## Creative Industries Policy and Evidence Centre

Led by Newcastle University





# Creative Destruction?

Creative firms, workers and residential gentrification

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## Abstract

## Please note: This discussion paper, which has not been externally peer-reviewed, combines a range of microdata at the Census Output Area level

An established theoretical and case study literature discusses how the creative industries, and Creative City policies, may drive neighbourhood gentrification. However, this literature is inconclusive on the size of these links; whether creative activity drives neighbourhood change or follows it, and how this happens; and differences across creative firms, workers and activities, notably the role of artists and 'the arts' versus other creative sectors. This paper seeks to clarify these questions by testing the links between creative activity presence and residential gentrification. We explore these issues for neighbourhoods in England and Wales, using rich microdata on creative firms and workers for the 2000s and 2010s. We find that the overall links between localised creative activity and subsequent gentrification is small, even in the most creatively-dense neighbourhoods. The role of creative firms is more stable, but substantively smaller, than that of creative workers. The overall picture hides important variations across places, properties and activity types.

Key Words: creative industries, cities, neighbourhoods, housing markets, gentrification

**JEL codes**: L8, O18, R3

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#### About the Creative Industries Policy and Evidence Centre

The Creative Industries Policy and Evidence Centre (PEC) works to support the inclusive and sustainable growth of the UK's Creative Industries through the production of independent and authoritative evidence and policy advice. Led by Newcastle University with the Royal Society of Arts and funded by the Arts and Humanities Research Council, the Centre comprises a core consortium of; Newcastle University, Work Advance, Sussex University and the University of Sheffield. The PEC works with a diverse range of industry partners. For more details visit http://www.pec.ac.uk and @CreativePEC

## Introduction

This paper explores the role of creative firms and creative workers in neighbourhood gentrification, using rich data for England and Wales. When a neighbourhood gentrifies, higher-income arrivals, typically graduates, push up property costs and change the local amenity mix, helping displace the original lower-income residents (Glass 1964, Smith 1987, Ley 1996, Lees 2000, Butler and Robson 2003, Hamnett 2003). Many scholars suggest that creative firms and workers are part of these processes (Zukin 1989, Ley 2003, Pratt 2009, Hutton 2015). In the classic account, artists 'upgrade' neighbourhoods and are then priced out themselves (Zukin 1989, Lees 2003, Grodach, Foster et al. 2016). More recent accounts highlight the role of creative workers, especially high-paid graduates in creative services (Florida 2002), and creative firms providing anchor amenities or changing local look and feel (Zukin 2008, Hutton 2015).

Academics and activists highlight the economic, social and political disruption from gentrification as a whole (Smith 1996, Zukin 2008, Lees, Slater et al. 2013, Minton 2016). Nevertheless, the existing literature is inconclusive on the role of creative economy actors in gentrification, how large effects are, and whether they differ across creative space, notably artists and 'the arts' versus other creative activities. At the same time, urban policymakers embrace 'creative city' strategies that actively seek to grow creative clusters as a means of driving urban economic growth (Mathews 2010).

In this paper we explore links from localised creative activity to subsequent neighbourhood gentrification, using a dynamic cross-section design at the Output Area (OA) level for England and Wales, 2001-2011. Our design and granular data allow us to test the influence of differences across creative actors and activities, property types, microclusters and the wider urban hierarchy on our main results. Our design also mitigates many, though not all, endogeneity issues.

We have four main results. First, we find creative activity is associated positively but very weakly to gentrification. A 10 percentage-point increase to creative businesses in 2001 is linked to a 0.002 increase in the probability of an OA to be gentrified in 2011. The impact of creative workers on gentrification is an order of magnitude larger but i) this is still a small effect (a 10 percentage point increase in creative workers' share is linked to a 0.02 increase in an OAs gentrification probability) and ii) we find evidence of influence from unobservables on this relationship.

Second, there is a strong urban footprint in the relationship between the creatives and gentrification. We find the strongest links when we look at the distribution of creative concentrations (90<sup>th</sup> percentile and above) and when we restrict our sample to London, Birmingham, Manchester, Liverpool, Bristol and Cardiff. The latter is corroborated by consistently significant results for terraced houses and flats, archetypical inner urban property types.

Third, we find important differences when we look at the impact mechanisms of creative firms and workers. When we look at creative businesses, their impact on gentrification is driven by changes in more expensive neighbourhoods and is linked to arts businesses rather than creative services. On the contrary, the impact of creative workers is linked to changes in cheaper areas and artists. These findings draw a picture where creative businesses are attracted to already gentrified areas, contributing little to their further gentrification whilst artists are drawn to cheaper areas that are more actively gentrified over the coming decade.

Fourth, when we look at the creative workers' location patterns, there is evidence of push and pull forces for different parts of the creatives. Creative workers concentrate in neighbourhoods with large shares of creative services workers but the more this share overshadows the artists, the smaller the pull to other creatives. Overall, there is suggestive evidence that the artists are often followed by creative services workers who tend to pull further creative services workers at a decreasing rate.

These findings have important policy implications. Whilst on the average, the influence of the creatives to gentrification is small, there are limited places where the connection and impacts will be more pronounced and visible. Policymakers should be aware of these nuances and engage in planning, pride in place and community building interventions together with active labour market policies to mitigate adverse effects.

We make multiple contributions to the existing literature and policy debates on gentrification. Our combination of a wide scope, and granular view, allow us to show both aggregate relationships and uncover a lot of nuances, specifically on i) the differential relationship of firms and workers to gentrification; ii) differences within the creative economy space; iii) the intensity of the relationship in different parts of the creative density distribution and the urban hierarchy, and iv) the varying effects among different property types. Finally, our findings help reconcile some of the existing gentrification debates on whether artists are following or fuelling gentrification with the nuance suggesting that arts firms follow gentrifiers whilst artists precede them.

The paper runs as follows. Section 2 surveys the gentrification literature, and the roles creative economy actors can play. Sections 3-4 outline our research design and data. Sections 5-7 present our descriptive analysis, creative firms and creative workers analysis respectively. Section 8 concludes and suggests areas of further research.

## 2. Framework

This paper sits at the intersection of two large fields: gentrification and its drivers; and creative firms and workers' role in gentrification processes. We review each briefly.

#### 2.1 Gentrification and its drivers

Neighbourhood gentrification involves three linked processes: growing shares of high-income arrivals, rising property costs, and displacement of lower-income residents.<sup>1</sup> As defined by Glass (1964), gentrification happens when inner-urban working-class neighbourhoods are 'taken over by the middle classes' (p22) and develop higher-income residential, recreational and other uses. As property prices and rents rise, better-off, better-educated newcomers partially or fully displace the original inhabitants.

<sup>1</sup> Residential gentrification is distinct from industrial gentrification, in which newer industries displace older ones (Yoon & Currid-Haclkett, 2014).

Researchers and activists have added many further layers to this story. Urban economists see gentrification as a highly localised outcome of high-level structural shifts (Rosenthal and Ross 2015).<sup>2</sup> As many countries become service-dominated, urban areas become increasingly 'post-industrial', with knowledge-intensive services, retail, leisure and culture taking up ever-larger activity shares (Glaeser 2011). These changes in industry mix often help power urban revival: complex service activities that rely on face-to-face interaction have raised demand for – and inflows of – highly-paid skilled workers (Moretti 2012, Yoon and Currid-Halkett 2014). Demand for local amenities also drives urban repopulation: new residents want access to restaurants, bars, theatres and venues, galleries and retail – that cluster in city cores (Moretti 2013, Couture and Handbury 2019). As 'reviving' neighbourhoods grow crowded and more expensive, and developers respond by constructing / repurposing housing stock, many of the original inhabitants are displaced (Guerrieri, Hartley et al. 2013, Couture, Gaubert et al. 2019).<sup>3</sup>

These accounts share much with 'demand-side' theories in urban sociology, which also emphasise postindustrial shifts (Scott 1988, Scott 1997, Hall 2000), producing cohorts of new middle class urban residents. Their demand for housing, specifically preferences for inner urban lifestyles, drive gentrification (Ley 1996, Butler 1997, Butler and Robson 2003, Hamnett and Whitelegg 2007).<sup>4</sup> Economic frameworks are also compatible with 'supply-side' accounts developed by critical geographers, which put the focus on profit-seeking developers /investors. Here, poor, inner urban neighbourhoods have 'rent gaps' between current and potential property values (Smith 1987, 1996). Developers and investors exploit these, buying up stock, raising property values and displacing residents (Slater 2017), sometimes including earlier gentrifiers (Lees 2003). Both demand and supplyside theories have some explanatory power (Hamnett 1991, Lees 2000), with Glass herself identifying multiple causes of neighbourhood change (ibid, p22).

#### 2.2 Gentrification and creative activity

How might creative firms and workers contribute to this complex picture? The creative industries are highly urbanised, both in the UK and other countries (Bloom, Camerani et al. 2020, Borowiecki and Dahl 2021, Reuschke, Long et al. 2021). Several scholars have also made linkages between clusters of creative actors in cities – specifically artists – and gentrification, notably Zukin (1989), Florida (2002), Ley (2003) and Pratt (2009) (see Mathews (2010) and Hutton (2015) for reviews).<sup>5</sup> Grodach et al (2016) summarise:

<sup>2</sup> Rosenthal and Ross also demonstrate that in most cities, neighbourhoods are very dynamic over the long term. In a sample of 35 big US cities, half of all census tracts in 1950 had very different positions in the urban income distribution 50 years later. Similar patterns have been found in many European countries.

