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Discussion Paper 2021/07

Do creative industries generate multiplier effects? Evidence from UK cities, 1997-2018

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July, 2021

City-REDI, the University of Birmingham; University College London

ISBN: 978-1-913095-42-0

Supported by

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Abstract

The creative industries have received much attention from economic geographers and others, both for their propensity to co-locate 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 creative industries on surrounding urban economies. Adapting Moretti's local multipliers framework, we build a new 20-year panel of UK cities, using fixed effects and a historic instrument to identify effects on non-creative firms and employment.

We find that each creative job generate at least 1.9 non-tradable jobs between 1998 and 2018: this is associated with creative business services employees' local spending, rather than visitors to urban amenities such as galleries and museums. We do not find the same effects for workplaces, and find no causal evidence for spillovers from creative activity to other tradable sectors, findings consistent with descriptive evidence on the increasing concentration of creative industries in a small number of cities. Given the small numbers of creative jobs in most cities, however, the overall effect size of the creative multiplier is small, and shapes only a small part of non-tradable urban employment change. Overall, our results suggest creative economy-led policies for cities can have positive – albeit partial – local economic impacts.

Key Words: Creative industries; local multipliers; cities; economic development

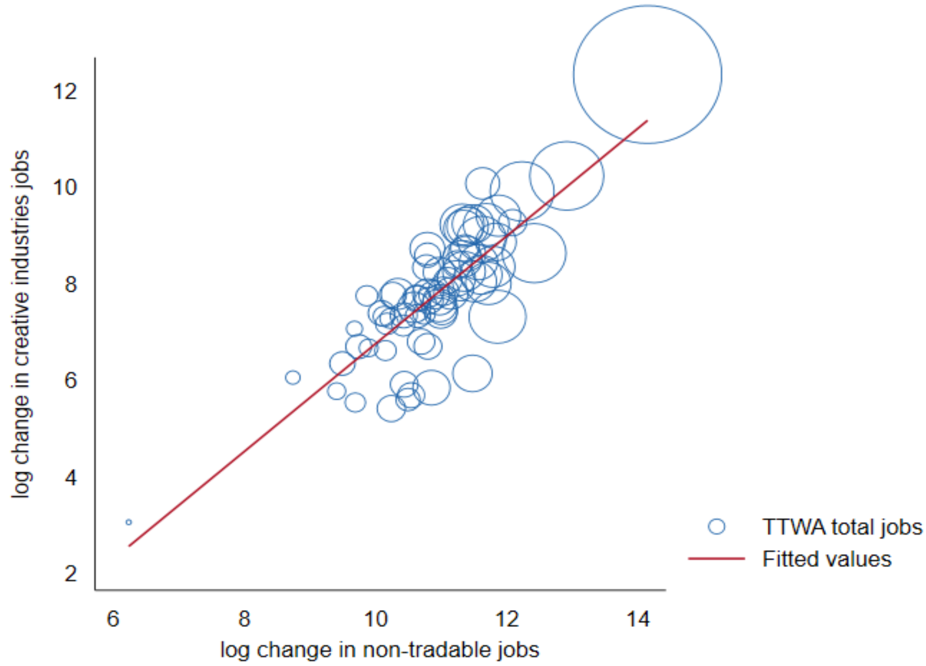
Introduction

Urban scholars and policymakers have extensively studied the creative and cultural industries (Scott 1988, Zukin 1995, Hall 1998, Throsby 2001, Florida 2005, Cooke and Lazzeretti 2008, Hutton 2008, Mould 2015, Van Damme, De Munck et al. 2017). The common thread running through these studies is that 'creative industries' are both urbanised and highly clustered in a few locations (Bloom, Camerani et al. 2020). In the UK, for example, over half (53%) of creative industries jobs and 44% of firms are found in just five cities (Mateos-Garcia, Klinger et al. 2018), and there is evidence that this concentration is increasing over time (Tether 2019).

There is a large academic literature describing these urbanisation patterns across countries (Lazzeretti, Boix et al. 2008, de Vaan, Boschma et al. 2013, Boix, Capone et al. 2014, Kemeny, Nathan et al. 2020), within countries (Bertacchini and Borrione 2013, Alfken, Broekel et al. 2015, Nuccio and Ponzini 2017, Mateos-Garcia, Klinger et al. 2018, Tao, Ho et al. 2019) and within cities (Catungal, Leslie et al. 2009, O'Connor and Gu 2014, Hracs 2015). What is the impact of such creative concentration on the wider urban economy? This is much less well understood.

Creative clustering might simply reflect structural evolution towards post-industrial economies (Zukin 1995, Scott 2006, Pratt and Jeffcut 2009), and the high attractiveness of such locations for creative individuals and firms (Hall 2000, Hutton 2008). However, agglomeration typically generates benefits and disbenefits, so in theory the presence of creative clusters in cities could generate halo effects on other sectors, displace other activities, or a combination of the two. Specifically, benefits might come about through increases in local spending, improved local supply chains and knowledge spillovers (Bakhshi and McVittie 2009, Lee 2014). Conversely, growing creative clusters might displace other industries, matching a process of industrial gentrification analogous to the residential shifts already extensively studied for example by Atkinson and Easthope (2009); Butcher and Dickens (2016); and Grodach et al (2016). Further, given the close links between creative and other sectors, impacts may vary substantively over the business cycle; they may also differ extensively within the different subsectors of the creative industries, given the inherent differences between (say) advertising, software and the visual arts.

Figure 1. Change in creative vs. non-tradable jobs, urban TTWAs, 1997-2018.



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).

The wider evidence base for these spillover effects is inconclusive, since much of the empirical evidence draws conclusions from single case studies (Bloom, Camerani et al. 2020). The small number of quantitative papers examining the wider impacts of creative industries on urban and regional economies are typically constrained by short time periods, non-causal research designs, or both. Our first descriptive statistics offer suggestive evidence that positive spillovers may have been at work for a long time. In Figure 1 we plot the log change in creative industries jobs in UK cities between 1997-2018 against the log change in local services ('non-tradables' such as retail and leisure) over the same period. At this stage we cannot say whether this positive relationship is causal: wealthier cities could have simply developed both more creative activity and more local services.

In this paper we therefore aim to identify the causal impacts of the creative industries on surrounding urban economies. Adapting Moretti's local multipliers framework (2010) to the creative industries setting, we build a new 20-year panel of UK cities using rich microdata from a range of sources accounting for the sectoral and geographical distribution of jobs and workplaces. We estimate both short and long term cumulative impacts from the late 1990s to 2018. We use instrumental variables – based on historic art schools and historic coalfields – to identify causal effects. Following Kemeny and Osman (2020), we use weak instrument-robust inference, presenting our causal results as lower bounds.

We have four main results. First, consistent with other studies (Mateos-Garcia, Klinger et al. 2018, Tether 2019), we find that from the late 1990s, creative firms and jobs became more concentrated in a small number of cities; creative employment became especially concentrated in the largest clusters. Second, we find robust, positive impacts of creative industries on local services in cities: cumulatively, each creative job generates at least 1.9 non-tradable jobs in local services over the 20-year period. While this is a rather larger multiplier than that found for tradable activities (0.3 jobs), its aggregate effect is smaller because there are far fewer creative jobs than those in the tradable sector as a whole.

At the start of our panel there are around 8,800 creative jobs and 70,200 tradable jobs in the average UK city (Table 1). While the creative multiplier is responsible for over 17,300 non-tradable jobs in the average city over the subsequent two decades, the tradables sector as a whole is linked to almost 21,000 non-tradables jobs in that city. By extension, "other tradable activity" (the tradables sector minus creative activity) is responsible for about 3,700 non-tradable jobs in the average UK city in this period. Since the average UK city has around 150,000 non-tradable jobs at the start of our panel, in most cities the bulk of the subsequent jobs growth in urban local services is not driven by multiplier effects from other industries. Conversely, creative multipliers generate more leverage in existing clusters. For example, if in 1997 we raised the number of creative jobs in the Birmingham TTWA (the fifth biggest cluster in 1997) to that of London (the biggest cluster in 1997), the city-region would add over 223,000 creative jobs – and an additional 478,000 non-tradable jobs – over the subsequent twenty-year period.

