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The Effects of Uber Diffusion on Mental Health in the UK

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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 2016 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. The impact of Uber diffusion on well-being is mixed among transportation workers. Indeed, mental health, as measured by the General Health Questionnaire, improves for self-employed drivers (and this effect is larger for women than men), but anxiety levels also increase among these 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 on mental health in the UK.

The relationship between mental health and gig economy work, which is characterized by self-employment[3] 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 changing 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] Today (and for our period of interest in our data), gig work is/was codified as "self-employment." However, these workers may be reclassified as "employees" in the future, following some court cases.

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 self-employment have a positive effect on mental health. For instance, gig economy type jobs (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 effect 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 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 use individual-level data on health, from Understanding Society, i.e. the UK household longitudinal study, between 2009 and 2016. To overcome identification concerns (reverse causation and common hidden factors), we use the diffusion of Uber at the area level and we compare individual health before and after Uber's introduction, for different samples of workers.

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. Interestingly, the impact of Uber diffusion is mixed: mental health, as measured by the General Health Questionnaire (GHQ), improves for self-employed drivers after Uber's introduction (and this effect is stronger for women than for men), but job-related anxiety also increases in this occupational category. Our results may thus reflect the two sides of Uber work (autonomy of working hours related to self-employment, but also uncertainty of pay and time of work), explaining why this type of jobs will improve some dimensions of mental health while deteriorating others.

As an alternate test of a health effect, we estimate the influence of self-employment on mental health, relying on variation in self-employment driven by the expansion of Uber, in the full sample of workers across all occupations. In other words, we employ an instrumental variable strategy, in which Google queries for the word "Uber," as well as Uber diffusion information, serve as instruments for self-employment. Our results are reasonably consistent across these alternate specifications.

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. It also incorporates additional data on gig economy activity (Uber diffusion and Google search queries on the gig economy) that has not been used in this strand of research so far. The advantage of these types of data is that they are able to capture the fairly recent emergence of the gig economy, which is not yet well-measured in national surveys.

The rest of the paper proceeds as follows. Section 2 briefly reviews the literature on employment types and health, section 3 outlines our data and methodology, section 4 presents our 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 (2009-2016) are worth mentioning. First, the unemployment rate has 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 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. In particular, experiencing both high job demands and low job control is the most stressful situation. Self-employed "Uber partners" may have a higher job control level than typical wage workers, because they have control over the organization of their working life (they chose their number of hours for instance). While gig workers 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). Moreover, this type of self-employment may be associated with a higher level of job demand than average (in particular, Uber drivers must take any customer when they are logged into the system), which may have a negative impact on health. Finally, uncertainty about pay and the time of their work may also negatively influence psychological well-being.

Self-Employment and Precarious Jobs

Our study relates to the literature on the impact of self-employment and of 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 (dynamic model, fixed effect model, and 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 is dependent 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 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 the worker employment instability. Using data on employee residents in the Lombardy region in Italy, the 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 self-assessed health (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 to estimate the causal effect of Uber spatial diffusion on individual health.

3. Data and Methodology

Understanding Society

Our individual-level data come from Understanding Society, the UK Household Longitudinal study. The survey provides longitudinal data between 2009 and 2016. 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. We first use the (reversed) Likert GHQ score, which runs from 0 (worst psychological health) to 36 (best psychological health). We also use dummies for the various subcomponents as dependent variables in their own right, 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. not self-employed). Workers are classified by their occupation, using the UK Standard Occupation Classification (SOC), 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. "Road Transport Drivers."

The data also provide information on sociodemographic characteristics including gender, race, age, household size, and income. Tables 1a and 1b present summary statistics for health, labor market status, and sociodemographic control variables, for the full sample and for self-employed and employed drivers in the SOC 821 occupation. The distribution of the GHQ score is shown in Figure 1a. The mean is around 24 out of 36 with the bulk of the responses between

[7] The full set of SOC 2010 occupational categories are listed in Appendix A.

20 and 30. GHQ distributions for self-employed drivers and employed drivers are shown in Figures 1b and 1c. 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 employment data and Google search data by year (see details below).

Aggregate Employment 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 indicator capturing Uber diffusion. This variable 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 in 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 20 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).

Empirical Specification

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 for each of 25 occupational categories, plus a category for unemployment, of the following form:

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

where $SelfEmployment_{ijt}$ is a dummy for whether a person i, who lives in TTWA j, is self-employed or not, 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 controls characteristics, that includes age (age group dummies), education (series of dummies), income (logarithm of household income plus one), and household size. We also include some time-varying controls for the TTWA in which the individual lives (V_{jt}), to account for TTWA-specific variables that may be correlated with Uber diffusion. Specifically, we control for the average income in the TTWA in year t to capture changes in the overall level of economic activity in the area over time, unemployment rate, and population size. Importantly, the regressions include individual fixed effects (μ_i) and time fixed effects (δ_t). This model is meant to confirm that the diffusion of Uber affects self-employment, and to explore whether this effect is localized in occupations likely to be affected by Uber or whether this is a more general effect.

We estimate a similar model for self-employment but using Google search data (for the word Uber) as a measure of the gig economy, instead of the Uber diffusion indicator. We describe the Google search data and our use of it to construct Uber search intensity in Appendix B below.

Following these models, we estimate the effect of Uber diffusion on worker mental health as follows:

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

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 or not), reverse causation running from individual health to the Uber indicator is highly unlikely. The coefficient on Uber diffusion compares individual health before and after Uber's introduction.

The model includes time varying controls for the individual[8] and for the TTWA (including population), TTWA fixed effect (ω_j), and wave fixed effects (δ_t). Note that our model controls for household income because we are interested in the health effect of Uber that is not mediated by income. We present models with and without individual fixed effects (μ_i), that capture worker fixed characteristics, such as immigrant status for instance. The inclusion of time-varying controls and fixed effects allows us to rule out a number of hidden common factors that may create a spurious relationship between Uber diffusion and health. Standard errors are clustered at the TTWA level.

We estimate Equation (2) using the sample of workers in the "Road Transport Drivers" (SOC 821), i.e. the occupation for which we observe an effect of Uber Diffusion on self-employment in Equation (1). Moreover, we estimate Equation (2) for self-employed and employed (i.e. not self-employed) workers (in SOC 821) separately. We separate these categories as we expect that effect of Uber diffusion may be quite different for the sample of self-employed drivers, that includes those who become Uber drivers, and the sample of employed drivers, who all work for regular taxi companies and may feel the competition from Uber drivers.

In Equation (2), the interpretation of the coefficient on Uber diffusion depends on whether individual fixed effects are included or not. When the sample contains self-employed drivers (in SOC 821) and individual fixed effects *are not included*, the coefficient on Uber Diffusion will compare the health of self-employed drivers before Uber's introduction, with that of self-employed drivers after the introduction. Note that these are not necessarily the same individuals.

[8] When we do not include individual fixed effects, the individual-level controls are the following: gender, race, age, education, income, and household size.

Indeed, some workers from other occupational categories may become "self-employed drivers in SOC 821" over time, in particular following Uber's introduction. Similarly, some workers may choose to stop being self-employed drivers at some point (because competition has become too intense after Uber's introduction, for instance). In other words, in the absence of individual fixed effects, workers may be selecting themselves in or out of SOC 821 following the introduction of Uber.

In contrast, when the sample contains self-employed workers (in SOC 821) and individual fixed effects *are included*, the coefficient on Uber Diffusion effect will compare the health of self-employed workers before Uber's introduction, with their health after the introduction. In other words, only individuals who remain self-employed in SOC 821 before and after Uber's introduction are used to estimate the coefficient on Uber diffusion. This approach thus captures the effect of Uber for individuals who were already self-employed in SOC 821 before Uber's introduction. Therefore, this empirical approach addresses selection in (or out of) the SOC 821 category.

We estimate the model using the total GHQ-36 score, but also the full subset of questions in the GHQ questionnaire and a measure of anxiety as dependent variables. In a heterogeneity analysis, models are estimated separately by education, gender, and income.

4. Results

4.1. Effect of Gig Economy on Self-Employment

We begin by presenting estimates of the direct effects of Uber diffusion on self-employment by occupational grouping (results from Equation (1) above). The results are displayed graphically in Figure 3. The diffusion of Uber has almost no effect on self-employment in any occupational category with the notable exception of SOC 821 which is "Road Transport Drivers." In other words, Uber diffusion increased the probability of workers being self-employed drivers, but did not otherwise have significant effects on the self-employment rates for other workers. This suggests that the most likely place to find an effect of an increase in gig economy work of this sort on worker mental health is within this category, where there are significant changes.

We perform a similar analysis for the effect of Google search volume on self-employment (see the presentation of the Google search data in Appendix B). We obtain consistent results (Figure 4): in the case of Google search, effects on self-employment are significantly different from zero for both "Road Transport Drivers" (SOC 821) at the 5% level and "Skilled Agriculture and Related Trades" (SOC 51) at the 10% level.

Given these results, we begin our analysis of the effects of Uber diffusion on mental health by focusing on workers within the "Road Transport Drivers" occupational category.

