ISSN 2042-2695

CENTRE *for* ECONOMIC PERFORMANCE

CEP Discussion Paper No 1648

August 2019

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

Max Nathan

THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

E·S·R·C ECONOMIC & SOCIAL RESEARCH COUNCIL

Abstract
Despite academic scepticism, cluster policies remain popular with policymakers. This paper evaluates the causal impact of a flagship UK technology cluster programme. I build a simple framework and identify effects using difference-in-differences and synthetic controls on rich microdata. I further test for timing, cross-space variation, scaling and churn channels. The policy grew and densified the cluster, but has had more mixed effects on tech firm productivity. I also find most policy 'effects' began before rollout, raising questions about the programme's added value.

Key words: cities, clusters, technology, economic development, synthetic controls
JEL Codes: L53; L86; O31; R30; R50

This paper was produced as part of the Centre's Urban and Spatial Programme. The Centre for Economic Performance is financed by the Economic and Social Research Council.

Thanks to Simon Collinson, Anne Green, Neil Lee, Henry Overman, Maria Sanchez-Vidal, Rosa Sanchis-Guarner and Emmanouil Tranos for input, Francesca Arduini for code, Cushman & Wakefield for rents data, and to Martin Dittus, Kat Hanna, Sandra Jones, Natalie Kane, Andy Pratt, Matt Spendlove, Emma Vandore, Georgina Voss, Jess Tyrell, Rob Whitehead and Jonty Wareing for fruitful discussions. Seminar participants at Birmingham, Middlesex, Bath and QMUL and at UEA Düsseldorf 2018 made many useful suggestions. Early parts of this research were funded through a Regional Studies Association Early Career Grant. I am grateful to the RSA for their support. This work includes analysis based on data from the Business Structure Database, produced by the Office for National Statistics (ONS) and supplied by the Secure Data Service at the UK Data Archive. The data is Crown copyright and reproduced with the permission of the controller of HMSO and Queen's Printer for Scotland. The use of the ONS statistical data in this work does not imply the endorsement of the ONS or the Secure Data Service at the UK Data Archive in relation to the interpretation or analysis of the data. This work uses research datasets that may not exactly reproduce National Statistics aggregates. All the outputs have been granted final clearance by the staff of the SDS-UKDA. This paper reflects my views, not those of the funders or the data providers.

Max Nathan, University of Birmingham and Centre for Economic Performance, London School of Economics.

Published by
Centre for Economic Performance
London School of Economics and Political Science
Houghton Street
London WC2A 2AE

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. Popularised by Michael Porter in the 1990s (Porter, 1996; 2000), it is accepted by policymakers, but disliked by many academics. Clusters – industrial districts of co-located, interacting firms – typically have market and co-ordination failures. In theory, public policy could then improve cluster welfare. But clustering results from many firm and worker decisions; so market 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), Chatterji et al (2014), and Urraya and Ramlogan (2013)). The handful of recent examples includes Falck et al (2010), Martin et al (2011), Nishimura and Okamuro (2011), Viladecans-Marsal and Arauzo-Carod (2012), Engel et al (2013) and Ben Abdesslem and Chiappini (2019).

This paper develops a rigorous impact evaluation of a flagship UK cluster programme. It also tests a recent iteration of cluster policy. Rather than Porter-style cluster mapping, or applying insights from evolutionary economics (Nathan and Overman, 2013), programmes today often use 'light touch' interventions (Markusen and Gadwa, 2010). These include marketing, business support and network-building, delivered by local government or by a bespoke agency. These approaches seek to learn from past policy failures by 'going with the grain' of cluster microfoundations. If successful, they hold lessons for other cities with technology clusters.

I study the 'Tech City' cluster policy that launched in London in late 2010. This programme aimed to grow the cluster of technology companies (c. 2,800 firms) centred on Shoreditch and Old St roundabout (Figure 1).

The cluster had been growing for years without direct policy input (Foord, 2013; Nathan and Vandore, 2014; Jones, 2017). It came to prominence in 2008 with a wave of media attention about 'Silicon Roundabout' (Butcher, 2013; Foord, 2013; Nathan et al., 2018). In November 2010, then-Prime Minister David Cameron announced the Tech City policy. The initiative aimed to ‘accelerate’ the cluster (Cameron, 2010), since expanding to cover the whole UK.[1]

The programme included a range of light-touch interventions. 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).[2]

Proponents claim this mix has worked well. The cluster is larger than it was, with firm growth in all parts of the zone (Figure 2, top panel). VC dealflow in London tech as a whole has increased substantially, from £384m in 2013 to £1.8bn in 2018,[3] and a number of high-profile, highly-valued companies have developed, including Last.FM, Songkick, Transferwise, Farfetch and Deliveroo. At the same time, cluster rents have risen, including relative to comparable submarkets (bottom panel). There is also extensive anecdotal evidence of displacement of smaller firms.[4]

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 mix could plausibly contribute

[1] 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.

[2] 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.

[3] https://media.londonandpartners.com/news/london-and-uk-top-european-tech-investment-tables, accessed 9 May 2019; https://www.ft.com/content/0ff8687c-8f52-11e4-b080-00144feabdc0, accessed 15 August 2018.

[4] 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.

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 no-policy development.

To do this I apply theoretical frameworks developed by Arzaghi and Henderson (2008), Duranton (2011) and Kerr and Kominers (2015). I first look at key economic changes in the area between 1997 and 2017, using rich microdata plus a range of other sources. Next, I use difference-in-differences and synthetic controls to identify policy effects on cluster size, density and local tech plant 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 high-growth tech firm activity; and run a before-and-after analysis of tech plant entry/exit patterns, for UK and foreign-owned firms.

I have three main results. First, the policy increased tech firm activity and densified the cluster, especially for 'digital technology' (mainly hardware and software). Here, plant counts rose 27% and job counts rose 44%, creating 108 extra plants and 1167 extra jobs in the post-policy period. For 'digital content' activities that historically dominated the cluster (such as advertising, media, design and web services), plant counts rose 7.9%, giving 367 extra plants overall. Effects on content employment are only marginally significant. Overall digitech plant density rose 21% and job density 81%, with activity clustering in the 250m zone around Old St roundabout. By contrast, digital content activity de-densified from the inner to the outer parts of the cluster. This is consistent with increased crowding, both within tech industry space and between tech/non-tech activities. This tight geography of moves also holds for in/out-movers, who mainly come from the rest of London.

Second, these shifts did not always raise tech firm productivity. For digital tech firms, I find a marginally significant *drop* in revenue/worker, with consistently positive effects only after 2015. By contrast, digital content firms' productivity rises 13.9% in the post-policy period. Churn has risen substantially, with the share of new entrants to the market doubling from 2009/10 to 2016/17. But I find no evidence that policy affected high-growth episodes via Schumpterian competition. This is consistent with crowding and competition channels dominating agglomeration channels for newer, smaller digitech firms. For larger, more established digital content firms, agglomeration effects seem to be strongest.

Third, I raise questions about the policy's added value. For some policymakers, a bigger, denser cluster is proof of success. Across a broader range of outcomes, the picture is less positive. The policy changed the composition of the cluster, arguably overheating parts of it. Entry was driven by UK-owned firms, rather than foreign investment. Most critically, I find clear evidence that most policy 'effects' began before 2011, when the cluster first came to media attention. Year by year outcome changes in 2008-10 are always larger than those in 2011-17. For digital tech firm productivity, I find suggestive evidence of a negative policy effect. Consistent with theory, this suggests that policy weakened the net benefits of cluster location (Duranton, 2011). Light-touch cluster policy can have some positive impacts. But as sceptics have argued, cluster interventions remain fundamentally challenging.

This is the first impact evaluation of the Tech City programme that I am aware of.[5] The paper also adds to a small set of studies on the East London tech milieu (Foord, 2013; Nathan and Vandore, 2014; Martins, 2015; Jones, 2017), plus a related set of studies covering London's post-industrial economic evolutions (see *inter alia* Hall (2000), Hamnett and Whitelegg (2007), Hutton (2008), Pratt (2009), and Harris (2012)). More broadly, the paper adds to the sparse cluster policy evaluation literature, and to the larger, related literature on economic area-based initiatives.[6] The closest comparator is probably Falck et al (2010), who look at the effects of high-tech cluster policies in Bavaria. Viladecans-Marsal and Arauzo-Carod (2012) test policies to attract firms into a planned 'creative district', but do not examine firm-level outcomes. Ben Abdesslem and Chiappini (2019) do look at firm outcomes, but for a top-down programme aimed at optical/photonic manufacturing.

2/ Data and definitions

I explore the cluster using multiple data sources. I start with the 9th edition of the Business

[5] 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.
[6] See Neumark and Simpson (2014), Glaeser and Gottlieb (2008), Kline and Moretti (2013) and What Works Centre for Local Economic Growth (2016) for reviews.

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 plants. I link live plants to 2011 Lower Super Output Areas (LSOAs), then aggregate the data to LSOA level.[7] 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 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.

As the cluster has no formal boundaries, I define it as a 1km ring around Silicon Roundabout, the consensus at policy introduction (Nathan and Vandore, 2014). Here, Tech City is the set of LSOAs whose centroids have a linear distance of 1km or less from the Eastings/Northings of the Old St roundabout.[8] 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.[9]

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.

I focus on three cluster outcomes. Cluster size is given by net LSOA tech plants and jobs in a given year.[10] I measure cluster density using annual LSOA shares of tech plants and tech employment. I measure cluster performance using annual LSOA averages of tech firm revenues

[7] Alternatives are a) working at plant level, rather than area level; b) using grid squares, rather than small administrative units. Given plants are mobile and there is substantial entry/exit from the cluster, plant-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.

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

[9] 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.

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

per worker, via enterprise-level BSD data.[11] Firms' revenue per worker is a rough measure of 'revenue productivity'. It will be driven up by improvements in labour productivity or TFP (reflecting increasing returns to scale); and driven down by rising market competition (lower revenue to the firm).

3/ Background and descriptive analysis

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 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 Puga 2004, 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).[12]

The cluster is 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.

The tech cluster is dominated by digital content industries. Content firms are more numerous, denser, have more employees and nearly double revenue productivity of digital tech firms. This

[11] For single plant firms (over 98% of the observations), enterprise and plant-level figures are the same. For multi-plant firms, I assign shares of enterprise-level revenue to plants based on each plant's share of enterprise-level employment.