Third, while we find large multiplier effects for jobs, we do not find them for workplaces, suggesting change is coming largely from the intensive margin (more jobs in existing non-tradable firms) rather than the extensive margin (more non-tradable firms). Exploring mechanisms further, we find suggestive evidence that impacts on local services reflect creative service spending more than urban amenities such as galleries and museums. Also notable is that these effects are declining over time, especially after the Great Financial Crisis from 2007: a result consistent with Lee (2014) and Lee and Clarke (2017).

Fourth, and in contrast, we find no causal evidence of spillovers from creative industries to jobs or firms in other tradable sectors. While this is at odds with predictions in the literature of positive spillovers from creative to other tradable activity, it is consistent with an evolutionary framework where creative clusters become ever larger and more specialised, a scenario that matches our descriptive evidence on the increasing concentration of creative industries in a small number of cities. Overall, our results suggest creative economy-led policies for cities can have positive – albeit partial – impacts on wider urban economies.

The paper makes three contributions to the creative industries literature. We advance on existing studies by using a robust causal framework for creative industries impacts, deriving a number of new results both for the creative industries as a whole, and for specific creative subsectors. In doing so we deploy very high quality, granular microdata over a long time frame, exploring variation across periods of economic growth and recession. We are also able to estimate impacts on non-creative activities as well as exploring mechanisms using very detailed industry groupings. Our identification strategy also improves on commonly-used shift-share designs, which we argue are problematic for the creative industries case. Our paper also tackles broader empirical limitations in the multipliers literature, notably arbitrary time periods and overly-aggregated sectoral definitions (Kemeny and Osman 2020).

The closest comparator to our work is Lee and Clark (2017), who directly estimate creative industry jobs multipliers for UK cities over a much shorter period, 2009-2015, using a shift-share instrument. Other related papers on creative industry impacts are Lee (2014) for wages and employment in UK local areas, Boix-Domenench and Soler-Marco (2017) for productivity in European regions, and Rodríguez-Pose and Lee (2020) for innovation in US cities.

The rest of the paper is organised as follows. Section 2 outlines the basic theoretical framework and reviews the empirical literature. Section 3 describes our data sources and panel build. Section 4 provides descriptive evidence. Section 5 outlines our research design. Sections 6 and 7 present our main results and extensions to the analysis. Section 8 summarises our findings, discusses some high-level policy implications, and identifies areas for further work.

Theoretical Framework

The urban footprint of creative industries naturally raises questions about their linkages to and possible effects on wider urban economies. Broadly speaking, we can pick out three perspectives on these issues. The first is that urbanised creative industries are simply the spatial manifestation of an evolving national economy, a post-industrial process Lash and Urry (1984) refer to as 'culturalisation' and which Scott (2014) dubs 'cognitive-cultural capitalism'. In this view, creativity, broadly defined, is increasingly embedded into mainstream economic and social processes (Thiel 2016). While this embedding might take different forms across different countries (Hutton 2008, Lorenzen and Andersen 2009, Boix, Capone et al. 2014, Kemeny, Nathan et al. 2020) it implies that creative industries do not necessarily have an impact on their wider urban economies. 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, Hall 2000).

A second, contrasting view is that creative industries have 'multiplier effects' on local economies. One possible channel is spending by creative workers, which may support jobs growth and firm creation, especially in local services like cafes, bars and shops (Hutton 2008, Lee 2014). Secondly, creative industries, particularly in the form of arts, cultural heritage and museums, can be powerful attractors that draw in visitors, including both residents and tourists, with similar local spending effects (Florida 2002, Pratt and Jeffcut 2009). Thirdly, creative firms and workers interactions with non-creative sectors may amplify urban agglomeration economies, favouring their micro-foundations based on the three mechanisms of sharing, matching and learning (Duranton and Puga, (2004). For example, creative industries 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 et al. 2009, Pratt and Jeffcut 2009, Boix-Domenech and Soler-Marco 2017).

A third view is that causality runs both ways. Creative industries activity levels, especially in creative business services, is highly pro-cyclical (Stam, De Jong et al. 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 et al. 2014).Moretti's seminal work (2010) offers a useful way to formalise these perspectives. The base case is a permanent change to a city's tradable activities (that is, goods and services that can be both consumed locally and exported to other locations). Such a change – here, growth in creative industries – might come through a major relocation, cluster growth, or through longer term structural shifts, such as a 'culturalisation' process. This change directly increases activity in the creative industries, but may also have indirect effects.

First, there may be a positive multiplier effect on local, 'non-tradable' activity (that is, services such as retail and leisure that are provided and consumed locally). On the intensive margin, existing non-tradables businesses add employment; on the extensive margin, new non-tradables businesses are created, also adding employment in those new firms. Estimating multipliers within creative industries subgroups helps pin down the channel. Creative services, especially knowledge-intensive business services such as advertising, design consulting, architecture, software and media have (at least some) highly-paid workers, so that multipliers 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. Second, there may be multiplier effects on other tradable sectors, via supply chain links, knowledge spillovers or both, as described above. These are a priori ambiguous and depend on the extent of a) cross-industry spillovers (positive multiplier) versus b) competition for inputs across sectors (negative multiplier).

Moretti and Thulin (2013) expand the analysis, suggesting that multipliers' size varies across industries and jobs and depends on type of workers, technologies involved and level of human capital. Any increase in local expenditure which positively affects non-tradable jobs can be the result both of consumer preferences for non-tradable services (e.g. high-street shops and urban amenities) and of more, better-paying high-skilled workers in the tradable sector. The magnitude of multipliers depends both on differences in wages and on labour-intensive technologies in the local services which increases jobs. Finally, when labour and housing supplies are locally elastic – because the mobility of workers is higher and labour cost stays lower – then multipliers will be larger. Van Dijk (2018) develops a detailed critique of Moretti's original implementation, suggesting several modifications that we draw on below.

This basic framework allows local multipliers and their drivers to be directly estimated, and a growing body of directly estimated multipliers work has developed since 2010. A recent OECD-wide review of the field (What Works Centre for Local Economic Growth 2019) finds that across the tradable sector, the average employment multiplier is 0.9, such that each additional job in the tradable sector generates almost an additional job in the untraded sector, but that 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. These typically use aggregated data over 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 to identify impacts, 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. Lee and Clarke (2017) 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. 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.

Data

Our main data source is the Business Structure Database (hereafter 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, geocoded into over 225,000 Output Areas for England, Wales, Scotland and Northern Ireland. Note that the data does not include self-employed workers with revenues below the UK sales tax threshold. Given that the creative industries have substantively more self-employed workers than the UK average, to the extent these workers are undercounted in the BSD, our results will underestimate the true size of job and firm multipliers.

We clean the raw data extensively, allowing us to robustly identify workplace entry and exit. We aggregate workplace-level information to 2011 Travel to Work Areas (TTWAs), which provide the best approximation for local spatial economies. Of the 228 TTWAs, we focus on the 78 that we classify as predominantly urban (following a typology by Gibbons et al. (2011)). Our resulting panel has 1716 TTWA*year observations for 22 years, 1997-2018 inclusive. Further details are given in Appendix A1.

We then 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 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 four-digit sector codes. We follow the DCMS structure, generating 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 as in 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. The intuition is that the more tradable an activity, the more spatially concentrated its production (to take advantage of localisation and urbanisation economies); conversely, non-traded activities are – by definition –distributed across all locations. We build new locational Ginis for detailed four-digit UK industries based on 2018 BSD data. Further details are given in Appendix A2.

