Creative Clusters and Creative Multipliers: Evidence from UK Cities

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Abstract

Economic geographers have paid much attention to the cultural and creative industries, both for their propensity to cluster in urban settings, and their potential to drive urban economic development. However, evidence on the latter is surprisingly sparse. In this paper we explore the long-term, causal impacts of the cultural and creative industries on surrounding urban economies. Adapting Moretti's local multipliers framework, we build a new 20-year panel of UK cities, using historical instruments to identify causal effects of creative activity on non-creative firms and employment. We find that each creative job generates at least 1.9 non-tradable jobs between 1998 and 2018. Prior to 2007, these effects seem more rooted in creative services employees' local spending than visitors to creative amenities. Given the low numbers of creative jobs in most cities, the overall impact of the creative multiplier is small. On average, the creative sector is responsible for over 16% of non-tradable job growth in our sample, though impacts will be larger in bigger clusters. We do not find the same effects for workplaces, and find no causal evidence for spillovers from creative activity to other tradable sectors. In turn, this implies that 'creative city' policies will have partial, uneven local economic impacts. Given extensive urban clusters of creative activity in many countries, our results hold value beyond the UK setting.

Keywords creative industries; local multipliers; cities; local economic development

JEL codes L8, O18, R11

Running head Do creative clusters generate multiplier effects?

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ACCEPTED VERSION, FORTHCOMING IN *ECONOMIC GEOGRAPHY*

1) Introduction

This paper tests the causal impacts of the creative and cultural industries on surrounding urban economies, specifically on non-creative jobs and firms. Economic geographers have extensively studied the creative and cultural industries (Scott 1988; Zukin 1995; Hall 1998; Throsby 2001; Florida 2005; Boschma and Fritsch 2009; Cooke and Lazzeretti 2008; Hutton 2008; Mould 2015; Van Damme, De Munck, and Miles 2017). There are two broad reasons for this. First, these sectors are highly clustered[1] in a few urban locations (Hesmondhalgh 2012; Bloom et al. 2020). In the UK, for example, 53% of creative industries jobs and 44% of firms are found in just five cities (Mateos-Garcia, Klinger, and Stathoulopoulos 2018), and this concentration is increasing over time (Tether 2019). Second, cultural and creative industries are also viewed as drivers of urban economic development: creative work is seen as highly-skilled, often high value-added, and with spillover effects on the wider area (Florida 2005; Boschma and Fritsch 2009; Marrocu and Paci 2012).[2] If the creative industries *do* have this urban growth potential, however, their unevenness may generate significant – and lasting – economic disparities across the wider urban system.

There is a large literature describing urban creative clusters across countries (Lazzeretti, Boix, and Capone 2008; de Vaan, Boschma, and Frenken 2013; Boix et al. 2014; Kemeny, Nathan, and O'Brien 2020), within countries (Bertacchini and Borrione 2013; Alfken, Broekel, and Sternberg 2015; Mateos-Garcia, Klinger, and Stathoulopoulos 2018; Nuccio and Ponzini 2017; Tao et al. 2019) and within cities (Catungal, Leslie, and Hii 2009; O'Connor

[1] We use 'co-located', 'concentrated' and 'clustered' synonymously.

[2] We use 'cultural and creative' and 'creative' industries interchangeably. We discuss terms further in Section 2.

and Gu 2014; Hracs 2015). However, the impact – if any – of such clusters on local economies is less well-understood, and is the focus of our paper.

Creative clustering may simply reflect shifts towards knowledge-based economies (Zukin 1995; Scott 2006; Pratt and Jeffcut 2009), and the benefits of big city location (Hall 2000; Hutton 2008). However, clusters could also generate halo effects on other sectors and/or displace other activities. Benefits might arise through higher local worker/visitor spending, improved local supply chains and knowledge spillovers (Bakhshi and McVittie 2009; Lee 2014). Conversely, clusters might displace other industries, a process of industrial gentrification (Yoon and Currid-Halkett 2014). These impacts may vary substantively over the business cycle, and may also differ extensively *within* the creative industries, given the differences between (say) advertising and the arts. The empirical base for these wider impacts is inconclusive. Most evidence draws on single case studies, or is constrained by one or both of short time periods and problematic research designs (Bloom et al. 2020).[3]

Figure 1 about here

At first glance, creative spillovers are indeed at work in UK cities: Figure 1 plots the log change in urban creative industries jobs between 1998-2018, per UK official industry definitions, against the log change in local services ('non-tradables' such as retail and leisure) over the same period. We cannot be sure that the creative industries *drive* this positive relationship: wealthier cities could have simply developed more creative activity and more local services.

[3] We discuss this literature in more detail in Section 2.

Our paper aims to identify the causal impacts of urban creative activity on jobs and firms in urban non-tradable and other tradable industries. We build a new 20-year panel of UK cities using rich microdata. Adapting Moretti's local multipliers framework (2010), we estimate short and long-term cumulative impacts from 1998 to 2018, using historic instruments – plus weak instrument-robust inference – to identify causal effects.

We have four main results. First, creative activity progressively concentrates in a small number of cities, though with diffusion across the biggest clusters. Second, we find robust, positive employment impacts of creative industries on urban local services. Taken together, this means that job multipliers are large, but overall effects are uneven: each creative job generates at least 1.96 non-tradable jobs over our 20-year period, or 16.4% of non-tradable job growth in the average TTWA in that period. For workplaces, we find no similar effects, and job multipliers decline substantially after the 2007 financial crisis. Third, impacts on local services reflect both creative workers' spending and visitors to urban amenities such as galleries and museums, although the former is stronger than the latter. Fourth, we find weak, suggestive evidence of spillovers from creative industries to activity in other tradable sectors.

The paper makes multiple contributions to both current debates in economic geography and the cultural and creative industries literature. Our findings contribute to the fundamental questions on city growth and the economic foundations and trajectories of post-industrial cities, in which 'creativity' is often presented as an economic driving force (Zukin 1995; Hall 1998; Florida 2002; Scott 2006; Hutton 2015). Given similar trends in creative clustering in other more developed countries, our results have resonance beyond the UK setting. We widen the horizon of existing creative industries analysis via a robust research design, high-quality granular data and a long time-frame, all issues flagged by Bloom et al (2020) in their review of the field. We also tackle broader empirical limitations in the local multipliers literature, notably arbitrary time periods and overly-aggregated sectoral definitions (Osman and Kemeny 2021).

Our results also hold important lessons for urban economic development policy, specifically the effective reach of 'creative city' programmes, where the creative economy is often assumed to have extensive local upsides and no downsides (Mathews 2010; Lindner 2018). Our results suggest creative economy-led policies can have positive local economic impacts, but they are subject to important spatial and sectoral constraints.

The rest of the paper runs as follows. Section 2 outlines our conceptual framework and reviews the empirical literature. Section 3 describes data and build. Section 4 provides descriptive evidence. Section 5 outlines our research design. Sections 6 and 7 present main results and extensions. Section 8 summarises findings, discusses policy implications, and identifies areas for further work.

2) Theoretical Framework

2.1 / Defining the creative industries

The cultural and creative industries 'supply goods and services that we broadly associate with cultural, artistic, or simply entertainment value' (Caves 2002) (p1). These are now taken to include the visual and performing arts, heritage, and cultural industries such as cinema, design, TV, fashion and computer games. Cultural products and services typically combine artistic and 'humdrum' inputs, involving a wide range of skillsets and short timeframes (Caves 2002); given winner-takes-all effects, creative industries make heavy use of contingent, project-based working and options-based contracts, with the largest firms focused on packaging and distribution over production. Creative workers perform highly skilled roles rich in problem-solving, using novel processes involving a high share of non-repetitive tasks and resistant to mechanisation (Bakhshi, Freeman, and Higgs 2012). Nevertheless, labour force conditions vary widely in creative sectors, with a large minority of well-paid secure positions in creative services such as advertising, architecture, software and the media, and an over-representation of insecure self-employment / portfolio working, especially in the arts (Brook, O'Brien, and Taylor 2020).

The accepted set of cultural and creative industries has broadened over time: from 'the arts', to a larger set of 'cultural products and services', and most recently to a wider set of activities with a critical mass of 'creative' activity (Flew 2002; Hesmondhalgh 2012).[4] As set out in Section 3, our industry definitions are also based on this creative intensity framework (Bakhshi, Freeman, and Higgs 2012). Cultural and creative industries are now seen as part of larger shifts towards service and knowledge-based economies, in which 'creativity' is an important input and consumption is a means of expressing identity: what Lash and Urry (1984) call 'culturalisation' and what Scott (2014) dubs 'cognitive-cultural capitalism'. This broader creative industry space is also closely linked to urban change, and the growth of creative clusters in post-industrial cities.

[4] Hesmondhalgh distinguishes between 'cultural industries' as a term of positive analysis, and 'creative industries' as a normative policy concept embodying strong claims about creativity's economic importance.

2.2 / The urban economic impacts of creative activity

The urban footprint of creative industries naturally raises questions about effects on their surroundings. A first view is that urbanised creative industries are simply the spatial manifestation of a 'culturalised' post-industrial economy. While creative embedding might differ across countries (Boix et al. 2014; Kemeny, Nathan, and O'Brien 2020), creative clusters then have no necessary wider local impact. Rather, creative firms co-locate in post-industrial cities because they benefit from agglomeration economies and other urban affordances (Scott 1988; Zukin 1995; Hall 1998, 2000).

A contrasting view is that creative industries have important local 'multiplier effects'. High-paid creative service workers' spending may support jobs growth and firm creation in local services like cafes, bars and shops (Hutton 2008; Lee 2014). In parallel, arts, heritage and museums can be powerful attractors for both residents and tourists, with similar local spending effects (Florida 2002; Pratt and Jeffcut 2009). Creative actors' interactions with non-creative sectors may also amplify urban agglomeration economies (Duranton and Puga, (2004). For example, creative industries might add value through supply chain linkages (Bakhshi and McVittie 2009), or by adding to the stock of ideas in a city, raising innovation and productivity (Müller, Rammer, and Trüby 2009; Pratt and Jeffcut 2009; Boix-Domenech and Soler-Marco 2017).

A third view is that causality runs both ways. Creative industries activity, especially in creative business services, is highly pro-cyclical (Stam, De Jong, and Marlet 2008). If wealthier and more productive cities have larger creative economies, this may reflect local demand from other industries and households, as well as (or instead of) creative multipliers (Hall 2000; Marco-Serrano, Rausell-Koster, and Abeledo-Sanchis 2014).

Moretti's seminal work (2010) offers a way to formalise these perspectives. The base case is a 'growth shock' to a city's tradable activities (that is, goods and services that can be both consumed locally and exported to other locations). A creative industries 'growth shock' might come through a major relocation, or through longer term structural shifts like culturalisation: Moretti and Thulin (2013) emphasise the role of deeper shifts in consumer preferences (e.g. for urban amenities and experiences).

The 'shock' directly increases creative activity, and may also have indirect effects. First, we may see multiplier effects on 'non-tradable' activity (that is, services such as retail and leisure that are provided and consumed locally). Second, there may be multiplier effects on other tradable sectors, via supply chain links, knowledge spillovers or both: these vary with the extent of a) cross-industry spillovers versus b) competition for inputs. Third, we may see these effects on the intensive margin (more jobs in existing non-creative firms) and/or the extensive margin (more non-creative firms).

Estimating multipliers *within* creative industries subgroups helps pin down mechanisms. Creative services, especially knowledge-intensive business services have (at least some) highly-paid workers. As such, multipliers from creative services on non-tradable activity are likely to derive from worker spend. By contrast, the lower-wage structure of employment in music, museums, art galleries and crafts implies that multipliers on non-tradables are more likely to derive from the value of urban amenities and related visitor expenditure.

2.3 / Existing evidence

This basic framework allows local multipliers and their drivers to be directly estimated, and a growing body of employment multiplier studies has developed since 2010. Van Dijk (2018) develops a detailed critique of Moretti's original implementation, suggesting several modifications that we draw on below. In a recent OECD-wide review of the field (What Works Centre for Local Economic Growth 2019), each additional job in the tradable sector generates on average 0.9 additional jobs in the untraded sector: skilled / high-tech activities have higher multipliers, averaging 2.5 and 1.9 additional non-tradable jobs respectively. However, none of these studies look at creative activity.

