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Working Paper
2019/23/EPS

The Effects of Self and Temporary Employment on Mental Health: The role of the Gig Economy in the UK

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May 2019

We study the effect of both self and temporary employment on mental health in the UK. We match individual-level information on health and sociodemographic characteristics from the UK Household Longitudinal Study (Understanding Society) between 2009 and 2016 with Google Trends data on the amount of search activity related to the gig economy. We use Google Trends data on Uber, Deliveroo, and Airbnb by commuting zone to instrument for the probability that an individual will be employed in a gig-type job. The Google Trends data are strong predictors of both self and temporary employment. Our findings suggest that self and temporary employment, as identified through gig-economy activity, have large positive effects on mental health. These effects exist for both men and women but are stronger for women and for older workers (ages 40-64). Our evidence points to issues of control in the job as potential drivers of the improvements in mental health.

Keywords: Mental health; Self-employment; Temporary jobs; Gig Economy.

Electronic copy available at: http://ssrn.com/abstract=3395144

Acknowledgements

We thank Marco Guido Palladino, Genevieve Jeffrey, and Viviane Azaïs for their excellent research assistance. We also thank Clément Carbonnier, Fabrice Etilé, Denis Fougère, Morgane Laouenan, Nathalie Morel, Anne Revillard, and participants at seminars at "Université Paris 1 Panthéon-Sorbonne," Sciences Po Liepp, and Copenhagen Business School (2019) for relevant comments and suggestions. Understanding Society is an initiative funded by the Economic and Social Research Council and various Government Departments, with scientific leadership by the Institute for Social and Economic Research, University of Essex, and survey delivery by NatCen Social Research and Kantar Public. The research data are distributed by the UK Data Service.

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).

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 have been growing among both children and adults. Depression, ADHD, conduct issues, as well as other chronic mental health problems have all risen substantially over the past 25 years (McManus et al., 2016). This paper explores the causal effect of self-employment and temporary work on mental health using British data.

The relationship between self-employment or temporary work and mental health is not, a priori, obvious. First, there may be a contextual effect of the type of employment on health. The sign of this effect is unclear: 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 or temporary employment have a positive effect on mental health. Many gig economy type jobs (Uber, Deliveroo, Airbnb, etc.) may provide flexibility, earnings potential for a given education level, or levels of autonomy that positively contribute to mental health. Historically,

[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

most empirical studies show that precarious employment is negatively correlated with health (Benavides et al., 2000). However, precarious employment can take various forms in various contexts depending on the social safety net, alternative options, and changing nature of work opportunities.

In addition, health status may have an impact on employment characteristics (reverse causation and selection). Indeed, the healthy may self-select into self-employment or precarious jobs. However, it is also possible that unhealthy people have a hard time finding an employee job, which may lead them to consider self-employment. In other words, there may be a selection issue in who decides to be self-employed or have a temporary job.

In this paper, we study the effect of self and temporary employment on mental health in the UK. We have a particular focus on employment generated through the gig economy. We match individual-level information on health and sociodemographic characteristics from Understanding Society, the UK household longitudinal study, between 2009 and 2016, with commuting area-level data on employment characteristics as well Google search data on the activity level in the gig economy. To address reverse causation and estimate the causal effect of self and temporary employment on health, we employ an instrumental variable strategy. We explore the effect of self and temporary employment induced by the gig economy by using Google search queries on terms associated with gig economy employment in an area (a proxy for gig economy demand) to instrument for the probability that an individual will be employed in a gig-type job. We then study the effect of self and temporary employment, instrumented with these google searches on the gig economy, on mental health and wellbeing.

This paper contributes to the large literature on the effect of employment types on health. Indeed, we use a data source on employment types (Google search queries on the gig economy) that has not been used in this strand of research so far. The advantage of Google search 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.

Our findings suggest that, contrary to some previous studies, self-employment and temporary employment are positively associated with mental health. This is true both when looking at those working, but also at all individuals of employment age. Further, examining sub-components of behavior associated with mental health (sleep, physical activity, medication, smoking, drinking), we find a consistent pattern of improvements in these drivers of mental health for those who are self or temporary employed. Our findings appear to be stronger for women, for older workers, and for those with less than a college education.

The rest of the paper proceeds as follows. Section 2 reviews the literature on precarious employment 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).[3] Self-employment has been rapidly growing since the turn of the century (12% of the labor force in 2001, versus 15.1% in 2017).[4] Moreover, the labor market has become more precarious: in particular, the number of temporary employees increased from 1,428 millions in January-March 2009 to 1,652 millions in January-March 2016 (with a peak in 2014).[5]

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, the report on characteristics exploits quantitative data collected in 2017 in Great Britain and 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 was the most common type of gig economy activity (18%). Deliveroo was mentioned by 12% of workers. 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 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. Previous research specifically on Uber drivers (Berger et al, 2018) suggests that the flexibility of working hours are a strong motivator of the

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

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

[5] See https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/articles/labourmarketeconomiccommentary/november2018#temporary-working-in-the-uk

decision to work for Uber. The authors survey Uber drivers in the London area and match these data to data on London workers. Their findings suggest that Uber drivers report higher levels of life satisfaction even among those earning lower wages.

Contextual and Selection Effects

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

To understand the contextual effect, theoretical insights from the Job Demands-Control model (Karasek, 1979; Karasek and Theorell, 1990; Theorell and Karasek, 1996) may be useful. In this approach, occupational stress depends on two factors: (1) job requirements (job demands) and (2) autonomy or decision-making authority (job control). The imbalance between job demands and job control results in different levels of stress. In particular, experiencing both high job demands and low job control is the most stressful situation. The self-employed may have a higher job control level than typical wage workers, because they have control over the organization of their working life and they have high decision authority, and this may benefit their health. However, self-employment is also associated with a higher level of job demand than average, which may have a negative impact on health.

Further, the selection effect means that the choice to be self-employed or to have a temporary job may depend on individual health status. For instance, individuals in poor health may have

less access to sources of external finance for their enterprises. This may lead healthier individuals to self-select into self-employment. In contrast, unhealthy people have a hard time finding a permanent employee job, which may lead them to consider self or temporary employment. In other words, there may be a selection issue in who decides to be self-employed or have a temporary job.

Self-Employment

The literature 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.

Precarious Jobs

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.

On a related matter, 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.

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. Specifically, results show a negative correlation between having a temporary job (compared to a permanent job) on SAH for females and males with low level of education, but a positive relationship for females and males with a high level of education. Correlations between temporary job and GHQ are neither significant for individuals with a low level of education nor for those with a high level.

Google Searches

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 the 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.

More generally, 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) and well-being (Algan et al., 2019; Ford et al., 2018). In addition, Stephens-Davidowitz (2014) uses Google search data to measure racial animus and finds that racism cost Obama substantial votes during the 2008 and 2012 US presidential elections.

