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# Job Mobility in and Around the Creative Economy

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## Abstract

The creative economy workforce can be thought of as having three segments: creative workers in a creative industry (specialist creatives); creative workers in a non-creative industry (embedded creatives), and non-creative workers in a creative industry (support workers). Drawing on data from the Labour Force Survey for the period 2011-2019, we show for the first time that the UK's creative workforce is more dynamic in geographic areas recognised as creative clusters. Creative clusters – which are defined as agglomerations of creative industries businesses that are competing and collaborating with each other – have become a key focus for UK industrial policy in recent years. Across all three segments of the creative economy, we see a higher rate of job change in creative clusters than elsewhere. This apparent cluster effect is weaker among the non-creative workforce, although still visible, especially among STEM workers. Workers in the creative economy who change jobs are less likely than other workers to change occupations or industries and again this is more pronounced in creative clusters. Where creative economy workers do change occupation, those in creative clusters are more likely to remain in creative occupations and industries.

Multivariate analysis, which controls for differences in workforce composition that might explain these patterns, suggests the cluster effect for occupations is strongest for embedded creatives and for industries is strongest for support workers. When considering 'distance' travelled in occupational space by job-changers, the cluster effect is only seen for support workers; those in a creative cluster are more likely to remain in the same occupation and less likely to enter an occupation that is only loosely related.

Taken together, the findings provide indicative evidence that creative clusters may support thick creative labour markets and embodied knowledge spillovers, which suggests that policymakers may be right to prioritise investment in them. The results also point to important variations in workforce dynamics between different parts of the creative economy.



*Keywords:* Creative workforce; creative clusters; labour market dynamism; thick markets

*JEL classification:* J24, J49, J61, J62



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# Job mobility in and around the creative economy[1]

Hasan Bakhshi[*] and Richard Dorsett[†]

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The creative economy workforce can be thought of as having three segments: creative workers in a creative industry (specialist creatives); creative workers in a non-creative industry (embedded creatives), and non-creative workers in a creative industry (support workers). Drawing on data from the Labour Force Survey for the period 2011-2019, we show for the first time that the UK's creative workforce is more dynamic in geographic areas recognised as creative clusters. Creative clusters – which are defined as agglomerations of creative industries businesses that are competing and collaborating with each other – have become a key focus for UK industrial policy in recent years. Across all three segments of the creative economy, we see a higher rate of job change in creative clusters than elsewhere. This apparent cluster effect is weaker among the non-creative workforce, although still visible, especially among STEM workers. Workers in the creative economy who change jobs are less likely than other workers to change occupations or industries and again this is more pronounced in creative clusters. Where creative economy workers do change occupation, those in creative clusters are more likely to remain in creative occupations and industries.

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## Introduction/motivation

The creative industries have received growing interest from policymakers in recent years. Consisting of a varied and heterogenous set of sub-sectors ranging from advertising and architecture to film, video games and music they share a common feature: the high percentage of their workforce employed in creative occupations (Bakhshi et al., 2013). In the UK, in 2020 the creative industries accounted for 2.2 million jobs, or 6.7% of the overall workforce. 2.5 million (7.5%) UK jobs – in the creative industries and beyond – were in creative occupations. Employment in the creative industries grew 4 times faster than the workforce as a whole in the preceding decade (DCMS, 2021). As a result of their outsized economic contribution the creative industries now as standard appear alongside advanced manufacturing, life sciences and other high-growth sectors in UK industrial strategies (HMG, 2017; HMG, 2021).

The creative industries are also amongst the most spatially imbalanced sectors in the UK economy, with almost 50% of jobs found in London and the South-East of England (DCMS, 2022). That is why policymakers have taken a particular interest in creative clusters – agglomerations of creative industries businesses competing and collaborating with each other – as these are thought to be hubs for creative industries growth wherever they are found (Mateos-Garcia et al., 2018). Investing in creative clusters, particularly those outside the South-East, is increasingly seen as a means of reducing the inter-regional imbalances in the creative economy (Bakhshi et al., 2015).

There are a number of theoretical reasons for thinking that local labour mobility within and between creative occupations and industries will be higher in creative clusters than in other areas. One possibility is that creative clusters host thick creative labour markets which have lower search costs and enable more efficient matching and therefore job mobility within creative roles (Acemoglu, 1996; Duranton and Puga, 2004). Alternatively, co-located firms may benefit from knowledge spillovers embodied in workers changing employers: firms recruiting those working in creative occupations or in non-creative roles in the creative industries can benefit from skills investment by neighbouring firms (Boschma, Eriksson and Lindgren, 2014). Labour mobility between creative occupations and industries is a key mechanism by which creative clusters benefit from the co-location of related (creative) occupations and from the presence of complex (creative) occupations which may support employment growth elsewhere in the economy (Hane-Weijman et al., 2022).[2] It may also contribute to making places more resilient to labour market shocks (Moro et al., 2021).

The benefits for employers of thick specialised labour markets might be expected to be particularly great for creative roles where the range of skills demanded is arguably more diverse and the requirements faster changing than for other roles. Or for support roles in areas like marketing or legal where domain knowledge in one creative sub-sector is relevant for another. Thick specialised labour markets will also be more beneficial in sectors where freelancers holding multiple roles are an

[2] In this context, we note that of the five most complex occupations identified by Hane-Weijman et al., 2022 using Swedish workforce data from 2002-2012, two (Writers and creative or performing artists and Computing professionals) are creative occupations.

important part of the workforce. Similarly, the importance to creative work of tacit knowledge and interpretative (as opposed to analytical) working methods (Lester and Piore, 2004; Oakley et. al., 2008) might suggest that skills-embodied knowledge spillovers in creative roles are more beneficial. In both cases, there may be associated market failures – in that the social benefits of firm co-location exceed the private benefits – which may justify public measures to support creative cluster development.

While there are good reasons to believe that local labour mobility indeed enhances knowledge exchange across co-located employers of workers in skills-related occupations or firms in skills-related industries – supporting the development of a cluster – the literature acknowledges that it may also hinder local human capital development. This is because of poaching which discourages firms from investing in their employees (Kim and Marschke, 2005; Combes and Duranton, 2006; Fallick et al, 2006). Equally, organisational learning may be negatively affected by high labour turnover (Darr et al., 1995). And while labour mobility may be associated with new skills absorption in firms recruiting the talent it may have negative consequences for firms in the cluster losing their employees.