For control variables and robustness checks we use the Annual Population Survey, Labour Force Survey, ONS Mid-Year Population Estimates, GVA per head and Household Disposable Income datasets, aggregating to TTWAs as before. Further details are given in Sections 5 and 6.

Descriptive analysis

Table 1 gives summary statistics for all years (Panel A), 1997 (Panel B) and 2018 (Panel C). Alongside substantial increases in overall economic activity, the average urban TTWA in 2018 also has more creative industries activity than 1997, which accounts for a slightly larger share of local economic activity.

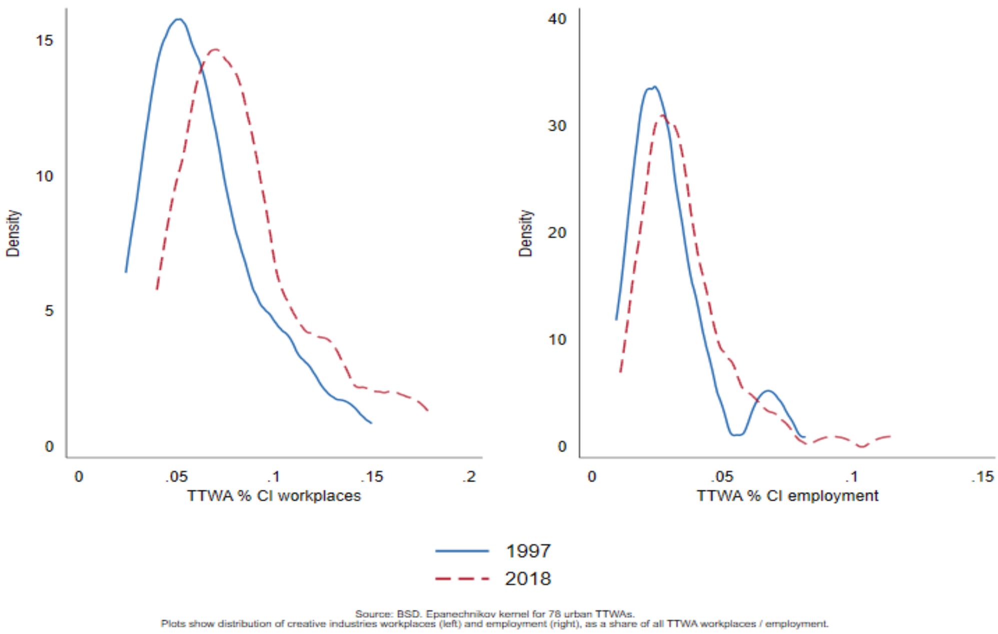
Table 1. Summary statistics.

	All years		**1997**		**2018**	
	Mean	**sd**	**Mean**	**sd**	**Mean**	**sd**
TTWA all workplaces	22278	43478	19006	36180	28790	61437
TTWA tradables workplaces	6325	15529	5186	12405	8608	22802
TTWA creative workplaces	2121	6512	1595	4862	3153	9961
TTWA other tradable workplaces	4204	9063	3592	7583	5455	12882
TTWA non-tradable workplaces	15952	28038	13819	23829	20181	38760
% tradable workplaces	0.284	0.042	0.273	0.04	0.299	0.047
% creative workplaces	0.095	0.03	0.084	0.028	0.110	0.033
% other tradable workplaces	0.189	0.021	0.189	0.023	0.189	0.02
% non-tradable workplaces	0.716	0.042	0.727	0.04	0.701	0.047
TTWA all jobs	251331	453762	220630	407733	307218	586922
TTWA tradables jobs	64774	130467	70237	144421	71997	163951
TTWA creative jobs	11280	36864	8849	27837	15513	53646
TTWA other tradable jobs	53494	94748	61388	117066	56484	110968
TTWA non-tradable jobs	186557	324487	150394	263847	235220	423705
% tradable jobs	0.258	0.053	0.318	0.048	0.234	0.037
% creative jobs	0.045	0.016	0.040	0.016	0.050	0.018
% other tradable jobs	0.213	0.054	0.278	0.049	0.184	0.034
% non-tradable jobs	0.742	0.053	0.682	0.048	0.766	0.037
TTWA*year observations	1716		78		78	

Source: BSD.

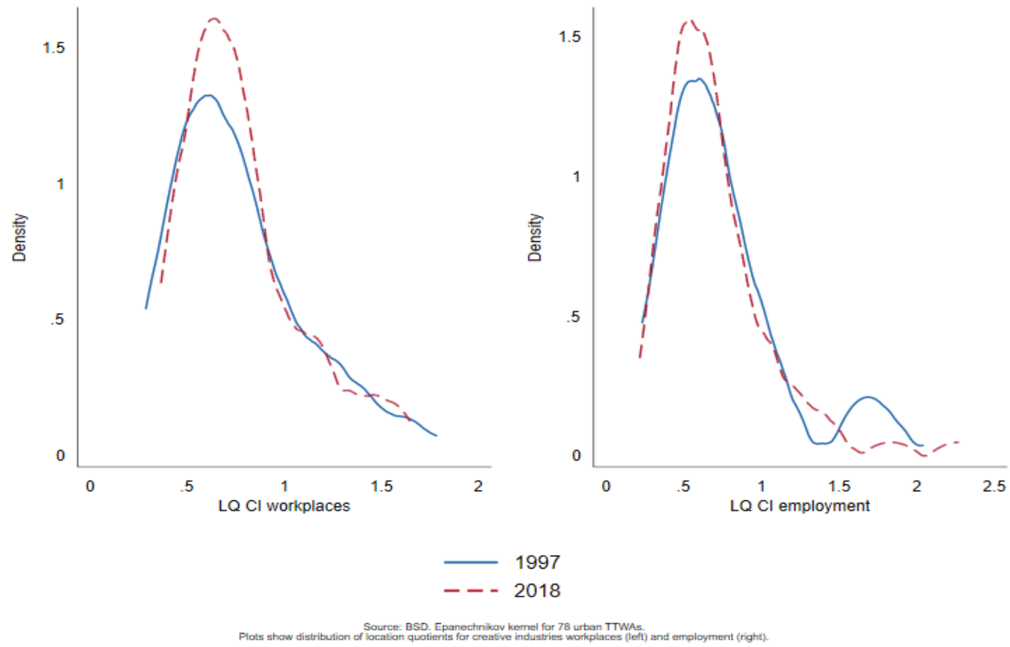
However, this aggregate picture hides much spatial variation. We highlight three key features here. First, while our sample period has seen a substantive increase in creative industries activity in UK cities, this is driven by co-location of firms and jobs in a few cities. Figure 2 is a kernel density distribution showing the shares of creative workplaces/firms (left hand side) and employment (right hand side) across all urban TTWAs in 1997 (blue) and 2018 (red). We can see an unambiguous shift right and down in the distribution, particularly for firms, as creative activity becomes more concentrated in fewer places (specifically, to the right of where the blue and red lines intersect). This pattern of increasing concentration, especially at the top end of the distribution (the right hand side of the graphs) is consistent with results in Mateos-Garcia et al (2018) and Tether (2019).

Figure 2. Kernel density plot of % creative industries workplaces and employment, urban TTWAs, 1997 and 2018. L: workplaces. R: jobs.



Second, patterns of creative specialisation suggest both clustering and slight diffusion. Figure 3 shows the distribution of location quotients for creative firms (left hand side) and jobs (right hand side) in 1997 and in 2018. Location Quotients (LQs) measure specialisation: an LQ over one indicates an industry is more concentrated in an area than its national share. As with activity shares, only a minority of cities have LQs over one, indicating clustering. However, while creative job specialisation has risen in cities at the very top of the distribution, creative workplace specialisation has fallen slightly. And on both measures maximum densities have increased over time, indicating there has also been diffusion across the urban system.

