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

Max Nathan*
University of Birmingham and CEP

*Birmingham Business School, Birmingham, B15 2TT. m.nathan@bham.ac.uk

Abstract

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 and synthetic controls to identify effects. I further test for timing, cross-space variation, and distributional change. The policy increased cluster size and density, especially for 'digital tech' plants, where revenue/worker and high-growth firm activity also rose. But for a larger set of incumbent 'digital content' plants, the policy also led to de-concentration and lower revenue productivity. Even light touch cluster programmes risk unintended consequences.

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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 – involve many market and co-ordination failures. In theory, public policy should be able to improve cluster welfare. But clustering is an outcome of many firm and worker decisions; market and co-ordination failures are complex; and this complexity may lead to policy failure (Duranton, 2011, Martin and Sunley 2003).

The real-world scale of these challenges is an empirical question: Duranton (2011), Chatterji et al (2014), and Urraya and Ramlogan (2013) review the evidence. Yet the empirical literature evaluating cluster policies is small. Within this, the set of robustly designed evaluations is smaller still. The handful of recent examples includes Falck et al (2010), Martin et al (2011), Nishimura and Okamuro (2011) and Engel et al (2013).

This paper develops a rigorous impact evaluation of a flagship UK cluster programme. In doing so, it tests the latest iteration of cluster policy as a whole. Rather than Porter-style cluster mapping, or applying insights from evolutionary economics (Nathan and Overman, 2013), cluster programmes today often use ‘light touch’ interventions. These include marketing, financial incentives, 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 (Cameron, 2010). Are they any more successful? If so, there are lessons for other cities with technology clusters. These include New York, San Francisco, Berlin, Stockholm, Lisbon and Paris, among others.

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.2500 firms) centred on Shoreditch and Old St roundabout, aka ‘Silicon Roundabout’ (Figure 1).

Figure 1 about here

The cluster had been growing for some time without direct policy input (Foord, 2013; Nathan and Vandore, 2014; Jones, 2017). It first came to public 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), and has since expanded to cover the whole UK. [1]

The programme included a range of light-touch interventions that aimed to improve the workings of the existing milieu. Place branding and marketing were used to grow the cluster and attract foreign investment. Business support programmes targeted selected local firms. The government introduced tax breaks for angel and venture capital firms. It also made extensive attempts to improve public-private networks and co-ordination, including establishing a one-stop delivery body, the Tech City Investment Organisation (TCIO).[2]

Policymakers claim this mix has worked well.[3] But how successful has the policy actually been? The cluster is much larger than it was, with firm growth in all parts of the zone (Figure 2, left panel). At the same time, cluster rents have risen, both in absolute terms and relative to comparable submarkets (right panel). There is also extensive anecdotal evidence of displacement of smaller firms and entrepreneurs.[4]

Figure 2 about here

Clusters involve both positive and negative feedback loops. As clusters grow and become denser, agglomeration economies get stronger. However, growth also raises crowding, and competition for resources and market share. The Tech City policy mix could plausibly

[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] See for example https://www.london.gov.uk/press-releases-6094, 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.

contribute to both channels. We need to understand the balance of these forces, how they fall across cluster space, and across different groups of firms.
To explore these issues 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 synthetic controls to identify policy effects on cluster size, density and local tech plant performance. I extend these findings with four further pieces of evidence. I run placebo-in-time tests to identify the timing of effects; use treatment intensity analysis to explore within-cluster shifts; test for effects on tech firm scaling, as defined by high-growth episodes; and run a before-and-after analysis of tech plant entry and exit patterns.

I have three main results. First, I find large policy effects on the net counts of technology plants and jobs. These are especially large for emerging ‘digital technology’ activities (mainly hardware and software), where plant counts rose 37% and job counts rose over 106%. These translate to 143 extra plants and over 4,500 extra jobs in the post period. Effects are smaller for ‘digital content’ activities (such as advertising, media, design and web services), where plant counts rose 19% and job counts rose 38%. Because these activities historically dominated the cluster, policy effects work out to 275 extra plants and over 8700 extra jobs in the post period. I find some evidence that policy ‘effects’ began in 2008, when the cluster first came to public attention. But for digitech firms, the post-2011 effect/year is greater than the 2008-10 outcomes.