[12] 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.

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). 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. Plant 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 plant counts and tech plant average revenue per worker over time. As expected, plant counts are very much higher in Shoreditch than the average rest of London LSOA, with stocks accelerating in the 2010s. By contrast, tech plant revenue per worker is more uneven over time.

4/ Analytical framework

Following Duranton (2011) we can think of a cluster as a dynamic Marshallian production district. As the cluster grows, firms' productivity rises (via agglomeration economies). At the same time, the costs of cluster location rise with cluster size (via crowding). Productivity and cost combine to give a net returns function that rises to a maximum – after which additional costs to firms in the cluster, usually expressed in rents, outweigh productivity gains. The exact slope of these curves is industry and location-specific, depending on the set of matching, sharing and learning economies (Duranton and Puga, 2004) and amenities (Currid, 2007; Hutton, 2008; Pratt, 2009) that local tech firms seek to access. Competing land uses will also influence rents (Hamnett and Whitelegg, 2007). The framework is completed with a supply curve of workers and firms, which will be upward-sloping if agents are not perfectly mobile.

Kerr and Kominers (2015) argue that clusters are effectively a set of overlapping industrial districts. Firms enter to access features that improve their productivity and thus revenue/worker. As in Arzaghi and Henderson (2008), firms trade-off access to some set of matching / sharing / learning economies and amenities, against the costs of location (rents). 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.

In this setting, the Tech City policy mix could have multiple impacts. First, place marketing complements existing media exposure (see also Section 5). This may co-ordinate entry decisions to the location, raising the number of tech firms and jobs. Over time, success stories – such as high-profile ‘unicorns’ – reinforce this channel. Other things being equal, raised entry will increase cluster density of tech activity. Increased size and density should amplify agglomeration effects, increasing firm productivity and thus revenue / worker. Note that incumbents, in established networks, may benefit most from these shifts.

Second, other elements in the policy mix (business support, networking / co-ordination activities), if effective, will steepen the productivity curve and improve revenue 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.

Fourth, higher cluster size/density also leads to higher market competition (Combes et al 2012). 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 act as a positive signal to other industries to locate in the area, including developers and 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

I look to identify the effect of the Tech City policy on cluster outcomes. As in Falck et al (2010) and Noonan (2013), the classical starting point is to compare changes in the treated area and control areas. Difference in differences gives a consistent 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: not accounting for these will bias up estimates of the true policy effect. First, rising media attention around ‘Silicon Roundabout’ from 2008 (Nathan et al., 2018; Foord 2013) could have induced firms and entrepreneurs into the area before the policy launched. Figure B3 gives a proxy of attention over time via counts of relevant Google searches pre and post-policy. While anticipation effects appear small, I check my main results using placebo-in-time tests.

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., 2018), and thus as good as random *compared to other tech hotspots in the* city. To test, 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 and Jeffcut, 2009; Currid and Williams, 2010; Harris, 2012; Foord, 2013; Nathan and Vandore, 2014; Martins, 2015). If assignment is quasi-random, treatment and control areas should balance on observables.

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. Matching brings treatment and control groups substantially closer together, and *t*-tests suggest no significant differences (except in one case), but 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 plant count regressions, and close-to-significant 'effects' in both plant 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.[13] 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, 2013; Faggio 2015; Gibbons et al., 2016) to allow policy effects to vary across 250m rings within cluster space.

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

5.2 / Estimation

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

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

lnY is the log of tech firm counts or tech job counts; sharesof 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 plant 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:

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

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, ... w_{i+1}) where weights sum to one.[14] 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.

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

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 plants. 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.

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

[14] 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.

(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.[15]

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:

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

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 plant 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.

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-

[15] 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.

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.

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 plant counts by 27%, or 4 net extra plants post-2011 compared to the pre-treatment mean. The cluster-wide effect is 25*4 = 108 extra plants across 25 LSOAs. For digital content, the policy effect is 7.9%, 15 extra plants 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 looks at changes to cluster density. I find a clear and growing policy effect on the treated area's share of digital tech plants, additional to natural change. Overall effects on digital content plant 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 plants and 3.1 percentage points to shares of digitech jobs, compared to the no-policy counterfactual. Effects on digital content plant 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 plants, an 86% change in digitech job shares, and a 27% change in digital content job shares. Notably, percentage changes in plant density are lower than raw counts, consistent with increased competition for space from non-tech activity.

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 productivity 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% productivity decline for the average digital tech firm across the whole post-policy period. For digital content firms, the policy adds 13.9% revenue productivity 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 plants and job counts, digitech and content plant density, and content job density are stable across specifications. Changes to digital content plant 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 plant 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 productivity.

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 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 productivity 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, consistent with no added value of the policy. Strikingly, the policy shifts digital content firms' productivity to positive and significant, consistent with agglomeration-driven growth. Conversely, statistically significant digitech productivity in 2008/10 turns non-significant during 2011/17, suggesting a negative effect consistent with crowding, competition or both. I explore these channels further below.

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 plant 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 plant-level cross-sections for three year pairs, 2009-10 (pre-policy), 2013-14 and 2016-17. For each year pair, I flag plants 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 plants, with shares expressed as a fraction of all tech firms.

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 plant 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 plants 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 DID treatment intensity estimator for LSOA *i* in year *t*:

$$\begin{aligned} \ln Y_{it} = {} & D250_i + D500_i + D750_i + D1000_i + T_t \\ & + a1TC250_{it} + a2TC500_{it} + a3TC750_{it} + a4TC1000_{it} \\ & + \boldsymbol{Xb}_{it-n} + e_{it} \qquad (6) \end{aligned}$$

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 plant 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 more dense within the cluster core. However, digital content activity gets less dense in the core, and more dense 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 plant 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 plant 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 plants. Table B8 gives results for high-growth episodes.[16] The left hand panel gives results for revenue / worker high-growth

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

episodes, the right hand panel for employment growth. I find no positive policy effects in either case.

8/ Conclusions

Despite academic scepticism, cluster policies remain popular with policymakers. This paper evaluates the causal impact of a flagship UK technology cluster programme. 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 plants, and with increasing impact over time. But this larger, denser cluster seems not to have consistently increased tech firm productivity, with only digital content firms seeing higher revenue / worker in the post-policy period. 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. 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 more mixed. 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 benefits.

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, and in one case generating a negative impact. In my framework, this is consistent with policy weakening the net benefits of cluster location. An important theoretical critique of cluster policy is that the complexity of real world 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 milieu, 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 it, I am unable to quantify the effect of growing 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 entrants, or movers versus incumbents. Finally, I do not directly test the effect of business support programmes – such as the Future Fifty[17] – in the policy mix. Evaluating their effectiveness and value for money is an important complement to this analysis.

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

References

Abadie A, Diamond A and Hainmueller J. (2010) Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program. *Journal of the American Statistical Association* 105: 493-505.

Abadie A, Diamond A and Hainmueller J. (2015) Comparative Politics and the Synthetic Control Method. *American Journal of Political Science* 59: 495-510.

Aghion P, Blundell R, Griffith R, et al. (2009) The Effects of Entry on Incumbent Innovation and Productivity. *Review of Economics and Statistics* 91: 20-32.

Arthur WB. (1989) Competing Technologies, Increasing Returns, and Lock-In by Historical Events. *The Economic Journal* 99: 116-131.

Arzaghi M and Henderson JV. (2008) Networking off Madison Avenue. *Review of Economic Studies* 75: 1011-1038.

Athey S and Imbens GW. (2017) The State of Applied Econometrics: Causality and Policy Evaluation. *Journal of Economic Perspectives* 31: 3-32.

Becker S, Heblich S and Sturm D. (2018) The Impact of Public Employment: Evidence from Bonn. *IZA Discussion Paper 11255.* Bonn: IZA.

Ben Abdesslem A and Chiappini R. (2019) Cluster policy and firm performance: a case study of the French optic/photonic industry. *Regional Studies* 53: 692-705.

Brynjolfsson E and McAfee. (2014) *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies,* New York: W. W. Norton & Company.

Butcher M. (2013) Goodbye Mr Silva — A Brief History Of East London's 'Tech City'. *TechCrunch.* 5 July: https://techcrunch.com/2013/07/05/goodbye-mr-silva-now-its-time-to-test-tech-city-yourself/.

Cameron D. (2010) East End Tech City speech. *4 November.* London.

Cavallo E, Galiani S, Noy I, et al. (2013) Catastrophic Natural Disasters and Economic Growth. *The Review of Economics and Statistics* 95: 1549-1561.

Chatterji A, Glaeser E and Kerr W. (2014) Clusters of Entrepreneurship and Innovation. *Innovation Policy and the Economy* 14: 129-166.

Combes P-P, Duranton G, Gobillon L, et al. (2012) The Productivity Advantages of Large Cities: Distinguishing Agglomeration from Firm Selection. *Econometrica* 80: 2543-2594.

Currid E. (2007) *The Warhol Economy: How Fashion, Art, and Music Drive New York City,* Princeton: Princeton University Press.

Currid E and Williams S. (2010) The geography of buzz: art, culture and the social milieu in Los Angeles and New York. *Journal of Economic Geography* 10: 423-451.

Duranton G. (2011) California Dreamin': The feeble case for cluster policies. *Review of Economic Analysis* 3: 3-45.

Duranton G and Kerr W. (2015) The Logic of Agglomeration. *NBER Working Paper 21452.* Cambridge, Mass: NBER.

Duranton G and Puga D. (2004) Micro-Foundations of Urban Agglomeration Economies. In: Henderson JV and Thisse J-F (eds) *Handbook of regional and urban economics 4.* The Hague: Elsevier, 2063-2117.

Einio E and Overman HG. (2013) The Effects of Spatially Targeted Enterprise Initiatives: Evidence from UK LEGI. *SERC Discussion Paper.* London: SERC.

Engel D, Mitze T, Patuelli R, et al. (2013) Does Cluster Policy Trigger R&D Activity? Evidence from German Biotech Contests. *European Planning Studies* 21: 1735-1759.