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. In particular, we study the following health indicators: mental health, smoking, drinking, sporting activity, the uptake of sleeping pills, and quality of life.

We measure mental health using the 12-item General Health Questionnaire (GHQ-12) as well as its sub-components. This questionnaire identifies minor psychiatric disorders and is widely used by psychologists and epidemiologists. The GHQ-12 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). The distribution of the score is shown in Figure 1. The mean is around 24 out of 36 with the bulk of the responses between 20 and 30. We also use dummies for the various sub-components as dependent variables in their own right, to examine how various inputs to the mental health index perform.

In addition, we examine questions on whether the individual is a smoker, how much money she spends on alcohol (the logarithm of household spending, adjusted for the number of family members over age 18 and conditional on spending money on alcohol), whether she takes medications to sleep, and whether and how often she does sporting activity.

As an additional check, we use three questions from the SF-12 health-related quality of life questionnaire. They indicate whether the individual felt downhearted and depressed, felt calm

and peaceful, and had a lot of energy, during the four weeks preceding the interview. To analyze the responses, we use three dummy variables that capture quality of life.

Understanding Society data also contain detailed information in each year on current economic activity of the respondent, and in particular asks whether the individual is self-employed (versus employed), and has a temporary position (versus a permanent one). The data also provide information on sociodemographics including gender, age, household size, and income. Table 1 presents summary statistics for health, labor market status, and sociodemographic control variables. 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, temporary employment, and population data, 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) of which we have Google search data for 200.

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.

Search Queries on Google

We use data from Google Trends which analyzes the popularity of Google searches across regions and times. We retrieve the number of hits for certain key words at the city/village/town level within the UK for each year between 2009 and 2016, corresponding with the Understanding Society data time frame. In particular, we capture data on three measures of the gig economy: Uber (starting in 2012), Deliveroo (starting in 2015), and Airbnb. 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, as shown by a recent report (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 that 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 such as "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 2 represents average hits between 2012 and 2015, for the words Uber (top left panel), Deliveroo (top right panel), and Airbnb (bottom left panel), and for the average of the three words (bottom right panel), across TTWAs. The maps highlight geographic variation in search intensity across the UK. Search intensity is particularly high in the London area, in Edinburgh, and in the South of England. It is also relatively high around Chester and Carlisle.

Figure 3 tracks the relative intensity of gig economy searches over time. Each of Uber, Deliveroo, and Airbnb has seen a strong increase in the number of searches over time with considerable within year variation as well. The spike in Uber searches in June of 2014 is likely due to a strike by taxi drivers in London (as well as other capitals) on June 11. As seen by the search volume, Deliveroo entered the market later in our sample period and hence we are only

able to use information from these searches in the very last years of our sample. As noted above, Google does not allow us to track the number of Google searches for a word relative to all words, but rather relative to itself over time.

Empirical Specification

We begin by estimating models of the effects of labor market status on the mental health outcomes described above, using a linear model (OLS):

$$MH_{ijt} = \alpha + \beta . LMS_{ijt} + \gamma . X_{ijt} + \delta_t + \epsilon_{ijt}$$

Where MH_{ijt} denotes mental health (the GHQ-12 and its subcomponents) for a person i, in TTWA j, in year t. LMS is labor market status, i.e. a dummy for being self-employed in some models or in a temporary job in other models. X is a vector of individual-level characteristics, that includes gender, age (age group dummies), education (series of dummies), income (i.e. logarithm of household income plus one), and household size. We also control for the average income in the TTWA in that year to capture changes in the overall level of economic activity in the area over time. Finally, δ_t captures year fixed effects. Standard errors are clustered at the TTWA level.

Because both self-employment and temporary employment are potential endogenous variables, we then instrument for them using information from Google trends. Our primary IV strategy focuses specifically on the role of the gig economy on generating self- employment or employment in temporary jobs. Ideally, we would like to have true use /capita of gig economy

services (number of rides or number of deliveries, etc.). As we are not able to use this information, we use Google trends to measure the google search intensity for Uber, Deliveroo, and Airbnb in a TTWA. We then use these measures as well as TTWA population as instruments to predict levels of self and temporary employment. Our hypothesis here is that Uber, Deliveroo, and Airbnb searches capture the demand for these services in a TTWA (along with population) and hence the supply of these services. In other words, we assume that these searches are a good proxy for the rate of employment in the gig economy in the area that is uncorrelated with other individual characteristics that may affect mental health.

Of course, searches for these terms could also be picking up people looking for this type of work, but we expect that the number of users far exceed the number of providers for each of these services. It is also possible that people are searching in their TTWA for services available elsewhere. This is more likely the case for Airbnb and less likely for Uber and Deliveroo. Many individuals also access these types of services using apps instead of Google. Nevertheless, we show that there is a sufficient volume of search through Google to generate variation over time and region.

Our identification strategy also assumes that search queries (and population) do not have a direct impact on health other than through the type of employment (self or temporary employment). However, search queries may be a proxy for the area's level of economic activity, and economic activity may be correlated with individual mental health. To address this concern, we include a control for economic activity by TTWA and year (specifically, the logarithm of the average income per capita, by TTWA and year) in our models.

Based on these considerations, we posit (and show first stage support) that the combination of gig economy terms services is an exogenous predictor for the probability of any individual in that area to be self-employed or has a temporary job, all else equal. Again, as the level of variation in this case is at the TTWA-year level, we cluster our standard errors at the TTWA.

Finally, we expand our analysis to include a series of dependent variables that are correlates and/or predictors of mental health such as smoking, alcohol use, medicine pill uptake, physical exercise, and quality of life, to help understand what may be underlying any effect we find on mental health.

The main sample for our analysis includes only individuals who are working. We exclude the unemployed and those out of the labor force for a few reasons. First, comparing self and temporary workers to other workers is a fundamentally different comparison to comparing these workers to those who are not working. Second, the level of unemployment in the UK over this period is very low, once again suggesting that those who are unemployed may have unobservable characteristics that are quite different from workers in our data. Nevertheless, for comparative purposes, we show results including those unemployed and out of the labor force in the Appendix.