Second, I find significant rises in cluster density, but these are smaller in percentage terms than increases in levels. Specifically, the LSOA share of digital tech plants rose 21%, and for content firms 6%. For jobs, the changes are 58% and 9% respectively. I find suggestive evidence of crowding between digital technology and digital content firms, and between tech and other industries. The cluster’s inner core saw large increases in digital tech firms and jobs, but digital content plants and jobs have (re)located to the edge. I also find post-treatment increases in tech plants relocating out of the cluster to the rest of London, and to the rest of the UK.

Third, I find that policy raised digital tech plants’ revenue / worker by 8% relative to the counterfactual. But I find declines – around 21% - for digital content firms. This implies that agglomeration effects dominate for digital technology activities, but competition effects dominate for content firms. Other evidence backs this up. Digital content plants increased revenue/worker between 2008-2010, when the cluster first became well known. But this turns negative after the Tech City policy begins. I also find small, robust increases in the count of high-growth episodes for digital technology plants, but much smaller, marginally significant increases for digital content high-growth activity. Churn analysis also shows increases in cluster entry, especially from the rest of the UK and plant births.

For some policymakers, a bigger cluster is proof of success. Across a broader range of outcomes, the results are mixed. A small, growing set of digital technology firms benefited – as reflected in higher densities, improved revenue productivity, and significant increases in high-growth plant activity. At the same time, the policy increased cluster crowding and competition, especially for digital content firms. These seem to have relocated to cluster edges, and have lower revenue/worker than pre-policy. These results imply that light-touch cluster policy can have some positive impacts. But as Duranton (2011) suggests, working with cluster microfoundations and market dynamics remains challenging. Policymakers run clear risks of generating unintended, negative results.

This is the first impact evaluation of the Tech City programme that I am aware of. Besides these novel results, this paper adds to a small set of studies on the wider cluster (Foord, 2013; Nathan and Vandore, 2014; Martins, 2015; Jones, 2017), as well as 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.[5] The closest comparator is probably Falck et al (2010), who look at the effects of high-tech cluster policies in Bavaria. The paper is also unusual in drawing on extensive qualitative fieldwork – with cluster participants and policy actors over several years – to inform research design. The closest comparator here is Arzaghi and Henderson (2008), who develop their quantitative study of advertising clusters in Manhattan

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

out of a number of semi-structured interviews. See Nathan and Vandore (2014) and Nathan et al (2018) for detail.

2/ Data and definitions

I explore the cluster using multiple data sources. I start with the latest (9^{th}) edition of the Business Structure Database, hence BSD (Office of National Statistics, 2017). The BSD covers over 99% of all UK economic activity and provides reliable postcode-level information for individual plants. I link plants to 2011 Lower Super Output Areas (LSOAs), then aggregate the data to LSOA level.[6] The resulting panel runs from 1997 - 2017 and contains 101,503 area*year observations for 4,835 LSOAs in Greater London. Further details and diagnostics 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 accepted limit at the time of policy introduction (Nathan and Vandore, 2014). Specifically, I define Tech City as the set of LSOAs whose centroids have a linear distance of 1km or less from the Eastings/Northings of the Old St roundabout.[7] 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.[8]

[6] Alternatives are a) working at plant level, rather than area level and b) using grid squares, rather than small administrative units. Given that 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 any non-BSD controls, since these are not fully geocoded.

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

[8] Other methods that would deliver 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 that would deliver 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.

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 the relevant SIC codes.

I focus on three cluster outcomes. Cluster size is given by net LSOA tech plants and jobs in a given year.[9] 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 per worker, via enterprise-level BSD data.[10] 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; Storper and Scott, 2009). 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 many such 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).

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

[10] 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.

The cluster is distinctive from the rest of Greater London, both in its overall characteristics and in the evolution of ICT industries over time. I show this first in cross-section. Table 1 shows mean characteristics for Tech City LSOAs versus the average rest of Greater London LSOA in the pre-policy period, 1997-2010. Table B1, in the appendix, repeats the analysis for LSOA amenities and wider demographics.