Figure 3. Kernel density plot of creative industries workplaces and employment LQs, urban TTWAs, 1997 and 2018. L: workplaces. R: jobs.



Third, as these patterns imply, some individual cities have shifted their position in the creative cluster league table. Appendix Tables B1-B3 give more detail for the 20 urban TTWAs with the largest 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 – perhaps surprisingly – Cambridge. The picture is broadly similar for creative industries shares, although compared to smaller, more specialised cities such as Reading, Slough and Milton Keynes, by 2018 London has a lower share of creative firms and jobs as a total of all activity. We find this same pattern with LQs, alongside significant creative specialisation in Brighton, Oxford, Cambridge and Bristol.Strikingly, Edinburgh emerges in 2018 as a top 20 creative industries cluster, having not featured in 1997. Consistent with Figure 3, Table B3 confirms that while a minority of the biggest clusters have increased their specialisation in the creative industries over time, the majority of the top 20 have lower firm and employment LQs than before.

Research design

We want to explore the causal links from creative industries activity to wider urban economies. To do this we adapt Moretti's 2010 framework for local employment multipliers for the creative industries setting. We start with the following OLS fixed effects regression for TTWA *i* in year *t:*

$$\text{Ln } NT_{it} = a + b1 \ln CI_{it} + b2 \ln OT_{it} + \mathbf{Xc}_{it-n} + I_i + T_t + e_{it} \quad (1)$$

Where NT, CI and OT is respectively the number of jobs or workplaces 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, and is varied in robustness checks), I and T are area and year fixed effects, and *e* is the error term. Our variable of interest is CI; specifically we are interested in its coefficient *b1*, the elasticity of non-tradable activity to CI activity. This can be interpreted as the percentage change in non-tradable employment from a 1% change in jobs in creative industries.

Given our preferred lag structure and controls we estimate (1) for 1998-2018; in addition, to explore multipliers across different parts of the UK business cycle we also estimate for 1998-2006 (pre-Great Financial Crisis) and 2007-2018 (post-crisis). In extensions we also look within creative industries subgroups, and look at impacts on the rest of tradable industry space.

Equation (1) leverages differences in levels of creative activity between years and across cities. Following Moretti (2010) and Lee and Clarke (2019) we also estimate cumulative change using long differences (LD), where *tbase* is 1998 and *t* is 2018. As above, we estimate elasticities in pre and post-crisis periods, and between creative and other tradable activity:

$$\Delta \ln NT_{it\text{-}tbase} = a + b1\Delta \ln CI_{it\text{-}tbase} + b2\Delta \ln OT_{it\text{-}tbase} + \Delta\mathbf{Xc}_{it\text{-}tbase} + T_t + e_{it} \quad (2)$$

We run alternative specifications for both (1) and (2) in robustness checks.

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

$$M = b1\_hat * (NT_{2007} / CI_{2007}) \quad (3)$$

Where *b1*_hat is the estimated coefficient from (3 & 4), NT_{2007} is the number of non-tradable jobs or workplaces in 2007 summed across TTWAs, and CI_{2007} gives the same for creative industries in 2007. We also calculate an alternative specification of the multiplier following Van Dijk (2018), which uses the base year in each time period, specifically to 1998 and 2007. This alternative approach corrects the possible over- or under-weighting of the size of the labour market in the years before or after a sole base year, by giving a more homogeneous treatment to the whole panel.

Identification

Our panel estimators account for all time-fixed area characteristics, and any cross-area shocks that, in a given year, may drive creative and non-tradable activity. As discussed in Sections 1 and 2, creative industries activity in a city is also likely to be affected by time-varying factors such as the skills and tastes of the workforce and population, agglomeration economies, and local labour market conditions. Our base regressions 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), as well as population density and the share of 16-24 year olds in the city (from ONS midyear population estimates). In robustness checks we vary controls and lag structure.

As discussed above and in Section 2, our base regressions do not control for simultaneity or reverse causation between creative and non-tradable activity. In the absence of a natural experiment, we use instrumental variables to deal with this identification challenge. The multipliers literature typically uses a shift-share ('Bartik') instrument (Kemeny and Osman 2020). The shift-share design uses a) historic shares of (say) high-tech activity in an area, interacted with b) national shifts in high-tech activity, minus the area in question, to derive c) predicted change in high-tech activity at the city level for that area. This 'leave-one-out' design cleans out localised shocks, allowing us to isolate the effect of high-tech activity on the rest of the local economy.

Borusyak et al (2018), Goldsmith-Pinkham et al (2018) and Jaeger et al (2018) critically evaluate the properties of shift-share instruments (see Broxterman and Larsen (2020) and Cerqua and Pellegrini (2020) for reviews). Depending on the context, shift-share identification can come from either the shocks or shares components. In the first case, if national shifts are not as-good-as-random, then the instrument will not be identified (Borusyak, Hull et al. 2018). In the second, if local shares are serially correlated, the instrument is also not identified, as the shifts will pick up the effects of past demand shocks as well as current ones (Goldsmith-Pinkham, Sorkin et al. 2018, Jaeger, Ruist et al. 2018).

As we show in Section 4, creative industries are highly clustered in the UK and this clustering persists over time. Further, there has been no large national shock to the creative economy during our sample period. Together, this makes it unlikely that shift-share instruments can be used to identify causal effects of creative industries in the UK. Our alternative, preferred approach, for creative industries is to use historical instruments, which exploit the long term effects of industrial structure and supporting institutions. For completeness we also construct a shift-share instrument using the leave-one-out design (see Appendix A3 for details), and use this to benchmark our preferred estimates, as well as to estimate broader impacts from tradables to non-tradables, since identifying assumptions are better founded in this case.

Our first historical instrument is based on notions of path-dependence developed by Chinitz (1961). Chinitz argues that cities and regions historically dominated by single industries, especially when these involve a few dominant firms, have weaker entrepreneurial cultures, and have lower levels of entrepreneurship today. Conversely, places with more diversified economies and more SMEs pass on stronger entrepreneurial cultures. We argue that a variant of this narrative applies to creative industries, which have higher shares of small firms and entrepreneurial activity than in the economy as a whole. (In 2017, the sector had a larger-than-average share of micro firms (95% vs 89% across all industries) and a smaller-than-average share of big firms (0.14% vs 0.37%). In 2015, over 26% of creative industries workers were self-employed, a common proxy for entrepreneurship, compared to just under 16% of all UK workers.) That is, we argue that cities historically dominated by single, oligopolistic industries are likely to have less creative industries activity today.

We use the mining industry to proxy for single, large-industry dependence. Specifically, we use cities' proximity to C19 mining deposits, an approach used successfully to predict entrepreneurial activity both in the US (Glaeser, Pekkala Kerr et al. 2015) and the UK (Stuetzer, Obschonka et al. 2016), whose data we deploy here. We use deposits rather than industry presence because the former is a historical given, while the latter is the result of human choices that might also influence long-term development (for example, whether or not to exploit coal deposits). 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 tracks creative industry development more directly, by using the location of Schools of Art and Design established in the Victorian and Edwardian era (1837-1914). Specifically, we build on the idea that historical cultural institutions make a long term difference in developing a vibrant art and cultural sector (Falck, Fritsch et al. 2011). As outlined in Lee and Clarke (2019), whose data we use here, in the UK such art and design Schools were set up in large part to ensure local supplies of skilled artists and artisans in a range of arts, crafts and design fields. Although the first Government School of Design was opened in Somerset House (London) in 1837, only after the Great Exhibition in 1851 was state-supported technical and art education perceived as strategic policy for Britain against the rising industrial powers (Jarrell 1998). Schools of design and applied arts (as opposed to Fine Art) flourished in virtually all industrial cities (Lawrence 2014) offering also 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 that places with such historic institutions, especially multiple cases, helped to root creative clusters, most obviously by supplying skilled workers to local firms, but also more broadly as a source of ideas about methods and tools, and through two-way linkages between teaching staff and local firms. Specifically, we suggest that cities with more historic art/design schools will have a greater creative industries presence today. Following the IV approach in Borowiecki (2013) and Lee and Clarke (2019) we assume that the cost of knowledge diffusion increases with distance and therefore these schools facilitated the concentration of art and technical workers and the expansion of the creative business. The list of Schools includes both London (15/52 Schools) and major cities, but also ex-industrial cities and more peripheral / coastal locations. Our instrument is the count of historic art schools, and we expect to see a positive connection from the count to creative activity today.