<sup>3</sup> An alternative – complementary – mechanism is that higher-income workers prefer inner urban locations because they want shorter commute times. Edlund et al (2022) find evidence for this in US cities.

<sup>4</sup> A related literature covers the role of 'marginalised' groups in neighbourhood change in the 1970s-90s, for example gay and lesbian communities. See Lees (2000) for a review.

<sup>5</sup> In these accounts, ironically, one type of creative – the artist – may end up being displaced by others – higher-paid creative service workers.

The common narrative is that artists move to a [cheaper] neighbourhood perceived as blighted and set the stage for gentrification by renovating and upgrading aging industrial, residential and commercial buildings. Their efforts serve to change the look and feel of urban neighbourhoods, which attract higher income groups that often displace long-time residents and businesses as well as the artists themselves. [p809]

We suggest that in fact there are at least three ways in which creative activity might gentrify a neighbourhood. First, as above, a specific *subset* of creative workers – artists – can help produce gentrification through 'neighbourhood upgrading'. Here, high and/or rising shares of artists living in a neighbourhood lead to gentrification later. Second, creative workers *as a whole* can also act as a gentrifying force. Most creative workers are graduates; those in creative services such as advertising, design and media, which dominates the creative workforce (DCMS 2022), are typically well-paid professionals very close to Glass' notion of middle-class incomers. In this account, neighbourhoods with large and/or increasing shares of residents working in the creative industries – especially those in creative services – may be more likely to gentrify. Third, creative *firms* locating in a neighbourhood may help it to gentrify: directly, by providing creative amenities such as arts or music venues; and/or indirectly, by contributing to a local creative milieu and thus changing a neighbourhood's 'look and feel' (Hutton, 2015). High and/or rising shares of creative firms raise the chances of subsequent gentrification.

These hypotheses also raise major questions, on which the empirical literature remains unclear. First, does creative activity *cause* gentrification? If middle-class urbanites have a taste for creative consumption, creative workers and firms might prefer to locate in established middle-class neighbourhoods, following gentrification instead of driving it. Behrens et al (2019) find that 'pioneer' industries in New York, almost all of whom are in creative sectors, locate in cheaper neighbourhoods and help predict future gentrification in the following decade. Conversely, Schuetz (2014) finds that art galleries locate in rich neighbourhoods in the city, not poorer 'bohemian' ones (see also Schuetz and Green 2014). Descriptive studies suggest that in some settings gentrification predicts growth in arts establishments but not the reverse (Grodach et al. 2016).

Second, what is the *mechanism* linking the creative activity and gentrification? Creative presence may attract middle-class gentrifiers who are looking for specific inner-urban lifestyles (Zukin 1989, Ley 2003). Grodach et al (2016) argue that artists produce gentrification through physical improvements and generating an attractive cultural milieux. A similar argument could be made at the firm level, with the presence of creative amenities – such as museums, galleries and other venues – the main drivers. Most broadly, if 'proximity to creativity' is an amenity in itself (Florida 2002) then creative services employees – such as designers, film-makers and the media – may also exert a pull. Creative presence of any kind may also be a signal that helps draw developers' attention to an area (Zukin 2008). Behrens et al (2019) find some support for this latter idea.

Third, these considerations suggest there may be important differences across creative activity space. We may observe differences between the effects of creative firms and workers. We may also observe different impacts within different worker and firm types: even within the arts, evidence shows some variation in location choices, for example between artists, art galleries, arts non-profits and fine arts (Stern and Seifert 2010, Grodach et al. 2014, Foster et al. 2016, Murdoch et al. 2016). Finally, we may see differences across physical space: most obviously between creative clusters and other neighbourhoods, but also between historically cheaper locations – more likely to have rent gaps – and more expensive neighbourhoods, perhaps less affordable to creative

workers but more attractive to some creative firms. In what follows we will explore all these dimensions.

## 3. Research design

Our framework sets out many linkages from growing creative activity in a neighbourhood, to neighbourhood change. There are also many challenges to testing these links empirically. First, gentrification processes can be self-reinforcing, with causation running both ways. Second, creative actors and residents may sort into neighbourhoods based on hard-to-observe characteristics; not accounting for these biases any creative industries 'effect' upwards. Third, macro forces – such as those driving urban renewal – may simultaneously change both creative firms' and residential location patterns: again, not controlling for these may yield spurious correlation. Fourth, the choice of spatial unit matters. Gentrification is typically very localised: but the literature is often vague on what constitutes a 'neighbourhood'. There is a risk of null results from measurement error (if units are too large) or spurious correlation via unobserved spatial spillovers (if units are too small). The latter need guarding against in any research design since they are likely to bias up results.

In what follows, we test links from UK neighbourhoods' creative firm and worker shares to the probability those neighbourhoods subsequently gentrify. We examine the heterogeneity of these effects across different levels of creative clustering, and mechanisms including historically cheaper / more expensive neighbourhoods, different property types, and inflows/outflows of different types of creative firms and workers. Overall, our objective is to cleanly estimate associations between creative activity and gentrifying neighbourhoods. As no obvious instrument or policy shifter is available, we do not seek to identify causal relationships.<sup>6</sup> Rather, we use long lags, fixed effects and rich microdata to mitigate most (though not all) endogeneity concerns.

In Sections 4 and 5, we build cross-sectional and panel datasets then run a series of descriptive exercises to test unconditional associations between creative activity presence-and shifts in gentrification, which we define as a neighbourhood experiencing both a) median property price increases and b) an increase in the share of graduates.<sup>7</sup>

In Sections 6 and 7, we use a dynamic cross-section to estimate links between neighbourhood creative firm and worker shares in 2001 and the probability of that neighbourhood gentrifying by 2011. This setting trades off some time variation, but allows us to take into account initial conditions and control for a rich array of relevant socio-economic characteristics. For neighbourhood *i* in local authority *c*, where *t* is 2011 and *tn* is 2001, we

<sup>6</sup> No obvious policy shifter is available: see Blanco and Neri (2021) for an example of such a shifter, for London housing estates. Many studies in the creative industries literature use shift-share instruments to help identify the impact of the creative industries on local economies. In the UK, creative industries are highly clustered in a few city-regions and this clustering persists over time. This makes shift-share instruments unsuitable for the creative industries case. Figure 1 confirms this is the case in our data. We also test out two historical instruments used at city-region level in Gutierrez-Posada et al (2022), who use areas' proximity to 19th-century art schools (positively predicting neighbourhood creative firm shares) and to historic coalfields (negatively predicting shares). While these instruments perform well at the urban level, they do not pass first-stage tests at the neighbourhood level.

<sup>7</sup> In sensitivity checks we test a range of alternative definitions of gentrification. See tables B5 & B9.

estimate:

$$Y_{it-tn} = a + bCI_{itn} + cG_{itn} + Xd_{itn} + C_c + e_{ic}$$

Here Y is a gentrification dummy taking the value one when an Output Area experiences rising graduate shares and property prices between 2001-2011. CI is the Output Area's share of creative industries firms over all OA firms, or residents working in creative industries over all OA residents. In variations we look at the role of various firm and worker subgroups. **X** is a vector of time-varying and invariant controls covering neighbourhoods' historic housing market change, age structure, occupational mix, human capital, industrial structure, population density, amenities and school performance (see Section 4 for details). C is a local authority fixed effect. In our basic specification standard errors are clustered on Output Areas; following Behrens et al (2019) we also run a more demanding regression with arbitrary spatial clustering (Colella, Lalive et al. 2019). As before, we test for the role of historically cheaper and more expensive neighbourhoods, creative services vs. arts, creative microcluster intensity, and differences across property types.

(1)

#### **3.1 Limitations**

Our design has three main limitations. First, our data does not allow us to systematically explore changes in neighbourhood-level incomes, an important component of gentrification.<sup>8</sup> In future versions of the paper we will validate our gentrification measure by correlating change in district-level graduate shares and median incomes. Second, our data does not include developers or construction activity, we cannot directly disentangle demand-side versus supply-side accounts.<sup>9</sup> Third, we cannot observe displacement in our data. Mapping displacement over time, either at area or at individual level, is extremely challenging (Lees, Slater et al. 2013).<sup>10</sup>

## 4. Data and build

#### 4.1 Creative industries data

Our main data source for creative industries presence is OpenCorporates (OC), supplemented with FAME and Orbis Financials data. OC provide a unique historical dataset of companies in the UK, by extracting the entire UK Companies House register every year via the Companies House API. This covers all active companies and business partnerships such as Limited Liability Partnerships (LLPs) active between 1995 and 2018, including

<sup>8</sup> Neighbourhood-level incomes data is usually gathered in national censuses. The UK Census is unusual in not asking questions about income. The best alternatives are workplace and labour force surveys such as ASHE and the APS. While neither has a large enough sample to be robust at neighbourhood level, in future versions of the paper we will use these data to run validation checks at the local authority district level.

<sup>9</sup> Linking EPC data to Land Registry data would allow us to see property age and new-builds. This is a promising avenue for future work.