A number of other papers do look at urban and regional impacts of the creative industries, but typically use short sample periods (under 10 years), and none look at mechanisms in detail (e.g. the role of arts vs. creative services). Several papers also use shift-share instruments, an approach we suggest has serious drawbacks in the creative industries case (see Section 5). Boix-Domenench and Soler-Marco (2017) use GMM to test links between creative services presence and labour productivity for 250 EU regions in 2008, finding a positive effect. Boix et al (2013) also find positive links between creative services and wealth in EU regions in 2008, using a shift-share instrument. Conversely, Marco-Serrano et al (2014) explore creative industry – GDP links for EU regions between 1999 and 2008, finding clear, both-ways, causation in a SEM estimator. For UK cities, Lee (2014) uses a shift-share instrument to explore links between creative industries employment and overall urban wages / employment between 2003 and 2008, finding positive wage links but no effect on jobs. Our closest comparator is Lee and Clarke (2017), who run a Moretti-style analysis for 2009-2015 with a shift-share instrument, again finding no evidence of creative employment multipliers.

Other studies test for associations rather than causal effects. For example, Rodríguez-Pose and Lee (2020) find that it is the simultaneous presence of creative and STEM workers that is associated with the highest patenting growth in US cities. In the UK, Lee and Rodríguez-Pose (2014) find that businesses in cities with high rates of creative businesses tend to be more innovative whilst Innocenti and Lazaretti (2019), studying Italian provinces, suggest that the co-location of creative industries and other closely related sectors is necessary to observe positive employment spillover effects. Stam et al (2008) show positive associations between creative industries presence and job growth in Amsterdam, but not in other Dutch cities.

3) Data

Our main data source is the Business Structure Database (BSD) (Office for National Statistics 2019). The BSD covers over 99% of all UK economic activity and provides reliable information for individual workplaces (plants) and jobs by sector. After extensive cleaning, detailed in Appendix A1, we aggregate workplace-level information to 2011 Travel to Work Areas (TTWAs), city-regional geographies that provide the best approximation for spatial economies. Of the 228 TTWAs, we focus on 78 that are predominantly urban, following Gibbons et al (2011). Our panel has 1716 urban TTWA-year observations for 22 years, 1997-2018 inclusive. (Note that the BSD does not include freelancers or self-employed workers with revenues below the UK sales tax threshold.[5] Freelancing and self-employment are common in the creative industries, so our raw data likely undercounts true levels of creative activity. See Section 5.2 for further discussion.)

[5] Currently £85,000 per year, or US$118,206.

We then build our key variables according to the framework developed in Section 2. We first decompose industries into tradable and non-tradable components. Tradable space includes creative industries, plus manufacturing and tradable services.[6] Non-tradable space includes public sector activities such as education and health care, and non-tradable services such are retail, leisure and hospitality.

We define creative and cultural industries using the UK's official creative industries definition (DCMS 2018), using crosswalks to make time-consistent sector codes for nine subgroups: advertising and marketing; architecture; crafts; design; film, TV, video, radio and photography; information technology (IT), software and computer services; publishing; museums, galleries and libraries; music, performing and visual arts.

Manufacturing and public sector activities are defined per Faggio and Overman (2014). To identify tradable and non-tradable services, we use locational Gini coefficients, as developed in Jensen et al (2005) and widely used in this literature. We build new locational Ginis for detailed four-digit UK industries based on 2018 BSD data. See Appendix A2 for details.

For control variables and robustness checks we use the Annual Population Survey, Labour Force Survey, and UK Office of National Statistics datasets covering population, GVA per head and household disposable income. As before, all datasets are aggregated to TTWA level. Further details are given in Sections 5 and 6.

[6] Some creative industries subgroups – notably crafts, museums, galleries and libraries – are arguably non-tradable. Overall they represent under 7% of total creative industries GVA (DCMS 2018). For this analysis we allocate them to tradable space.

4) Descriptive analysis

How has urban creative activity evolved over time, and across cities? Table 1 gives summary statistics for 1998-2018 (Panel A), 1998 (Panel B) and 2018 (Panel C). Alongside substantial increases in overall economic activity, the average urban TTWA in 2018 has more creative activity than 1998, and this accounts for a larger share of local economic activity.

Table 1 about here

This aggregate picture hides much spatial variation. First, only a few cities drive overall rises. Figure 2 is a kernel density distribution showing urban TTWAs' local shares of creative workplaces/firms (left hand side) and employment (right hand side) in 1998 (blue) and 2018 (red). Most areas have very low shares. Local shares of creative activity grow, but with the biggest shifts at the top of the distribution. These patterns are consistent with other UK work by Mateos-Garcia et al (2018) and Tether (2019), as well as the broader cross-country literature discussed in Section 1.

Figure 2 about here

Second, patterns of creative specialisation suggest both clustering *and* diffusion. Figure 3 shows the distribution of location quotients (LQs) for creative firms (left hand side) and jobs (right hand side) in 1998 and in 2018. An LQ over one indicates an industry is more concentrated in an area than its national share, indicating clustering. As shown by the grey veritcals, only a minority of cities have LQs over one. On both workplaces and jobs measures, overall distributions have become more extreme. Creative job specialisation has risen at the very top of the distribution, but fallen in other clusters; workplace specialisation has diffused in all clusters.

Figure 3 about here

This spatial and time persistence has important implications for our regression analysis, as we discuss in Section 5 below. Nevertheless, some individual cities have also shifted position in the creative cluster league table. Appendix Tables B1-B3 give more detail for the 20 urban TTWAs with the largest initial creative industries counts, shares and LQs respectively. Not surprisingly, London and its wider mega-region (including Slough, Guildford, Luton and Reading) dominates in creative firm and employment counts. Outside mega-London, other major cities with large counts include Manchester, Birmingham, Bristol and Cambridge. The picture is broadly similar for shares, although compared to smaller, more specialised cities such as Reading, Slough and Milton Keynes, by 2018 London has a lower local share of creative activity. All of the biggest clusters have lower workplace LQs in 2018 than 1998, with Edinburgh emerging as a top 20 cluster in 2018. For jobs LQs, Luton, Crawley and Tunbridge Wells have technically declustered between 1998 and 2018; in contrast Bristol has emerged as a cluster for both creative workplaces and employment.

5) Research design

We now take our framework formally to the data. Per Section 2, to explore causal links from creative industries activity to non-creative activity, we start with the following OLS fixed effects regression for TTWA *i* in year *t:*

$$ln(\mathrm{NT})_{it} = a + b1ln(\mathrm{CI})_{it} + b2ln(\mathrm{OT})_{it} + \mathbf{X}\boldsymbol{c}_{it-n} + \mathrm{I}_i + \mathrm{T}_t + e_{it} \quad (1)$$

Where NT, CI and OT are respectively activity counts in non-tradable, creative industries and other tradable sectors, as defined in Section 3; **X** is a vector of controls lagged *n* years (n = 1, varied in robustness checks), and I and T are area and year fixed effects. Our variable of interest is CI, where $b1$ is the elasticity of non-tradable activity to CI activity. We interpret this as the percentage change in non-tradable activity from a 1% change in creative industry activity. Following our theoretical framework, we are interested in impacts on both the intensive margin (more jobs) and the extensive margin (more firms). We estimate (1) in levels for 1998-2018, and for start and end years only, equivalent to the long differences approach in Moretti (2010) and Lee and Clarke (2019). We run alternative specifications for both settings in robustness checks. To cover the full UK business cycle we estimate for the sub-periods 1998-2006 and 2007-2018 (broadly, pre and post-Great Financial Crisis). In extensions we also look within creative subgroups, and at impacts on other tradables.

We then calculate multipliers, where M gives the number of additional non-tradable jobs (or workplaces) arising from one extra creative job (or workplace):

$$\mathrm{M} = \hat{b}1 * (\mathrm{NT}_{2007} / \mathrm{CI}_{2007}) \quad (2)$$

Where $\hat{b}1$ is the estimated coefficient from (1), NT_{2007} is the sum of non-tradable jobs or workplaces in 2007 across TTWAs, and CI_{2007} gives the same for creative industries in 2007. We also calculate an alternative specification following Van Dijk (2018), using both 1998 and 2007 as base years to better follow labour market time trends.

5.1 / Identification

Our panel estimators handle time-fixed area characteristics and cross-area shocks in a given year. Urban creative activity is also influenced by time-varying skills and tastes of the workforce and population, agglomeration economies, and local labour market conditions. We therefore control for 1-period lags of the share of graduate residents in a TTWA and the TTWA's ILO unemployment rate (from APS and LFS data), plus population density and the share of 16-24 year olds in the city (from ONS mid-year population estimates). In robustness checks we vary these controls and lag structure.

Our base regressions may also suffer from simultaneity or reverse causation between creative and non-tradable activity. Lacking a natural experiment, we turn to instrumental variables. The multipliers literature typically uses shift-share instruments (Osman and Kemeny 2021).[7] Several recent studies critically evaluate such instruments (Broxterman and Larson 2020; Cerqua and Pellegrini 2020). If national shifts are not as-good-as-random, the instrument will not be identified (Borusyak, Hull, and Jaravel 2018). If local shares are serially correlated, the instrument also fails, as it incorporates past and current demand shocks (Goldsmith-Pinkham, Sorkin, and Swift 2018; Jaeger, Ruist, and Stuhler 2018). Per Section 4, UK creative industries are highly clustered, and this persists over time. Further, there has been no large national shock to creative industries in our sample period. It is thus unlikely that shift-share instruments can convincingly identify causal effects of creative industries in the UK. Our

[7] See Boix et al 2013, Moretti and Thulin 2013, Lee 2014, Van Dijk 2018, Lee and Clarke 2019, and Kemeny and Osman 2020 for recent examples.

alternative approach is to use historical instruments, exploiting the long-term effects of industrial structure and supporting institutions.[8]

Our first instrument builds on Chinitz (1961), who argues that cities historically dominated by small firms and SMEs have persistently stronger entrepreneurial cultures today. We argue that these dynamics also apply to creative industries, which have notably larger-than-average share of micro firms and self-employment.[9] Thus, cities historically dependent on single-industry, large-firm dominance should also have less *creative* activity today. To proxy for this dependence, we use cities' proximity to 19th century mining deposits, an exogenous feature used successfully to predict entrepreneurial activity in the US (Glaeser, Pekkala Kerr, and Kerr 2015) and the UK (Stuetzer et al. 2016). Our instrument is the log distance from a TTWA centroid to the nearest historic active coalfield. We expect to see a positive link from distance to creative industries activity.

Our second instrument builds on the idea that historical cultural institutions make a long-term impact on local cultural clusters today (Falck, Fritsch, and Heblich 2011). Specifically, we use historic Schools of Art and Design established in the Victorian and Edwardian eras, 1837-1914 (Lee and Clarke 2019). The first Government School of Design opened in London in 1837; in subsequent years such schools flourished in many industrial cities (Lawrence

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[8] For completeness we also construct a shift-share instrument using a leave-one-out design (see Appendix A3 for details). We use this to 1) benchmark our main estimates, and 2) estimate impacts from tradables to non-tradables since identifying assumptions are better founded here.

[9] In 2017 the creative industries had 95% micro firms and 0.14% large firms, vs 89% and 0.37% respectively across all industries (BRES data accessed via www.nomisweb.co.uk, accessed 26 August 2020). In 2015, over 26% of creative industries workers were self-employed, versus 16% of all UK workers (DCMS (2016) DCMS Sectors Economic Estimates, via https://tinyurl.com/ycfx47hr, accessed 26 August 2020).

2014), offering urban working-class children the opportunity to learn engineering and chemistry alongside then-new creative technologies related to design, photography, film and printing. We argue such historic institutions helped root creative cluster, by supplying skilled workers to local firms, as a source of ideas, and through two-way linkages between teaching staff and local firms. Our list includes both London (15/52 Schools) and major cities, but also ex-industrial and more peripheral locations. Our instrument is the count of historic Art and Design Schools in TTWA, and we expect to see a positive connection from the count to creative activity today.

For these instruments to be valid they must only directly affect creative industries activity, and leave non-tradable activity unaffected (except through changes in creative activity). Table 2 shows results of a diagnostic regression of our instruments on employment (Panel A) and workplaces (Panel B) in our different industry groupings. For each panel we show results for creative industries (column 1), non-tradables (column 2) and other tradables (column 3).

Table 2 about here

Encouragingly, we find the expected positive links for the coalfields instrument to creative employment and workplaces, and find no significant links to non-tradable activity. We also find weak negative links from our instruments to other tradables activity. In robustness checks we therefore treat both creative and other tradables activity as endogenous: this does not affect our main result. Where we test creative-to-other tradable linkages, we use only the art schools instrument.