Unfortunately, we do not have access to UK micro data on business performance that is linked to data on creative jobs, especially at the levels of occupational, sectoral and geographic resolution needed to evaluate the business impact of local creative labour mobility. So in this paper we set ourselves the less ambitious task of quantifying the extent of intra-occupational and intra-sectoral creative job flows and assessing whether these indeed differ between creative clusters and other places, leaving the task of evaluation of these job flows to future research.[3] Specifically, we examine year-on-year transitions of the creative workforce in order to quantify this mobility and assess whether the degree of occupational change is different in creative clusters compared with other areas.

We draw on existing literature to characterise the workforce according to the creative 'trident' capturing whether individuals work in creative occupations in creative industries ('specialist' creative workers), in creative occupations outside the creative industries 'embedded' creative workers) or in non-creative occupations in creative industries ('support' workers).[4] Following Higgs et al., 2008 we call the sum of these

[3] Ideally, we would be able to also comment on whether those changing jobs remain in their creative cluster (or indeed remain outside). While this is not possible with the Labour Force Survey (LFS) data we use, it is likely that a high proportion of job changes do not involve a geographic move. Evidence from the Annual Survey of Hours and Earnings (ASHE) shows that most job changers in the UK labour force stay within the same region (see Table 2 here), with the lowest geographic mobility seen in London and the East Midlands where about three-quarters of job changes are within-region. However, since there is considerable within-region variation in the proportion of jobs lasting a year or more (see section 4.2.1 of Dorsett and Hug, 2022, for related evidence), geographical stability at the regional level does not imply geographic stability at the TTWA level. While we are not aware of any statistics on the proportion of job changes involving a change of TTWA, BHPS evidence suggests only 5% of job changes involve a move of any sort (Gardner, Pierre and Oswald, 2001). As a partial explanation of this, Manning and Petrongolo (2017) show that the attractiveness of jobs to applicants reduces sharply with distance.

[4] Of course, there will also be individuals employed in non-creative roles specifically supporting creative workers outside the creative industries but we have no obvious way of identifying these in the data.

workforce segments the 'creative economy'. For benchmarking purposes, we compare our findings with that of STEM (Science, Technology, Engineering and Mathematics) occupations and STEM-intensive industries, using the occupation and industry classifications in Bakhshi, et. al. (2015a). The STEM economy is another skills-intensive and geographically concentrated part of the workforce that has received much attention from policymakers. Indeed, some commentators (Howkins, 2001) have suggested that STEM occupations should be considered as part of the creative workforce.[5] For creative clusters, we use the 47 Travel-to-Work Areas (TTWAs) identified in Mateos-Garcia and Bakhshi, 2016.[6] Their method involves first, identifying groups of creative sub-sectors that are similar to each other in terms of their tendency to co-locate (considering both employment and business counts), and second, looking for TTWAs where these sub-sectors are concentrated and fast growing.

We consider several specific questions:

1. Are workers in creative occupations more likely to change jobs than non-creative workers and does this vary depending on whether they are in creative clusters?
2. Are creative workers who change jobs more likely to remain in the creative economy than non-creative workers changing jobs are to remain in the non-creative economy and does this vary depending on whether they are in creative clusters?
3. Are they more likely to be working in the same occupation/industry or one that is in some sense 'similar' and does this vary depending on whether they are in creative clusters?

We hope our answers to these questions will provide some indicative evidence of whether creative clusters are indeed sites of the labour market benefits described earlier and their possible associated market failures.

## Data

The analysis is based on individual-level data from the quarterly Labour Force Survey (QLFS). We use April-June waves only since these include questions on employment status 12 months earlier, enabling us to observe changes over that period.[7] The approach used to achieve consistency over time in the classification of economic status is shown in the Appendix.

We create a dataset with the following variables:

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[5] Bakhshi, e. al., 2015b develop a machine learning classifier of creative occupations using detailed data on the skills requirements for different roles and find that the resulting set include Computer, Engineering and Science occupations alongside the usual occupations in Arts and Media.
[6] As explained in the Appendix, we exclude the Belfast creative cluster from the analysis.
[7] An alternative might have been to use the five-quarter longitudinal LFS. However, this does not provide the geographic variables used in this paper to define creative clusters. Furthermore, using quarterly LFS maximises the size of the dataset available for analysis. Longitudinal LFS exists only for the subset of the quarterly LFS respondents who also provide information one year after their initial survey.

- Characteristics at time of survey interview
    - Gender
    - Age
    - Ethnicity
    - Ethnicity
    - Highest qualification
    - Region
    - TTWA
        - Whether living in a creative cluster
- Economic status at time of survey interview
    - Status – employed, self-employed, unemployed, inactive
    - SIC2007 for employed and self-employed
        - Whether working in a creative industry
    - SOC2010 for employed and self-employed
        - Whether working in a creative occupation
- Recall of economic status 12 months prior to survey interview
    - Status – employed, self-employed, unemployed, inactive
    - SIC2007 for employed and self-employed
        - Whether working in a creative industry
    - SOC2010 for employed and self-employed
        - Whether working in a creative occupation.

## Definitions and sample selection

We use data from 2011 to 2019 on 18-59 year-olds. This year selection was adopted in order to focus on a relatively stable period (post-global financial crisis and pre-COVID19). The age selection was adopted to avoid complications arising from the influence of retirement decisions among older workers. Analysis uses data pooled across all years. About 20% of respondents do not state their circumstances 12 months earlier. We restrict the sample to those with status observed in both periods.[8]

We use DCMS definitions of creative occupations (CO) and creative industries (CI). Combining these, we identify a five-way categorisation of employment status:

1. CO and CI
2. CI only
3. CO only
4. Neither CO nor CI
5. Not working.

We define creative clusters according to the identification in Mateos-Garcia and Bakhshi, 2016. This identification is on the basis of the TTWA. Since these are not available for Northern Ireland, we restrict all analysis to GB only.

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[8] It is possible that non-random selection resulting from this approach could bias results. We could in principle construct weights to control for this. However, the analysis uses sampling weights supplied with the LFS to control for non-response to interview. Producing *ad hoc* weights to control for item non-response – that is, not answering the lagged employment status question – risks compromising the sampling weights.

Tables 1 and 2 show the relationship between CO and CI. Table 1 column 1 shows that, while COs are much more likely than non-COs to work in CI (specialist creatives), many work outside CI (embedded creatives). This varies by CO. Among those working in CI, most common is to work in the corresponding industry. However, the degree of this specialisation varies. Publishing as an occupation, for example, is spread across several CIs.

< Table 1>

Table 2 presents analogous results for industry. Row 1 shows that support workers (those outside CO) are important across all industries. Other than Crafts, IT & Software and Museums & Galleries, the majority of workers in CIs are specialist (CO). Architecture and Design are the two industries where the proportion of workers in the matching occupation exceed 50%.