For our historical 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 regression of our instruments on employment (Panel A) and workplaces (Panel B) in our different industry groupings. Regressions include our full set of controls and year dummies, with standard errors clustered on TTWAs. For each panel we show results for creative industries (column 1), non-tradables (column 2) and other tradables (column 3).

Table 2. Historical instruments diagnostics tests.

	A. Employment			**B. Workplace**		
	(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	0.10	0.02	-0.06*	0.02	0.01	-0.01
schools	(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, controls per main specification. Standard errors clustered on TTWA. Constant not shown.

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. This undermines the exclusion condition if not corrected for. In robustness checks for our main results we therefore treat both creative and other tradables activity as endogenous, instrumenting for both. In extensions, where we test the impacts of creative industries on other tradable activities, we use only the art schools instrument.

Inference

As Kemeny and Osman (2020) point out, weak instruments are pervasive in the multipliers literature. In Tables 4 and 5 we fit both the usual Kleibergen-Papp and also Montiel Olea-Pflueger (MOP) Effective F statistics, often finding results under 10, the conventional cutoff for IV inference. Following Kemeny and Osman, we therefore use the weak instrument-robust methods developed by Andrews et al (2019) for cases where our IVs do not pass cutoffs. The intuition of these methods is that when an instrument is valid but weak, as in this case, there is a set of values under which we can infer an unbiased, consistent result. Specifically, the Anderson-Rubin statistic tests for the null hypothesis of instrument exogeneity for the value of the point estimate b. For an exactly identified regression, the subsequent Anderson-Rubin confidence set is the set of values for b for which exogeneity cannot be rejected. (Note that such a confidence set can exist even when the overall test of instrument exoegenity is failed.)

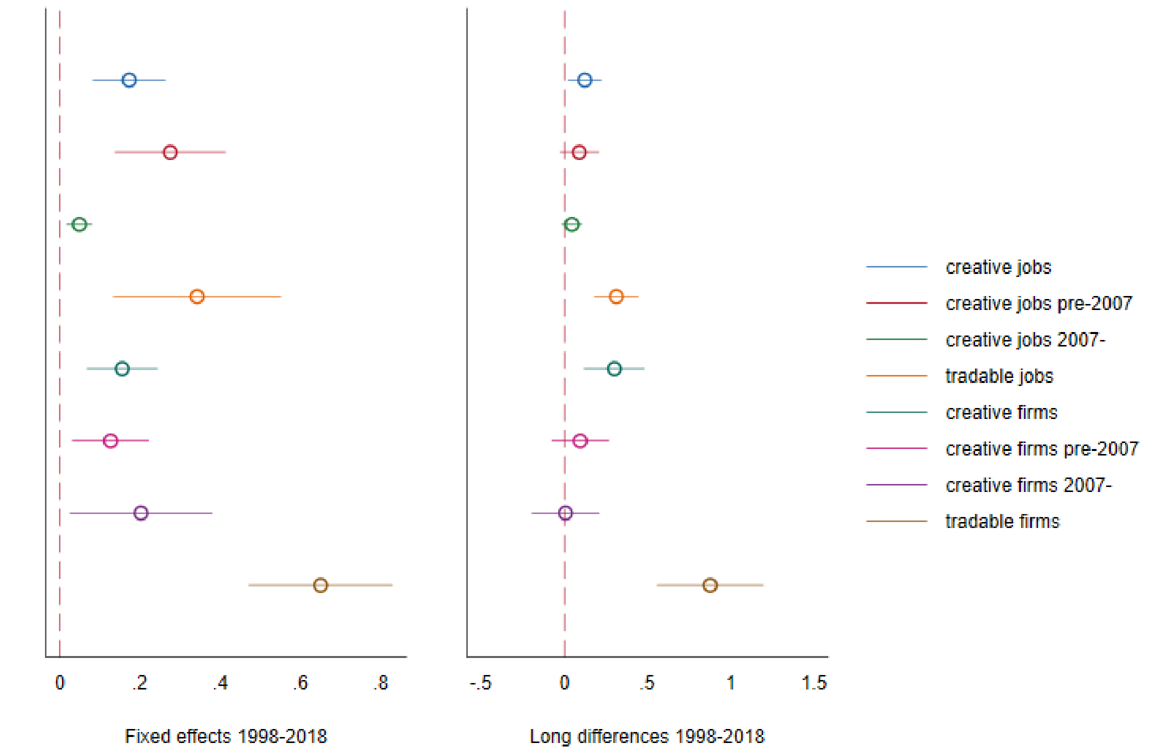
Results

This section gives our headline results. We first summarise the OLS estimates for the fixed effects and long difference models, for jobs and for workplaces, and show that these results survive multiple robustness checks. We then show IV results using our historic instruments. The next section presents two extensions to the main analysis.

OLS results

We summarise our OLS results for jobs and workplaces in Figure 4. 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 links from creative to non-tradable activity, but these links are not always statistically significant, and are always smaller than for other tradable sectors.

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.

The left hand graph shows results for the fixed effects estimator. The first three estimates show the average (non-causal) link between creative industries jobs and non-tradable jobs in urban areas: for all years, 1998-2006, and 2007-2018 respectively. We see a significant, positive link from creative industries jobs to non-tradable jobs overall. Specifically, a 10% increase in creative employment in a TTWA is linked to 1.7% growth in non-tradable jobs (Appendix Table B4, column 2). This is explained by larger changes pre-2006 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, which shows the cumulative link between creative and non-tradable jobs / workplaces over 1998-2018, 1998-2006 and 2007-2018 respectively, with tradables again as a benchmark. Here, 10% growth in creative jobs between 1998-2018 is robustly linked to 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). In both cases, there is not enough sub-period variation to give a significant association (Tables B6-B7, columns 2-4). Again, coefficients on tradables (and other tradables) are always larger than those for creative industries.

OLS multipliers

Multipliers give us a simple alternative heuristic for interpreting results. Table 3 summarises statistically significant jobs and workplace multipliers from the OLS analysis above.

Table 3. Summary of OLS multipliers.

A. Fixed effects		B. Long differences	
Employment		**Employment**	
Creative, all years	2.844	Creative, all years	2.126
Creative, 1998-2006	4.526	Creative, 1998-2006	
Creative, 2007-2018	0.798	Creative, 2007-2018	
Tradables, all years	0.996	Tradables, all years	0.709
Workplaces		**Workplaces**	
Creative, all years	1.158	Creative, all years	2.516
Creative, 1998-2006	1.027	Creative, 1998-2006	
Creative, 2007-2018	1.429	Creative, 2007-2018	
Tradables, all years	1.632	Tradables, all years	2.365

Source: authors' elaboration from BSD, LFS/APS, ONS. Multipliers calculated from Equation (3), using van Dijk (2018) specification of base years. Blank field indicates point estimate is non-significant.

For example, the OLS jobs multiplier for tradables is around 1 in the fixed effects setting, and around 0.8 in long differences, a result that benchmarks well to the existing literature (see Section 2). This implies that each tradables job was linked to 0.8-1 non-tradables jobs between 1998-2018, depending on whether we consider the average across all years (fixed effects), or the cumulative change from start to end years (long differences). By contrast, every new creative job was linked to between 2-2.8 non-tradable jobs, depending on specification. Note that these are simply associations, not causal relationships.