5.2 / Inference

Weak instruments are pervasive in the multipliers literature (Osman and Kemeny 2021). Following Osman and Kemeny, we use the weak instrument-robust methods developed by Andrews et al (2019) for cases where our IVs do not pass cutoffs. The intuition is that when an instrument is valid but weak, as here, there is a set of values under which we can infer a consistent result. Specifically, the Anderson-Rubin statistic tests for the null hypothesis of instrument exogeneity for the value of the point estimate $\hat{b}1$. For an exactly identified regression, the subsequent Anderson-Rubin confidence set is the set of values for $\hat{b}1$ for which exogeneity cannot be rejected (and this set can exist even when overall tests of instrument exogeneity fail). We use the minima of these sets to present our results as lower bounds. We do this for two reasons. First, using minima gives a more straightforward interpretation. Second, as flagged in Section 3, our raw data undercounts the true numbers of creative firms and jobs.

6) Results

This section gives headline results. We first summarise OLS estimates, then our preferred IV regressions.

6.1 / OLS results

Figure 4 summarises OLS results for jobs and workplaces. Each graph gives point estimates and 95% confidence intervals for the variable of interest, in a fully specified model with controls and fixed effects. (Appendix Tables B4-B7 give full results for coefficients, standard errors and model fit.). Overall, we find positive associations between creative to non-tradable activity, but these links are not always statistically significant, and are always smaller than for other tradable sectors.

Figure 4 about here

The left-hand graph shows results for the fixed effects estimator. The first three estimates show the average (non-causal) link between creative and non-tradable jobs in urban areas: for 1998-2018, 1998-2006, and 2007-2018 respectively. We see a significant, positive link from creative to non-tradable jobs overall. Specifically, a 10% increase in creative employment in a TTWA is associated with 1.7% growth in non-tradable jobs (Appendix Table B4, column 2). This is explained by larger changes pre-2007 rather than after. The fourth estimate shows the link for all tradable activity as a benchmark: it is notably larger than the creative industries coefficients, as are those for other tradables. The next four estimates repeat the analysis for workplaces (Table B5 gives full results). We find a robust positive link from creative to non-tradable firms, which is now stronger from 2007.

The right-hand graph repeats these results for the long difference estimator, showing the *cumulative* link between creative and non-tradable jobs / workplaces over 1998-2018, 1998-2006 and 2007-2018 respectively. Here, 10% growth in creative jobs between 1998-2018 is associated with 1.2% growth in non-tradable jobs in a TTWA (Table B6, column 2). For workplaces, the overall cumulative link is also robust (Table B7, column 2). There is not enough sub-period variation to give a significant association (Tables B6-B7, columns 2-4). Again, coefficients on (other) tradables are always larger than those for creative industries.

6.2 / Robustness checks

We run OLS results through a battery of robustness checks (Tables B8-B12). Our first set of checks cover alternative control variables and time splits (Tables B8-B9, for our fixed-effects and long difference estimators respectively). Reassuringly, our main results are stable across these alternative specifications. Our second set of checks cover functional form. Table B10 estimates in first differences: estimates are very similar to fixed effects coefficients. Table B11 gives results for an alternative long difference model with base year controls only (a growth rate setting). For both outcomes, the coefficient of creative activity is now slightly smaller. For jobs the coefficient is now only marginally significant, although model fit is also much lower. For workplaces it remains robust. Table B12 fits 1-period lags of creative and other tradable activity, as well as lagged controls. Coefficients of creative activity fall by around 50%. For jobs the result remains robust, while for workplaces it becomes marginally significant. As before, model fit also declines.

6.3 / IV results

We now turn to causal regressions with our historical instruments. As discussed in Section 5, we estimate the *cumulative* causal impact of creative on non-tradable activity in UK cities.

Tables 3 and 4 report OLS results (column 1), IV for creative industries (columns 2-4) and a benchmarking IV regression for tradable activity (column 5), for jobs and workplaces respectively. First stage results for the instruments are in italics. Under each column, we show Montiel Olea-Pflueger Effective F statistics (Andrews et al. 2019) alongside a conventional weak instrument F-test. In most cases the former scores under 10, indicating the need for weak instrument-robust inference. In these cases, we show Anderson-Rubin confidence sets alongside raw coefficients, and generate multipliers from the minima. For jobs (Table 3), confidence sets show a 10% increase in creative jobs causes between 1.12% and 6.2% more non-tradable jobs in UK cities between 1998 and 2018, compared to a 1.2% increase in the OLS setting. As before, the overall change is driven by the pre-2007 period.

Table 3 about here

Multipliers give us a simple alternative heuristic for interpreting our results. While the OLS multiplier is 2.13, the IV multiplier is at least 1.96. This implies that over the period 1998-2018, each urban creative job generates at least 1.96 non-tradable jobs (the multiplier drops from 2.48 jobs pre-2007 to 0.8 jobs from 2007). What does this mean in practice? Creative *multipliers* are larger than the cross-OECD average for tradables, which is 0.9 (What Works Centre for Local Economic Growth, 2018).[10] But the creative sector is relatively small (see Table 1), so the *overall effect* of the multiplier is modest. The 6,663 creative jobs added in the average UK city between 1998-2018 are responsible for 13,020 new non-tradable jobs, or 16.4% of all non-tradable jobs growth during that period. Nevertheless, this is a positive contribution to what is largely a self-fuelled non-tradable jobs expansion. For workplaces (Table 4) the picture is very different. IV coefficients are smaller and now all are non-significant. Multipliers are also reduced, with all around zero.

[10] Our multiplier of tradable on non-tradable activity (0.287) is rather lower than the cross-country average of 0.9 in the WWC review, but rather higher than their minimum of 0.13. US estimates covered in the review range from 0.53 to 1.6.

Table 4 about here

These results are robust to alternative estimations pooling across all years (Tables B13-B14), to alternative specifications using a shift-share instrument, and to instrumenting for *both* creative and other tradable activity (Tables B15-B16). In the latter case IV estimates are always larger than our main results. Since other tradable activity is also an endogenous variable of interest (see Section 5), this is reassuring, and implies that we can treat our main results with some confidence.

Overall, our analysis suggests that creative multipliers on non-tradables come through the intensive margin – that is, more jobs in non-tradable businesses – rather than the extensive margin – more non-tradable firms. Creative industries' pro-cyclicality, as discussed in Section 2, likely explains why effects die back after the shock of the Great Financial Crisis.

7) Extensions

We now explore the other two parts of our conceptual framework. We first test for multiplier effects from creative industries to other tradable sectors. Per Section 2, these could reflect 'matching effects' through supply chains and/or 'learning effects' through broader urban knowledge spillovers. Next, we decompose our main results for non-tradable jobs across creative industry subgroups. This helps explain how non-tradable jobs multipliers may operate: worker spending, visitor spending or both.

7.1 / Creative multipliers in tradable space

We test links between creative industries activity and activity in other tradables by estimating in long differences, for TTWA *i* in year *t*:

$$\Delta \ln \mathrm{OT}_{it\text{-}tbase} = a + b1\Delta \ln \mathrm{CI}_{it\text{-}tbase} + b2\Delta \ln \mathrm{NT}_{it\text{-}tbase} + \Delta \mathbf{X}\boldsymbol{c}_{it\text{-}tbase} + \mathrm{T}_t + e_{it} \quad (3)$$

Here, OT is either jobs or workplaces in other tradable manufacturing/services, and other terms and controls are defined as before. Table 5 gives results, using the art school instrument only. Panel A covers jobs and Panel B, workplaces. For each, column 1 gives OLS results, and columns 2-4 give results for 1998-2018, 1998-2006 and 2007-2018 respectively.

Table 5 about here

While OLS results suggest spillovers from creative to other tradable activity, this is non-causal. By contrast, we find no significant results for IV regressions. However, IV estimators are poorly fitted, and confidence sets are empty, implying mis-specification (Andrews, Stock, and Sun 2019). Alternative specifications combining the art school and shift-share IVs (for creative or other tradable activity) also almost always yield non-significant results.

Overall, we interpret these findings as suggestive, non-causal evidence of spillovers to other tradable activity, noting their consistency with other studies (Müller, Rammer, and Trüby 2009; Pratt and Jeffcut 2009; Boix-Domenech and Soler-Marco 2017). Further research using alternative research designs could confirm the extent and direction of these effects.

7.2 / Decomposing creative job multipliers

Here we provide exploratory, non-causal evidence on how creative job multipliers may operate on non-tradable employment. Per Section 2, we can do this by exploring mutlipliers for creative industry subgroups. If these are large and statistically significant in creative services versus arts, this is evidence that multipliers operate through worker spending versus visitor spending, and the converse.

Figure 5 summarises OLS results and 95% confidence intervals for each of the nine DCMS subgroups in turn, for 1998-2006 (left hand panel) and 2007-2018 (right hand panel). Coefficients represent the relative 'effect' of each subgroup, controlling for other creative industries, other tradable activity, with controls and fixed effects as before. Appendix Table B17 gives full details.

Figure 5 about here

For 1998-2006, we find some evidence for creative service spending power over visitor amenity spending, with robust coefficients for architecture, design, film and publishing. However, the channel works unevenly, with no robust links for advertising/marketing and IT, two high-wage subgroups. We speculate that this may reflect the former activities' broader upstream entanglements versus the latter's more specialised functions. We also find some support for the amenities channel, with robust coefficients for museums & libraries, and for the arts. Consistent with our overall results, subgroup coefficients get substantially smaller and non-significant after 2007, and services vs amenities differences also largely disappear at this point.

8) Conclusions

Economic geographers have paid much attention to the creative industries, because they cluster in cities (Zukin 1995; Hall 1998; Hutton 2008; Scott 2014), and because they may drive urban growth (Florida 2005; Boschma and Fritsch 2009; Marrocu and Paci 2012). However, evidence on the latter is surprisingly sparse (Bloom et al. 2020). In this paper we explore the long-term, causal impacts of the creative industries on surrounding urban economies. Using a new 20-year panel of UK cities, we directly estimate causal effects of creative on non-creative activity. Given high and increasing urban concentrations of creative activity in many countries (Boix et al. 2014; Alfken, Broekel, and Sternberg 2015; Tao et al. 2019; Nuccio and Ponzini 2017), our results hold value beyond the UK setting.

We have four main findings. First, consistent with other recent studies (Tether 2019; Mateos-Garcia, Klinger, and Stathoulopoulos 2018; Nuccio and Ponzini 2017; Boix et al. 2014), we find creative industries activity becoming increasingly clustered in a small number of cities, albeit with diffusion *within* these clusters. Second, we find significant, positive employment multipliers of creative jobs on surrounding local service employment. In the average city, each creative job adds at least 1.96 non-tradable jobs over our twenty-year sample period.[11] Consistent with creative activity being highly procyclical, effects are driven by the pre-Crisis period. Given the relatively small size of the creative sector, and the extreme clustering of

[11] As discussed in Sections 3 and 5, we know that creative jobs are likely to be undercounted in our data. In turn this may overstate our multipliers, given the construction of equation (2). In practice, adjusting for this is unlikely to change our story hugely. For example, if we conservatively assume that we are undercounting true creative employment by as much as 10%, our multiplier reduces from 1.96 to 1.73. In turn, this reduces the non-tradable jobs effect in the average city from around 12,200 to 11,200 or 13% of the non-tradable growth during 1998-2018.

creative activity, the creative multiplier's overall impact is both modest and uneven. On average, the creative sector is responsible for 16.4% of non-tradable job growth 1998-2018, though impacts will be larger in bigger clusters. We find no statistically significant causal impacts for workplaces – which suggests that change is coming from the intensive (more jobs in existing non-tradable businesses) rather than the extensive margin (more non-tradable businesses creating more jobs).

Third, we suggest that multiplier effects are associated with both creative business services employees' local spending and amenity visitor spending, although the former, albeit uneben, outweighs the latter. However, we find both overall and subgroup impacts reducing in the post-2007 era, in line with Lee (2014) and Lee and Clarke (2017). Fourth, we find weak, suggestive evidence of spillovers to other tradable activities, consistent with Lee (2014), Bakhshi and McVittie (2009) and Boix-Domenech and Soler-Marco (2017) who highlight the impact of creative industries on supply innovation and productivity spillovers.

More broadly, these results may challenge some common perceptions on the effects of 'creative city' policies (Mathews 2010; Lindner 2018) at the urban level. First, such policies will have partial and uneven local economic impacts. Specifically, our results suggest that spatially and sectorally blind, creative-led economic policies are unlikely to be efficient in both addressing regional disparities and maximising employment growth in specific areas. Rather, any positive effects will be focused on a few large urban areas, with the risk of further exclusion of marginal areas. Second, spillovers likely stimulate existing activities over new businesses, and our strongest evidence points to impacts on impacts on local services rather than other 'high-value' tradables. This goes against notions of the creative city as a broad-based urban economic development strategy (Florida, 2002). Or to put it more constructively, the extent to which creative industries *specifically* favour further innovative activities and quality jobs still needs to be empirically proved.