4. Results

We begin by presenting OLS estimates of the relationship between self and temporary employment and our mental health measures and related variables. The results are reported in Table 2. Panels A and B show results for self and temporary employment separately. Panel C presents estimates for self and temporary employment combined (i.e. the explanatory variable

is a dummy for whether the individual is either self or temporarily employed, versus neither self nor temporarily employed). OLS regressions show that the self-employed are healthier. Indeed, self-employment is positively and significantly associated with mental health and with physical activity. It is also positively associated with alcohol spending. The magnitude of the effect on mental health is small though (0.3 point for GHQ in Panel A, given that the GHQ score ranges from 0 to 36). In contrast, temporary employment is negatively associated with health: indeed, temporary jobs are negatively associated with the GHQ (-0.3 point in Panel B) and positively associated with the uptake of sleeping pills. Combining these two groups yields a positive and significant coefficient on mental health (although smaller than self-employed alone). In Panels D, E, and F, we include a control for lagged mental health, as used in Rietveld et al. (2015), to proxy for selection into self-employment and temporary employment by those with worse (or better) health. Unlike Rietveld et al (2015), we continue to find a positive and significant effect of self-employment on mental health and the negative effect of temporary employment goes away. These estimates are, of course, subject to endogeneity and sorting concerns but provide a baseline for comparison to our IV results.

Tables 3 presents our main IV specifications which use Google search data on gig economy words along with population to instrument for individual self and temporary employment. In this specification, we exclude Deliveroo as an instrument as we only have data on Deliveroo searches for two of the five years in the sample. Once again, the first two panels present results for self-employed and temporarily employed separately and the third panel contains estimates combining these two variables. First stage F-statistics and J-statistics for the Hansen test of overidentifying restrictions are reported for each model. In contrast to the OLS specification, we find a very significant and large effect of self-employment on mental health as measured by the GHQ score. Self-employment increases mental health by 8.1 points (out of 36). The

instruments are strong, with F-statistics greater than 10, and the p-value of the Hansen test is high, which suggests that the instruments are valid. This large effect of self-employment on mental health is not completely inconsistent with previous literature (as noted above) that suggests that flexibility, lack of hierarchy, and sense of purpose are all potentially positive inputs into mental health.

Perhaps the more surprising result is the effect of temporary employment on mental health. Like the effects of self-employment, we find an IV result that is positive, significant, and large. The magnitude, 6.9 point increase out of the 36-point scale, is very similar to that for self-employment. Combining the two measures, unsurprisingly, yields a similarly positive and large point estimate of 5.8 points.

We perform some specification/robustness checks on our instruments and samples. First, we exclude Airbnb from our instrument set as some Airbnb workers are not traditional laborers and it may be easier to hold other jobs simultaneously. Our findings, reported in Table A1 (columns (1) and (2)) in the Appendix, show that our results are mostly unchanged with this reduced instrument set. We also estimate this model in a sample that contains both working and non-working individuals. Results, reported in columns (3) and (4) are qualitatively similar. Finally, we examine whether including part time workers together with self and temporary employed workers affects our estimates. While part time workers separately are not well instrumented by gig economy searches, including them with self and temporary workers has little effect on our results (Appendix A2).

We also re-estimate our models first, excluding TTWA population as an additional instrument (but including Uber and Airbnb), second, limiting our sample from 2014 onwards when we

have more search data, and third, including Deliveroo as an additional instrument (requiring us to use 2015 data only). In every case our results remain qualitatively unchanged (when we reduce our sample to only 2015 and onwards, our estimates are only significant at the 10% level). These results are available upon request.

The limited number of years in our sample leaves insufficient variation in our instrument over time to include TTWA fixed effects and have robust first stages. For self-employed, including TTWA fixed effects results in a first stage F stat of 3.5, which is weaker than would be ideal for inference. Nevertheless, the effect of self-employed on mental health using fixed effects – IV is still strong and positive, and slightly larger than the results in table 3 (14 points on the 36 point scale). The first stage for temporary-employment when we include fixed effects is very weak given the limited variation (F=0.8). Hence, for the remainder or the paper we focus on models that include direct controls for TTWA economic activity and population.

Decomposing the Effects on Mental Health

In order to better understand what is driving the positive effect on mental health, we look at several variables that are often predictive of mental health, and we break down the mental health scale into its component parts. Table 3 shows results for the effects of self and temporary employment on smoking, alcohol expenditure, sleep medication, and physical activity. Across all panels, we find a significant and large decrease in alcohol expenditure among those that have positive expenditure in the range of 200%. This is perhaps partly explained by increases in full time work but also by our use of gig economy instruments that involve driving/biking and doing so during evening hours, thereby necessitating less alcohol consumption.

Table 4 examines the sub-components of the mental health index. As noted above, these span issues of sleep, self-perception, and emotional status. The results display some interesting patterns. We find a strong and significant relationship between self-employment and ability to concentrate, not being constantly under strain, confidence, belief in self-worth, and happiness. The effects are positive for both self-employment and for the combination of self and temporary employment, although we do not find a similar pattern for temporary employment. For temporary employment, the results are mixed with no clear pattern. Referring back to the job demands-control model cited earlier, the findings here are consistent with potential benefits of having more control in the job and their effects on mental health. The other components of the mental health score, in contrast, are mostly insignificant.

The Understanding Society questionnaire offers a few additional questions related to quality of life including whether the respondent felt downhearted or depressed, felt calm and peaceful, and whether the respondent had a lot of energy. We use these questions as additional outcome variables and report the results in Table 5. Of the three measures, we find consistently positive and significant effects of both self and temporary employment only on the question "had a lot of energy" with no effects for the other two questions in any of our specifications.

Differences by Age, Gender, and Education

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 opinions regarding the gig economy may depend on sex, age, and education level, we examine whether the effects of self and temporary

employment on mental health significantly differ across these characteristics, when we use gig economy activity as an instrument. We estimate our main models above (for the gig IV specification only) separately by category. Table 5 reports results by gender and age group, and Table 6 by education within gender.

Overall, we find some interesting differences by both age and gender. The effects of self-employment on mental health are positive for both men and women, but are much larger for women. This is also true for temporary employment and combining self and temporary employment. The effects on mental health also appear to be slightly larger for older workers (ages 40-64) relative to younger workers (ages 18-39).

We further decompose our results by gender and education (Table 7). The effects of self and temporary employment on mental health are concentrated among the less educated for both men and women. Splitting the sample in this way reveals no statistically significant effect for college educated workers and a much larger effect for less than college educated workers. This is true whether we look at self-employment, temporary employment, or both combined.

Finally, we look at parents versus those without children. A priori it is not clear whether self and temporary employment identified through gig economy activity should benefit parents more or less. On the one hand, parents may value the flexibility offered by self-employment. On the other hand, particularly in gig economy type of employment, a good deal of activity can take place after school hours, making scheduling difficult for parents. Our results, presented in Table 9, suggest that the second effect may dominate. The positive effect of self and temporary employment on mental health is much stronger for both men and women without children than it is for parents, and there appears to be no effect for fathers. For mothers, the effect is

completely driven by temporary employment rather than self-employment. Overall, we find that our results are quite heterogenous, with the mental health benefits being stronger for females, for older workers, for those with less than a college education, and for people without children.