< Table 2 >

Table 3 shows the importance of self-employment, which is well known to account for a disproportionate number of jobs in the creative economy. Self-employment accounts for 28-29% of workers in creative occupations or industries compared with 14% of workers in the whole economy. With the exception of Museums & Galleries, self-employment is more common among CO and CI. In Music & Performing Arts occupations it accounts for the vast majority of workers, but it is also common in Film & TV, Publishing, Crafts and Design occupations. By industry, self-employment is most common in Music & Performing Arts and Design.

< Table 3 >

We focus on transitions over the preceding year. We compare transitions among the creative economy workforce with those among the non-creative STEM economy workforce. That is, to avoid double counting we exclude from our STEM economy employment measure STEM occupations and STEM-intensive industries that are also included in the DCMS classifications of creative occupations and creative industries. Table 4 shows that across all creative economy workers who were in work at the time of the survey and 12 months earlier but who changed their firm (either as an employee or self-employed) over this time, there is a slightly higher rate of job change (11%) in creative clusters than elsewhere (9%). This difference is less apparent for non-creative STEM economy workers (9% vs 8%) and for workers as a whole (10% vs 9%). Among the creative economy workforce, we see this 'cluster effect' for support workers, embedded creatives and specialist creatives. Among the non-creative STEM economy workforce, the cluster effect is greatest for specialist STEMs (those working in a STEM occupation within a STEM-intensive industry), highlighting the dynamism of creative clusters for the STEM economy workforce. Outside creative clusters, the proportion of creative workers changing employer is more similar to that for non-creative STEM economy workers, with the exception of specialist STEMs whose mobility rate is somewhat dampened (6%). The evidence in Table 4, therefore, is broadly consistent with creative clusters being a more dynamic employment environment for creative workers and for specialist STEM workers outside the creative workforce too.

< Table 4>

Also of interest is the degree to which creative workers move between different creative occupations and industries and how this differs according to whether the individual lives in a creative cluster (as a cluster might be expected to enable either the thick labour market and/or embodied knowledge spillovers discussed earlier). Table 5 provides an indication of the dynamism of occupation and industry for individuals who are working both at the time of the survey and 12 months earlier but who have changed their firm (either as an employee or self-employed) over this time. A change in occupation is defined here as a change in the 4-digit SOC code. Similarly, a change in industry is defined as a change in the 4-digit SIC code.

Among creative economy workers who changed employer, rates of occupation change (41%) and, to a lesser extent, industry change (68%) are lower than among workers as a whole (52% and 71%). Occupation change among non-creative STEM economy workers (42%) is similar to that for creatives but industry change is more common (74%). There is evidence of a cluster effect for both creative economy and STEM economy workers. Occupation change is less likely by 11 and 8 percentage points respectively within clusters. This tallies with the idea that there are more opportunities within clusters for creative (STEM) workers to change employer while maintaining their occupation, and thus consistent with the possibility that there are either thicker creative/STEM labour markets and/or more knowledge spillovers between firms in creative clusters. Industry change is less likely by 7 percentage points for creative and STEM economy workers considered together. The cluster effect is noticeably smaller for workers considered as a whole.

Intuitively, among the creative economy workforce, support workers, whose skills are arguably more likely to be transferable, are most likely to change occupation (51%) while specialist creatives are least likely (29%). By industry, it is embedded creatives who are most likely to move (77%) and again specialised creatives are least likely (56%). The cluster effect is strongest for support workers and specialist workers. Both are 13 percentage points less likely to change occupation in clusters and 10-13% less likely to change industry. In contrast, for embedded workers, occupation change is 7 percentage points less likely in clusters while industry change is, if anything, slightly more likely. The greater degree of inter-occupation and inter-industry job mobility for embedded creatives is consistent with the possibility that such individuals have a greater propensity than specialist creatives for creative work in different settings or that they are employed in roles that are by their nature less specific to industry domains than similar roles within the creative industries (Hearn, Bridgstock, Goldsmith and Rogers, 2014).

Among non-creative STEM economy workers, support workers (non-STEM workers in STEM industries) are again most likely to change occupation (47%) and specialist STEMs are least likely (32%). The stabilising effect of being in a creative cluster is again apparent across all types of STEM economy worker (and especially specialist STEM workers). As with creatives, this is less the case when considering industry change.

< Table 5 >

We can delve deeper into this by examining whether creative workers who change jobs to a new occupation remain in a creative occupation and, similarly, whether those who change industry remain in the creative sector. This is shown in the top panel of Table 6. For those changing occupation, the proportion remaining in a creative occupation is shown. This stands at around a quarter, highlighting the potential for knowledge spillover from creative to non-creative occupations. We also see a cluster effect which echoes what we found with job changes not involving occupational change: those in creative clusters are more likely than those living elsewhere to remain in a creative occupation. It is interesting to note that support workers – who by definition are not in a creative occupation – are more likely to move into a creative occupation if they are in a cluster. For creatives changing industry, the overall finding is broadly similar, with a move to non-creative industries being the norm. Specialist creatives are again most likely to remain in the creative sector. And again, there is a striking cluster effect for all creative economy workers, with those changing industry more likely to remain in the creative sector if they live in a cluster than if they live elsewhere.

The bottom panel of Table 6 presents analogous results for the for non-creative STEM economy. For those changing occupation, there is some evidence of a cluster effect for embedded STEM workers; those living in a cluster are 9 percentage points more likely to remain in a STEM occupation. By industry, the cluster effect appears smaller.

< Table 6 >

## Multivariate analysis of transitions

To assess the statistical significance of the cluster effects presented above, Table 7 presents the results of using logistic regression analysis. The results control for compositional differences (age, sex, education and ethnicity (white/non-white)) in the workforce. Two regressions are shown. The first estimates the probability of being in a creative occupation after changing employer and the second the probability of being in a creative industry. In both cases, estimates are based on all those who 12 months earlier were working but for a different employer. We include the equivalent results for the STEM economy.

The 'Cluster' coefficient in both columns indicates that, after controlling for compositional differences, there is an across-the-board 1 percentage point hike in the probability of working in a creative occupation or industry for job changers living in a cluster. The occupation regression suggests that it is among the embedded creatives that the cluster occupation effect is strongest, increasing the probability of being in a creative occupation upon changing employer by 7 percentage points. Analogously, the industry regression suggests that the cluster industry effect is strongest among creative support workers (17 percentage points). This stands in contrast with the descriptive results discussed earlier, which suggested relatively stronger effects for specialist creatives. Part of the explanation for this difference may be that the descriptive results have a different focus – changing employer (Table 4), changing occupation (Table 5) or, for this latter group, staying in a creative occupation (Table 6) – whereas the regression results in Table 7 relate to being in a creative occupation for all those who change employer (not just those who change occupation). Another part of the explanation may be that the apparent effect of being a specialist creative reflects the characteristics of the individuals who make up this category. For instance, should employment in a creative role within the creative as opposed to other industries reflect experience, controlling for age in the regression may remove the effect of specialisation. This in turn highlights an important aspect of how the results should be interpreted. Part of the cluster effect apparent when considering descriptive statistics may be attributable to the particular characteristics of workers in such areas. Should the cluster effect no longer be visible in regression results that control for those characteristics, it does not imply that there is no such effect; rather, that the effect appears to arise from the concentration of specific circumstances.

