Innovation and Self-Employment — Source link

Tommaso Ciarli, Mattia Di Ubaldo, Maria Savona

Published on: 18 Apr 2020 - Research Papers in Economics (Essen: Global Labor Organization (GLO))

Topics: Unemployment and Investment (macroeconomics)

Ciarli, Tommaso; Di Ubaldo, Mattia; Savona, Maria

Working Paper

Innovation and Self-Employment

GLO Discussion Paper, No. 449

Provided in Cooperation with:
Global Labor Organization (GLO)

Innovation and Self-Employment[1]

Tommaso Ciarli[2], Mattia Di Ubaldo[3], Maria Savona[4]

Abstract

The paperadds to the literature on innovation and employment by looking at the relationship between R&D investments and the rise of alternative work arrangements, particularly self-employment (SE). A literature review on the determinants of the emergence of non-standard work, alternative work arrangements and self-employment if offered first. The contributions that have looked at SE in relation to innovation strategies is surprisingly limited. General trends of SE in Europe are considered. The empirical contribution is focused on the analysis of local labour markets in the UK (Travel-To-Work-Areas, TTWAs), where their initial concentration of routinized and non-routinized jobs is considered. The probability that an individual shifts from paid employment to either unemployment or self-employment over the period 2001-13, as linked to changes in R&D investments in the TTWA is empirically accounted for. Results show that overall R&D has negligible effects on the probability of workers to become self-employed. R&D increases the probability of moving from unemployment to paid employment, especially in routinized areas, and reduces the permeability between routinised and non-routinised workers. Also, a non-negligible increase in the probability that a routinized worker becomes SE as a result of R&D increase is found in low routinised local labour markets, but not in highly routinised areas. The papersheds new lights on the effect of R&D on employment and self-employment in areas with different degrees of routinization, and adds to the discussion on the more general raise of alternative work arrangements in Europe by disentangling the characteristics of self-employment as resulting from R&D investments.

Keywords: R&D, employment, unemployment, self-employment, routinized local labour markets

JEL codes: J6; O3; O32

[1] This paper is forthcoming as a chapter in the Handbook of Labour, Human Resources and Population Economics (2020) (Edited by Klaus Zimmermann) Springer. A different version of this paper is also available as SPRU Working Paper 2019-17 @ www.sussex.ac.uk/spru/swps2019-17. The authors wish to warmly thank the Editors of the Handbook, the Editorial Board of the SPRU Working Paper Series and an anonymous referee for the encouraging and constructive comments. All errors and omissions are ours.

[2]: T.Ciarli@sussex.ac.uk @ SPRU, Science Policy Research Unit, University of Sussex, UK

[3] M.Di-Ubaldo@sussex.ac.uk @ Department of Economics, University of Sussex, UK.

[4] Corresponding author @ SPRU, Science Policy Research Unit, Jubilee Building Falmer Brighton BN1 9SL,University of Sussex. UK M.Savona@sussex.ac.uk.

Introduction

The effects of technical change on jobs has historically sparked a great deal of 'technological anxiety', to put it in Mokyr et al.'s (2015) words. Concerns on the effects of innovation on job displacement and the nature of work relations have evolved hand in hand with different technological waves. To start with, the well-known Luddites' movement resisting the introduction of textile machines during the first industrial revolution in Britain was more concerned about the changing *conditions of work*, rather than capital replacing labour (Freeman and Soete, 1994; Mokyr et al., 2015). The largely studied diffusion of Information and Communication Technology as a General Purpose Technology (GPT) has also sparked a great deal of concerns around the degree of automation of low skilled workforce, feeding into the skill bias and routine biased technical change approaches (Freeman and Soete, 1994; Brynjolfsson and McAfee, 2012; Goos et al., 2014). More recently, academic and popular debates around the role of Artificial Intelligence (AI) and Robotization have revolved around their nature as a GPT (Trajtenberg, 2018), and the replacement of non-routinised tasks and services as a result of their adoption, with whole segments of the labour markets hollowing out (Graetz and Michaels, 2015; Brynjolfsson and Mitchell, 2017).

While the literature has mainly been focusing on the effects of technical change on employment, surprisingly quite a limited effort has been devoted on whether technological innovation affects the nature of work relationships and/or the employment composition towards alternative work arrangements and self-employment. Recent evidence in the US and the EU shows a surge in self-employment and alternative work arrangements that has been particularly dramatic over the past decade (Katz and Kreuger 2017a; Bell and Blanchflower, 2018; Ciarli et al., 2018a).

The hype and concerns seem to focus on *digital platform workers* and non-standard work relations that are mediated by digital platforms. The current, and ongoing, debate alternates between different views, one that welcomes this as a more flexible arrangement for categories of workers that would not be entering the labour markets otherwise (due to gender, skills, location constraints), another one that considers this as a form of precarisation of the labour force across countries. In terms of policy this represents a concrete challenge (see Pesole et al., 2018).

However, evidences show that the surge of self-employment is well beyond the incidence of digital platform and gig workers (Pesole et al., 2018; Rheine and Walwei, 2018). It might be a structural phenomenon that is becoming more intrinsically associated to innovation strategies in firms, with a more general reflection on innovation and self-employment currently missing. Increased technological opportunities spurred by innovation are likely to create incentives to move towards an entrepreneurial form of self-employment (Levine and Rubinstein, 2017). Increased technological opportunities might also need new skills and will result in the dismission of obsolete skills or the outsourcing of non-core tasks by innovative firms (Åstebro et al., 2011). Self-employment might therefore also represent a coping strategy for dismissed or under-employed workers (Frankish et al., 2014). Incidentally, platforms would in this case be particularly suitable as they provide a mean for alternative work arrangements opportunities. Currently, there is no theoretical ground that can predict the effect of innovation on an entrepreneurial or 'refuge' self-employment.

In a prior contribution (Ciarli et al., 2018a) the effects of *R&D investments* on employment and self-employment in the UK local labour markets (TTWAs) have been considered. The evidence thereby presented shows that self-employment is indeed an important component of the impact of innovation on labour markets.

This paperbuilds on Ciarli et al., (2018a) and focuses on the relationship between innovation and self-employment. The paperanalyses occupational transition matrices of individuals working in TTWAs with different initial intensity of routinised jobs as related to changes in the R&D investments in the areas. Individuals shift from paid employment to unemployment when dismissed, or might decide to move to self-employment, with or without employees, depending on the levels and growth of R&D investments in the relevant area.

