321)	(2.486)
Characteristics measured in	2011	2011	2009-11
N	53	53	53
R^2	0.337	0.555	0.500

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

Table 3: Correlation between Uber and GHQ (0-12 Scale)
for Self-Employed Workers in SOC 821

	(1)	(2)	(3)	(4)	(5)
Uber	0.402**	0.405**	0.435**	0.413**	0.421**
	(0.183)	(0.186)	(0.198)	(0.203)	(0.201)
25-39	-0.278	-0.269	-0.262	-0.340	-0.305
	(0.404)	(0.400)	(0.413)	(0.400)	(0.394)
40-54	0.047	0.030	0.061	-0.034	-0.008
	(0.379)	(0.384)	(0.394)	(0.400)	(0.392)
55-64	0.239	0.239	0.268	0.242	0.221
	(0.451)	(0.449)	(0.449)	(0.445)	(0.443)
Female	-0.442	-0.457	-0.464	-0.297	-0.342
	(0.484)	(0.479)	(0.482)	(0.498)	(0.499)
College	-0.119	-0.105	-0.092	-0.049	-0.061
	(0.286)	(0.275)	(0.278)	(0.269)	(0.270)
White	0.260	0.381*	0.276	0.392*	0.366*
	(0.204)	(0.195)	(0.202)	(0.200)	(0.197)
Household income (/1000)	0.093**	0.092**	0.095**		0.099*
	(0.046)	(0.046)	(0.045)		(0.053)
Share of workers in SOC 821		3.524		4.130	4.031
		(2.846)		(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		-1.598**		-1.625**	-1.559**
		(0.696)		(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		-0.452	-1.227	-0.207	-0.298
		(1.540)	(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)		-1.352	-1.263	-1.705	-1.979
		(1.604)	(1.616)	(1.442)	(1.444)
Constant	10.021***	28.960	29.060	35.118*	38.811**
	(0.530)	(21.379)	(22.030)	(19.434)	(19.432)
TTWA & year FE	Y	Y	Y	Y	Y
Linear time trend	N	N	N	N	N
N	1688	1688	1688	1688	1688
R-sq	0.172	0.175	0.174	0.175	0.179

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

Table 4: Correlation between Uber and GHQ (0-12 scale) for Employed Workers in SOC 821

	(1)	(2)	(3)	(4)	(5)
Uber	-0.207	-0.203	-0.214	-0.219	-0.233
	(0.149)	(0.146)	(0.148)	(0.152)	(0.154)
25-39	-0.073	-0.077	-0.041	-0.094	-0.055
	(0.317)	(0.317)	(0.318)	(0.316)	(0.317)
40-54	-0.051	-0.054	-0.027	-0.066	-0.035
	(0.316)	(0.316)	(0.318)	(0.313)	(0.317)
55-64	0.191	0.188	0.196	0.148	0.182
	(0.334)	(0.334)	(0.337)	(0.332)	(0.336)
Female	-0.271	-0.269	-0.270	-0.229	-0.219
	(0.204)	(0.206)	(0.206)	(0.197)	(0.200)
College	-0.017	-0.019	-0.009	0.038	0.043
	(0.187)	(0.187)	(0.187)	(0.189)	(0.190)
White	0.350^{**}	0.337^{**}	0.354^{**}	0.387^{**}	0.344^{**}
	(0.159)	(0.160)	(0.161)	(0.156)	(0.162)
Household income (/1000)	0.102^{***}	0.102^{***}	0.103^{***}		0.104^{***}
	(0.026)	(0.027)	(0.026)		(0.028)
Share of workers in SOC 821		-0.217		-0.516	-0.520
		(1.822)		(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		0.245		0.267	0.330
		(0.517)		(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		0.399	0.980	1.310	1.297
		(0.939)	(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)		0.155	0.525	0.273	0.377
		(1.371)	(1.341)	(1.370)	(1.378)
Constant	10.094***	7.824	6.307	9.183	7.870
	(0.366)	(17.656)	(17.742)	(18.076)	(18.206)
TTWA & year FE	Y	Y	Y	Y	Y
Linear time trend	N	N	N	N	N
N	3772	3772	3772	3772	3772
R-sq	0.107	0.107	0.109	0.106	0.110