4.2. Effect of Gig Economy on the General Health Questionnaire Score

We here present our main estimates from Equation (2) which explores the direct relationship between Uber diffusion and the mental health of workers as measured by the GHQ index. This model includes wave and TTWA fixed effects, as well as time variant controls for the TTWA economy and individual characteristics. As noted above, we focus our analysis on workers in the occupational category 821, "Road Transport Drivers." Findings are reported in Table 2. The first two columns report results for self-employed workers and the second two columns report results for employed workers. We use the sample of workers classified in the 821 occupational code for their primary job (columns 1 and 3) and workers classified in this code for either their primary or secondary job (columns 2 and 4). Uber diffusion has a positive and significant effect on the mental health of self-employed drivers. More precisely, our results suggest a 2.2-point increase in the 36-point scale for self-employed workers (column 1). The effect is slightly larger for workers in the 821 category for either their primary or secondary job (column 2). In contrast, Uber diffusion has no effect on the mental health of workers doing the same task but who are regularly employed (i.e. not self-employed) (columns 3 and 4).

In Table 3, we estimate the same models for both self- and non-self-employed workers but including worker fixed effects. When the sample contains self-employed drivers, the Uber effect is estimated using individuals who were already self-employed drivers before Uber's introduction and who remained in this category after the introduction (only). While this is a heavily specified equation given the small sample sizes within the occupational group, we find little change in our estimates which remain positive, significant, and of similar magnitudes for self-employed drivers, and insignificant for non-self-employed drivers.

As a robustness check to our estimates on the effect of Uber diffusion on GHQ, we perform similar analyses to Table 3 above for the other occupational categories. We present these results in Figure 5. For 25 other SOC occupational categories, we find insignificant effects in 23 of 25 cases. In two cases (science, engineering and technology professionals; leisure, travel and related personal service occupations), the effects are smaller than for driving occupations, but positive and significant.

A recent report by the UK government suggests that gig economy workers tend to be younger than the general population, but that they have a similar gender profile and similar levels of educational attainment (BEIS, 2018a). Given that experiences in the gig economy may depend on individual characteristics, we next examine whether the effects of gig economy diffusion on mental health depend on gender, education, and income. In each case, we interact the effect of Uber diffusion with a dummy variable for gender, for having some post-secondary education, and for having family income that exceeds the median family income.

Table 4 presents our estimates by gender. For the non-self-employed (columns 3 and 4), there are no differences by gender. However, for the self-employed (columns 1 and 2), the coefficient on Uber diffusion is large and mostly offset by the coefficient on the interaction term between Uber diffusion and male. That is, while there is small effect of Uber diffusion on mental health for men, it is considerably larger for women. We note a caveat here which is that the driver occupational category is heavily male (approximately 90%), and so the robustness of this large results should be interpreted with some caution.

Table 5 contains results by education. Including an interaction term between Uber diffusion and a dummy for some post-secondary education reduces the main coefficient on Uber diffusion by between one half and one quarter for the two self-employed samples. The interaction term is large, although only statistically significant at the 10% level in the case of self-employed individuals in SOC 821 in their primary job. This provides some, but inconclusive, evidence that the effect of Uber diffusion might be larger for more educated workers.

The results for the interaction with median family income (Table 6) suggest no difference in the effect of Uber diffusion for self-employed workers from higher income families, but in this case, we find that non-self-employed workers from higher income families have worse mental health (of slightly smaller magnitude to the positive effect on self-employed workers) from Uber diffusion. While it is perhaps not surprising that the group most likely to feel the competition from gig economy workers might experience worse mental health, it is interesting that this effect is focused on those workers from families with higher than the median family income.

4.3. Decomposing the Effect on the General Health Questionnaire Score

The GHQ health variable is composed of 12 individual questions. While the variable is best used as an aggregate of the entire set of questions in order to predict mental health and well-being, the individual components can provide some insight into which elements of mental health may be most affected by the diffusion of the gig economy. We therefore estimate our main specification of the effect of Uber diffusion on mental health for each element of the GHQ and report the results in Table 7. The top panel of Table 7 contains results for self-employed workers and the bottom panel for non-self-employed workers. In keeping with the results for the entire GHQ variable, none of the subcomponents of the GHQ variable are significant for non-self-employed workers. For self-employed workers, the effects on mental health appear to be concentrated in three areas: better sleep, less under strain, and more enjoyment of daily activities. Including individual fixed effects in the model results in significant results for more enjoyment of daily activities and the ability to face problems while the other coefficients remain positive but lose significance at conventional levels (results available upon request). These results are consistent with an increase in autonomy and working time control.

4.4. Effect on Anxiety

We also estimate models using a measure of job anxiety (constructed from the 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 8.[9] As with the main results discussed above, the first two columns report results for self-employed workers within the driving occupation code and the second two columns for non-self-employed workers also within the driving occupation code. In contrast to our models of mental health above, we find that Uber diffusion is associated with an increase in job anxiety (a decrease in the scale) of approximately 2 points, on a scale running from 3 to 15. This detrimental effect may be due to the uncertainty of pay and time of work in Uber work. As with the GHQ variable, there is no effect of Uber diffusion on non-self-employed workers. This finding is in keeping with the previous literature on Uber drivers in London, that finds improvements in life satisfaction but increases in anxiety (Berger et al., 2018b).

As a robustness check on the anxiety analysis, we plot the effect of Uber diffusion on anxiety for all occupations (as we do above for the GHQ analysis). Once again, we find a negative effect on anxiety only for self-employed drivers and no other negative effects in other occupational categories. This robustness analysis is presented in Figure 6.

4.5. Alternative Specification

As a check on our decision to focus on a particular set of occupation codes, we estimate models using the full sample of employed individuals in Understanding Society. In this approach, we use Uber diffusion and Google search data as instruments for being self-employed. That is,

[9] Because the anxiety in available in three waves only, the sample size is smaller and we do not include individual fixed effects in this model.

instead of estimating the direct effect of Uber diffusion on mental health, we are estimating the effect of self-employment on mental health, relying on variation in self-employment driven by the gig economy. Our models include TTWA fixed effects to control for local fixed characteristics. Appendix C presents this estimation strategy, discusses its limitations (in particular the validity of instruments), and presents the associated findings. The results, consistent with the analysis above, show a negative effect on GHQ of self-employment instrumented by the Uber diffusion variables.

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 the mental health. We find that Uber's introduction has had a beneficial impact on mental health, as measured by the GHQ score, for workers most likely to be affected, i.e. self-employed workers in driving occupations. This positive impact is driven by improved sleep quality, a decrease in psychological strain, and more enjoyment of daily activities. The beneficial effect on the GHQ is stronger for women -- who are underrepresented in the driver category -- than men. However, we also find evidence of a detrimental effect on job anxiety for these workers. We hypothesize that these mixed findings may be due to greater autonomy over working time, improved work-life balance, and increased earning opportunities when needed, on the one hand, combined with uncertainty of pay and time of work, on the other hand.

Our mixed results on the health effect of Uber are in line with descriptive research looking specifically at Uber drivers in London in 2018 (Berger et al., 2018b). Moreover, our results on the positive effect on the GHQ score is consistent with findings from a recent report which highlights that more than half of those working in the gig economy are satisfied with their experience, due to the independence and flexibility aspects of their work (BEIS, 2018a).

We are cautious about suggesting that the effects of self-employment outside of those jobs that offer more control (zero-hour contract jobs for example) would have similar positive effects on some dimension of mental health. We suspect (but not examine this issue directly) that this may not be the case. We also note that given that our study focuses on the rollout of Uber between 2012 and 2016 in the UK, it reflects the economic and working conditions in the gig economy at that time.

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 both positive and negative impacts on different dimensions of worker mental health. 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 1a: Descriptive Statistics

	Observations	Means	SD	Min	Max
Health: GHQ and Anxiety					
GHQ-36	210,599	24.73	5.68	0	36
Able to Concentrate	211,722	0.82	0.38	0	1
Loss of Sleep	211,767	0.81	0.39	0	1
Playing a Useful Role	211,580	0.87	0.34	0	1
Capable of Making Decisions	211,657	0.91	0.29	0	1
Constantly Under Strain	211,615	0.75	0.43	0	1
Problem Overcoming Difficulties	211,568	0.85	0.36	0	1
Enjoy Day-to-Day Activities	211,676	0.83	0.38	0	1
Ability to Face Problems	211,619	0.89	0.31	0	1
Unhappy or Depressed	211,678	0.79	0.41	0	1
Losing Confidence	211,664	0.84	0.37	0	1
Believe in Self-Worth	211,624	0.91	0.29	0	1
General Happiness	211,651	0.85	0.35	0	1
Anxiety	70,483	11.97	2.62	3	15
Uber					
Uber Diffusion	253,415	0.15	0.36	0	1
Uber Google Search	93,392	60.3	29.6	8.5	100
Labor Market Status					
Self-Employed	180,335	0.13	0.34	0	1
Individual-Level Controls					
Age	253,818	41,33	13,12	18	64
Male	253,815	0,46	0,50	0	1
Household size	187,992	3.182	1.524	1	16
Education: High school or less	250,797	0.614	0.487	0	1
Education: Some post-secondary	250,797	0.119	0.323	0	1
Education: Post-secondary	250,797	0.267	0.443	0	1
Race: White	241,517	0.803	0.398	0	1
Race: Mixed	241,517	0.018	0.134	0	1
Race: Asian	241,517	0.115	0.319	0	1
Race: Black	241,517	0.049	0.215	0	1
Race: Other	241,517	0.015	0.123	0	1
Gross Household Monthly Income	252,688	4029.04	2933.73	0	20,000

