Does Light Touch Cluster Policy Work? Evaluating the Tech City Programme

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Abstract

Cluster policies are popular with policymakers, but we know surprisingly little about their effectiveness. This paper evaluates the causal impact of a flagship UK technology cluster programme that uses 'light touch', market-orientated interventions. I build a simple framework and identify effects using synthetic controls plus placebo tests to handle programme endogeneity concerns. I implement this design on rich workplace-level microdata from the Business Structure Database, alongside a range of other administrative sources. I explore mechanisms through further tests for timing, cross-space variation, scaling and churn. The policy grew and densified the cluster, but has much weaker, partial effects on tech firm performance. I also find most policy 'effects' began before rollout, raising questions about the programme's added value. More careful policy design could make future interventions more effective.

Keywords: Clusters, technology policy, economic development, synthetic controls
JEL codes: L53; L86; O31; R30; R50

POST-PRINT, FORTHCOMING IN RESEARCH POLICY

1/ Introduction

Clusters have been a well-known feature of urban economies since Marshall first identified them in 1918. A vast literature explores their determinants and characteristics (Duranton and Kerr, 2015). Cluster *policy* is more controversial: it is popular with policymakers but disliked by many academics (Tödtling and Trippl, 2005). Clusters – industrial districts of co-located, interacting firms – typically have market and co-ordination failures. In theory, public policy can improve cluster-level outcomes, outcomes for cluster participants or both. But clustering results from many firm and worker decisions; so market/co-ordination failures are complex; and this complexity may lead to policy failure (Duranton, 2011, Martin and Sunley 2003). The scale of these challenges is an empirical question. However, the literature evaluating cluster policies is small, and the set of robustly designed evaluations smaller still (see reviews by Duranton (2011), Urraya and Ramlogan (2013) and Chatterji et al (2014)).

Broadly speaking, we can distinguish three families of cluster policies. The first involves top-down, formal partnerships backed by grants or subsidies, usually generated through competitive calls for entry. Examples include French Local Productive Systems (Duranton et al, 2010, Martin et al, 2011) and *Pôles de Compétitivité* (Fontagné et al, 2013, Ben Abdesslem and Chiappini, 2019, Lucena-Piquero and Vicente, 2019); Japan's METI programmes (Nishimura and Okamuro, 2011); Innovation Network Denmark (DAMVAD, 2011) and German schemes such as BioRegio and BioProfile (Engel et al, 2013, Graf and Broekel, 2020) or Bavaria's High-Tech Offensive (Falck et al, 2010). These evaluations generally find positive impacts, although effect sizes are often modest. A second set of interventions centres on physical redevelopment, typically an ex-industrial neighbourhood in a city. For example, the 22@ cluster in Barcelona involved re-zoning the Poblenou area, extensive landscaping and construction, and incentives for new 'knowledge-based' firms (Viladecans-Marsal and Arauzo-Carod, 2012). The US 'Innovation Districts' movement advocates similar approaches (Katz and Wagner, 2014). These interventions are less well-studied, although the 22@ evaluation found small shifts in industry composition (ibid). A third group involves light-touch, market-orientated interventions, mainly targeted at existing clusters. Building on work by Porter (1996; 2000) these programmes emphasise business support, improving firm-firm linkages, expanding market access and tackling other market/co-ordination failures. Examples include the Regional Innovation Cluster programme in the US (Yu and Jackson, 2011), and City Growth Strategies in the UK (McDonald et al., 2007). These tools are now often combined with place-branding interventions (Lundequist and Power, 2002; Markusen and Gadwa, 2010). These programmes are most commonly evaluated by participant surveys, with few or no quantitative impact evaluations to date (Urraya and Ramlogan, 2013).[1]

This paper develops a rigorous impact evaluation of a recent light-touch cluster policy. I study the UK flagship Tech City programme that launched in London in late 2010,[2] and aimed to grow the cluster of technology companies (c. 2,800 firms in 2010) centred on Shoreditch and Old St roundabout. The cluster had been growing for years without direct policy input (Foord, 2013). It came to prominence in 2008 with a wave of media attention about 'Silicon Roundabout' (Butcher, 2013; Foord, 2013; Nathan et al., 2019). The Tech City initiative aimed to 'accelerate' the cluster by 'going with the grain' of the existing ecosystem (Cameron, 2010), combining business support, tax breaks, place-branding and network-building elements. While proponents argue the policy has been very successful (Mayor of London, 2014; Osborne and Schmidt, 2012), these claims have never been robustly tested.

Clusters involve both positive and negative feedback loops. As they get larger and denser, agglomeration economies get stronger. However, such growth also raises crowding, and competition for market share. I argue that the Tech City policy could plausibly contribute to all three channels. As the cluster was growing pre-policy, and has continued to grow since, I need to identify any *additional* policy effects relative to the counterfactual of continued 'organic' development. To do this I apply theoretical frameworks developed by Arzaghi and Henderson (2008), Duranton (2011) and Kerr and Kominers (2015). I first explore economic changes in the area between 1997 and 2017. Next, I use difference-in-differences and synthetic controls on rich microdata to identify overall policy effects on cluster size, density and local tech firm performance. I explore mechanisms with four further pieces of evidence. I run placebo-in-time tests to identify effect timing; use treatment intensity analysis to explore within-cluster shifts; test for changes in high-growth tech firm activity; and run a before-and-after analysis of tech firm entry/exit patterns, for UK and foreign-owned firms.

[1] McDonald et al (2007) perform cross-sectional analysis on a number of UK clusters, finding that associations between cluster conditions and performance do not support Porter's framework.
[2] The programme has since gone through several evolutions and expansions. In late 2014 TCIO was rebranded 'Tech City UK' and refocused on cities across the country. Tech City UK rebranded as Tech Nation from Spring 2018, confirming its UK-wide remit.

I find that policy led to a larger and denser cluster, with an influx of hardware and software ('digital tech') companies, changing the composition of industry space. However, effects on firm performance are much less stable, with 'digital content' firms (such as those in media, marketing and webs services) gaining revenue/worker in some specifications, but no clear effect for digital tech businesses. I also find increased churn and spatial disruption. Finally, many policy 'effects' began when the cluster first came to media attention, rather than when the policy launched. Year-on-year outcome changes are often weaker in the latter period, and I find a negative policy effect for one group of firms. Consistent with theory, this suggests that the programme weakened the net benefits of cluster location (Duranton, 2011). Given the intention to 'accelerate' the cluster, the policy has had – at best – mixed impacts on the area and on the firms in it.

It is critical to develop a stronger evidence base for local economic development policies, including cluster programmes. This is the first quantitative impact evaluation of a light touch cluster policy that I am aware of.[3] It complements other recent studies exploring clusters and local/regional economic performance, such as Delgado et al (2014) and Iammarino and McCann (2006). More broadly, the paper adds to the sparse cluster policy evaluation literature, and to a larger, related literature on economic area-based initiatives.[4] The paper also adds to a small set of studies on London's post-industrial economic evolutions (see *inter alia* Hall (2000), Hamnett and Whitelegg (2007), Hutton (2008), Pratt (2009), and Harris (2012)).

2/ Background

The Tech City area is located in a set of ex-industrial East London neighbourhoods between Islington, Tower Hamlets, Hackney and the City of London. It shares many characteristics of inner urban creative/technology districts such as Silicon Alley (New York) and SoMa (San

[3] In 2017 the UK Department of Culture, Media and Sport published an evaluation of Tech City UK, with exploratory analyses of three business support programmes. Estimates of economic benefits have 'a strong 'health warning' attached' (p. iv). The report is available at: https://bit.ly/2U8nSTP, accessed 9 May 2019.
[4] See Neumark and Simpson (2014), Glaeser and Gottlieb (2008), Kline and Moretti (2013) and What Works Centre for Local Economic Growth (2016) for reviews.

Francisco) including a tight cluster shape, use of ex-industrial buildings, abundant social amenities and a gritty physical appearance (Zukin, 1995; Indergaard, 2004; Hutton, 2008). Cluster protagonists make extensive use of matching, sharing and learning economies that such tight co-location affords (Duranton and Kerr 2015). As with other milieux, the area's gradual evolution from depressed ex-industrial neighbourhood to vibrant post-industrial district was 'organic', with no direct policy interventions until the Tech City programme (Pratt, 2009; Harris, 2012; Foord, 2013; Nathan and Vandore, 2014).[5] The cluster has no formal boundaries, so I define it as a 1km ring around Silicon Roundabout (Figure 1). This corresponds with evidence from local firms at the time (Nathan and Vandore, 2014).

Figure 1 about here

In November 2010, then-Prime Minister David Cameron announced the Tech City policy. The initiative aimed to 'accelerate' the cluster by 'going with the grain' of the existing ecosystem (Cameron, 2010). Place branding and marketing aimed to grow the cluster and attract foreign investment. Business support programmes targeted selected local firms, with tax breaks for early-stage investors. Policymakers also made extensive attempts to improve public-private networks and firm-firm co-ordination, including establishing a 'one-stop shop', the Tech City Investment Organisation (TCIO).[6]

I explore the cluster using multiple data sources. I start with the 9th edition of the Business Structure Database, hence BSD (Office of National Statistics, 2017). The BSD covers over 99% of all UK economic activity and provides reliable postcode-level information for individual workplaces (hence 'firms').[7] I link live firms to 2011 Lower Super Output Areas (LSOAs), then aggregate the data to LSOA level.[8] The resulting panel runs from 1997 – 2017, with 101,503 area*year observations for 4,835 LSOAs in Greater London. Further details are set out in Appendix A. As BSD cross-sections are taken in April of each year, I place the Tech

[5] The cluster is not mentioned in two key 2000s policy frameworks: the 2003 City Fringe City Growth Strategy and the 2001 DTI UK cluster-mapping exercise.
[6] All except the tax incentives were spatially focused on the Old St area, but policymakers did not draw formal boundaries. A potential Olympic Park linkup was dropped as unfeasible within a year.
[7] Single workplace firms comprise over 98% of the observations.
[8] Alternatives are a) working at firm level; b) using grid squares. Given firms are mobile and there is substantial entry/exit from the cluster, firm-level analysis makes matching highly complex. Working in grid space is more feasible but would disallow the use of non-BSD controls, since these are not geocoded.

City initiative in BSD year 2011, not 2010. For further controls I use 1991, 2001 and 2011 Census data, ONS Mid-Year Population Estimates 1997-2016, and TfL stations data 1997-2017. I then define Tech City as the set of LSOAs whose centroids have a linear distance of 1km or less from the Eastings/Northings of the Old St roundabout.[9] Following Arzaghi and Henderson (2008), I use 250m distance rings to divide cluster space. The area is thus constructed as 25 LSOAs, with 250m, 500 and 750m distance rings covering 1, 7 and 13 LSOAs respectively.[10]

I define 'tech' industries using the ONS typology of science and technology sectors (Harris, 2015). I distinguish ‘digital technology’ activities (mainly hardware and software industries) and ‘digital content’ (such as advertising, design, media and the creative industries, where product/services are increasingly online). Appendix A lists time-consistent SIC codes.

In what follows, I focus on three cluster outcomes. Cluster size is given by net LSOA tech firms and jobs in a given year.[11] I measure cluster density using annual LSOA shares of tech firms and tech employment. I measure cluster performance using annual LSOA averages of tech firm revenues per worker, via enterprise-level BSD data.[12] Firms’ revenue per worker is a rough measure of ‘revenue productivity’.[13] It will be driven up by productivity improvements in productivity (reflecting agglomeration effects); and driven down by rising market competition (lower revenue to the firm).

3/ Descriptive analysis

[9] E532774, N182493, from gridreferencefinder.com, accessed 1 October 2017.

[10] Other methods delivering similar results include: in step 1, calculating the mean centroid of the two 'roundabout LSOAs'; in step 1, using each roundabout LSOA centroid. An alternative method delivering slightly larger numbers of LSOAs would be to change step 3 to include all LSOAs within the distance rings, regardless of whether their centroids fell within the relevant ring.

[11] Entrants minus exits. I lack occupational level data, so this is a measure of all jobs in a tech firm.

[12] The vast majority of firms have one workplace, so enterprise and firm-level figures are the same. For multi-workplace firms, I assign revenue shares based on workplaces’ share of enterprise-level employment.

[13] In theory one could use the ARDx dataset to directly estimate labour productivity for firms. The main limitation in this case is coverage. The ARDx is a UK-wide census for large firms but is sampled for SMEs, with 42,000 - 57,000 overall cases annually. Analysis in a small set of London neighbourhoods in sectors dominated by SMEs is therefore likely to run up against severe sampling error. For more information see: https://doc.ukdataservice.ac.uk/doc/7989/mrdoc/pdf/7989_ardx_userguide.pdf, accessed 13 February 2020.

Since the introduction of the Tech City programme, the cluster has got both bigger and more expensive. There is tech firm growth in all parts of the zone (Figure 2, top panel). At the same time, rents have risen relative to comparable submarkets (bottom panel). There is also extensive anecdotal evidence of displacement of smaller firms.[14]

Figure 2 about here

The Tech City area is also distinctive from the rest of Greater London, both in its overall characteristics and in tech industry evolution. Table 1 shows mean characteristics for Tech City LSOAs versus the average rest of Greater London LSOA in the pre-policy period, 1997-2010. Appendix table B1 provides further detail.

Table 1 about here

The tech cluster is dominated by 'digital content' industries (such as advertising, design, media and the creative industries). This is consistent with historical and case study evidence, which stresses the importance of the creative industries in the emergence London tech (Foord, 2013; Nathan and Vandore, 2014; Martins, 2015). Notably, content firms are more numerous, denser, have more employees and nearly double the revenue/worker of 'digital tech' firms (such as IT manufacturing, software and consultancy). These different industry bloc characteristics imply some differences in preferences and behaviour (see Section 4).

Figure 3 about here

The area's industry and demographic mix is also very different from the average rest-of-London neighbourhood. In particular, tech activity is much denser. Figure 3 looks at LSOA firm and job shares for digital content over time (top row) and digital technology (bottom row), comparing the average Tech City neighbourhood with the average rest of London neighbourhood. The area maintains a well-above-average density of digital content activity.

[14] https://www.theguardian.com/media-network/2016/apr/12/startups-abandon-tech-city-commercial-rent-soars-east-london-shoreditch; https://www.uktech.news/news/tech-london-advocates-spiralling-rent-costs-are-hampering-startup-growth-20150417. Both accessed 15 August 2018.

Firm density falls slightly post-policy, implying that other sectors are growing faster as a share of all firms. Digital technology activity is much sparser than digital content, and pre-policy, Tech City LSOAs are much closer to the rest of the capital in digital tech density. However, post-policy the two groups visibly diverge.

Figures B1 and B2 show, respectively, LSOA net tech firm counts and tech firm average revenue per worker over time. As expected, firm counts are very much higher in Shoreditch than the average rest of London LSOA, with stocks accelerating in the 2010s. By contrast, tech firm revenue per worker is more uneven over time.

4/ Analytical framework

A cluster is a dynamic industrial production district. Four core dynamics condition its growth and change. As a cluster grows and gets denser, knowledge spillovers and other agglomeration economies raise participants' productivity. But the costs of cluster location also rise with participant numbers, crowding some firms out of the district (Duranton 2011). A larger cluster also increases market competition between participants (Combes et al 2012). Competing land uses further influence costs, especially in large cities (Hamnett and Whitelegg, 2007). Crucially, because costs *and* benefits rise with the number of participants, at some point the net benefits of cluster location may go flat or even negative for the marginal entrant (Duranton 2011).

These exact shape of these benefit and cost 'curves' is industry and location specific. Kerr and Kominers (2015) and Arzaghi and Henderson (2008) model clusters as a set of overlapping neighbourhoods, where firms trade-off access to some set of agglomeration economies and amenities, against the costs of location. They leave a given neighbourhood if location costs start to exceed productivity advantages. As that district fills up, net benefits decline; at some point movers / entrants shift to the 'next-best' district (specifically, the marginal entrant/mover will choose the next available site with the largest 'spillover radius'). Cost and spillover decay functions set the overall cluster shape. For industries such as tech, where face-to-face interaction is important, clusters tend to be small and dense (Hutton, 2008; Pratt, 2009). Given the importance of big cities as 'nurseries' for startups (Duranton and Puga, 2001), we might expect the smaller, younger ‘digital tech’ firms in Shoreditch to be the most location-sensitive, with strong preferences to be at the core of the cluster in close proximity to others. Again, this is consistent with case study evidence (Foord, 2013).

How might the Tech City policy mix influence these trends? In principle, it could affect both cluster-level outcomes (such as cluster size and density) and outcomes for individual cluster participants (through processes generating winners and losers). First, place marketing and FDI efforts boost area profile, and this will affect firm entry. Firms often lack information on optimal location(s): clusters can act as signals that influence location behaviour (Appold, 2005, Vicente, 2018) specifically about the kinds of firm that can thrive there (Romanelli and Khessina, 2005). Programmes that raise public awareness of a cluster thus amplify this signal, and individual success stories – such as high-profile ‘unicorns’ – further reinforce this channel. Increased size and density should amplify agglomeration effects, increasing firm productivity. Note that incumbents, in established settings, may benefit most from these shifts.

Second, other elements in the policy mix (business support, networking / co-ordination activities), if effective, will improve average firm productivity for a given cluster size. Networking and co-ordination activity may improve firm-firm matching, knowledge spillovers or both, feeding into firm performance. Business support policies in Tech City have only targeted very small numbers of high-potential firms – typically 50 or less – but may increase high-growth episodes for those companies.

Third, higher entry may also induce crowding. Even if productivity is rising, cost increases may induce relocation if these outweigh productivity gains (i.e. if the net returns curve is sloping down). These relocations will likely be highly localised – to less central cluster locations or to neighbourhoods just outside it – but may still be disruptive to movers. Fourth, higher entry / in-movement, including through FDI, also leads to higher market competition. This may simply involve higher overall churn. However, in a Schumpetarian setting (Aghion et al., 2009), a few more innovative 'winners' raise their productivity, while 'losers' shed revenue and staff or exit.

Finally, cluster policy may also signal to other industries, both complementary and competing uses (such as residential property). If growth in tech firms is balanced by growth in other activities, cross-sector competition for space may exacerbate tech firm relocation. It will also dampen changes in cluster density, and in extremis may decrease it, if other activities outcompete tech firms for space in the cluster.