The findings show a sharp increase in self-employment occurred in the UK over the past decade, which is a specific feature of the UK and the Netherlands labour markets in the European context. Within this context, the evidence shows that R&D growth has only a weak effect on individual shifts from any occupational category to self-employment. High skilled and less routinised workers are not more likely to get into self-employment, they rather tend to remain into paid jobs. Also, R&D investments tend to 'protect' low skilled, more routinised jobs, which would otherwise shift to unemployment. When looking at areas with different degrees of routinisation of the labour force, in local labour markets with a higher concentration of non-routinised jobs, routinised workers are more likely to shift to self-employment than in areas with a high concentration of routinised jobs. Overall, however, innovation seems to only weakly affect occupational choices towards self-employment, which might therefore be the results of specific institutional characteristics of the UK labour markets, that have a marked structural tendency to self-employment, similar to the trends in the US.

The paperis organised as follows: it briefly reviews the relevant literature and evidence on trends of self-employment and alternative work arrangements, in the US and the EU. It then provides a descriptive snapshot of trends of self-employment and innovation in the EU over the past decades. The following sections zoom in the case of the UK. After a brief description of the micro data and the empirical strategy, results on occupational choice between standard employment, unemployment and self-employment with or without employees are discussed. A summary of the main contribution concludes.

The nature of self-employment. What does innovation have to do with it?

Self-employment and the raise of alternative work arrangements

The rise in alternative work arrangements over the past decade has been particularly steep in the US labour markets. Katz and Kreuger (2017a) focus on a range of alternative work arrangements, including *independent contractors* (this category being the closest to the 'self-employed' considered here, as it includes individuals who report that they obtain customers on their own as an independent contractor); *independent consultants*; *freelance workers* (Katz and Krueger, 2017a)); *on-call workers*; *temporary help agency workers*; *workers provided by contract firms*, based on the Rand-Princeton-led Contingent Work Survey for the US Bureau of Labour Statistics (RPCWS). The empirical evidence shows that, while between 1995 and 2005 hardly any change occurred in this broad category of workers, a striking growth of about 6% over the period 2005-15, representing almost 95% of the net employment growth in the US economy (Katz and Krueger, 2017a, p. 8) was experienced.

Part of this growth is certainly attributable, the authors argue, to the harsh effect of the financial crisis. Even so, this seems to be more of a structural change in the nature of work rather than a conjunctural one. One of the most plausible – albeit country-specific - explanations is that the rise in alternative work arrangements is attributable to substantial changes in the recruitment and rent-sharing strategies of high-profit firms (Katz and Krueger, 2017a). These tend to keep high skilled core workers and rent-share a wage premium with these (see also Song et al., 2016), and rather prefer to contract out lower-skilled, non-core, non-tradable services, avoiding rent-sharing with these. This would explain not only the labour market dynamics observed, but also the increased wage-inequality in the US.

The role of the strategic behaviours of the so -called 'superstar firms' is at the centre of similar claims by Autor et al., (2017). Super-star firms, it is argued, are typically those that benefit the most from innovation and enter foreign markets at better conditions, thereby reaping most of the value added and profits, although contributing comparatively little to employment creation. Autor et al. (2017) attribute the trends of falling labour shares since the beginning of the eighties to the increased concentration of high rent in these large and very large firms in the US. Further, as super star firms tend to contract out jobs that were previously insourced, falling labour shares might be hiding forms of underemployment and rise in alternative work arrangements.

An interesting similar view is put forward by Bell and Blanchflower (2018), who look at trends of under-employment in the US and the EU. The received wisdom is that at times of crises, with a slack labour market, it is easier for firms to reduce working hours of the employed rather than fire them (with the consequences in terms of wages illustrated by Card et al., 2018 and in the UK by Blundell et al., 2014 and Ciarli et al., 2018b). However, particularly in recession, firms might prefer to hoard a 'core' of (usually high skilled) employed workers alongside a 'reserve army' of underemployed, usually less 'core', that not only fill gaps of unexpected demand but help keeping wages down: "*Underemployment is personal in a way that unemployment is not*" (Bell and Blanchflower, 2018, p. 3). If this is the case in the US, this 'reserve army' might be more prone to resort to self-employment and alternative work arrangement if it is substantially under-employed within their firm, or indeed in their local areas, as shown for the UK by Frankish et al., (2014).

Trends of self-employment in the EU and the UK depict a similar picture. The growth of self-employment seems to have more of a structural rather than conjunctural nature and hides a large variety of workers. Based on their proposed measure of under-employment, Bell and Blanchflower (2018) show that after the recession and over the recovery period, underemployment in Europe did not fall back to pre-recession levels. Underemployment seems to have replaced a recession-led levels of unemployment, which in fact has been found to fall back to pre-recession levels. Incidentally, in the case of the UK, this has had a side-effect of pushing wages down, supported by evidence of very low elasticity of wages to productivity increases (Haldane, 2016; Ciarli et al., 2018b and 2018c).

Self-employment and innovation

Within this context, it is worth asking what are the underlying determinants of the growth of alternative work arrangements, more specifically of self-employment, particularly those determinants that pertain to firms' innovation investment strategies. For instance, high rent superstar firms, that have been argued to bear the main responsibility for these trends, are usually those that are also highly innovative.

In a prior contribution focused on the UK (Ciarli et al., 2018a), it is argued that an increase in self-employment might be related to firms' decision to invest in R&D.

R&D investments are a broad proxy of innovation *strategy*, rather than *performance*, which is commonly measured by patents. R&D investments are composite in nature, including both capital and labour, and are also highly correlated with investments in other intangibles (Corrado et al., 2009, 2013), including human capital, and have therefore an effect on firms' hiring preferences, directly and indirectly (Ciarli et al., 2018a). Investing in R&D might also affect decisions to outsource non-core tasks that feed non-standard work. Alternatively or in addition, R&D creates innovation opportunities that might represent an incentive to move to self-employment as an entrepreneurial venture.

Albeit there is no explicit theory, three possible effects of R&D investments on self-employment are envisaged here.

First, a Schumpeterian creation of new opportunities and ventures. R&D investments might create new or improved technological opportunities (Feldman and Kogler, 2010) and incentives for workers to exploit these by moving to a new top-end venture, a form of entrepreneurial self-employment (Blanchflower and Oswald, 1998; Coad et al., 2011; Levine and Rubinstein, 2017). Entrepreneurial opportunities arise and are usually exploited by workers that are predominantly exposed to R&D, i.e. working in highly intensive R&D firms or local labour markets (Faggio and Silva, 2014; Coad et al., 2017).