Why is the creative industries multiplier larger than its all-tradables equivalent – even though raw coefficients for tradables are substantively bigger than those for creative industries? This is partly driven by the way the multiplier is specified in equation (3), with industry size as the denominator: other things being equal, the smaller the industry the larger the multiplier. But because the creative industries involve far fewer workplaces or jobs than the tradable sector as a whole, the overall effect size of the tradables multiplier, in terms of aggregate urban job or firm creation, will be greater than that of the creative industries.

Robustness checks

We run OLS results through a battery of robustness checks, set out in Tables B8-B11 inclusive. Our first set of checks cover alternative control variables and time splits. In Table B8, for the fixed effects model, Panel A experiments with a number of different time splits for the employment analysis. Panel B varies the control vector, drawing on the creative industries literature covered in Sections 1 and 2. Panels C and D redo for the workplaces analysis. Table B9 repeats for the long difference estimations. Reassuringly, all our main results are stable across these alternative specifications.

Our second set of checks cover functional form. Table B10 estimates in first differences (year-on-year changes in creative activity across TTWAs). Panel A contains results for jobs, Panel B for workplaces. In both cases Column 1 fits the main levels result for comparison; Column 2 fits first differences for creative industries and in other tradables; Column 3 adds in controls from our main specification; Columns 4 and 5 fit pre-crisis and post-crisis periods. Estimates are very similar to fixed effects coefficients. Table B11 gives results for an alternative long difference model with controls only in the base year (essentially, a growth rate setting). Panel A contains results for jobs, Panel B for workplaces. In each case column 1 contains our main result, and column 2 the alternative specification. For both jobs and workplaces, the growth rate coefficient of creative jobs is now slightly smaller. For jobs the coefficient is now only marginally significant (model fit is also much lower), while for workplaces it remains robust.

IV results

We now turn to regressions with our historical instruments, which we use to estimate causal effects of the creative industries on non-tradable activity. As discussed in Section 5, we focus on the long differences setting. That is, we are estimating the cumulative causal impact of creative industries activity on non-tradable activity in UK cities.

Tables 4 and 5 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. Under each column, we show Montiel Olea-Pflueger Effective F statistics alongside a conventional weak instrument F-test for the first stage. In most cases scores are under 10, indicating the need for weak instrument-robust inference. In these cases we show Anderson-Rubin confidence sets alongside raw coefficients. We then take lower bounds as a conservative estimate of causal effects, and generate multipliers from these.

Table 4. 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).

For jobs (Table 4), IV coefficients are significant and substantially larger than OLS counterparts. However, given the weak instrument setting we interpret our result using confidence sets, which 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.

We use lower bounds of confidence sets to derive multipliers. While the OLS multiplier is 2.126, the IV multiplier 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? As noted before, while creative multipliers are larger than that typically found for tradables (0.287 jobs, in our case), the overall effect size is smaller because there are far fewer creative than tradable jobs. At the start of our panel there are around 8,850 creative jobs and 70,200 tradable jobs in the average UK city (Table 1). While the creative multiplier is responsible for over 17,300 non-tradable jobs in the average over the subsequent two decades, the tradables sector as a whole is linked to almost 21,000 non-tradables jobs. Since the average UK city has around 150,000 non-tradable jobs at the start of our panel, the bulk of the subsequent jobs growth in local urban services is not driven by multipliers from tradable industry space, creative or otherwise. Conversely, creative multipliers generate more leverage in existing clusters. For example, if in 1997 policymakers had raised the number of creative jobs in the Birmingham TTWA (the fifth biggest cluster in 1997) to that of London (the biggest cluster in 1997), the city-region would have added over 223,000 creative jobs – and an additional 478,000 non-tradable jobs – over the subsequent twenty-year period.

Table 5. 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. 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 5 (tradable workplaces).

For workplaces (Table 5) the picture is very different. IV coefficients are smaller and now all are non-significant. Multipliers are also reduced, with all around zero. These results are robust to alternative estimations pooling across all years (Tables B12-B13), and to alternative specifications (Tables B14-B15) using a Bartik instrument, and by instrumenting for both creative and other tradable activity using different strategies. In the latter case IV estimates are always larger than in 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, in terms of our framework, 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.

Extensions

In this section we explore the other two parts of our conceptual framework. We first test for multiplier effects from creative industries to other tradable sectors. As discussed in 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. In turn, this provides evidence for how non-tradable jobs multipliers may operate: worker spending, visitor spending or both.

Creative multipliers in tradable space

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

$$\Delta \ln OT_{it\text{-}tbase} = a + b1\Delta \ln CI_{it\text{-}tbase} + b2\Delta \ln NT_{it\text{-}tbase} + \Delta \mathbf{Xc}_{it\text{-}tbase} + T_t + e_{it} \qquad (4)$$

OT is either jobs or workplaces in other tradable manufacturing or tradable services, and other terms and controls are defined as before. Table 6 gives results for this long difference estimator, 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 the whole sample period, 1998-2006 and 2007-2018 respectively.

Table 6. 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.

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 et al. 2019). Alternative specifications combining the art school instrument with our leave-one-out Bartik IV (for creative or other tradable activity) also almost always yield non-significant results.

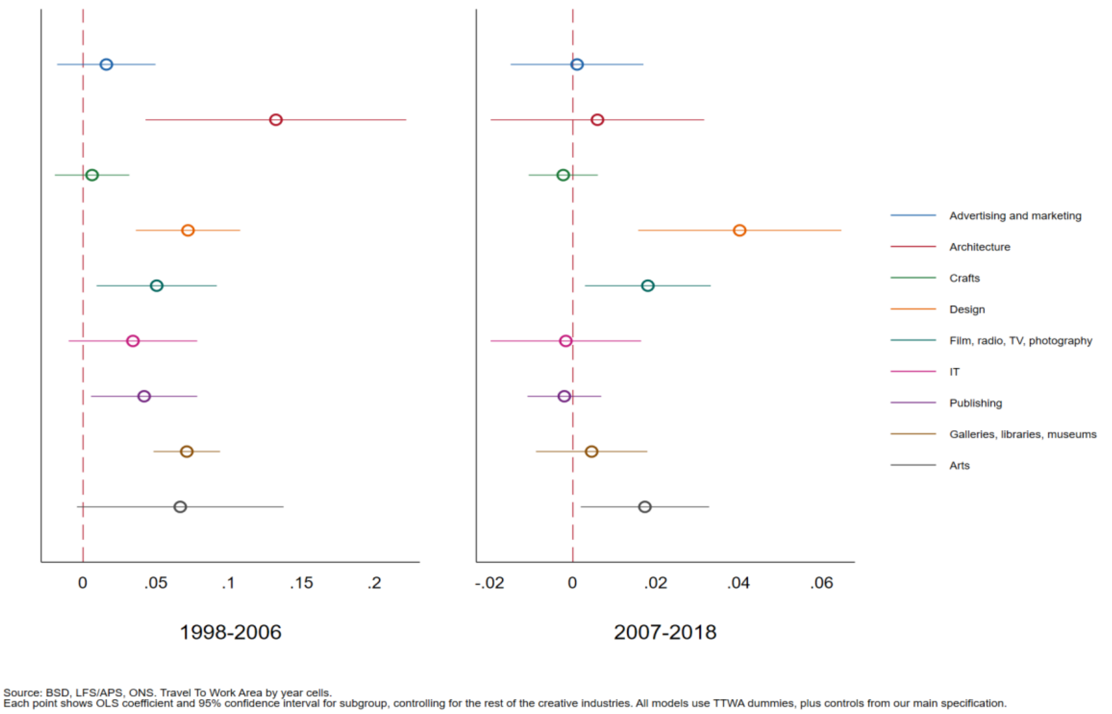
Overall, we interpret these findings as showing no causal evidence for spillovers to other tradable activity – as distinct from 'evidence for no spillovers'. This result is at odds with predictions in the creative industries literature, that creative activity would have positive effects on other tradable activity through supply chain links and ideas flow. However, it is explicable in an evolutionary framework in which creative clusters become progressively larger and more specialised, a scenario that is consistent with our descriptive evidence.