5/ Research design

5.1 / Identification

Evaluating cluster programmes is inherently difficult because of the lack of clear comparators (Duranton, 2011). Cluster evaluations typically compare changes in the treated area/firms to some set of control areas/firms. Difference in differences gives a consistent average treatment effect on the treated (ATT), conditional on observables and on parallel pre-trends in treated and control groups. Causal inference requires that LSOA-specific time-varying unobservable characteristics affecting outcomes are independent of treatment status, conditional on included controls (Gibbons et al., 2016).

There are two main identification challenges in my case: not accounting for these will bias up estimates of the true policy effect. First, rising media and public attention around 'Silicon Roundabout' from 2008 could have induced firms and entrepreneurs into the area before the policy launched (Nathan et al., 2019; Foord, 2013). Figure B3 gives a sense of overall levels of public interest pre and post-policy using Google Trends data, which shows a rising relative share of UK Google searches on 'Silicon Roundabout' and 'Tech City' over time.[15] Historical and case study work also shows suggests that entrants were as likely to base location decisions on media coverage of the area as on linkages to firms in the cluster (Nathan and Vandore 2014). Given these background forces, I check my main results using placebo-in-time tests.

[15] Google Trends data is sampled from all daily searches on Google. Specifically, for a given geography*time period it gives the relative frequency of searches for a given term T1 versus all other search terms T2 ... Tn. Searches are normalised on a 0-100 scale to allow comparison of search behaviour across places with different underlying search volumes. Google's dominance of the search market means that Trends data can be considered representative of overall internet searching. Here, we can interpret Trends data as the level of UK interest in (say) Silicon Roundabout versus everything else the public might be interested in for the UK at that time. See https://support.google.com/trends/answer/4365533?hl=en, accessed 13 February 2020.

Second, time-varying unobervables may have driven both area selection and subsequent outcomes. Policymakers' rationale for choosing Shoreditch is not clear-cut. By 2010 Ministers were claiming 'something special' for the Inner East London cluster (Cameron, 2010; Osborne and Schmidt, 2012). Other accounts depict policy origins as chaotic (Butcher, 2013; Nathan et al., 2019), and thus as good as random *compared to other tech hotspots in the* city.

If assignment is quasi-random, a necessary condition is that treatment and control areas balance on observables. To test this, I use propensity score matching to identify observably similar tech hotspot LSOAs in London. I select the vector of observables from the recent empirical literature on urban technology and creative clusters (Florida, 2002; Indergaard, 2004; Hutton, 2008; Pratt, 2009; Currid and Williams, 2010; Harris, 2012; Foord, 2013; Nathan and Vandore, 2014; Martins, 2015). I match on the nearest neighbour and to avoid contamination, restrict to control LSOAs at least 1km away from the cluster edge. Table B2 shows the matching results for the 25 Tech City LSOAs and 213 matched control LSOAs with the 25% highest propensity scores. While *t*-tests suggest no significant differences (except in one case), other diagnostics suggest the two samples remain unbalanced. Results of balancing tests for treated units and nearest neighbours are shown in Figure B4. I find significant pre-treatment 'effects' in both firm count regressions, and close-to-significant 'effects' in both firm density regressions.

Taken together, timing, selection, balance and pre-trend issues suggest that conventional difference in differences may not give consistent estimates. My preferred approach is thus a synthetic control design, using the matched sample as a donor pool (Abadie et al 2010). Details of the synthetic control build are given in the next section.[16] Crucially, the estimator gives a consistent ATT even in the presence of time-varying unobservables (Helmers and Overman 2016, Becker et al., 2018). I follow the design of Becker et al (2018) and compare synthetic control results to difference-in-differences results for the matched sample.

Given the lack of formal treatment and impact geographies, in extensions I use spatial differencing (Mayer et al., 2015) and treatment intensity approaches (Einio and Overman,

[16] An alternative to the synthetic control would be the interactive fixed effects design developed by Bai (2009) and elucidated by Gobillon and Magnac (2016).

2013; Faggio 2015; Gibbons et al., 2016) to allow policy effects to vary across 250m rings within cluster space.

5.2 / Estimation

For the matched sample, a generalised difference in differences regression for LSOA *i* and year *t* is given by:

$$\ln Y_{it} = I_i + T_t + a TC_{it} + \mathbf{X}\boldsymbol{b}_{it-n} + e_{it} \qquad (1)$$

lnY is the log of tech firm counts or tech job counts; shares of tech firms or tech jobs; or the log of tech firm revenue / worker. TC is a dummy variable taking the value 1 for Tech City LSOAs in the post-treatment period, and a_i is the ATT for a Tech City LSOA. Control LSOAs are tech hotspots at least 1km away from the cluster edge.

X is a set of time-varying controls. These cover local economic conditions (lags of LSOA all-sector firm entry, LSOA all-sector revenue/worker, LSOA Herfindahl Index); tech-friendly amenities (LSOA counts of cafes and restaurants, bars/pubs/clubs, co-working spaces, galleries and museums, libraries, hotels, other accommodation, arts and arts support, venues, universities); infrastructure (the count of tube and rail stations in the LSOA); plus local area demographics (population size, shares of migrants and shares of under-30s in the local authority district surrounding the LSOA). I cluster standard errors on LSOAs and, given nearest neighbour matching, regress on the matched sample.

The synthetic control is an extension of (1) where the synthetic control unit is a weighted average of the matched set of control LSOAs (Athey and Imbens, 2017). Here, the outcome is the linear combination of the treatment effect for a Tech City LSOA and the outcome in synthetic Tech City:

$$\ln Y_{it} = \ln Y^{N}_{it} + a TC_{it} \qquad (2)$$

The ATT for the treated unit – here, unit 1– is then given by:

$$\hat{a}_1 = \Sigma_{i\geq 2} \ln Y_{it} - \mathbf{W}_i \ln Y_{it} \quad (3)$$

Where $\Sigma_{i\geq 2} \ln Y_{it}$ is the sum of the weighted outcome for all the non-treated units, and **W** is a ix1 weights vector ($w_2, \ldots w_{i+1}$) where weights sum to one.[17] The optimal set of weights **W*** minimises the difference between $\mathbf{X}_1$, the vector of pre-treatment characteristics of the treatment zone, and $\mathbf{X}_0$, the vector of pre-treatment characteristics for control LSOAs, where **V** is a vector of predictor importance.

$$\mathbf{W}^* = \min(\mathbf{X}_1 - \mathbf{X}_0\mathbf{W})`\mathbf{V}(\mathbf{X}_1 - \mathbf{X}_0\mathbf{W})` \quad (4)$$

Setting **V** and **X** appropriately is crucial (Kaul et al., 2018; Ferman et al., 2018). **V** is usually chosen to maximise the overall pre-treatment 'fit' of the synthetic unit, specifically to minimise the treatment-control gap in the outcome. This is given by the root mean squared of the predicted error (RMSPE) (Abadie et al., 2010). **V** can also be chosen through cross-validation, where the pre-treatment period is split in two: optimal **V** minimises the RMSPE in the training period and the validation period (Cavallo et al., 2013). Alternatively, **V** can be an identity matrix (Gobillon and Magnac, 2016). The latter has the attractions that predictor importance is identical across all regressions, and that outcomes and controls can be fitted together for all pre-treatment periods. I use this approach, and run robustness checks on alternative specifications of **V** and **W**.

Reassuringly, synthetic Tech City is more closely matched to Tech City than the matched sample as a whole. Table 2 compares mean pre-treatment outcomes and control variables for the Tech City area, synthetic Tech City and matched LSOAs for the log of digital tech firms. Table B3 replicates this for all other outcomes. Table B4 shows the LSOAs chosen for the synthetic control and the weights assigned, for all outcomes of interest.

Table 2 about here

[17] Strictly speaking, in diff-in-diff specifications $\hat{a}$ gives the ATT for the average Tech City LSOA, while in synthetic control specifications $\hat{a}_1$ gives the ATT for a single Tech City zone with characteristics averaged across all Tech City LSOAs. I treat these as equivalent.

Inference for synthetic controls is done through permutation. Abadie et al (2010, 2015) first calculate yearly treatment 'effects' for each donor pool unit, comparing distributions for the treated and donor units in the post period. If the placebo runs generate effect sizes smaller (larger) than the treatment unit, this suggests a real (spurious) treatment effect. Placebo effects may be large for units poorly matched pre-treatment. To fix this, Galiani and Quistorff (2016) suggest weighting treatment and placebo effects by pre-treatment RMSPE.[18]

For the overall ATT, Abadie et al compare the ratio of post/pre-treatment RMSPE for the treated unit, R_{1t}, and the donor units, R_{jt}. A large post-treatment RMSPE indicates a gap between the treated unit and the synthetic control, suggesting a true effect; however, a large pre-treatment RMSPE suggests that the synthetic control does not fit the data well before the policy, so the effect may be spurious. The test statistic p then calculates the probability that any placebo effect 'fit' is larger than that of the treatment unit. It can be interpreted as a p-value:

$$p = \Sigma_{i \neq 1} 1 \left(| R_{jt} | \geq | R_{1t} | \right) / \mathrm{N} \qquad (5)$$

6/ Overall policy effects

Estimates of overall policy impact are given below. The next section explores what is driving these.

Figure 4 shows results for cluster size. The left column shows changes in log digital tech and digital content firm counts in Tech City versus synthetic Tech City. The right column shows effect sizes for Tech City and 213 placebo units. Effect sizes are weighted by pre-treatment RMSPEs, so these graphs show *relative effect size* controlling for fit.

Figure 4 about here

[18] The more common alternative, as proposed by Abadie et al (2010), is to use a cut-off to remove poorly-matched placebos: for example, only including controls with a pre-treatment RMSPE up to five times the treated unit.

I find clear policy effects on digitech firm counts, with smaller change in content firm counts. Placebo tests show that the digitech result is more robust than for digital content. In 2017, digitech effects are around 28 times higher than the nearest placebo, controlling for pre-treatment fit; for digital content, the figure is less than 10 times, and one placebo often shows a larger (random) effect than the policy. Figure B5 repeats the analysis for employment, this time showing clear increases in digitech jobs but not digital content. For all outcomes, there are signs of pre-policy treatment-control divergence, an issue I return to in the next section.

Table 3 about here

The top panel of Table 3 gives point estimates. Diagnostics show that the estimator fits the data well. Diff-in-diff results show similar coefficients, although there are differences in effect robustness.

Since Y is in logs, $\hat{a}$ can be interpreted as a percentage. In my preferred estimates, the policy increases digitech firm counts by 27%, or 4 net extra firms post-2011 compared to the pre-treatment mean. The cluster-wide effect is 25*4 = 108 extra firms across 25 LSOAs. For digital content, the policy effect is 7.9%, 15 extra firms per LSOA or 382 overall. The policy adds 47 net digitech jobs per LSOA (a 44.4% rise), cashing out at 1167 additional jobs overall post-2011. For digital content, a 12.3% increase gives over 6,000 additional jobs cluster-wide, but this effect is only marginally significant.

Figure 5 about here

Figure 5 looks at changes to cluster density. I find a clear and growing policy effect on the treated area's share of digital tech firms, additional to natural change. Overall effects on digital content firm density are close to zero. Figure B6 repeats the analysis for employment shares. Here we see clearly increased job density, especially for digital content. In both cases, there are signs of pre-policy divergence.

The middle panel of Table 3 shows the corresponding ATTs. As Y is now in shares, $\hat{a}$ gives the ATT across *all* treated units. Synthetic control and DID estimates have similar magnitudes, although significance differs. For the former, the policy adds 1.3 percentage points to shares of digitech firms and 3.1 percentage points to shares of digitech jobs, compared to the no-policy counterfactual. Effects on digital content firm density are marginally significant, but digital content job density rises 4.9 percentage points. Given pre-treatment means, these translate to a 21% increase in the share of digitech firms, an 86% change in digitech job shares, and a 27% change in digital content job shares. Notably, percentage changes in firm density are lower than raw counts, consistent with increased competition for space from non-tech activity.

Figure 6 about here

Figure 6 looks at tech firm performance, measured by log tech firm revenue / worker in the LSOA. For digital tech firms, while the overall post-policy effect is small and barely significant, we can see that the policy initially lowered revenue/worker to 2013, compared to the counterfactual, but increased it from 2015. Year-by-year estimates are significant for 2013, 2014 and 2017. For digital content firms, the policy led to consistently higher revenue/worker across the post-policy period, with significant year-on-year effects except for 2017. Again, there are signs of pre-policy divergence. Point estimates in the bottom panel of Table 3 are very similar for digitech, but there is some divergence for digital content between synthetic control and diff in diff. The synthetic control estimator gives a marginally significant 4.3% revenue/worker decline for the average digital tech firm across the whole post-policy period. For digital content firms, the policy adds 13.9% revenue/worker to the average digital content firm, significant at 5%.

6.1 / Robustness checks

Table B5 runs a series of specification checks on the synthetic control results. Tests 1-3 progressively reduce the number of pre-treatment outcomes, with the third row running only controls as predictors. The fourth test uses a data-driven **V** as in Abadie et al (2010); this puts zero weights on controls, rendering them irrelevant (Kaul et al., 2018). The fifth and sixth tests split the pre-treatment period and use cross-validation to set **V**, as in Cavallo et al (2013). Tests 7 and 8 match on trends, respectively long differences and first differences.

In the spirit of Ferman et al (2018), these tests look for stability (or otherwise) of results across different specifications. These alternative specifications all use less information than my main estimator, so we should expect worse fit; at least some results to differ; some to be non-significant. Given the main results, I consider outcomes that are statistically significant in at least half the tests to be stable. On that basis, increases in digital tech firms and job counts, digitech and content firm density, and content job density are stable across specifications. Changes to digital content firm and job counts; digitech job density are less stable, with significant estimates in only 3/8 tests. For tech firm performance, signs and coefficients move around a lot, and none of the alternative specifications are significant. This is almost always driven by poor model fit. Given the volatility in revenue/worker over time (see Figure B2) this is not surprising.

7/ Explaining policy effects

The analysis throws up three main findings. First, compared to a no-policy counterfactual, the policy raised firm and job counts, especially for digital tech activity, with weaker and less stable effects on digital content. Second, cluster density has increased, particularly job density. Third, this bigger, denser cluster does not always increase tech firm performance.

Using Section 4’s framework, I explore the mechanisms behind these results. First, given the pre-policy divergence between Tech City and synthetic Tech City, I explore the dynamics of policy effects via placebo-in-time tests. Second, I dig into drivers of cluster size changes by identifying entrants, leavers and movers over time. This also provides insights into density (through in/out mover geography) and competition channels (via churn). Third, I use treatment intensity analysis to look at co-location patterns within the cluster. Finally, I test for Schumpeterian competition, focusing on effects for the subset of high-growth tech firms. This exercise also gives suggestive evidence on business support components of the policy mix.

7.1/ Timing

I start with the timing and spatial focus of overall policy effects. The cluster became well known through the media in 2008; a persistent policy criticism has been that government was 'riding the wave' and adding little or nothing to existing growth trends. Conversely, it is possible that when policy went London-wide in 2014, the cluster received less attention and policy effects died away.

Table 4 about here

Table 4 tests these hypotheses. Panel A shows the main synthetic control results. Panel B runs a placebo-in-time check (Abadie et al 2015), starting the policy in 2008 rather than 2011. In 7/10 cases, I find a significant pre-policy effect. This is prima facie evidence that the Tech City programme 'rode the wave'. The 2008 performance effect is much larger for digital tech firms, but much smaller for digital content firms. Panels C and D explore these dynamics in more detail: Panel C breaks out the 2008-10 component, while Panel D gives a simple 'effect/year' metric for 2008-10 and 2011-2017. In most cases, the 2008-10 effect/year is stronger than its 2011/17 counterpart, suggesting little added value. Strikingly, the policy shifts digital content firms' performance to positive and significant. Conversely, statistically significant digitech performance in 2008/10 turns non-significant during 2011/17. For content firms, policy strengthens agglomeration effects. For digitech firms, policy overheats the cluster, with net benefits disappearing.

Panel E looks policy effects from 2011-2014, the programme phase where only the Shoreditch cluster was targeted. Coefficients here test the effect of the localised policy vs. the London-wide policy. Results are almost all significant, and in 5/10 cases effects/year are weaker than the 2011/17 period, in line with the shorter timescale. In the other cases, I find a weakening effect of the policy, although the differences are very small. Overall, these findings go against the hypothesis that policy effects died off when the spatial focus changed. I speculate that self-reinforcing cluster mechanisms help the policy 'work' despite refocusing.

7.2 / Entry, exit and movers

Next I look at patterns of firm entry, exit and movement in and out of the cluster. This helps explain drivers of cluster size change, as well as cost and competition-induced churn and patterns of firm movement. I combine firm-level cross-sections for three year pairs, 2009-10 (pre-policy), 2013-14 and 2016-17. For each year pair, I flag firms present in the cluster in both years (stayers), those present only in the first year (leavers) and those present only in the last year (entrants). I decompose entrants and leavers into those moving from /to the rest of London, the rest of the UK, or arriving/leaving the dataset. Results are given in Table 5. The top panel gives results for all tech firms. The bottom panel shows results for foreign-owned firms, with shares expressed as a fraction of all tech firms.

Table 5 about here

First, Panel A changes to cluster size are driven by a rising share of new entrants to the market, with a falling share of leavers overall. Leavers are dominated by firm exits, but the share of outmovers has also risen over time. Second, these dynamics are very largely driven by UK-owned firms rather than foreign-owned businesses (Panel B). The share of new foreign-owned firms has consistently fallen since policy implementation. Third, in and outmovers typically come from / go to the rest of London rather than the rest of the UK, consistent with a tight cluster geography. Fourth, churn has risen, driven by new entrants, suggesting higher levels of competition in the cluster over time.

7.3 / Co-location within the cluster

As clusters get bigger and denser, higher costs lead firms to move. Urban tech clusters typically have tight shapes, implying that relocation geographies will be small. To explore, following Faggio (2015), I estimate a difference-differences treatment intensity estimator for LSOA *i* in year *t*:

$$\begin{aligned} \ln Y_{it} = {} & D250_i + D500_i + D750_i + D1000_i + T_t \\ & + a1 TC250_{it} + a2 TC500_{it} + a3 TC750_{it} + a4 TC1000_{it} \\ & + \mathbf{X}\boldsymbol{b}_{it-n} + e_{it} \end{aligned} \tag{6}$$

Where D250-D1000 are dummies taking the value 1 for LSOAs in distance rings 0-250m, 250-500m, 500-750m and 750-1000m from Old St roundabout. Coefficients of interest are *â1- â4*, which give the relative effect of treatment on LSOAs *in that distance ring*, versus control LSOAs.