Faggio G. (2015) Relocation of Public Sector Workers: The local labour market impact of the Lyons Review *SERC Discusssion Paper 155.* London: LSE.
Falck O, Heblich S and Kipar S. (2010) Industrial innovation: Direct evidence from a cluster-oriented policy. *Regional Science and Urban Economics* 40: 574-582.
Ferman B, Pinto C and Possebom V. (2018) Cherry-Picking with Synthetic Controls. Mimeo.
Florida R. (2002) Bohemia and economic geography. *Journal of Economic Geography* 2: 55-71.
Foord J. (2013) The new boomtown? Creative city to Tech City in east London. *Cities* 33: 51-60.
Galiani S and Quistorff B. (2016) The synth_runner Package: Utilities to Automate Synthetic Control Estimation Using synth. Mimeo. University of Maryland.
Gibbons S, Overman HG and Sarvimäki M. (2016) The local economic impacts of regeneration projects. Mimeo. London: LSE.
Glaeser E and Gottlieb JD. (2008) The Economics of Place-Making Policies. *Brookings Papers on Economic Activity* 2008: 155-239.
Gobillon L and Magnac T. (2016) Regional Policy Evaluation: Interactive Fixed Effects and Synthetic Controls. *The Review of Economics and Statistics* 98: 535-551.
Hall P. (2000) Creative Cities and Economic Development. *Urban Studies* 37: 639-649.
Hamnett C and Whitelegg D. (2007) Loft conversion and gentrification in London: from industrial to postindustrial land use. *Environment and Planning A* 39: 106-124.
Harris A. (2012) Art and gentrification: pursuing the urban pastoral in Hoxton, London. *Transactions of the Institute of British Geographers* 37: 226-241.
Harris J. (2015) Identifying Science and Technology Businesses in Official Statistics. London: ONS.
Helmers C and Overman H. (2016) My precious! The location and diffusion of scientific research: evidence from the Synchrotron Diamond Light Source. *The Economic Journal*.
Hutton T. (2008) *The New Economy of the Inner City: Restructuring, regeneration and dislocation in the twenty-first century metropolis,* Abingdon: Routledge.
Indergaard M. (2004) *Silicon Alley: The Rise and Fall of a New Media District,* Oxford: Routledge.
Jones E. (2017) Planning for Tech City in post-recession London. Mimeo. London: UCL.
Kaul A, Kloßner S, Pfeifer G, et al. (2018) Synthetic Control Methods: Never Use All Pre-Intervention Outcomes Together With Covariates. Mimeo.
Kerr W and Kominers S. (2015) Agglomerative Forces and Cluster Shapes. *Review of Economics and Statistics* 97: 877-899.
Kerr W, Lerner J and Schoar A. (2011) The Consequences of Entrepreneurial Finance: Evidence from Angel Financings. *Review of Financial Studies*.
Kline P and Moretti E. (2013) People, Places and Public Policy: Some Simple Welfare Economics of Local Economic Development Programs. *National Bureau of Economic Research Working Paper Series No. 19659.* Cambridge, MA: NBER.
Markusen A and Gadwa A. (2010) Creative Placemaking. Washington DC: NEA.
Martin P, Mayer T and Mayneris F. (2011) Public support to clusters: A firm level study of French "Local Productive Systems". *Regional Science and Urban Economics* 41: 108-123.
Martin R and Sunley P. (2003) Deconstructing clusters: chaotic concept or policy panacea? *Journal of Economic Geography* 3: 5-35.
Martins J. (2015) The Extended Workplace in a Creative Cluster: Exploring Space(s) of Digital Work in Silicon Roundabout. *Journal of Urban Design* 20: 25–145.

Mayer T, Mayneris F and Py L. (2015) The impact of Urban Enterprise Zones on establishment location decisions and labor market outcomes: evidence from France. *Journal of Economic Geography*.

Nathan M and Overman H. (2013) Agglomeration, clusters, and industrial policy. *Oxford Review of Economic Policy* 29: 383-404.

Nathan M and Vandore E. (2014) Here be startups: exploring London's 'Tech City' digital cluster. *Environment and Planning A* 46: 2283-2299.

Nathan M, Vandore E and Voss G. (2018) Spatial Imaginaries and Tech Cities: Place-branding East London’s digital economy. *Journal of Economic Geography*, online May 2018, https://doi.org/10.1093/jeg/lby018

Neumark D and Simpson H. (2014) Place-Based Policies. *NBER Working Paper 20049.* Cambridge, MA: NBER.

Nishimura J and Okamuro H. (2011) Subsidy and networking: The effects of direct and indirect support programs of the cluster policy. *Research Policy* 40: 714-727.

Noonan DS. (2013) How US Cultural Districts Reshape Neighborhoods. *Cultural Trends* 22: 203-212.

Office of National Statistics. (2017) Business Structure Database, 1997-2017 SN: 6697. *Secure Data Service Access [computer file]*. Colchester: UK Data Archive.

Osborne G and Schmidt E. (2012) California Dreaming in such a British way. *Financial Times.* 28 March.

Porter ME. (1996) The competitive advantage of the inner city. In: LeGates R and Stout F (eds) *The City Reader.* Abingdon: Routledge, 274-286.

Porter ME. (2000) Location, competition, and economic development: Local clusters in a global economy. *Economic Development Quarterly* 14: 15-34.

Pratt AC and Jeffcut P. (2009) Creativity, Innovation and the Cultural Economy. Abingdon: Routledge.

Pratt AC. (2009) Urban Regeneration: From the Arts `Feel Good' Factor to the Cultural Economy: A Case Study of Hoxton, London. *Urban Studies* 46: 1041-1061.

Uyarra E and Ramlogan R. (2013) The Effects of Cluster Policy on Innovation. *MIoIR Compendium of Evidence on Innovation Policy.* London: NESTA / University of Manchester.

Viladecans-Marsal E and Arauzo-Carod J-M. (2012) Can a knowledge-based cluster be created? The case of the Barcelona 22@ district. *Papers in Regional Science* 91: 377-400.

What Works Centre for Local Economic Growth. (2016) Evidence Review 10: Area-Based Initiatives: Enterprise Zones. London: WWCLEG.

Zukin S. (1995) *The Cultures of Cities,* Oxford: Blackwell.

Tables and figures.

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 plant entry	3.500	0.963
ONS digital tech plant entry	0.251	0.088
ONS digital content plant entry	0.677	0.109
ONS digitech & content plant entry	0.929	0.197
LSOA total plant count	259.646	75.356
ONS digital tech plant count	15.954	4.323
ONS content plant count	56.551	9.319
ONS digitech & content plant count	72.406	13.616
% plants ONS digital tech	0.063	0.071
% plants ONS content	0.204	0.113
% plants 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 plant employment	898.126	74.236
ONS digitech & content plant 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 plant revenue	8838.698	1409.111
Total ONS digitech & content plant revenue	10654.802	1838.854
LSOA mean plant 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 plants (1997)	.	1.123	0.712
Log digitech plants (1998)	.	1.457	1.013
Log digitech plants (1999)	.	1.664	1.266
Log digitech plants (2000)	.	1.753	1.247
Log digitech plants (2001)	1.895	1.857	1.238
Log digitech plants (2002)	1.788	1.805	1.158
Log digitech plants (2003)	2.231	2.220	1.559
Log digitech plants (2004)	2.068	2.116	1.502
Log digitech plants (2005)	2.101	2.075	1.464
Log digitech plants (2006)	2.159	2.185	1.473
Log digitech plants (2007)	2.184	2.209	1.503
Log digitech plants (2008)	2.342	2.326	1.669
Log digitech plants (2009)	2.303	2.282	1.666
Log digitech plants (2010)	2.282	2.255	1.617
Plant 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 plants, 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 musuems 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	**Plants**		**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	**% plants**		**% 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**		
Sythentic 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 plant 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	**Plants**		**Jobs**		**% plants**		**% 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

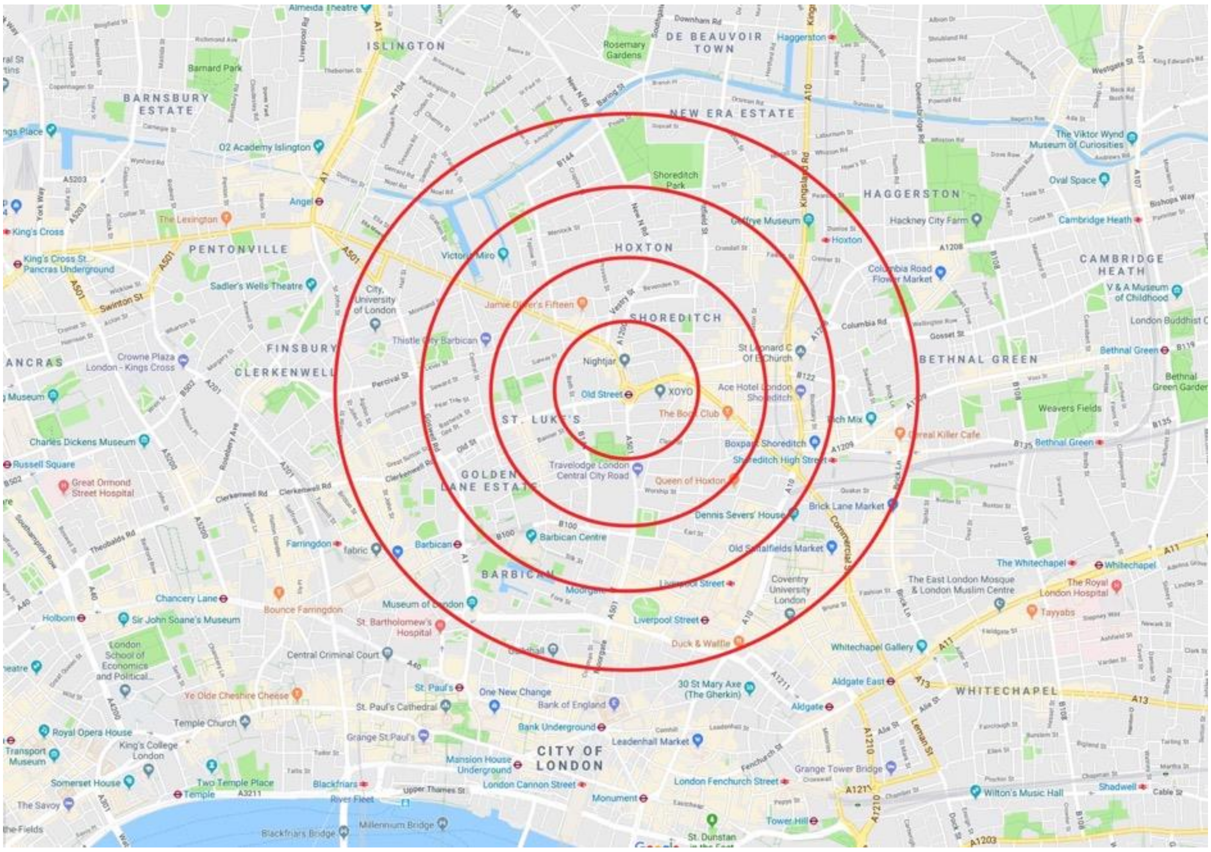
Notes as in Table 3.