<sup>10</sup> Directly tracking displacement at the individual level is extremely challenging and often requires manual data gathering (Minton, A. 2016) or modelling on fine-grained data (Reades et al, 2023).

companies in administration or dissolved during the sample timeframe. We build on work by Draca et al (2021) who extensively clean and improve the raw OC data, merging it with FAME and Orbis data, both to fill in missing information and to identify real-world businesses – rather than their corporate structures, which may be very complex. We make further improvements to location variables, in order to work with the data at small area level. These cleaning steps and diagnostic exercises are summarised in <u>Appendix A1</u>. Our input sample covers 5.6m firm-level observations from 2000-2018 inclusive, which we aggregate to small area level for England and Wales only.

#### 4.2 Creative workers data

We use bespoke Census 2001 and 2011 data tables from the ONS to identify creative workers at the OA level in England and Wales. Because we are interested in gentrification, we look at residents of a neighbourhood who work in creative occupations rather than workplace data.<sup>11</sup> Note that the set of creative occupations, as defined by the UK government, includes workers who are likely to work in creative industries firms – such as actors, architects, or advertising directors – and those who are 'embedded' in non-creative firms, such as town planners or public relations professionals. We return to this in Section 4.4.

#### 4.3 Housing market data

Housing market data comes from two sources. Property price data for England and Wales is provided by the Land Registry. Details of all property transactions are legally required to be filed with the Registry. The PricePaid dataset consists of just under 24 million property-level observations from 1995-2018, including full postcodes of the property in question. Details are given in <u>Appendix A2</u>.

#### 4.4 Main variables

We define neighbourhood creative activity as the share of share of creative industries firms over all OA firms, or residents working in creative industries over all OA residents. Creative industries firms and workers are defined using the standard SIC2007, SOC2010 and SOC2000 codes defined by the UK Government (DCMS 2018). In extensions we subset both creative firms and workers into 'creative services' and 'arts'. See <u>Appendix A3</u> for details. For housing costs, we construct measures of median annual prices in 2015 prices (using a 2015 CPI deflator, hence 'median property prices'). This gives us a measure of actual price changes in time-consistent money terms.

We measure gentrification in a neighbourhood by combining property price shifts and changes in neighbourhood composition taken from the 2001 and 2011 UK Census. Specifically, we build a gentrification dummy for each OA which takes the value one if that neighbourhood has experienced both a rise in median property prices between 2001 and 2011, and an increase in the share of graduate residents over the same period.

<sup>11</sup> This refers to usual residents aged 16-74 in employment in the Census reference week.

## 4.4 Control variables

We also need to account for multiple factors that may shape both creative activity and gentrification in England and Wales. We source controls from the Land Registry, 2001 England and Wales Census (via Nomis), from Ordnance Survey Points of Interest data (via the ONS Geography Portal and Edina) and from the UK Department for Education. Specifically, we account for the socio-economic composition of OAs in our base year (2001 median age, the share of population in managerial, professional, associate professional and technical, administrative and skilled trades occupations, the share of population with NVQ level 1-4 qualifications, the share of small employers according to NS-SEC) as well as spatial data (population density, counts of parks and recreational areas within 500 meters of an OA centroid). Finally, we include information on the quality of local schools, a factor shown to have a major influence on local property costs (Cheshire and Sheppard 2004). Specifically we use Key Stage 2 scores (pupils aged 7-11, tests at age 11), from Koster and Pinchbeck (2022). For each OA, we take the average of KS2 scores for the four closest schools to each postcode in the OA. Then for each OA, we average these scores and end up with the OA average KS2 score of each OA postcode's four closest schools. Finally, to handle pre-trends, we also include the growth rate of OA house prices in the five years prior to 2001.

#### 4.5 Build

We build datasets of creative presence and housing costs restricting to locations in England and Wales where we have coverage of property prices, change in graduate shares or both. We focus on Output Areas (OAs), the most detailed geographies available. OAs are clusters of postcodes designed to represent discrete neighbourhoods averaging 300 people per OA and a minimum of 100 people (Office for National Statistics 2014). For our cross-sectional analysis, our data consists of 85,092 OA observations for the year 2001 or the period 2001-2011.

## 5. Descriptive analysis

We first explore the basic properties of our data, and test unconditional links between key variables.

Table 1 presents summary statistics on the OA-level variables included in our analysis in 2001. We can see panels highlight significant spatial variation in the share of creative firms, property prices and rents, and the associated 10-year change. In our main analyses we therefore run sensitivity checks for outliers.

Variable	N	Mean	Median	Min	Max
% Cl firms, 2001	85,092	0.10	0.00	0.00	1.00
% Cl workers, 2001	85,092	0.08	0.07	0.00	0.41
10-year change in % CI firms, 2001- 11	83,810	0.01	0.00	-1.00	1.00
10-year change in % CI workers, 2001-11	83,810	-0.02	-0.02	-0.32	0.24
gentrification dummy, 2001-11	85,092	0.84	1.00	0.00	1.00
Controls, 2001					
median age	85,092	22.73	22.30	0.00	54.60
share managers	85,092	17.38	16.60	0.00	69.60
share professionals	85,092	13.26	12.20	0.00	83.10
share associate prof and technical	85,092	14.65	14.20	0.00	76.30
share administrative	85,092	13.35	13.20	0.00	33.60
share skilled trades	85,092	10.99	10.70	0.00	47.30
share with level 1 qualification	85,092	15.60	15.70	0.00	38.10
share with level 2 qualification	85,092	19.96	20.20	0.00	62.00
share with level 3 qualification	85,092	8.58	8.00	0.00	78.50
share with level 4 qualification	85,092	24.49	22.10	1.10	86.20
share small employers	85,092	8.14	7.40	0.00	54.10
population density	85,092	43.23	33.36	0.02	9,350
# recreational areas per OA	85,071	17.84	16.50	0.50	96.00
Key Stage 2 score	81,344	0.80	O.81	0.25	0.99

Table 1. Summary	/ statistics,	<b>Output Areas</b> ,	2001 and 2001-11	L.
	,			

Source: Open Corporates, Orbis, Land Registry, Census 2001 and 2011, Edina, Department of Education

<u>Figure 1</u> gives more detail on our main variables. The top panel shows the distribution of output area creative firm shares in 2001 and 2011. The middle panel repeats the exercise for creative worker shares in the same years. Because our gentrification variable is a dummy, the bottom panel aggregates to medium super output area level (MSOA)<sup>12</sup> and shows MSOA shares of gentrified output areas in 2011.

<sup>12</sup> MSOAs are aggregations of Output Areas, with an average of around 7,000 people and a minimum of 5,000 people per MSOA.





Source: Open Corporates, Orbis, Census.

Top panel shows output area share of creative industries firms. Middle panel shows output area share of residents working in creative industries.

Bottom panel shows Medium Super Output Area shares of gentrified OAs in 2011. Creative industries firms and workers defined using DCMS industry and occupation typologies.

Overall, we see extensive clustering of creative firms, and to a lesser extent creative workers; clustering in the former is highly persistent, while the latter have become more co-located over the 2000s. This is consistent with other studies of creative clustering in the UK and elsewhere (Bloom, Camerani et al. 2020).<sup>13</sup> By contrast, the median MSOA has seen an increase in property prices and graduate share – our measure of gentrification – in the majority of its neighbourhoods

The histograms of share creative firms (top left) suggest some neighbourhood-level diffusion between 2001 and 2011: specifically, a drop in the most creative-dense OAs, and a growth in OAs with at least some creative presence. Appendix tables <u>B1</u> and <u>B2</u> explore these shifts in more detail, focusing on local authority districts' counts and shares of 'creative-dense' OAs in 2001 and 2011 (where 'creative-dense' is defined as an OA with 50% creative industries firms or more). In these areas, counts show a striking shift over time out of London into London satellites, and smaller cities and towns.<sup>14</sup> Normalising for district size using shares, these patterns are still observable though less stark.

Figure 2 explores the unconditional relationships between MSOA creative activity in 2001 and intensity of gentrification in 2011, for firms (top panel) and workers (bottom panel).

<sup>13</sup> Appendix Figure B1 provides broader context, showing that our data is part of a larger growth in creative industries activity during the 2000s and 2010s, and one which is observed across all kinds of neighbourhoods.

<sup>14</sup> Note that we do not track individual firms over time, so these findings cover changes in overall distributions rather than actual firm moves. There are at least four complementary explanations for these patterns. First, a process of culturalization, where every place gets a higher share of creative firms, as creative activity permeates the economy. Second, as big city economies grow and diversify, the relative shares of CI firms fall in those neighbourhoods, more than the rest of the country. Third, a combination of industrial and residential gentrification may price out / displace creative firms and workers. Fourth, at least in some cases, the results may be driven by OAs with few firms, so that small changes to firm counts generate large percentage changes.



Figure 2. Creative activity and change in MSOA gentrification, 2001-2011. Top: Creative firms. Bottom: Creative workers

Source: Open Corporates, Orbis, Land Registry. Each observation is an MSOA, weighted by total firms.

Surprisingly given the rhetoric around creatives and gentrification, but consistent with Figure 1, we see a weakly negative relationship for creative firm shares, and a stronger negative link for creative workers. These figures are raw correlations, and once we fit controls, these relationships turn weakly positive – see Sections 6 and 7.