Decomposing creative job multipliers

Here we provide suggestive (non-causal) evidence on how creative job multipliers may operate on non-tradable employment. As outlined in Section 2, we can do this by exploring how multipliers differ within creative industry space. Specifically, 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). Each result controls for the rest of the creative industries and for other tradable activity, controls and fixed effects as before. Appendix Table B16 shows coefficients and standard errors.

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



As in our main results, we find that jobs multipliers get substantively smaller after 2007. Within the creative industries, creative services such as architecture, design, film/TV/radio and publishing have the largest and most robust multipliers in the pre-2007 period; the only 'arts' subgroup is libraries and museums. After 2007 only design, film/TV/radio and the visual/other arts have significant multipliers. This suggests that creative jobs multipliers on non-tradable urban employment arise from worker spend more than visitor spend. That is, our results are consistent with the idea that creative multipliers for the local urban economy arise from creative services, more than creative urban amenities.

Conclusions

In the UK and elsewhere, the creative industries are highly clustered in urban areas, and so have received increasing attention for their potential to drive urban economic development. However, there is surprisingly little convincing evidence on this issue. In this paper we explore the long-term, causal impacts of the creative industries on surrounding urban economies. Adapting Moretti's local multipliers framework, we build a new 20-year panel of UK cities, using fixed effects and historic instruments to identify effects on non-creative firms and employment.

We have four main results. First, consistent with other recent UK studies, we find increasing concentration of creative industries activity from the late 1990s in a small number of cities, especially creative employment in the largest clusters. Second, we find large, significant, positive multiplier effects of creative industries 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. Third, we find suggestive evidence that this is driven by creative business services employees' spending more than that of visitors attracted to urban amenities such as galleries and museums. We also do not find these effects for workplaces. Fourth, and in contrast, we find no causal evidence of spillovers to other tradable activities. This goes against previous predictions (Bakhshi and McVittie 2009, Lee 2014), but is consistent with an evolutionary framework in which creative clusters become ever larger and more specialised. That framework fits our descriptive evidence of the increasing concentration of creative industries in a small number of cities.

Overall, our results suggest creative economy-led policies for cities – at least in the UK – can have positive economic impacts, but these are probably limited in scope, and may differ substantively within creative industry space. What does this imply for policymaking? We suggest that city leaders – especially outside London – will need a better understanding of the composition of a city's local creative industries, in particular the relative distributions of creative services versus the arts. We find little evidence of multiplier effects from the latter, but this is not to take away from the important non-economic effects of the arts on wider welfare. Conversely, the pattern of ever-increasing concentration, with only limited diffusion, suggests that city leaders in non-cluster locations have little chance of developing new creative industries clusters from scratch, absent major spatial interventions (such as the BBC's partial relocations to Cardiff and Salford, DCMS' planned partial move to Salford, and Channel 4's HQ2 in Leeds). Further such moves are currently under discussion in the UK as part of the 'levelling up' agenda: our findings suggest some caution in what such moves should be expected to achieve in terms of economic development impacts.

Our research has a number of limitations, which open up space for further work. First, we lack occupation-level data so are unable to test for the impacts of creative occupations, either inside or outside creative industries firms (Bakhshi, Freeman et al. 2012). Second, we look at city-wide impacts and do not explore within-city change, for example in specific creative districts or neighbourhoods (Hutton 2015). Third, we focus on labour market and business stock impacts, and do not consider wider impacts on (for example) the housing market. Fourth, our work is for the UK only. While our findings could plausibly transfer to other country contexts, cross-country studies also reveal substantive differences in national creative economies (Boix et al 2014, Kemeny, Nathan et al 2020). 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 encourage others to pursue further work along these lines.

Acknowledgements

Thanks to Hasan Bakhshi, Tom Kemeny, Bruce Tether, an anonymous PEC reviewer and participants at CRRESY, Geoinno 2020, RC2020 and SRERC for helpful contributions. Neil Lee and Michael Stuetzer kindly shared data for historical instruments. This research is funded by the Creative Industries Policy and Evidence Centre (PEC), part of the Creative Industries Clusters Programme led by the Arts and Humanities Research Council (AHRC) and funded through the Industrial Strategy Challenge Fund.

This work includes analysis based on data from the Business Structure Database, Annual Population Survey and Labour Force Survey produced by the Office for National Statistics (ONS) and supplied by the Secure Data Service at the UK Data Archive. The data is Crown copyright and reproduced with the permission of the controller of HMSO and Queen's Printer for Scotland. The use of the ONS statistical data in this work does not imply the endorsement of the ONS or the Secure Data Service at the UK Data Archive in relation to the interpretation or analysis of the data. This work uses research datasets that may not exactly reproduce National Statistics aggregates. All the outputs have been granted final clearance by the staff of the SDS-UKDA. This paper represents the view of the authors, not the funders or the data providers.

Disclaimer

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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.1 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). 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

[1] 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.

of enterprise-level employment.

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:

$$G_{jt} = \Sigma_i [(E_i / E) - (E_{ij} / E_j)]^2 \quad (1)$$

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:

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

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. 1997-2018			B. 1997			C. 2018		
2011 TTWA	**firms**	**jobs**	**2011 TTWA**	**firms**	**jobs**	**2011 TTWA**	**firms**	**jobs**
London	56342	319928	London	42778	244121	London	87808	473429
Slough and Heathrow	9940	51621	Slough & Heathrow	7888	43787	Slough & Heathrow	15110	64117
Manchester	6706	35922	Manchester	4844	24287	Manchester	9944	52308
Guildford, Aldershot	4104	20977	Guildford & Aldershot	3362	15560	Birmingham	5990	32787
Birmingham	3801	23580	Birmingham	3223	27145	Reading	5457	36192
Reading	3718	22577	Luton	2767	10635	Guildford & Aldershot	5340	24964
Luton	3650	13765	Crawley	2518	10075	Luton	4981	17757
Crawley	3053	12868	Cambridge	2313	11520	Bristol	4468	23673
Cambridge	2976	15442	High Wycombe & Aylesbury	2286	10733	Crawley	4103	15087
Bristol	2900	15652	Reading	2261	12232	Cambridge	4073	21329
High Wycombe and Aylesbury	2625	11150	Bristol	2174	11391	Glasgow	3898	25006
Glasgow	2472	18504	Oxford	1841	14816	Edinburgh	3669	18025
Oxford	2451	17342	Glasgow	1806	23497	Milton Keynes	3474	12067
Edinburgh	2157	12449	Leeds	1497	12102	High Wycombe & Aylesbury	3375	13156

Southampton	1977	10904	Edinburgh	1472	7817	Leeds	3198	22288
Leeds	1955	14763	Leicester	1423	6441	Oxford	3140	20415
Leicester	1922	7952	Nottingham	1341	8390	Leicester	3042	10691
Milton Keynes	1892	8278	Tunbridge Wells	1303	4459	Southampton	2927	14642
Brighton	1843	6086	Milton Keynes	1285	5791	Brighton	2871	8779
Liverpool	1745	8921	Stevenage & Welwyn	1284	5139	Chelmsford	2437	8039

Source: BSD. Sorted by CI workplace counts.