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

A. All tech plants	**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 plant	*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 plants	**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 plant	*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.

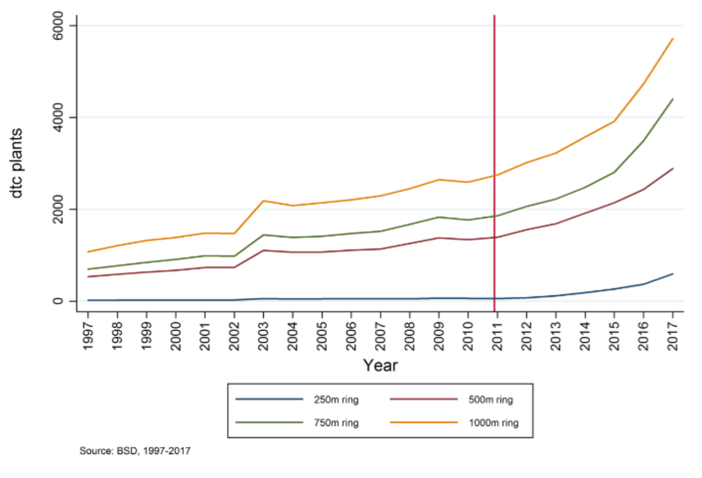
Figure 1. The Tech City area.



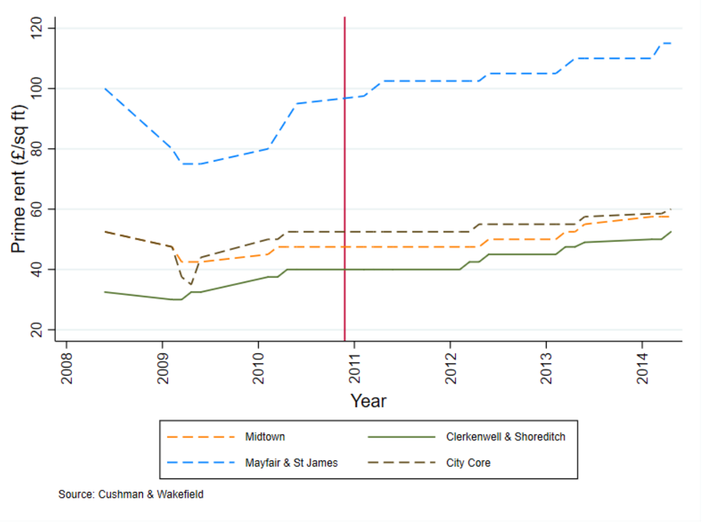
Source: Google Maps. Red circles show approx. 250m rings around Old St roundabout. The cluster zone is defined as the 1km ring from the roundabout.

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

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



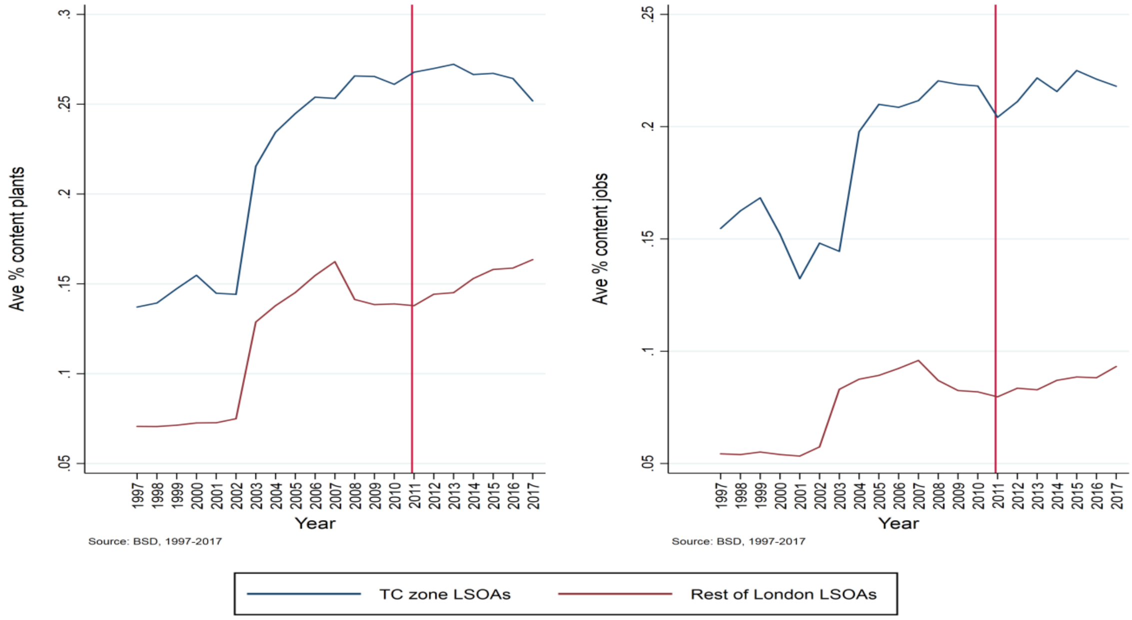
B. Prime rents for Clerkenwell and Shoreditch submarket, 2008-2014.



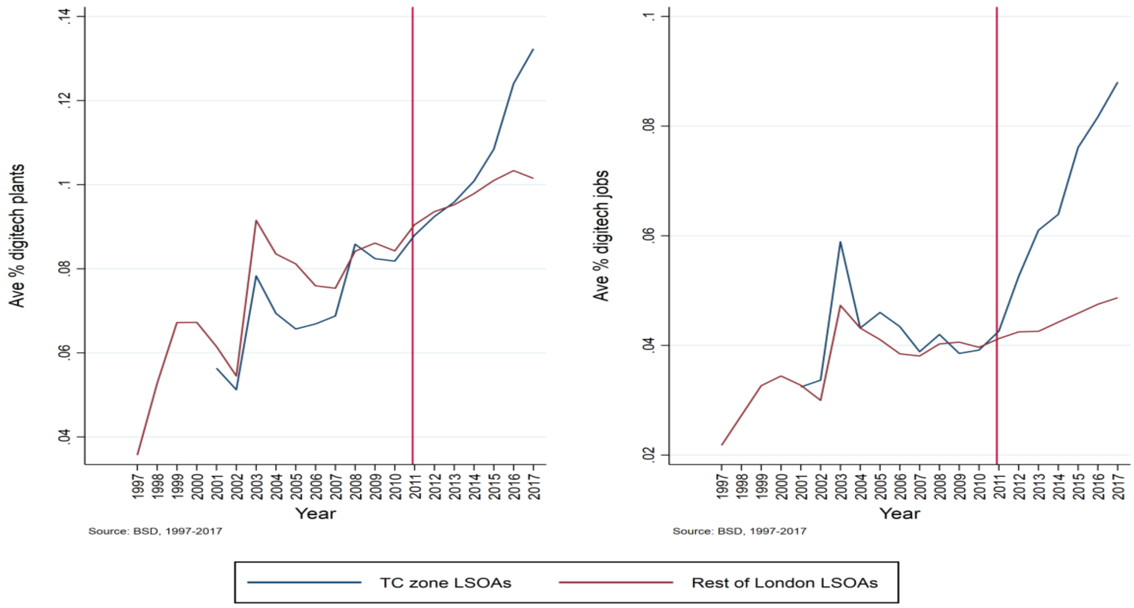
Source: BSD, Cushman & Wakefield. Plant counts are cumulative, so area total is given by 1km ring. Prime rents for four Inner London C&W 'submarket geographies', Clerkenwell and Shoreditch, Mayfair and St James, Midtown (Holborn and Temple), City Core (City of London).

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

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



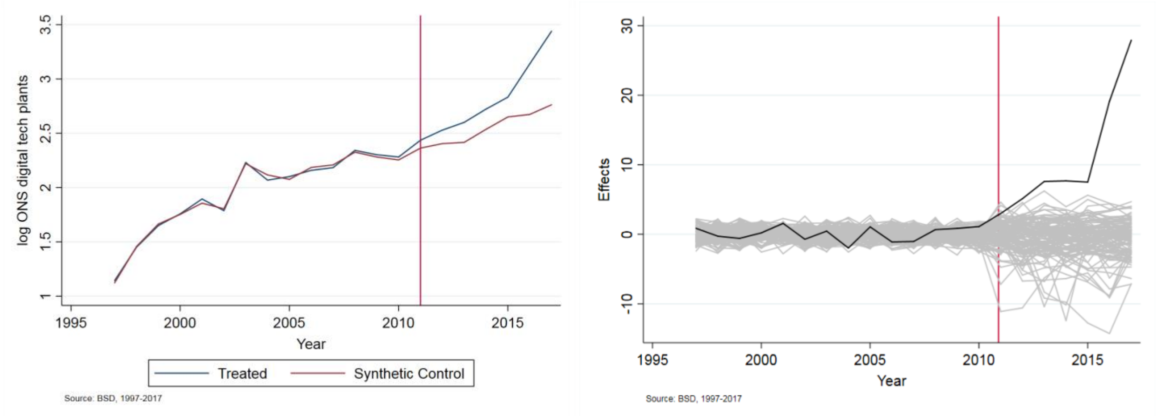
B. Digital technology. L: plants / all plants. R: jobs / all jobs