Table 1b: Descriptive Statistics for SOC 821 Subsample

SOC 821:	Self-Employed: Primary or Secondary					Employed: Primary or Secondary				
	Observations	Means	SD	Min	Max	Observations	Means	SD	Min	Max
Health: GHQ and Anxiety										
GHQ-36	484	25.345	5.037	0	36	798	26.005	4.725	1	36
Able to Concentrate	485	0.862	0.345	0	1	800	0.905	0.293	0	1
Loss of Sleep	485	0.845	0.362	0	1	800	0.889	0.315	0	1
Playing a Useful Role	485	0.870	0.337	0	1	800	0.911	0.285	0	1
Capable of Making Decisions	485	0.938	0.241	0	1	800	0.944	0.231	0	1
Constantly Under Strain	484	0.806	0.396	0	1	800	0.864	0.343	0	1
Problem Overcoming Difficulties	485	0.878	0.327	0	1	800	0.892	0.310	0	1
Enjoy Day-to-Day Activities	485	0.837	0.370	0	1	800	0.910	0.286	0	1
Ability to Face Problems	484	0.907	0.291	0	1	799	0.929	0.258	0	1
Unhappy or Depressed	485	0.845	0.362	0	1	800	0.856	0.351	0	1
Losing Confidence	485	0.891	0.312	0	1	799	0.900	0.300	0	1
Believe in Self-Worth	484	0.930	0.256	0	1	800	0.936	0.244	0	1
General Happiness	485	0.901	0.299	0	1	800	0.912	0.283	0	1
Anxiety	184	11.886	2.802	3	15	328	12.601	2.444	3	15
Uber										
Uber Diffusion	772	0.398	0.490	0	1	1201	0.256	0.437	0	1
Uber Google Search	467	52.870	27.540	8.476	100	605	50.282	27.278	8.476	100
Labor Market Status										
Self-Employed	767	0.917	0.277	0	1	1205	0.000	0.000	0	0
Individual-Level Controls										
Age	773	43.313	9.844	18	64	1205	43.393	11.420	18	64
Male	773	0.938	0.241	0	1	1205	0.946	0.226	0	1
Household Size	656	4.248	1.728	1	12	1037	3.577	1.815	1	14
Education: High school or less	717	0.748	0.435	0	1	1164	0.860	0.347	0	1
Education: Some post-secondary	717	0.092	0.289	0	1	1164	0.066	0.249	0	1
Education: Post-secondary	717	0.160	0.367	0	1	1164	0.074	0.262	0	1
Race: White	682	0.452	0.498	0	1	1062	0.783	0.412	0	1
Race: Mixed	682	0.006	0.076	0	1	1062	0.015	0.122	0	1
Race: Asian	682	0.459	0.499	0	1	1062	0.131	0.337	0	1
Race: Black	682	0.069	0.253	0	1	1062	0.057	0.233	0	1
Race: Other	682	0.015	0.120	0	1	1062	0.013	0.114	0	1
Gross Household Monthly Income	766	3471.195	2677.413	0	20000	1197	3632.027	1738.931	280	20000

Table 2: Effect of Uber Diffusion on the General Health Questionnaire Score

	Dependent Variable: GHQ-36			
	(1)	(2)	(3)	(4)
Sample:	SOC 821 Self-Employed Primary	SOC 821 Self-Employed Primary or Secondary	SOC 821 Employed Primary	SOC 821 Employed Primary and Secondary
Uber Diffusion	2.192*	2.474**	-0.245	-0.257
	(1.178)	(1.061)	(0.797)	(0.793)
Wave FE	Yes	Yes	Yes	Yes
TTWA FE	Yes	Yes	Yes	Yes
Observations	294	335	626	625
R^2	0.362	0.346	0.332	0.334

Notes: Each column is from an individual regression. GHQ-36 is the mental health scale running from 0 (worst mental health) to 36 (best mental health). Controls include: sex, race, age, education, household size, log income, log TTWA average income, population aged between 16-64, unemployment rate, and wave and TTWA fixed effects. Clustered standard errors at the TTWA level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Effect of Uber Diffusion on the General Health Questionnaire Score, Including Individual Fixed Effects

	Dependent Variable: GHQ-36			
	(1)	(2)	(3)	(4)
Sample:	SOC 821 Self-Employed Primary	SOC 821 Self-Employed Primary or Secondary	SOC 821 Employed Primary	SOC 821 Employed Primary and Secondary
Uber Diffusion	2.080* (1.167)	2.047* (1.134)	-0.265 (0.703)	-0.265 (0.704)
Wave FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Observations	294	335	626	625
No. of Individuals	175	206	342	341
R^2	0.228	0.223	0.074	0.074

Notes: Each column is from an individual regression. GHQ-36 is the mental health scale running from 0 (worst mental health) to 36 (best mental health). Controls include: age, education, household size, log income, population aged between 16-64, unemployment rate, log TTWA average income, population aged between 16-64, unemployment rate, and wave fixed effects. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Effect of Uber Diffusion on the General Health Questionnaire Score, by Gender

	Dependent Variable: GHQ-36			
	(1)	(2)	(3)	(4)
Sample:	SOC 821 Self-Employed Primary	SOC 821 Self-Employed Primary or Secondary	SOC 821 Employed Primary	SOC 821 Employed Primary or Secondary
Uber Diffusion	22.577**	13.416**	-1.319	-1.344
	(8.618)	(5.437)	(2.548)	(2.537)
Male	13.053***	8.374**	0.764	0.778
	(4.299)	(4.121)	(1.081)	(1.079)
Uber Diffusion * Male	-20.345**	-11.288**	1.134	1.147
	(8.463)	(5.545)	(2.444)	(2.436)
Wave FE	Yes	Yes	Yes	Yes
TTWA FE	Yes	Yes	Yes	Yes
Observations	294	335	626	625
R^2	0.413	0.376	0.333	0.335

Notes: Each column is from an individual regression. GHQ-36 is the mental health scale running from 0 (worst mental health) to 36 (best mental health). Controls include: age, race, education, household size, log income, population aged between 16-64, unemployment rate, log TTWA average income, and wave and TTWA fixed effects. Clustered standard errors at the TTWA level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Effect of Uber Diffusion on the General Health Questionnaire Score, by Educational Level

	Dependent Variable: GHQ-36			
	(1)	(2)	(3)	(4)
Sample:	SOC 821 Self-Employed Primary	SOC 821 Self-Employed Primary or Secondary	SOC 821 Employed Primary	SOC 821 Employed Primary or Secondary
Uber Diffusion	1.064	1.480	-0.447	-0.469
	(1.237)	(1.129)	(0.859)	(0.851)
College	-2.380	-2.595	-0.997	-0.976
	(2.535)	(2.437)	(1.026)	(1.036)
Uber Diffusion * College	4.178*	3.694	1.153	1.207
	(2.481)	(2.340)	(1.077)	(1.074)
Wave FE	Yes	Yes	Yes	Yes
TTWA FE	Yes	Yes	Yes	Yes
Observations	294	335	626	625
R^2	0.380	0.360	0.333	0.335

Notes: Each column is from an individual regression. GHQ-36 is the mental health scale running from 0 (worst mental health) to 36 (best mental health). Controls include: sex, race, age, household size, log income, population aged between 16-64, unemployment rate, log TTWA average income, and wave and TTWA fixed effects. Clustered standard errors at the TTWA level in parentheses.

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

Table 6: Effect of Uber Diffusion on the General Health Questionnaire Score, by Income Level

	Dependent Variable: GHQ-36			
	(1)	(2)	(3)	(4)
Sample:	SOC 821 Self-Employed Primary	SOC 821 Self-Employed Primary or Secondary	SOC 821 Employed Primary	SOC 821 Employed Primary or Secondary
Uber Diffusion	2.220*	2.505**	0.937	0.899
	(1.228)	(1.175)	(0.937)	(0.915)
Above Median Income Dummy	2.144	1.441	1.026**	1.024**
	(1.902)	(1.671)	(0.496)	(0.495)
Uber Diffusion *Above Median Income Dummy	-0.453	-0.371	-2.521***	-2.468***
	(3.025)	(2.193)	(0.930)	(0.901)
Wave FE	Yes	Yes	Yes	Yes
TTWA FE	Yes	Yes	Yes	Yes
Observations	296	337	626	625
R^2	0.346	0.329	0.342	0.344

Notes: Each column is from an individual regression. GHQ-36 is the mental health scale running from 0 (worst mental health) to 36 (best mental health). Controls include: sex, race, age, education, household size, log TTWA average income, population aged between 16-64, unemployment rate, and wave and TTWA fixed effects. The income variable is gross monthly household income. Clustered standard errors at the TTWA level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Effect of Uber Diffusion on the General Health Questionnaire Subcomponents