Second, a reduced demand for workers with low skills and/or in routine tasks. R&D investments create demand for high skilled workers and abstract tasks that might displace workers with obsolete or mismatched existing skills and routine tasks (Åstebro et al., 2011; Vona and Consoli, 2015). The dismissed or unmatched workers might resort to self-employment as a coping strategy, similarly to the shift to "entrepreneurship as a way out of deprivation" (Frankish et al., 2014, p. 1091).

Third, an increased demand for personal and other services by new workers in R&D companies. R&D might create a demand for complementary, low skilled services (Mazzolari and Ragusa, 2013) outsourced by the R&D firm (Bell and Blanchflowers, 2018) or demanded by new workers hired in relation to the innovative activity. These low skilled service workers might resort to self-employment to complement their income and/or end up being trapped in unwanted alternative work arrangements.

To summarise, the types of self-employment that innovation and firms' R&D strategies might lead to are different. Some self-employed could be at the bottom-end of the alternative work arrangements categories mentioned above, as a form of coping or 'refuge' self-employment (Frankish et al., 2014), or 'hidden unemployment' (Blundell et al., 2014; Thurik et al., 2008). Some self-employed could also be at the top end of the categories, one that is essentially entrepreneurial in nature, depending on the technological opportunities.

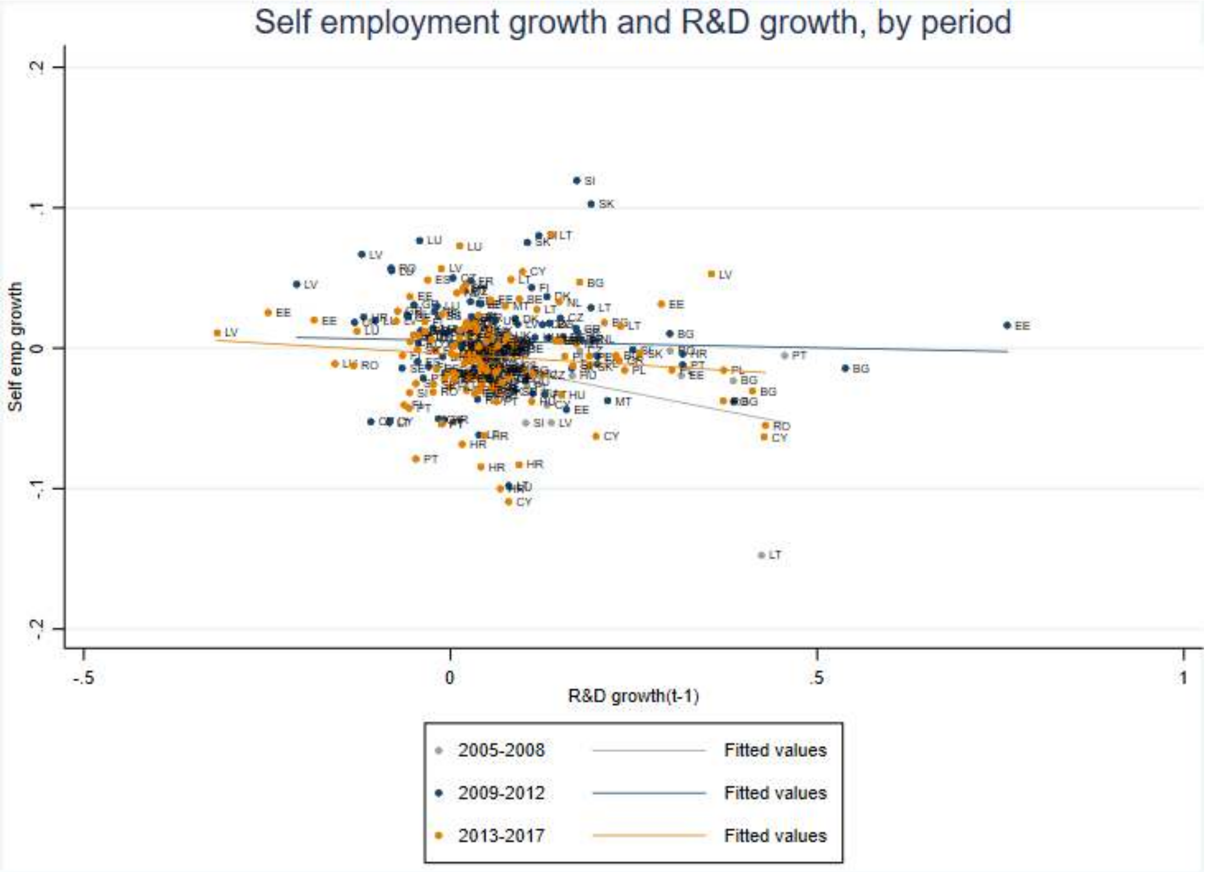
A glance on innovation and self-employment trends in the EU and UK

In this section some visual overview of the association between R&D growth and the evolution of the rate of self-employment, from a cross-country perspective are provided.

In order to construct a measure of self-employment growth, data on self-employment and total employment from the Labour Force Survey (EUROSTAT), from 1998 to 2017 are extracted. A self-employment rate, as a ratio of self- over total employment is constructed, alongside data on business R&D expenditure per capita from BERD (EUROSTAT), from 2005 to 2017. It is worth noting that the choice of the time span has been guided by data availability (self-employment data for most of the EU-28 countries are available from 1998, but BERD data are available only since 2005). Figure 1 shows the association between the annual growth of the self-employment rate and the (lagged) annual growth of R&D expenditure, across EU-28 countries, over the 2005-2017 period.

Figure 1 does not allow to find a statistically significant association between the growth of (lagged) R&D expenditure and the growth of the rate of self-employment. The relationship is particularly flat in the central part of the sample used here, i.e. over the years which follow the financial crisis of 2008-2009. In the first period (2005-2008) R&D and self-employment exhibit a mild negative relationship (statistically significant at 10%), but this relationship vanishes completely in the subsequent time period, possibly due to a persistence of self-employment over time coupled with a slowdown of R&D expenditure during the crisis years. In the third time period (2013-2017), graphically the relationship turns negative again, but it lacks statistical significance (the coefficients and standard errors relating to the association of the growth of self-employment and R&D expenditure are available upon request).