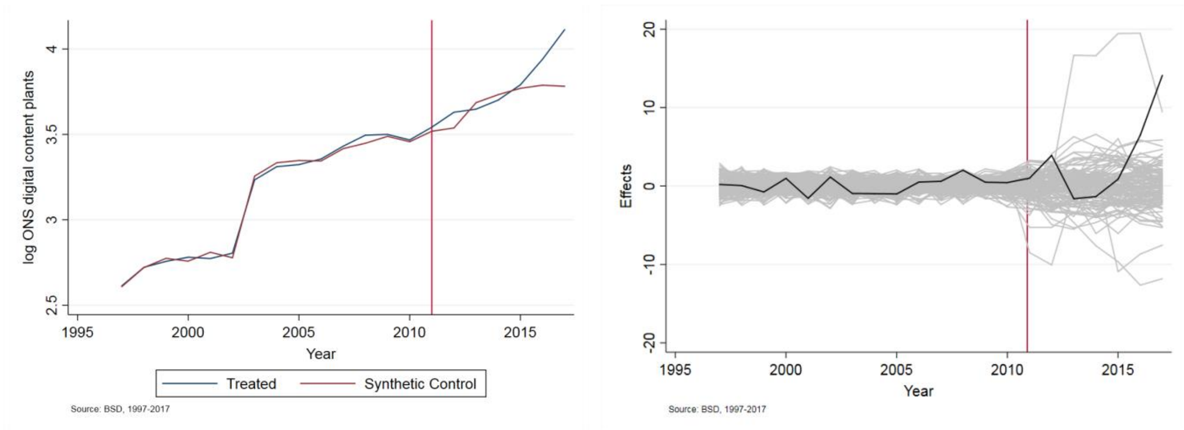
Graphs show % tech plants (jobs) as a share of all plants (jobs) in all industries, for average Tech City LSOA vs average rest of London LSOA. Top row: digital content. Bottom row: digital technology. Digital content activity includes advertising, media, design and web services Digital tech activity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

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

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



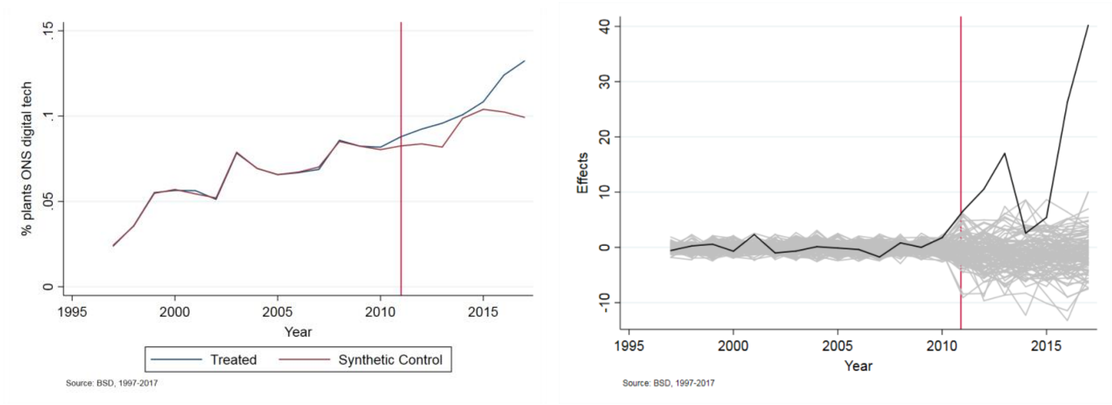
B. Log digital content plants: treatment vs. control (L); weighted effect sizes (R)



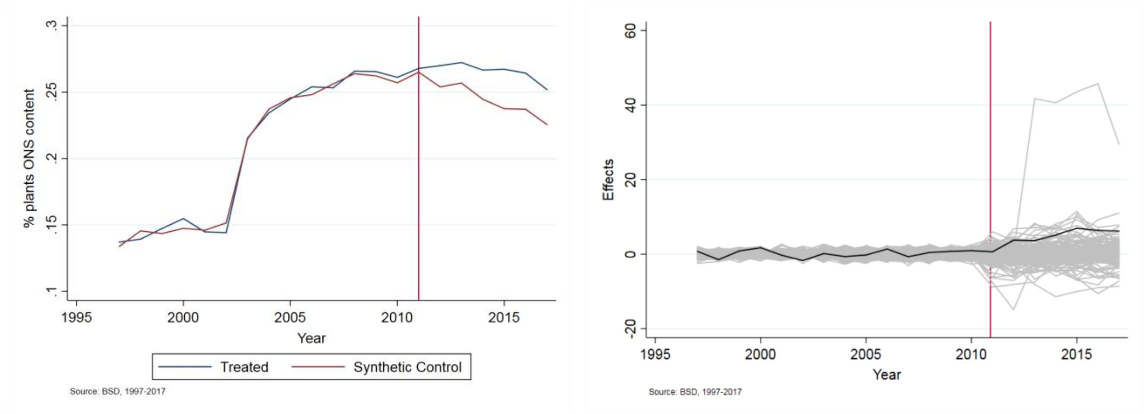
The left column shows outcomes for Tech City LSOAs (blue) vs. synthetic Tech City (red), the no-policy counterfactual scenario. The right column shows precision-weighted effect sizes for Tech City (black) versus 213 placebo units in the donor pool (grey). Effect sizes are weighted by pre-treatment RMSPE.

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

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



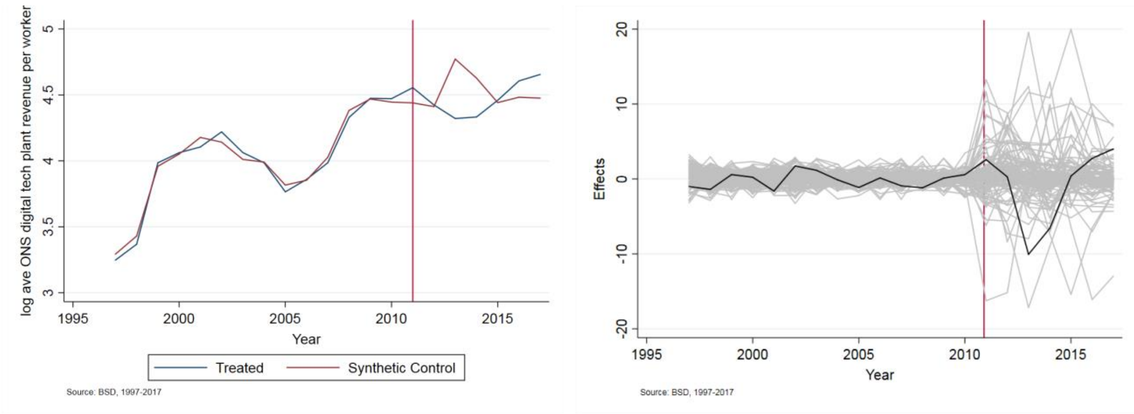
B. Digital content plants/all plants: treatment vs. control (L); weighted effect sizes (R)



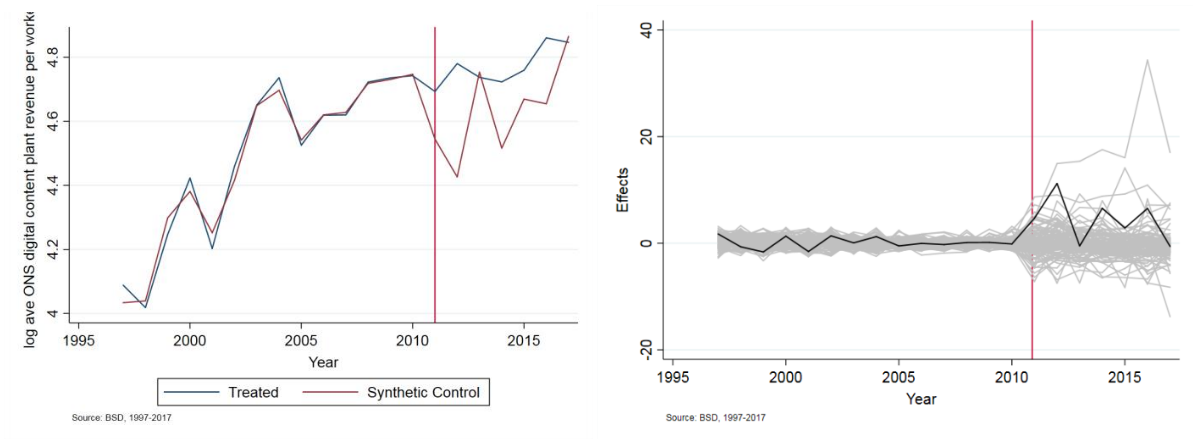
The left column shows outcomes for Tech City LSOAs (blue) vs. synthetic Tech City (red), the no-policy counterfactual scenario. The right column shows precision-weighted effect sizes for Tech City (black) versus 213 placebo units in the donor pool (grey). Effect sizes are weighted by pre-treatment RMSPE.

Figure 6. Policy effects on cluster 'performance'. Changes in Tech City tech firm productivity 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.

ONLINE APPENDICES

Appendix A: Panel build

A1 / BSD data

To build the main panel for analysis I use plant-level microdata 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 plants, coded to postcode level. Variables include plant 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 plant 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 plants 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

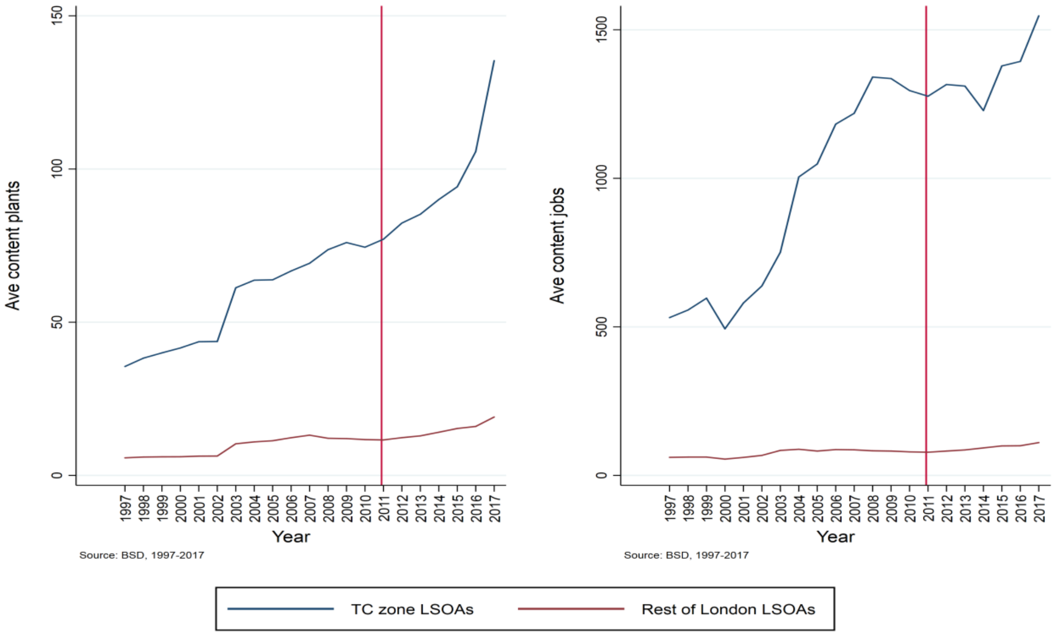
B. Digital content.