< Table 7 >

To explore occupational dynamism more broadly, we construct a measure of 'distance' between current status and status 12 months earlier.

Our approach exploits the nested structure of the SOC 2010 hierarchy. The intuition is that 4-digit SOC codes (the most detailed classification) within the same 3-digit SOC code are likely to be more 'closely related' than 4-digit SOC codes in different 3-digit SOC codes. Hence, someone whose job at the time of survey has the same 4-digit SOC code as their job 12 months earlier is regarded as having 'travelled' the least distance in occupation terms. Someone for whom this does not hold yet their job is in the same 3-digit SOC code is regarded as having travelled greater distance in occupation terms but less than someone whose jobs are only within the same 2-digit SOC code (and so on).

Through this process, we identify five categories:

1. Working in the same 4-digit SOC occupation as before
2. Working in the same 3-digit SOC occupation as before
3. Working in the same 2-digit SOC occupation as before
4. Working in the same 1-digit SOC occupation as before
5. Working in a different 1-digit SOC occupation from before.

This classification captures the extent to which individuals move away from their initial occupation. Category 1 comprises individuals who have changed employer but whose new job is within the same 4-digit SOC. In the context of the SOC hierarchy, they remain in the same unit group. To give an impression of the specificity of this, unit group 3543, for instance, is "Marketing associate professionals". Those in the next category are in a different but closely related occupation. To continue the example, someone in unit group 3543 would no longer be in that unit group but would be in minor group 354 "Sales, marketing and related associate professionals". The next category corresponds to the sub-major group ("Business and public service associate professionals". The 1-digit category corresponds to the major group ("Associate professional and technical occupations").

We present multinomial logistic regression results of estimating the probability of workers being in each category of the SOC distance measure. Estimation is again based on all workers who have changed employer in the last 12 months. Results are shown first as estimated coefficients. These capture the extent to which a characteristic is associated with a particular category of the outcome. The values of these coefficients are not straightforward to interpret and are presented only to show the sign and statistical significance of each association. Statistical significance is denoted by asterisks for each type of move (column) and by daggers for the joint test across columns. A positive value of the coefficient signifies that, relative to the base category of previous employment (non-creative, non-STEM economy employment) the characteristic is associated with a higher probability of being in that category rather than the base outcome category (employed in an occupation different at the 1-digit level from their occupation 12 months before). A later table presents average marginal effects; the change in the probability of each category associated with characteristics.

Table 8 shows that, relative to non-creative, non-STEM economy workers, embedded creatives are on the whole more likely to move to a job with the same 4- or 3-digit SOC than they are to move into a completely unrelated occupation. This may be consistent with embodied knowledge spillovers between ‘similar’ occupations. Support workers in contrast are relatively more likely to be in an occupation only loosely related (at the 1-digit level) to their previous occupation. The associations for specialist creatives appear weaker for each individual equation but the joint test rejects the null hypothesis of no overall impact more emphatically. This reflects the fact that, while specialist creatives appear no different from base category workers in the probability of their new job being in the same SOC category, it is significantly more likely that their move is to a job in the same 4-digit SOC than to move to a job that is only loosely related (i.e. at the 1-digit level).[9] For non-creative STEM economy workers, those who are embedded appear more likely to move within the same unit group. This is also true for specialised STEM workers. However, the joint test does not reject the null hypothesis of no overall variation.

Of particular interest is how this changes in creative clusters. There is some suggestion that living in a cluster increases the general probability of a move being to a job within the same 4-digit SOC, although the joint test fails to reject the null hypothesis of no overall effect. The interaction terms show how the cluster effect varies by type of worker. For embedded creatives, there is no significant additional cluster effect, suggesting that local factors may have little bearing on the occupational transitions of embedded creatives. Perhaps this is intuitive; such workers have already demonstrated that they can secure creative employment outside creative industries so may be less reliant on availability of creative industries opportunities locally. For support workers, being in a cluster is associated with an increase in the probability of remaining in the same 4-digit SOC and a reduction in the probability of changing job to an occupation that is similar at the 1-digit level. For specialist creatives, the main cluster effect is to increase the probability of the new job being only loosely related, again consistent possibly with embodied knowledge spillover. However, it is only among support workers in creative industries that the

[9] The test of the specialist creative coefficient being the same across columns 1 and 4 of Table 8 is rejected with a p-value of 0.026.

joint test rejects the null hypothesis of no overall effect. This reflects the fact that support workers are more likely to start a job in the same 4-digit SOC than a job that is only loosely related (i.e. at the 1-digit level).[10]

For embedded non-creative STEM workers, being in a cluster is associated with an increased probability of a job move being within the same 3- or 4-digit SOC. For STEM support workers, the results suggest moves to similar (3-digit SOC) and loosely-related (1-digit SOC) jobs are both relatively more likely in creative clusters than they are for non-creative, non-STEM economy workers. No significant cluster associations are seen for specialised STEM workers. Across all types of STEM workers, however, the joint test fails to reject the null hypothesis of no overall effect.

< Table 8 >

The results in Table 9 are intended to make the associations more concrete.[11] The first row (A) shows the distribution across the SOC distances at the time of the survey for all workers changing employer. Most common is for individuals to be working in the same occupation (to the 4-digit level) as they were 12 months earlier. This accounts for nearly half of all cases. Next most common (accounting for roughly two fifths) is to move to an unrelated occupation. Intermediate changes (remaining in the same 3-, 2- or 1-digit SOC) are relatively rare. This implies that large estimated coefficients in Table 8 may translate into relatively small absolute changes in the distribution of SOC distances.

Panel (B) shows marginal effects. These represent how the probability of being in each outcome category varies by characteristic. Embedded creatives who change job are more likely than non-creative, non-STEM economy workers to be in the same or a closely related occupation. These differences are just under 6 and 3 percentage points respectively. Support creatives on the other hand are almost 6 percentage points more likely to move to an occupation that is only loosely related (same 1-digit SOC). For specialist creatives, there is a considerably higher probability of remaining in the same occupation. Notably, a similar pattern is seen for non-creative STEM economy workers. Both embedded and specialised STEM workers are more likely to remain in the same occupation (roughly 8 and 22 percentage points respectively).