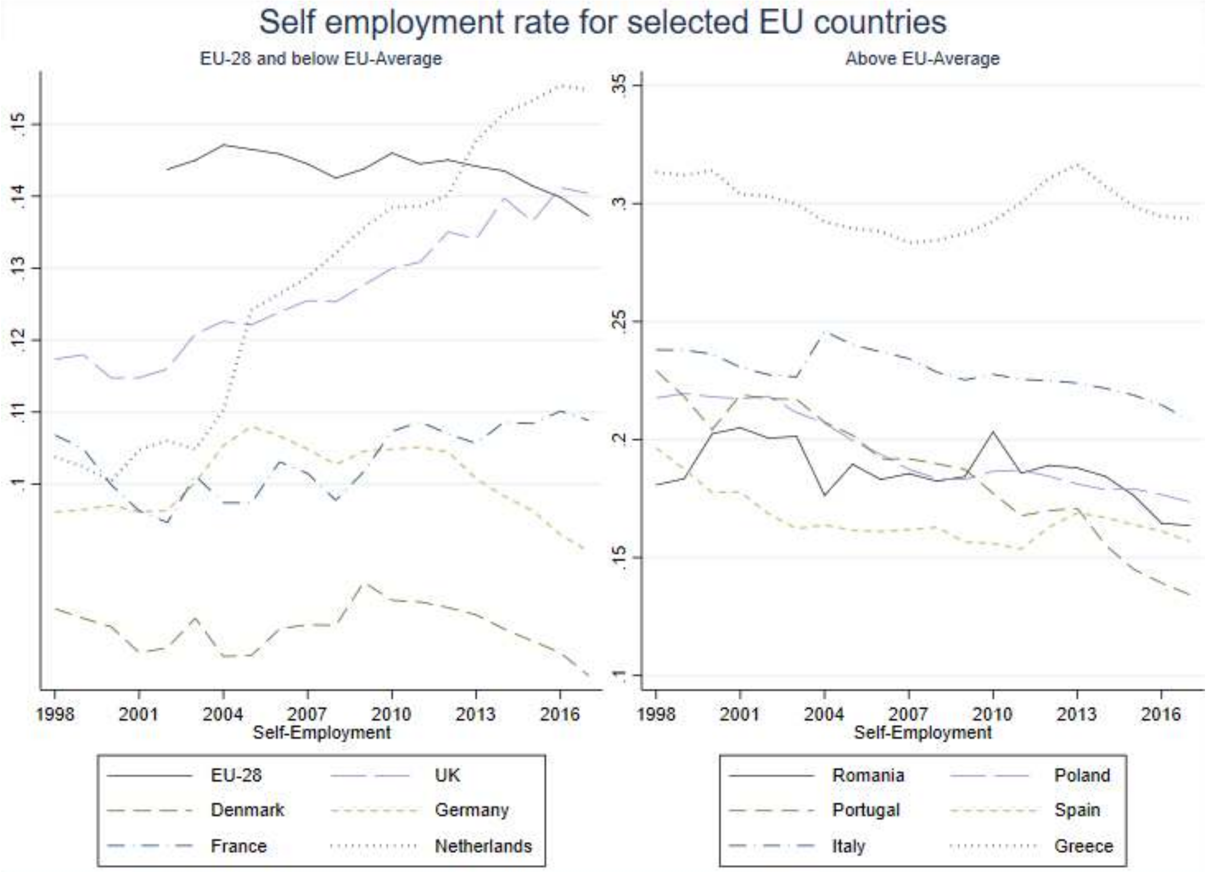
Figure 1



Note: Authors' elaboration on LFS and BERD data (EUROSTAT), 2005-2017, for EU-28 countries. The graph plots the annual growth of the rate of self-employment at time *t* against the annual growth of R&D expenditure per capita at time *t-1*, by three time periods. The rate of self-employment is constructed the ratio of self- over total-employment, and the its growth is computed as the ratio of the change of the rate of self-employment from *t-1* to *t*, relative to the rate of self-employment at time *t-1*. The same procedure is followed to compute the growth of R&D expenditure per capita. Before growth rates are computed, yearly fluctuations in both the rate of self-employment and R&D expenditure are smoothed by computing "rolling averages", as the average of two consecutive time periods (t and t-1).

The lack of a relationship between self-employment and R&D in the cross-country setting suggests digging further into national differences in the evolution of self-employment over time. In order to do so, the full time span available in the self-employment rate series (1998-2017) and plot the trend of self-employment for two groups of selected EU economies is exploited.

Figure 2



Note: Authors' elaboration with LFS (EUROSTAT) data, 1998-2017. The graph plots the evolution of the rate of self-employment (ratio of self- over total-employment) over time, for two groups of economies, below and above the EU-28 average.

Figure 2 provides useful insights into the reasons why, at the EU-wide level, a statistically significant association between R&D and self-employment is not observable. The main European countries exhibit very different paths of the rates of self-employment over the last two decades. On the one side, the group of Germany, France and Denmark, characterised by low and stable rates of self-employment; on the other side, the group of southern-EU economies (Italy, Spain, Poland, Portugal, Greece and Romania), exhibiting flat or downward sloping self-employment rates, but at a level about twice as high as the first group of countries. Important exceptions from this picture are the UK and the Netherlands: these countries show a steady growth of the rate of self-employment over time, suggesting very different labour market structure and dynamics in these economies, compared to the remaining ones.

Put together, this visual evidence suggests that the analysis of the effect of R&D on self-employment is an exercise which is better suited to single rather than cross-countries studies. The UK and the Netherlands, due to their growing rates of self-employment over time, appear to be prominent cases where to investigate whether R&D had some role in determining the pattern of self-employment that we observe.

R&D and occupational choices in the UK local labour market

This section focuses on a detailed individual-level econometric analysis, performed with UK data, of the effect of R&D expenditure on self-employment. Specifically, the estimations test how changes in R&D activity in the local labour market, defined at the Travel to Work Area (TTWA), affect the probability of moving across jobs from one year to the other.

Data and empirical strategy

The analysis is based on the British Household Panel Survey (BHPS) and Understanding Society (US), from 2001 to 2013, which provide us with information on the occupational status of a representative sample of British individuals, together with additional covariates that are used in the empirical analysis. The UK Census dataset is exploited, to identify local labour market areas (TTWAs), and the Business Expenditure on Research and Development survey (BERD) to collect data on R&D activity.

From the BHPS-US datasets a categorical variable identifying the job status of an individual, exploiting information about their employed or self-employed status, their socio-economic class (to identify the routine-type of occupation), the presence of hired employees and their current economic activity (to identify unemployed individuals) is obtained. The National Statistics Socio-Economic Class classification (NS-SEC) to aggregate the socio-economic class information and define routine occupations is used. These variables are then combined into a categorical indicator with five job statuses:

- Routinized employee: if employed in occupations classified as NS-SEC 6 or NS-SEC 7.
- Non-routinized employee: if employed in occupations classified as NS-SEC 1, NS-SEC 2, NS-SEC 3, NS-SEC 4 or NS-SEC 5.