Table 1 about here

Two main features stand out. First, tech activity in the average treated LSOA is dominated by digital content industries. This is consistent with historical and case study evidence (Foord, 2013; Nathan and Vandore, 2014; Martins, 2015). Second, the area's industry and demographic mix is very different from the average rest-of-London neighbourhood. In particular, tech activity is much denser than the rest of the capital.

Figure 3 about here

Figure 3 provides more detail. The top row looks at LSOA firm and job shares for digital content over time; the bottom row does the same for digital technology. In each case I compare the average Tech City neighbourhood with the average rest of London neighbourhood. We can see that the area maintains a well-above-average density of digital content activity. This remains true in the post-policy period, although plant density falls slightly, implying that other sectors are growing faster as a share of all firms. Digital technology activity is much sparser than digital content (bottom row), and in the pre-policy period Tech City LSOAs are much closer to the rest of the capital in digital tech density. However, in the post-policy period 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 Marshallian production district. As the cluster grows, firms' productivity rises (via agglomeration economies), which should feed through to improved revenue/worker. At the same time, the costs of cluster location rise with cluster size (via crowding). Productivity and cost curves combine to give a net returns curve 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 tech firms seek to access. Competing land uses will also drive 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) consider firms' location choices in more detail. Clusters are effectively a set of overlapping industrial districts. Firms enter the cluster 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 district 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'). The decay functions of these costs / benefits help set location parameters for individual firms and thus the overall cluster shape. For industries such as tech, where face-to-face interaction is important (Charlot and Duranton, 2004) clusters tend to be small and dense.

The Tech City programme aimed both to increase cluster size and to support participant firm growth. The framework above suggests several possible policy effects. First, the programme may raise the number of tech firms and jobs (as captured in LSOA counts). Second, other things being equal, this will increase the density of tech activity in the cluster (as captured in LSOA shares). Third, increased size and density should amplify agglomeration effects, increasing firms' innovation, productivity and thus revenue / worker. Fourth, however, it will also induce crowding and thus costs to firms (higher rents). Even if productivity is rising, cost rises may induce firm relocation if these outweigh productivity effects (i.e. if the net returns curve is sloping down). In the case of tech startups, these relocations will often be highly localised – to less central locations within the cluster or to neighbourhoods just outside it.

Three other forces may also shape outcomes. First, other elements in the policy mix (business support, co-ordination activities), if effective, will steepen the productivity curve and improve revenue productivity. Second, increases in cluster size/density raise both agglomeration economies *and* competition (Combes et al 2012). In a Schumpetarian setting (Aghion et al., 2009), 'winners' raise revenues/worker further, while 'losers' shed revenues/worker and some may exit the cluster. This will increase churn and may dampen overall revenue/worker changes. Third, the cluster policy may 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 level and within-cluster outcomes. As in Falck et al (2010) and Noonan (2013), my basic setting compares changes in the treated area against changes in some control areas. In my main estimates I use synthetic controls in the 1km ring, as in Helmers and Overman (2016) and Becker et al (2018). 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; Gibbons et al., 2016) to allow policy effects to vary across 250m rings within cluster space.

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 to such an approach.

First, the media attention around ‘Silicon Roundabout’ from 2008 (Nathan et al., 2018; Foord 2013) could have induced firms and entrepreneurs into the area beforehand, effectively anticipating the policy. Figure B3 shows Google searches before and after the policy, and suggests anticipation effects will be small. In the next section I test for anticipation using placebo-in-time checks.

Second, the area might have been selected by policymakers for growth potential, either on observables on unobservables. Positive selection would bias effect sizes up. While tech activity in the area had been neglected by public policy,[11] by 2010 Ministers were convinced that there was 'something special' about the Inner East London cluster (Cameron, 2010; Osborne and Schmidt, 2012). However, Nathan et al (2018) and Butcher (2013) suggest that assignment was as good as random *compared to other tech hotspots in the* city, via a series of serendipitous events. This origin story implies that the policy is a 'quasi-random' exogenous shock to the area. To test this, I use propensity score matching to identify a set of tech hotspot LSOAs that share observable characteristics. 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.

Table 2 shows the matching results. 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.