Dependent variable:	Concen- -tration	Sleep	Playing Useful Role	Capable of Decisions	Under Strain	Overcome Difficulties	Enjoy Daily Activities	Ability to Face Problems	Unhappy or Depressed	Loss of Confidence	Believe in Self Worth	General Happiness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Sample of Self-Employed, primary or secondary												
Uber Diffusion	-0.030	0.172^{*}	0.108	0.032	0.259^{***}	0.033	0.183^{*}	0.036	0.124	0.135	-0.032	0.046
	(0.105)	(0.089)	(0.113)	(0.097)	(0.084)	(0.062)	(0.094)	(0.088)	(0.087)	(0.112)	(0.065)	(0.078)
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TTWA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	336	336	336	336	335	336	336	335	336	336	335	336
R^2	0.348	0.312	0.314	0.280	0.386	0.325	0.323	0.238	0.289	0.335	0.344	0.291
Panel B: Sample of Employed, primary or secondary												
Uber Diffusion	0.024	-0.006	-0.018	0.023	-0.017	-0.015	-0.004	-0.021	-0.008	-0.027	-0.002	0.001
	(0.052)	(0.063)	(0.058)	(0.042)	(0.062)	(0.059)	(0.050)	(0.052)	(0.077)	(0.050)	(0.048)	(0.049)
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TTWA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	627	627	627	627	627	627	627	626	627	626	627	627
R^2	0.278	0.273	0.283	0.257	0.262	0.263	0.318	0.237	0.309	0.280	0.274	0.280

Notes: Panel A restricts the sample to individuals that are either self-employed in SOC 821 in their primary job *or* in their secondary job. Panel B restricts the sample to those who are employed in SOC 821 in their primary job *and* in their secondary job they are either employed in SOC 821 or list another occupation. Each column is from an individual regression. Each dependent variable takes the value of 0 or 1, with 1 indicating the more positive response (i.e. in the case of Concentration 1 indicates "better than usual" and in the case of Under Strain it indicates "not at all"). Controls include: sex, race, age, education, household size, log income, population aged between 16-64, unemployment rate, log TTWA average income, and wave and TTWA fixed effects. The income variable is gross monthly household income. Clustered standard errors at the TTWA level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

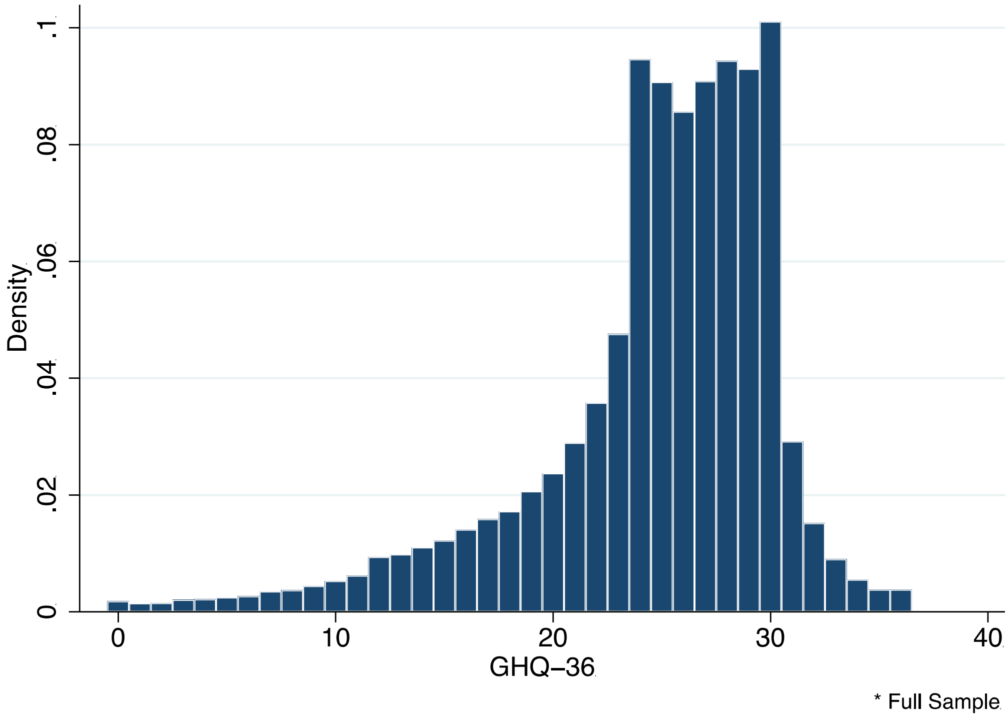
Table 8: Effect of Uber Diffusion on Anxiety

	Dependent Variable: Anxiety			
	(1)	(2)	(3)	(4)
Sample:	SOC 821 Self-Employed Primary	SOC 821 Self-Employed Primary or Secondary	SOC 821 Employed Primary	SOC 821 Employed Primary or Secondary
Uber Diffusion	-2.041*	-2.014*	0.689	0.689
	(1.100)	(1.031)	(0.809)	(0.809)
Wave FE	Yes	Yes	Yes	Yes
TTWA FE	Yes	Yes	Yes	Yes
Observations	123	147	294	294
R^2	0.597	0.621	0.452	0.452

Notes: Each column is from an individual regression. The dependent variable is the Job-related Wellbeing Scale where higher values on the scale represent lower levels of anxiety. Controls include: sex, race, age, education, household size, population aged between 16-64, unemployment rate, log TTWA average income, and wave and TTWA fixed effects. The income variable is a gross monthly household income measure. Clustered standard errors at the TTWA level in parentheses.

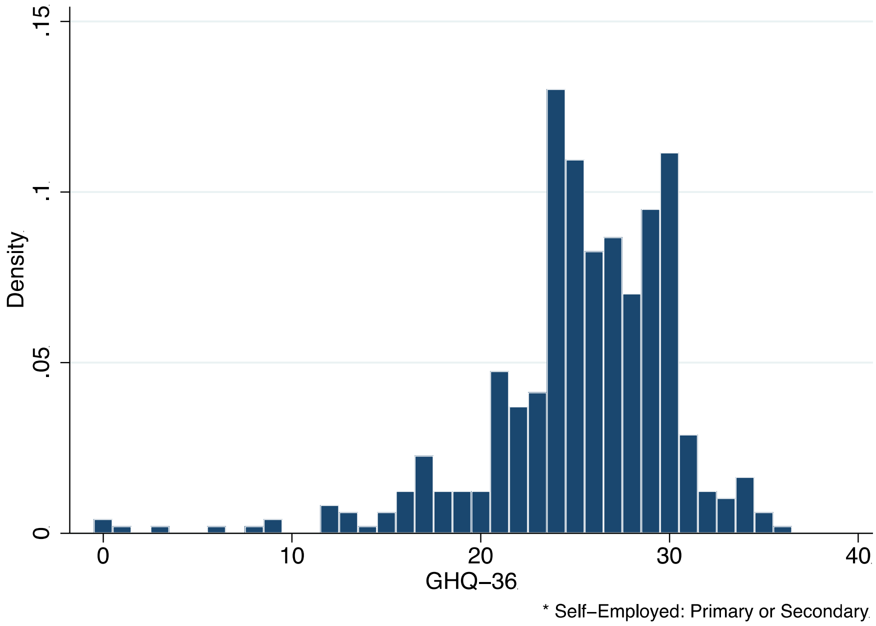
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 1a: Distribution of the General Health Questionnaire Score
Across All Indiviuals



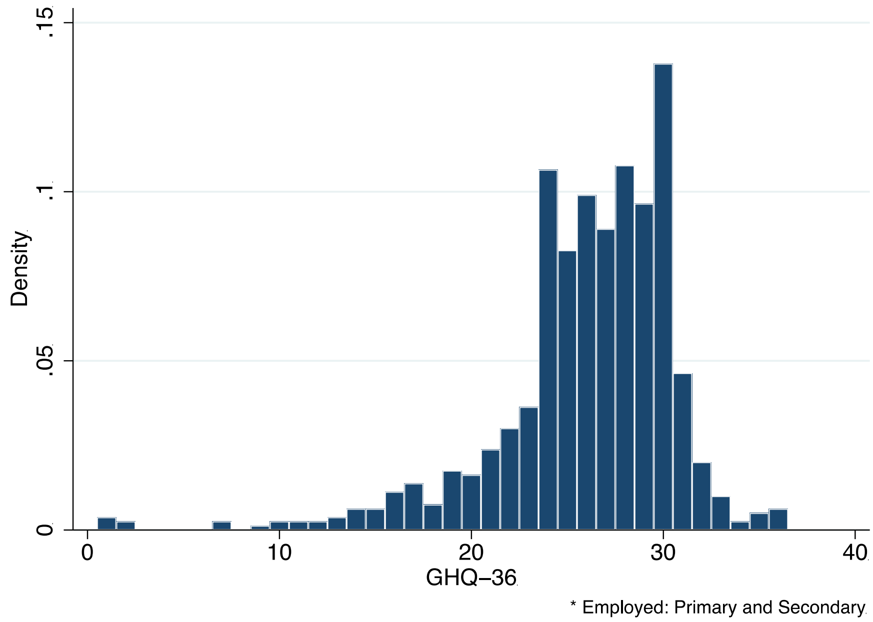
Notes: GHQ-36 is the mental health scale running from 0 (worst mental health) to 36 (best mental health).