Finally, we turn to differences in the spatial distributions of creative firms and workers. Table <u>B3</u> shows pairwise correlations across OAs. Different types of creative firms are tightly co-located, per existing literature. Overall, creative industries firms have a very strong correlation (0.9) to creative services (Advertising and marketing; Architecture; Design; Film, TV, video, radio and photography; IT, software and computer services; Publishing) and less so to Arts establishments (0.4) (Crafts; Museums, galleries and libraries; Music, performing and visual arts). However, when we compare businesses to the location of workers (based on residence), the spatial distribution of firms is completely unrelated to the location of workers. Indeed, the highest correlation coefficient is between Cl firms and the share of Cl workers in the total employees in an OA at 0.1. To the best of our knowledge, approximately 2/3 of creative employees in the UK work in creative industries (Kemeny et al., 2020). As such, the lack of correlation between creative firms and creative workers is likely to signal varying location preferences between them, rather than an overwhelming presence of creative workers in non-creative businesses. This is suggestive evidence that creative workers may have different impacts on residential gentrification and house prices.

To examine this further, Figure 3 shows binscatters of creative firms and workers. Specifically, on the vertical axis we have the share of (all, services and arts) creative firms in 2001 and on the horizontal axis we show the 10-year change in the share of (all, services and arts) creative employees. For all creative industries and arts, we see a positive relationship suggesting that the presence of firms is linked to an increase in the presence of workers in the neighbourhood. This is not the case though for creative services firms and employees where neighbourhoods with higher shares of creative services businesses in 2001 are associated with smaller increases in the local share of creative services workers in the subsequent decade.





Source: Open Corporates, Orbis. Census 2001, 2011. Each observation is a group of Output Areas. Relationships conditional on main controls

Overall, this picture is broadly consistent with the framework in Section 3: there are many forces working on neighbourhood housing costs and gentrification, so that the creative activity channel may not be that strong.

## 6. Results: gentrification and creative firms

Here, we focus on gentrification, and links between neighbourhood-level creative industry presence and subsequent neighbourhood change.

#### 6.1 Main results

We run a linear probability model that links OA creative industries shares in 2001 to the probability an OA has gentrified by 2011, controlling for a range of covariates. Our gentrification measure is a dummy taking the value 1 if a neighbourhood experiences median property price growth 2001-2011, and a rise in OA graduate share 2001-2011. Results are summarised in Figure 4, which shows point estimates and 95% confidence intervals as before. We give full results in Table 2.

## Figure 4. Neighbourhood gentrification and share creative industries. Linear probability model, OAs, 2001 and 2011.



Our results show a robust link from neighbourhood creative shares to gentrification – although the effect size is very small. Specifically, for the average OA a 10 percentage point increase in the share of creative firms correlates to a 0.002 change in the probability the neighbourhood will gentrify over the following decade. As anticipated in our framework, this is a much thinner link than some other gentrification channels. For example, if in 2001 average KS2 test scores for schools in the neighbourhood rise by 10 points, this correlates to a 0.02 increase in the probability the neighbourhood rise by 10 points, this correlates to a 0.02 increase in the probability the neighbourhood has gentrified by 2011: an effect size around ten times larger.<sup>15</sup> Table 2 also shows

<sup>15</sup> Full results available on request.

that the stepwise introduction of controls has little impact on the creative industries coefficient.

The rest of <u>Figure 4</u> explores the main potential mechanisms. We find that these overall links are driven by neighbourhoods with historically higher property prices for their city-regions (TTWAs). This is consistent with a story where creative firms follow neighbourhood change rather than driving it, locating to be closer to richer consumers. We also find larger coefficients for the arts (museums, galleries, artists and musicians etc.) than for creative services (advertising, media, design etc.). This is consistent with the conventional gentrification narrative outlined in our framework.

	No controls	Controls_1	Controls_2	Controls_3	Controls_4	Controls_5	All controls	Expensive	Cheap	Creative Services	Arts	Creative Services & Arts
Chara areative firme	0.026***	0.025***	0.023***	0.029***	0.026***	0.024***	0.023***	0.032***	0.005			
Share creative jims	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.008)			
Chara conjigan										0.019***		0.020***
Shule services										(0.005)		(0.005)
Charo arta											0.042***	0.044***
Share arts											(0.012)	(0.012)
Price Growth		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Median Age			Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation & SEC Controls				Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Qualification controls					Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Place Controls						Yes	Yes	Yes	Yes	Yes	Yes	Yes
School Performance							Yes	Yes	Yes	Yes	Yes	Yes
Ν	85,092	84,058	84,058	84,058	84,058	84,038	80,345	48,947	31,398	80,345	80,345	80,345
F	27.476	13.341	100.163	168.764	210.292	186.639	174.529	88.452	104.744	173.987	174.239	164.566
R <sup>2</sup>	0.031	0.032	0.035	0.050	0.065	0.066	0.068	0.063	0.106	0.068	0.068	0.068

#### Table 2. Neighbourhood gentrification and creative industry shares. Linear probability model, OAs. 2001 and 2011.

Source: Land Registry Orbis, Open Corporates, ONS.

**Notes**: cross-sectional LPM regressions. The dependent variable is the probability an OA gentrifies in 2011. All regressions include local authority district (LAD) dummies. Columns 1-7 show gradual introduction of controls for an OAs price growth 1995-2000 (Col 2 onwards), median age (Col 3 onwards), share in managerial, professional, associate professional and technical, administrative and skilled trades occupations & share of small employers according to NS-SEC (Col 4 onwards), share of population with NVQ Level 1, 2, 3, 4 qualifications (Col 5 onwards), population density and the number of recreational areas per OA (col 6 onwards) and our preferred specification including the average KS2 test scores of the closest schools in an OA (Col 7 onwards). Standard errors clustered on OA. \* p<0.0, \*\*\* p<0.01.

#### 6.2 Robustness checks

Our firm results survive an extensive set of robustness and sensitivity checks, detailed in Tables <u>B4</u> and <u>B5</u> respectively. In Table <u>B4</u>, Column 1 gives our main result. Column 2 explores the relative importance of unobservables using tests from Oster (2019). The delta of 5.99 is reassuring, implying that unobservables would have to be almost six times more important than our controls to explain away our main result. Columns 3 and 4 respectively show results for a Probit estimator and its marginal effect: using the "correct" functional form gives us a very similar outcome to our preferred estimator. Finally, column 5 estimates an arbitrary correlation regression (Colella et al 2020) which allows for much more flexible spatial autocorrelation within and across neighbourhoods. Coefficients are identical to our main result.

Table <u>B5</u> runs a battery of further tests covering sensitivity to outliers (Panel A) as well as alternative definitions of creative industries and gentrification (Panel B). In each panel, column 1 shows our main result. In Panel A, we drop London (column 2), drop London and major cities (3), include only big cities (4), and drop outliers in terms of neighbourhood property prices (5) and creative firm shares (6). Coefficients on OA creative firm shares remain robust, dropping slightly when London and/or big cities are excluded, and rising when the sample is restricted to the top of the urban system or creative industries outliers are removed. This suggests that gentrification effects are stronger in London and larger cities and robust to the exclusion of outliers.

In Panel B, column 2 redefines creative industries using US creative pioneer sectors, per Behrens et al (2019), giving a very similar result. Columns 3 -7 use alternative definitions of our gentrification dummy, mostly swapping qualification levels for a different metric. <sup>16</sup> These typically shrink the coefficient share of creative firms, and in Column 5, where the definition of gentrification does not consider education but the share of small employers, it becomes insignificant. This is arguably the definition that is furthest away from the notion of gentrification since the share of small employers does not necessarily indicate a higher position in the hierarchy of socio-economic classification.

#### 6.3 Extensions

We build out two extensions to the main analysis. First, we explore how effects vary across neighbourhoods with different levels of creative firm clustering. Second, we explore how gentrification probabilities vary across property types.

Table <u>B6</u> gives results for the intensity analysis. As before, we show our main result (column 1), then results for OA dummies in the 50<sup>th</sup>, 75<sup>th</sup>, 90<sup>th</sup> and 95<sup>th</sup> percentiles of the overall share creative firms' distribution (columns 2-5). These give the 'effect' of creative industries presence in those neighbourhoods versus all other neighbourhoods. Our main result is driven by the most creatively dense areas, specifically neighbourhoods in the 90<sup>th</sup> and 95<sup>th</sup> percentiles.

Table <u>B7</u> summarises the results of our property types regression. Here we are – in effect – exploring specific gentrification trajectories, as embodied in property transactions by property type. The results confirm the positive relationship in our preferred specification and suggest that the gentrification link is twice as strong for flats. This is not unexpected given the concentration of creative industries in urban cores and the earlier results for London and the big cities.

<sup>16</sup> Col 3 - based on share managers and professionals (SOC classes1, 2) rather than education level; Col 4 - based on share lower managerial occupations (NS-SEC class) instead of education level; Col 5 - based on the share small employers (NS-SEC class) instead of education, SOC and NS-SEC group; Col 7 - based on education, SOC, NS-SEC but not house prices

## 7. Results: gentrification and creative workers

The geographies of creative workers and creative firms differ, as we show in Section 5. We now explore whether the location of creative workers affects gentrification in the same ways as creative firms. The data also allow us to test the relationship between creative services and arts workers and how do they influence the concentration of creative employees.