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

Table 5: Decomposition of the GHQ Score for Self-Employed Workers in SOC 821

	Outcome: Subcomponents. SOC 821 Self-Employed											
	(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 & 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.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Correlation between Uber and Anxiety Levels
for Self-Employed Workers in SOC 821

	Outcome: Anxiety. SOC 821 Self-Employed					
	(1)	(2)	(3)	(4)	(5)	(6)
Uber	0.278	0.333	0.269	0.323	0.327	0.400
	(0.418)	(0.399)	(0.441)	(0.407)	(0.407)	(0.550)
25-39	-1.095	-1.261	-1.038	-1.241*	-1.178	-1.360
	(0.823)	(0.820)	(0.745)	(0.735)	(0.736)	(0.821)
40-54	-1.062	-1.228	-1.035	-1.216*	-1.168	-1.182
	(0.816)	(0.817)	(0.729)	(0.724)	(0.728)	(0.752)
55-64	-0.797	-0.930	-0.737	-0.894	-0.857	-0.858
	(0.851)	(0.848)	(0.769)	(0.758)	(0.760)	(0.782)
Female	0.277	0.322	0.274	0.404	0.386	0.462
	(0.421)	(0.417)	(0.433)	(0.436)	(0.420)	(0.507)
College	-0.068	-0.052	-0.032	-0.020	-0.023	-0.025
	(0.219)	(0.225)	(0.229)	(0.231)	(0.233)	(0.266)
White	0.663	0.648	0.663	0.665	0.645	0.468
	(0.405)	(0.423)	(0.406)	(0.426)	(0.419)	(0.486)
Household income (/1000)	0.067	0.069	0.077		0.082	0.102
	(0.057)	(0.056)	(0.056)		(0.061)	(0.068)
Share of workers in SOC 821		31.897***		32.618***	32.172***	26.963**
		(8.060)		(9.005)	(9.073)	(12.757)
Share of females in SOC 821				-0.876	-0.919	-0.713
				(1.316)	(1.304)	(2.597)
Share of college drivers in SOC 821				-0.427	-0.461	2.938
				(1.256)	(1.235)	(2.109)
Share of white drivers in SOC 821		-0.266		-0.270	-0.317	0.280
		(0.958)		(1.074)	(1.071)	(1.919)
Share of self-employed drivers in SOC 821				-0.107	-0.142	-0.433
				(0.763)	(0.785)	(1.128)
Mean income in SOC 821				0.077	-0.023	-0.208
				(0.124)	(0.141)	(0.201)
Share of female workers			-8.527*	-4.513	-4.513	1.734
			(4.799)	(5.123)	(5.129)	(6.626)
Share of college educated workers		4.273	2.020	4.410	4.435	3.177
		(3.878)	(3.956)	(4.118)	(4.084)	(5.674)
Share of workers 25-39			2.760	3.771	3.281	6.146
			(4.547)	(4.779)	(4.790)	(5.987)
Share of workers 40-54			8.174*	8.608	8.585*	11.079
			(4.862)	(5.203)	(5.159)	(7.807)
Share of workers 55-64			10.195**	11.408**	11.232**	18.071**

	(1)	(2)	(3)	(4)	(5)	(6)
			(5.098)	(5.478)	(5.486)	(8.393)
Mean income of workers			0.034	0.166	0.195	0.537
			(0.353)	(0.362)	(0.360)	(0.545)
TTWA population (ln)		-3.483	-1.159	-3.864	-4.068*	-0.741
		(2.182)	(2.911)	(2.359)	(2.336)	(3.242)
Constant	11.680***	55.586*	24.844	55.838*	58.731*	-47.610
	(0.839)	(29.001)	(38.531)	(30.673)	(30.422)	(191.797)
TTWA & year FE	Y	Y	Y	Y	Y	Y
Linear time trend	N	N	N	N	N	Y
N	857	857	857	857	857	857
R-sq	0.256	0.267	0.264	0.271	0.274	0.347