Figure 1b: Distribution of the General Heath Questionnaire Score
for the SOC 821 Self-Employed Subsample



Notes: GHQ-36 is the mental health scale running from 0 (worst mental health) to 36 (best mental health). This sample consists of individuals that are either self-employed in SOC 821 in their primary job or in their secondary job.

Figure 1c: Distribution of General Health Questionnaire Score
for the SOC 821 Employed Subsample



Notes: GHQ-36 is the mental health scale running from 0 (worst mental health) to 36 (best mental health). This sample consists of those who are employed in SOC 821 in their primary job and in their secondary job they are either employed in SOC 821 or list another occupation.

Figure 2: Uber UK Entry Date by Area

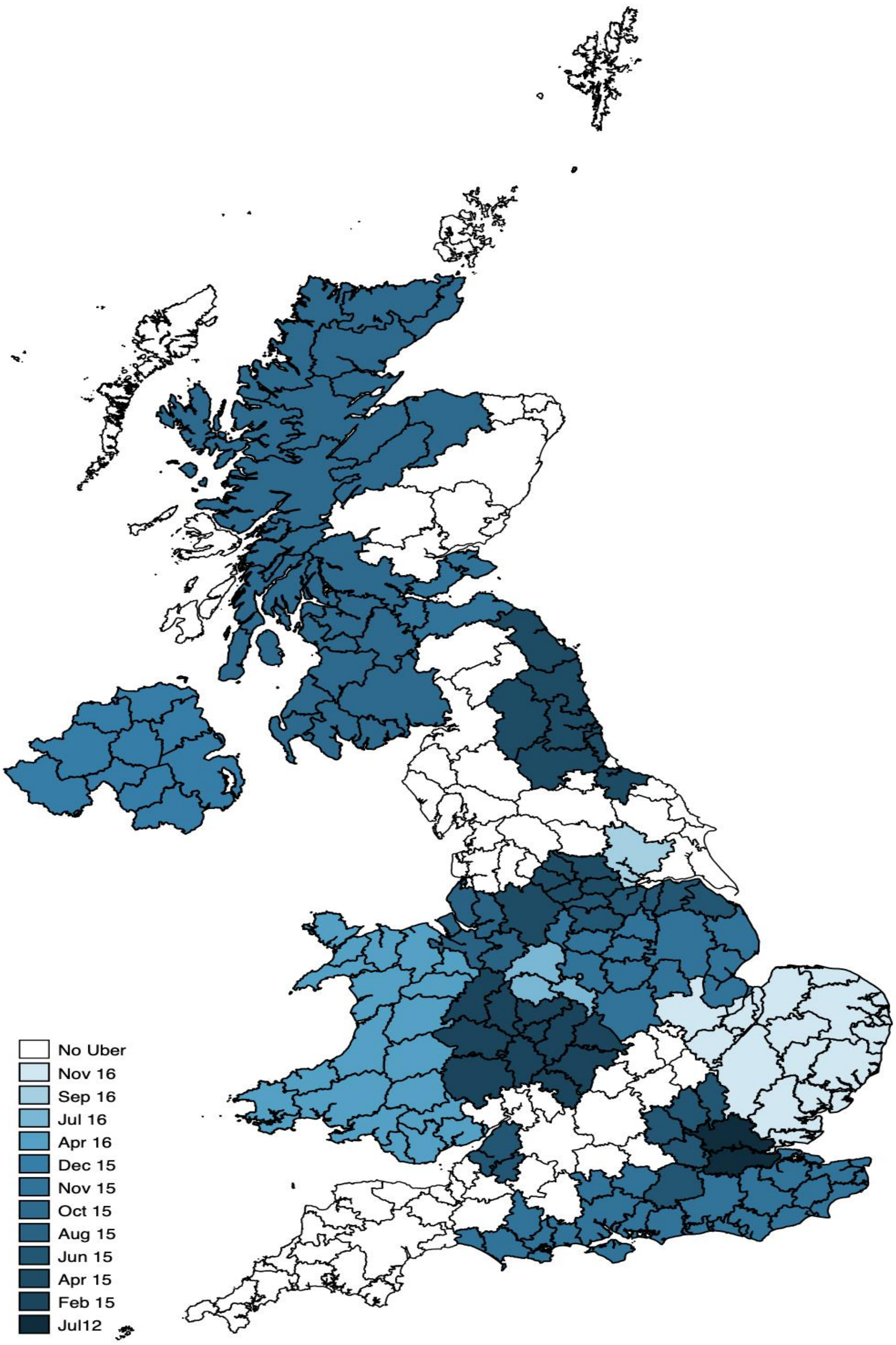
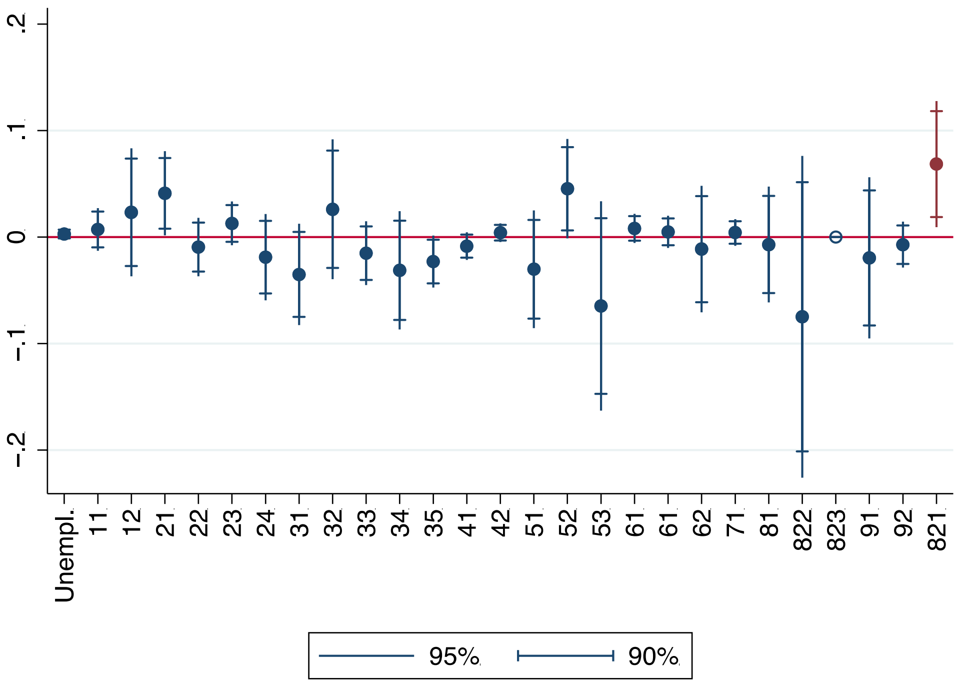
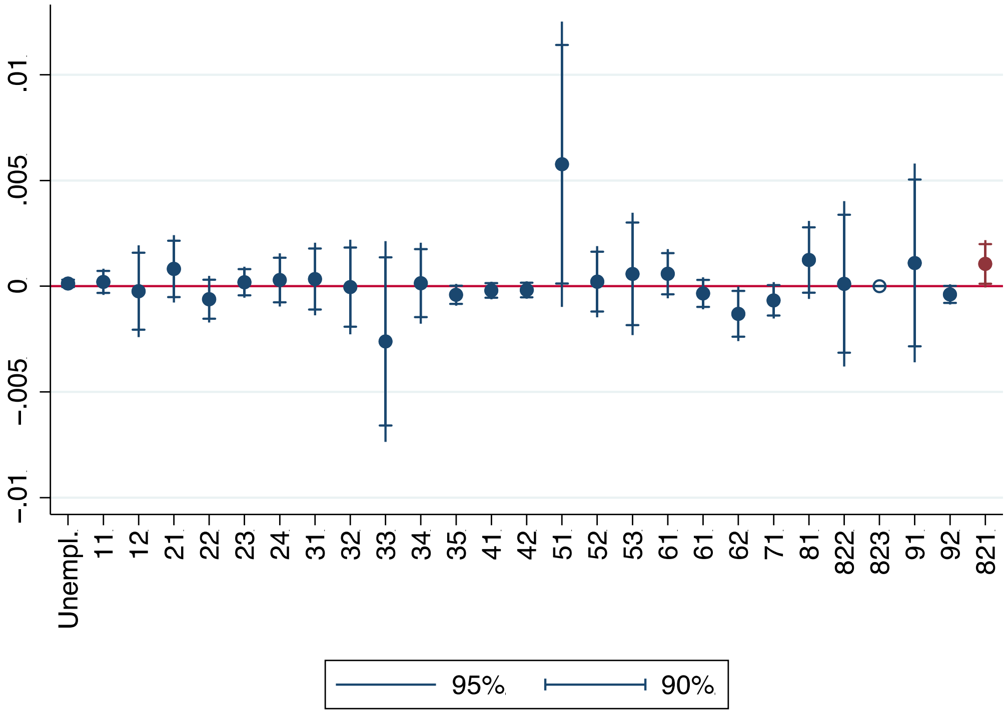


Figure 3: Effect of Uber Diffusion on Self-Employment,
Including Individual Fixed Effects, by Occupation