Our research has a number of limitations, which open up space for further work. First, our contribution is limited to economic spillovers, neglecting the relevant social effects of the arts, museums and cultural heritage. Second, we lack worker-firm data so cannot explore the economic impacts of creative occupations, either inside or outside creative firms (Bakhshi, Freeman, and Higgs 2012). Third, we do not explore within-city change, for example in specific creative districts or neighbourhoods (Hutton 2015). Fourth, we do not consider wider impacts on (for example) the housing market. Finally, we focus on aggregate effects and do not explicitly consider winners and losers, either in terms of firm outcomes or individuals' labour market / life chances. We look forward to future research exploring these spaces.

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Tables

Table 1. Summary statistics.

	A. All years		**B. 1998**		**C. 2018**	
	Mean	**sd**	**Mean**	**sd**	**Mean**	**sd**
TTWA all workplaces	22433	43798	19846	37959	28790	61437
TTWA tradables workplaces	6380	15663	5364	12758	8608	22802
TTWA creative workplaces	2146	6580	1721	5151	3153	9961
TTWA other tradable workplaces	4233	9128	3643	7651	5455	12882
TTWA non-tradable workplaces	16054	28225	14482	25255	20181	38760
% tradable workplaces / all workplaces	0.284	0.042	0.270	0.041	0.299	0.047
% creative workplaces / all workplaces	0.095	0.030	0.087	0.030	0.110	0.033
% other tradable workplaces / workplaces	0.189	0.021	0.184	0.022	0.189	0.020
% non-tradable workplaces / all workplaces	0.716	0.042	0.730	0.041	0.701	0.047
TTWA all jobs	252793	455899	223984	406268	307218	586922
TTWA tradables jobs	64513	129808	68314	131554	71997	163951
TTWA creative jobs	11396	37242	8870	28537	15513	53646
TTWA other tradable jobs	53118	93580	59444	103773	56484	110968
TTWA non-tradable jobs	188279	327061	155670	275172	235220	423705
% tradable jobs / all jobs	0.255	0.051	0.305	0.050	0.234	0.037
% creative jobs / all jobs	0.045	0.017	0.039	0.015	0.050	0.018
% other tradable jobs / all jobs	0.210	0.052	0.265	0.053	0.184	0.034
% non-tradable jobs / all jobs	0.745	0.051	0.695	0.050	0.766	0.037
*TTWA*year observations*	*1638*		*78*		*78*	

Source: BSD.

Table 2. Historical instruments diagnostics tests.

	A. Employment			B. Workplaces		
	(1)	(2)	(3)	(1)	(2)	(3)
log TTWA-coalfield distance	0.17***	0.01	-0.11***	0.12***	0.01	-0.03***
	(0.051)	(0.020)	(0.027)	(0.038)	(0.014)	(0.012)
TTWA frequency of art schools	0.10	0.02	-0.06*	0.02	0.01	-0.01
	(0.069)	(0.028)	(0.038)	(0.062)	(0.023)	(0.025)
Log other tradable jobs	0.13	0.60***		1.39***	0.96***	
	(0.147)	(0.045)		(0.189)	(0.071)	
Log non-tradable jobs	1.06***		0.93***	-0.21		0.72***
	(0.165)		(0.096)	(0.197)		(0.049)
Log creative industries jobs		0.26***	0.05		-0.05	0.26***
		(0.040)	(0.054)		(0.049)	(0.030)
Observations	1638	1638	1638	1638	1638	1638
R^2	0.91	0.96	0.95	0.94	0.97	0.98
F-statistic	403.41	1067.61	987.32	977.97	1568.95	1926.00

Source: BSD, LFS/APS, ONS. All specifications include year dummies and controls per main specification.
Standard errors clustered on TTWA. Constant not shown.

Table 3. IV regression for impact of creative employment on non-tradables. Long difference estimator 1998/2018.

	OLS	IV			
	(1)	(2)	(3)	(4)	(5)
Log creative industries jobs	0.12**	0.36***	0.37***	0.24***	
	(0.051)	(0.081)	(0.071)	(0.079)	
Log other tradable jobs	0.25***	0.53***	0.50***	0.62***	
	(0.066)	(0.074)	(0.068)	(0.078)	
Log tradable jobs					0.13
					(0.225)
log TTWA-coalfield distance		*0.24****	*0.26****	*0.23****	
		(0.061)	*(0.061)*	*(0.057)*	
TTWA frequency of art schools		*0.19***	*0.19***	*0.18***	
		(0.093)	*(0.093)*	*(0.081)*	
Log Bartik tradable employment					*1.42****
					(0.366)
Observations	156	156	156	156	156
R^2	0.94	0.96	0.96	0.96	0.70
Kleibergen-Paap F-statistic		9.52	11.33	9.66	15.15
Montiel Olea-Pflueger Effective F		7.465	8.710	8.944	15.15
Anderson-Rubin confidence set		[0.112, 0.620]	[0.141, 0.557]	[0.046, 0.437]	
Multiplier - Van Dijk	2.126	[1.961, 10.888]	[2.476, 9.784]	[0.797, 7.568]	0.287

Source: BSD, LFS/APS, ONS. Travel to Work Area (TTWA)-by-year cells. All models use controls as in our main specification. Standard errors in parentheses, clustered on TTWA. * 10%, ** 5%, *** 1% significance. Confidence sets are confidence intervals around point estimates for creative industries jobs, except for column 5 (tradable jobs).

Table 4. IV regression for impact of creative workplaces on non-tradables. Long difference estimator 1998/2018.

	OLS	IV			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Log creative industries firms	0.30***	0.06	0.07	-0.08	
	(0.092)	(0.105)	(0.084)	(0.127)	
Log other tradable firms	0.65***	0.85***	0.82***	1.02***	
	(0.140)	(0.122)	(0.097)	(0.151)	
Log tradable firms					-0.05
					(0.527)
log TTWA-coalfield distance		*0.13****	*0.15****	*0.12****	
		(0.045)	*(0.046)*	*(0.036)*	
TTWA frequency of art schools		*0.03*	*0.02*	*0.04*	
		(0.064)	*(0.069)*	*(0.056)*	
Log Bartik tradable firms					*0.58**
					(0.328)
Observations	156	156	156	156	156
R^2	0.91	0.97	0.98	0.98	0.59
Kleibergen-Paap F-statistic		4.22	5.36	5.44	3.14
Montiel Olea-Pflueger Effective F		4.975	5.960	6.176	3.145
Anderson-Rubin confidence set		[0.209, 0.553]	[0.171, 0.383]	[-0.493, 0.364]	[., 0.467]
Multiplier - Van Dijk	2.516	[1.761, 4.657]	[1.438, 3.327]	[-4.076, 3.014]	[., 1.261]

Source: BSD, LFS/APS, ONS. Notes as in Table 3.

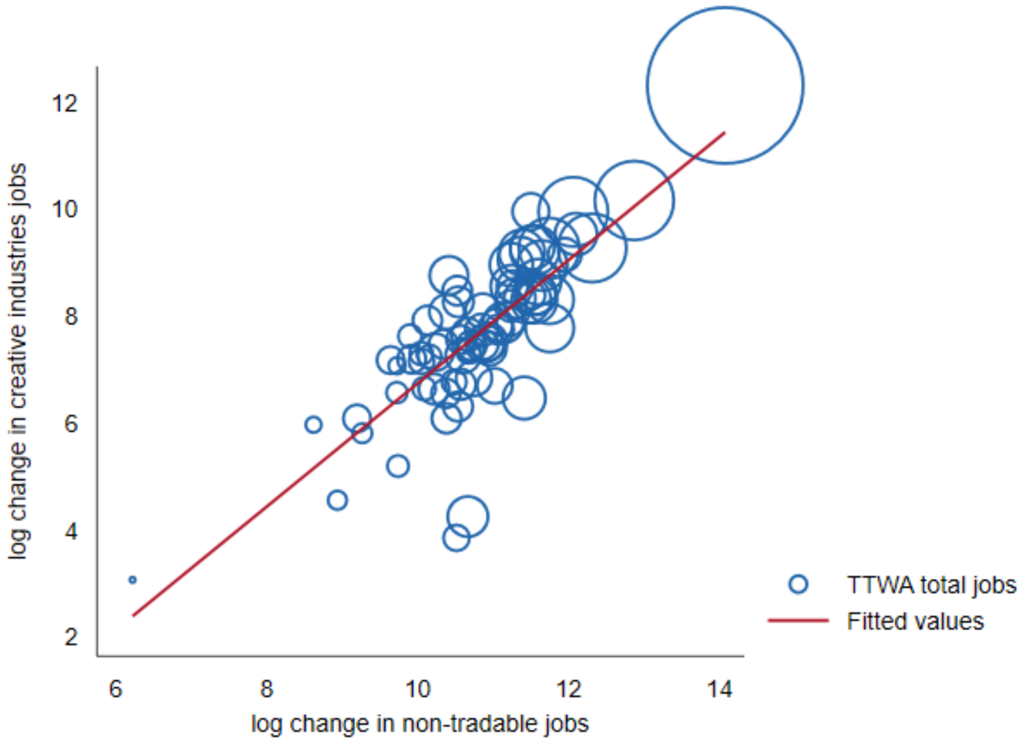
Table 5. IV regression of creative and other tradable activity. Long difference estimator, 1998/2018.

	OLS	IV	IV	IV
A. Employment	**(1)**	**(2)**	**(3)**	**(4)**
Log creative industries jobs	0.20*	-0.29	4.93	-0.32
	(0.110)	(1.776)	(102.09)	(2.559)
Log non-tradable jobs	0.95***	1.30	-4.73	1.38
	(0.232)	(1.994)	(118.33)	(2.832)
TTWA frequency of art schools		*0.02*	*-0.00*	*0.01*
		(0.076)	*(0.073)*	*(0.067)*
Observations	156	156	156	156
R^2	0.47	0.93	-3.10	0.93
Kleibergen-Paap F-statistic		0.06	0.00	0.05
Montiel Olea-Pflueger Effective F		0.06	0.003	0.05
Anderson-Rubin Chi^2		0.0237	0.222	0.0176
Anderson-Rubin confidence set		[.,.]	[.,.]	[.,.]
B. Workplaces	**(1)**	**(2)**	**(3)**	**(4)**
Log creative industries firms	0.22**	0.13	0.12	0.08
	(0.090)	(0.354)	(0.307)	(0.581)
Log non-tradable firms	0.70***	0.86**	0.90**	0.92
	(0.074)	(0.415)	(0.365)	(0.670)
TTWA frequency of art schools		*-0.06*	*-0.07*	*-0.04*
		(0.069)	*(0.065)*	*(0.058)*
Observations	156	156	156	156
R^2	0.93	0.98	0.98	0.98
Kleibergen-Paap F-statistic		0.81	1.26	0.45
Montiel Olea-Pflueger Effective F		0.81	1.26	0.45
Anderson-Rubin Chi^2		0.106	0.141	0.0169
Anderson-Rubin confidence set		[.,.]	[.,.]	[.,.]

Source: BSD, LFS/APS, ONS. Travel to Work Area (TTWA)-by-year cells. All models use TTWA and year dummies, plus controls as in our main specification. Standard errors in parentheses, clustered on TTWA. * 10%, ** 5%, *** 1% significance.