#### 7.1 Main results

Figure 5 shows our main results for creative workers (Table 3 gives full results).

## Figure 5. Neighbourhood gentrification and share creative workers. Linear probability model, OAs, 2001 and 2011.



For the average OA a 10 percentage-point increase in the share of creative workers correlates to a 0.02 change in the probability the neighbourhood will gentrify over the following decade. This is still a small effect, but also an order of magnitude larger compared to the effect of creative businesses. These outcomes appear to be driven more by changes in cheaper OAs and are related to concentrations of arts rather than creative services workers. We also find that areas with high concentrations of services workers among their creative residents in 2001 is associated with lower probability for an OA to gentrify by 2011.

Overall, these results support a picture where creative services workers in 2001 are located in gentrified areas with peak house prices (e.g. new city-centre developments) that have reduced by 2011, potentially as an impact from the 2008 crisis. On the other hand, artists in 2001 have located in cheaper areas that gentrified over the next decade.

	Baseline	Controls_2	Controls_3	Controls_4	Controls_5	All controls	Expensive	Cheap	Creative Services	Arts	Creative Services & Arts	CS /CI share
Share creative firms	0.023*** (0.005)											
Share creative workers		-0.759*** (0.036)	-0.160*** (0.048)	0.187*** (0.049)	0.185*** (0.049)	0.197*** (0.050)	0.145** (0.063)	0.270*** (0.083)				
Share services workers									0.053 (0.058)	0.500***	0.055 (0.058)	
Share arts workers										(0.094)	(0.094)	
Share services to creative workers												-0.02*** (0.006)
Price Growth	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Median Age	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation & SEC Controls	Yes		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Qualification controls	Yes			Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Place Controls	Yes				Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School Performance	Yes					Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ν	80,345	84,058	84,058	84,058	84,038	80,345	48,947	31,398	80,345	80,345	80,345	76,855
F	174.529	244.165	166.938	209.912	186.467	174.435	87.081	105.785	173.481	176.022	165.717	166.030
R <sup>2</sup>	0.068	0.041	0.050	0.065	0.066	0.068	0.063	0.107	0.068	0.068	0.068	0.068

#### Table 3. Neighbourhood gentrification and creative worker shares. Linear probability model, OAs. 2001 and 2011.

Source: Land Registry Orbis, Open Corporates, ONS.

**Notes**: cross-sectional LPM regressions. The dependent variable is the probability an OA gentrifies in 2011. Share Services uses the OA share of creative services workers such as advertising, design and media. Share Arts uses the OA share of the arts, including visual arts, musicians, museums and galleries. All regressions include local authority district (LAD) dummies. Column 1 is the creative firms' baseline. Other notes as per Table 2.

#### 7.2 Robustness checks

Tables <u>B8</u> and <u>B9</u> replicate the robustness checks and sensitivity analysis for creative firms. The results broadly follow the business analysis with few exceptions. Column 2 in Table <u>B8</u> uses the Oster delta parameter; in contrast to our firm results we find that unobservables likely influence the relationship between creative workers and gentrification. Thus, our creative worker results are notably less stable than those for creative firms. Similarly, columns 2 and 4 in Table <u>B9</u> show that when we proxy gentrification i) by the growth in the share of managers and professionals (SOC classes1, 2) rather than education level and ii) by the growth in the share of small employers (NS-SEC class) instead of education level, the relationship between creative workers and gentrification is negative. This could be the result of poor approximation of gentrification by these occupations and socio-economic class. In particular if managers and professionals tend to cluster in already gentrified or more expensive OAs, then it is to be expected that the result of our preferred specification is reversed in a similar way that we find a negative relationship between the concentration of creative services workers and gentrification in 2011 (previous paragraph).

In our main regressions we estimate results for creative firms and creative workers separately. Given their nonoverlapping spatial distributions, we can also fit both variables jointly, dealing with any concerns about omitted variable bias. Table <u>B10</u> shows the results of this exercise, including Oster deltas. Columns 1- 2 reproduce our main results; Columns 3-4 jointly estimate creative firm and worker effects, with deltas estimated for each term separately. Reassuringly, our main results are essentially unchanged.

#### 7.3 Extensions

Our extensions look at the creative intensity of neighbourhoods and the separation of effects by property type. Table <u>B11</u> shows the intensity analysis. As previously seen for creative firms, the positive relationship in our main result is mainly driven by the highest concentrations of creative workers in neighbourhoods at the 90<sup>th</sup> and 95<sup>th</sup> percentile whilst in the median (50<sup>th</sup> percentile) the relationship is negative. Also, as per the business analysis, the gentrification effects are stronger for flats and terraced houses (Table <u>B12</u>). These findings corroborate the story of the impact being greater in urban areas (and property types) with higher concentrations of creative workers. They are also indicative of the differing locational preferences and the opposing effects to gentrification that we observe between creative services workers and artists.

Finally, Table <u>B13</u> looks at the residential dynamics among creative workers and subgroups. We want to explore possible clustering or crowding out effects within the creative industries by looking into the relationship between the share of creatives in 2001 and 2011. As such, the dependent variable in columns 1-2 is the share of creative workers in total employed residents in 2011; in column 3 is the share of creative services workers and in column 4 the share of arts workers in total employed residents in 2011.

Column 1 shows a positive relationship between the share of creative services workers in 2001 and all creative workers in 2011, essentially highlighting a clustering effect. Column 2 however, suggests that the higher the ratio of services to arts workers in 2001, the lower the share of creative workers in an OA in 2011, pointing to decreasing marginal agglomeration effects. Columns 3 & 4 show positive attraction effects from artists in 2001 to creative services workers in 2011 (3) and vice versa (4) albeit with a much smaller coefficient. Overall, we find positive agglomeration forces that increase clusters in time. These appear to be stronger when artists dominate

the creative cluster in 2001 echoing the finding that artists move into an area, followed by creative services and other higher income workers that eventually gentrify that neighbourhood.

## 8. Discussion

'Creative city' policies look to actively use creative activity to drive urban growth (Mathews (Mathews 2010, Lindner 2018). However, many scholars and activists worry that boosting creative activity helps drive gentrification in urban neighbourhoods (Zukin 1989, Ley 2003, Hutton 2015). The existing literature is inconclusive on whether these links exist, how large they are, and whether they differ across creative space. In this paper we test links from localised creative activity to subsequent neighbourhood gentrification, using a range of rich data for neighbourhoods in England and Wales. Our design allows us to explore the many nuances between creative firms and workers, levels of creative co-location, and differences in creative activity, neighbourhood and property types.

We have four main findings, which we suggest help to reconcile these conflicting accounts. First, we find positive overall links from neighbourhood-level creative activity to gentrification, but these linkages are very small. Aggregate creative firm links are miniscule: in the average neighbourhood, a 10 percentage-point rise in creative firm share in 2001 corresponds to a 0.002 rise in the probability that neighbourhood will gentrify by 2011. Creative worker links are an order of magnitude larger (a 0.02 change in the probability of gentrification in the average neighbourhood) but are less stable, with neighbourhood or household unobservables likely to drive at least part of this result.

Second, these overall patterns have a clear urban / big city footprint. Creative activities' links to neighbourhood gentrification are much in big cities, in neighbourhoods with high concentrations of creatives (90<sup>th</sup> percentile and above) and are consistently significant for terraced houses and flats, typical property types in big cities.

Third, we find important differences between creative firms and workers, both in their effect sizes and the underlying channels. For firms, the overall link is explained by shifts in neighbourhoods with 2001 property prices above their city-region (TTWA) median price; arts businesses seem to have the greater influence as opposed to creative services. This is in line with Schuetz (2014), Schuetz and Green (2014) and Grodach et al (2016). For workers, overall links are explained by change in historically cheaper neighbourhoods and is driven by artists rather than creative services workers. This is consistent with Behrens et al (2019), who highlight the role of pioneer businesses and individuals in neighbourhood change.

Fourth, we find evidence of push and pull factors in creative workers' location dynamics, consistent with very localised agglomeration and displacement forces. The share of creative workers is increasing in neighbourhoods with higher shares of creative services workers, but decreasing with larger ratios of creative services to arts workers. The share of artists also has significant and positive correlations to the share of creative services workers, with more modest results for the opposite relationship. This suggests dynamics where artists move into an area, attracting creative services workers who further attract creative workers at a decreasing marginal rate.

Taken together these findings help reconcile the range of results we see in the literature. Creative activities' links to gentrification are highly urbanised, and most severe in big cities and in localised clusters in those cities. Creative workers, as part of a large graduate workforce, have a bigger role to play than creative firms. Results for artists and arts businesses are consistent with the classical accounts of creative-led gentrification and displacement. Conversely, creative firms as a whole tend to follow neighbourhood change, locating in richer locales and likely catering to existing higher-income residents.

In aggregate, and consistent with Glass (1964), creative activity is just one of many channels driving gentrification, and plays a minor role in the *average* neighbourhood. Nevertheless, it is important to note that there are *urban* neighbourhoods with high concentrations of arts activities that do seem to draw higher income residents, often creative services workers, and contribute to gentrification. In these cases, targeted planning, community building and employment/upskilling policies can alleviate local tensions.