5. Conclusion

The aim of this paper is to investigate whether being self-employed or temporarily employed has an effect on mental health. While previous studies have explored the relationship between employment and health, the evidence on the relationship between types of employment and health is rather contradictory. Importantly, associations between types of employment and health could be explained by the causal influence of types of employment on health, but also by a selection effect. We offer a new way to deal with the selection into employment type: using changes in demand for gig economy type employment. Hence our results are both free from selection effects, and identified through a particular kind of self and temporary employment, the emerging gig economy. We find a strong and positive effect of these types of employment on mental health, consistent across a variety of specifications. Our evidence suggests that the effects are driven by happiness and control in the job. Our results are consistent with findings from a recent report (BEIS, 2018a) 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 and also consistent with research looking specifically at Uber drivers (Berge et al 2018). In our sample, the effects appear to be stronger for women, older workers, and less educated workers. We are cautious about suggesting that the effects of self and temporary employment outside of those jobs that offer more control and satisfaction (zero-hour

contract jobs for example) would have similar effects on mental health. We suspect (but not examine this issue directly) that this may not be the case. However, to the extent that changes in the labor market are towards offering more flexible forms of self and temporary employment, our results suggest that these jobs may also have positive effects on worker wellbeing. Exploring the exact mechanism driving these results, or on other organizational factors that may affect job satisfaction, is a topic for future research.

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Table 1: Descriptive Statistics

	Observations	Means	SD	Min	Max
Health					
GHQ-12	210,599	24.73	5.68	0	36
Smoker	50,293	0.19	0.39	0	1
Money Spent on Alcohol	158,541	3.88	0.97	0.69	8.78
Takes Medicine to Sleep	55,003	0.08	0.27	0	1
Felt Downhearted or Depressed	161,649	0.38	0.48	0	1
Felt Calm and Peaceful	176,823	0.53	0.50	0	1
Had a Lot of Energy	176,778	0.48	0.50	0	1
Labor Market Status					
Self-Employed	180,335	0.13	0.34	0	1
Temporary	180,217	0.08	0.27	0	1
Part-Time	163,840	0.26	0.44	0	1
Controls					
Age	253,818	41,33	13,12	18	64
Male	253,815	0,46	0,50	0	1
Household Size	187,992	3,18	1.52	1	16
Gross Household Monthly Income	252,688	4029.04	2933.73	0	20,000
Instruments					
Uber	93,392.0	60.3	29.6	8.5	100
Airbnb	102,385.0	56.0	23.7	15.0	100

Table 2: OLS Estimates of the Effect of Self and Temporary Employment on Mental Health

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome	GHQ-12	Smoker	Money spent on alcohol (per capita)	Take medicine to sleep	Sport Activity	Sport Frequency
Panel A						
Self-Employed	0.33***	0.00	0.09***	0.00	0.21***	0.02
	(0.07)	(0.00)	(0.02)	(0.00)	(0.06)	(0.04)
N	82710	36414	50522	39367	22211	16434
R^2	0.02	0.05	0.09	0.00	0.09	0.02
Panel B						
Temporary	-0.32***	0.00	-0.02	0.01**	0.07	0.05
	(0.08)	(0.00)	(0.02)	(0.00)	(0.07)	(0.04)
N	82634	36358	50483	39342	22205	16432
R^2	0.02	0.05	0.09	0.00	0.09	0.02
Panel C						
Self/Temporary	0.13*	0.00	0.06***	0.00	0.16**	0.03
	(0.06)	(0.00)	(0.01)	(0.00)	(0.05)	(0.03)
N	82659	36367	50500	39343	22210	16434
R^2	0.02	0.05	0.095	0.00	0.093	0.02
Panel D: Controlling for lag health						
Self-Employed	0.23***	0.00	0.09***	0.00	0.21**	-0.01
	(0.05)	(0.00)	(0.02)	(0.00)	(0.06)	(0.04)
N	71064	31212	31084	34155	18949	13941
R2	0.232	0.06	0.13	0.02	0.09	0.02
Panel E: Controlling for lag health						
Temporary	-0.04	-0.00	0.02	0.01**	0.11	0.08
	(0.06)	(0.00)	(0.02)	(0.00)	(0.08)	(0.04)
N	70999	31166	31078	34129	18943	13939
R2	0.23	0.06	0.13	0.02	0.09	0.02
Panel F: Controlling for lag health						
Self/Temporary	0.16***	0.00	0.07***	0.00	0.17**	0.01
	(0.04)	(0.00)	(0.02)	(0.00)	(0.05)	(0.03)
N	71023	31175	31084	34134	18948	13941
R2	0.233	0.056	0.127	0.02	0.09	0.02

Notes: Each column row coefficient is from an individual regression. GHQ-12 is the mental health scale running from 0 (worst mental health) to 36 (best mental health). Controls include: sex, age, household size, log income, log TTWA average income, and wave fixed effects. Clustered standard errors at the TTWA level in parentheses. * p<0.05 ** p<0.01 *** p<0.001.

Table 3: IV Estimates of the Effect of Self and Temporary Employment on Mental Health Using Google Search Data on the Gig Economy as Instruments

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome	GHQ-12	Smoker	Money spent on alcohol (per capita)	Take medicine to sleep	Sport Activity	Sport Frequency
Panel A						
Self-Employed	8.05***	-0.20	-2.01***	0.11	2.14	-1.40
	(1.99)	(0.23)	(0.60)	(0.09)	(3.12)	(0.73)
N	39121	23184	24951	16113	8147	5899
F-stat	49.53	21.63	56.64	25.85	8.31	12.42
J-stat (p-value)	0.96	0.39	0.18	0.61	0.05	0.40
Panel B						
Temporary	6.92***	-0.02	-2.74***	0.11	-0.16	-1.96
	(1.85)	(0.17)	(0.51)	(0.12)	(3.02)	(1.09)
N	39077	23148	24935	16104	8146	5901
F-stat	77.47	33.34	77.27	25.95	16.28	15.83
J-stat (p-value)	0.28	0.28	0.67	0.55	0.01	0.53
Panel C						
Self/Temporary	5.76***	-0.14	-1.63**	0.10	1.14	-0.99
	(1.42)	(0.17)	(0.50)	(0.08)	(2.12)	(0.57)
N	39121	31249	24940	16104	8146	5901
F-stat	61.57	21.84	47.50	20.65	12.43	13.94
J-stat (p-value)	0.76	0.38	0.23	0.61	0.03	0.37

Notes: Each column row coefficient is from an individual regression with the first stage F- and J-stats reported. GHQ-12 is the mental health scale running from 0 (worst mental health) to 36 (best mental health). Controls include: sex, age, household size, log income, log TTWA average income, and wave fixed effects. Instruments include: Uber search, Airbnb search, and TTWA population. Clustered standard errors at the TTWA level in parentheses.