Figures

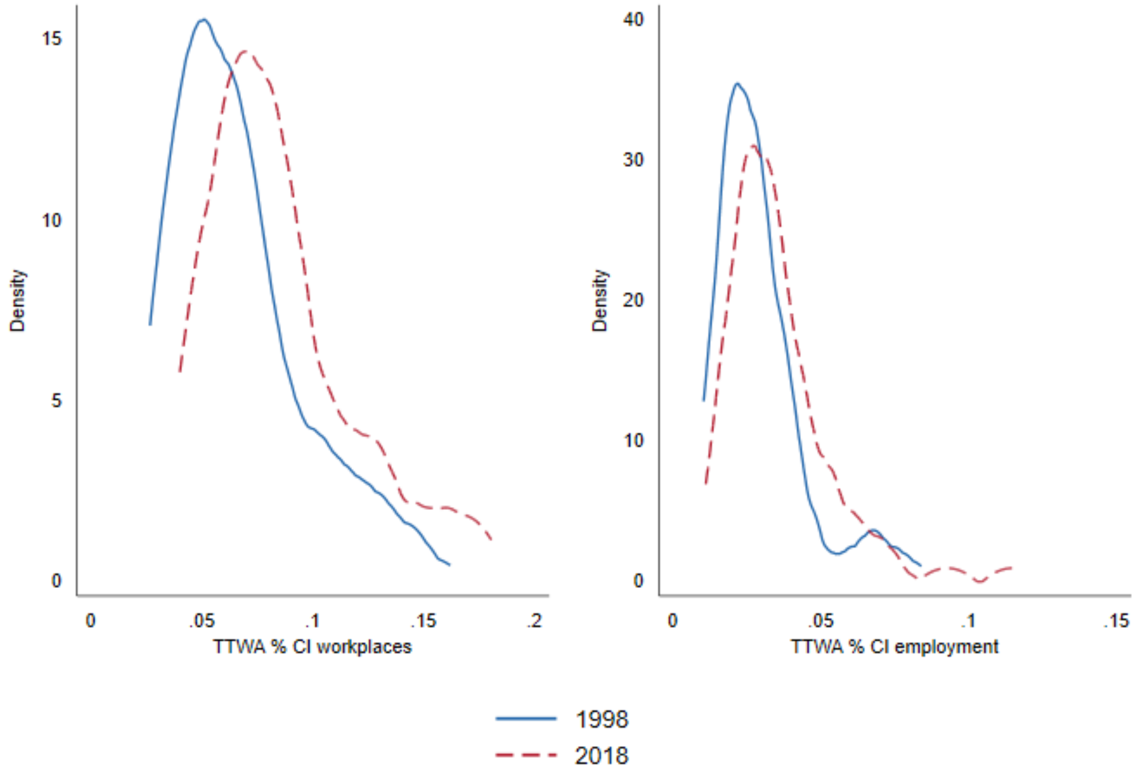
Figure 1. Change in creative vs. non-tradable jobs, urban TTWAs, 1998-2018.



Source: BSD. 78 urban TTWAs weighted by #workplaces.
Plot shows correlation between log change in non-tradable jobs (x-axis) and creative industries jobs (y-axis).
Creative industries and non-tradables defined as in Section 3.

Figure 2. Kernel density plot of % creative industries workplaces and employment, urban TTWAs, 1998 and 2018.

L: workplaces. R: jobs.



Source: BSD. Epanechnikov kernel for 78 urban TTWAs.
Plots show distribution of creative industries workplaces (left) and employment (right), as a share of all TTWA workplaces / employment.

Figure 3. Kernel density plot of creative industries workplaces and employment LQs, urban TTWAs, 1998 and 2018.

L: workplaces. R: jobs.

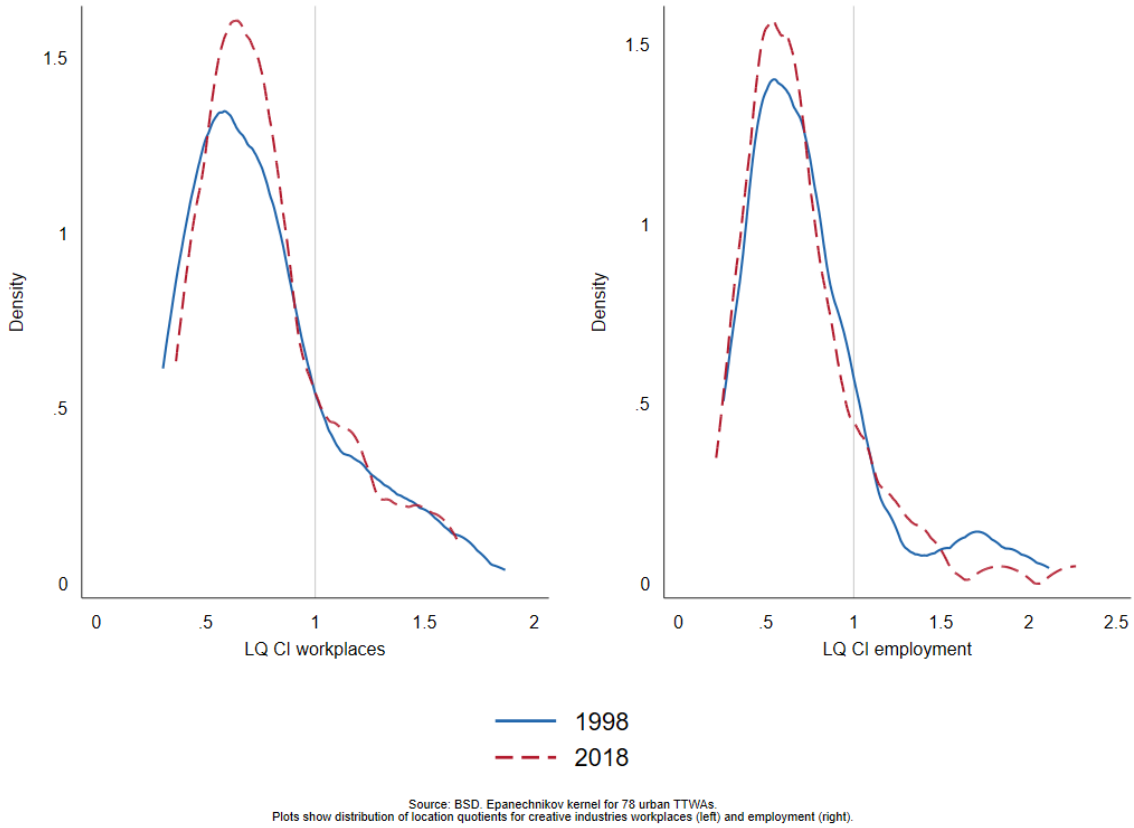
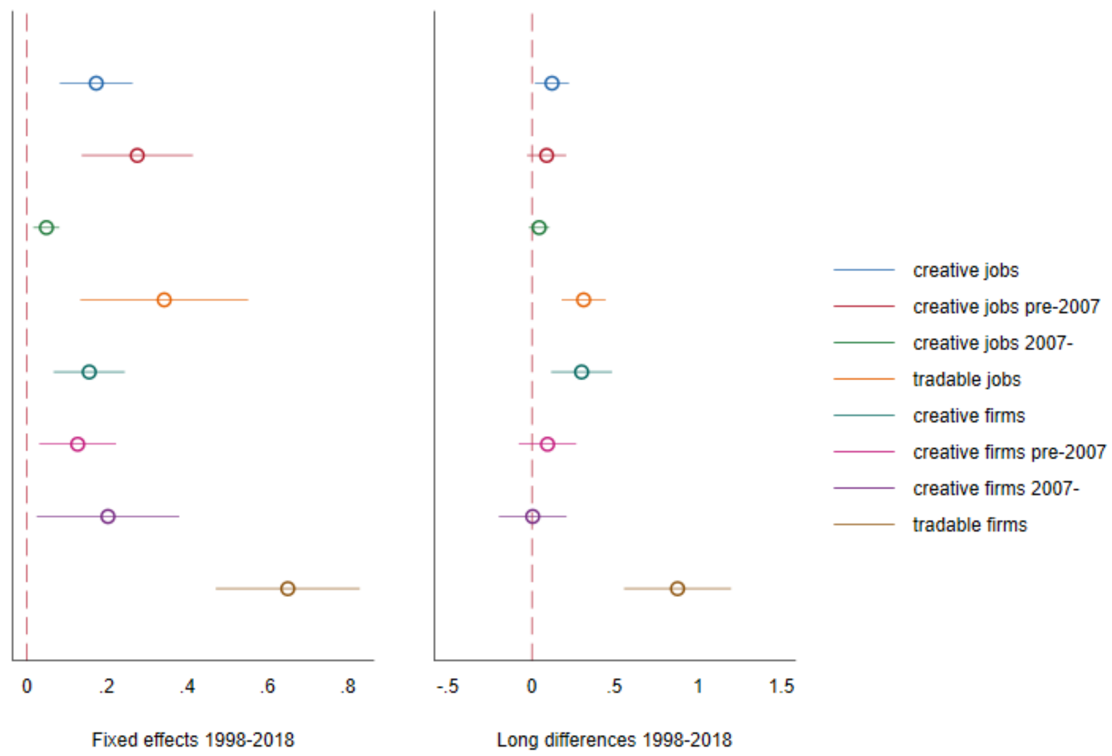
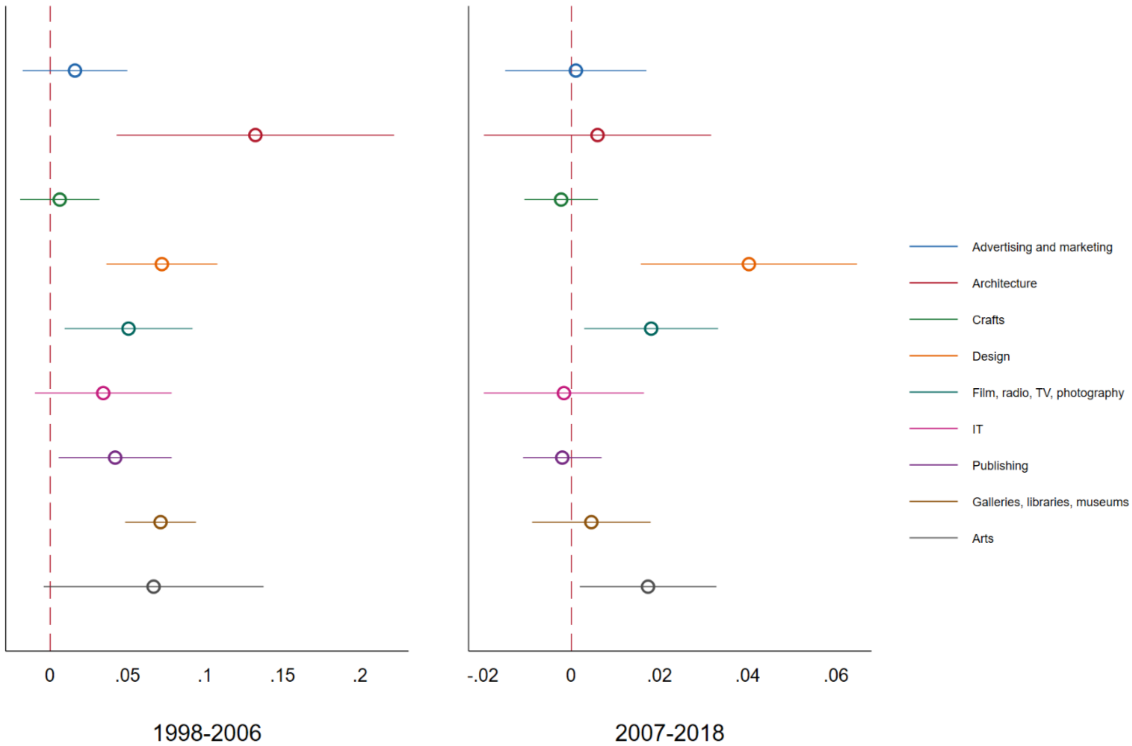


Figure 4. Plot of OLS regression of creative activity on non-tradable activity.



Source: BSD, LFS/APS, ONS. Travel To Work Area by year cells.
Each point shows OLS coefficient and 95% confidence interval. All models use TTWA dummies, plus controls from our main specification.

Figure 5. Plot of OLS regression of creative subgroup employment on non-tradables.



Source: BSD, LFS/APS, ONS. Travel To Work Area by year cells.
Each point shows OLS coefficient and 95% confidence interval for subgroup, controlling for the rest of the creative industries. All models use TTWA dummies, plus controls from our main specification.

CREATIVE CLUSTERS AND CREATIVE MULTIPLIERS:

EVIDENCE FROM UK CITIES

Online Appendices

Appendix A: Data and build

A1/ Panel build

Our main data source is firm-level microdata from the 10th edition of the Business Structure Database, hence BSD (ONS 2019) for England, Wales, Scotland and Northern Ireland. The BSD covers over 99% of all UK economic activity and provides high quality information for individual workplaces and their underlying enterprises, coded to 2011 Output Area (OA) level. There are over 170,000 OAs in England, over 10,000 in Wales and over 46,000 in Scotland.[12] Variables include workplace and enterprise location, industry, employment, turnover and entry/exit dates from multiple sources including company tax returns, VAT data (UK sales tax) and Companies House filings.

In the raw BSD data, firms enter the database conditional on having at least one employee and/or making at least £75,000 annual revenue (the threshold for VAT, the UK's sales tax). Firms leaving the raw data may either fall below those thresholds, returning later, or actually exit the market. Using routines developed in CEP, our cleaned data keeps live firms in each year, including those temporarily exit the dataset, imputing values in the latter case. The vast majority of firms have one workplace, so enterprise and firm-level figures are the same. For multi-workplace firms, we assign revenue shares based on workplaces' share of enterprise-level employment.

[12] https://webarchive.nationalarchives.gov.uk/20160107193025/http://www.ons.gov.uk/ons/guide-method/geography/beginner-s-guide/census/output-area--oas-/index.html; https://www.scotlandscensus.gov.uk/census-geographies; both accessed 24 August 2020.