Table 2 about here

[11] See discussions in Pratt (2009) and Foord (2013), among others. The cluster is also not mentioned in two key policy frameworks in the 2000s: the 2003 City Fringe City Growth Strategy or the 2001 DTI UK cluster-mapping exercise.

Results of balancing tests 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.

Given the lack of clear-cut control areas, I therefore use a synthetic control approach to construct an alternative counterfactual, using the matched sample as a donor pool (Abadie et al 2010). Details of the synthetic control build are given in the next section.[12] Among other attractive features, the estimator gives a consistent ATT even in the presence of time-varying unobservables. I follow the research design of Becker et al (2018) and compare synthetic control results to difference-in-differences results for the matched sample.

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 one of the log of tech firm counts or tech job counts; shares of tech firms or tech jobs; or the log of tech firm revenue / worker. TC is a dummy variable taking the value 1 for Tech City LSOAs in the post-treatment period, and a_i is the ATT for a Tech City LSOA.

X is the set of time-varying controls used in matching. These cover local economic conditions (lags of LSOA all-sector plant entry, LSOA all-sector revenue/worker, LSOA Herfindahl Index); a vector of 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 TFL tube and rail stations); plus local area demographics (local authority district shares of migrants and shares of under-30s). I cluster standard errors on LSOAs and weight regressions by the propensity score.

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

The synthetic control is an extension of (1) where the synthetic control unit is a weighted average of a donor pool (the matched set of 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:

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

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

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

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.[13] This allows us to interpret Synthetic Tech City as a weighted average of the non-treated units. 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** can be chosen to maximise the overall pre-treatment 'fit' of the synthetic unit, specifically to minimise the gap in the outcome variable between the treated unit and the synthetic control. 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). This third approach has the attractions that predictor importance is identical across all regressions, and that outcomes and controls to be fitted together for all pre-treatment periods. I use this

[13] 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.

approach in my main regressions, and run robustness checks on alternative specifications of **V** and **W**.

Diagnostics suggest that as hoped, synthetic Tech City is more closely matched to Tech City than the matched sample as a whole. Table 3 compares mean pre-treatment outcomes and control variables for the Tech City area, synthetic Tech City and the matched control units for the log of digital tech plants. Table B2 replicates this for all other outcomes. Table B3 shows the LSOAs chosen for the synthetic control and the weights assigned, for all outcomes of interest.

Table 3 about here

Inference for synthetic controls is done through permutation rather than significance testing. Abadie et al (2010, 2015) first calculate yearly treatment 'effects' for each unit in the donor pool, comparing the distribution of effects for the treated and donor units in each post-treatment year. If the placebo runs for the donor units generate effect sizes smaller (larger) than the treatment unit, this suggests a real (spurious) treatment effect. A test statistic, which can interpreted as a *p*-value, shows the probability of obtaining a placebo effect size larger than that of the treatment effect. Placebo effects may be large for units not matched well in the pre-treatment period, which means that raw test statistics will be too conservative. To fix this, Galiani and Quistorff (2016) suggest weighting treatment and placebo effects by pre-treatment RMSPE.[14]

Second, 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:

[14] 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 that of the treated unit.

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

6/ Results

Estimates of policy impact are given below. Figure 4 shows synthetic control results for cluster size, specifically plant counts. The left hand column shows the change in logs of net digital tech plant counts and digital content plant counts in Tech City compared to synthetic Tech City. The right hand column shows effect sizes from Tech City versus the 185 placebo units in the donor pool. Effect sizes are weighted by pre-treatment RMSPEs, so these graphs show *relative effect size* controlling for fit.

Figure 4 about here

The left column suggests unambiguous policy effects on digitech firms and job counts, and smaller effects on digital content activity. Both are increasing over time. There are also signs of treatment-control divergence before the policy begins, an issue I return to in Section 7. Figure B5 repeats the analysis for employment.

Controlling for pre-treatment fit, the placebo tests show that effect sizes for digitech activity are stronger than for digital content activity (right column). For example, in 2017, policy effects are log digitech plants are around 200 times higher than for the nearest placebo effect; but for digital content, the 2017 gap is under 40 times, and the overall distribution of placebo effects is rather closer to the actual treatment. The synthetic control for the treated unit is well fitted in both cases (see Table 4) so this suggests that the content industries effect is weaker.