- Self-employed with employees: if self-employed and with hired employees
- Self-employed without employees: if self-employed without hired employees
- Unemployed.

From the UK Census dataset, 212 TTWAs across England, Scotland and Wales are located. These areas allow to identify local labour market areas over which to investigate the effect of R&D.

From the BERD survey, firm-level information on R&D expenditure per employee, are extracted, which are averaged at the TTWA level. The change in TTWA level R&D expenditure between 2001 and 2011 is then taken, to get a measure how much more (or less) spending went into R&D at the local labour market level, over the decade under analysis.

Formally, the following equation is estimated, fitting a multinomial logit model:

$$job_{i,a,t} = \alpha job_{i,a,t-1} + \beta \Delta RD_a + \theta\left(job_{i,a,t-1} * \Delta RD_a\right) + \sum \gamma X_{it} + \sum \delta A_a + \rho_t + \tau + \varepsilon_{i,a,t}$$

The dependent variable is a categorical variable identifying the five job statuses mentioned above, defined at individual level i, TTWA a and year t. This is regressed on the first lag of itself (the past job status), the change in R&D expenditure per employee at the TTWA level, and an interaction term between the past job status and the change in R&D expenditure. The α coefficient identifies the probability of transition between types of employment or unemployment, whereas the θ coefficient identifies the additional effect of R&D on the transition probabilities. An X vector or individual level controls is added (age-class, in three categories of 16-24, 25-34 and 35-65; marital status, in the five categories of married, couple, widowed, divorced and never married; and level of education, in the three categories of high, medium and low) and an A vector of TTWA level controls (employment rate and log-population at the beginning of the period), time fixed effects and a linear time trend τ.

The estimation of β and θ, the relation between R&D and job status as well as their interaction, might be biased due to various forms of endogeneity (omitted factors, reverse causality and measurement error). In order to avoid the endogeneity, building on Ciarli et al. (2018a) and construct a shift-share instrument, whereby the change in R&D in TTWA *a* is instrumented with the initial (2001) composition of output across sectors in TTWAs, interacted with the nationwide change in industry R&D. More specifically, the initial output share of sectors in TTWA *a* is used to predict the change in R&D in *a*, multiplying the national R&D change (excluding TTWA *a*) by *a*'s sector shares. In this way it is possible to isolate the change in R&D across TTWAs due to changes in nation-wide R&D dynamics from shocks in TTWA *a* that would be otherwise correlates with labour outcomes in that TTWA. Further details on the instrumentation strategy are in Ciarli et al. (2018a).

The final sample consists of 30,604 observations across the five job categories. The share of routinized employees in the total at the TTWA level is exploited to identify high-routinized areas (HRA) and low routinized areas (LRA): HRAs are defined as those with an above median share of workers employed in routinized occupations. Table 1 reports the number of workers by job status, split by two groups in which TTWA areas have been divided. The median share of workers employed in routinized occupations is 31%, with a minimum of 17% and a maximum of 45%.

Table 1: No. of workers by job status, in HRA and LRA

Job categories	**LRA**	**HRA**	**Total**
Employed routinized	4,050	3,313	7,363
Employed non-routinized	11,522	7,025	18,547
Self Employed with employees	580	387	967
Self Employed no employees	1,850	991	2,841
Unemployed	482	404	886
Total	18,484	12,120	30,604

Note: Authors' elaboration on BHPS-US and UK Census data.

Table 2: Transition probabilities, full sample

	(1) Emp. rout	(2) Emp. Rout (R&D)	(3) Emp. non-rout	(4) Emp. Non-rout (R&D)	(5) Self emp. with emp	(6) Self emp. with emp (R&D)	(7) Self emp. no emp.	(8) Self emp. no emp. (R&D)	(9) Unemp.	(10) Unemp. (R&D)
Emp. rout. (t-1)	0.788*** (0.00561)	0.0435*** (0.00972)	0.170*** (0.00518)	-0.0377*** (0.00847)	0.00134*** (0.000468)	0.00109 (0.000719)	0.0189*** (0.00183)	-0.00133 (0.00244)	0.0218*** (0.00168)	-0.00560** (0.00251)
Emp. non-rout (t-1)	0.0482*** (0.00172)	-0.0121*** (0.00248)	0.923*** (0.00211)	0.0189*** (0.00330)	0.00272*** (0.000389)	-0.00135*** (0.000315)	0.0118*** (0.000811)	-0.00346*** (0.000952)	0.0143*** (0.000938)	-0.00205 (0.00150)
Self emp. with emp (t-1)	0.00731** (0.00299)	-0.00238 (0.00154)	0.0717*** (0.00915)	-0.00665 (0.00992)	0.779*** (0.0151)	0.0221 (0.0179)	0.134*** (0.0119)	-0.0137 (0.0156)	0.00800** (0.00355)	0.000670 (0.00285)
Self emp. no emp. (t-1)	0.0306*** (0.00339)	-0.000660 (0.00397)	0.0653*** (0.00503)	-0.00932* (0.00539)	0.0428*** (0.00411)	-0.000988 (0.00590)	0.843*** (0.00755)	0.0108 (0.0101)	0.0184*** (0.00279)	0.000166 (0.00368)
Unemp. (t-1)	0.243*** (0.0154)	0.0310 (0.0268)	0.289*** (0.0168)	0.0116 (0.0245)	0.00836** (0.00377)	0.00145 (0.00398)	0.0800*** (0.0108)	-0.00844 (0.0163)	0.380*** (0.0175)	-0.0357 (0.0303)
N	30604	30604	30604	30604	30604	30604	30604	30604	30604	30604