We aggregate the data to 2011 Travel to Work Areas (TTWAs) using the 2016 ONS Postcode Directory, which provide the best approximation for spatial economies. From these, we focus our analysis on the 78/228 TTWAs that are classified as predominantly urban, containing a settlement with more than 125,000 inhabitants (following a typology by Gibbons et al. (2011)). We then add in control variables from the the Annual Population Survey, Labour Force Survey, ONS Mid-Year Population Estimates, GVA per head and Household Disposable Income datasets. Our resulting panel has 1716 TTWA*year observations for 22 years, 1997-2018 inclusive.

A2 / Defining creative industries over time

Given our panel timeframe, we use ONS crosswalks to create time-consistent SIC2003 4-digit codes for all sectors (from SIC2007 after 2007 and SIC1992 pre-2003). For precision, we build both unweighted and weighted measures of CCIs and other sectors, the latter using ONS aggregation weights. ONS crosswalks provide correspondence tables for workplace-level analysis plus weights for use in aggregate data. Unweighted variables use the correspondence table only, so that a given SIC07 code maps to all SIC03 codes in the crosswalk, regardless of fit quality. Where there is not a 1:1 match, this approach generates noise. It may generate bias if some SIC07 codes match systematically less well to SIC03 codes. Weighted variables use SIC03-07 aggregation weights, which are given separately for workplace counts, turnover and employment. For a given SIC03 code, we sum the weights for each instance of a SIC03-07 correspondence. As with Moretti (2010) and others, we remove agriculture, mining and quarrying, private household activity, and extra-terrestrial organisations from the analysis.

After classifying sectors consistently, we decompose industry space into tradable and non-tradable components. Tradable space includes creative industries, plus manufacturing and tradable services. Non-tradable space includes public sector activity and non-tradable services. To build this taxonomy, we use locational Gini Indexes in the fashion of Jensen et al. (2015), but rather than directly borrowing their original classification for the US, based on 1999 data, we calculate our own Gini measures based on 2018 BSD data. We do this partly because of changes in industrial organisation since 1999, and also because it is plausible that the US and UK have different industrial structures and geographies (see Kemeny et al. (2020) for an analysis along these lines for creative industries in the US and the UK).

Specifically, we build a TTWA*year panel where each cell gives the Gini for a 4-digit SIC03 industry bin in that year. The Gini for industry *j* across a set of *i* TTWAs in year *t* is:

$$G_{jt} = \Sigma_i [(\mathrm{E}_i / \mathrm{E}) - (\mathrm{E}_{ij} / \mathrm{E}_j)]^2 \qquad (1)$$

With E being the number of jobs, so the first element at the left-hand side of the equation would be the comparison between local and national employment as a whole, while the second one compares local sectoral jobs with national sectoral ones. Excluding agricultural activity, we classify 494 industry bins in 2018. Three Gini classes are created by dividing these bins into 3 roughly equal groups based on their Gini scores. Gini class 1 will have the lowest Gini score and will denote the least tradable sectors, class 2 will identify the sectors of intermediate tradability and class 3 the most tradable SIC03 industries.

To test the accuracy of the Gini score as a classifier, we use manufacturing industries as an example. We typically assume manufacturing activity is largely tradable: manufacturers can usually export their products in a way that (say) hairdressers cannot easily do. If the Gini is a plausible classifier for UK industries, it should place all or almost all of them in our 'tradable' categories. We find that more than 95% of manufacturing SIC03 codes fall within classes 2 and 3 (intermediate and most tradable) and consider this confirmation of the applicability of the Gini score as our classifier of industry tradability.

A3/ Shift-share instrument

As is common in the multipliers literature, we develop a shift-share / Bartik instrument which predicts creative industries employment or workplaces in a given city, by ascribing a share of UK-wide activity using historic local activity. Specifically, for TTWA *i* in year *t*, the IV is given by:

$$IV_{it} = CI_{it-1} * [(\Delta CI_t - \Delta CI_{t-1}) / CI_{t-1}] \qquad (2)$$

Where CI_{it-1} is creative industry employment (workplaces) in year t-1 in TTWA *i*, and $(\Delta CI_t - \Delta CI_{t-1}) / CI_{t-1}$ is the national growth rate in creative industry employment (workplaces), excluding the TTWA in question. Following Faggio and Overman (2014), we exclude TTWA *i* from the growth rate term to ensure that activity in any given TTWA does not influence national changes. Given that the creative industries are highly clustered in a few locations this is an important step. For both employment and workplaces, we fit this instrument in both the two-way fixed effects specification and in long differences.

Appendix B: Additional results

Table B1. Creative industries firms/workplaces and job counts. Top 20 TTWAs.

A. 1998-2018			**B. 1998**			**C. 2018**		
2011 TTWA	**firms**	**jobs**	**2011 TTWA**	**firms**	**jobs**	**2011 TTWA**	**firms**	**jobs**
London	56988	323538	London	45238	251080	London	87808	473429
Slough and Heathrow	10038	51994	Slough and Heathrow	8754	43160	Slough and Heathrow	15110	64117
Manchester	6795	36476	Manchester	5002	26413	Manchester	9944	52308
Guildford and Aldershot	4140	21235	Guildford and Aldershot	3965	17167	Birmingham	5990	32787
Birmingham	3829	23411	Birmingham	3323	22121	Reading	5457	36192
Reading	3787	23069	Luton	3252	12097	Guildford and Aldershot	5340	24964
Luton	3692	13914	Reading	2866	15137	Luton	4981	17757
Crawley	3079	13001	Crawley	2787	9862	Bristol	4468	23673
Cambridge	3008	15628	Cambridge	2636	12726	Crawley	4103	15087
Bristol	2935	15855	High Wycombe and Aylesbury	2516	9917	Cambridge	4073	21329
High Wycombe and Aylesbury	2641	11169	Oxford	2058	16241	Glasgow	3898	25006
Glasgow	2503	18266	Glasgow	1925	14399	Edinburgh	3669	18025
Oxford	2480	17462	Bristol	1726	9861	Milton Keynes	3474	12067
Edinburgh	2190	12670	Edinburgh	1571	8242	High Wycombe and Aylesbury	3375	13156
Southampton	2020	11232	Leeds	1571	12042	Leeds	3198	22288
Leeds	1976	14890	Leicester	1568	6629	Oxford	3140	20415
Leicester	1946	8024	Milton Keynes	1511	6871	Leicester	3042	10691
Milton Keynes	1921	8397	Nottingham	1477	7489	Southampton	2927	14642
Brighton	1877	6216	Tunbridge Wells	1468	4753	Brighton	2871	8779
Liverpool	1768	9026	Stevenage and Welwyn Garden City	1454	5181	Chelmsford	2437	8039

Source: BSD. Sorted by CI workplace counts.

Table B2. Creative industries firm/workplace and job shares. Top 20 TTWAs.

A. 1998-2018			B. 1998			C. 2018		
2011 TTWA	**% firms**	**% jobs**	**2011 TTWA**	**% firms**	**% jobs**	**2011 TTWA**	**% firms**	**% jobs**
Reading	0.155	0.089	Reading	0.162	0.084	Reading	0.18	0.115
London	0.148	0.082	Slough and Heathrow	0.141	0.063	Slough & Heathrow	0.166	0.074
Slough & Heathrow	0.146	0.072	London	0.136	0.071	Milton Keynes	0.166	0.056
Guildford & Aldershot	0.132	0.072	Guildford and Aldershot	0.135	0.068	London	0.163	0.093
Brighton	0.13	0.049	High Wycombe & Aylesbury	0.13	0.061	Brighton	0.158	0.057
High Wycombe & Aylesbury	0.129	0.067	Luton	0.12	0.043	Guildford & Aldershot	0.144	0.069
Luton	0.127	0.047	Milton Keynes	0.117	0.052	High Wycombe & Aylesbury	0.141	0.063
Milton Keynes	0.125	0.053	Stevenage & Welwyn Garden City	0.113	0.037	Luton	0.132	0.046
Stevenage & Welwyn Garden City	0.111	0.042	Tunbridge Wells	0.107	0.045	Tunbridge Wells	0.129	0.047
Tunbridge Wells	0.11	0.048	Crawley	0.107	0.04	Edinburgh	0.127	0.047
Oxford	0.109	0.072	Oxford	0.103	0.075	Stevenage & Welwyn Garden City	0.125	0.039
Crawley	0.107	0.047	Brighton	0.101	0.035	Crawley	0.12	0.046
Swindon	0.102	0.037	Cambridge	0.098	0.046	Oxford	0.118	0.068
Cambridge	0.101	0.052	Swindon	0.096	0.032	Cheltenham	0.117	0.055
Bristol	0.097	0.043	Cheltenham	0.09	0.041	Bristol	0.117	0.052
Cheltenham	0.096	0.049	Bedford	0.088	0.033	Swindon	0.116	0.037
Edinburgh	0.094	0.039	Bristol	0.086	0.041	Cambridge	0.111	0.058
Bedford	0.09	0.031	Southampton	0.082	0.035	Worthing	0.101	0.031
Worthing	0.084	0.039	Chelmsford	0.081	0.034	Bedford	0.099	0.032
Chelmsford	0.083	0.033	Ipswich	0.077	0.026	Chelmsford	0.099	0.038

Source: BSD. Cells give TTWA creative industries plants or jobs as a share of all TTWA plants or jobs. Sorted by CI plant shares.

Table B3. Creative industries firm/workplace and job LQs. Top 20 TTWAs.

A. 1998-2018			B. 1998			C. 2018		
2011 TTWA	LQ firms	LQ jobs	2011 TTWA	LQ firms	LQ jobs	2011 TTWA	LQ firms	LQ jobs
Reading	1.632	1.978	Reading	1.867	2.115	Reading	1.646	2.269
London	1.557	1.819	Slough & Heathrow	1.621	1.597	Slough & Heathrow	1.516	1.456
Slough and Heathrow	1.533	1.598	London	1.563	1.797	Milton Keynes	1.513	1.104
Guildford & Aldershot	1.393	1.612	Guildford & Aldershot	1.554	1.709	London	1.486	1.833
High Wycombe & Aylesbury	1.364	1.494	High Wycombe & Aylesbury	1.495	1.541	Brighton	1.447	1.13
Brighton	1.359	1.089	Luton	1.388	1.075	Guildford & Aldershot	1.317	1.374
Luton	1.343	1.051	Milton Keynes	1.344	1.302	High Wycombe & Aylesbury	1.286	1.24
Milton Keynes	1.304	1.171	Stevenage & Welwyn Garden City	1.301	0.933	Luton	1.207	0.907
Stevenage & Welwyn Garden City	1.174	0.937	Tunbridge Wells	1.234	1.138	Tunbridge Wells	1.174	0.938
Tunbridge Wells	1.154	1.063	Crawley	1.232	1.021	Edinburgh	1.156	0.93
Oxford	1.146	1.601	Oxford	1.184	1.882	Stevenage & Welwyn Garden City	1.142	0.779
Crawley	1.133	1.041	Brighton	1.161	0.886	Crawley	1.098	0.907
Swindon	1.069	0.816	Cambridge	1.128	1.171	Oxford	1.075	1.342
Cambridge	1.066	1.167	Swindon	1.106	0.82	Cheltenham	1.07	1.088
Bristol	1.021	0.963	Cheltenham	1.037	1.038	Bristol	1.064	1.025
Cheltenham	1.009	1.083	Bedford	1.016	0.824	Swindon	1.058	0.729
Edinburgh	0.98	0.862	Bristol	0.991	1.023	Cambridge	1.009	1.151
Bedford	0.943	0.691	Southampton	0.947	0.891	Worthing	0.921	0.61
Worthing	0.879	0.881	Chelmsford	0.931	0.86	Bedford	0.904	0.637
Chelmsford	0.878	0.732	Ipswich	0.885	0.663	Chelmsford	0.901	0.751

Source: BSD. Cells give location quotients for creative industries workplaces or jobs. Sorted by CI workplace LQs.

Table B4. OLS regression of creative and non-tradable jobs. Two-way fixed effects 1998-2018.