Table 4 about here

Table 4 gives cluster size results in detail, and confirms this pattern. The top panel shows synthetic control ATTs and *p*-values from the permutation test. Diagnostics show that the synthetic control fits the data well. The bottom panel shows DID ATTs, which are almost all similar to synthetic control coefficients.

Since Y is in logs, $\hat{a}$ can be interpreted as a percentage. Using synthetic control results, the policy increases the count of digitech plants by 36.7%, or 5.7 net extra plants in the post-treatment period compared to the pre-treatment mean. Across 25 treated LSOAs, the cluster-wide net gain is 25*5.7 = 143 extra plants. For digital content, the policy effect is 19.1%, 11 net extra plants per LSOA, or 275 overall. The policy adds net 183 digitech jobs per LSOA on the pre-treatment mean (a substantial increase of 106.2%) and raises digital content employment by nearly 38% (350 net extra jobs per treated LSOA). Cluster-wide, this cashes out as 4,575 and 8,750 extra tech jobs respectively. To put this in context, the policy effect accounts for over 12% of the employment change in *all* sectors in the post-treatment period.

Figure 5 shows synthetic controls and placebo tests for cluster density measures. The left column compares outcomes for Tech City versus synthetic Tech City, for the LSOA share of digital tech plants and digital content plants. The right hand column shows placebo tests. Figure B6 repeats the analysis for employment shares.

Figure 5 about here

The graphs show clear and growing policy effects on digitech density, but these are smaller than changes in net counts. That is, changes in counts did not translate 1:1 into changes in density, implying other sectors were also moving into the area at the time, especially after 2012 when digitech density is decreasing. Effects on digital content density are slightly smaller overall, but much spikier over time. Table 5 shows ATTs as before. As Y is now in shares, $\hat{a}$ gives the ATT across *all* treated units. The policy adds 1.3 percentage points to shares of digitech plants and 2.1 percentage points to shares of digitech jobs, with slightly smaller effects on digital content activity. Given pre-treatment means, these translate to a 21% increase in the pre-treatment share of digitech plants, and a 58% increase in the share of digitech jobs. For digital content activity, we see a 5.7% increase in plants on the pre-treatment mean, and an 8.7% increase in jobs.

Table 5 about here

Figure 6 gives results for tech firm performance, measured by logs of LSOA mean tech firm revenue/worker. The policy caused an overall increase in revenue per worker for digitech firms, which kicked in after 2012; by contrast, revenue/worker declines for digital content firms relative to the synthetic control. This is consistent with 1) policy-driven agglomeration effects improving the revenue productivity of digitech firms, and 2) for digital content firms, agglomeration effects outweighed by increasing market competition.

Figure 6 about here

Table 6 shows ATTs for synthetic control and DID estimates as before. For the synthetic control the policy effect is an 8% increase in digitech firm revenue/worker, but a 21% drop for digital content firms. Notably, policy effects for the synthetic control are much larger and more robust than those for the DID. DID model fit is also lowest for performance regressions.

Table 6 about here

6.1 / Robustness checks

In Appendix B, Table B4 runs a series of specification checks on the synthetic control results. The first three tests 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); as Kaul et al (2018) point out, this puts zero weights on controls, rendering them irrelevant. The fifth and sixth tests split the pre-treatment period and use cross-validation to set **V**, as in Cavallo et al (2013). Finally, I run the main result in long differences and then in first differences.

In the spirit of Ferman et al (2018) given the lack of clear guidance on synthetic control setup, the aim of these tests is to show stability (or otherwise) of effect size, sign and robustness across different specifications. Given that many of these specifications use less information than my main specification, we should expect synthetic controls to be less precisely specified so that coefficients will not always be significant.

Overall, plant and job count regressions are the most robust to specification changes. Effect signs stay the same and magnitudes change a little. Of these, the content jobs result becomes non-significant in a couple of cases, especially when only 50% of pre-treatment outcomes are used in the synthetic control. Density measures are a little less stable, especially when less information is used to build the synthetic control. Again, signs and magnitudes stay about the same, although results become non-significant in a few specifications. Of these, digitech results are more stable than those for digital content firms. Tech firm performance measures are much less stable. Signs stay the same, but coefficient size moves around a lot, and results are almost always insignificant. However, alternative specifications have much higher error rates than the main results, often by orders of magnitude. Long difference and first difference specifications are the least well fitted, with very high RMSPEs. Overall, these checks suggest that a) cluster size results are the most robust, b) cluster density results are also robust, c) tech firm performance results are more suggestive and d) results for digital tech firms hold better than for digital content firms.