In Table B6, the top row gives the cluster-level policy effect for the 1km zone, from the main analysis. Other rows decompose this effect into 250m ring increments. In line with the framework in Section 4, tech firms move small distances within cluster space, and there is some evidence of crowding out from core to periphery, with digital tech firms displacing content firms. Specifically, aggregate increases in firm counts are clearly driven by entry to the cluster core. Drivers of tech job increases vary within industry space. Digital tech employment grows at the core, and to a lesser extent in the outermost ring; content employment increases in the periphery, with no change in the core. Cluster density shifts also vary within the tech industry. Digital tech activity gets denser within the cluster core. However, digital content activity gets less dense in the core, and denser in the periphery.

7.4 / High-growth firms

In the tech industry, the combination of increasing returns plus network effects often leads to winner-takes-all scenarios, where a few firms scale rapidly to dominate a market (Arthur, 1989; Brynjolffson and McAfee, 2014). We might expect an effective cluster policy to amplify these market dynamics. Even if average revenue/worker changes are zero, a few firms may experience rapid growth. In my framework, scaling indicates a form of Schumpetarian competition in the cluster, with a few innovative 'winners' (Aghion et al 2009). Testing for scaling also provide preliminary evidence on the effectiveness of targeted business support components of the policy mix.

In my panel setting, firms move into and out of high-growth states (‘episodes’). I define high-growth episodes using the OECD definition, as a tech firm that experiences revenue/worker or employment growth of at least 20% for any three-year period. 'Gazelles' are high-growth episodes for tech firms five years old or less. A firm may have more than one high-growth episode in the panel; in practice this is rare. Table B7 shows the average number of high-growth episodes by LSOA type, 2000-2010. The average Tech City LSOA experiences substantially more high-growth activity than the average control area. Figure B7 shows balancing tests for the various high-growth outcomes. It confirms that the parallel pre-trends assumption fails in a number of cases, so I run regressions using synthetic controls only.

I specify the synthetic control as in the main analysis, but start the pre-treatment phase in 2000, the first year in which I can observe high-growth / gazelle firms. Table B8 gives results for high-growth episodes.[19] The left hand panel gives results for revenue / worker high-growth episodes, the right hand panel for employment growth. I find no positive policy effects in either case.

8/ Conclusions

This paper evaluates the causal impact of a flagship UK technology cluster programme, which uses 'light-touch', market-enabling interventions to 'accelerate' the cluster and firms within it. It is the first impact evaluation of this strand of cluster policy that I am aware of. I use rich microdata in a synthetic control setting to estimate overall impacts relative to continued 'organic' growth, and the mechanisms behind these.

I find that the policy substantively increased cluster size and density, most clearly for the younger, newer group of digital tech firms, and with increasing impact over time. But I find much less stable effects on tech firm performance: only digital content firms see higher revenue / worker in the post-policy period, and these results do not hold across alternative specifications. The results imply that for these firms, size and density-driven agglomeration economies dominated changes in costs or competition; for smaller, younger digital tech firms, it was the converse. Since the area was on an upward growth path before the policy rolled out, a key welfare question is to what extent the programme added value. For most outcomes, I find that policy 'effects' began before the programme took place, and that annualised effect sizes are smaller in the post-policy period than the two years immediately preceding it. For at least some participants, the policy weakened the net benefits of cluster location.

Overall, the policy 'worked' in the basic sense of growing the cluster. For some policymakers this will count as success. From a broader welfare perspective, the results are less positive. The policy changed the characteristics of the cluster, and overheated parts of it. In turn, distributional impacts are highly uneven, with only some firms experiencing economic

[19] The scarcity of gazelle episodes means the algorithm fails to converge in almost all cases.

benefits. An important theoretical critique of cluster policy is that the complexity of actual clusters' microfoundations makes it hard to identify appropriate interventions, let alone enact them effectively (Duranton 2011). My results give some support to this reading, and suggest that even light touch cluster programmes require cautious implementation. Further, while we could reasonably expect similar effect sizes in other large cities with growing tech milieux, it is less clear that such interventions would work in smaller cities and towns, or in rural areas.

This paper's limitations present opportunities for future research. First, I do not directly examine effects on firm formation: my data contains 99% of UK enterprises, but pre-revenue startups are disproportionately concentrated in sectors such as tech. Analysis using company registers could plug this gap. Second, while I control for its influence, I am unable to directly quantify the effect of angel and venture capital finance on firm growth. This may be an important means for SMEs to scale (Kerr et al., 2011). Third, my distributional analysis focuses on technology industry space. An alternative approach could explore outcomes for cluster movers versus incumbents, wages or housing market impacts (Kemeny and Osman 2018; Lee and Clarke 2019). Fourth, I cannot directly test *how* firm behaviour changes, in particular how knowledge spillovers and networks may influence innovation. Unlike more formalised cluster programmes, proxies such as co-patenting (Graf and Broekel, 2020) or consortia membership (Lucerna- Piquero and Vicente, 2019) are not available, but future reseach could look at innovation via reported product launches, or network structures via local MeetUp memberships (Mateos-Garcia et al, 2018). Finally, and relatedly, I do not directly test the effect of business support programmes – such as the Future Fifty[20] – in the policy mix. Evaluating their effectiveness – for example, by comparing outcomes for participants versus unsuccessful applicants – is an important complement to this analysis.

[20] https://technation.io/programmes/future-fifty/, accessed 15 August 2018.

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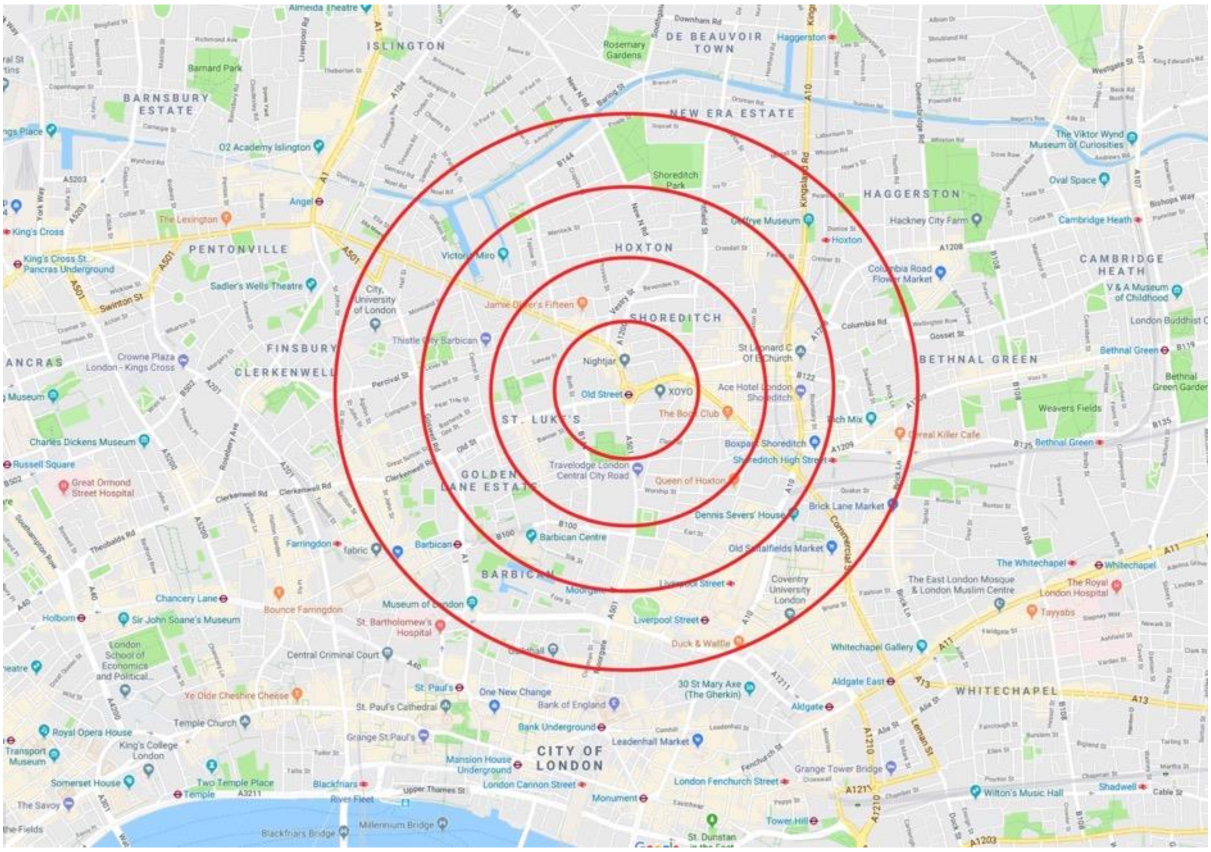
Figures.

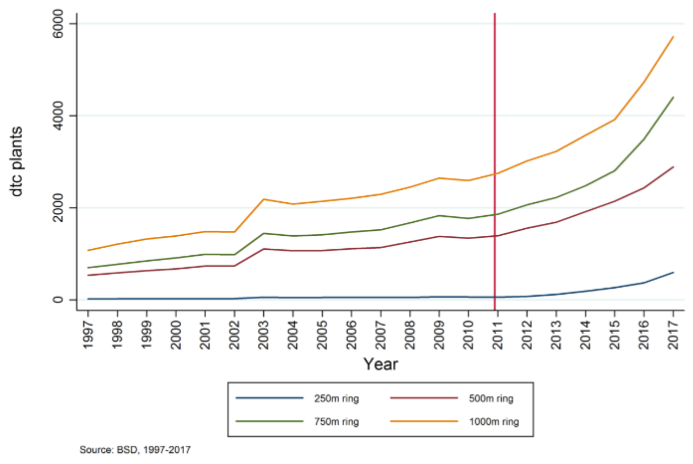
Figure 1. The Tech City area.



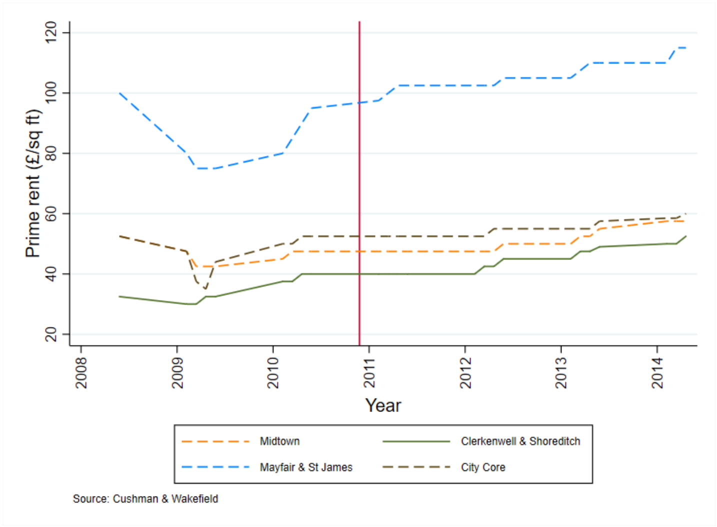
Source: Google Maps. Red circles show approx. 250m rings around Old St roundabout. The cluster zone is defined as the 1km ring from the roundabout.

Figure 2. Tech City over time: tech firm counts vs. rents.

A. Tech firm counts in the Tech City Zone, 1997-2017.



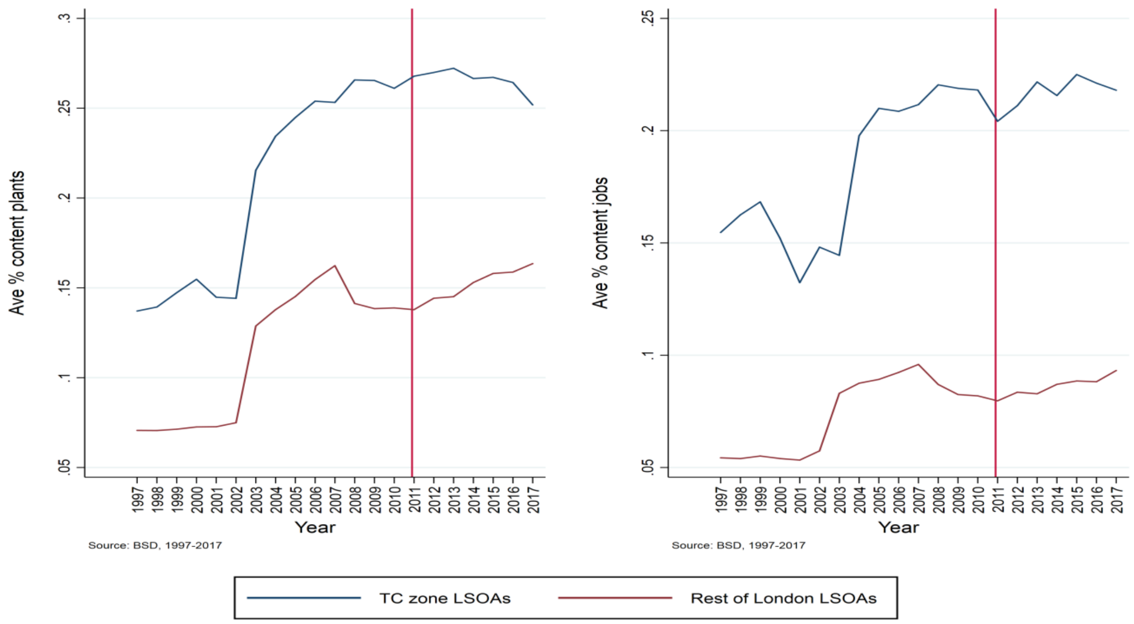
B. Prime rents for Clerkenwell and Shoreditch submarket, 2008-2014.



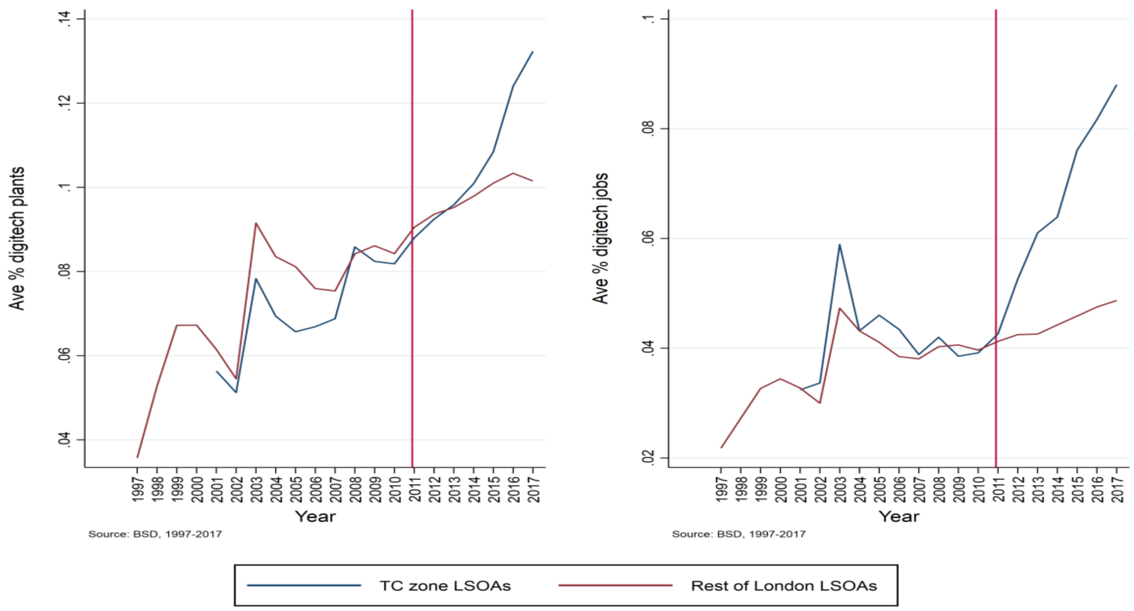
Source: BSD, Cushman & Wakefield. Firm counts are cumulative, so area total is given by 1km ring. Prime rents for four Inner London C&W 'submarket geographies', Clerkenwell and Shoreditch, Mayfair and St James, Midtown (Holborn and Temple), City Core (City of London).

Figure 3. Mean tech firm and job shares for Tech City LSOAs versus rest of Greater London LSOAs, 1997-2017.