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 plant and job counts for Tech City neighbourhoods versus Rest of Greater London neighbourhoods, 1997-2017.

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



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

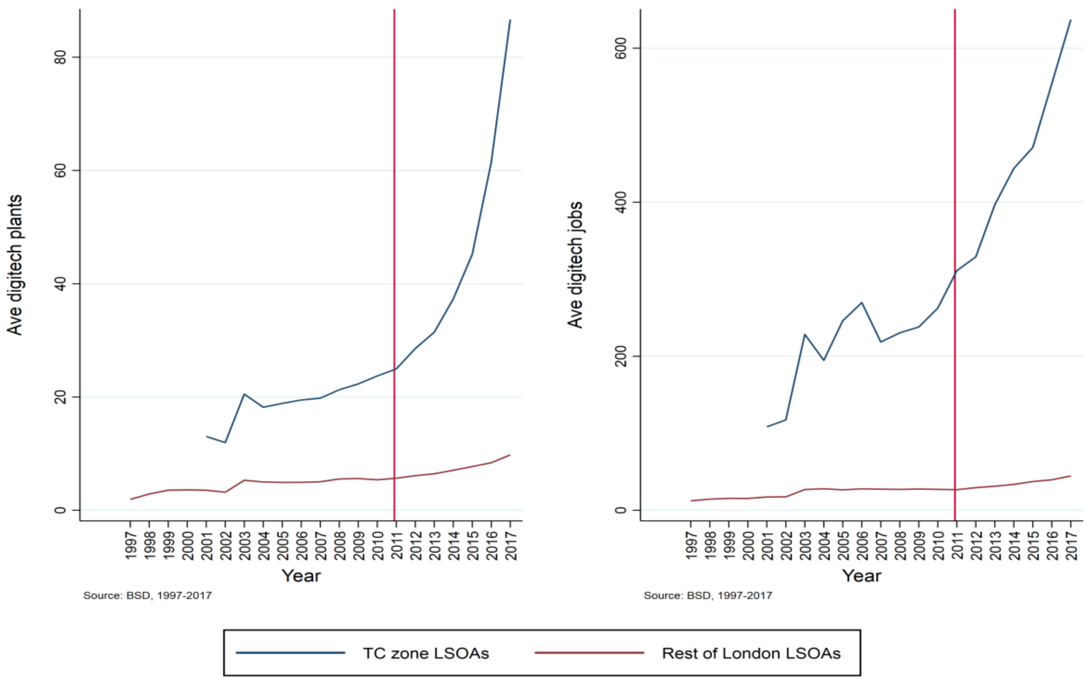


Figure B2. LSOA mean tech plant revenue per worker for Tech City neighbourhoods versus Rest of Greater London neighbourhoods, 1997-2017.

L: digital technology. R: digital content.

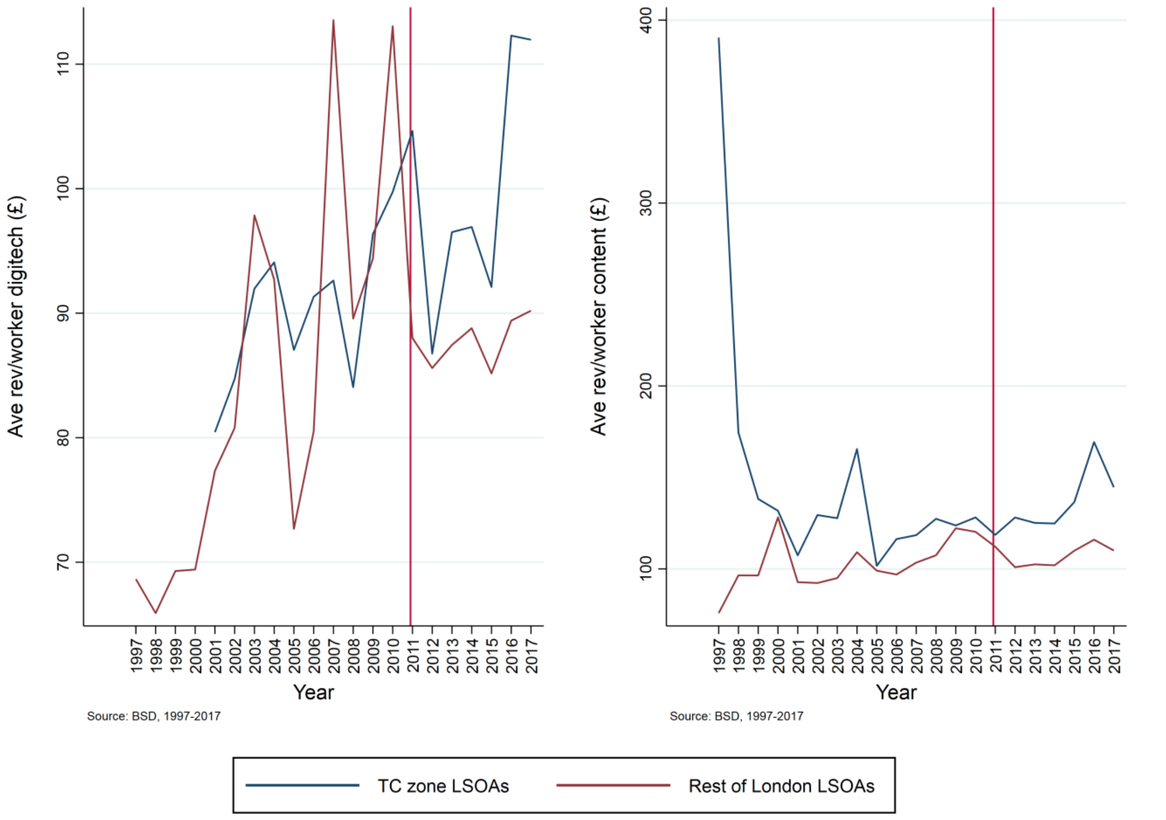
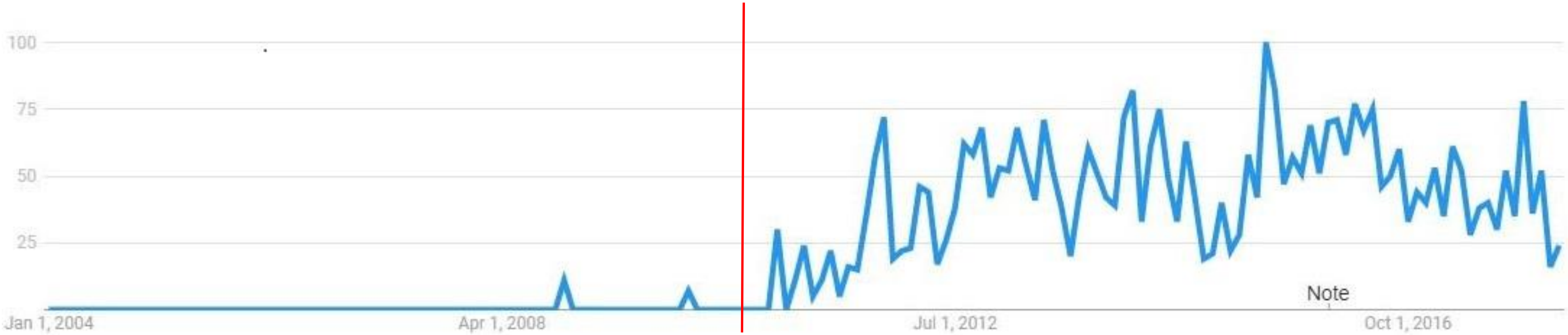


Figure B3. Google Trends analysis.