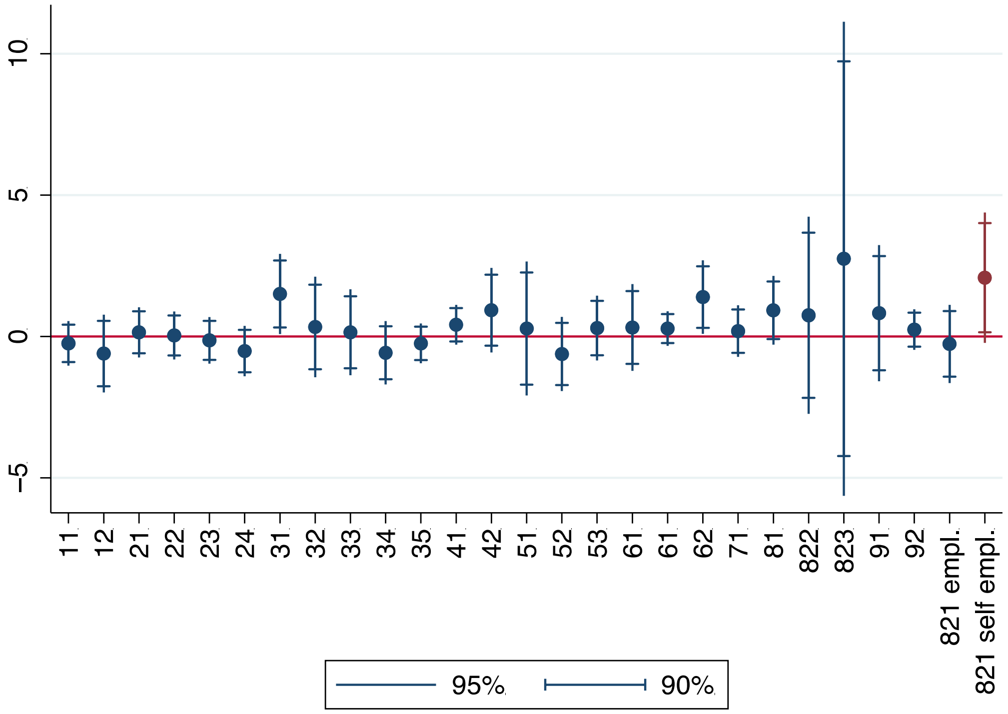
Notes: The dependent variable is a dummy for self-employment in all the cases where there are SOC codes. In the first case, the dependent variable is a dummy for unemployment. The points & lines represent individual regressions and display the coefficient and confidence intervals on the uber diffusion independent variable. The 2-digit SOC codes are used aside from SOC 82 which is split into its 3-digit components. The regressions contain individual fixed effects. Controls include: sex, race, age, education, household size, log income, population aged between 16-64, unemployment rate, log TTWA average income, and wave fixed effects.

Figure 4: Effect of Uber Google Search on Self-Employment,
Including Individual Fixed Effects



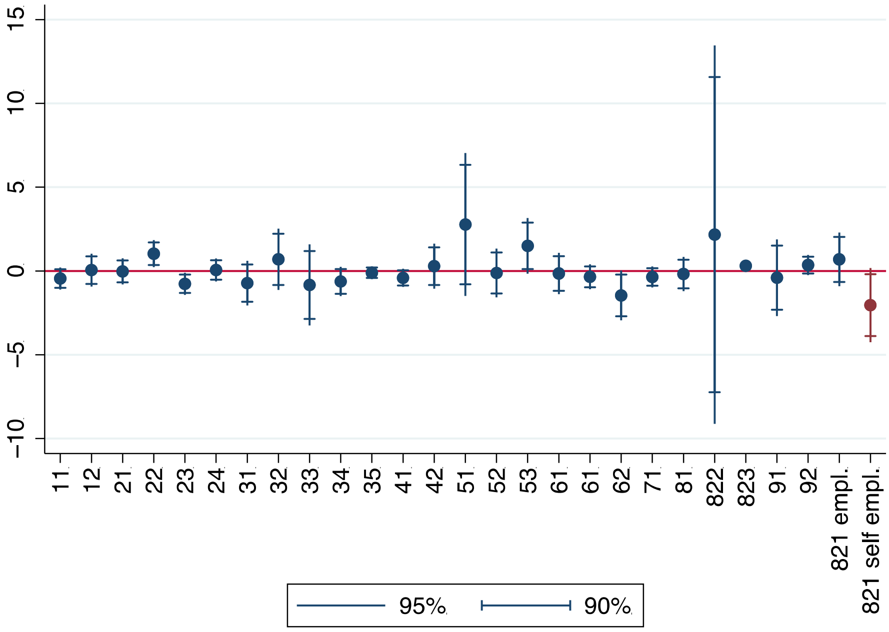
Notes: The dependent variable is a dummy for self-employment in all the cases where there are SOC codes. In the first case, the dependent variable is a dummy for unemployment. The points & lines represent individual regressions and display the coefficient and confidence intervals on the Uber Google search independent variable. The 2-digit SOC codes are used aside from SOC 82 which is split into its 3-digit components. The regressions contain individual fixed effects. Controls include: age, education, household size, log income, log TTWA average income, and wave fixed effects.

Figure 5: Effect of Uber Diffusion on the General Health Questionnaire Score, Including Individual Fixed Effects, By Occupation



Notes: The dependent variable, GHQ, is the mental health scale running from 0 (worst mental health) to 36 (best mental health). The points and lines represent individual regressions and display the coefficient and confidence intervals on the uber diffusion independent variable. The 2-digit SOC codes are used aside from SOC 82 which is split into its 3-digit components. SOC 821 is further split between those who are self-employed or employed in this category. The regressions contain individual fixed effets. Controls include: age, education, household size, log income, population aged between 16-64, unemployment rate, log TTWA average income, and wave fixed effects.

Figure 6: Effect of Uber Diffusion on Anxiety,
By Occupation



Notes: The dependent variable is the anxiety score. The points and lines represent individual regressions and display the coefficient and confidence intervals on the Uber Google search independent variable. The 2-digit SOC codes are used aside from SOC 82 which is split into its 3-digit components. SOC 821 is further split between those who are self-employed or employed in this category. Controls include: sex, race, age, education, household size, log income, population aged between 16-64, unemployment rate, log TTWA average income, and wave and TTWA fixed effects.

Appendix A: SOC 2010 Job Classification Codes

Major Group	Sub-Major Group	Minor Group
1: Managers, Directors and Senior Officials	11: Corporate Managers and Directors	111: Chief Executives and Senior Officials
		112: Production Managers and Directors
		113: Functional Managers and Directors
		115: Financial institution Managers and Directors
		116: Managers and Directors in Transport and Logistics
		117: Senior Officers in Protective Services
		118: Health and Social Services Managers and Directors
		119: Managers and Directors in Retail and Wholesale
	12: Other Managers and Proprietors	121: Managers and Proprietors in Agriculture Related Services
		122: Managers and Proprietors in Hospitality and Leisure Services
		124: Managers and Proprietors in Health and Care Services
		125: Managers and Proprietors in Other Services
2: Professional Occupations	21: Science, Research, Engineering and Technology Professionals	211: Natural and Social Science Professionals
		212: Engineering Professionals
		213: information Technology and Telecommunications Professionals
		214: Conservation and Environment Professionals
		215: Research and Development Managers
	22: Health Professionals	221: Health Professionals
		222: Therapy Professionals
		223: Nursing and Midwifery Professionals
	23: Teaching and Educational Professionals	231: Teaching and Educational Professionals
	24: Business, Media and Public Service Professionals	241: Legal Professionals
		242: Business, Research and Administrative Professionals
		243: Architects, Town Planners and Surveyors
		244: Welfare Professionals
		245: Librarians and Related Professionals
		246: Quality and Regulatory Professionals
		247: Media Professionals
3: Associate Professional and Technical Occupations	31: Science, Engineering and Technology Associate Professionals	311: Science, Engineering and Production Technicians
		312: Draughtspersons and Related Architectural Technicians
		313: information Technology Technicians
	32: Health and Social Care Associate Professionals	321: Health Associate Professionals
		323: Welfare and Housing Associate Professionals

	33: Protective Service Occupations	331: Protective Service Occupations
	34: Culture, Media and Sports Occupations	341: Artistic, Literary and Media Occupations
		342: Design Occupations
		344: Sports and Fitness Occupations
	35: Business and Public Service Associate Professionals	351: Transport Associate Professionals
		352: Legal Associate Professionals
		353: Business, Finance and Related Associate Professionals
		354: Sales, Marketing and Related Associate Professionals
		355: Conservation and Environmental Associate Professionals
		356: Public Services 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
		415: Other Administrative Occupations
		416: Administrative Occupations: Office Managers and Supervisors
	42: Secretarial and Related Occupations	421: Secretarial and Related Occupations
5: Skilled Trades Occupations	51: Skilled Agricultural and Related Trades	511: Agricultural and Related Trades
	52: Skilled Metal, Electrical and Electronic Trades	521: Metal Forming, Welding and Related Trades
		522: Metal Machining, Fitting and instrument Making Trades
		523: Vehicle Trades
		524: Electrical and Electronic Trades
		525: Skilled Metal, Electrical and Electronic Trades Supervisors
	53: Skilled Construction and Building Trades	531: Construction and Building Trades
		532: Building Finishing Trades
		533: Construction and Building Trades Supervisors
	54: Textiles, Printing and Other Skilled Trades	541: Textiles and Garments Trades
		542: Printing Trades
		543: Food Preparation and Hospitality Trades
		544: Other Skilled Trades
6: Caring, Leisure and Other Service Occupations	61: Caring Personal Service Occupations	612: Childcare and Related Personal Services
		613: Animal Care and Control Services
		614: Caring Personal Services
	62: Leisure, Travel and Related Personal Service Occupations	621: Leisure and Travel Services
		622: Hairdressers and Related Services
		623: Housekeeping and Related Services
		624: Cleaning and Housekeeping Managers and Supervisors
		711: Sales Assistants and Retail Cashiers