* $p<0.05$ ** $p<0.01$ *** $p<0.001$.

Table 4: IV Estimates of the Effects of Self and Temporary Employment on GHQ Sub-Components Using Google Search Data on the Gig Economy as Instruments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Outcome	Concen tration	Loss of sleep	Playing a useful role	Capable of making decisions	Constantly under strain	Problems overcoming difficulties	Enjoy day-to-day activities	Ability to face problems	Unhappy or depressed	Losing confidence	Believe in self-worth	General happiness
Panel A												
Self-Employed	0.33*	-0.07	0.07	0.10	0.31*	-0.19	0.05	-0.12	0.22	0.55***	0.22**	0.30*
	(0.14)	(0.12)	(0.13)	(0.08)	(0.15)	(0.12)	(0.13)	(0.08)	(0.17)	(0.11)	(0.07)	(0.13)
N	39232	39238	39207	39226	39236	39222	39237	39228	39229	39226	39224	39232
F-stat	48.97	49.17	49.48	49.84	49.62	49.45	50.20	50.08	49.30	49.93	49.92	49.43
J-stat (p value)	0.26	0.69	0.08	0.39	0.78	0.48	0.17	0.07	0.33	0.53	1.00	0.27
Panel B												
Temporary	0.22	-0.11	-0.05	0.03	0.25	-0.21**	0.05	-0.21**	0.14	0.48***	0.20*	0.18
	(0.12)	(0.11)	(0.09)	(0.07)	(0.13)	(0.08)	(0.12)	(0.07)	(0.14)	(0.12)	(0.08)	(0.11)
N	39188	39194	39164	39182	39191	39178	39193	39184	39186	39183	39181	39188
F-stat	79.78	79.59	79.32	79.19	79.09	79.19	79.01	78.85	78.72	78.28	77.94	78.22
J-stat (p value)	0.13	0.79	0.03	0.34	0.50	0.77	0.16	0.22	0.28	0.21	0.81	0.10
Panel C												
Self/Temporary	0.23*	-0.06	0.04	0.06	0.23*	-0.13	0.04	-0.10	0.15	0.40***	0.15**	0.20*
	(0.10)	(0.09)	(0.09)	(0.06)	(0.11)	(0.08)	(0.10)	(0.06)	(0.12)	(0.08)	(0.05)	(0.09)
N	39201	39207	39177	39195	39205	39191	39206	39197	39199	39196	39194	39201
F-stat	63.02	63.08	63.21	63.15	62.99	62.98	63.26	63.39	62.62	62.63	62.93	62.31
J-stat (p value)	0.25	0.70	0.06	0.39	0.74	0.51	0.15	0.08	0.33	0.65	0.98	0.22

Notes: Each column row coefficient is from an individual regression with the first stage F- and J-stats reported. Controls include: sex, age, household size, log income, log TTWA average income, and wave fixed effects. Instruments include: Uber search, Airbnb search, and TTWA population. Clustered standard errors at the TTWA level in parentheses.
* p<0.05 ** p<0.01 *** p<0.001.

Table 5: IV Estimates of the Effects of Self and Temporary Employment on Alternate Measures of Mental Health and Stress Using Google Search Data on the Gig Economy as Instruments

	(1)	(2)	(3)
Outcome	Felt downhearted or depressed	Felt calmful and peaceful	Had a lot of energy
Panel A			
Self-Employed	0.16	-0.05	0.71***
	(0.24)	(0.16)	(0.16)
N	33768	38071	38072
F-stat	33.37	45.06	44.91
J-stat (p-value)	0.21	0.59	0.73
Panel B			
Temporary	-0.08	0.03	0.63***
	(0.14)	(0.18)	(0.17)
N	33732	38032	38033
F-stat	85.55	76.79	76.47
J-stat (p-value)	0.26	0.59	0.43
Panel C			
Self/Temporary	0.06	-0.02	0.52***
	(0.15)	(0.12)	(0.11)
N	33739	38042	38043
F-stat	47.33	60.99	61.05
J-stat (p-value)	0.21	0.59	0.80

Notes: Each column row coefficient is from an individual regression with the first stage F- and J-stats reported. GHQ-12 is the mental health scale running from 0 (worst mental health) to 36 (best mental health). Controls include: sex, age, household size, log income, log TTWA average income, and wave fixed effects. Instruments include: Uber search, Airbnb search, and TTWA population. Clustered standard errors at the TTWA level in parentheses.
* p<0.05 ** p<0.01 *** p<0.001.

Table 6: IV Estimates of the Effect of Self and Temporary Employment on Mental Health by Gender and Age
Using Google Search Data on the Gig Economy as Instruments

	(1)	(2)	(3)	(4)
Outcome	GHQ-12	GHQ-12	GHQ-12	GHQ-12
Sample	Female	Male	18-39	40-64
Panel A				
Self-Employed	11.07**	6.19***	4.60**	11.60**
	(3.44)	(1.79)	(1.56)	(3.63)
N	21083	18443	16876	22245
F-stat	57.62	22.61	50.23	15.10
J-stat (p-value)	0.51	0.67	0.58	0.65
Panel B				
Temporary	10.59***	6.40**	3.91*	8.99**
	(2.85)	(2.34)	(1.52)	(2.80)
N	18976	18423	16845	22232
F-stat	12.70	55.77	49.10	46.93
J-stat (p-value)	0.31	0.30	0.71	0.05
Panel C				
Self/Temporary	8.55***	5.51**	2.88**	9.17***
	(2.05)	(1.77)	(1.10)	(2.43)
N	21064	18432	16853	22238
F-stat	30.94	25.71	72.96	24.45
J-stat (p-value)	0.08	0.79	0.70	0.44

Notes: Each column row coefficient is from an individual regression with the first stage F- and J-stats reported. GHQ-12 is the mental health scale running from 0 (worst mental health) to 36 (best mental health). Controls include: sex, age, household size, log income, log TTWA average income, wave fixed effects. Instruments include: Uber search, Airbnb search, and TTWA population. Clustered standard errors at the TTWA level in parentheses.
* $p<0.05$ ** $p<0.01$ *** $p<0.001$.