Limitations in our study highlight opportunities for further research. Our dynamic cross-section design controls for many endogeneity challenges but is not causal. We lack individual / household income data at neighbourhood level. We also do not observe individual or household inflows/outflows. We encourage future researchers to exploit new, fine-grained data and/or policy shocks to build on our findings here.

## **Appendices**

### Appendix A: Data build

#### A1 / Company and firm microdata

Our main data source for creative industries presence is OpenCorporates, who provide a unique historical dataset of companies in the UK. The raw dataset has been extensively cleaned and improved by a team of researchers at UCL-Warwick-LSE-Milan, including one of the co-authors of this paper. The detailed procedure is given in Draca et al (2021) and summarised here.

- OpenCorporates (OC) extracts the entire UK Companies House register every year via the Companies House API. OC provided extracts from 2010 to September 2018 inclusive, covering all active companies and business partnerships such as LLPs, plus companies in administration or dissolved up to 15 years beforehand. While UK companies vary in their reporting requirements, we only use firm formation and dissolution year, industry (SIC) and location information, which all companies are technically required to provide when registering or which Companies House always provides.
- The OC time series is truncated from 2000, before which it is very sparse. The resulting company-level data runs from 2000-2018 inclusive and includes 11,253,821 distinct observations. Among these, 5,901,414 have dissolved by 2018, 5,658,581 do not report postcodes and 5,071,706 do not report a SIC code.
- Draca et al then run a number of cleaning steps. First, company-level observations are adjusted to best-fit real-world firms. As explained in Nathan and Rosso (2015), companies are legal entities not actual firms. It is therefore important to identify the underlying stand-alone enterprise, rather than (say) keep companies that are actually 100% owned by another company. To do this, Draca et al merge OC data with Orbis Financials data (1978-2019) and FAME to identify company group structures. This provides information on a company's ultimate owner, and all child companies that link back to it. The cleaning process reduces the sample from 11,253,821 company observations to 10,800,609 firms. We call this dataset 'OC-FAME'.
- Second, companies provide their own SIC information when registering at Companies House. Not all do so, as is clear from the raw data above. Draca et al fill SIC gaps using Orbis Financials data, and fit time-consistent SIC2007 codes using ONS proportional mapping. We call this dataset 'Orbis'.

To work with this data at small-area / neighbourhood level, we need reliable company location information. However, when setting up at Companies House, companies are only required to provide a registered address rather than an actual trading location. While the two may be the same, a registered address may also be the home address of a company founder, or the address of a lawyer or accountant. This means we cannot rely on location information in 'OC-FAME' without running further checks. Happily, the 'Orbis' sample provides verified trading addresses for some firms. We therefore link Orbis to OC-FAME data, and run a series of matching routines at the unique firm level. We segment our data by reliability:

• Our most robust subsample is firms for which we have trading addresses in Orbis and which we can match to OpenCorporates-FAME (which we dub OOC\_1). This consists of 259, 581 firms, 2.4% of our cleaned

OC data.

- Our second most robust subsample is firms where we have different registered addresses in OC and Orbis (OOC\_2). It is plausible that one of these is the trading address. We calculate the straight-line distance between addresses. In 24,382 cases, both addresses are in the same Output Area, our smallest unit of analysis. We keep this subsample, which consists of a further 0.83% of our cleaned OC data.
- Our third most robust subsample is firms for which the only available address data is the registered address from OC and Orbis (OOC\_3). Here we find 9,767,896 matches, 90.4% of cleaned OC firms. While it's plausible that one of these is the trading location, it is possible that other address information exists. We manually validate this for 50 randomly selected firms by searching their websites and search engines for further address information. 10 have additional address information online; in two further cases we are able to confirm the trading address is the registered address. This suggests that on the basis of existing information, there is an 80% chance that the registered address as the true trading location.
- The rest of the data (1.2% of cleaned OC firms, OOC\_4) is not merged to Orbis. We drop this data, 98% of which is for firms in the Republic of Ireland, with the rest in the Isle of Man or Channel Islands.

Table A1 summarises our matching steps and results.

Stage / sample	# obs	# unique firms	Notes
Input 1			
All OC-Fame	10,800,632	10,800,609	Matched OpenCorporates and FAME data
Input 2			
All Orbis	15,099,658	14,673,621	Orbis Financials data
Of which			
Orbis_T	1,748,898	1,748,404	Obs with trading address, <u>kept</u>
Orbis_R	12,655,504	12,229,961	Obs with registered address, <u>kept</u>
Orbis_M	695,256	695,256	Obs with missing address info, discarded
Matching			
From Orbis_T			
OOC_1		259,581	Obs with trading address, matched to OC-FAME. <b>Used</b>
Orbis_NT		1,488,823	Not matched, <b>discarded</b>
From Orbis_R			
00C_2		642,148	Matched to OC-FAME, different registered addresses
Of which same OA		24,382	Matched, different registered addresses, but same OA. <b>Used.</b>
OOC_3		9,767,896	Matched to OC-FAME, same registered addresses. <b>Used.</b>
Orbis_NR		1,819,917	Not matched to OC-FAME, discarded
00C_4		130,984	OC-FAME obs not matched, discarded

#### Table A1. OpenCorporates / Orbis address matching and validation routines.

This gives us 10,051,859 observations (OOC\_1 plus the usable part of OOC\_2 plus OOC\_3).

However, a non-trivial number amount of observations (4,448,690 out of 10,051,859 million observations) are missing SIC information. This renders them unusable for our purposes and hence they are dropped from our working sample of firms. Our input sample is then 5,603,169 observations.<sup>17</sup>

#### A2 / Property prices data

Property price data for England and Wales is provided by the Land Registry.<sup>18</sup> Details of all property transactions are legally required to be filed with the Registry. The PricePaid dataset consists of just under 24 million property-level observations from 1995-2018, including full postcodes of the property in question.

We construct measures of median annual property prices in 2015 prices (using a 2015 CPI deflator) and 2015prices rents indexed to 1995. The former gives us a measure of actual price changes in time-consistent money terms. The latter gives us percentage point changes in prices from the starting year of our data.

We build panels of median prices at a range of spatial scales: 2011 Output Areas (OA), 2011 Medium Super Output Areas (MSOA) and 2011 Travel to Work Areas. We assign properties to these larger units by linking postcodes with the November 2020 ONS National Postcode Directory.

<sup>&</sup>lt;sup>17</sup> To test the impact of this decision, we randomly select 500, observations from each group (with and without SIC information) and test the differences between the two groups on observables. On average, companies without SIC information have less cash reserves, assets, liabilities and subsidiary firms. They also have more employees, are older, but also more likely to have dissolved earlier and concentrated in London. Finally, businesses with missing SIC information tend to have more missing values among the above attributes.

<sup>&</sup>lt;sup>18</sup> https://www.gov.uk/government/statistical-data-sets/price-paid-data-downloads, accessed 27 April 2021.

#### A3/ Defining creative activity

We define creative industries using the standard UK Government definitions, which use nine industry groups (DCMS, 2016). We subset these into two blocs, creative services and arts, to use in extensions to our main results. Table A2 summarises our definitions.

Industry group	SIC2007	Description	Category
	7021	Public relations and communication activities	
Advertising and marketing	7311	Advertising agencies	Creative
marketing	7312	Media representation	Services
Architecture	7111	Architectural activities	
Crafts	3212	Manufacture of jewellery and related articles	Arts
Design: product, graphic and fashion design	7410	Specialised design activities	
	5911	Motion picture, video, television production	
	5912	Motion picture, video, television post-production	
	5913	Motion picture, video, television distribution	
Film, TV, video, radio and	5914	Motion picture projection activities	
photography	6010	Radio broadcasting	
	6020	Television programming / broadcasting activities	
	7420	Photographic activities	Croativo
	5821	Publishing of computer games	Services
IT, software and	5829	Other software publishing	
computer services	6201	Computer programming activities	
	6202	Computer consultancy activities	
	5811	Book publishing	
	5812	Publishing of directories and mailing lists	
Dubliching	5813	Publishing of newspapers	
Publishing	5814	Publishing of journals and periodicals	
	5819	Other publishing activities	
	7430	Translation and interpretation activities	
Museums, galleries and	9101	Library and archive activities	
libraries	9102	Museum activities	
	5920	Sound recording and music publishing activities	
	8552	Cultural education	Arte
Music, performing and	9001	Performing arts	AILS
visual arts	9002	Support activities to performing arts	
	9003	Artistic creation	
	9004	Operation of arts facilities	

Table A2. DCMS creative industries and creative su	ubgroups.
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Source: Table 8 Annex C DCMS (2016). The distinction between creative services and arts is done by the authors.

For the creative workers analysis we also work at occupation level. Table A3 sets out creative occupations, again using Government definitions of creative jobs.