7: Sales and Customer Service Occupations	71: Sales Occupations	712: Sales Related Occupations 713: Sales Supervisors
	72: Customer Service Occupations	721: Customer Service Occupations 722: Customer Service Managers and Supervisors
8: Process, Plant and Machine Operatives	81: Process, Plant and Machine Operatives	811: Process Operatives 812: Plant and Machine Operatives 813: Assemblers and Routine Operatives 814: Construction Operatives
	82: Transport and Mobile Machine Drivers and Operatives	821: Road Transport Drivers 822: Mobile Machine Drivers and Operatives 823: Other Drivers and Transport Operatives
9: Elementary Occupations	91: Elementary Trades and Related Occupations	911: Elementary Agricultural Occupations 912: Elementary Construction Occupations 913: Elementary Process Plant Occupations
	92: Elementary Administration and Service Occupations	921: Elementary Administration Occupations 923: Elementary Cleaning Occupations 924: Elementary Security Occupations 925: Elementary Sales Occupations 926: Elementary Storage Occupations 927: Other Elementary Services Occupations

Appendix B: Presentation of the Google Search Data

Web-based search data, including Google data, are being increasingly used as measures of economic activity or demand. As far as we know, Ettredge et al. (2005) published the first article on the usefulness of web-search data to forecast economic conditions. They show that rates of employment-related searches are correlated with future official unemployment levels, in the US. Similarly, Askitas and Zimmermann (2009) and D'Amuri and Marcucci (2010) highlight the predictive power of Google search data in forecasting unemployment rates in Germany and the US. Moreover, Choi and Varian (2012) show that search engine data from Google Trends may be used to "predict the present" and provide examples for initial claims for unemployment benefits, automobile sales, travel planning, and consumer confidence, in several countries.

Interestingly, a growing literature in the social sciences exploits Google data to capture data that are hard to measure in surveys. For instance, some papers employ these data to capture health (Gunn and Lester, 2013, for suicide), well-being (Algan et al., 2019; Ford et al., 2018), and racial animus (Stephens-Davidowitz, 2014). Our motivation for using Google search data is similar to that of these authors: given that we lack information on gig jobs in general population surveys such as Understanding Society, we believe that Google data may be helpful to capture the presence and the strength of the gig economy across the UK.

In our robustness check, we use these data from Google Trends, which reflects the popularity of Google searches across regions and times, as instruments. We retrieve the number of hits for the word "Uber" at the city/village/town level within the UK for each year between 2009 and 2016, corresponding with the Understanding Society data time frame. Note that using information on Uber searches is all the more relevant as providing services through this platform is the most common type of gig economy activity in the UK (BEIS, 2018a).

We first download city-level Google Trends data for each city-year separately. Using a sample of searches, Google Trends provides the percentage of an area's searches for a given word, divided by the percentage of searches on a given word in the city with the highest share of searches for that same word, multiplied by 100. The resulting data is therefore relative with the city having the highest share of searches at time t equal to 100. Specifically, for area j for a certain time period t, the score for the word "W" is defined as follows:

$$Score_{jt} = 100 \times \frac{\left[\frac{Google\ searches\ including\ the\ word\ \mathrm{W}}{Total\ Google\ searches}\right]_{jt}}{\left[\frac{Google\ searches\ including\ the\ word\ W}{Total\ Google\ searches}\right]_{j\ max,t}}$$

Google Trends does not provide any score for "W" when the absolute volume of searches is too low. To overcome this problem, we use a strategy similar to Stephens-Davidowitz (2014). We collect the search volume for a word that is very common in searches, namely "weather." We then collect the search volume for "weather or our keyword of interest" which provides search volumes for either of the two words. We then use information on searches of "weather or our keyword of interest" and of "weather" to predict the missing search volume of "keyword of interest," for those areas where the search volume is too low.

Finally, in order to map the Google search data into our TTWA zones for the Understanding Society and aggregate data, we map every city/village/town into its corresponding TTWA and then we average the Google searches within the TTWA weighting by population of the city/village/town.

Figure B1 represents average hits between 2012 and 2015 for the word Uber. The map highlights geographic variation in search intensity across the UK. Search intensity is particularly high in the London area and Manchester and Leeds. It is also relatively high around Newcastle, Durham and the South of England.

Figure B2 tracks the relative intensity of searches over time. Uber has seen a strong increase in the number of searches over time with considerable within year variation as well. The spike in searches in June of 2014 is likely due to a strike by taxi drivers in London (as well as other capitals) on June 11.

Figure B1: Average Google Searches for the Word “Uber” Between 2012 and 2016 Across TTWAs

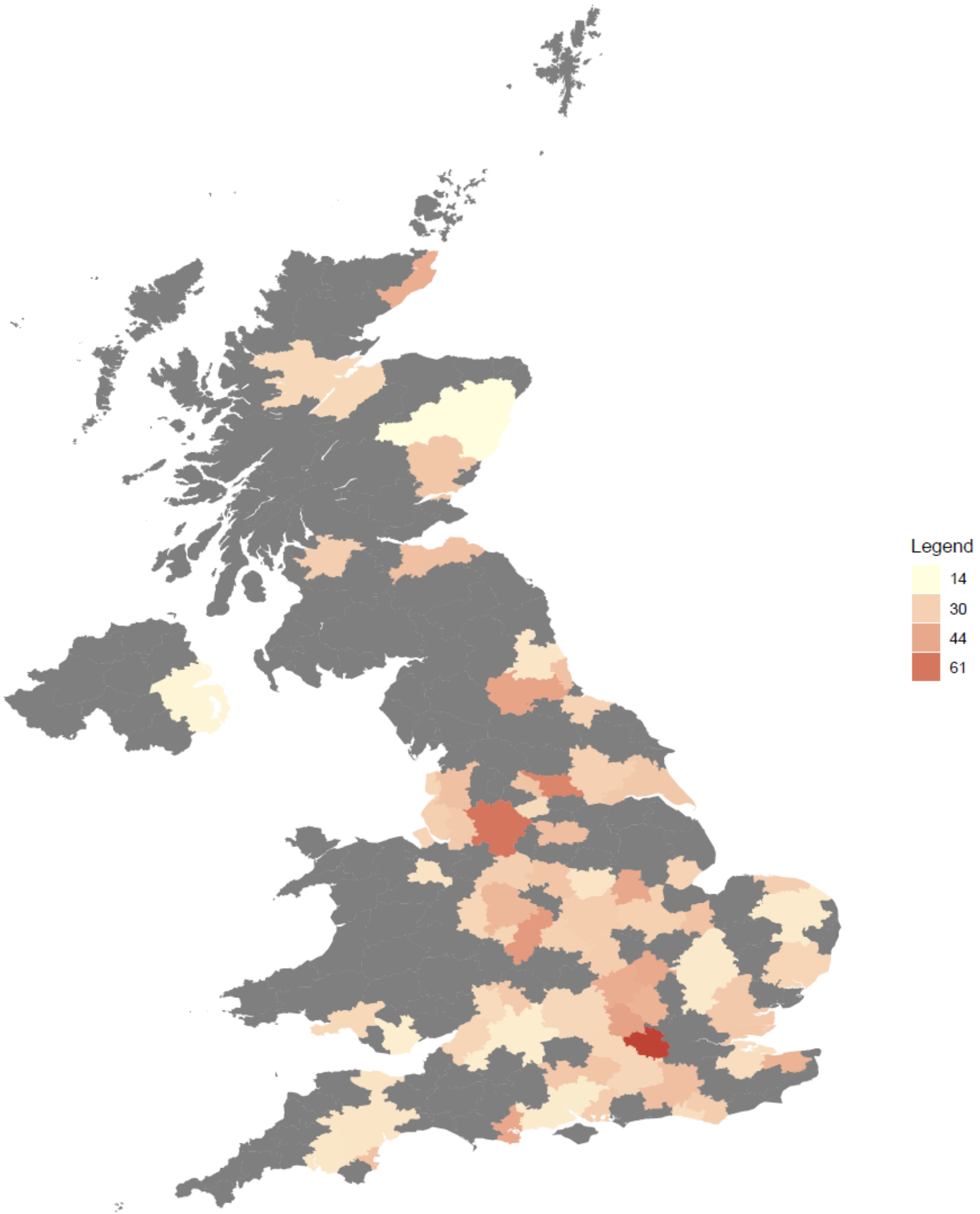
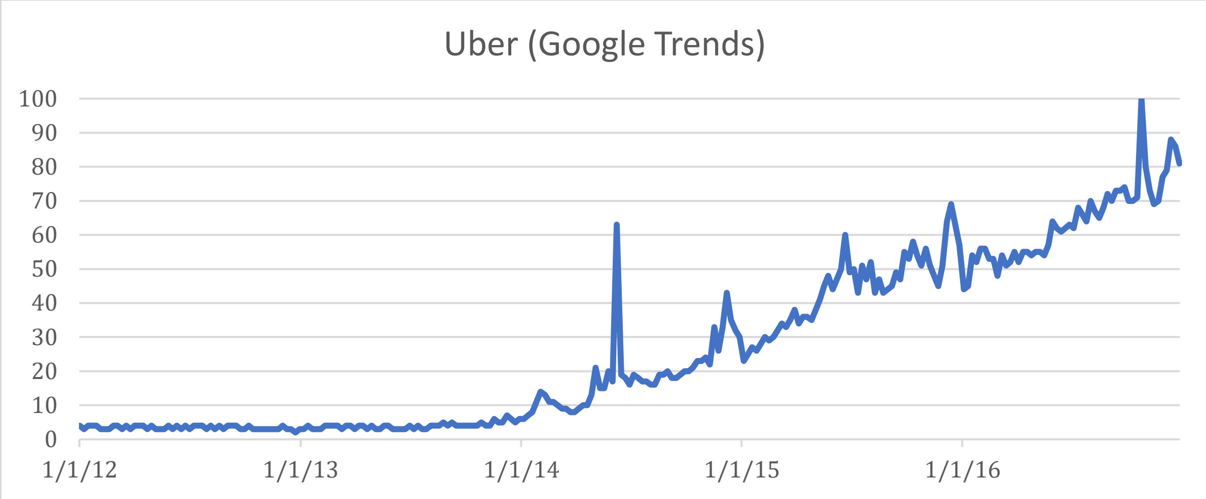