A. Google Trends: searches for “Tech City” + London. As of 1 March 2018.



B. Google Trends: searches for “Silicon Roundabout” + London. As of 1 March 2018.

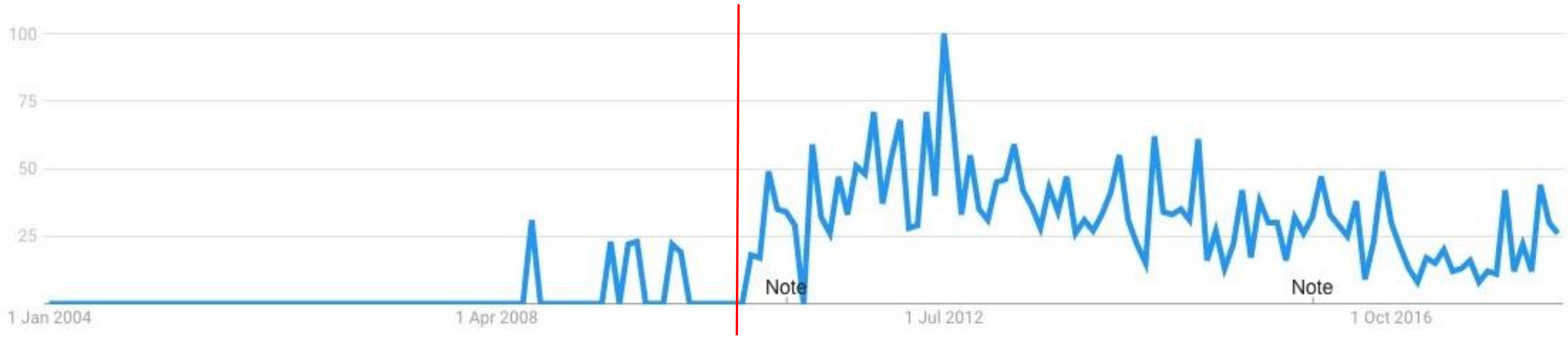
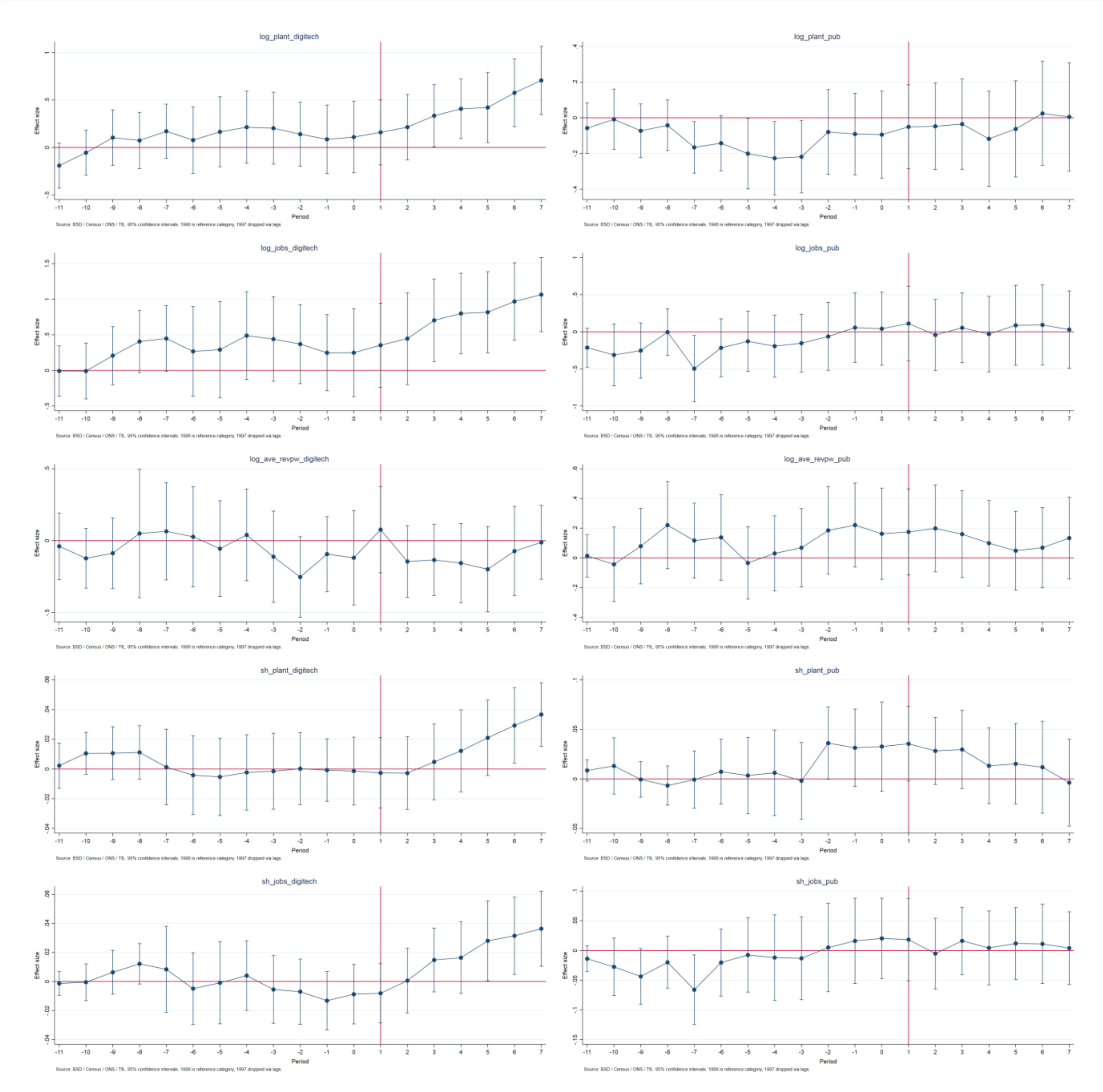


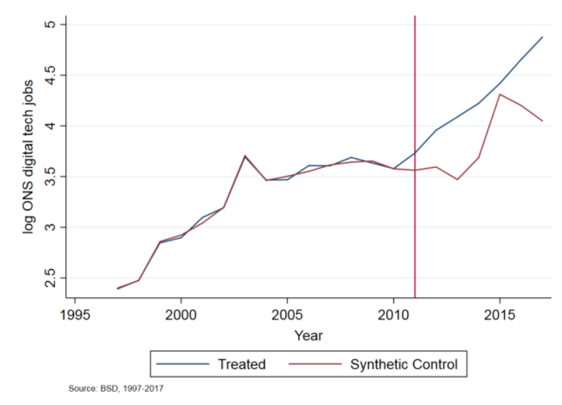
Figure B4. Balancing regressions for Tech City zone vs. matched sample of control LSOAs, 1999-2017.

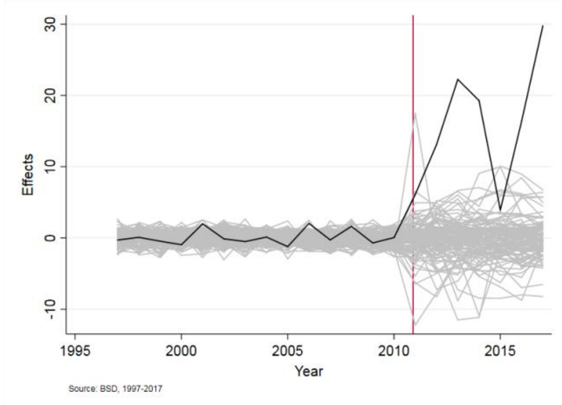


Source: BSD, Census, ONS mid-year population estimates, TFL. 95% confidence intervals. 1998 is reference category, 1997 dropped via lags. All regressions fit LSOA and year dummies. Time-varying controls fitted are one-year lags of LSOA all-sector plant entry, LSOA all-sector revenue/worker, LSOA Herfindahl 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.

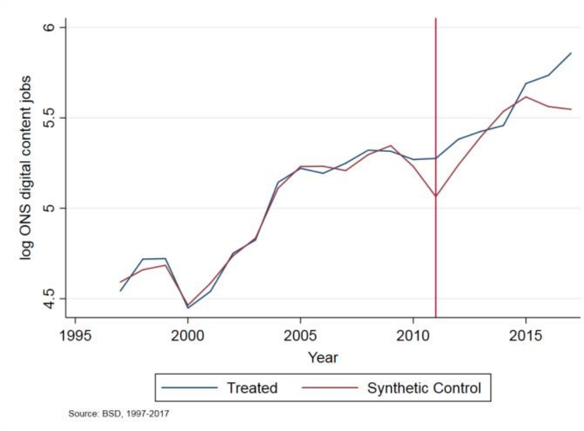
Figure B5. Policy effects on cluster size. Changes in Tech City tech jobs vs. synthetic counterfactual.

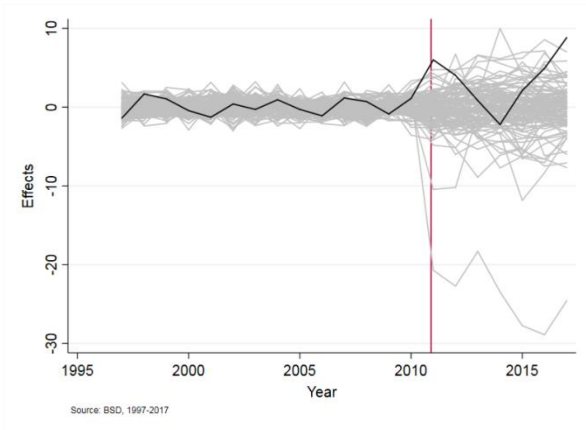
A. Log digital tech jobs: treatment vs. control (L); weighted effect sizes (R)





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

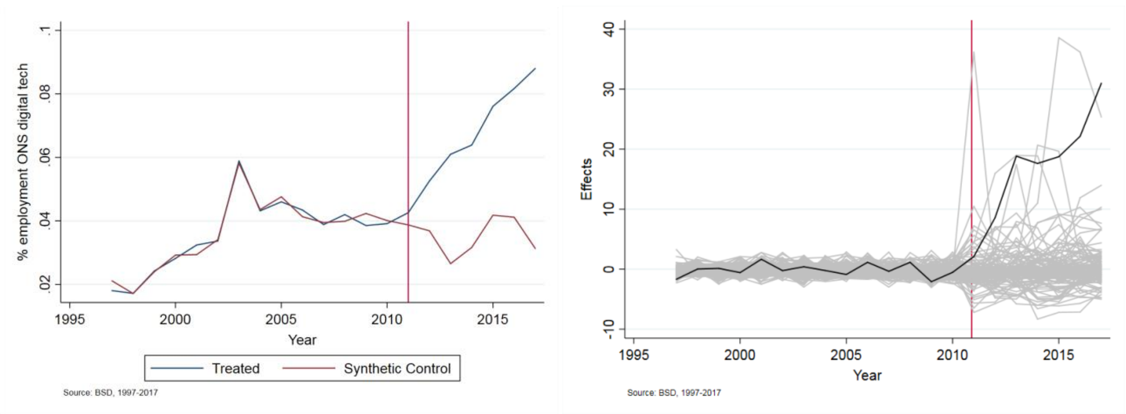




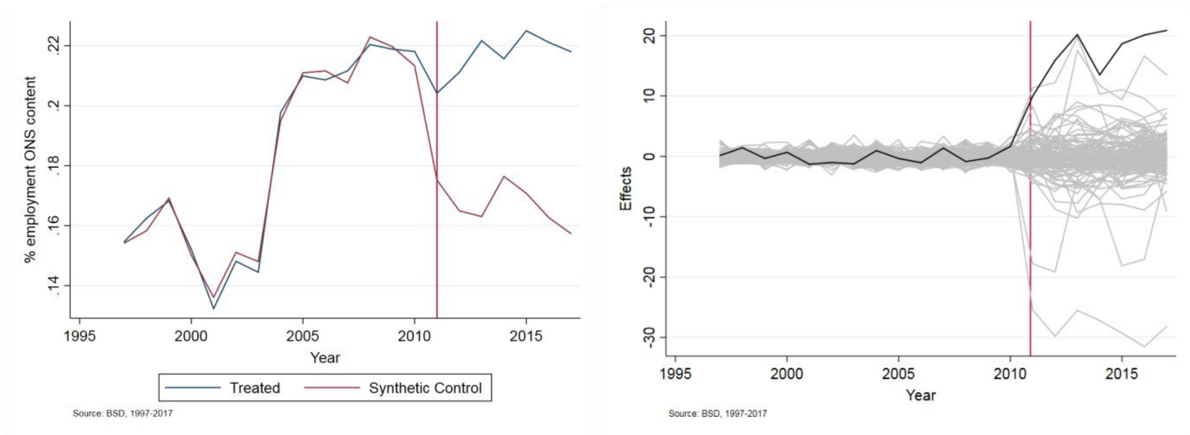
The left column shows outcomes for Tech City LSOAs (blue) vs. synthetic Tech City (red), the no-policy counterfactual scenario. The right column shows precision-weighted effect sizes for Tech City (black) versus 213 placebo units in the donor pool (grey). Effect sizes are weighted by pre-treatment RMSPE.