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

Table 7: Understanding the Correlation between Uber Entry
and the General Health Questionnaire Score (OLS and Fixed-Effect models)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample	Self-Employed	Self-Employed Before and After	Self-Employed	Self-Employed	Employed	Employed	Employed
Model	OLS with time trend	OLS	FE	FE	OLS with time trend	FE	FE
Uber	0.290 (0.254)	0.217 (0.293)	0.029 (0.221)	0.024 (0.222)	-0.323* (0.190)	-0.254 (0.162)	-0.276* (0.163)
25-39	-0.469 (0.430)		-0.860 (0.928)	-0.806 (0.943)	-0.043 (0.332)	0.068 (0.616)	0.062 (0.608)
40-54	-0.146 (0.408)	0.400 (0.440)	-0.349 (1.014)	-0.315 (1.017)	-0.040 (0.332)	0.194 (0.659)	0.192 (0.653)
55-64	0.167 (0.459)	0.752 (0.503)	-0.595 (1.084)	-0.529 (1.085)	0.162 (0.357)	0.212 (0.711)	0.203 (0.706)
Female	-0.365 (0.532)	0.316 (0.407)			-0.204 (0.200)		
College	0.022 (0.280)	-0.345 (0.604)	2.428 (3.941)	2.398 (3.876)	-0.030 (0.208)	0.115 (0.208)	0.236 (0.221)
White	0.308 (0.213)	0.473 (0.373)			0.369** (0.165)		
Household income (/1000)	0.097* (0.057)	0.034 (0.085)	-0.048 (0.046)	-0.069 (0.053)	0.107*** (0.029)	0.046 (0.036)	0.027 (0.038)
Share of workers in SOC 821	1.488 (3.765)	12.219* (6.762)		-0.085 (2.753)	0.717 (1.905)		1.273 (1.894)
Share of females in SOC 821	-1.613 (1.096)	-3.134** (1.175)		-1.966** (0.845)	-0.647 (0.492)		-0.031 (0.456)
Share of college drivers in SOC 821	0.404 (0.881)	-0.243 (1.025)		-0.028 (0.585)	-1.273** (0.546)		-0.678 (0.447)
Share of white drivers in SOC 821	-0.463 (0.973)	0.183 (1.164)		-0.230 (0.746)	-0.088 (0.584)		0.290 (0.540)
Share of self-employed drivers in SOC 821	-0.351 (0.490)	0.304 (0.727)		0.447 (0.404)	0.422 (0.367)		0.543* (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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1a: Distribution of the General Health Questionnaire Score (0-12 Scale)
Across All Individuals

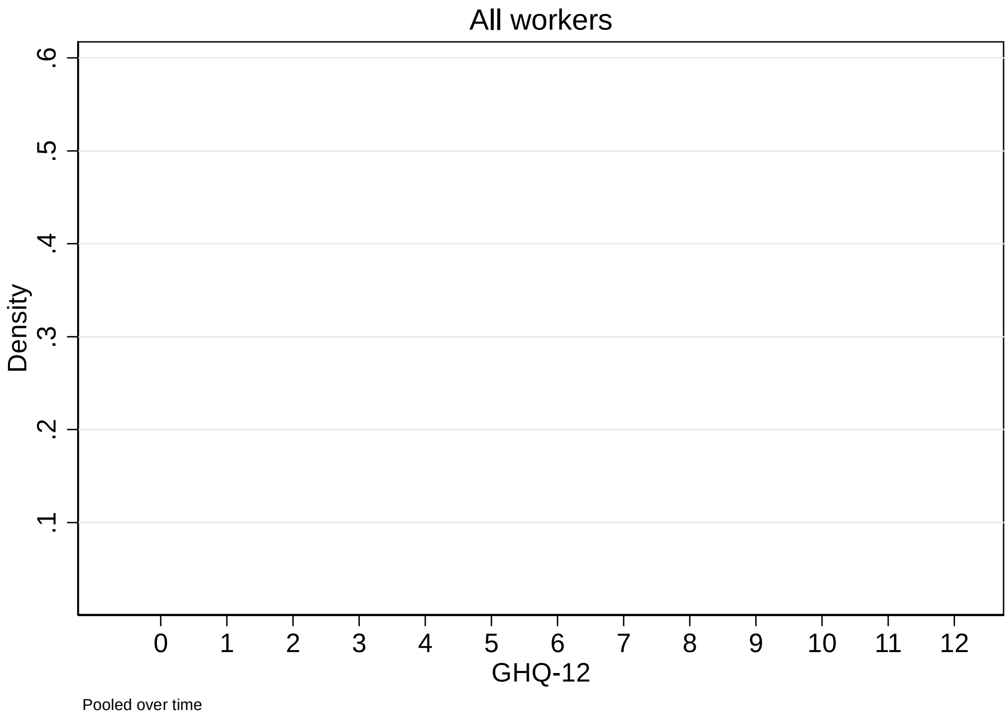


Figure 1b: Distribution of the General Health Questionnaire Score (0-12 Scale)
in the SOC 821 Category