Table 7: IV Estimates of the Effect of Self and Temporary Employment on Mental Health by Education and Gender
Using Google Search Data on the Gig Economy as Instruments

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome	GHQ-12	GHQ-12	GHQ-12	GHQ-12	GHQ-12	GHQ-12
Sample	Male	Male College	Male No College	Female	Female College	Female No College
Panel A						
Self-Employed	6.19***	0.70	5.83*	11.07**	-4.48	15.04***
	(1.79)	(2.42)	(2.27)	(3.44)	(4.43)	(3.31)
N	18443	9451	8977	21083	9647	11046
F-stat	22.61	17.43	25.39	57.62	7.14	32.82
J-stat (p-value)	0.67	0.88	0.42	0.51	0.55	0.56
Panel B						
Temporary	6.40**	0.12	8.19*	10.59***	2.36	10.65**
	(2.34)	(1.97)	(3.82)	(2.85)	(3.32)	(3.37)
N	18423	9439	8969	18976	9634	11035
F-stat	55.77	64.11	18.63	12.70	12.70	30.94
J-stat (p-value)	0.30	0.89	0.47	0.31	0.31	0.08
Panel C						
Self/Temporary	5.51**	0.54	6.02**	8.55***	-1.09	10.52***
	(1.77)	(1.88)	(2.11)	(2.05)	(2.64)	(2.67)
N	18432	9443	8974	21064	9636	11038
F-stat	25.71	22.64	23.94	30.94	13.18	51.37
J-stat (p-value)	0.79	0.89	0.58	0.08	0.43	0.32

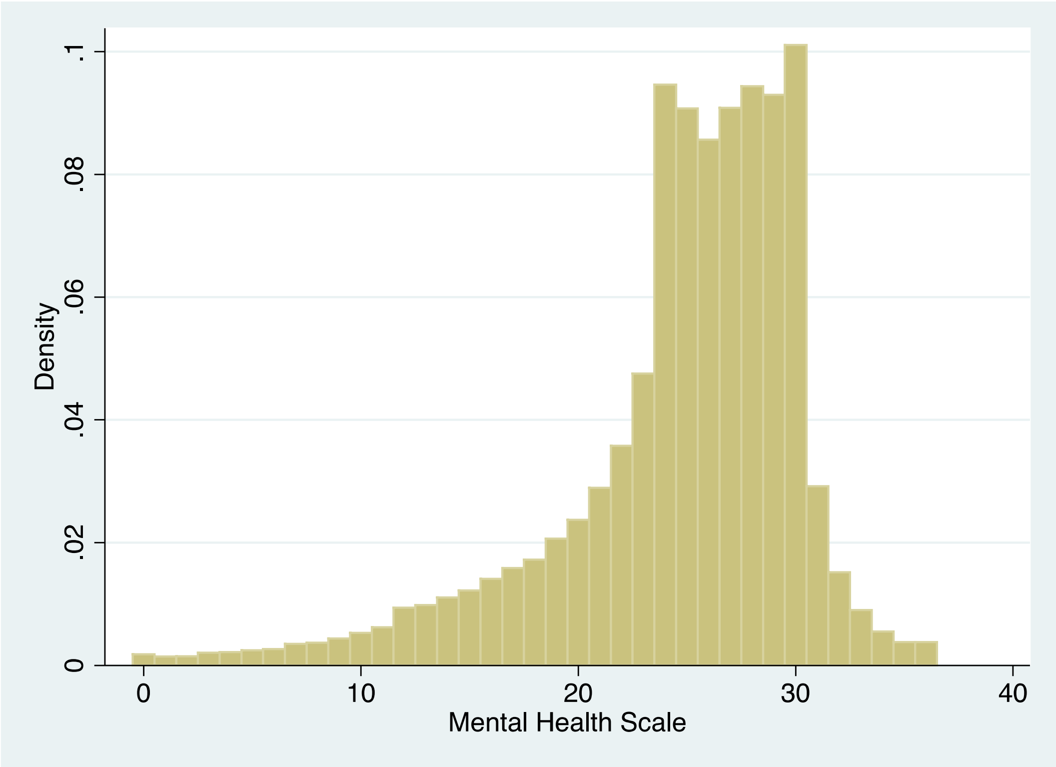
Notes: Each column row coefficient is from an individual regression with the first stage F- and J-stats reported. GHQ-12 is the mental health scale running from 0 (worst mental health) to 36 (best mental health). Controls include: sex, age, household size, log income, log TTWA average income, and wave fixed effects. Instruments include: Uber search, Airbnb search, and TTWA population. Clustered standard errors at the TTWA level in parentheses.
* $p<0.05$ ** $p<0.01$ *** $p<0.001$.

Table 8: IV Estimates of the Effect of Self and Temporary Employment on Mental Health by Parental Status and Gender
Using Google Search Data on the Gig Economy as Instruments

	(1)	(2)	(3)	(4)
Outcome	GHQ-12	GHQ-12	GHQ-12	GHQ-12
Sample	Non-Parents Female	Non-Parents Male	Mothers	Fathers
Panel A				
Self-Employed	8.76**	7.83***	11.76	-0.96
	(3.18)	(2.36)	(6.52)	(2.80)
N	12698	11529	7995	6899
F-stat	28.08	19.71	4.33	7.92
J-stat (p-value)	0.26	0.51	0.36	0.32
Panel B				
Temporary	11.95***	8.29**	8.31*	-1.10
	(3.32)	(2.82)	(3.28)	(4.78)
N	12683	11514	7986	6894
F-stat	18.42	34.27	18.62	14.20
J-stat (p-value)	0.87	0.32	0.05	0.27
Panel C				
Self/Temporary	7.84***	7.22**	8.39*	-0.92
	(2.19)	(2.31)	(3.47)	(2.69)
N	12684	11521	7990	6896
F-stat	26.79	14.57	7.85	10.30
J-stat (p-value)	0.75	0.81	0.67	0.29

Notes: Each column row coefficient is from an individual regression with the first stage F- and J-stats reported. GHQ-12 is the mental health scale running from 0 (worst mental health) to 36 (best mental health). Controls include: sex, age, household size, log income, log TTWA average income, wave fixed effects. Instruments include: Uber search, Airbnb search, and TTWA population. Clustered standard errors at the TTWA level in parentheses.
* $p<0.05$ ** $p<0.01$ *** $p<0.001$.

Figure 1: Distribution of the GHQ-12 (Mental Health Scale)



Notes: GHQ-12 is the mental health scale running from 0 (worst mental health) to 36 (best mental health).