A. Digital content. L: firms / all firms. R: jobs / all jobs



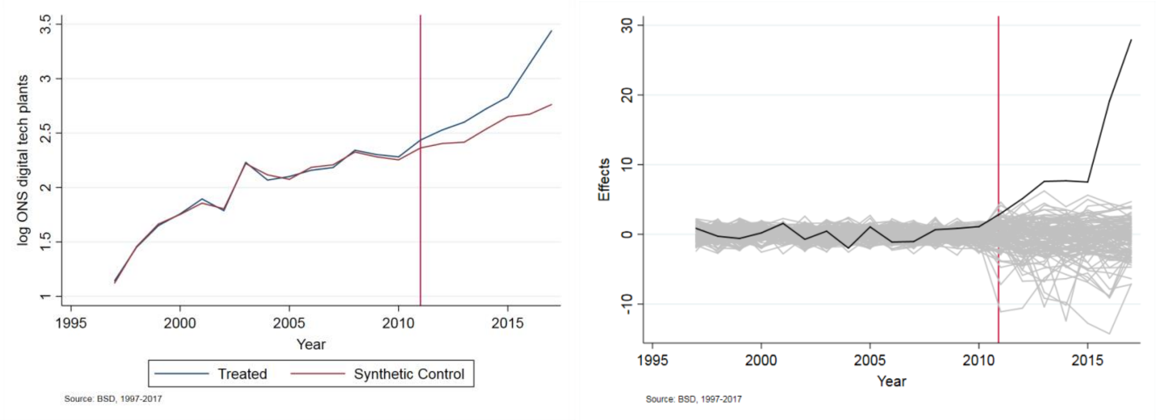
B. Digital technology. L: firms / all firms. R: jobs / all jobs



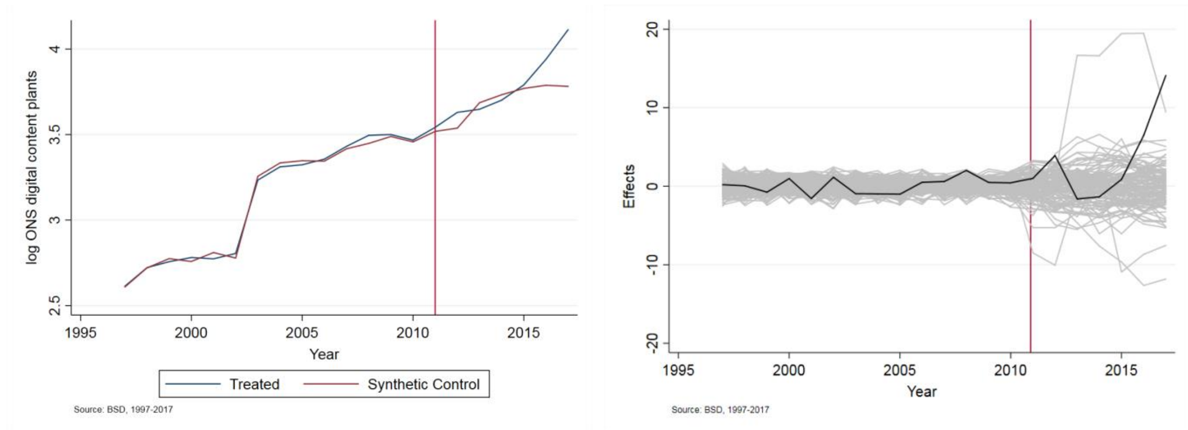
Graphs show % tech firms (jobs) as a share of all firms (jobs) in all industries, for average Tech City LSOA vs average rest of London LSOA. Top row: digital content. Bottom row: digital technology. Digital content activity includes advertising, media, design and web services Digital tech activity includes ICT hardware, software and IT consulting. Source: BSD 1997-2017.

Figure 4. Policy effects on cluster size. Changes in Tech City tech firms vs. synthetic counterfactual.

A. Log digital tech firms: treatment vs. control (L); weighted effect sizes (R)



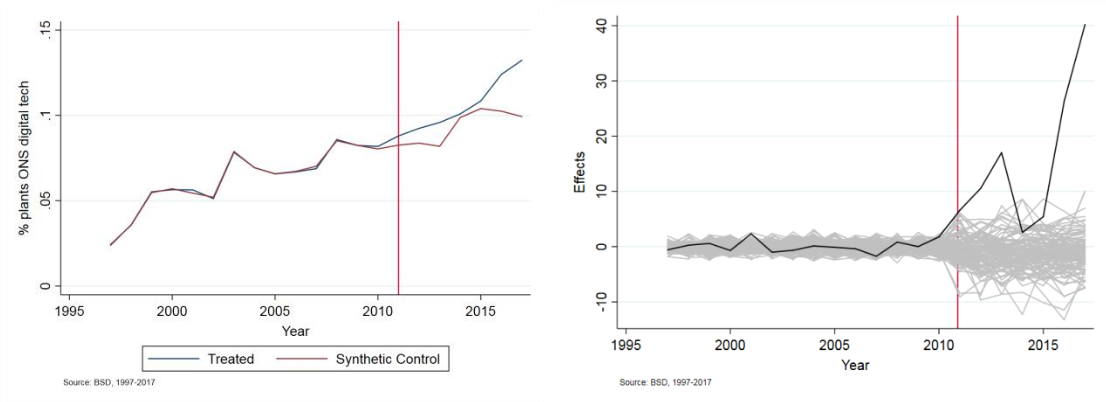
B. Log digital content firms: treatment vs. control (L); weighted effect sizes (R)



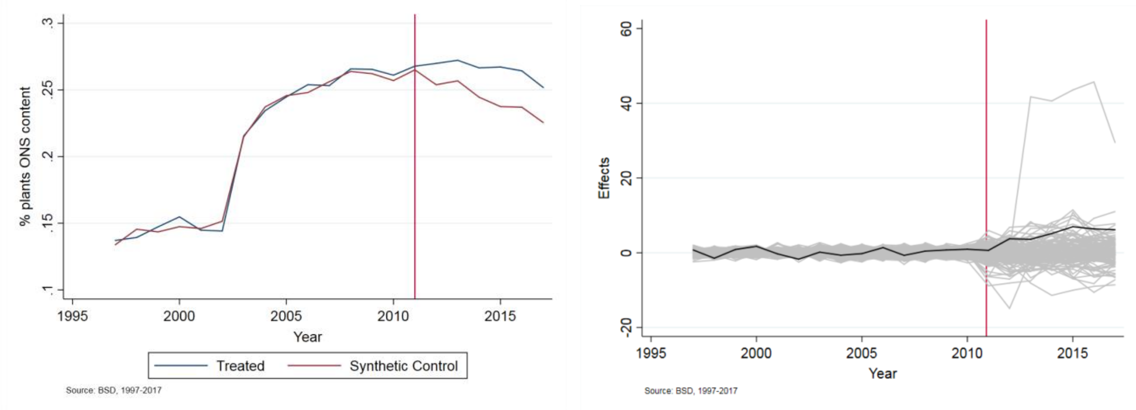
The left column shows outcomes for Tech City LSOAs (blue) vs. synthetic Tech City (red), the no-policy counterfactual scenario. The right column shows precision-weighted effect sizes for Tech City (black) versus 213 placebo units in the donor pool (grey). Effect sizes are weighted by pre-treatment RMSPE.

Figure 5. Policy effects on cluster density. Changes in Tech City tech firm shares vs. synthetic counterfactual.

A. Digital tech firms/all firms: treatment vs. control (L); weighted effect sizes (R)



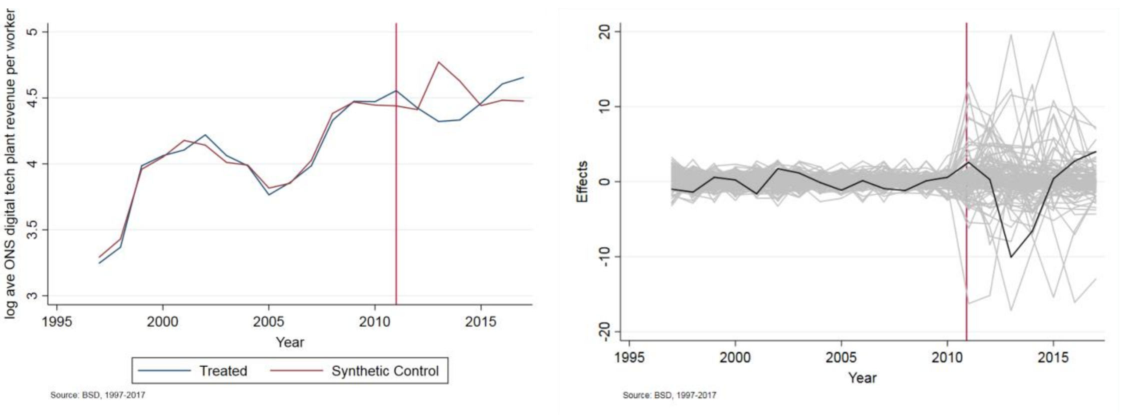
B. Digital content firms/all firms: treatment vs. control (L); weighted effect sizes (R)



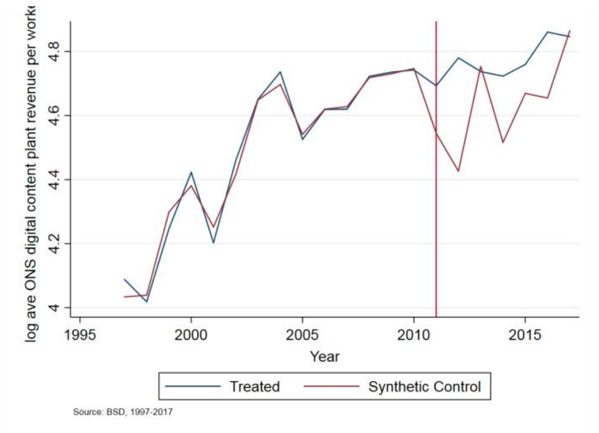
The left column shows outcomes for Tech City LSOAs (blue) vs. synthetic Tech City (red), the no-policy counterfactual scenario. The right column shows precision-weighted effect sizes for Tech City (black) versus 213 placebo units in the donor pool (grey). Effect sizes are weighted by pre-treatment RMSPE.

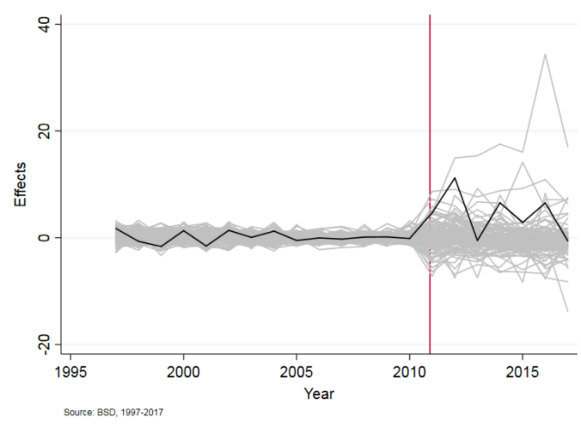
Figure 6. Policy effects on cluster 'performance'. Changes in Tech City tech firm revenue/worker vs. synthetic counterfactual.

A. Log digital tech mean revenue/worker: treatment vs. control (L); weighted effect sizes (R)



B. Log digital content mean rev/worker: treatment vs. control (L); weighted effect sizes (R)





The left column shows outcomes for Tech City LSOAs (blue) vs. synthetic Tech City (red), the no-policy counterfactual scenario. The right column shows precision-weighted effect sizes for Tech City (black) versus 2013 placebo units in the donor pool (grey). Effect sizes are weighted by pre-treatment RMSPE.

Tables.

Table 1. Mean LSOA characteristics for Tech City neighbourhoods versus Rest of Greater London neighbourhoods, 1997-2010.

Variable	**Tech City**	**Rest of Greater London**
LSOA total firm entry	3.500	0.963
ONS digital tech firm entry	0.251	0.088
ONS digital content firm entry	0.677	0.109
ONS digitech & content firm entry	0.929	0.197
LSOA total firm count	259.646	75.356
ONS digital tech firm count	15.954	4.323
ONS content firm count	56.551	9.319
ONS digitech & content firm count	72.406	13.616
% firms ONS digital tech	0.063	0.071
% firms ONS content	0.204	0.113
% firms ONS digital tech & content	0.267	0.184
LSOA total employment	4199.506	796.347
ONS digital tech employment	172.891	22.266
ONS content firm employment	898.126	74.236
ONS digitech & content firm employment	1070.226	96.179
% employment ONS digital tech	0.036	0.036
% employment ONS content	0.182	0.073
% employment ONS digital tech & content	0.218	0.109
LSOA total revenue per worker	1.35e+05	17763.513
Total ONS digital tech revenue	1829.877	438.710
Total ONS content firm revenue	8838.698	1409.111
Total ONS digitech & content firm revenue	10654.802	1838.854
LSOA mean firm revenue per worker	274.280	110.875
Mean ONS digital tech revenue per worker	86.119	85.264
Mean ONS content revenue per worker	146.662	102.894
Mean ONS digitech & content revenue per worker	142.313	92.411
Observations	*350*	*67144*

Source: BSD. Table compares pre-2011 means for an LSOA in the Tech City zone (25 LSOAs) for an LSOA in the rest of Greater London (c. 4800 LSOAs).

Table 2. Mean characteristics of Tech City vs. synthetic Tech City vs. matched sample of LSOAs, 1997-2010.

Variable	**Tech City**	**Synthetic Tech City**	**Matched sample**
Log digitech firms (1997)	.	1.123	0.712
Log digitech firms (1998)	.	1.457	1.013
Log digitech firms (1999)	.	1.664	1.266
Log digitech firms (2000)	.	1.753	1.247
Log digitech firms (2001)	1.895	1.857	1.238
Log digitech firms (2002)	1.788	1.805	1.158
Log digitech firms (2003)	2.231	2.220	1.559
Log digitech firms (2004)	2.068	2.116	1.502
Log digitech firms (2005)	2.101	2.075	1.464
Log digitech firms (2006)	2.159	2.185	1.473
Log digitech firms (2007)	2.184	2.209	1.503
Log digitech firms (2008)	2.342	2.326	1.669
Log digitech firms (2009)	2.303	2.282	1.666
Log digitech firms (2010)	2.282	2.255	1.617
Firm entry, all sectors	3.260	3.229	1.793
Revenue / worker, sectors	258.774	255.562	134.660
Herfindahl Index	0.136	0.136	0.146
LSOA firms, all sectors	238.760	224.800	127.748
LSOA jobs, all sectors	3836.394	3672.770	1467.235
LSOA total cafes and restaurants	7.074	6.990	4.045
LSOA total bars pubs and clubs	3.074	2.949	1.545
LSOA total coworking spaces	1.523	1.971	1.658
LSOA total museums and galleries	0.169	0.161	0.156
LSOA total libraries	0.311	0.302	0.084
LSOA total other accommodation	0.063	0.062	0.065
LSOA total arts and arts support activities	10.669	11.277	5.596
LSOA total supporting arts orgs	0.249	0.313	0.153
LSOA total HEIs	0.506	0.513	0.255
LSOA count of TFL stations	0.111	0.126	0.098
LA population	187283.078	188829.734	2.36e+05
LA share of non-UK born	0.309	0.307	0.348
LA share of residents aged 18-29	0.229	0.230	0.241
Observations	*350*	*2982*	*2982*

Source: BSD 1997-2010, 1991/2001/2011 Census, ONS mid-year population estimates, TFL. Some observations suppressed to avoid disclosure.

Table 3. Policy effects on cluster size, density and performance.

A. Cluster size	Firms		Jobs	
	Digitech	**Content**	**Digitech**	**Content**
Synthetic control ATT	0.270***	0.079**	0.440***	0.123*
p-value	0.005	0.023	0.005	0.061
Pre-treatment RMSPE	0.024	0.023	0.028	0.035
Average pre-treatment quality	1	1	1	1
Diff-in-diff ATT	*0.28****	*0.06*	*0.42****	*0.13*
	-0.104	*-0.068*	*-0.131*	*-0.115*
Observations	*4500*	*4646*	*4494*	*4639*
R^2	*0.8*	*0.91*	*0.8*	*0.87*
Pre-treatment mean	15.954	56.551	172.891	898.126
B. Cluster density	**% firms**		**% jobs**	
	Digitech	**Content**	**Digitech**	**Content**
Synthetic control ATT	0.013***	0.02*	0.031***	0.049***
p-value	0.005	0.084	0.009	0.009
Pre-treatment RMSPE	0.001	0.004	0.002	0.003
Average pre-treatment quality	1	1	1	1
Diff-in-diff ATT	*0.01**	*0*	*0.02***	*0.02*
	-0.007	*-0.009*	*-0.008*	*-0.017*
Observations	*4760*	*4760*	*4760*	*4760*
R^2	*0.58*	*0.7*	*0.47*	*0.6*
Pre-treatment mean	0.063	0.204	0.036	0.182
C. Cluster firm performance	**Revenue / worker**			
	Digitech	**Content**		
Synthetic control ATT	-0.043*	0.139**		
p-value	0.07	0.042		
Pre-treatment RMSPE	0.045	0.032		
Average pre-treatment quality	0.986	0.986		
Diff-in-diff ATT	*-0.02*	*0.03*		
	-0.062	*-0.092*		
Observations	*4489*	*4637*		
R^2	*0.35*	*0.48*		
Pre-treatment mean	86.119	146.662		

Source: BSD / Census / ONS / TfL. Synthetic control panel shows *p*-values from permutation test on 2013 placebos , pre-treatment error rate and proportion of placebos with pre-treatment error rate ≥ average of the treated unit. Regressions fit lagged outcome predictors 1997-2010 plus 1-year lags of LSOA all-sector firm entry, LSOA all-sector revenue/worker, LSOA Herfindahl Index, a vector of amenities (LSOA counts of cafes and restaurants, bars/pubs/clubs, co-working spaces, galleries and museums, libraries, other accommodation, arts and arts support, venues, universities), TFL station count, LA share of migrants, LA share of under-30s. Weights optimised defining **V** as an identity matrix. DID regressions fit LSOA and year dummies plus controls as above. Standard errors clustered on LSOA. * significant at 10%, ** 5%, *** 1%.

Table 4. Tech City policy effects: timing / falsification tests.

Specification	Firms		Jobs		% firms		% jobs		Ave rev/worker	
	Digitech	Content	Digitech	Content	Digitech	Content	Digitech	Content	Digitech	Content
A. Main synthetic control ATT	0.270***	0.079**	0.440***	0.123*	0.013***	0.02*	0.031***	0.049***	-0.043*	0.139**
p-value	*0.005*	*0.023*	*0.005*	*0.061*	*0.005*	*0.084*	*0.009*	*0.009*	*0.07*	*0.042*
RMSPE	*0.024*	*0.023*	*0.028*	*0.035*	*0.001*	*0.004*	*0.002*	*0.003*	*0.045*	*0.032*
B. Start treatment in 2008	0.451**	0.248**	0.495***	0.168	0.018***	0.038**	0.007*	0.064**	0.382**	0.048
p-value	*0.014*	*0.014*	*0.005*	*0.248*	*0.005*	*0.023*	*0.051*	*0.033*	*0.023*	*0.327*
RMSPE	*0.028*	*0.032*	*0.038*	*0.054*	*0.001*	*0.003*	*0.002*	*0.005*	*0.038*	*0.047*
C. Start treatment in 2008, end in 2010	0.347**	0.188**	0.284**	0.183	0.015***	0.034**	-0.013*	0.023*	0.679***	-0.017
p-value	*0.019*	*0.037*	*0.014*	*0.229*	*0.005*	*0.019*	*0.07*	*0.065*	*0.009*	*0.902*
RMSPE	*0.028*	*0.032*	*0.038*	*0.054*	*0.001*	*0.003*	*0.002*	*0.005*	*0.038*	*0.047*
D. End treatment in 2014	0.142**	0.011	0.422***	0.076	0.008***	0.014	0.022**	0.043**	-0.155**	0.173**
p-value	*0.042*	*0.238*	*0.005*	*0.112*	*0.005*	*0.168*	*0.014*	*0.019*	*0.047*	*0.028*
RMSPE	*0.024*	*0.023*	*0.028*	*0.035*	*0.001*	*0.004*	*0.002*	*0.003*	*0.045*	*0.032*
Effect size / year, 2011-2017	*0.039*	*0.011*	*0.063*	*0.018*	*0.002*	*0.003*	*0.004*	*0.007*	*-0.006*	*0.020*
Effect size / year, 2008-10	*0.116*	*0.063*	*0.095*	*0.061*	*0.005*	*0.011*	*-0.004*	*0.008*	*0.226*	*-0.006*
Effect size / year, 2011-2014	0.036	0.003	0.105	0.019	0.002	0.004	0.005	0.011	-0.039	0.043

Notes as in Table 3.