	Creative Occupations Group	Category
1132	Marketing and sales directors	
1134	Advertising and public relations directors	
2472	Public relations professionals	
2473	Advertising accounts managers and creative directors	Cure at la co
3543	Marketing associate professionals	services
2431	Architects	00111000
2432	Town planning officers	
2435	Chartered architectural technologists	
3121	Architectural and town planning technicians	
5211	Smiths and forge workers	
5411	Weavers and knitters	
5441	Glass and ceramics makers, decorators and finishers	Arts
5442	Furniture makers and other craft woodworkers	
5449	Other skilled trades not elsewhere classified	
3421	Graphic designers	
3422	Product, clothing and related designers	
3416	Arts officers, producers and directors	
3417	Photographers, audio-visual and broadcasting equipment operators	Creative
1136	Information technology and telecommunications directors	Services
2135	IT business analysts, architects and systems designers	
2136	Programmers and software development professionals	
2137	Web design and development professionals	
2471	Journalists, newspaper and periodical editors	
3412	Authors, writers and translators	
2451	Librarians	
2452	Archivists and curators	Arts
3411	Artists	7 11 13
3413	Actors, entertainers and presenters	
3414	Dancers and choreographers	
3415	Musicians	

#### Table A3. DCMS creative workers and creative subgroups - SOC 2010

#### SOC 2000

	Creative Occupation Group	Category
1132	Marketing and sales managers	
1134	Advertising and public relations managers	
3433	Public relations officers	Questing
3543	Marketing associate professionals	Services
2431	Architects	
2432	Town planners	
3121	Architectural and town planning technicians	
5211	Smiths and forge workers	
5411	Weavers and knitters	
5491	Glass and ceramics makers, decorators and finishers	Arts
5492	Furniture makers, other craft woodworkers	
5499	Hand craft occupations n.e.c.	
3421	Graphic designers	
3422	Product, clothing and related designers	
3416	Arts officers, producers and directors	
3434	Photographers and audio-visual equipment operators	Creative
1136	Information technology and telecommunications directors	Services
2131	IT strategy and planning professionals	
2132	Software professionals	
3431	Journalists, newspaper and periodical editors	
3412	Authors, writers	
2451	Librarians	
2452	Archivists and curators	Arts
3411	Artists	
3413	Actors, entertainers	
3414	Dancers and choreographers	
3415	Musicians	

Source: Table 7 Annex B DCMS (2016). The definitions of creative occupations are built using SOC 2010 codes. Data for the 2001 Census is classified using SOC 2000 and hence we provide both in the table above. The distinction between creative services and arts is done by the authors and differs from the one in table A3 in that workers in Publishing (Journalists, newspaper and periodical editors; Authors, writers and translators) are now classed as Arts workers.

## **Appendix B: Additional results**



Figure B1. Neighbourhood shares of creative industry firms over time, 2000-2018.

Source: Open Corporates, Orbis, Land Registry. Expensive / cheaper OAs defined by surrounding TTWA median property price in 2000. Urban OAs defined for England and Wales only.





Top: Creative firms. Bottom: Creative workers

Source: Open Corporates, Orbis, Land Registry. Each observation is an MSOA, weighted by total firms. Urban MSOAs defined as those with over 50% urban OAs, for England and Wales only.

20	<u>01</u>	2011			
LAD	# CI-dense OAs	LAD	# CI-dense OAs		
Wiltshire	101	Gateshead	200		
Buckinghamshire	99	Birmingham	153		
Birmingham	92	Bristol, City of	90		
Richmond upon Thames	85	Brighton and Hove	79		
Ealing	82	Cornwall	78		
Cornwall	80	Manchester	76		
Bournemouth, Christchurch and Poole	78	Wiltshire	72		
Lambeth	78	Buckinghamshire	67		
Cheshire East	78	Coventry	66		
Lewisham	72	Cheshire West and Chester	66		
Croydon	71	Lewisham	64		
Wokingham	70	Liverpool	62		
Bromley	69	Lambeth	61		
Dorset	69	Croydon	61		
Brighton and Hove	67	Bromley	60		
Wandsworth	63	Ealing	60		
Barnet	63	Haringey	59		
Bristol, City of	62	Milton Keynes	57		
Stockport	61	Cheshire East	57		
Brent	61	Wirral	56		
Southwark	60	Wandsworth	56		
Haringey	57	Stockport	55		
Milton Keynes	57	Reading	55		
Cheshire West and Chester	57	Southend-on-Sea	55		
Waltham Forest	54	Waltham Forest	54		
Hounslow	54	Bournemouth, Christchurch and Poole	53		
Redbridge	53	County Durham	53		
South Gloucestershire	52	Hackney	52		
Merton	51	Dorset	52		
Sutton	49	South Gloucestershire	51		

#### Table B1. Number of CI-dense Output Areas per LAD. Top 30 LADs. 2001 and 2011.

Source: Open Corporates, Orbis

Note: An Output Area is considered CI-dense if the share of Creative Industries in total firms is above 50%

2001	2011			
LAD	% CI-dense OAs	LAD	% CI-dense OAs	
Bracknell Forest	22.1%	Gateshead	38.8%	
Wokingham	20.2%	City of London	22.2%	
Cambridge	18.9%	Bracknell Forest	17.6%	
Reading	18.5%	Reading	15.3%	
Oxford	18.0%	Hackney	13.9%	
Stevenage	17.2%	Woking	13.4%	
Rushmoor	17.1%	Cambridge	12.9%	
Basingstoke and Deane	16.7%	North Hertfordshire	12.6%	
Richmond upon Thames	16.1%	Wokingham	12.2%	
Southwark	16.1%	Chelmsford	12.1%	
Crawley	15.7%	Oxford	12.0%	
Swindon	15.6%	Exeter	12.0%	
East Hertfordshire	15.3%	Norwich	11.8%	
Mendip	15.1%	Southend-on-Sea	11.8%	
Lewisham	15.1%	Basildon	11.1%	
Milton Keynes	15.1%	Islington	11.1%	
lpswich	14.8%	Portsmouth	11.1%	
Surrey Heath	14.8%	Milton Keynes	11.0%	
Tamworth	14.7%	Gedling	10.6%	
South Cambridgeshire	14.7%	Lewes	10.6%	
St Albans	14.6%	Cherwell	10.3%	
Hart	14.4%	Broxtowe	10.3%	
Lambeth	14.2%	Brighton and Hove	10.3%	
Norwich	14.2%	Gloucester	10.2%	
Waltham Forest	14.0%	Spelthorne	10.2%	
Tower Hamlets	13.7%	Swindon	10.1%	
Cheltenham	13.6%	Wyre Forest	10.1%	
Worthing	13.6%	Colchester	10.1%	
Exeter	13.6%	Haringey	10.1%	
Gloucester	13.5%	Rushmoor	10.0%	

#### Table B2. Share of CI-dense Output Areas per LAD. Top 30 LADs. 2001 and 2011.

Source: Open Corporates, Orbis

Note: An Output Area is considered CI-dense if the share of Creative Industries in total firms is above 50.

#### Table B3. Creative workers and firms (pair-wise) correlation table.

	CI firms	CS firms	Arts firms
OA share of CI firms	1.000		
OA share of CS firms	0.915	1.000	
OA share of Arts firms	0.370	-0.036	1.000
OA Share CI workers in OA total employees	0.090	0.075	0.049
OA Share CS workers in OA total employees	0.095	0.086	0.037
OA Share Arts workers in OA total employees	0.032	0.012	0.052
OA Share CS workers in OA total CI employees	0.025	0.033	-0.014
OA Share Arts workers in OA total CI employees	-0.025	-0.033	0.014
OA CS to OA Arts workers ratio	0.084	0.089	0.005

Source: Open Corporates, Orbis, ONS.

#### Table B4. Creative firms: robustness checks.

	(1)	(2)	(3)	(4)	(5)
	0.0235***	0.0235***	0.106***	0.0236***	0.0234***
Share creative firms	(0.005)	(0.005)	(0.025)	(0.006)	(0.005)
N	80,345	80,345	80,345	80,345	80,280
F	174.5	15.46			
R <sup>2</sup>	0.0680	0.0680			0.0680
Delta		5.986			

Source: Land Registry Orbis, Open Corporates, ONS.

**Notes**: cross-sectional LPM regressions. Column 1 fits our main result. Column 2 includes a delta test following Oster (2019). Column 3 fits a Probit estimator. Column 4 gives the marginal effect from the probit. Column 5 fits an arbitrary correlation estimator following Colella et al (2019). Standard errors clustered on OA except in column 5, where these are calculated using OA lat/lon coordinates. Other notes as per Table 2.

#### Table B5. Creative firms: sensitivity checks.

Panel A – Outliers								
	(1)	(2)	(3	(3)		(5)	(6)	
	0.0235***	0.0172***	0.0166***		0.0426***	0.0186***	0.0384***	
Share creative	(0.005)	(0.005)	(0.0	(0.006)		(0.004)	(0.009)	
N	80,345	66,553	59,	047	21,297	75,778	76,741	
F	174.5	157.4	130	6.7	50.30	136.7	164.8	
R <sup>2</sup>	0.0680	0.0571	0.0	574	0.0909	0.0740	0.0682	
	Panel B - Alternative definitions							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
	0.0235***		0.0420***	0.0195***	0.00907	0.0183**	0.0139**	
Share creative	(0.005)		(0.007)	(0.007)	(0.006)	(0.007)	(0.007)	
		0.0273***						
Share pioneers		(0.006)						
N	80,345	80,345	80,335	80,345	80,230	80,230	80,230	
F	174.5	174.4	1076.9	302.5	398.6	353.1	447.0	
R <sup>2</sup>	0.0680	0.0943	0.180	0.102	0.103	0.0928	0.127	

Source: Land Registry, Orbis, Open Corporates, ONS.