Note: Robust Standard errors in parentheses, * p<0.10, ** p<0.05, *** p<0.01

Table 3: Transition probabilities, Low routinized areas (LRA)										
	(1) Emp. rout	(2) Emp. Rout (R&D)	(3) Emp. non-rout	(4) Emp. Non-rout (R&D)	(5) Self emp. with emp	(6) Self emp. with emp (R&D)	(7) Self emp. no emp.	(8) Self emp. no emp. (R&D)	(9) Unemp.	(10) Unemp. (R&D)
Emp. rout. (t-1)	0.777*** (0.00786)	0.0325** (0.0128)	0.183*** (0.00731)	-0.0287** (0.0112)	0.00125** (0.000594)	0.00212** (0.00100)	0.0214*** (0.00266)	-0.00237 (0.00300)	0.0169*** (0.00199)	-0.00356 (0.00295)
Emp. non-rout (t-1)	0.0433*** (0.00206)	-0.0129*** (0.00264)	0.926*** (0.00261)	0.0196*** (0.00387)	0.00309*** (0.000532)	-0.00145*** (0.000371)	0.0130*** (0.00107)	-0.00261** (0.00130)	0.0149*** (0.00121)	-0.00262 (0.00188)
Self emp. with emp (t-1)	0.00842** (0.00423)	-0.00226 (0.00221)	0.0699*** (0.0120)	-0.00870 (0.0118)	0.771*** (0.0204)	0.0345* (0.0203)	0.142*** (0.0162)	-0.0261 (0.0164)	0.00869* (0.00498)	0.00252 (0.00613)
Self emp. no emp. (t-1)	0.0298*** (0.00411)	0.00468 (0.00609)	0.0669*** (0.00629)	-0.0102* (0.00561)	0.0368*** (0.00456)	0.00136 (0.00687)	0.849*** (0.00913)	-0.00199 (0.0126)	0.0177*** (0.00343)	0.00618 (0.00574)
Unemp. (t-1)	0.210*** (0.0193)	0.0318 (0.0352)	0.339*** (0.0230)	-0.0154 (0.0395)	0.00869* (0.00519)	0.00999 (0.00777)	0.0883*** (0.0150)	-0.0131 (0.0248)	0.354*** (0.0226)	-0.0132 (0.0436)
N	18484	18484	18484	18484	18484	18484	18484	18484	18484	18484

- Note: Robust Standard errors in parentheses, * p<0.10, ** p<0.05, *** p<0.01

Table 4: Transition probabilities, Highly routinized areas (HRA)										
	(1) Emp. rout	(2) Emp. Rout (R&D)	(3) Emp. non-rout	(4) Emp. Non-rout (R&D)	(5) Self emp. with emp	(6) Self emp. with emp (R&D)	(7) Self emp. no emp.	(8) Self emp. no emp. (R&D)	(9) Unemp.	(10) Unemp. (R&D)
Emp. rout. (t-1)	0.806*** (0.00776)	0.0563*** (0.0143)	0.149*** (0.00706)	-0.0458*** (0.0127)	0.00145** (0.000725)	-0.000127 (0.000854)	0.0152*** (0.00235)	0.00102 (0.00324)	0.0280*** (0.00284)	-0.0114** (0.00507)
Emp. non-rout (t-1)	0.0560*** (0.00301)	-0.0106** (0.00516)	0.919*** (0.00356)	0.0170*** (0.00645)	0.00217*** (0.000556)	-0.000991 (0.000769)	0.0100*** (0.00123)	-0.00459*** (0.00170)	0.0131*** (0.00147)	-0.000785 (0.00259)
Self emp. with emp (t-1)	0.00622 (0.00436)	-0.00471 (0.00392)	0.0774*** (0.0147)	-0.00598 (0.0212)	0.786*** (0.0227)	0.00405 (0.0363)	0.123*** (0.0179)	0.00881 (0.0271)	0.00768 (0.00536)	-0.00216 (0.00252)
Self emp. no emp. (t-1)	0.0327*** (0.00602)	-0.00891 (0.00687)	0.0642*** (0.00869)	-0.00605 (0.0144)	0.0537*** (0.00829)	-0.00586 (0.0132)	0.829*** (0.0136)	0.0303 (0.0228)	0.0202*** (0.00493)	-0.00951 (0.00664)
Unemp. (t-1)	0.292*** (0.0254)	0.0506 (0.0405)	0.218*** (0.0241)	0.0315 (0.0304)	0.00729 (0.00511)	-0.00410 (0.00330)	0.0676*** (0.0155)	-0.00494 (0.0199)	0.415*** (0.0276)	-0.0731 (0.0452)
N	12120	12120	12120	12120	12120	12120	12120	12120	12120	12120

Note: Robust Standard errors in parentheses, * p<0.10, ** p<0.05, *** p<0.01

Results

Tables 2-4 report marginal effects (i.e. predicted probabilities) of moving across type of occupation, for the 5 possible occupational outcomes – employed (routinised or not), SE (with or without employees) and unemployed. They show both the overall transition probabilities (odd number columns), and the impact of R&D, captured by an interaction of past occupation with an instrumented R&D measure (even number columns). Only marginal effects for the past employment status and omit all the other controls are reported. The base category for the multinomial model, in all tables, is the category of employees in non-routinised occupations.

The tables report the occupational status of an individual in time *t-1* in the rows, and the status of the same individual in time *t* in columns. For example, the coefficient in column 1 (Tab. 2) for *Emp. rout.*, shows that, in the UK, a worker employed in a routinized occupation has, on average, a 0.79 probability of staying in the same type of occupation. It is worth noting that the place and type of work may change, but not the occupation category as defined in this chapter.

Remaining a routinized employee, one year to the next, is substantially more likely than for workers in other occupational statuses to move into this job category: on average, one in four unemployed individuals find a job in a routinized occupation; 4 in 100 workers with a job in a non-routinized occupation move to a routinized occupation; 3 out of 100 SE without employees find a routinized job; and less than one 1 in a 100 SE with employed move to a routinised job. Columns (3), (5), (7) and (9) provide the same information, but with respect to moving into the other occupations.

As expected, focusing on the diagonal entries of the table (for odd columns), it is found that most individuals tend to stick to their occupational category from one year to the next, with the highest degree of same-occupation probability being found for non-routinized employees. On average, non-routinized employees have a 0.92 probability of staying in the same occupational category, whereas SE without employees have a 0.84 probability of remaining SE (without employees). The lowest same-occupation probability is found for unemployed category, who over the years covered in this paperhad a 0.38 probability of remaining unemployed, a 0.24 probability of finding a job in a routinised occupation, and a 0.29 probability of finding a job in a non-routinised occupation. Eight in 100 move to SE without employees, and less than one in a 100 become SE with their own employees.

How does R&D intensity in a TTWA impact on these probabilities, if at all? First, an increase in R&D reduces the permeability between routinized and non-routinized jobs: workers in (non) routine occupations are (two) four percentage points more likely to remain in a similar occupation, and (one) four percentage points less likely to change to a (routine) non-routine occupation. However, R&D also reduces slightly the probability that routinized workers become unemployed, by 0.5 percentage points. Given that the probability that a routinized worker becomes unemployed in the following year is 2 percentage points, R&D reduces that probability by one quarter.

With respect to SE, evidence that, overall, R&D significantly increases the probability that workers move to a SE status does not emerge. On average, (1) 2 out of 100 (non) routinized workers become SE. This is unchanged as companies' R&D in a given TTWA increases, across the UK. However, R&D decreases the probability that non-routinised workers become SE (with-) with-out employees – from (0.02) 0.1 to (0.01) 0.08 respectively.