Table 5. Churn in the cluster: tech firm entry, exit and movement.

A. All tech firms	**2009-2010**		**2013-2014**		**2016-2017**	
	count	**%**	**count**	**%**	**count**	**%**
In the UK	460,926		498,082		595,583	
In Tech City Zone	3,469		3,985		6,323	
Stayers	2,208	63.7	2,277	57.1	3,516	55.6
Entrants	635	18.3	988	24.8	2,082	32.9
Leavers	626	18.0	720	18.1	718	11.4
Entrants						
Movers from rest of London	*173*	*27.2*	*187*	*18.9*	*488*	*23.4*
Movers from rest of UK	*37*	*5.8*	*67*	*6.8*	*130*	*6.2*
New firm	*425*	*67*	*734*	*74.3*	*1,471*	*70.4*
Leavers						
Moved to rest of London	*158*	*25.2*	*222*	*30.8*	*310*	*43.2*
Moved to rest of UK	*45*	*7.2*	*35*	*4.9*	*79*	*11*
Died	*423*	*67.6*	*463*	*64.3*	*329*	*45.8*
B. Foreign-owned tech firms	**2009-2010**		**2013-2014**		**2016-2017**	
	count	**% all**	**count**	**% all**	**count**	**% all**
In the UK	45,628	9.9	53,647	10.8	14,309	2.4
In Tech City Zone	690	19.9	916	23	366	5.8
Stayers	496	22.5	592	26.0	228	6.5
Entrants	135	21.3	179	18.1	89	4.3
Leavers	59	9.4	145	20.1	49	6.8
Entrants						
Movers	*35*	*39.6*	*60*	*45.5*	*27*	*5.9*
New firm	*100*	*23.5*	*119*	*16.2*	*63*	*[4.3]*
Leavers						
Movers	*33*	*28.8*	*57*	*40.1*	*25*	*11.9*
Died	*26*	*6.2*	*88*	*19*	*24*	*7.3*

Source: BSD.

Does Light Touch Cluster Policy Work?
Evaluating the Tech City Programme

ONLINE APPENDICES

Appendix A: Panel build

A1 / BSD data

To build the main panel for analysis I use firm-level microdata (specifically, individual workplaces) from the latest (9th) edition of the Business Structure Database (BSD). The BSD covers over 99% of all UK economic activity and provides high quality information for individual firms, coded to postcode level. Variables include firm location (to postcode level), industry, employment, turnover and entry/exit dates from multiple sources including company tax returns, VAT data (UK sales tax) and Companies House filings. I use the 2016 National Statistics Postcode Database (NSPD) to link firm postcodes to 2011 LSOAs. I then aggregate the data to LSOA level. The resulting panel runs from 1997 - 2017 and contains 101,502 area*year observations for 4,835 LSOAs in Greater London.

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 (thus paying VAT). Firms leaving the raw data may either fall below those thresholds, returning later, or actually exit the market. Using routines developed in CEP, my cleaned data keeps live firms in each year, including those temporarily exit the dataset, imputing values in the latter case.

Because BSD cross-sections are taken in April of each year, rather than calendar years, the Tech City initiative takes place in BSD year 2011. In what follows, I will refer to BSD years 2011 and after as the post-treatment period.

A2 / Commercial rents data

Commercial rents data comes from Cushman and Wakefield (C&W), a leading UK property analysis firm, and covers the period December 2008 to September 2014. Data is provided in quarters for four C&W 'submarket geographies', Clerkenwell and Shoreditch, Mayfair and St James, Midtown (Holborn and Temple), City Core (City of London). These are rather less precise than postcode level information, and as such are used to extend and help interpret the main results, rather in regression analysis. Clerkenwell and Shoreditch is an acceptable proxy for the Tech City area; City Core covers the area immediately to the South, one of London's financial centres; and Midtown covers the area immediately to the West, which has a mix of commercial, office, retail and leisure uses. Mayfair and St. James is an established super-prime location in central London. Rents data covers prime rents, which are defined as the average of the top 3-5% of all lettings in each submarket. They are thus a useful leading indicator for wider local property market change.

A3/ Defining the technology sector

I define 'tech' industries using the ONS typology of science and technology sectors (Harris, 2015). The ONS typology is based on an extensive cross-national analysis and standardisation exercise and represents a robust baseline. Specifically, I use the set of 'digital technology' activities (mainly hardware and software industries) and the set of 'publishing and broadcasting' activities. In practice, the latter are highly overlapping with 'digital content' (such as advertising, design, media and the creative industries, where product/services are increasingly online). The ONS industries are specified using SIC07 codes. Because my data goes back to 1997, I convert these codes to SIC03, using an ONS-supplied crosswalk, to make them time-consistent. The full list of SIC03 codes is given in Table A2. SIC codes were originally designed for manufacturing and so provide much more detail for digital technology activities, where there are many small industry bins, than for digital content, where bins are fewer but larger.

Table A1. SIC03 codes and descriptors used to define technology industry space.

A. Digital technology.

SIC03	SIC03 descriptor
2465	Manufacture of prepared unrecorded media
2466	Manufacture of other chemical products not elsewhere classified (n.e.c.)
2924	Manufacture of other general purpose machinery n.e.c.
3002	Manufacture of computers and other information processing equipment
3110	Manufacture of electric motors, generators and transformers
3120	Manufacture of electricity distribution and control apparatus
3130	Insulated wire and cable
3162	Manufacture of other electrical equipment n.e.c.
3210	Electronic valves and tubes and other electronic components
3220	Manufacture of telegraph and telephone apparatus and equipment
3230	Television/radio receivers, sound or video recording or producing apparatus
3310	Manufacture of medical and surgical equipment and orthopaedic appliances
3320	Instruments and appliances for measuring, checking, testing, navigating, or other purposes
3330	Manufacture of electronic industrial process control equipment
3340	Manufacture of precision optical instruments, spectacles and unmounted lenses
3350	Manufacture of watches and clocks
3650	Manufacture of professional and arcade games and toys
7210	Computer Hardware consultancy
7221	Publishing of software
7222	Other software consultancy and supply
7230	Data processing
7240	Database activities
7250	Maintenance and repair of office, accounting and computing machinery
7260	Other computer related activities

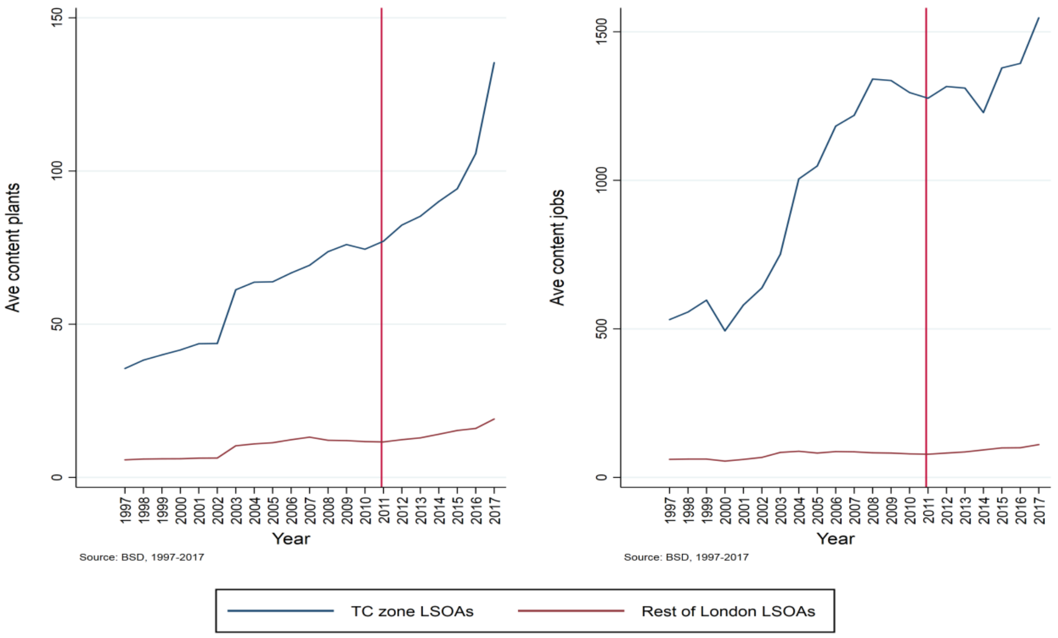
B. Digital content.

SIC03	SIC03 descriptor
2211	Publishing of books
2212	Publishing of newspapers
2213	Publishing of journals and periodicals
2214	Publishing of sound recordings
2215	Other publishing
2222	Printing not elsewhere classified
5274	Repair of communication equipment and equipment nec
6420	Telecommunications
7240	Database activities
7413	Market research and public opinion polling
7440	Advertising
7481	Photographic activities
7487	Speciality design activities
9211	Motion picture and video production
9213	Motion picture projection
9220	Radio & TV
9240	News agency activities

Appendix B. Additional results

Figure B1. LSOA mean tech firm and job counts for Tech City neighbourhoods versus Rest of Greater London neighbourhoods, 1997-2017.

A. Digital content. L: firms. R: jobs



B. Digital technology. L: firms. R: jobs

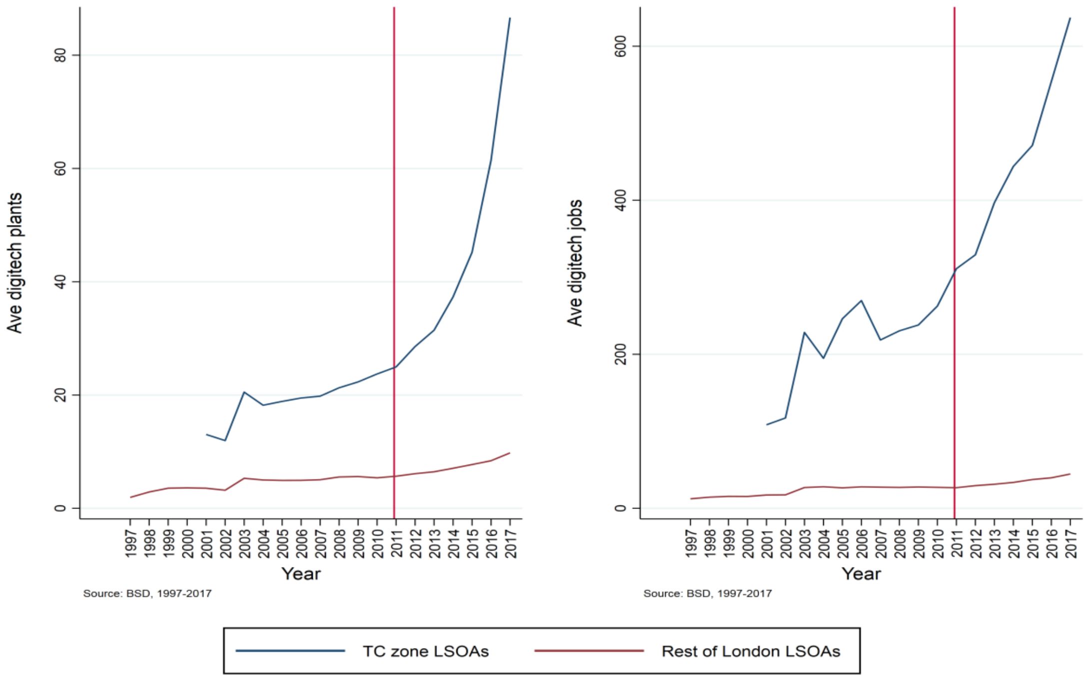


Figure B2. LSOA mean tech firm revenue/worker for Tech City neighbourhoods versus Rest of Greater London neighbourhoods, 1997-2017.

L: digital technology. R: digital content.

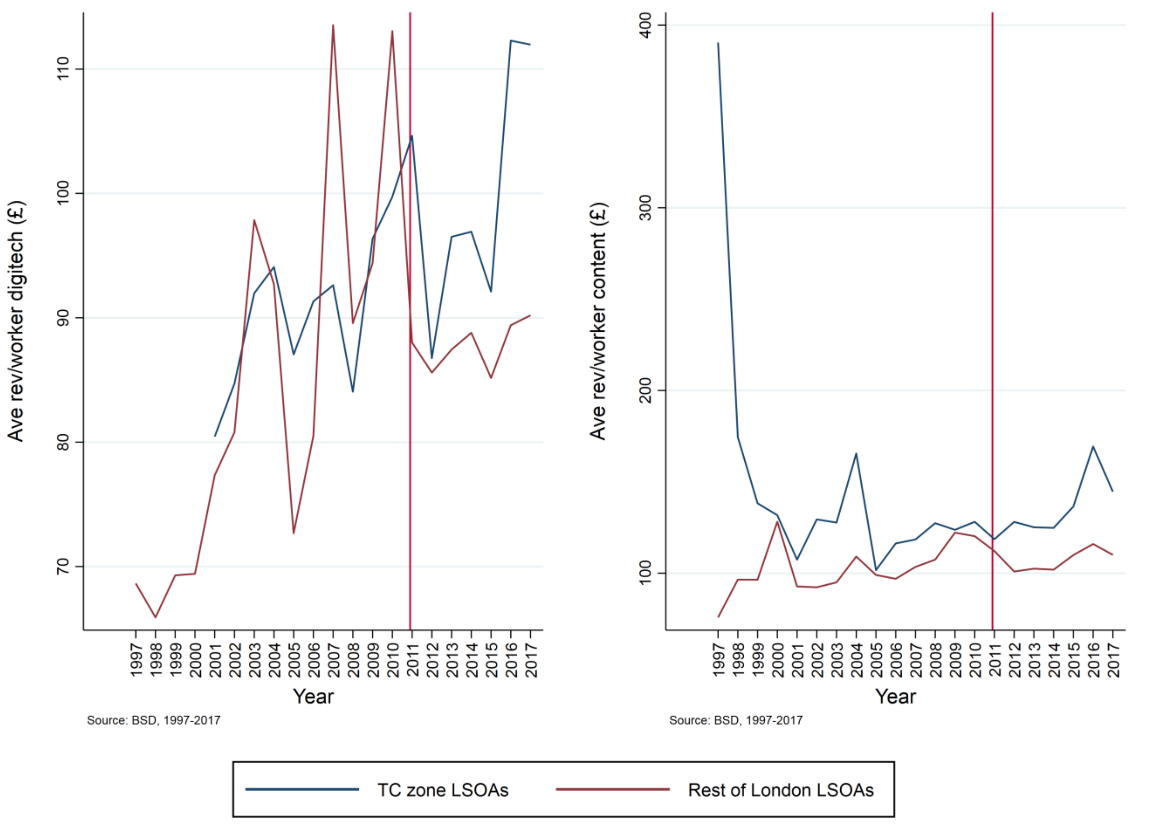
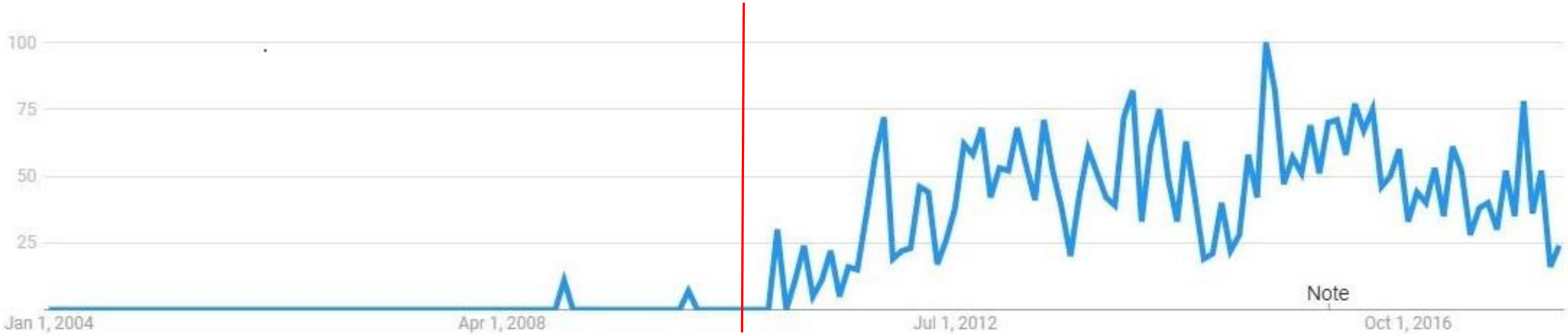


Figure B3. Google Trends analysis.