Overall, being in a cluster is associated with an increase in the probability of remaining in the same occupation of just shy of 2 percentage points. We see that for all types of creative workers – embedded creatives, support workers and specialised creatives – being in a creative cluster is associated with an increased likelihood of remaining within the same occupation (4-digit SOC). The cluster effect is quite substantial, especially for support and specialist creatives for whom occupational stability is increased by about 12 percentage points. But this is also the case for non-creative STEM economy workers, and for specialist STEMs especially.

[10] The test of the specialist creative coefficient being the same across columns 1 and 4 of Table 8 is rejected with a p-value of 0.004.

[11] Repeating the analysis for Britain excluding London produced very similar findings, suggesting that London is not driving our results.

< Table 9 >

## Conclusions

While workers in creative industries are naturally disproportionately employed in creative roles (specialist creatives), many creative workers (embedded creatives) are employed in other industrial sectors. At the same time, large numbers of workers in non-creative roles (support workers) are employed in the creative industries. This suggests that it is important to consider workforce dynamics in all three segments – specialist creatives, embedded creatives and support workers – that make up the workforce in the creative economy.

Drawing on data from the quarterly Labour Force Survey for the period 2011-2019, we show for the first time that the creative workforce is more dynamic in the UK's creative clusters. Workers employed in all three segments of the creative economy are more likely to change jobs in creative clusters than elsewhere. This tendency, though weaker, is seen in the rest of the workforce too, especially for specialist (non-creative) STEM workers (those working in STEM occupations within STEM-intensive industries) where the cluster effect is even greater than for specialist creatives.

In general, workers in the creative economy and to some extent in the (non-creative) STEM economy who change jobs are less likely than other workers to change occupations or industries (both defined at the 4-digit level). This tendency is again more pronounced in creative clusters, tallying with the idea that there are more opportunities within creative clusters for creative (STEM) workers to change employer while maintaining their occupation.

Amongst creative economy workers, support workers, whose skills are arguably more likely to be transferable, are most likely to change occupation while specialist creatives are least likely. By industry, embedded creatives are more likely than even support workers to move, consistent with the possibility that such individuals have a high propensity to do creative work in different settings or that they are employed in creative roles that are by their nature less specific to industry domains than similar roles within the creative industries.

Strikingly, we again see parallels in job dynamics between (non-creative) STEM and creative economy workers, with STEM support workers being most likely to change occupation and STEM specialists least likely, and embedded STEMs being much more likely than STEM specialists to change industry.

When we examine which specific occupations creative economy workers who change occupations move to we find that in general only a quarter remain in a creative occupation, highlighting the potential for knowledge spillovers from creative to non-creative occupations. Echoing what we see for job changes not involving occupational (industrial) change, we see that those residing in creative clusters are more likely to remain in creative occupations (industries). Interestingly, support workers (i.e. those not in creative occupations) in creative clusters are more likely to move into creative occupations and more generally are much more likely to move into jobs in the creative industries.

Taken together, the descriptive results presented indicate that creative clusters are associated with higher levels of workforce dynamism, but that job changes in the creative economy and (non-creative) STEM economy workforces are less likely than other jobs to involve changes in occupations or industries defined at the 4-digit level. This finding is consistent with the possibility that creative and STEM labour markets are thicker in creative clusters and/or that they support more knowledge spillovers between firms. However, there are notable differences between the segments that make up the creative economy, with support workers most likely to change occupation and embedded workers most likely to change industry. Furthermore, of those workers that do change occupation, the vast majority – around three-quarters – do so to a non-creative occupation, thus raising the possibility of embodied knowledge spillovers from creative to non-creative occupations too.

However, it is possible that the creative cluster effects have nothing to do with labour market thickness effects or the potential for knowledge spillovers, but rather reflect differences in other workforce characteristics between creative clusters and other areas that determine creative workforce dynamics.

To investigate this possibility we use multivariate analysis which controls for differences in workforce composition in age, sex, education and ethnicity to estimate the probability that those changing employer are working in a creative occupation (industry). The findings suggest that after controlling for these differences, the cluster effect for occupations is in fact strongest for embedded creatives and for industries is strongest for support workers.

To explore occupational dynamism more broadly, we consider the 'distance' travelled in occupational space by those changing employer in our sample, making the identifying assumption that 4-digit SOC codes within the same 3-digit SOC code are likely to be more 'closely related' than 4-digit SOC codes in different 3-digit SOC codes which in turn are more closely related than those in different 2-digit SOC codes, and so on. We find that embedded creatives are significantly more likely to move to a job within the same 4- or 3-digit SOC than they are to move to an unrelated occupation, which may be consistent with embodied knowledge spillovers between 'similar' occupations, but there is no significant cluster effect, suggesting that local factors may have little bearing on the occupational transitions of embedded creatives. In contrast, for support workers, being in a creative cluster is associated with an increase in the probability of remaining in the same 4-digit SOC and a reduction in the probability of changing job to an occupation that is only loosely related. For specialist creatives, the only significant cluster effect is to increase the probability of the new job being loosely related.

In quantitative terms, for all segments of the creative workforce, the marginal effects of living in a creative cluster on the likelihood of remaining within the same occupation (4-digit SOC) are substantial, especially for support and specialist creatives for whom the probability of occupational stability is raised by about 12 percentage points. This is also the case for (non-creative) STEM economy workers, and for specialist STEMs especially.

Taken together, the findings in this paper provide strong indicative evidence that creative clusters may support thick creative labour markets and embodied knowledge spillovers. Indeed, these features may give rise to scale economies which help to explain why some areas are creative clusters and others are not in the first place (Chapain et al., 2010). They may also point to the existence of market failures which may help account for the growing interest in creative clusters from industrial policymakers. However, the results also point to important variations in workforce dynamics within the creative economy, specifically between creative workers working in the creative industries, support workers in non-creative occupations and those employed in creative roles outside the creative industries. The multivariate regression analysis suggests that there are other important differences between clusters in the demographic composition of their creative workforces that need to be taken into account. Lastly, the paper has uncovered striking similarities between workforce dynamics in the creative economy and (non-creative) STEM economy in creative clusters that warrant further investigation.

An important feature of our analysis is that the Labour Force Survey data we use to capture job changes covers the 2011-2019 period. We restrict the data to this period because we believe including the years in the immediate wake of the global financial and Covid19 crises may cloud the picture of underlying differences in workforce dynamics between creative clusters and other places. We believe our analysis provides a baseline assessment, against which future research on the post-2019 Labour Force Survey data can be compared. Possible reasons for believing that the Covid19 pandemic may have altered the importance of creative clusters for creative workforce dynamics include the increased importance of home- and hybrid working arrangements and the possible exodus of workers from the creative workforce of venue-based creative sub-sectors like the performing arts and museums which were amongst the most severely hit by lockdown restrictions.