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

A. 1997-2018			B. 1997			C. 2018		
2011 TTWA	**% firms**	**% jobs**	**2011 TTWA**	**% firms**	**% jobs**	**2011 TTWA**	**% firms**	**% jobs**
Reading	0.155	0.088	Reading	0.15	0.07	Reading	0.18	0.115
London	0.147	0.081	London	0.135	0.069	Slough and Heathrow	0.166	0.074
Slough and Heathrow	0.145	0.071	Slough and Heathrow	0.133	0.068	Milton Keynes	0.166	0.056
Guildford & Aldershot	0.131	0.072	High Wycombe & Aylesbury	0.125	0.064	London	0.163	0.093
High Wycombe & Aylesbury	0.129	0.067	Guildford and Aldershot	0.122	0.065	Brighton	0.158	0.057
Brighton	0.129	0.048	Luton	0.11	0.042	Guildford & Aldershot	0.144	0.069
Luton	0.126	0.047	Milton Keynes	0.109	0.048	High Wycombe & Aylesbury	0.141	0.063
Milton Keynes	0.124	0.052	Stevenage & Welwyn Garden City	0.107	0.037	Luton	0.132	0.046
Stevenage and Welwyn Garden City	0.111	0.042	Crawley	0.103	0.042	Tunbridge Wells	0.129	0.047
Tunbridge Wells	0.109	0.047	Brighton	0.102	0.033	Edinburgh	0.127	0.047
Oxford	0.108	0.072	Tunbridge Wells	0.101	0.042	Stevenage & Welwyn Garden City	0.125	0.039
Crawley	0.107	0.046	Oxford	0.098	0.07	Crawley	0.12	0.046
Swindon	0.101	0.036	Cheltenham	0.093	0.038	Oxford	0.118	0.068
Cambridge	0.101	0.052	Swindon	0.091	0.031	Cheltenham	0.117	0.055
Bristol	0.097	0.043	Cambridge	0.091	0.043	Bristol	0.117	0.052

Cheltenham	0.096	0.048	Southampton	0.089	0.034	Swindon	0.116	0.037
Edinburgh	0.093	0.038	Bristol	0.082	0.038	Cambridge	0.111	0.058
Bedford	0.089	0.031	Bedford	0.082	0.029	Worthing	0.101	0.031
Worthing	0.084	0.039	Worthing	0.079	0.027	Bedford	0.099	0.032
Chelmsford	0.083	0.033	Chelmsford	0.078	0.028	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. 1997-2018			B. 1997			C. 2018		
2011 TTWA	**LQ firms**	**LQ jobs**	**2011 TTWA**	**LQ firms**	**LQ jobs**	**2011 TTWA**	**LQ firms**	**LQ jobs**
Reading	1.639	1.968	Reading	1.786	1.753	Reading	1.646	2.269
London	1.559	1.814	London	1.605	1.714	Slough and Heathrow	1.516	1.456
Slough and Heathrow	1.535	1.603	Slough and Heathrow	1.59	1.699	Milton Keynes	1.513	1.104
Guildford & Aldershot	1.396	1.612	High Wycombe & Aylesbury	1.486	1.592	London	1.486	1.833
High Wycombe & Aylesbury	1.37	1.499	Guildford & Aldershot	1.45	1.62	Brighton	1.447	1.13
Brighton	1.352	1.077	Luton	1.313	1.058	Guildford & Aldershot	1.317	1.374
Luton	1.341	1.051	Milton Keynes	1.298	1.191	High Wycombe & Aylesbury	1.286	1.24
Milton Keynes	1.303	1.172	Stevenage & Welwyn Garden City	1.27	0.92	Luton	1.207	0.907
Stevenage and Welwyn Garden City	1.178	0.936	Crawley	1.23	1.04	Tunbridge Wells	1.174	0.938
Tunbridge Wells	1.156	1.062	Brighton	1.212	0.832	Edinburgh	1.156	0.93
Oxford	1.147	1.607	Tunbridge Wells	1.199	1.039	Stevenage & Welwyn Garden City	1.142	0.779
Crawley	1.137	1.041	Oxford	1.164	1.733	Crawley	1.098	0.907
Swindon	1.07	0.814	Cheltenham	1.114	0.942	Oxford	1.075	1.342
Cambridge	1.067	1.163	Swindon	1.09	0.779	Cheltenham	1.07	1.088
Bristol	1.019	0.961	Cambridge	1.08	1.081	Bristol	1.064	1.025

Cheltenham	1.013	1.076	Southampton	1.06	0.841	Swindon	1.058	0.729
Edinburgh	0.974	0.852	Bristol	0.977	0.936	Cambridge	1.009	1.151
Bedford	0.945	0.693	Bedford	0.976	0.726	Worthing	0.921	0.61
Worthing	0.882	0.872	Worthing	0.947	0.681	Bedford	0.904	0.637
Chelmsford	0.88	0.73	Chelmsford	0.927	0.698	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	-0.01	0.05**	-0.01
		(0.007)	(0.007)	(0.02)	(0.008)
Lag population density (population / square kilometres)		0	0	-0.00**	0
		(0)	(0)	(0)	(0)
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.

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* (0.048)	0.12** (0.051)	0.09 (0.059)	0.04 (0.031)	
Log other tradables jobs	0.26*** (0.065)	0.25*** (0.066)	0.32*** (0.090)	-0.02 (0.080)	
Lag share of graduates in population (residence basis)		-0.01 (0.025)	0.00 (0.030)	0.04 (0.048)	-0.01 (0.027)
Lag population density (population / square kilometres)		0.00 (0.000)	-0.00 (0.000)	-0.00 (0.000)	0.00 (0.000)
Lag share of population aged 16-24		-0.32** (0.140)	0.02 (0.132)	-0.50 (0.440)	-0.18 (0.138)
Lag share ILO unemployed in workforce (residence basis)		0.18 (0.124)	0.09 (0.112)	-0.08 (0.240)	0.17 (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** (0.087)	0.30*** (0.092)	0.09 (0.087)	0.00 (0.102)	
Log other tradables workplaces	0.69*** (0.130)	0.65*** (0.140)	0.66*** (0.085)	0.55*** (0.201)	
Lag share of graduates in population (residence basis)		0.01 (0.031)	0.00 (0.029)	0.02 (0.060)	0.00 (0.032)
Lag population density (population / square kilometres)		0.00 (0.000)	0.00 (0.000)	-0.00 (0.000)	0.00 (0.000)
Lag share of population aged 16-24		-0.21 (0.145)	-0.03 (0.115)	-0.81** (0.366)	-0.15 (0.150)
Lag share ILO unemployed in workforce (residence basis)		0.25** (0.123)	0.27*** (0.091)	0.36* (0.211)	0.23* (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*** (0.069)	0.05*** (0.016)	0.26*** (0.067)	0.05*** (0.018)	0.07** (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*** (0.045)	0.17*** (0.047)	0.18*** (0.047)	0.17*** (0.045)	0.17*** (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** (0.048)	0.20** (0.089)	0.14** (0.054)	0.23** (0.104)	0.24* (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*** (0.044)	0.17*** (0.044)	0.16*** (0.044)	0.15*** (0.044)	0.15*** (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	156	156	156	156	156
Overall R^2	0.85	0.87	0.86	0.85	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	156	156	156	156	156
Overall R^2	0.94	0.92	0.91	0.94	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	156	156	156	156	156
Overall R^2	0.87	0.79	0.82	0.87	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	156	156	156	156	156
Overall R^2	0.91	0.91	0.89	0.90	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**	0.09*
	(0.051)	(0.048)
Log other tradables jobs	0.25***	0.25***
	(0.066)	(0.069)
Observations	156	78
Overall R^2	0.94	0.39
Panel B. Workplaces	**(1) main**	**(2)**
Log creative industries plants	0.30***	0.26***
	(0.092)	(0.084)
Log other tradables plants	0.65***	0.65***
	(0.140)	(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. 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 B13. 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 B14. 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 B15. 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 B16. 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.

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