Depvar = non-tradables jobs	**(1)** base	**(2)** controls	**(3)** pre-07	**(4)** post-07	**(5)** tradables
Log creative industries jobs	0.16***	0.17***	0.27***	0.05***	
	(0.041)	(0.045)	(0.069)	(0.016)	
Log other tradables jobs	0.25***	0.24***	0.42***	-0.01	
	(0.064)	(0.073)	(0.1)	(0.036)	
Lag share of graduates in population (residence basis)		0.00	-0.01	0.05**	-0.01
		(0.007)	(0.007)	(0.02)	(0.008)
Lag population density (population / square kilometres)		0.00	0.00	-0.00**	0.00
		(0.000)	(0.000)	(0.000)	(0.000)
Lag share of population aged 16-24		-0.18**	-0.21***	-0.15	-0.13
		(0.082)	(0.058)	(0.151)	(0.1)
Lag share ILO unemployed in workforce (residence basis)		0	-0.15*	-0.04*	-0.02
		(0.02)	(0.077)	(0.021)	(0.023)
Log tradable jobs					0.34***
					(0.105)
Jobs multiplier for creative industries - Moretti		2.979	4.746	0.835	
Jobs multiplier for creative industries - Van Dijk		2.844	4.526	0.798	
Jobs multiplier for tradable industries - Moretti					1.004
Jobs multiplier for tradable industries - Van Dijk					0.996
Observations	1638	1560	624	936	1560
Overall R^2	0.93	0.83	0.83	0.09	0.8

Source: BSD, LFS/APS, ONS. Travel to Work Area (TTWA)-by-year cells. Standard errors in parentheses, clustered on TTWA. * 10%, ** 5%, *** 1% significance.

Table B5. OLS regression of Creative Industries and non-tradables (workplaces). Two-way fixed effects 1998-2018.

Depvar = non-tradables workplaces	**(1)** base	**(2)** controls	**(3)** pre-07	**(4)** post-07	**(5)** tradables
Log creative industries workplaces	0.15***	0.15***	0.13**	0.20**	
	(0.043)	(0.044)	(0.048)	(0.089)	
Log other tradables workplaces	0.56***	0.52***	0.69***	0.34***	
	(0.075)	(0.081)	(0.087)	(0.127)	
Lag share of graduates in population		-0.00	0.00	0.02	-0.00
(residence basis)		(0.004)	(0.002)	(0.023)	(0.004)
Lag population density		0.00	-0.00	-0.00	0.00
(square kilometres)		(0.000)	(0.000)	(0.000)	(0.000)
Lag share of population aged 16-24		-0.11***	-0.12***	-0.16	-0.12***
		(0.031)	(0.043)	(0.124)	(0.032)
Lag share ILO unemployed in workforce		0.04	0.09**	-0.01	0.04
(residence basis)		(0.027)	(0.040)	(0.021)	(0.028)
Log tradable workplaces					0.65***
					(0.090)
Workplaces multiplier - Moretti		1.281	1.043	1.665	
Workplaces multiplier - Van Dijk		1.158	1.027	1.429	
Workplaces multiplier - Moretti					1.712
Workplaces multiplier - Van Dijk					1.632
Observations	1638	1560	624	936	1560
Overall R^2	0.97	0.96	0.97	0.91	0.96

Source: BSD, LFS/APS, ONS. Travel to Work Area (TTWA)-by-year cells. Standard errors in parentheses, clustered on TTWA. * 10%, ** 5%, *** 1% significance.

Table B6. OLS regression of creative and non-tradable jobs. Long difference 1998/2018.

Depvar = non-tradables jobs	**(1)** base	**(2)** controls	**(3)** pre-07	**(4)** post-07	**(5)** tradables
Log creative industries jobs	0.09*	0.12**	0.09	0.04	
	(0.048)	(0.051)	(0.059)	(0.031)	
Log other tradables jobs	0.26***	0.25***	0.32***	-0.02	
	(0.065)	(0.066)	(0.090)	(0.080)	
Lag share of graduates in population (residence basis)		-0.01	0.00	0.04	-0.01
		(0.025)	(0.030)	(0.048)	(0.027)
Lag population density (population / square kilometres)		0.00	-0.00	-0.00	0.00
		(0.000)	(0.000)	(0.000)	(0.000)
Lag share of population aged 16-24		-0.32**	0.02	-0.50	-0.18
		(0.140)	(0.132)	(0.440)	(0.138)
Lag share ILO unemployed in workforce (residence basis)		0.18	0.09	-0.08	0.17
		(0.124)	(0.112)	(0.240)	(0.125)
Log tradable jobs					0.31***
					(0.067)
Jobs multiplier for creative industries - Moretti		2.096	1.537	0.760	
Jobs multiplier for creative industries - Van Dijk		2.126	1.559	0.760	
Jobs multiplier for tradable industries - Moretti					0.915
Jobs multiplier for tradable industries - Van Dijk					0.709
Observations	156	156	156	156	156
Overall R^2	0.87	0.86	0.94	0.25	0.82

Source: BSD, LFS/APS, ONS. Travel to Work Area (TTWA)-by-year cells. Standard errors in parentheses, clustered on TTWA. * 10%, ** 5%, *** 1% significance.

Table B7. OLS regression of Creative Industries and non-tradables (workplaces). Long difference 1998/2018.

Depvar = non-tradables workplaces	**(1)** base	**(2)** controls	**(3)** pre-07	**(4)** post-07	**(5)** tradables
Log creative industries workplaces	0.22**	0.30***	0.09	0.00	
	(0.087)	(0.092)	(0.087)	(0.102)	
Log other tradables workplaces	0.69***	0.65***	0.66***	0.55***	
	(0.130)	(0.140)	(0.085)	(0.201)	
Lag share of graduates in population (residence basis)		0.01	0.00	0.02	0.00
		(0.031)	(0.029)	(0.060)	(0.032)
Lag population density (population / square kilometres)		0.00	0.00	-0.00	0.00
		(0.000)	(0.000)	(0.000)	(0.000)
Lag share of population aged 16-24		-0.21	-0.03	-0.81**	-0.15
		(0.145)	(0.115)	(0.366)	(0.150)
Lag share ILO unemployed in workforce (residence basis)		0.25**	0.27***	0.36*	0.23*
		(0.123)	(0.091)	(0.211)	(0.129)
Log tradable workplaces					0.88***
					(0.162)
Workplaces multiplier - Moretti		2.473	0.779	0.041	
Workplaces multiplier - Van Dijk		2.516	0.793	0.041	
Workplaces multiplier - Moretti					2.312
Workplaces multiplier - Van Dijk					2.365
Observations	156	156	156	156	156
Overall R^2	0.96	0.96	0.92	0.38	0.95

Source: BSD, LFS/APS, ONS. Travel to Work Area (TTWA)-by-year cells. Standard errors in parentheses, clustered on TTWA. * 10%, ** 5%, *** 1% significance.

Table B8. Robustness checks for fixed effects specification, 1998-2018.

Panel A.	**(1) 1998-2006**	**(2) 2007-2018**	**(3) 1997-2007**	**(4) 2008-2018**	**(5) 2012-2018**
Log creative jobs	0.27***	0.05***	0.26***	0.05***	0.07**
	(0.069)	(0.016)	(0.067)	(0.018)	(0.027)
Observations	624	936	702	858	546
Overall R^2	0.73	0.73	0.76	0.74	0.78
Panel B.	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Log creative jobs	0.17***	0.17***	0.18***	0.17***	0.17***
	(0.045)	(0.047)	(0.047)	(0.045)	(0.045)
Observations	1560	1482	1482	1560	1560
Overall R^2	0.82	0.81	0.81	0.82	0.82
Panel C.	**(1) 1998-2006**	**(2) 2007-2018**	**(3) 1997-2007**	**(4) 2008-2018**	**(5) 2012-2018**
Log creative workplaces	0.13**	0.20**	0.14**	0.23**	0.24*
	(0.048)	(0.089)	(0.054)	(0.104)	(0.128)
Observations	624	936	702	858	546
Overall R^2	0.85	0.81	0.86	0.83	0.88
Panel D.	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Log creative workplaces	0.15***	0.17***	0.16***	0.15***	0.15***
	(0.044)	(0.044)	(0.044)	(0.044)	(0.045)
Observations	1560	1482	1482	1560	1560
Overall R^2	0.84	0.82	0.82	0.84	0.84

Source: BSD, LFS/APS, ONS. Travel to Work Area (TTWA)-by-year cells. Constant not reported. All models use TTWA and year dummies. Standard errors in parentheses, clustered on TTWA. * 10%, ** 5%, *** 1% significance. In Panels A and C, we report alternative time splits. Columns 1 and 2 use the original time split (1997-2006 and 2007-2018). Columns 3 and 4 give splits for 1997-2007 and 2008-2018, varying the start of the Great Financial Crisis. Column 5 covers the post-crisis period, 2012-2018. In Panels B and D we report alternative control vectors. Column 1 is our original specification; column 2 fits the shares of the population in different age groups, the household disposable income per head and the gross value added per head; column 3 the share of the working-age population, the household disposable income per head and the gross value added per head; column 4, population density (square kilometres) and revenue per worker; column 5, the share of graduates in the workforce, the population density, the share of the population aged 16-64, and the share of ILO unemployment.

Table B9. Robustness checks for long difference specification, 1998/2018.

Panel A.	**(1) 1998-2006**	**(2) 2007-2018**	**(3) 1997-2007**	**(4) 2008-2018**	**(5) 2012-2018**
Log creative jobs	0.09 (0.059)	0.04 (0.031)	0.09* (0.049)	0.08** (0.030)	0.03 (0.026)
Observations Overall R^2	156 0.85	156 0.87	156 0.86	156 0.85	156 0.86
Panel B.	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Log creative jobs	0.12** (0.051)	0.32*** (0.079)	0.34*** (0.085)	0.10** (0.043)	0.12** (0.052)
Observations Overall R^2	156 0.94	156 0.92	156 0.91	156 0.94	156 0.94
Panel C.	**(1) 1998-2006**	**(2) 2007-2018**	**(3) 1997-2007**	**(4) 2008-2018**	**(5) 2012-2018**
Log creative workplaces	0.09 (0.087)	0.00 (0.102)	0.20** (0.095)	0.09 (0.173)	0.04 (0.121)
Observations Overall R^2	156 0.87	156 0.79	156 0.82	156 0.87	156 0.90
Panel D.	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Log creative workplaces	0.30*** (0.092)	0.23** (0.087)	0.22** (0.089)	0.22** (0.089)	0.30*** (0.089)
Observations Overall R^2	156 0.91	156 0.91	156 0.89	156 0.90	156 0.91

Source: BSD, LFS/APS, ONS. Travel to Work Area (TTWA)-by-year cells. Constant not reported. All models use TTWA and year dummies. Standard errors in parentheses, clustered on TTWA. * 10%, ** 5%, *** 1% significance. In Panels A and C, we report alternative time splits. Columns 1 and 2 use the original time split (1997-2006 and 2007-2018). Columns 3 and 4 give splits for 1997-2007 and 2008-2018, varying the start of the Great Financial Crisis. Column 5 covers the post-crisis period, 2012-2018. In Panels B and D we report alternative control vectors. Years are as above except where stated Column 1 is our original specification; column 2 fits the shares of the population in different age groups, the household disposable income per head and the gross value added per head, 1999-2016; column 3 the share of the working-age population, the household disposable income per head and the gross value added per head, 1999-2016; column 4, population density (square kilometres) and revenue per worker; column 5, the share of graduates in the workforce, the population density, the share of the population aged 16-64, and the share of ILO unemployment.

Table B10. Robustness checks: first differences estimator.

Panel A. Jobs	**(1) main**	**(2)**	**(3)**	**(4) pre-07**	**(5) post-07**
Log creative industries jobs	0.17*** (0.045)	0.22*** (0.063)	0.18*** (0.047)	0.28*** (0.068)	0.05*** (0.016)
Log other tradables jobs	0.24*** (0.073)	0.42*** (0.112)	0.39*** (0.116)	0.50*** (0.130)	-0.03 (0.031)
Observations	1560	1560	1482	546	936
Overall R^2	0.82	0.46	0.40	0.50	0.27
Panel B. Workplaces	**(1) main**	**(2)**	**(3)**	**(4) pre-07**	**(5) post-07**
Log creative industries workplaces	0.15*** (0.044)	0.23*** (0.052)	0.23*** (0.055)	0.20*** (0.041)	0.32*** (0.097)
Log other tradables workplaces	0.52*** (0.081)	0.74*** (0.074)	0.72*** (0.086)	0.82*** (0.079)	0.17* (0.096)
Observations	1560	1560	1482	546	936
Overall R^2	0.84	0.85	0.82	0.89	0.76

Source: BSD, LFS/APS, ONS. Travel to Work Area (TTWA)-by-year cells. Constant not reported. Standard errors in parentheses, clustered on TTWA. * 10%, ** 5%, *** 1% significance. Column 1 fits the FE coefficient. Column 2 fits FD with only creative industries activity and other tradables. Column 3 adds in controls from our main specification. Columns 4 and 5 fit pre-crisis and post-crisis periods.