A. Google Trends: searches for "Tech City" + London as share of all searches. As of 1 March 2018.



B. Google Trends: searches for "Silicon Roundabout" + London as share of all searches. As of 1 March 2018.

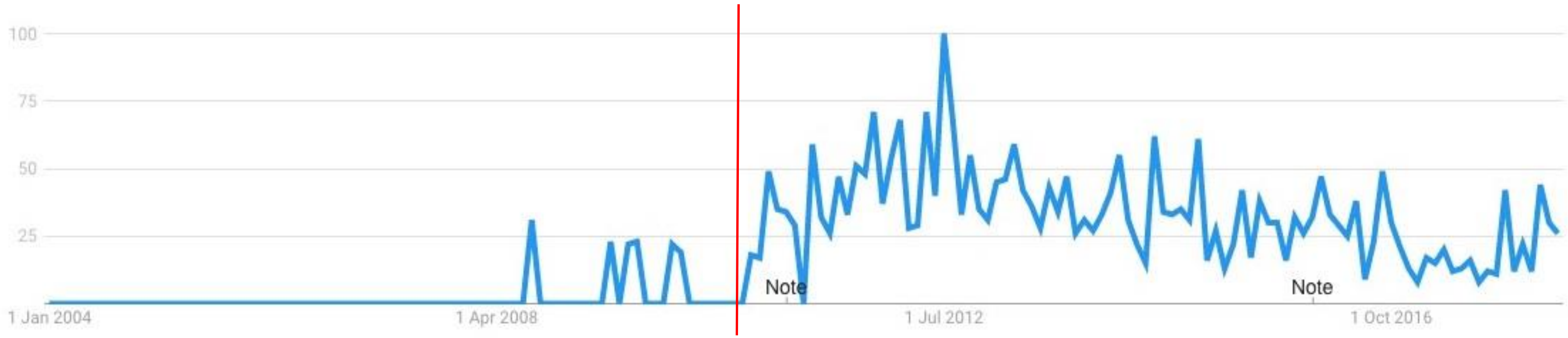
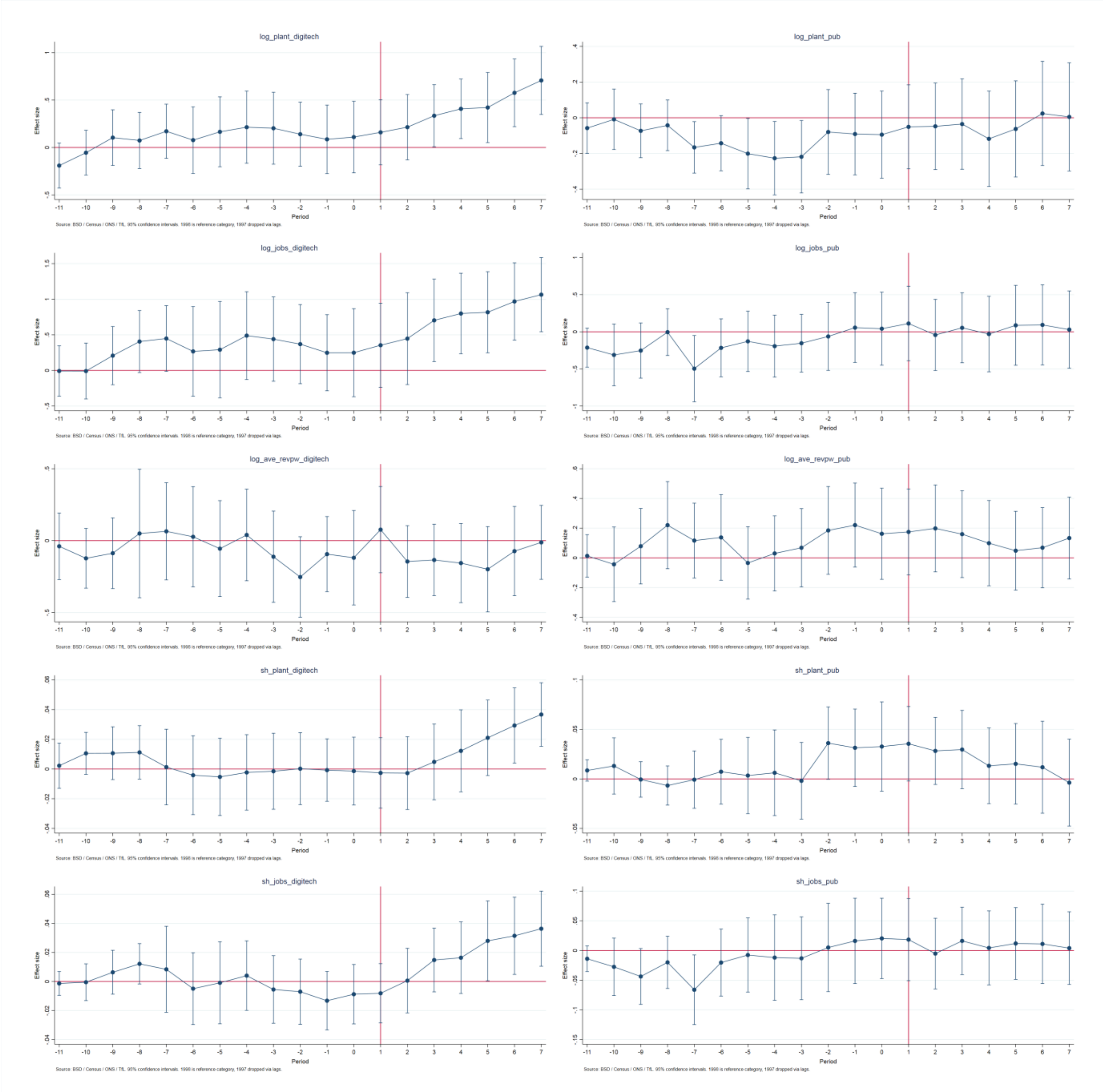


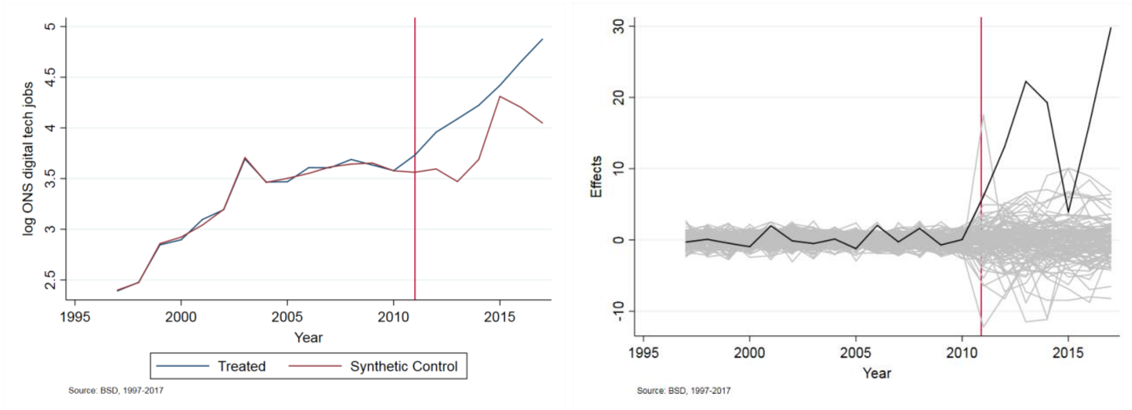
Figure B4. Balancing regressions for Tech City zone vs. matched sample of control LSOAs, 1999-2017.



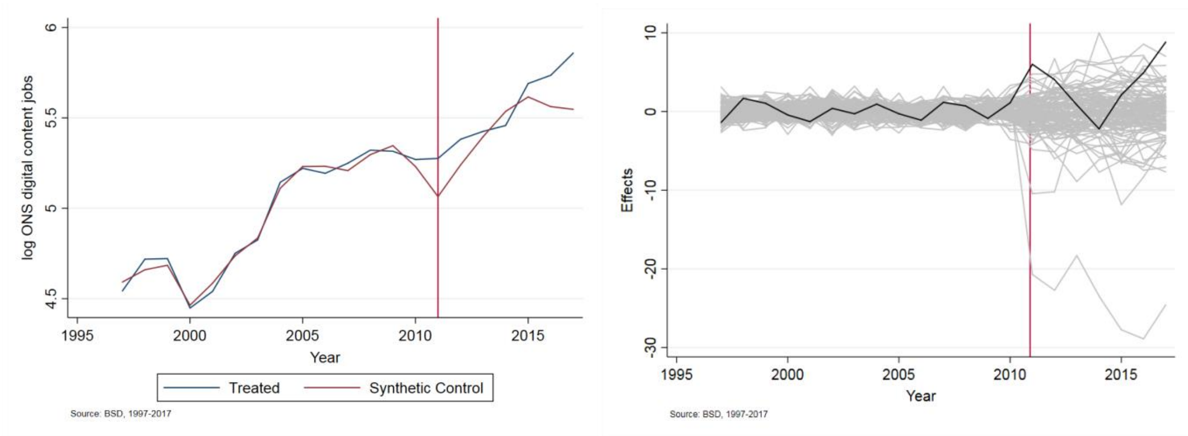
Source: BSD, Census, ONS mid-year population estimates, TFL. 95% confidence intervals. 1998 is reference category, 1997 dropped via lags. All regressions fit LSOA and year dummies. Time-varying controls fitted are one-year lags of LSOA all-sector firm entry, LSOA all-sector revenue/worker, LSOA Herfindahl Index, a vector of amenities (LSOA counts of cafes and restaurants, bars/pubs/clubs, co-working spaces, galleries and museums, libraries, accommodation, arts and arts support, venues, universities), TFL station count, LA share of migrants, LA share of under-30s. Standard errors clustered on LSOA.

Figure B5. Policy effects on cluster size. Changes in Tech City tech jobs vs. synthetic counterfactual.

A. Log digital tech jobs: treatment vs. control (L); weighted effect sizes (R)



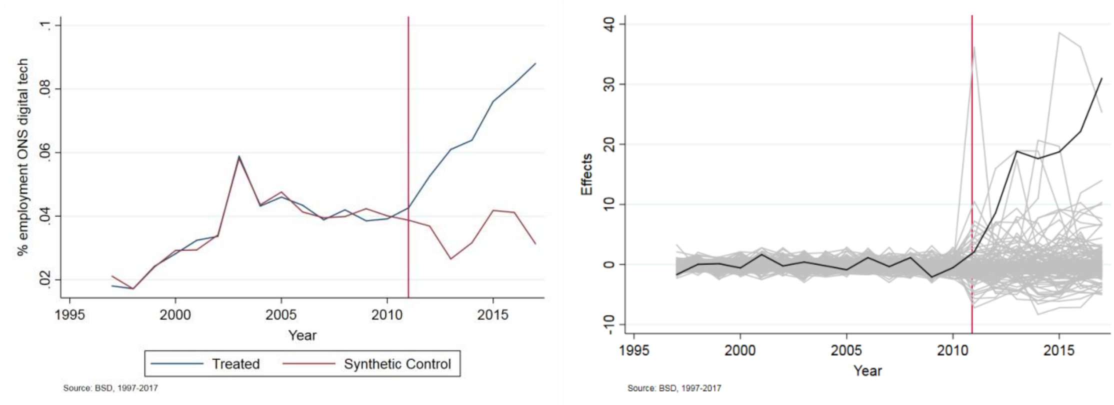
B. Log digital content jobs: treatment vs. control (L); weighted effect sizes (R)



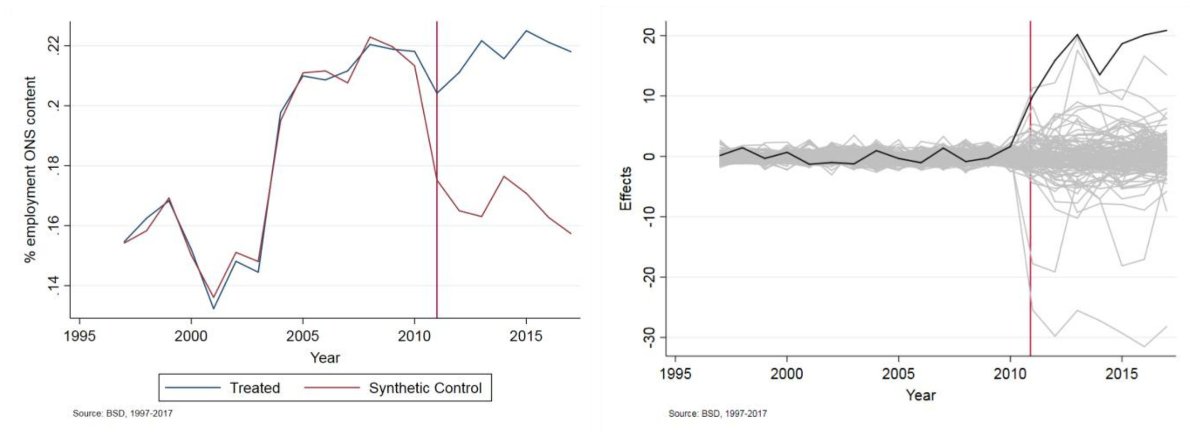
The left column shows outcomes for Tech City LSOAs (blue) vs. synthetic Tech City (red), the no-policy counterfactual scenario. The right column shows precision-weighted effect sizes for Tech City (black) versus 213 placebo units in the donor pool (grey). Effect sizes are weighted by pre-treatment RMSPE.

Figure B6. Policy effects on cluster density. Changes in Tech City tech job shares vs. synthetic counterfactual.

A. Digital tech jobs/all jobs: treatment vs. control (L); weighted effect sizes (R)

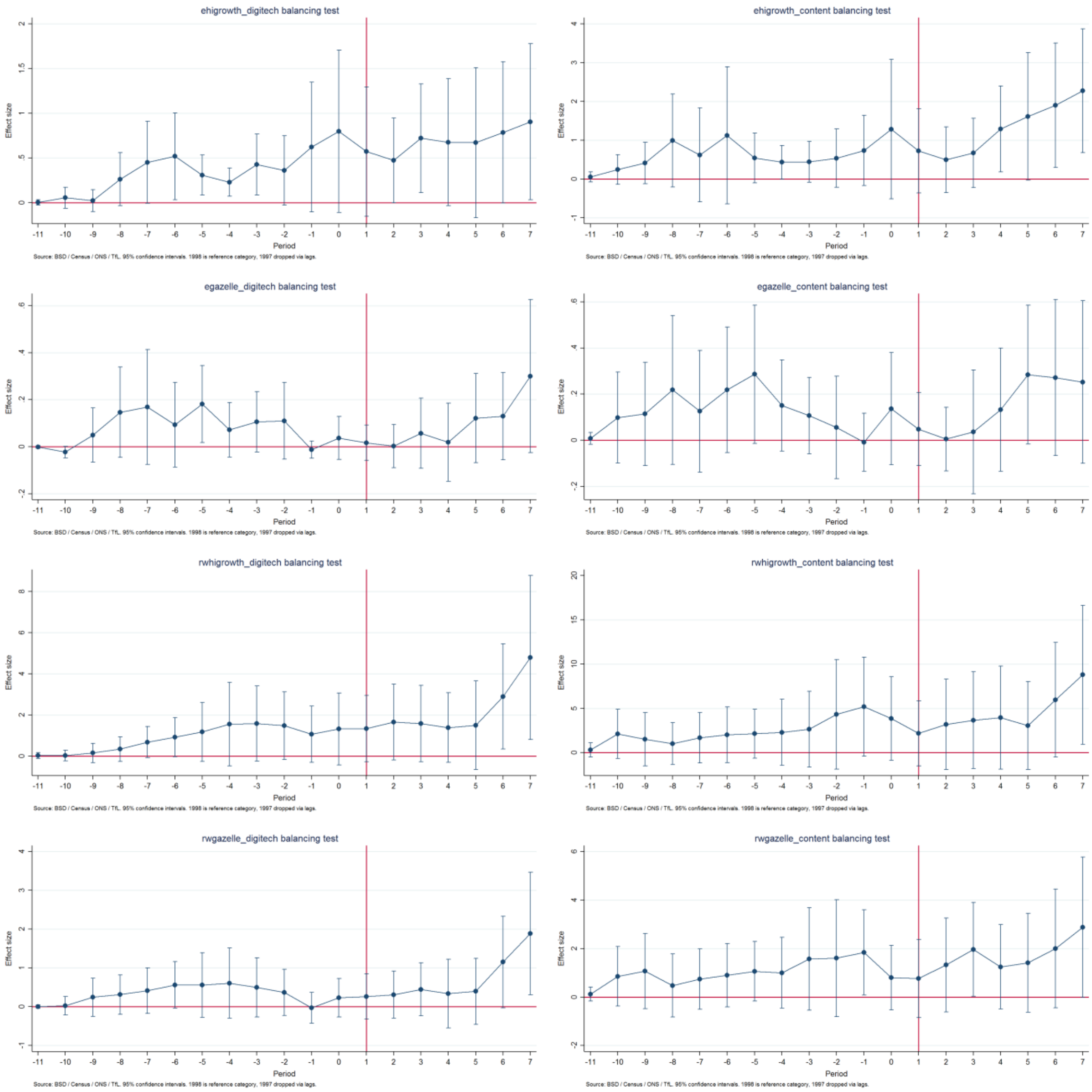


B. Digital content jobs/all jobs: treatment vs. control (L); weighted effect sizes (R)



The left column shows outcomes for Tech City LSOAs (blue) vs. synthetic Tech City (red), the no-policy counterfactual scenario. The right column shows precision-weighted effect sizes for Tech City (black) versus 213 placebo units in the donor pool (grey). Effect sizes are weighted by pre-treatment RMSPE.

Figure B7. Scaling analysis: balancing regressions, 1999-2017.



Source: BSD, Census, ONS mid-year population estimates, TFL. 95% confidence intervals. 1998 is reference category, 1997 dropped via lags. All regressions fit LSOA and year dummies. Time-varying controls fitted are 1-year lags of LSOA all-sector firm entry, LSOA all-sector revenue/worker, LSOA Herfindahl Index, a vector of amenities (LSOA counts of cafes and restaurants, bars/pubs/clubs, co-working spaces, galleries and museums, libraries, accommodation, arts and arts support, venues, universities), TFL station count, LA share of migrants, LA share of under-30s. Standard errors clustered on LSOA.

Table B1. Mean LSOA characteristics for Tech City neighbourhoods versus Rest of Greater London neighbourhoods, 1997-2010: amenities and demographics.

Variable	**Tech City**	**Rest of Greater London**
Herfindahl Index	0.148	0.150
LSOA total cafes and restaurants	7.734	2.511
LSOA total bars pubs and clubs	3.340	0.989
LSOA total coworking spaces	1.740	0.646
LSOA total museums and galleries	0.180	0.048
LSOA total libraries	0.323	0.085
LSOA total hotels	0.000	0.000
LSOA total other accommodation	0.080	0.057
LSOA total arts and arts support activities	11.349	2.573
LSOA total supporting arts orgs	0.271	0.068
LSOA total HEIs	0.557	0.143
LSOA count of TFL stations	0.120	0.098
LA share of non-UK born	0.310	0.256
LA share of residents aged 18-29	0.231	0.197
Observations	*350*	*67144*

Source: BSD, Census, ONS, TfL. Table compares pre-2011 means for an LSOA in the Tech City zone (25 LSOAs) for an LSOA in the rest of Greater London (c. 4800 LSOAs).

Table B2. Control units: results of propensity score matching on treatment status, 1997-2010.