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## Appendix – defining activity status and creative industries, occupations and clusters

Our definition of economic status allows for four categories. Current status is derived from the "inecac05" variable. This is the basic activity status variable in the LFS and combines responses to a number of questions relating to employment, job search, education, and so on. Economic status 12 months prior to the survey is taken form the "oycirc" variable:

> *OYCIRC – EMPLOYMENT 12 MONTHS AGO*
>
> *CODE 1st THAT APPLIES*
>
> *I should (also) like to ask you now about your situation twelve months ago, that is in [date], Were you...*
>
> *1 Working in a paid job or business?*
>
> *2 Laid off or on short time at firm?*
>
> *3 Unemployed, actively seeking work?*
>
> *4 On a special government scheme?*
>
> *5 Doing unpaid work for your or a relative?*
>
> *6 A full-time student or pupil?*
>
> *7 Looking after the family or home?*
>
> *8 Temporarily sick or injured?*
>
> *9 Long-term sick or disabled?*
>
> *10 Retired from paid work?*
>
> *11 None of these.*

Those who report working at that time are asked whether they worked as an employee or were self-employed (variable "oystat"):

> *OYSTAT – Employed/Self-employed (asked IF OYCIRC=1 or 2)*
>
> *May I just check, in your occupation twelve months ago, were you...*
>
> *1 working as an employee?*
> *2 or were you self-employed?*

Combined, oycirc and oystatus allow the status 12 months ago to be summarised by the same four categories as status at the time of interview.

The classifications for inecac05 and oycirc/oystat are different so to reconcile we adopt the coding shown in the table below. Note that, consistent with ILO definitions, unpaid family workers are included in the self-employed category. We treat government employment and training schemes (inecac05=3) and special government schemes (oycirc=4) as essentially the same. This is a simplification; inecac05 is a derived variable while oycirc instead captures respondents' self-classification. In the case of inecac05, employment programmes feature prominently among individuals for whom inecac05=3. While not verifiable, we assume this would also be the case among respondents reporting oycirc=4. In view of the fact that they are not employees or self-employed but are involved in some effort to find work, we include such schemes in the "Unemployed" category.

| Constructed status | Current status: Inecac05 | | Status 12 months prior: Oycirc | | Oystat | |
|---|---|---|---|---|---|---|
| Employee | 1 | Employee | 1 | Working in a paid job or business | 1 | Working as employee |
| Self-employed | 2 | Self-employed | | | 2 | Self-employed |
| | 4 | Unpaid family worker | 5 | Doing unpaid work for yourself or a relative | | |
| Unemployed | 3 | Government employment & training programmes | 2 | Laid off, or on short time at firm | | |
| | 5 | ILO unemployed | 3 | Unemployed, actively seeking work | | |
| | | | 4 | On a special government scheme | | |
| Inactive | 6-34 | Inactive | 6-10 | Inactive | | |
| Missing | missing | Missing | 11, missing | Missing | | |

Creative clusters are defined in Mateos-Garcia and Bakhshi (2016) using the 2011 definition of TTWAs. This definition of TTWAs was not available throughout the period considered in this paper. To allow for the longer time series of observations, we defined creative clusters prior to 2016 on the basis of the 2001 TTWA definitions. The list of TTWAs regarded as creative clusters is provided in the table below. Note that since TTWA information is not available for Northern Ireland it is not possible to identify the Belfast creative cluster.

| **2016 onwards** | **pre-2016** |
|---|---|
| Basingstoke | Basingstoke |
| Bath | Bath |
| Bournemouth | Bournemouth |
| Brighton | Brighton |
| Bristol | Bristol |
| Cambridge | Cambridge |
| Canterbury | Canterbury |
| Cardiff | Cardiff |
| Chelmsford | Chelmsford and Braintree |
| Cheltenham | Cheltenham and Evesham |
| Chester | Chester and Flint |
| Chichester and Bognor Regis | Chichester and Bognor Regis |
| Colchester | Colchester |
| Crewe | Crewe and Northwich |
| Eastbourne | Eastbourne |
| Edinburgh | Edinburgh |
| Exeter | Exeter and Newton Abbot |
| Glasgow | Glasgow |
| Guildford and Aldershot | Guildford and Aldershot |
| Harrogate | Harrogate and Ripon |
| Hastings | Hastings |
| High Wycombe and Aylesbury | Wycombe and Slough |
| Leamington Spa | Warwick and Stratford-upon-Avon |
| Leeds | Leeds |
| Liverpool | Liverpool |
| London | London |
| Luton | Luton and Watford |
| Manchester | Manchester |
| Medway | Maidstone and North Kent |
| Middlesbrough and Stockton | Middlesbrough and Stockton |
| Milton Keynes | Milton Keynes and Aylesbury |
| Newbury | Newbury |
| Newcastle | Newcastle and Durham |
| Northampton | Northampton and Wellingborough |
| Norwich | Norwich |
| Oxford | Oxford |
| Penzance | Penzance and Isles of Scilly |
| Peterborough | Peterborough |
| Reading | Reading and Bracknell |
| Sheffield | Sheffield and Rotherham |
| Slough and Heathrow | |
| Southampton | Southampton |
| Southend | Southend and Brentwood |
| Trowbridge | Trowbridge and Warminster |

| | |
|---|---|
| Tunbridge Wells | Tunbridge Wells |
| Warrington and Wigan | Warrington and Wigan |

## Tables

Table 1: Creative occupation type by creative industry type, (row percentages)

| | *CI type (SIC07):* Not CI | Advertising & Marketing | Architecture | Crafts | Design | Film & TV | IT & Software | Publishing | Museums & Galleries | Music & Performing | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *CO type (SOC10):* | | | | | | | | | | | |
| - Not CO | 97 | | | | | | 1 | | | | 100 |
| - Advertising & Marketing | 74 | 12 | | | 1 | 2 | 5 | 4 | | 1 | 100 |
| - Architecture | 40 | | 59 | | | | | | | | 100 |
| - Crafts | 88 | 3 | | 3 | 3 | | | | | 2 | 100 |
| - Design | 39 | 5 | 1 | | 41 | 2 | 3 | 6 | | 1 | 100 |
| - Film & TV | 21 | 4 | | | | 61 | | 1 | | 12 | 100 |
| - IT & Software | 52 | 1 | | | | 1 | 43 | 2 | | | 100 |
| - Publishing | 21 | 6 | | | | 9 | 2 | 45 | | 18 | 100 |
| - Museums & Galleries | 60 | | | | | 5 | | | 33 | 2 | 100 |
| - Music & Performing Arts | 30 | 2 | | | 2 | 5 | | | | 60 | 100 |
| Total | 94 | | | | | | 2 | | | | 100 |