Figure B2: Google Searches for the Word “Uber” Over Time



Appendix C: Instrumental Variable Approach

As a check on our decision to focus on a particular set of occupation codes, we now estimate an alternative model for the full sample of (self-employed or employed) individuals in Understanding Society. Instead of estimating the direct effect of Uber diffusion on mental health in a certain occupation group, we estimate the effect of self-employment on mental health, relying on variation in self-employment driven by the expansion of Uber, in the full sample. We employ an instrumental variable strategy.

Estimation Strategy

We suggest using Uber diffusion and Google searches as instruments for self-employment. Our instruments are meant to be a proxy for the share of "Uber partners." Our hypothesis here is that these instruments capture the demand for the services provided in a TTWA, and hence the supply self-employed workers providing these services. In other words, we assume that diffusion and searches are a good proxy for the rate of employment in the gig economy in the area.

The instrumental variable model assumes that instruments are uncorrelated with other characteristics that may affect mental health.

We first estimate a regression that does not include TTWA fixed effects. A limitation of this approach is that Google searches may pick permanent or near permanent local characteristics – amenities, congestion, pollution, etc. – that may not be fully reflected into our control variables, while having an independent impact on mental health. To address this concern, we then estimate a model that includes TTWA fixed effects.

We acknowledge some limitations of this instrumental variable approach. First, Google searches may not perfectly capture demand for Uber services. Indeed, many individuals access Uber services using apps instead of Google. It is also possible that people are searching in their TTWA for Uber services available elsewhere.

Second, the exclusion restriction for the validity of our instruments may be problematic. Given that our sample undoubtedly contains a number of Uber passengers/consumers, and assuming that Uber has a direct influence on passenger well-being, there could be a direct effect running from our Google search instrument to mental health in the sample. This is one of the main reasons we focus on drivers in the main analysis.

Results

First stage results for this specification (for the full sample of workers) are reported in Table C1. Both instruments are significant predictors of self-employment but F-statistics equal 5 (when TTWA fixed effects are not included) and 7 (when they are included) approximately.

Table C2 presents our second-stage results. The first column excludes TTWA fixed effects and the second includes them. We find a positive and fairly large effect of self-employment on mental health using this specification – self-employment is associated with between a 6- and 11-point increase in the mental health scale. The coefficient on self-employment is not statistically significant when we do not include TTWA fixed effects, but becomes so with their inclusion to capture fixed differences across these areas.

We also estimate models where we break down the subcomponents of the mental health score, as presented above, to see whether we can say something further about the areas of mental health that are most affected. These results (presented in Table C3) show that in the IV specification, the effect of self-employment on mental health is present across a large range of measures: concentration, playing a useful role, capable of decisions, under strain, ability to face problems, depression, loss of confidence, and general happiness.

Table C1: Instrumental Variable Estimates -- First stage

	(1)	(2)
Dependent Variable:	Self-Employment	
Uber Diffusion	0.013**	0.014**
	(0.006)	(0.006)
Uber Google Search	-0.000***	-0.000***
	(0.000)	(0.000)
Male	0.074***	0.074***
	(0.005)	(0.005)
16-19	-0.104***	-0.103***
	(0.009)	(0.009)
20-24	-0.095***	-0.095***
	(0.008)	(0.008)
25-29	-0.057***	-0.057***
	(0.009)	(0.009)
30-34	-0.035***	-0.035***
	(0.007)	(0.007)
35-39	-0.008	-0.007
	(0.007)	(0.007)
45-49	0.008	0.008
	(0.008)	(0.008)
50-54	0.022*	0.021
	(0.013)	(0.013)
55-59	0.042***	0.041***
	(0.012)	(0.012)
60-64	0.090***	0.090***
	(0.011)	(0.011)
HH Size	0.013***	0.013***
	(0.003)	(0.003)
Some Post-Secondary	0.005	0.005
	(0.006)	(0.006)
Post-Secondary	0.026***	0.026***
	(0.007)	(0.007)
Mixed	-0.005	-0.006
	(0.012)	(0.012)
Asian	-0.009	-0.011
	(0.018)	(0.018)
Black	-0.060***	-0.060***
	(0.017)	(0.017)
Other	-0.002	-0.002
	(0.011)	(0.011)
Ln(Income)	-0.061***	-0.061***
	(0.007)	(0.007)
Wave FE	Yes	Yes
Uber Region FE	Yes	No
TTWA FE	No	Yes
Observations	39,888	39,888
F-stat	7.509	5.611
J stat (p-value)	0.806	0.227

Notes: Controls include: sex, race, age, education, household size, log income, log TTWA average income, and wave and Uber region FE in column 1 and TTWA fixed effects in column 2. The income variable is a gross monthly household income measure. Clustered standard errors at the Uber region level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C2: Instrumental Variable Estimates -- Second Stage
for the General Health Questionnaire score

	Dependent Variable: GHQ-36	
	(1)	(2)
Instruments:	Uber Diffusion and Google Search	Uber Diffusion and Google Search
Self-Employed	6.445	11.431*
	(3.924)	(6.265)
Wave FE	Yes	Yes
Uber Region FE	Yes	No
TTWA FE	No	Yes
Observations	39,888	39,888
F-stat	7.509	5.611
J stat (p-value)	0.806	0.227

Notes: Each column is from an individual IV regression. GHQ-36 is the mental health scale running from 0 (worst mental health) to 36 (best mental health). Controls include: sex, race, age, education, household size, log income, log TTWA average income, and wave and Uber region FE in column 1 and TTWA fixed effects in column 2. The income variable is a gross monthly household income measure. Clustered standard errors at the Uber region level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C3: Instrumental Variable Estimates – Second Stage for the General Health Questionnaire Subcomponents

Dependent Variable:	Concentration	Sleep	Playing Useful Role	Capable of Decisions	Under Strain	Overcome Difficulties	Enjoy Daily Activities	Ability to Face Problems	Unhappy or Depressed	Loss of Confidence	Believe in Self Worth	General Happiness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Instrments: Uber Diffusion and Uber Google Search												
Self Employed	0.648**	-0.164	0.418*	0.601**	0.737**	0.096	-0.207	0.388*	0.584*	0.526*	-0.046	0.568**
	(0.297)	(0.295)	(0.224)	(0.238)	(0.355)	(0.189)	(0.243)	(0.205)	(0.307)	(0.313)	(0.180)	(0.242)
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Uber Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	39,999	40,005	39,974	39,994	40,003	39,989	40,004	39,995	39,997	39,992	39,991	39,999
F-stat	6.934	6.983	7.498	7.486	7.544	7.509	7.807	7.537	7.507	7.537	7.429	7.564
J stat (p-value)	0.619	0.890	0.338	0.959	0.820	0.498	0.442	0.501	0.945	0.678	0.827	0.432

Notes: Each column is from an individual IV regression. Each dependent variable takes the value of 0 or 1, with 1 indicating the more positive response (i.e. in the case of Concentration 1 indicates "better than usual" and in the case of Under Strain it indicates "not at all"). Controls include: sex, race, age, education, household size, log income, log TTWA average income, and wave and Uber region fixed effects. The income variable is a gross monthly household income measure. Clustered standard errors at the Uber region level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

End of the Appendix