Variable	Means, 1997-2010 Treated	Control	%bias	T-test *t*	*p>t*	V_e(T)/ V_e(C)
# firm entry ONS digitech & content	1.669	0.571	35.7	10.26	0	4.26*
Mean revenue ONS digitech & content	1441	1440	0	0	0.997	0.19*
Mean revenue/worker ONS digitech & content	136	138	-0.7	-0.09	0.925	0.17*
% firms ONS digital tech and content	0.302	0.264	33.5	6.98	0	0.84*
% employment ONS digital tech and content	0.240	0.196	29.1	5.95	0	0.92
Herfindahl Index	0.158	0.155	5.1	0.91	0.365	0.37*
% cafes and restaurants	0.028	0.027	4.3	0.93	0.351	0.73*
% bars cafes and clubs	0.015	0.015	-2.5	-0.46	0.645	0.58*
% coworking and shared offices	0.008	0.008	-3.8	-0.87	0.384	0.88
% galleries and museums	0.002	0.001	7.1	1.11	0.269	0.46*
% libraries	0.001	0.001	-2.9	-0.49	0.621	0.17*
% other accommodation	0.000	0.001	-3.7	-0.79	0.431	0.37*
% artists and performers	0.040	0.045	-13.6	-2.47	0.014	0.33*
% arts facilities and supp	0.001	0.001	5.7	1.45	0.146	1
% universities and colleges	0.002	0.002	5.3	1.14	0.255	0.33*
Count of TFL stations	0.120	0.103	5	1.02	0.306	0.76*
LA share of non-UK born	0.332	0.348	-23.9	-4.32	0	0.33*
LA share of residents aged 18-29	0.232	0.240	-25.5	-5.67	0	1.13
Observations	*350*	*2982*	*n/a*	*n/a*	*n/a*	*n/a*
Summary stats	*MeanBias*	*MedBias*	*B*	*R*		
	11.5	*5.2*	*71.5**	*1.26*		

Source: BSD 1997-2010, 1991/2001/2011 Census, ONS mid-year population estimates, TFL. Probit regression using nearest neighbour matching (nn = 1) where dependent variable = LSOA is in the Tech City Zone. Results shown for 25 Tech City LSOAs and 213 matched control LSOAs with the 25% highest propensity scores of all controls. Variance ratio should equal 1 if matched group is perfectly balanced with treatment group. * = variance ratio is 'of concern', i.e. variance ratio in [0.84, 1.19). B and R indicate Rubin's B and R ratios. For samples to be sufficiently balanced, B < 25 and 0.25 < R < 2. * = values outside these ranges.

Table B3. Comparing mean characteristics of Tech City neighbourhoods vs. synthetic Tech City vs. matched control neighbourhoods, 1997-2010. Results for all other outcomes.

Variable	Tech City	Synthetic Tech City	Matched sample
Log content firms (1997)	2.613	2.609	1.626
Log content firms (1998)	2.722	2.721	1.645
Log content firms (1999)	2.757	2.775	1.665
Log content firms (2000)	2.781	2.758	1.698
Log content firms (2001)	2.773	2.810	1.747
Log content firms (2002)	2.805	2.778	1.754
Log content firms (2003)	3.234	3.256	2.260
Log content firms (2004)	3.311	3.334	2.335
Log content firms (2005)	3.323	3.347	2.414
Log content firms (2006)	3.356	3.344	2.485
Log content firms (2007)	3.431	3.417	2.563
Log content firms (2008)	3.495	3.448	2.448
Log content firms (2009)	3.500	3.488	2.454
Log content firms (2010)	3.468	3.457	2.413
Firm entry, all sectors	3.260	3.182	1.793
Revenue / worker, sectors	258.774	255.350	134.660
Herfindahl Index	0.136	0.136	0.146
LSOA firms, all sectors	238.760	228.364	127.748
LSOA jobs, all sectors	3836.394	3789.643	1467.235
LSOA total cafes and restaurants	7.074	7.135	4.045
LSOA total bars pubs and clubs	3.074	2.965	1.545
LSOA total coworking spaces	1.523	1.958	1.658
LSOA total museums and galleries	0.169	0.165	0.156
LSOA total libraries	0.311	0.303	0.084
LSOA total other accommodation	0.063	0.062	0.065
LSOA total arts and arts support activities	10.669	10.900	5.596
LSOA total supporting arts orgs	0.249	0.314	0.153
LSOA total HEIs	0.506	0.507	0.255
LSOA count of TFL stations	0.111	0.126	0.098
LA population	187283.078	188577.406	2.36e+05
LA share of non-UK born	0.309	0.311	0.348
LA share of residents aged 18-29	0.229	0.230	0.241
Observations	*350*	*2982*	*2982*

Source: BSD 1997-2010, 1991/2001/2011 Census, ONS mid-year population estimates, TFL.

Table B3 continued.

Variable	Tech City	Synthetic Tech City	Matched sample
Log digitech jobs (1997)	.	2.400	1.420
Log digitech jobs (1998)	.	2.475	1.673
Log digitech jobs (1999)	.	2.859	1.891
Log digitech jobs (2000)	.	2.923	1.886
Log digitech jobs (2001)	3.097	3.042	1.900
Log digitech jobs (2002)	3.193	3.196	1.776
Log digitech jobs (2003)	3.694	3.708	2.337
Log digitech jobs (2004)	3.466	3.463	2.302
Log digitech jobs (2005)	3.469	3.503	2.301
Log digitech jobs (2006)	3.608	3.551	2.250
Log digitech jobs (2007)	3.607	3.614	2.288
Log digitech jobs (2008)	3.689	3.643	2.373
Log digitech jobs (2009)	3.634	3.654	2.432
Log digitech jobs (2010)	3.579	3.577	2.383
Firm entry, all sectors	3.260	3.148	1.793
Revenue / worker, sectors	258.774	256.765	134.660
Herfindahl Index	0.136	0.136	0.146
LSOA firms, all sectors	238.760	221.991	127.748
LSOA jobs, all sectors	3836.394	3748.257	1467.235
LSOA total cafes and restaurants	7.074	7.155	4.045
LSOA total bars pubs and clubs	3.074	3.025	1.545
LSOA total coworking spaces	1.523	1.911	1.658
LSOA total museums and galleries	0.169	0.160	0.156
LSOA total libraries	0.311	0.308	0.084
LSOA total other accommodation	0.063	0.063	0.065
LSOA total arts and arts support activities	10.669	10.596	5.596
LSOA total supporting arts orgs	0.249	0.297	0.153
LSOA total HEIs	0.506	0.512	0.255
LSOA count of TFL stations	0.111	0.119	0.098
LA population	187283.078	187981.172	2.36e+05
LA share of non-UK born	0.309	0.308	0.348
LA share of residents aged 18-29	0.229	0.229	0.241
Observations	*350*	*2982*	*2982*

Source: BSD 1997-2010, 1991/2001/2011 Census, ONS mid-year population estimates, TFL. Some observations suppressed to avoid disclosure.

Table B3 continued.

Variable	Tech City	Synthetic Tech City	Matched sample
Log content jobs (1997)	4.543	4.592	2.919
Log content jobs (1998)	4.719	4.660	2.864
Log content jobs (1999)	4.721	4.685	2.936
Log content jobs (2000)	4.448	4.464	2.910
Log content jobs (2001)	4.540	4.585	2.990
Log content jobs (2002)	4.751	4.737	3.028
Log content jobs (2003)	4.825	4.835	3.512
Log content jobs (2004)	5.144	5.111	3.613
Log content jobs (2005)	5.221	5.231	3.653
Log content jobs (2006)	5.193	5.233	3.718
Log content jobs (2007)	5.249	5.208	3.770
Log content jobs (2008)	5.322	5.297	3.687
Log content jobs (2009)	5.315	5.346	3.597
Log content jobs (2010)	5.270	5.231	3.582
Firm entry, all sectors	3.260	3.024	1.793
Revenue / worker, sectors	258.774	257.506	134.660
Herfindahl Index	0.136	0.136	0.146
LSOA firms, all sectors	238.760	222.702	127.748
LSOA jobs, all sectors	3836.394	3823.425	1467.235
LSOA total cafes and restaurants	7.074	7.297	4.045
LSOA total bars pubs and clubs	3.074	2.974	1.545
LSOA total coworking spaces	1.523	2.074	1.658
LSOA total museums and galleries	0.169	0.156	0.156
LSOA total libraries	0.311	0.310	0.084
LSOA total other accommodation	0.063	0.062	0.065
LSOA total arts and arts support activities	10.669	10.667	5.596
LSOA total supporting arts orgs	0.249	0.285	0.153
LSOA total HEIs	0.506	0.496	0.255
LSOA count of TFL stations	0.111	0.117	0.098
LA population	187283.078	188216.391	2.36e+05
LA share of non-UK born	0.309	0.310	0.348
LA share of residents aged 18-29	0.229	0.230	0.241
Observations	*350*	*2982*	*2982*

Source: BSD 1997-2010, 1991/2001/2011 Census, ONS mid-year population estimates, TFL.

Table B3 continued.

Variable	Tech City	Synthetic Tech City	Matched sample
share digitech firms (1997)	.	0.024	0.038
share digitech firms (1998)	.	0.036	0.056
share digitech firms (1999)	.	0.055	0.072
share digitech firms (2000)	.	0.057	0.068
share digitech firms (2001)	0.056	0.054	0.066
share digitech firms (2002)	0.051	0.052	0.063
share digitech firms (2003)	0.078	0.079	0.100
share digitech firms (2004)	0.069	0.069	0.093
share digitech firms (2005)	0.066	0.066	0.090
share digitech firms (2006)	0.067	0.067	0.086
share digitech firms (2007)	0.069	0.070	0.086
share digitech firms (2008)	0.086	0.085	0.099
share digitech firms (2009)	0.082	0.082	0.096
share digitech firms (2010)	0.082	0.080	0.095
Firm entry, all sectors	3.260	3.109	1.793
Revenue / worker, sectors	258.774	257.416	134.660
Herfindahl Index	0.136	0.136	0.146
LSOA firms, all sectors	238.760	223.520	127.748
LSOA jobs, all sectors	3836.394	3727.677	1467.235
LSOA total cafes and restaurants	7.074	7.047	4.045
LSOA total bars pubs and clubs	3.074	3.046	1.545
LSOA total coworking spaces	1.523	2.096	1.658
LSOA total museums and galleries	0.169	0.164	0.156
LSOA total libraries	0.311	0.307	0.084
LSOA total other accommodation	0.063	0.062	0.065
LSOA total arts and arts support activities	10.669	10.615	5.596
LSOA total supporting arts orgs	0.249	0.294	0.153
LSOA total HEIs	0.506	0.513	0.255
LSOA count of TFL stations	0.111	0.119	0.098
LA population	187283.078	188211.563	2.36e+05
LA share of non-UK born	0.309	0.309	0.348
LA share of residents aged 18-29	0.229	0.229	0.241
Observations	*350*	*2982*	*2982*

Source: BSD 1997-2010, 1991/2001/2011 Census, ONS mid-year population estimates, TFL. Some observations suppressed to avoid disclosure.

Table B3 continued.

Variable	Tech City	Synthetic Tech City	Matched sample
share content firms (1997)	0.137	0.134	0.104
share content firms (1998)	0.139	0.146	0.101
share content firms (1999)	0.147	0.144	0.103
share content firms (2000)	0.155	0.147	0.108
share content firms (2001)	0.145	0.146	0.111
share content firms (2002)	0.144	0.152	0.114
share content firms (2003)	0.215	0.215	0.184
share content firms (2004)	0.234	0.237	0.197
share content firms (2005)	0.245	0.246	0.209
share content firms (2006)	0.254	0.248	0.218
share content firms (2007)	0.253	0.256	0.226
share content firms (2008)	0.266	0.264	0.200
share content firms (2009)	0.265	0.262	0.201
share content firms (2010)	0.261	0.257	0.196
Firm entry, all sectors	3.260	3.153	1.793
Revenue / worker, sectors	258.774	247.131	134.660
Herfindahl Index	0.136	0.136	0.146
LSOA firms, all sectors	238.760	223.317	127.748
LSOA jobs, all sectors	3836.394	3559.234	1467.235
LSOA total cafes and restaurants	7.074	6.483	4.045
LSOA total bars pubs and clubs	3.074	3.004	1.545
LSOA total coworking spaces	1.523	2.264	1.658
LSOA total museums and galleries	0.169	0.152	0.156
LSOA total libraries	0.311	0.296	0.084
LSOA total other accommodation	0.063	0.062	0.065
LSOA total arts and arts support activities	10.669	10.827	5.596
LSOA total supporting arts orgs	0.249	0.333	0.153
LSOA total HEIs	0.506	0.508	0.255
LSOA count of TFL stations	0.111	0.137	0.098
LA population	187283.078	189422.828	2.36e+05
LA share of non-UK born	0.309	0.314	0.348
LA share of residents aged 18-29	0.229	0.230	0.241
Observations	*350*	*2982*	*2982*

Source: BSD 1997-2010, 1991/2001/2011 Census, ONS mid-year population estimates, TFL.

Table B3 continued.

Variable	Tech City	Synthetic Tech City	Matched sample
share digitech jobs (1997)	.	0.021	0.029
share digitech jobs (1998)	.	0.017	0.032
share digitech jobs (1999)	.	0.024	0.040
share digitech jobs (2000)	.	0.029	0.043
share digitech jobs (2001)	0.032	0.029	0.041
share digitech jobs (2002)	0.034	0.034	0.038
share digitech jobs (2003)	0.059	0.058	0.066
share digitech jobs (2004)	0.043	0.044	0.062
share digitech jobs (2005)	0.046	0.048	0.059
share digitech jobs (2006)	0.043	0.041	0.051
share digitech jobs (2007)	0.039	0.039	0.055
share digitech jobs (2008)	0.042	0.040	0.060
share digitech jobs (2009)	0.039	0.042	0.061
share digitech jobs (2010)	0.039	0.040	0.057
Firm entry, all sectors	3.260	3.147	1.793
Revenue / worker, sectors	258.774	257.978	134.660
Herfindahl Index	0.136	0.136	0.146
LSOA firms, all sectors	238.760	228.132	127.748
LSOA jobs, all sectors	3836.394	3689.284	1467.235
LSOA total cafes and restaurants	7.074	6.831	4.045
LSOA total bars pubs and clubs	3.074	3.080	1.545
LSOA total coworking spaces	1.523	2.177	1.658
LSOA total museums and galleries	0.169	0.165	0.156
LSOA total libraries	0.311	0.308	0.084
LSOA total other accommodation	0.063	0.060	0.065
LSOA total arts and arts support activities	10.669	10.472	5.596
LSOA total supporting arts orgs	0.249	0.288	0.153
LSOA total HEIs	0.506	0.510	0.255
LSOA count of TFL stations	0.111	0.121	0.098
LA population	187283.078	189001.563	2.36e+05
LA share of non-UK born	0.309	0.309	0.348
LA share of residents aged 18-29	0.229	0.230	0.241
Observations	*350*	*2982*	*2982*

Source: BSD 1997-2010, 1991/2001/2011 Census, ONS mid-year population estimates, TFL. Some observations suppressed to avoid disclosure.

Table B3 continued.

Variable	Tech City	Synthetic Tech City	Matched sample
share content jobs (1997)	0.155	0.154	0.103
share content jobs (1998)	0.163	0.158	0.099
share content jobs (1999)	0.168	0.169	0.107
share content jobs (2000)	0.152	0.150	0.111
share content jobs (2001)	0.132	0.136	0.118
share content jobs (2002)	0.148	0.151	0.115
share content jobs (2003)	0.144	0.148	0.160
share content jobs (2004)	0.198	0.195	0.175
share content jobs (2005)	0.210	0.211	0.177
share content jobs (2006)	0.209	0.212	0.179
share content jobs (2007)	0.212	0.208	0.185
share content jobs (2008)	0.220	0.223	0.173
share content jobs (2009)	0.219	0.220	0.161
share content jobs (2010)	0.218	0.213	0.155
Firm entry, all sectors	3.260	3.055	1.793
Revenue / worker, sectors	258.774	255.744	134.660
Herfindahl Index	0.136	0.136	0.146
LSOA firms, all sectors	238.760	221.777	127.748
LSOA jobs, all sectors	3836.394	3672.932	1467.235
LSOA total cafes and restaurants	7.074	6.843	4.045
LSOA total bars pubs and clubs	3.074	2.885	1.545
LSOA total coworking spaces	1.523	2.115	1.658
LSOA total museums and galleries	0.169	0.174	0.156
LSOA total libraries	0.311	0.303	0.084
LSOA total other accommodation	0.063	0.061	0.065
LSOA total arts and arts support activities	10.669	11.046	5.596
LSOA total supporting arts orgs	0.249	0.321	0.153
LSOA total HEIs	0.506	0.500	0.255
LSOA count of TFL stations	0.111	0.126	0.098
LA population	187283.078	188844.750	2.36e+05
LA share of non-UK born	0.309	0.308	0.348
LA share of residents aged 18-29	0.229	0.230	0.241
Observations	*350*	*2982*	*2982*

Source: BSD 1997-2010, 1991/2001/2011 Census, ONS mid-year population estimates, TFL.

Table B3 continued.