Figure 2: Average Google Searches Between 2012 and 2016 Across TTWAs

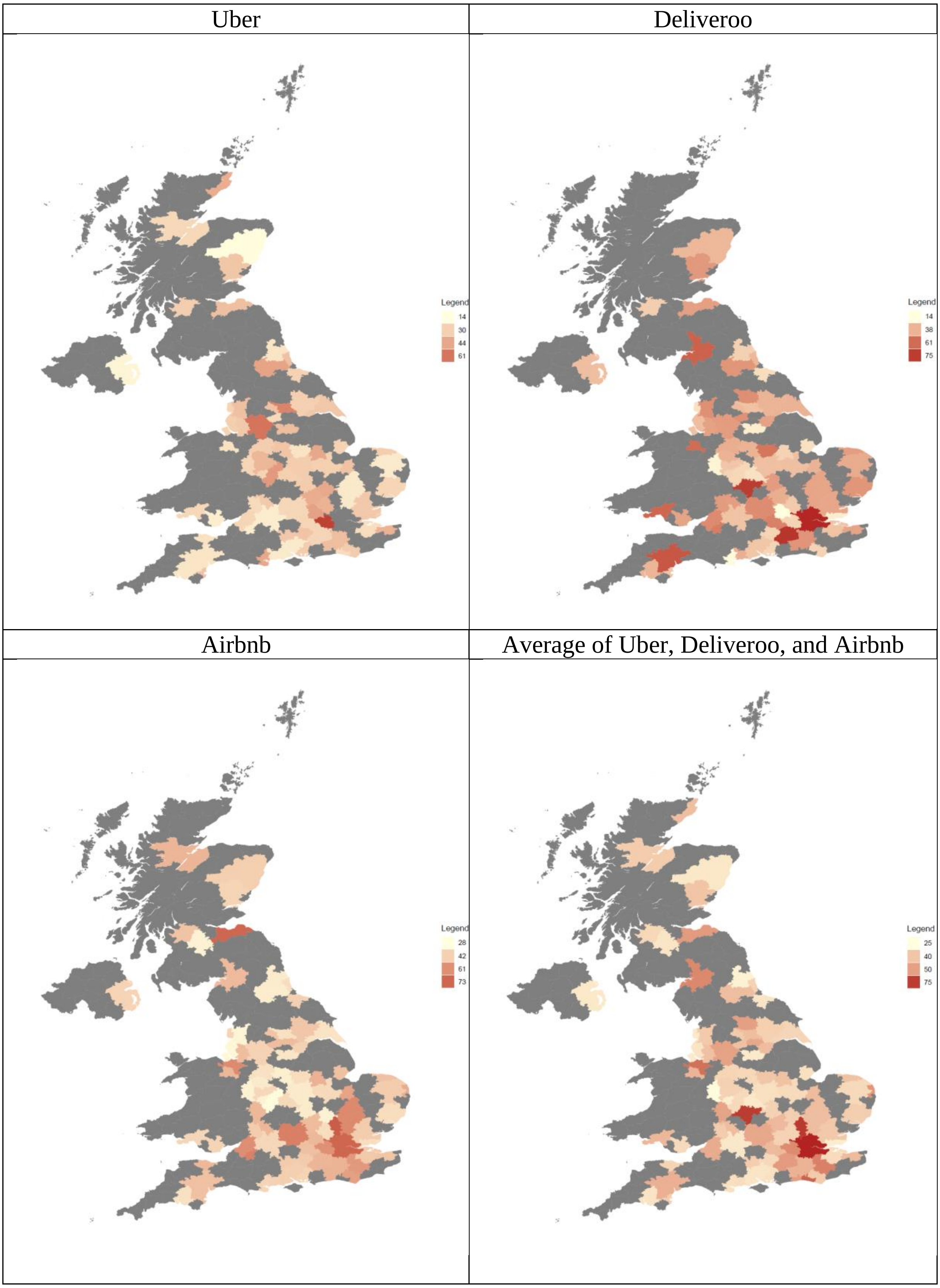
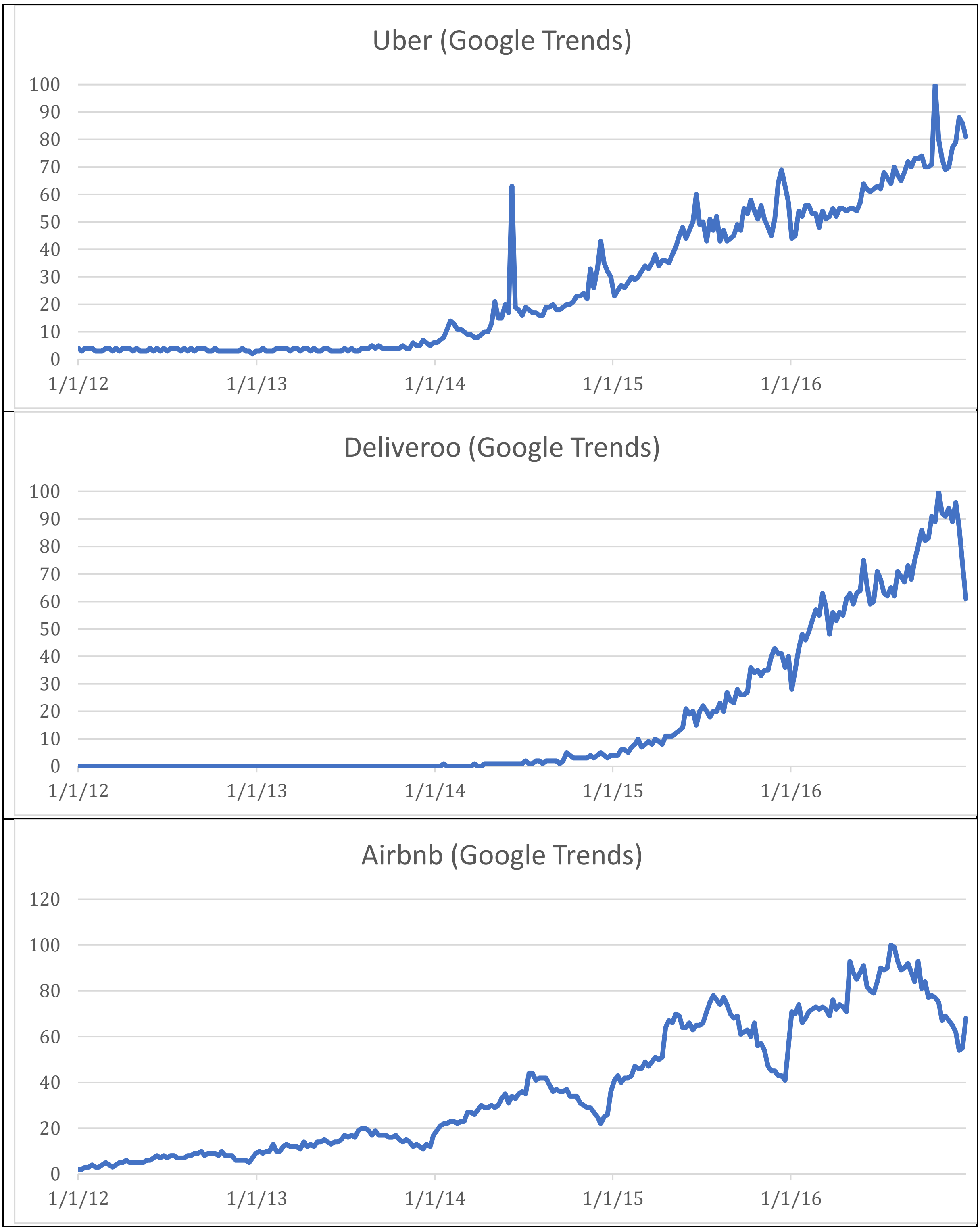