Results are based on pooled 2011-2019 data on 18-59 year-olds, weighted to account for survey non-response. Cells<1% are suppressed to aid visualisation

Table 2: Creative industry type by creative occupation type, (column percentages)

| | *CI type (SIC07):* Not CI | Advertising & Marketing | Architecture | Crafts | Design | Film & TV | IT & Software | Publishing | Museums & Galleries | Music & Performing | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *CO type (SOC10):* | | | | | | | | | | | |
| - Not CO | 96 | 45 | 37 | 54 | 38 | 39 | 56 | 44 | 76 | 33 | 93 |
| - Advertising & Marketing | 1 | 35 | | 11 | 5 | 6 | 3 | 10 | 2 | 3 | 2 |
| - Architecture | | | 60 | | | | | | | | |
| - Crafts | | 2 | | 31 | 2 | | | | | | |
| - Design | | 5 | 2 | 4 | 51 | 2 | | 5 | | 1 | |
| - Film & TV | | 3 | | | | 41 | | | | 9 | |
| - IT & Software | 1 | 4 | | | 1 | 3 | 39 | 5 | 4 | | 2 |
| - Publishing | | 5 | | | | 6 | | 34 | | 13 | |
| - Museums & Galleries | | | | | | | | | 16 | | |
| - Music & Performing Arts | | 1 | | | 2 | 3 | | | | 39 | |
| Total | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |

Results are based on pooled 2011-2019 data on 18-59 year-olds, weighted to account for survey non-response. Cells<1% are suppressed to aid visualisation

Table 3: Self-employment proportion by creative occupation and industry (cell percentages)

| | Occupation | Industry |
|---|---|---|
| *Creative occupation/industry:* | | |
| - Not CO | 13 | 13 |
| - Advertising & Marketing | 15 | 18 |
| - Architecture | 20 | 24 |
| - Crafts | 40 | 27 |
| - Design | 39 | 58 |
| - Film & TV | 54 | 37 |
| - IT & Software | 14 | 19 |
| - Publishing | 45 | 24 |
| - Museums & Galleries | 4 | 5 |
| - Music & Performing Arts | 83 | 66 |
| All creative industries/occupations | 28 | 29 |
| All industries/occupations | 14 | 14 |

Results are based on pooled 2011-2019 data on 18-59 year-olds, weighted to account for survey non-response.

Table 4: Proportion of those in work who had changed employer in past 12 months by type of industry/occupation and creative cluster (cell percentages)

| | Non-Creative Cluster | Creative Cluster |
|---|---|---|
| *Type of industry /occupation 12 months earlier:* | | |
| - CI only (support workers) | 9 | 12 |
| - CO only (embedded creatives) | 9 | 11 |
| - CI and CO (specialised creatives) | 8 | 10 |
| - Non-creative, STEM Industry only | 8 | 9 |
| - Non-creative, STEM occupation only | 8 | 8 |
| - Non-creative, STEM industry and STEM occupation | 6 | 9 |
| | | |
| - All creative industries/occupations | 9 | 11 |
| - All non-creative STEM industries/occupations | 8 | 9 |
| - All creative and STEM industries/occupations | 8 | 10 |
| - All industries/occupations | 9 | 10 |

Results are based on pooled 2011-2019 data on 18-59 year-olds, weighted to account for survey non-response.

Table 5: Proportion changing 4-digit SOC or SIC among those in work who had changed employer in past 12 months by type of industry/occupation and creative cluster (cell percentages)

| | Changed occupation | | | Changed industry | | |
|---|---|---|---|---|---|---|
| | Non-CC | CC | All | Non-CC | CC | All |
| *Type of industry /occupation 12 months earlier:* | | | | | | |
| - CI only (support workers) | 60 | 47 | 51 | 75 | 65 | 68 |
| - CO only (embedded creatives) | 47 | 40 | 42 | 76 | 78 | 77 |
| - CI and CO (specialised creatives) | 40 | 27 | 29 | 66 | 53 | 56 |
| - Non-creative, STEM Industry only | 50 | 45 | 47 | 80 | 78 | 79 |
| - Non-creative, STEM occupation only | 42 | 35 | 38 | 75 | 69 | 72 |
| - Non-creative, STEM industry and occupation | 40 | 28 | 32 | 61 | 59 | 59 |
| | | | | | | |
| - All creative industries/occupations | 49 | 38 | 41 | 73 | 65 | 68 |
| - All non-creative STEM industries/occupations | 47 | 39 | 42 | 77 | 72 | 74 |
| - All creative and STEM industries/occupations | 48 | 38 | 41 | 75 | 68 | 70 |
| - All industries/occupations | 55 | 50 | 52 | 74 | 70 | 71 |

Results are based on pooled 2011-2019 data on 18-59 year-olds, weighted to account for survey non-response.

Table 6: Proportion of creative/STEM workers changing to a new occupation (industry) who remain in a creative/STEM occupation (industry) (cell percentages)

| | Changed occupation | | | Changed industry | | |
|---|---|---|---|---|---|---|
| | Non-CC | CC | All | Non-CC | CC | All |
| | % in creative occupation | | | % in creative industry | | |
| *Creative industry /occupation 12 months earlier:* | | | | | | |
| - CI only (support workers) | 19 | 25 | 23 | 9 | 23 | 19 |
| - CO only (embedded creatives) | 21 | 28 | 26 | 25 | 29 | 28 |
| - CI and CO (specialised creatives) | 20 | 30 | 28 | 29 | 40 | 37 |
| | % in STEM occupation | | | % in STEM Industry | | |
| *STEM industry /occupation 12 months earlier:* | | | | | | |
| - Non-creative, STEM Industry only | 12 | 15 | 14 | 17 | 22 | 20 |
| - Non-creative, STEM occupation only | 17 | 26 | 22 | 33 | 37 | 35 |
| - Non-creative, STEM industry and occupation | 28 | 25 | 27 | 38 | 43 | 41 |

Results are based on pooled 2011-2019 data on 18-59 year-olds, weighted to account for survey non-response.