Table B11. Robustness checks: alternative long difference estimator.

Panel A. Jobs	**(1) main**	**(2)**
Log creative industries jobs	0.12** (0.051)	0.09* (0.048)
Log other tradables jobs	0.25*** (0.066)	0.25*** (0.069)
Observations	156	78
Overall R^2	0.94	0.39
Panel B. Workplaces	**(1) main**	**(2)**
Log creative industries plants	0.30*** (0.092)	0.26*** (0.084)
Log other tradables plants	0.65*** (0.140)	0.65*** (0.151)
Observations	156	78
Overall R^2	0.91	0.72

Source: BSD, LFS/APS, ONS. Travel to Work Area (TTWA)-by-year cells. Constant not reported. Standard errors in parentheses, clustered on TTWA. * 10%, ** 5%, *** 1% significance. Column fits original long differences model. Column 2 runs a growth rate specification, with controls only in the initial period.

Table B12. Robustness check with lagged independent variables.

Log non-tradable activity	**A. Employment**		**B. Workplaces**	
	(1)	**(2)**	**(1)**	**(2)**
Log creative industries jobs	0.17***	0.09***		
	(0.045)	(0.025)		
Log other tradable jobs	0.24***	0.04		
	(0.073)	(0.036)		
Log creative industries firms			0.15***	0.07*
			(0.044)	(0.036)
Log other tradable firms			0.52***	0.27***
			(0.081)	(0.073)
L.% graduates in population residence basis	-0.00	-0.00	-0.00	-0.00
	(0.007)	(0.006)	(0.004)	(0.004)
L.population density (square kilometres)	-0.00	-0.00	0.00	0.00**
	(0.000)	(0.000)	(0.000)	(0.000)
L.% population aged 16-24	-0.18**	-0.16*	-0.11***	-0.10***
	(0.082)	(0.081)	(0.031)	(0.035)
L.% ILO unemployed in workforce residence basis	-0.00	-0.01	0.04	0.01
	(0.020)	(0.023)	(0.027)	(0.016)
Observations	1560	1560	1560	1560
R^2	0.83	0.31	0.96	0.94

Source: BSD, LFS/APS, ONS. Travel to Work Area (TTWA)-by-year cells. Constant not reported. Standard errors in parentheses, clustered on TTWA. * 10%, ** 5%, *** 1% significance. Columns (1) and (3) show unlagged variables of creative and other tradable activity. Columns (2) and (4) use one-period lags.

Table B13. Pooled OLS and IV regressions of creative and non-tradable jobs. Fixed effects estimator 1998-2018.

	OLS		IV			
	(1)	(2)	(3)	(4)	(5)	(6)
Log creative industries jobs	0.17***	0.26***	0.29***	0.36***	0.25***	
	(0.041)	(0.037)	(0.076)	(0.073)	(0.082)	
Log other tradable jobs	0.25***	0.59***	0.57***	0.50***	0.61***	
	(0.065)	(0.039)	(0.075)	(0.070)	(0.082)	
Log tradable jobs						0.17
						(0.352)
log TTWA-coalfield distance			*0.24****	*0.25****	*0.22****	
			(0.060)	*(0.064)*	*(0.057)*	
TTWA frequency of art schools			*0.16**	*0.18**	*0.15**	
			(0.085)	*(0.093)*	*(0.076)*	
Log Bartik tradable employment						*0.67**
						(0.340)
Observations	1638	1638	1638	702	936	1638
R^2	0.82	0.96	0.96	0.96	0.96	0.72
Kleibergen-Paap Weak instrument F			9.34	9.36	8.17	3.84
Montiel Olea-Pflueger Effective F			8.26	7.65	8.70	3.84
Anderson-Rubin confidence set			[0.058, 0.506]	[0.119, 0.560]	[-0.002, 0.472]	[.,0.552]
Multiplier - Van Dijk		4.649	[1.024, 8.872]	[2.088, 9.837]	[-0.029, 8.167]	[.,1.257]

Source: BSD, LFS/APS, ONS. Travel to Work Area (TTWA)-by-year cells. All models use controls as in our main specification. Standard errors in parentheses, clustered on TTWA. * 10%, ** 5%, *** 1% significance. Confidence sets are confidence intervals around point estimates for creative industries jobs, except for column 6 where they are produced for tradable jobs.

Table B14. Pooled OLS and IV regressions of creative and non-tradable workplaces. Fixed effects estimator 1998-2018.

	(1)	(2)	(3)	(4)	(5)	(6)
Log creative industries firms	0.16***	-0.05	-0.02	0.04	-0.05	
	(0.044)	(0.046)	(0.112)	(0.088)	(0.141)	
Log other tradable firms	0.55***	0.96***	0.93***	0.85***	0.97***	
	(0.077)	(0.067)	(0.133)	(0.104)	(0.166)	
Log tradable firms						0.04
						(0.390)
log TTWA-coalfield distance			*0.12****	*0.14****	*0.10****	
			(0.039)	*(0.044)*	*(0.035)*	
TTWA frequency of art schools			*0.02*	*0.01*	*0.02*	
			(0.061)	*(0.067)*	*(0.053)*	
Log Bartik tradable plant						*0.57***
						(0.258)
Observations	1638	1638	1638	702	936	1638
R^2	0.84	0.97	0.97	0.97	0.98	0.65
Kleibergen-Paap Weak instrument F			4.78	5.09	4.43	4.84
Montiel Olea-Pflueger Effective F			5.27	5.72	4.93	4.84
Anderson-Rubin confidence set			[0.347, 0.400]	[0.237, 0.305]	[0.487, 0.498]	[.,0.459]
Multiplier - Van Dijk		-0.395	[2.923, 3.365]	[1.998, 2.570]	[4.030, 4.121]	[.,1.240]

Source: BSD, LFS/APS, ONS. Travel to Work Area (TTWA)-by-year cells. All models use controls as in our main specification. Standard errors in parentheses, clustered on TTWA. * 10%, ** 5%, *** 1% significance. Confidence sets are confidence intervals around point estimates for creative industries workplaces, except for column 6 where they are produced for tradable workplaces.

Table B15. IV regressions of creative and non-traded employment. Specification checks, long differences estimator 1998/2018.

	OLS	**Main**	**Bartik**	**M2**	**M3**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Log creative industries jobs	0.12**	0.36***	0.14	0.39**	0.73***
	(0.051)	(0.081)	(0.087)	(0.165)	(0.260)
Log other tradable jobs	0.25***	0.53***	0.74***	0.54***	0.41***
	(0.066)	(0.074)	(0.090)	(0.079)	(0.135)
Log Bartik creative employment			*0.31****		
			(0.090)		
log TTWA-coalfield distance		*0.24****		*-0.20****	*-0.11***
		(0.061)		*(0.050)*	*(0.049)*
TTWA frequency of art schools		*0.19***		*-0.01*	*0.05*
		(0.093)		*(0.135)*	*(0.129)*
Log Bartik other tradable jobs					*0.88****
					(0.282)
Observations	156	156	156	156	156
R^2	0.94	0.96	0.95	0.96	0.89
Kleibergen-Paap F-statistic		9.52	11.90	0.48	0.89
Montiel Olea-Pflueger Effective F		7.47	11.90		
Anderson-Rubin confidence set		[0.112, 0.620]			
Multiplier - Van Dijk	2.126	[1.961, 10.888]	2.379		

Source: BSD, LFS/APS, ONS. Travel to Work Area (TTWA)-by-year cells. All models use controls as in our main specification. Standard errors in parentheses, clustered on TTWA. * 10%, ** 5%, *** 1% significance. Column 1 fits OLS. Column 2 is our main IV specification, Column 3 fits a leave-one-out Bartik instrument, Columns 4 and 5 instrument for both creative and other tradable jobs. Confidence sets are confidence intervals around point estimates for creative industries jobs. For columns 4 and 5, confidence sets are given as a three-dimensional space covering both endogenous variables. Results available on request.

Table B16. IV regressions of creative and non-traded workplaces. Specification checks, long differences estimator 1998/2018.

	OLS	Main	Bartik	M2	M3
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Log creative industries firms	0.30***	0.06	-0.22***	0.31	-0.58
	(0.092)	(0.105)	(0.061)	(1.198)	(1.040)
Log other tradable firms	0.65***	0.85***	1.18***	1.06	0.33
	(0.140)	(0.122)	(0.096)	(1.031)	(0.949)
Log Bartik creative workplaces			*0.65****		
			(0.047)		
Log TTWA-coalfield distance		*0.13****		*-0.06*	*-0.07*
		(0.045)		*(0.054)*	*(0.054)*
TTWA frequency of art schools		*0.03*		*0.02*	*0.03*
		(0.064)		*(0.133)*	*(0.134)*
Log Bartik other tradable firms					*0.30*
					(0.539)
Observations	156	156	156	156	156
R^2	0.91	0.97	0.97	0.85	0.27
Kleibergen-Paap F-statistic		4.22	189.97	0.03	0.15
Montiel Olea-Pflueger Effective F		4.98	190.0		
Anderson-Rubin confidence set		[0.209, 0.553]			
Multiplier - Van Dijk	2.516	[1.761, 4.657]	-1.887		

Source: BSD, LFS/APS, ONS. Travel to Work Area (TTWA)-by-year cells. All models use controls as in our main specification. Standard errors in parentheses, clustered on TTWA. * 10%, ** 5%, *** 1% significance. Column 1 fits OLS. Column 2 is our main IV specification, Column 3 fits a leave-one-out Bartik instrument, Columns 4 and 5 instrument for both creative and other tradable workplaces. Confidence sets are confidence intervals around point estimates for creative industries workplaces. For columns 4 and 5, confidence sets are given as a three-dimensional space covering both endogenous variables. Results available on request.

Table B17. OLS regression of creative industries subgroup jobs on non-tradable jobs. Fixed effects estimator.

Panel A. 1998-2006	**(1) AM**	**(2) ARCH**	**(3) CRAFTS**	**(4) DES**	**(5) FILM**	**(6) IT**	**(7) PUB**	**(8) LIB**	**(9) ARTS**
Log creative industries subgroup	0.02	0.13***	0.01	0.07***	0.05**	0.03	0.04**	0.07***	0.07*
	(0.017)	(0.045)	(0.013)	(0.018)	(0.021)	(0.022)	(0.018)	(0.011)	(0.036)
Log other creative industries	0.27***	0.22***	0.18***	0.24***	0.24***	0.28***	0.24***	0.18***	0.23***
	(0.064)	(0.059)	(0.039)	(0.067)	(0.059)	(0.052)	(0.056)	(0.054)	(0.063)
Multiplier for subgroup - Moretti	2.507	44.091	17.631	26.023	5.683	1.845	4.808	20.185	12.142
Multiplier for subgroup - Van Dijk	2.267	43.589	11.894	29.888	5.479	1.836	4.280	19.879	10.690
Observations	624	624	584	624	624	624	624	618	624
R^2	0.81	0.86	0.72	0.90	0.85	0.89	0.83	0.78	0.86
Panel B. 2007-2018	**(1) AM**	**(2) ARCH**	**(3) CRAFTS**	**(4) DES**	**(5) FILM**	**(6) IT**	**(7) PUB**	**(8) LIB**	**(9) ARTS**
Log creative industries subgroup	0.00	0.01	-0.00	0.04***	0.02**	-0.00	-0.00	0.00	0.02**
	(0.008)	(0.013)	(0.004)	(0.012)	(0.008)	(0.009)	(0.004)	(0.007)	(0.008)
Log other creative industries	0.05***	0.04***	0.05***	0.03**	0.04***	0.05***	0.05***	0.04**	0.04***
	(0.015)	(0.016)	(0.017)	(0.013)	(0.016)	(0.016)	(0.017)	(0.016)	(0.015)
Multiplier for subgroup - Moretti	0.161	1.978	-6.565	14.526	2.033	-0.090	-0.234	1.287	3.161
Multiplier for subgroup - Van Dijk	0.145	1.855	-8.312	15.232	2.147	-0.073	-0.282	1.559	3.069
Observations	936	936	835	936	936	936	936	936	936
R^2	0.08	0.08	0.18	0.02	0.04	0.11	0.08	0.10	0.09

Source: BSD, LFS/APS, ONS. Travel to Work Area (TTWA)-by-year cells. Constant not reported. All models use TTWA and year dummies, plus controls from our main specification. Standard errors in parentheses, clustered on TTWA. * 10%, ** 5%, *** 1% significance. AM = advertising and marketing, ARCH = architecture, CRAFTS = crafts, DES = design, FILM = film radio and TV, IT = information technology, PUB = publishing, LIB = libraries and museums, ARTS = visual and other arts.