**Notes**: cross-sectional LPM regressions. In each panel column 1 fits our main result. Panel A: columns 2 and 3 respectively exclude London and big cities. Column 4 restricts sample only on big cities. Cols 5 and 6 respectively exclude outliers (outside 3 standard deviations from the mean) for property prices and share creative firms. Panel B: column 2 replaces share creative industries firms with the share of pioneers a la Behrens et al (2019). Columns 3-7 use alternative definitions of the gentrification dummy (col 3 - based on share managers and professionals (SOC classes1, 2) rather than education level; col 4 - based on share lower managerial occupations (NS-SEC class) instead of education level; col 5 - based on the share small employers (NS-SEC class) instead of education level; col 6 - based on price, education, SOC and NS-SEC group; col 7 - based on education, SOC, NS-SEC). Other notes as per Table 2.

#### Table B6. Creative firms: heterogeneity test. CI microclusters.

	Main result	50th	75th	90th	95th
		percentile	percentile	percentile	percentile
Channe and the firmer	0.0235***				
Share creative firms	(0.005)				
		0.000902			
Dummy (50th percentile)		(0.003)			
			0.00221		
Dummy (75th percentile)			(0.003)		
				0.0195***	
Dummy (90th percentile)				(0.004)	
					0.0198***
Dummy (95th percentile)					(0.005)
N	80,345	80,345	80,345	80,345	80,345
F	174.529	173.435	173.421	174.642	174.459
R <sup>2</sup>	0.068	0.068	0.068	0.068	0.068

Source: Land Registry, Open Corporates, Orbis, ONS

**Notes**: cross-sectional LPM regressions. The dependent variable is the probability an OA gentrifies in 2011. Dummies take the value one for OAs in the 50/75/90/95<sup>th</sup> percentile of share creative firms. Other notes as per Table 2.

#### Table B7. Creative firms: property type extension.

	All properties					
	Main	Detached	Semis	Terraces	Flats	
	0.0235***	0.0195**	0.0262***	0.0170**	0.0532***	
Share creative	(0.005)	(0.009)	(0.006)	(0.008)	(O.015)	
Ν	80,345	26,201	27,580	25,843	14,471	
F	174.5	29.75	53.76	67.68	44.24	
R <sup>2</sup>	0.0680	0.0424	0.0649	0.0865	0.112	

Source: Land Registry, Open Corporates, Orbis.

**Note**: The dependent variable is the probability an OA gentrifies in 2011, split by property types. Share creative is the OA share of creative industries firms. Other notes as per Table 2.

#### Table B8. Creative worker regressions: robustness checks.

	(1)	(2)	(3)	(4)	(5)
	0.197***	0.197***	0.787***	0.175***	0.197***
Share creative workers	(0.050)	(0.050)	(0.195)	(0.043)	(0.051)
N	80,345	80,345	80,345	80,345	80,280
F	174.4	15.47			
R <sup>2</sup>	0.0680	0.0680			0.0680
Delta		0.184			

Source: Land Registry Orbis, Open Corporates, ONS.

**Notes**: cross-sectional LPM regressions. Column 1 fits our main result. Column 2 includes a delta test following Oster (2019). Column 3 fits a Probit estimator. Column 4 gives the marginal effect from the probit. Column 5 fits an arbitrary correlation estimator following Colella et al (2019). Standard errors clustered on OA except in column 5, where these are calculated using OA lat/lon coordinates. Other notes as per Table 3.

#### **Panel A - Outliers** (2)(1) (3) (5) (4) (6) 0.197\*\*\* 0.0303 0.0732 0.356\*\*\* 0.207\*\*\* 0.155\*\*\* Share creative (0.050) (0.056) (0.059) (0.093) (0.045) (0.052) 80.345 66.553 59.047 21.297 75.778 79.090 Ν 174.4 157.0 136.4 50.42 137.1 172.5 F 0.0680 0.0569 0.0573 0.0910 0.0742 0.0672 R<sup>2</sup> Panel B - Alternative definitions (3) (4) (5) (6) (1) (2) 0.197\*\*\* 1.042\*\*\* 0.867\*\*\* -0.177\*\*\* -0.107\*\* 0.807\*\*\* Share creative (0.050) (0.058) (0.059) (0.054) (0.061) (0.061) 80,345 80,345 80,230 80,230 80,230 80,335 Ν 174.4 1072.8 465.5 323.1 398.9 367.6 F 0.0680 0.179 0.103 0.0932 0.0953 0.115 R<sup>2</sup>

#### Table B9. Creative worker regressions: sensitivity checks.

Source: Land Registry Orbis, Open Corporates, ONS.

**Notes**: cross-sectional LPM regressions. In each panel column 1 fits our main result. Panel A: columns 2 and 3 respectively exclude London and big cities. Column 4 restricts sample only on big cities. Cols 5 and 6 respectively exclude outliers (outside 3 standard deviations from the mean) for property prices and share creative firms. Panel B: Column 2-6 use alternative definitions of the gentrification dummy (col 2 - based on share managers and professionals (SOC classes1, 2) rather than education level; col 3 - based on share lower managerial occupations (NS-SEC class) instead of education level; col 4 - based on the share small employers (NS-SEC class) instead of education level; col 5 - based on price, education, SOC and NS-SEC group; col 6 - based on education, SOC, NS-SEC). Other notes as per Table 3.

#### Table B10. Robustness test fitting creative firms and workers together.

	(1)	(2)	(3)	(4)
	0.0235***		0.0231***	0.0231***
Share creative firms	(0.005)		(0.005)	(0.005)
		0.197***	0.194***	0.194***
Share creative workers		(0.050)	(0.050)	(0.050)
N	80,345	80,345	80,345	80,345
F	15.46	15.47	15.48	15.48
R <sup>2</sup>	0.0680	0.0680	0.0682	0.0682
Delta	5.986	0.184	6.066	0.182

Source: Land Registry Orbis, Open Corporates, ONS.

**Notes**: cross-sectional LPM regressions. Columns 1 and 2 fit our main results for firms and workers including the delta test as per Oster (2019). Column 3 includes the delta test for creative firms when both firms and workers are included in the regression. Column 4 includes the delta test for creative workers when both firms and workers are included in the regression. Other notes as per Tables 2 and 3.

#### Table B11. Creative workers: heterogeneity test. CI microclusters.

	Main result	50th	75th	90th	95th
		percentile	percentile	percentile	percentile
Channe and atting	0.197***				
Share creative	(0.050)				
		-0.00796**			
Dummy (50th percentile)		(0.003)			
			-0.00203		
Dummy (/5th percentile)			(0.004)		
				0.0155***	
Dummy (90th percentile)				(0.005)	
					0.0369***
Dummy (95th percentile)					(0.007)
N	80,345	80,345	80,345	80,345	80,345
F	174.435	174.885	173.710	174.310	176.316
R <sup>2</sup>	0.068	0.068	0.068	0.068	0.068

Source: Land Registry, Open Corporates, FAME / Orbis, ONS

**Notes**: cross-sectional LPM regressions. The dependent variable is the probability an OA gentrifies in 2011. Dummies take the value one for OAs in the 50/75/90/95<sup>th</sup> percentile of share creative workers. Other notes as per Table 3.

#### Table B12. Creative worker regressions. Property type extension.

	All properties						
	Main	Detached	Semis	Terraces	Flats		
Share creative	0.197***	0.0634	-0.0891	0.176**	0.431***		
workers	(0.050)	(0.089)	(0.081)	(0.082)	(0.102)		
Ν	80,345	26,201	27,580	25,843	14,471		
F	174.4	29.34	52.90	67.75	44.96		
R <sup>2</sup>	0.0680	0.0422	0.0645	0.0865	0.112		

**Source**: Land Registry, Open Corporates, FAME / Orbis.

**Note**: The dependent variable is the probability an OA gentrifies in 2011, split by property types. Share creative is the OA share of creative industries firms. Other notes as per Table 3.

#### Table B13. Creative workers' influence on residential dynamics.

	CI workers	CI workers	CS workers	Arts workers
Share services workers	0.199***			0.0224***
	(0.005)			(0.002)
Services to arts workers ratio		-0.0007***		
		(0.000)		
Share arts workers			O.144***	
			(0.006)	
Price Growth	Yes	Yes	Yes	Yes
Median Age	Yes	Yes	Yes	Yes
Occupation & SEC Controls	Yes	Yes	Yes	Yes
Qualification controls	Yes	Yes	Yes	Yes
Place Controls	Yes	Yes	Yes	Yes
School Performance	Yes	Yes	Yes	Yes
N	80,345	43,547	80,345	80,345
F	2065.875	1042.845	1869.269	485.538
R <sup>2</sup>	0.707	0.724	0.669	0.431

Source: Land Registry, Orbis, Open Corporates, ONS.

**Notes**: cross-sectional OLS regressions at the OA level. Column 1 shows the impact of creative services' workers in 2001 on creative industries' workers in 2011. Column 2 shows the impact of creative services to arts workers' ratio in 2001 on creative industries' workers in 2011. Column 3 shows the impact of arts workers' in 2001 on creative services' workers in 2011 and Column 4 shows the impact of creative services' workers in 2001 on arts' workers in 2011. Other notes as per Table 3.