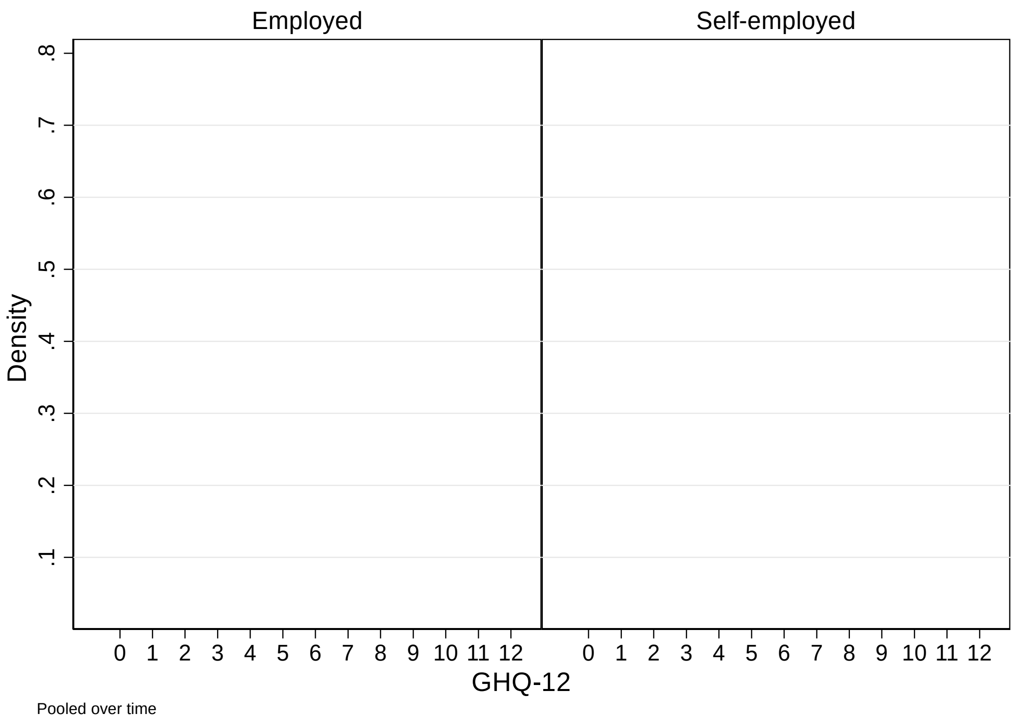


Figure 2: Uber UK Entry Date by Area

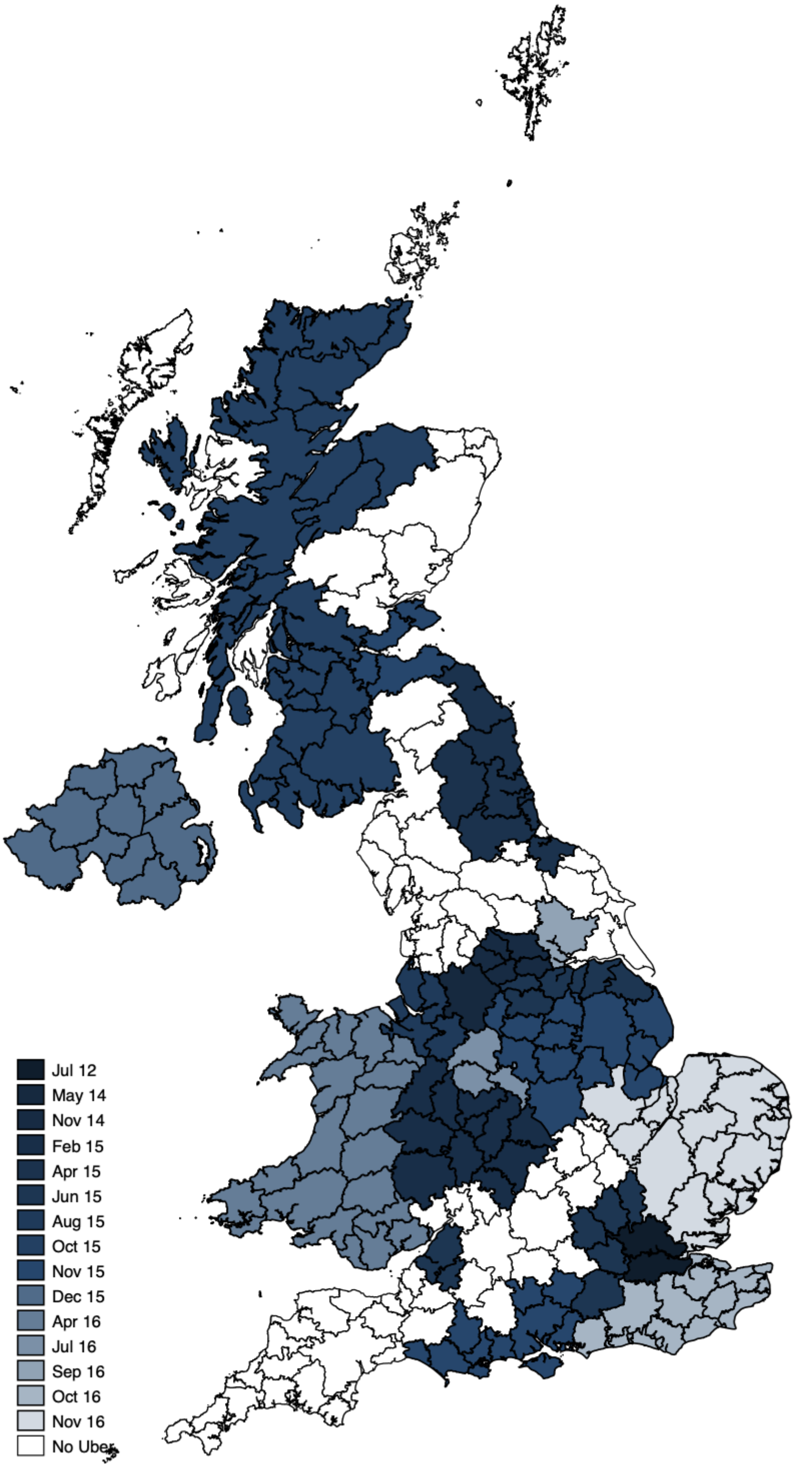
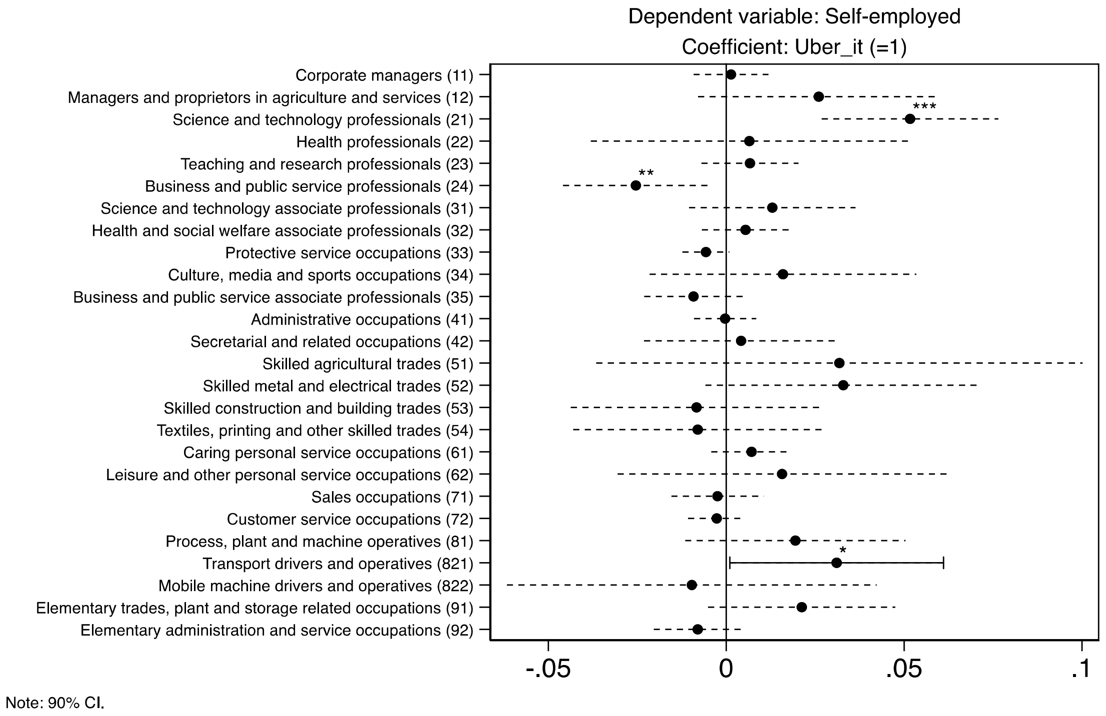
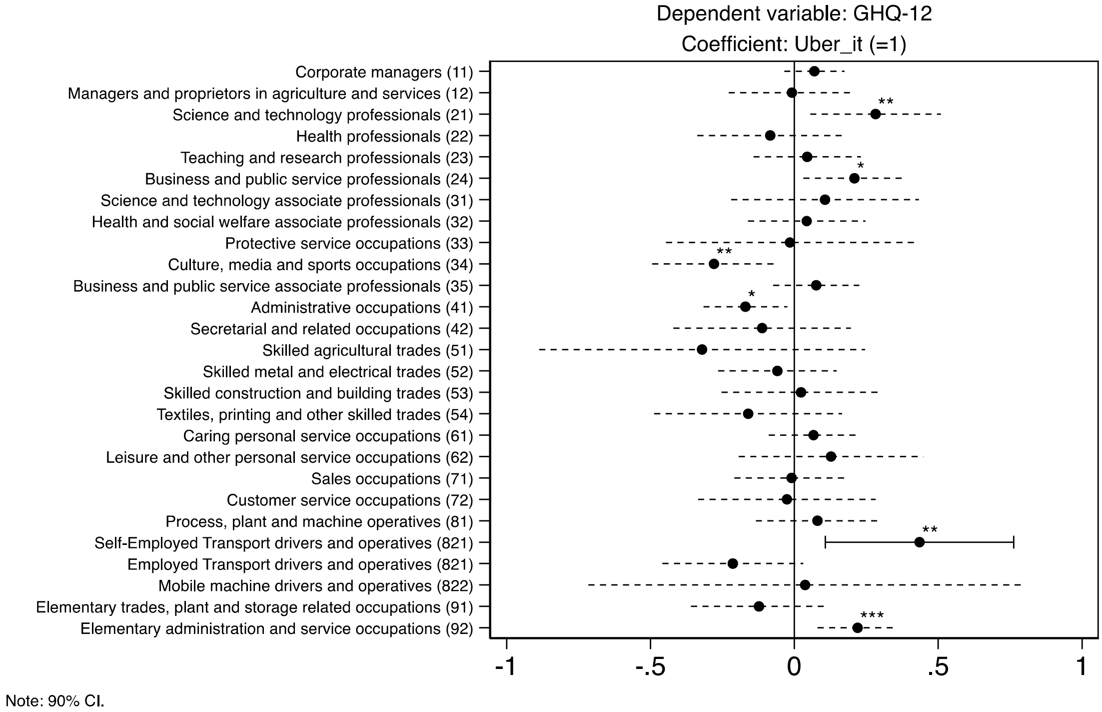


Figure 3: Effect of Uber Diffusion on Self-Employment



Notes: The graph presents the coefficient on Uber diffusion, from a set of regressions (for each SOC) on a dummy for self-employment on Uber diffusion, controlling for female, age groups, white, college, household income (/1000), share of workers that are female / are in each age group / have a college degree, the mean household income of workers in the TTWA-year, population (ln) in the TTWA-year, and year and TTWA FE. The 2-digit SOC codes are used aside from SOC 82 which is split into its three-digit components (821 and 822). Standard errors are clustered at the TTWA level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 4: Correlation between Uber Diffusion and GHQ (0-12 Scale)



Notes: The graph presents the coefficient on Uber diffusion from a set of regressions (for each SOC) of GHQ-12 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 FE.

The 2-digit SOC codes are used, aside from SOC 82 which is split into its three-digit components.

Standard errors are clustered at the TTWA level.

* p < 0.10, ** p < 0.05, *** p < 0.01.

Appendix: 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
		811 Process operatives

8 Process, Plant and Machine Operatives	81 Process, plant and machine operatives	812 Plant and machine operatives
		813 Assemblers and routine operatives
		814 Construction operatives
	82 Transport and mobile machine drivers and operatives	821 Transport drivers and operatives
		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