Figure 3: Gig Economy Searches Over Time



APPENDIX

Table A1: IV Estimates of Self and Temporary Employment on Mental Health Excluding Airbnb in the Instrument Set

	(1)	(2)	(3)	(4)
Outcome	GHQ-12	GHQ-12	GHQ-12	GHQ-12
Explanatory variable	Self-Employed	Temporary	Self-Employed	Temporary
Sample	Working	Working	Working or not	Working or not
Explanatory variable	7.90***	10.57***	6.34***	11.33***
	(1.62)	(2.32)	(1.81)	(2.47)
N	39185	39141	53332	53288
F-stat	38.61	81.49	40.71	77.13
J-stat (p-value)	0.80	0.11	0.20	0.99

Notes: Each column row coefficient is from an individual regression with the first stage F- and J-stats reported.
GHQ-12 is the mental health scale running from 0 (worst mental health) to 36 (best mental health).
Controls include: sex, age, household size, log income, log TTWA average income, and wave fixed effects.
Instruments include: Uber search and TTWA population.
Clustered standard errors at the TTWA level in parentheses.
* p<0.05 ** p<0.01 *** p<0.001.

APPENDIX

Table A2: IV Estimates of Self, Temporary, and Part-Time Employment on Mental Health Using Google Search Data as Instruments

	(1)	(2)	(3)	(4)
Outcome	GHQ-12	GHQ-12	GHQ-12	GHQ-12
Explanatory variable	Self/Temporary	Self/Temporary	Self/Temporary /Part-time	Self/Temporary /Part-time
Sample	Working	Working or not	Working	Working or not
Explanatory variable	5.76***	9.36**	7.78**	4.21
	(1.42)	(3.01)	(2.79)	(3.46)
N	39091	53228	38587	52724
F-stat	61.57	23.55	14.61	3.69
J-stat (p-value)	0.76	0.49	0.51	0.11

Notes: Each column row coefficient is from an individual regression with the first stage F- and J-stats reported.
GHQ-12 is the mental health scale running from 0 (worst mental health) to 36 (best mental health).
Controls include: sex, age, household size, log income, log TTWA average income, and wave fixed effects.
Instruments include: Uber search, Airbnb search, and TTWA population.
Clustered standard errors at the TTWA level in parentheses.
* p<0.05 ** p<0.01 *** p<0.001.

APPENDIX

Table A3: IV Estimates of Self and Temporary Employment on Mental Health Using Google Search Data on the Gig Economy as Instruments, Including TTWA Fixed Effects

	(1) GHQ-12	(2) Smoker	(3) Money spent on alcohol (per capita)	(4) Take medicine to sleep	(5) Sport Activity	(6) Sport Frequency
Panel A						
Self-Employed	11.06	-0.25	1.28	0.06	1.40	0.40
	(6.84)	(0.68)	(1.32)	(0.25)	(3.54)	(1.55)
N	39121	23184	24951	16113	8147	5899
F-stat	2.47	0.80	1.80	2.71	1.86	2.66
J-stat (p-value)	0.07	0.72	0.34	0.60	0.69	0.76
Panel B						
Temporary	0.820	0.33	3.66	-0.13	-0.49	-0.11
	(6.16)	(0.43)	(4.65)	(0.60)	(4.68)	(2.47)
N	39077	23148	24935	16104	8146	5901
F-stat	2.57	2.98	0.37	0.66	1.83	1.48
J-stat (p-value)	0.00	0.90	0.64	0.61	0.64	0.72
Panel C						
Self/Temporary	19.94	0.16	1.38	0.04	0.35	0.17
	(13.73)	(0.46)	(1.30)	(0.22)	(3.29)	(1.38)
N	39091	23155	24940	16104	8146	5901
F-stat	1.00	1.36	1.44	2.46	1.59	2.38
J-stat (p-value)	0.54	0.69	0.47	0.58	0.63	0.73

Notes: Each column row coefficient is from an individual regression with the first stage F- and J-stats reported. GHQ-12 is the mental health scale running from 0 (worst mental health) to 36 (best mental health).
Controls include: sex, age, household size, log income, log TTWA average income, wave fixed effects, TTWA fixed effects.
Instruments include: Uber search, Airbnb search, and TTWA population.
Clustered standard errors at the TTWA level in parentheses.
* p<0.05 ** p<0.01 *** p<0.001.

APPENDIX

Table A4: IV Estimates of Self and Temporary Employment on Mental Health
Using Google Search Data on the Gig Economy as Instruments
Including Workers and Non-Workers

	(1) GHQ-12	(2) Smoker	(3) Money spent on alcohol (per capita)	(4) Take medicine to sleep	(5) Sport Activity	(6) Sport Frequency
Panel A						
Self-Employed	11.02**	0.15	-1.99*	0.24	5.15	-0.84
	(3.51)	(0.50)	(0.87)	(0.19)	(4.59)	(0.98)
N	53258	31249	10866	22219	12854	8750
F-stat	30.80	10.23	48.11	16.38	6.12	6.83
J-stat (p-value)	0.34	0.12	0.33	0.50	0.18	0.10
Panel B						
Temporary	11.65**	0.74**	-4.25**	0.29	3.31	-1.84
	(3.82)	(0.26)	(1.46)	(0.20)	(5.76)	(1.61)
N	53214	31213	10867	22210	12853	8752
F-stat	36.97	17.21	37.89	11.67	7.96	9.60
J-stat (p-value)	0.33	0.31	0.32	0.51	0.05	0.18
Panel C						
Self/Temporary	9.36**	0.10	-1.85*	0.26	3.89	-0.70
	(3.01)	(0.41)	(0.89)	(0.17)	(3.29)	(0.81)
N	53228	31220	10867	22208	12853	8750
F-stat	23.55	8.83	19.72	9.47	6.55	7.15
J-stat (p-value)	0.49	0.14	0.30	0.57	0.22	0.12

Notes: Each column row coefficient is from an individual regression with the first stage F- and J-stats reported.
GHQ-12 is the mental health scale running from 0 (worst mental health) to 36 (best mental health).
Controls include: sex, age, household size, log income, log TTWA average income, and wave fixed effects.
Instruments include: Uber search, Airbnb search, and TTWA population.
Clustered standard errors at the TTWA level in parentheses.
* $p<0.05$ ** $p<0.01$ *** $p<0.001$.