Hence, while in general a significant shift from routinised workers to SE occurs from one year to the next, when R&D increases are controlled for, a similar proportion of routinized workers become SE, but a lower proportion of non-routinised workers become SE. This results in an increased share of SE that used to work in routine occupations with respect to those that used to work in non-routine-occupations, in line with the results in Ciarli et al. (2018a).

With respect to the three potential effects of R&D on SE discussed above, it emerges that, across the UK, skilled workers (predominantly those in non-routine occupation) do not take on entrepreneurial opportunities. If anything, they are less likely to become SE, with or without employees. Instead, as R&D increases, low skilled workers (predominantly those in routine occupations) are less likely to be dismissed, but not more likely to move to SE as a response to potential increased demand for personal services. None of the three mechanisms seem to be at play in the UK between 2001-2011 (or the R&D signal is not strong enough at TTWA level).

Building on the evidence in Ciarli et al (2018a), the analysis focuses on whether path-dependence and the initial employment structure play a role in determining the impact of R&D. The analysis distinguishes between routinized (HRA) and non-routinised TTWA (LRA). That is, TTWAs in which the share of workers before 2001 was, respectively, above/below the median TTWA share. Results are reported in Tables 3 (LRA) and 4 (HRA).

It is shown that the effect on the reduction in the permeability between routine and non-routine occupations is still present in both areas, and is higher in routinized TTWAs. In areas in which the proportion of routinized workers was higher in 2000, R&D reduces even more the probability that they find a job in a non-routine occupation. However, the evidence shows that the reduction in the probability that routinized workers become unemployed is significant only in HRA.

With respect to SE, it emerges that a non-negligible increase in the probability that a routinized worker becomes SE as R&D increase in LRA: the probability almost doubles. The same effect in HRA does not occur.

In terms of the three potential effects of R&D on SE discussed above, in LRA the R&D might induce forms of 'refuge' or coping self-employment: workers in occupations that are likely to be made redundant are twice as likely to become SE as R&D increases. This is likely to be due to the fact that they are made redundant and have no other choice, or because there may be an increase in the demand for personal services (following the positive impact of R&D on the probability that workers remain in their non-routine occupation).

Concluding remarks

The paperhas contributed to the literature on the impact of technical change on labour markets, by focusing on the effects of R&D investments' changes over the 2001-2011 period on the growth of self-employment (SE). The analysis focuses on the UK as a whole, and TTWAs with different degrees of routinised occupations, thereby extending the analysis by Ciarli et al. (2018a). Here, the empirical analysis looks at the probabilities that workers in any of the occupational status of paid employment (routinised and non-routinised), self-employment (with or without own employees) or unemployed at time t, shift occupation in the following period, in general and specifically as a result of increases in R&D investments in relevant (high or low routinised) areas.

The relevance of this contribution is two-fold. First, while there is an increasing interest in the growth of alternative work arrangements that include self-employment, predominantly due to the hype on digital platforms and gig workers, very few contributions in the literature have attempted at examining whether this trend is linked to innovation more at large, and particularly to R&D investments. Second, it is shown here that these trends are particularly remarkable in the UK within the European context, paired only by the Netherlands over the period 1998-

2015. A group of Southern European countries, instead, start from higher levels of self-employment but experience a declining trend. Patterns of self-employment in the UK seem to resonate much with those in the US, a context where most of the literature points to a dramatic increase in alternative work arrangements. This papertherefore empirically fills a gap in the literature by focusing on a particularly interesting context.

As there is not a theory that predicts the effects of R&D investments on employment, let alone self-employment, the paperlooks at the empirical literature and identifies three main mechanisms through which R&D might induce shifts to self-employment.

First, a purely Schumpeterian effect: R&D investments generate new technological opportunities that might create incentives for entrepreneurial ventures and shifts of (most likely non routinise and high skilled) workers to move to self-employment, the top-end segment of SE (Coad et al., 2017; Levine and Rubinstein, 2017).

Second, a skill mismatch effect: R&D investments are likely to increase the demand for high skilled and reduce that of low skilled workers (Vona and Consoli, 2015). As shown, this might lead innovative firms to outsource routinised, low and non-core skills, or keep them in the firm but substantially under-employed (Bell and Blanchflowers, 2018). In both cases, (dismissed or under-employed), workers might shift to a 'refuge' self-employment, either as an alternative to paid employment or as a complementary way to top-up their income in case of under-employment, for instance in deprived areas (Frankish et al., 2014).

Third, an (extreme) skill complementarity effect: this is a different mechanisms which might lead to a trend similar to the one mentioned above. It has been found that highly innovative firms induce demand for complementary services, such as transport, trade, personal services (Mazzolari and Ragusa, 2013; Bell and Blanchflowers, 2018). This additional labour demand might equally be met by paid employees or by self-employment. Some of the earlier findings in Ciarli et al., (2018a) supported evidence of this latter mechanism.

The findings in this papershow that overall R&D is weakly linked to this trend, in terms of yearly individual occupational transitions.

R&D seems to reduce the permeability between routinised and non-routinised employed, and the probability that a routinised employee becomes unemployed. In general, R&D does not seem to have a large effect on the transition to self-employment, surely not in the case of non-routinised employees. However, when the empirical analysis distinguished across TTWAs with different (initial) degree of routinised work force, in low routinised areas there is a non-negligible increase in the probability that a routinized worker becomes SE as a result of R&D increases, which seems to support the second and third mechanisms highlighted above.

Overall, R&D in the UK does not seem to affect a Schumpeterian-like entrepreneurial self-employment, not even before the crisis. The results allow to infer that - in general - what occurs is a shift to a coping self-employment which is however only partially linked to R&D and seem to be in line with what pointed by Frankish et al. (2014), although not specifically linked to innovation. It seems that the UK has experienced a structural transformation of its labour market, potentially linked to institutional changes, and demographic and migration changes that are not explicitly accounted for here, but would deserve a higher research effort.

As there is somewhat a trade-off between supporting R&D and tackling its side effects, policies to lift the bottom-end of self-employment from a 'trap' become even more relevant, ideally coupled with what has been advocating more recently as 'place-sensitive distributed development policies' (Iammarino et al., 2017). These latter are no silver bullet, but arguably should take into account the innovation and the potential range of different self-employment categories that might follow.

There are certainly common policy challenges with other forms of non-standard work and alternative working arrangements, including platform workers, gig workers. These relate for instance to social security, retraining, and wage protection. A thorough analysis of the policy implications of these trends, their determinants and their effects of different segments of society is a worth research agenda for both labour and innovation economists.