Variable	Tech City	Synthetic Tech City	Matched sample
Log digitech revenue/worker (1997)	.	3.292	3.130
Log digitech revenue/worker (1998)	.	3.430	3.530
Log digitech revenue/worker (1999)	.	3.959	3.678
Log digitech revenue/worker (2000)	.	4.052	3.692
Log digitech revenue/worker (2001)	4.105	4.178	3.673
Log digitech revenue/worker (2002)	4.220	4.142	3.663
Log digitech revenue/worker (2003)	4.063	4.011	3.822
Log digitech revenue/worker (2004)	3.985	3.991	3.887
Log digitech revenue/worker (2005)	3.765	3.816	3.931
Log digitech revenue/worker (2006)	3.859	3.853	3.936
Log digitech revenue/worker (2007)	3.986	4.027	4.064
Log digitech revenue/worker (2008)	4.329	4.382	4.278
Log digitech revenue/worker (2009)	4.474	4.469	4.247
Log digitech revenue/worker (2010)	4.472	4.446	4.279
Firm entry, all sectors	3.260	3.047	1.793
Revenue / worker, sectors	258.774	252.347	134.660
Herfindahl Index	0.136	0.136	0.146
LSOA firms, all sectors	238.760	225.949	127.748
LSOA jobs, all sectors	3836.394	3746.423	1467.235
LSOA total cafes and restaurants	7.074	7.043	4.045
LSOA total bars pubs and clubs	3.074	2.865	1.545
LSOA total coworking spaces	1.523	2.267	1.658
LSOA total museums and galleries	0.169	0.186	0.156
LSOA total libraries	0.311	0.298	0.084
LSOA total other accommodation	0.063	0.061	0.065
LSOA total arts and arts support activities	10.669	10.484	5.596
LSOA total supporting arts orgs	0.249	0.345	0.153
LSOA total HEIs	0.506	0.502	0.255
LSOA count of TFL stations	0.111	0.123	0.098
LA population	187283.078	191567.984	2.36e+05
LA share of non-UK born	0.309	0.308	0.348
LA share of residents aged 18-29	0.229	0.231	0.241
Observations	*350*	*2982*	*2982*

Source: BSD 1997-2010, 1991/2001/2011 Census, ONS mid-year population estimates, TFL. Some observations suppressed to avoid disclosure.

Table B3 continued.

Variable	Tech City	Synthetic Tech City	Matched sample
Log content revenue/worker (1997)	4.088	4.033	3.941
Log content revenue/worker (1998)	4.018	4.039	3.914
Log content revenue/worker (1999)	4.247	4.299	3.948
Log content revenue/worker (2000)	4.423	4.381	4.090
Log content revenue/worker (2001)	4.203	4.252	4.165
Log content revenue/worker (2002)	4.459	4.416	4.153
Log content revenue/worker (2003)	4.651	4.649	4.370
Log content revenue/worker (2004)	4.736	4.697	4.491
Log content revenue/worker (2005)	4.525	4.541	4.501
Log content revenue/worker (2006)	4.619	4.620	4.509
Log content revenue/worker (2007)	4.620	4.628	4.551
Log content revenue/worker (2008)	4.722	4.718	4.533
Log content revenue/worker (2009)	4.736	4.731	4.527
Log content revenue/worker (2010)	4.742	4.747	4.571
Firm entry, all sectors	3.260	3.192	1.793
Revenue / worker, sectors	258.774	257.599	134.660
Herfindahl Index	0.136	0.135	0.146
LSOA firms, all sectors	238.760	220.470	127.748
LSOA jobs, all sectors	3836.394	3669.025	1467.235
LSOA total cafes and restaurants	7.074	7.146	4.045
LSOA total bars pubs and clubs	3.074	2.990	1.545
LSOA total coworking spaces	1.523	1.956	1.658
LSOA total museums and galleries	0.169	0.149	0.156
LSOA total libraries	0.311	0.304	0.084
LSOA total other accommodation	0.063	0.060	0.065
LSOA total arts and arts support activities	10.669	10.852	5.596
LSOA total supporting arts orgs	0.249	0.306	0.153
LSOA total HEIs	0.506	0.515	0.255
LSOA count of TFL stations	0.111	0.122	0.098
LA population	187283.078	188625.078	2.36e+05
LA share of non-UK born	0.309	0.309	0.348
LA share of residents aged 18-29	0.229	0.229	0.241
Observations	*350*	*2982*	*2982*

Source: BSD 1997-2010, 1991/2001/2011 Census, ONS mid-year population estimates, TFL.

Table B4. Synthetic control: LSOAs used and weights assigned, by outcome.

digital tech firms		content firms		digital tech jobs		content jobs		digital tech revenue/worker	
LSOA	weight	LSOA	weight	LSOA	weight	LSOA	weight	LSOA	weight
15	0.007	15	0.008	3	0.037	3	0.012	3	0.001
34	0.043	51	0.035	21	0.07	4	0.049	8	0.006
65	0.009	65	0.008	52	0.015	15	0.002	21	0.115
66	0.03	73	0.123	65	0.019	51	0.013	72	0.096
70	0.004	76	0.009	71	0.003	53	0.024	86	0.011
72	0.07	88	0.173	75	0.01	65	0.013	88	0.004
73	0.027	96	0.11	76	0.008	66	0.025	103	0.058
75	0.019	112	0.152	84	0.063	73	0.016	109	0.033
85	0.04	114	0.024	85	0.006	78	0.026	112	0.028
93	0.073	115	0.113	88	0.055	79	0.025	114	0.094
96	0.096	116	0.037	90	0.01	82	0.138	116	0.019
103	0.046	143	0.016	93	0.082	88	0.052	133	0.247
106	0.008	209	0.027	96	0.047	96	0.009	164	0.023
112	0.069	214	0.052	103	0.045	112	0.181	203	0.038
114	0.103	218	0.035	112	0.097	114	0.044	205	0.003
115	0.099	221	0.042	114	0.154	115	0.075	208	0.016
116	0.011	223	0.002	115	0.018	116	0.039	209	0.045
119	0.022	228	0.002	116	0.025	122	0.046	214	0.066
132	0.013	234	0.033	208	0.008	170	0.001	218	0.056
208	0.04			209	0.035	173	0.018	234	0.043
209	0.031			214	0.064	208	0.006		
214	0.061			216	0.025	209	0.043		
218	0.037			218	0.03	214	0.052		
234	0.04			222	0.003	218	0.049		
				228	0.008	222	0.001		
				232	0.026	228	0.01		
				234	0.036	234	0.032		

Source: BSD / Census / ONS / TfL.

Table B4 continued.

content revenue/worker		% digital tech firms		% content firms		% digital tech jobs		% content jobs	
LSOA	weight	LSOA	weight	LSOA	weight	LSOA	weight	LSOA	weight
4	0.023	3	0.023	3	0.001	3	0.014	3	0.001
27	0.021	4	0.03	4	0.028	4	0.129	4	0.028
34	0.016	49	0.037	50	0.004	26	0.012	50	0.004
46	0.008	52	0.078	51	0.108	50	0.008	51	0.108
65	0.007	65	0.008	64	0.067	65	0.006	64	0.067
72	0.041	66	0.021	65	0.016	72	0.018	65	0.016
78	0.001	72	0.036	73	0.037	78	0.071	73	0.037
93	0.073	73	0.027	88	0.108	82	0.072	88	0.108
95	0.025	76	0.033	91	0.01	84	0.102	91	0.01
103	0.033	81	0.027	103	0.011	88	0.058	103	0.011
112	0.134	84	0.075	108	0.031	96	0.036	108	0.031
114	0.022	85	0.01	110	0.091	103	0.063	110	0.091
115	0.223	88	0.078	112	0.194	112	0.161	112	0.194
116	0.016	92	0.003	115	0.051	120	0.017	115	0.051
117	0.005	93	0.01	116	0.018	170	0.022	116	0.018
162	0.044	112	0.161	170	0.032	208	0.024	170	0.032
170	0.017	114	0.024	209	0.034	209	0.053	209	0.034
171	0.001	115	0.012	214	0.06	214	0.065	214	0.06
179	0.033	116	0.022	215	0.013	217	0.005	215	0.013
208	0.031	133	0.052	218	0.051	218	0.05	218	0.051
209	0.038	140	0.001	233	0.005	222	0.001	233	0.005
214	0.065	208	0.024	234	0.03	234	0.014	234	0.03
216	0.052	209	0.047						
218	0.026	214	0.064						
234	0.044	218	0.063						
		228	0.005						
		234	0.029						

Source: BSD / Census / ONS / TfL.

Table B5. Tech City policy effects: robustness checks.

	Firms		Jobs		% firms		% jobs		Ave rev/worker	
	Digitech	**Content**	**Digitech**	**Content**	**Digitech**	**Content**	**Digitech**	**Content**	**Digitech**	**Content**
Diff in diff ATT	*0.28****	*0.06*	*0.42****	*0.13*	*0.01**	*0.00*	*0.02***	*0.02*	*-0.02*	*0.03*
	(0.104)	*(0.068)*	*(0.131)*	*(0.115)*	*(0.007)*	*(0.009)*	*(0.008)*	*(0.017)*	*(0.062)*	*(0.092)*
Synthetic control ATT	0.270***	0.079**	0.440***	0.123*	0.013***	0.02*	0.031***	0.049***	-0.043*	0.139**
p-value	*0.005*	*0.023*	*0.005*	*0.061*	*0.005*	*0.084*	*0.009*	*0.009*	*0.07*	*0.042*
RMSPE	*0.024*	*0.023*	*0.028*	*0.035*	*0.001*	*0.004*	*0.002*	*0.003*	*0.045*	*0.032*
75% lag outcomes + covariates + ID V	0.577*	0.333	0.563**	0.107	0.017	0.036	0.012	0.052	0.357	-0.036
p-value	*0.098*	*0.121*	*0.037*	*0.556*	*0.154*	*0.299*	*0.257*	*0.117*	*0.257*	*0.514*
RMSPE	*0.189*	*0.124*	*0.144*	*0.145*	*0.006*	*0.016*	*0.01*	*0.018*	*0.371*	*0.083*
50% lag outcomes + covariates + ID V	0.510**	0.514	0.746**	0.206	0.011***	0.072	0.021	0.075*	0.187	-0.135
p-value	*0.019*	*0.136*	*0.07*	*0.407*	*0.009*	*0.126*	*0.201*	*0.098*	*0.379*	*0.299*
RMSPE	*0.148*	*0.224*	*0.274*	*0.172*	*0.005*	*0.03*	*0.015*	*0.03*	*0.553*	*0.124*
Covariates + ID V	0.391**	0.476	0.151	0.258	0.011	0.058	-0.01	0.062	-0.204	-0.125
p-value	*0.019*	*0.107*	*0.607*	*0.379*	*0.248*	*0.112*	*0.78*	*0.173*	*0.196*	*0.785*
RMSPE	*0.141*	*0.273*	*0.382*	*0.383*	*0.01*	*0.035*	*0.032*	*0.044*	*0.422*	*0.63*
All lagged outcomes, data-driven V	0.271***	0.108***	0.415**	0.319	0.001*	0.016*	0.024**	0.042*	0.086	0.143
p-value	*0.005*	*0.005*	*0.042*	*0.145*	*0.051*	*0.098*	*0.028*	*0.075*	*0.327*	*0.332*
RMSPE	*0*	*0*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*

Notes as in Table 3, main paper.

Table B5 continued.

	Firms		Jobs		% firms		% jobs		Ave rev/worker	
	Digitech	**Content**	**Digitech**	**Content**	**Digitech**	**Content**	**Digitech**	**Content**	**Digitech**	**Content**
Diff in diff ATT	*0.28****	*0.06*	*0.42****	*0.13*	*0.01**	*0.00*	*0.02***	*0.02*	*-0.02*	*0.03*
	(0.104)	*(0.068)*	*(0.131)*	*(0.115)*	*(0.007)*	*(0.009)*	*(0.008)*	*(0.017)*	*(0.062)*	*(0.092)*
Synthetic control ATT	0.270***	0.079**	0.440***	0.123*	0.013***	0.02*	0.031***	0.049***	-0.043*	0.139**
p-value	*0.005*	*0.023*	*0.005*	*0.061*	*0.005*	*0.084*	*0.009*	*0.009*	*0.07*	*0.042*
RMSPE	*0.024*	*0.023*	*0.028*	*0.035*	*0.001*	*0.004*	*0.002*	*0.003*	*0.045*	*0.032*
75% lag outcomes + cov + cross-vali V	0.446*	0.356*	0.316	0.207	0.021	0.025	0.008	0.043**	0.28	-0.024
p-value	*0.093*	*0.089*	*0.192*	*0.598*	*0.136*	*0.724*	*0.607*	*0.033*	*0.271*	*0.827*
RMSPE	*0.107*	*0.072*	*0.123*	*0.142*	*0.006*	*0.019*	*0.011*	*0.007*	*0.211*	*0.092*
50% lag outcomes + cov + cross-vali V	0.443**	0.453**	0.313**	0.291	0.024**	0.047	-0.011	0.05	-0.029	-0.104
p-value	*0.023*	*0.037*	*0.042*	*0.187*	*0.033*	*0.35*	*0.579*	*0.388*	*0.449*	*0.86*
RMSPE	*0.101*	*0.12*	*0.1*	*0.142*	*0.006*	*0.026*	*0.018*	*0.033*	*0.308*	*0.292*
Long difference 1997-2010 + ID V	0.071	-0.096	0.272*	-0.095	0.006*	0.008	0.018*	0.04	-0.306	-0.18
p-value	*0.383*	*0.71*	*0.093*	*0.925*	*0.065*	*0.379*	*0.051*	*0.36*	*0.276*	*0.715*
RMSPE	*0.217*	*0.256*	*0.22*	*0.359*	*0.009*	*0.015*	*0.009*	*0.041*	*0.437*	*0.614*
First differences + ID V	0.104	-0.004	0.524***	0.104	0.008	0.019	0.029***	0.004*	-0.14	-0.136
p-value	*0.654*	*0.117*	*0.005*	*0.486*	*0.313*	*0.173*	*0.005*	*0.075*	*0.224*	*0.822*
RMSPE	*0.272*	*0.057*	*0.098*	*0.165*	*0.012*	*0.008*	*0.001*	*0.008*	*0.177*	*0.36*

Notes as in Table 3, main paper.

Table B6. Policy effects: within-cluster DID using treatment intensity estimator.

	Firms		Jobs		% firms		% jobs		Ave rev/worker	
	Digitech	**Content**	**Digitech**	**Content**	**Digitech**	**Content**	**Digitech**	**Content**	**Digitech**	**Content**
Diff in diff ATT	*0.28****	*0.06*	*0.42****	*0.13*	*0.01**	*0.00*	*0.02***	*0.02*	*-0.02*	*0.03*
	(0.104)	*(0.068)*	*(0.131)*	*(0.115)*	*(0.007)*	*(0.009)*	*(0.008)*	*(0.017)*	*(0.062)*	*(0.092)*
Roundabout + 250m	1.03***	0.68***	0.76***	0.12	0.03***	-0.05***	0.00	-0.04	-0.14	-0.46***
	(0.063)	(0.119)	(0.189)	(0.188)	(0.011)	(0.013)	(0.012)	(0.026)	(0.094)	(0.096)
Roundabout + 500m	-0.06	-0.11	-0.06	0.03	0.01	0.01	-0.01	-0.06	-0.06	0.13
	(0.258)	(0.126)	(0.316)	(0.223)	(0.017)	(0.015)	(0.021)	(0.046)	(0.116)	(0.169)
Roundabout + 750m	0.16	-0.10	0.01	-0.49**	0.01	-0.04**	0.02	0.02	0.04	-0.27
	(0.286)	(0.104)	(0.304)	(0.187)	(0.016)	(0.016)	(0.019)	(0.044)	(0.116)	(0.176)
Roundabout + 1000m	0.18	0.12	0.40**	0.37**	0.00	0.02*	0.01	0.03	-0.02	0.15
	(0.143)	(0.094)	(0.175)	(0.147)	(0.009)	(0.013)	(0.008)	(0.021)	(0.094)	(0.111)
Observations	4500	4646	4494	4639	4760	4760	4760	4760	4489	4637
R^2	0.80	0.91	0.80	0.87	0.58	0.70	0.47	0.60	0.35	0.48
Area controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Pre-treatment controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Source: BSD / Census / ONS / TfL. Difference in difference analysis on matched sample. Distance ring coefficients give the relative effect of treatment on neighbourhoods in that distance ring, relative to control LSOAs outside the cluster. Controls are 1-year lags of LSOA all-sector firm entry, firm counts and job counts, LSOA all-sector revenue/worker, LSOA Herfindahl Index, LSOA counts of cafes and restaurants, bars/pubs/clubs, co-working spaces, galleries and museums, libraries, hotels and other accommodation, arts and arts support, venues, universities, count of tube and rail stations, LA population, LA share of migrants, LA share of under-30s, plus LSOA and year dummies. Standard errors clustered on LSOA. * significant at 10%, ** 5%, *** 1%.

Table B7. Scaling analysis: average high growth and gazelle firm instances, 2000-2010: Tech City LSOAs vs. matched sample LSOAs.

	Tech City LSOAs	**Matched sample LSOAs**
High jobs growth, digital tech	0.354	0.057
High jobs growth, digital content	1.006	0.187
High jobs growth, gazelle digital tech	0.083	0.012
High jobs growth, gazelle digital content	0.186	0.035
High revenue/worker growth, digital tech	1.446	0.532
High revenue/worker growth, digital content	5.149	1.410
High revenue/worker growth, gazelle digital tech	0.551	0.207
High revenue/worker growth, gazelle digital content	1.911	0.475
Observations	*350*	*24,780*

Source: BSD. Note: Table shows average number of high-growth episodes / gazelle episodes in a Tech City LSOA versus a control LSOA between 2000 and 2010. High-growth episodes are firm-level jobs or revenue/worker growth of at least 20% per year for any 3-year period. Gazelle episodes are high-growth episodes for firms aged five years or less. The same firm can enter a high-growth phase more than once.

Table B8. Scaling analysis: synthetic control results.

	# High-growth episodes: revenue/worker		# High-growth episodes: jobs	
	digitech	**content**	**digitech**	**content**
Synthetic control ATT	1.082	0.503	0.261	0.279
p-value	0.103	0.178	0.276	0.150
Number of placebos	213	213	213	213
Pre-treatment RMSPE	0.184	0.700	0.072	0.123
Average pre-treatment quality	0.793	0.502	0.183	0.437
Pre-treatment mean	*36.143*	*127.214*	*9.00*	*24.71*

Source: BSD / Census / ONS / TfL. Synthetic control panel shows *p*-values from permutation test, number of placebos used, pre-treatment error rate and proportion of placebos with pre-treatment error rate ≥ average of the treated unit. Regressions fit lagged outcome predictors 1997-2010 plus 1-year lags of LSOA all-sector firm entry, LSOA all-sector revenue/worker, LSOA Herfindahl Index, a vector of amenities (LSOA counts of cafes and restaurants, bars/pubs/clubs, co-working spaces, galleries and museums, libraries, other accommodation, arts and arts support, venues, universities), TFL station count, LA share of migrants, LA share of under-30s. Weights optimised defining **V** as an identity matrix. DID regressions fit LSOA and year dummies plus controls as above. Standard errors clustered on LSOA. * significant at 10%, ** 5%, *** 1%.