Table 7: Key coefficients from regression of whether in creative occupation (first column) and whether in creative industry (second column) on workforce status 12 months earlier, plus interactions with whether in creative cluster

| | Creative occupation Coeff [s.e] | | Creative industry Coeff [s.e] | |
|---|---|---|---|---|
| Embedded creative | 0.598 | *** | 0.155 | *** |
| | [0.030] | | [0.024] | |
| Support creative | 0.089 | *** | 0.284 | *** |
| | [0.022] | | [0.032] | |
| Specialised creative | -0.037 | | 0.050 | |
| | [0.053] | | [0.057] | |
| Embedded STEM | -0.005 | | 0.022 | |
| | [0.012] | | [0.017] | |
| Support STEM | 0.016 | | 0.007 | |
| | [0.010] | | [0.010] | |
| Specialised STEM | -0.015 | | 0.017 | |
| | [0.014] | | [0.023] | |
| Cluster | 0.009 | *** | 0.009 | *** |
| | [0.002] | | [0.003] | |
| Embedded creative x cluster | 0.073 | ** | 0.024 | |
| | [0.037] | | [0.033] | |
| Support creative x cluster | -0.015 | | 0.172 | *** |
| | [0.027] | | [0.040] | |
| Specialised creative x cluster | 0.057 | | -0.058 | |
| | [0.062] | | [0.071] | |
| Embedded STEM x cluster | -0.006 | | 0.020 | |
| | [0.017] | | [0.026] | |
| Support STEM x cluster | 0.009 | | 0.052 | *** |
| | [0.017] | | [0.018] | |
| Specialised STEM x cluster | 0.009 | | -0.005 | |
| | [0.022] | | [0.032] | |
| Observations | 22,057 | | 22,057 | |

Results are based on pooled 2011-2019 data on 18-59 year-olds, weighted to account for survey non-response. Regressions are estimated for workers who have changed employer. Regressions control for age, sex, education and being white. Robust standard errors in brackets. Asterisks denote statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Key coefficients from multinomial regression of occupational distance category on creative workforce status 12 months earlier, plus interactions with whether in creative cluster

| | (1) SOC same at 4-digit level | (2) SOC same at 3-digit level | (3) SOC same at 2-digit level | (4) SOC same at 1-digit level | |
|---|---|---|---|---|---|
| Embedded creative | 0.285** | 0.673*** | -0.689 | 0.105 | †† |
| | [0.140] | [0.255] | [0.469] | [0.333] | |
| Support creative | -0.152 | 0.369 | -0.0580 | 0.844*** | ††† |
| | [0.157] | [0.308] | [0.361] | [0.270] | |
| Specialised creative | 0.355 | -0.954 | -0.464 | -1.137* | †† |
| | [0.283] | [0.597] | [0.934] | [0.688] | |
| Embedded STEM | 0.355** | 0.143 | -0.330 | 0.478 | |
| | [0.165] | [0.390] | [0.473] | [0.353] | |
| Support STEM | 0.0948 | -0.594* | -0.00955 | -0.372 | |
| | [0.107] | [0.333] | [0.234] | [0.305] | |
| Specialised STEM | 0.618** | 0.695 | 0.843* | 0.424 | |
| | [0.248] | [0.475] | [0.472] | [0.558] | |
| Cluster | 0.0618* | -0.0291 | 0.00294 | -0.0624 | |
| | [0.0338] | [0.0827] | [0.0769] | [0.0799] | |
| Embedded creative x cluster | 0.257 | 0.156 | 0.551 | 0.103 | |
| | [0.186] | [0.328] | [0.550] | [0.439] | |
| Support creative x cluster | 0.337* | 0.0353 | -0.105 | -0.713* | †† |
| | [0.192] | [0.377] | [0.459] | [0.369] | |
| Specialised creative x cluster | 0.0882 | 0.251 | 0.806 | 1.479* | |
| | [0.352] | [0.719] | [1.083] | [0.840] | |
| Embedded STEM x cluster | 0.444* | 0.960** | 0.0908 | 0.486 | |
| | [0.238] | [0.483] | [0.675] | [0.472] | |
| Support STEM x cluster | 0.163 | 0.742* | 0.185 | 0.721* | |
| | [0.153] | [0.416] | [0.342] | [0.399] | |
| Specialised STEM x cluster | 0.518 | -0.670 | 0.123 | 0.605 | |
| | [0.328] | [0.727] | [0.630] | [0.695] | |
| Observations = 22,057 | | | | | |

Results are based on pooled 2011-2019 data on 18-59 year-olds, weighted to account for survey non-response. Regression is estimated for workers who have changed employer. Regressions control for age, sex, education and being white. Robust standard errors in brackets. Asterisks denote statistical significance: *** p<0.01, ** p<0.05, * p<0.1 (for tests of no association in specific equation); ††† p<0.01, †† p<0.05, † p<0.1 (for joint tests of no association across equations).

Table 9: Average marginal effects from estimated multinomial logit regression of SOC distance

| | *(1) SOC same at 4-digit level* | *(2) SOC same at 3-digit level* | *(3) SOC same at 2-digit level* | *(4) SOC same at 1-digit level* | *(5) SOC different at 1-digit level* |
|---|---|---|---|---|---|
| (A) Probability | *47.8* | *4.4* | *4.3* | *4.3* | *39.3* |
| | | | | | |
| (B) Marginal effects (%-points) | | | | | |
| *Relative to non-creative, non-STEM workers not in a cluster*: | | | | | |
| - Embedded creative | *5.9* | *2.9* | *-2.6* | *-0.2* | *-6.0* |
| - Support creative | *-6.7* | *1.9* | *-0.3* | *5.7* | *-0.6* |
| - Specialised creative | *13.4* | *-0.5* | *-3.4* | *-1.5* | *-8.0* |
| - Embedded STEM | *7.7* | *-0.2* | *-1.8* | *1.5* | *-7.1* |
| - Support STEM | *3.9* | *-2.0* | *-0.1* | *-1.4* | *-0.4* |
| - Specialised STEM | *22.2* | *-1.5* | *-0.6* | *-0.5* | *-19.7* |
| - Cluster | *1.7* | *-0.2* | *-0.1* | *-0.4* | *-1.0* |
| *Relative to same type of worker not in a cluster*: | | | | | |
| - Embedded creative x cluster | *6.4* | *-0.5* | *0.8* | *-0.6* | *-6.2* |
| - Support creative x cluster | *12.0* | *-0.7* | *-0.8* | *-6.0* | *-4.5* |
| - Specialised creative x cluster | *12.4* | *-0.5* | *1.1* | *0.9* | *-13.9* |
| - Embedded STEM x cluster | *7.5* | *3.2* | *-0.6* | *0.4* | *-10.4* |
| - Support STEM x cluster | *2.6* | *1.7* | *0.1* | *1.9* | *-6.4* |
| - Specialised STEM x cluster | *11.5* | *-0.1* | *-1.8* | *4.3* | *-13.9* |

Results are based on pooled 2011-2019 data on 18-59 year-olds, weighted to account for survey non-response. Cells show the change in percentage points in the probability of being in the category associated with each variable