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)

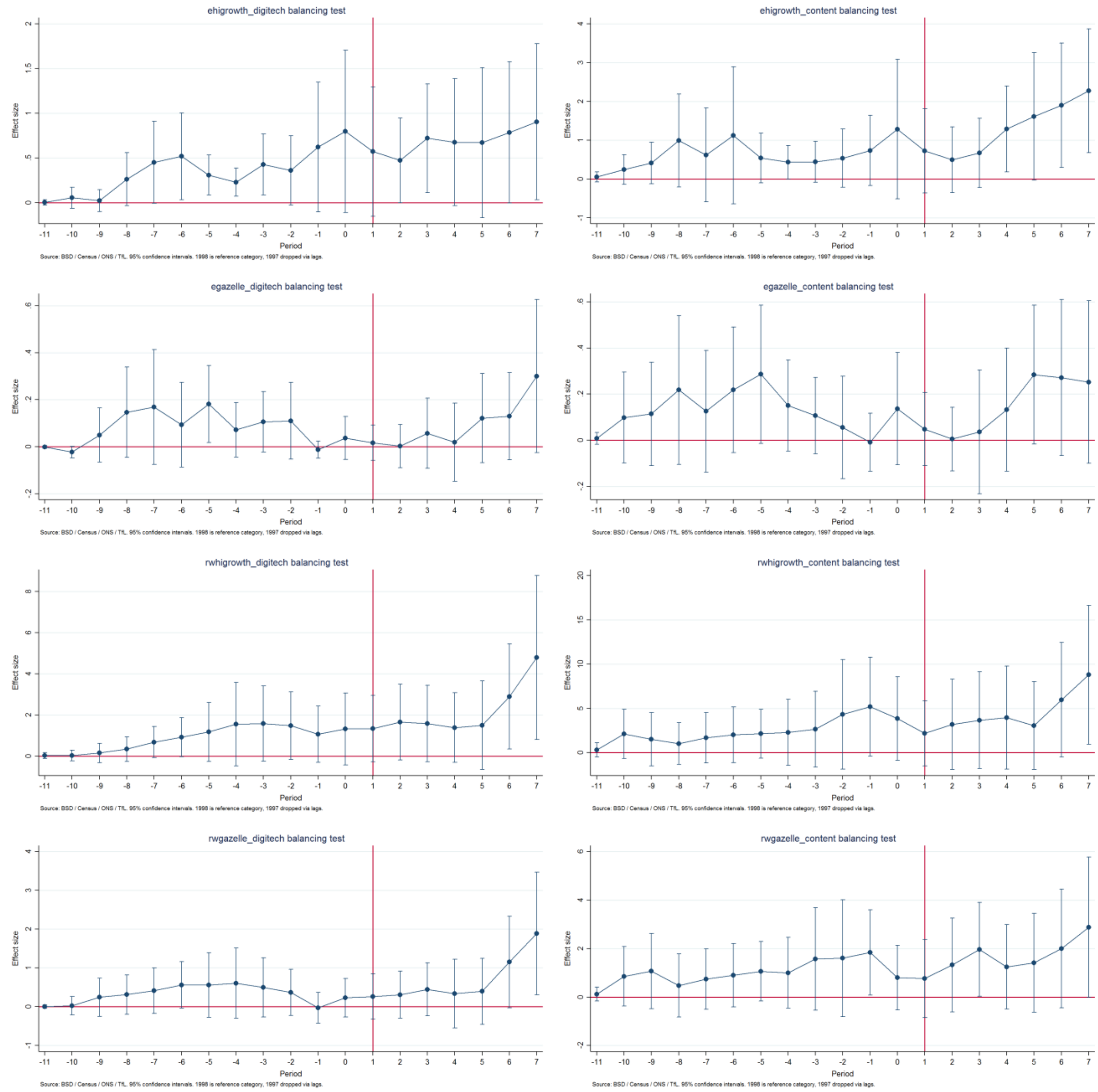


B. Digital content jobs/all jobs: treatment vs. control (L); weighted effect sizes (R)



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 plant 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 musuems 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)
# plant 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*
% plants 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 plants (1997)	2.613	2.609	1.626
Log content plants (1998)	2.722	2.721	1.645
Log content plants (1999)	2.757	2.775	1.665
Log content plants (2000)	2.781	2.758	1.698
Log content plants (2001)	2.773	2.810	1.747
Log content plants (2002)	2.805	2.778	1.754
Log content plants (2003)	3.234	3.256	2.260
Log content plants (2004)	3.311	3.334	2.335
Log content plants (2005)	3.323	3.347	2.414
Log content plants (2006)	3.356	3.344	2.485
Log content plants (2007)	3.431	3.417	2.563
Log content plants (2008)	3.495	3.448	2.448
Log content plants (2009)	3.500	3.488	2.454
Log content plants (2010)	3.468	3.457	2.413
Plant 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 plants, 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 musuems 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
Plant 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 plants, 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 musuems 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
Plant 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 plants, 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 musuems 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 plants (1997)	.	0.024	0.038
share digitech plants (1998)	.	0.036	0.056
share digitech plants (1999)	.	0.055	0.072
share digitech plants (2000)	.	0.057	0.068
share digitech plants (2001)	0.056	0.054	0.066
share digitech plants (2002)	0.051	0.052	0.063
share digitech plants (2003)	0.078	0.079	0.100
share digitech plants (2004)	0.069	0.069	0.093
share digitech plants (2005)	0.066	0.066	0.090
share digitech plants (2006)	0.067	0.067	0.086
share digitech plants (2007)	0.069	0.070	0.086
share digitech plants (2008)	0.086	0.085	0.099
share digitech plants (2009)	0.082	0.082	0.096
share digitech plants (2010)	0.082	0.080	0.095
Plant 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 plants, 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 musuems 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 plants (1997)	0.137	0.134	0.104
share content plants (1998)	0.139	0.146	0.101
share content plants (1999)	0.147	0.144	0.103
share content plants (2000)	0.155	0.147	0.108
share content plants (2001)	0.145	0.146	0.111
share content plants (2002)	0.144	0.152	0.114
share content plants (2003)	0.215	0.215	0.184
share content plants (2004)	0.234	0.237	0.197
share content plants (2005)	0.245	0.246	0.209
share content plants (2006)	0.254	0.248	0.218
share content plants (2007)	0.253	0.256	0.226
share content plants (2008)	0.266	0.264	0.200
share content plants (2009)	0.265	0.262	0.201
share content plants (2010)	0.261	0.257	0.196
Plant 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 plants, 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 musuems 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
Plant 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 plants, 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 musuems 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
Plant 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 plants, 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 musuems 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
Plant 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 plants, 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 musuems 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
Plant 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 plants, 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 musuems 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 plants		content plants		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 plants		% content plants		% 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.

	Plants		Jobs		% plants		% 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.

	Plants		Jobs		% plants		% 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.

	Plants		Jobs		% plants		% 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 plant entry, plant 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 plant 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 plant-level jobs or revenue/worker growth of at least 20% per year for any 3 year period. Gazelle episodes are high-growth episodes for plants aged five years or less. The same plant 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 plant 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%.

CENTRE FOR ECONOMIC PERFORMANCE
Recent Discussion Papers

1647	Stuart Campbell Lindsey Macmillan Richard Murphy Gill Wyness	Inequalities in Student to Course Match: Evidence from Linked Administrative Data
1646	Cong Peng	Does E-Commerce Reduce Traffic Congestion? Evidence from Alibaba Single Day Shopping Event
1645	Dan Andrews Chiara Criscuolo Peter N. Gal	The Best versus the Rest: Divergence across Firms during the Global Productivity Slowdown
1644	Christopher Cornwell Ian M. Schmutte Daniela Scur	Building a Productive Workforce: The Role of Structured Management Practices
1643	Paul Dolan Georgios Kavetsos Christian Krekel Dimitris Mavridis Robert Metcalfe Claudia Senik Stefan Szymanski Nicolas R. Ziebarth	Quantifying the Intangible Impact of the Olympics Using Subjective Well-Being Data
1642	Xavier Jaravel Erick Sager	What are the Price Effects of Trade? Evidence from the US and Implications for Quantitative Trade Models
1641	Johannes Boehm Jan Sonntag	Vertical Integration and Foreclosure: Evidence from Production Network Data
1640	Teodora Borota Fabrice Defever Giammario Impullitti	Innovation Union: Costs and Benefits of Innovation Policy Coordination
1639	Monica Langella Alan Manning	Residential Mobility and Unemployment in the UK

1638	Christos Genakos Mario Pagliero	Competition and Pass-Through: Evidence from Isolated Markets
1637	Holger Breinlich Elsa Leromain Dennis Novy Thomas Sampson	Voting With Their Money: Brexit and Outward Investment by UK Firms
1636	Maria Sanchez-Vidal	Retail Shocks and City Structure
1635	Felipe Carozzi Sefi Roth	Dirty Density: Air Quality and the Density of American Cities
1634	Nicholas Bloom John Van Reenen Heidi Williams	A Toolkit of Policies to Promote Innovation
1633	Stephan E. Maurer Ferdinand Rauch	Economic Geography Aspects of the Panama Canal
1632	Nikhil Datta	Willing to Pay for Security: A Discrete Choice Experiment to Analyse Labour Supply Preferences
1631	Gabriel M. Ahlfeldt Volker Nitsch Nicolai Wendland	Ease Versus Noise: Long-Run Changes in the Value of Transport (Dis)amenities
1630	Grace Lordan Alistair McGuire	Widening the High School Curriculum to Include Soft Skill Training: Impacts on Health, Behaviour, Emotional Wellbeing and Occupational Aspirations
1629	Per-Anders Edin Tiernan Evans Georg Graetz Sofia Hernnäs Guy Michaels	Individual Consequences of Occupational Decline

The Centre for Economic Performance Publications Unit
Tel: +44 (0)20 7955 7673 Email info@cep.lse.ac.uk
Website: http://cep.lse.ac.uk Twitter: @CEP_LSE