References

Åstebro J. C. and P. T. Thomas (2011). Stars and Misfits: Self-Employment and Labor Market Frictions. *Management Science* 57(11):1999-2017.

Autor, D., Dorn, D., L. F. Katz, C. Patterson, J. Van Reenen (2017). The Fall of the Labour Share and the Rise of Superstar Firms. NBER Working Chapter No. 23396

Bell, D. N. F. and Blanchflower, D. G. (2018). Underemployment in the US and Europe. NBER Working Chapter 24927.

Blanchflower, D. G. and Oswald, A. J. (1998). What Makes an Entrepreneur? *Journal of Labor Economics*, 16(1):26–60.

Blundell, R., Crawford, C., and Jin, W. (2014). What can wages and employment tell us about the UK's productivity puzzle? *Economic Journal*, 124(576):377–407.

Brynjolfsson, E., McAfee, A., and Spence, M. (2014). New World Order: Labor, Capital, and Ideas in the Power Law Economy. *Foreign Affairs*, (July/August).

Brynjolfsson, E. and Mitchell, T. (2017). What can machine learning do? workforce implications. *Science*, 358(6370):1530–1534.

Ciarli, T., Marzucchi, A., Salgado, E., and Savona, M. (2018a). The effects of R&D growth on employment and self-employment in local labour markets. SPRU, University of Sussex Working Chapter 2018-08 (March).

Ciarli, T., Salgado-Chavez, E., Savona, M. (2018b). Do Low Wage workers benefit from Productivity Growth recovery? Joseph Rowntree Foundation report, 2018.

Ciarli, T., Marzucchi, A., Salgado, E., and Savona, M. (2018c). Firm innovation and wage inequality. SPRU, Mimeo.

Coad, A., Nielsen, K., and Timmermans, B. (2017). My first employee: an empirical investigation. *Small Business Economics*, 48(1):25–45.

Corrado, C. A., D. E. Sichel & C. R. Hulten (2009). Intangible capital and U.S. Economic growth. *Review of Income and Wealth*, 85: 661–685.

Corrado, C., J. Haskel, C. Jona-Lasinio & M. Iommi (2013). Innovation and intangible investment in Europe, Japan and the United States. *Oxford Review of Economic Policy*, 29: 261-286.

Institute for Social and Economic Research, NatCen Social Research, University of Essex. Kantar Public. (2018). *Understanding Society: Waves 1-1, 2009-2017 and Harmonized BHPS Waves 1-18, 1991-2009* [data collection]. 1*1th edition* UK Data Service, SN 6614.

Faggio, G. and Silva, O. (2014). Self-employment and entrepreneurship in urban and rural labour markets. *Journal of Urban Economics*, 84:67–85.

Feldman, M. P. and Kogler, D. F. (2010). Stylized Facts in the Geography of Innovation. In Hall, B. H. and Rosenberg, N., editors, *Handbook of the Economics of Innovation*, volume 1 of *Handbook of the Economics of Innovation*, pages 381–410. Elsevier.

Freeman, C. and Soete, L. (1994). *Work for All or Mass Unemployment? Computerised Technical Change into the 21st Century*. London and New York, Pinter.

Frankish, J. S., Roberts, R. G, Coad, A. and Storey, D. J. (2014) Is entrepreneurship a route out of deprivation*? Regional Studies*, 48 (6). pp. 1090-1107.

Goos, M., Manning, A., and Salomons, A. (2014). Explaining Job Polarization: Routine Biased Technological Change and Offshoring. *American Economic Review*, 104(8):2509–2526.

Graetz, G. and Michaels, G. (2015). Robots at work. Centre for Economic Performance, Discussion Chapter No 1335.

Haldane, Andrew G, “Work,Wages and Monetary Policy,” 2017 (https://www.bankofengland.co.uk/speech/2017/work-wages-and-monetary-policy).

Iammarino, S., Rodriguez-Pose, A., Storper, M. (2017). Why Regional Development matters for Europe’s Economic Future. European Commission, DG Regio, WP. 07/2017.

Kahneman, D., Knetsch, J. L., and R. Thaler (1986). Fairness as a Constraint on Profit Seeking: Entitlements in the Markets. *American Economic Review* 76:728-41.

Katz, L. F. and Krueger, A. B. (2017a). The Rise and Nature of Alternative Work Arrangements in the United States, 1995-2015. MIT mimeo.

Katz, L. F. and Krueger, A. B. (2017b).The Role of Unemployment in the Rise in Alternative Work Arrangements. *American Economic Review,* 107(5):388-92.

Levine, R. and Y. Rubinstein (2017). Smart and Illicit: Who Becomes an Entrepreneur and Do They Earn More?. *The Quarterly Journal of Economics*, Volume 132, Issue 2, 1 May 2017: 963-1018.

Mas, A. and Pallais, A., (2017). Valuing Alternative Work Arrangements. *American Economic Review*, 2017, No. 107(12): .3722-3759.

Mazzolari, F. and Ragusa, G. (2013). Spillovers from High-Skill Consumption to Low-Skill Labor Markets. *Review of Economics and Statistics*, 95(1):74–86.

Mokyr, J., Vickers, C., and Ziebarth, N. L. (2015). The History of Technological Anxiety and the Future of Economic Growth: Is This Time Different? *Journal of Economic Perspectives*, 29(3):31–50.

Office for National Statistics; National Record of Scotland Northern Ireland Statistics and Research Agency (2016): 2011 Census aggregate data (Edition June 2016), UK Data Service.

Office for National Statistics (2018), Business Expenditure on Research and Development, 1994-2016: Secure Access. [data collection] 7th edition, UK Data Service. SN:6690

Pesole, A., Urzí Brancati, M.C, Fernández-Macías, E., Biagi, F., González Vázquez, I. (2018). Platform Workers in Europe. European Commission Joint Research Centre Science for Policy Report.

Rhein, T. and Walwei, U. (2018). Forms of Employment in European Comparison, IAB 2018, https://www.iab-forum.de/en/forms-of-employment-in-european-comparison/

Thurik, A. R., Carree, M. A., van Stel, A., and Audretsch, D. B. (2008). Does self-employment reduce unemployment? *Journal of Business Venturing*, 23(6):673–686.

Trajtenberg, M. (2018). AI as the next GPT. A political economy perspective. NBER 24245.

Vona, F. and Consoli, D. (2015a). Innovation and skill dynamics: a life-cycle approach. *Industrial and Corporate Change*, 24(6):1393–1415.