7/ Extensions

The analysis so far throws up three main findings. First, the policy has led to substantial increases in tech firm and job counts, especially for digital technology activities. Second, cluster density has also increased, but by a much smaller amount. Third, the revenue productivity of digitech plants has improved, but for digital content firms it has deteriorated. This section explains these results in more detail. I use four pieces of evidence to do this. First, I explore the timing of policy effects via placebo-in-time tests. Second, I look at policy effects within the cluster, using treatment intensity analysis. Third, I test whether the policy increased the numbers of high-growth tech firms, comparing this against overall changes in industry revenue/worker. Finally, I look at descriptive patterns of tech firm entry and exist across the cluster.

7.1/ Timing

First, I look at the timing of the policy effect. The cluster became well known in the media in 2008; a persistent criticism of the Tech City policy has been that government was 'riding the wave' and adding little or nothing to existing trends. Conversely, when policy went London-wide in 2014, the cluster might have received less attention so that policy effects died away.

Table 7 about here

Table 7 tests these hypotheses. The first row shows the main synthetic control results. The next row runs a placebo-in-time check (Abadie et al 2015), starting the policy in 2008 rather than 2011. I find significant policy effects in almost all cases, with larger coefficients; for digital content revenue per worker, the effect is insignificant but the effect turns from negative to positive and becomes close to zero.

The third row breaks out the 2008-10 component of these results. We can see that there is some Silicon Roundabout effect, but that the majority of the impact comes after the policy is launched. This implies that the policy amplified existing trends for digital tech firms, broadly as intended. The exception is for digital content firms, where annual outcome growth is always higher in the 2008-2010 period (see bottom panel). Strikingly, statistically significant growth in revenue per worker in 2008-2010 turns negative significant from 2011. This confirms the negative policy effect.

The fourth row 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 all significant (except for digital content jobs) but the overall effect size is smaller, as expected. Rather than dying away, annual policy effect sizes when the policy goes London-wide are larger in 4/10 cases, and smaller in 6/10 cases. In the majority of cases, policy effects in Tech City weaken but when the policy is refocused. This provides further evidence that a causal policy effect is identified. In the other cases, self-reinforcing cluster mechanisms may help the policy 'work' despite the spatial refocusing.

7.2 / Within-cluster analysis

Next, I look at outcome changes within the cluster. The fact that cluster density effects are much smaller than increases in net plants and jobs implies some crowding effects, between tech firms and/or between tech and other activities. Following Fangio (2015) I estimate a DID treatment intensity estimator for LSOA *i* in year *t*:

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

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

Results are given in Table B5. The top row gives the cluster-level policy effect for the 1km zone. Other rows decompose this effect into 250m ring increments. Note that coefficients pick up relative change in a single distance ring – this may be too small to be statistically significant, even if variation across the 1km zone *is* significant.

The analysis shows important differences in outcomes across cluster space and industry space. First, digital tech activity shows significant growth in firm and job counts in the innermost / 250m ring, driving the overall policy effect. Subsequent effects on cluster density are positive here, but not significant. Second, digital content activity also shows significant firm growth in the innermost ring, but jobs growth shrinks here, and is strongest at the cluster edge (750-1000m). Moreover, there is evidence of plant and job de-clustering in the innermost ring, and plant re-clustering in the outermost ring.

Overall, in the post-policy period the core of the cluster has become significantly in digitech activity and less rich in digital content activity; digital content jobs have significantly densified at the cluster edge. This is consistent with one or more of: increasing tech firm competition for space; larger digital content firms (re)locating at the cluster edge; and other activities competing with tech (especially digital content) for space. The rest of this section, which explores market outcomes in more detail, is consistent with increased competition for space within the tech sector.

7.3 / High-growth firms

I also look at whether the policy increased counts of high-growth tech firms. In the tech industry, the combination of increasing returns plus network effects often leads to winner-takes-all scenarios, where a small number of 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. That is, even if average revenue/worker changes are quite small, a small number of firms may grow rapidly. In a panel setting, firms move into and out of high-growth states (‘episodes’). I define high-growth episodes following the standard OECD definition, as a tech plant that experiences revenue/worker or employment growth of at least 20% for any three-year period. I define 'gazelles' as high-growth episodes for tech firms five years old or less. A plant may have more than one high-growth episode in the panel.

Table B6 shows incidences of high-growth activity in 1999-2010. Specifically, it shows the average number of high-growth episodes by LSOA type. The average Tech City LSOA experiences substantially more high-growth activity than the average control area. The extent of revenue/worker high-growth is greater than high-growth employment, and gazelle episodes are very rare. These descriptive patterns suggest it is unlikely that a standard diff-in-diff approach will give consistent estimates. Balancing tests shown in Figure B7 confirm this. I therefore run regressions using synthetic controls only. I specify the synthetic control as in the main analysis. Given the rarity of high-growth instances, I regress counts rather than logs as the dependent variable.

Table B7 gives results for high-growth episodes.[15] The left panel shows revenue/worker scaling. I find significant positive policy effects for digital tech firms. Counts increase by just over 28%, or over 10 more high-growth digitech episodes per treated LSOA compared to the

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

pre-treatment mean. Across the 25 Tech City neighbourhoods, this sums to over 250 extra high-growth episodes. By contrast, policy effects on high-growth digital content activity are only marginally significant, and much weaker. Counts increase by 0.25%, or just over three extra high-growth digital content episodes per LSOA. The right panel shows employment growth episodes. Here I find larger policy effects, but none is statistically significant.

Overall, I find positive revenue/worker effects for digital tech firms, plus significant evidence of small scaling effects. For digital content firms, I find negative overall revenue/worker changes, plus weak evidence of scaling. This is further evidence that the policy has amplified agglomeration economies for digital tech firms, but that crowding and competition effects dominate for digital content firms.

7.4 / Churn

Finally, to explore market outcomes in more detail, I work at the plant level. I combine cross-sections for three year-pairs, 2009 and 2010 (pre-policy), 2013-2014 and 2016-2017. For each pair, I flag tech plants present in the 1km cluster zone 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 (either dying, or leaving the BSD due to laying off all staff, revenues dropping below £75k/year, or both). Results are given in Table 8.

Table 8 about here

The results clearly show the growing size of the cluster, and the increase in plant churn since the Tech City policy was implemented. The count of tech firms has increased substantially, but the share of stayers has fallen since 2009-10. Entry rates have risen since the policy started, dominated by new plant births; the share of movers from the rest of London has fallen, and the share from the rest of the UK has risen. Strikingly, the overall exit rate has fallen since the policy started, explained by falling exits from the BSD. Conversely, within the set of leavers cluster exit has risen, both to the rest of UK and to the rest of London.

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 impacts, testing for timing, cross-space variation, and distributional change. I find that the policy substantively increased cluster size and density, especially for 'digital tech' entrants where revenue/worker and high-growth episodes rose. However, it also raised crowding and churn, with de-concentration – and loss of revenue productivity – for a much larger set of incumbent 'digital content' plants. 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 appears to have overheated parts of it. In turn, the programme’s distributional impacts are highly uneven. 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.

This paper has some limitations, which 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-level data could plug this gap. Second, I am unable to look directly at linkages from angel and venture capital finance to firm growth. Other studies suggest this is an important channel for SMEs to scale (Kerr et al., 2011), and VC dealflow has increased greatly in London since 2011.[16] Third, my distributional analysis focuses on technology industry space. An alternative analysis could explore outcomes for cluster entrants versus incumbents. Finally, I do not directly test the effect of business support programmes – such as the Future Fifty[17] – within the policy mix. Evaluating their effectiveness and value for money is an important complement to this aggregate analysis.

[16] https://www.ft.com/content/0ff8687c-8f52-11e4-b080-00144feabdc0, accessed 15 August 2018.
[17] https://technation.io/programmes/future-fifty/, accessed 15 August 2018.

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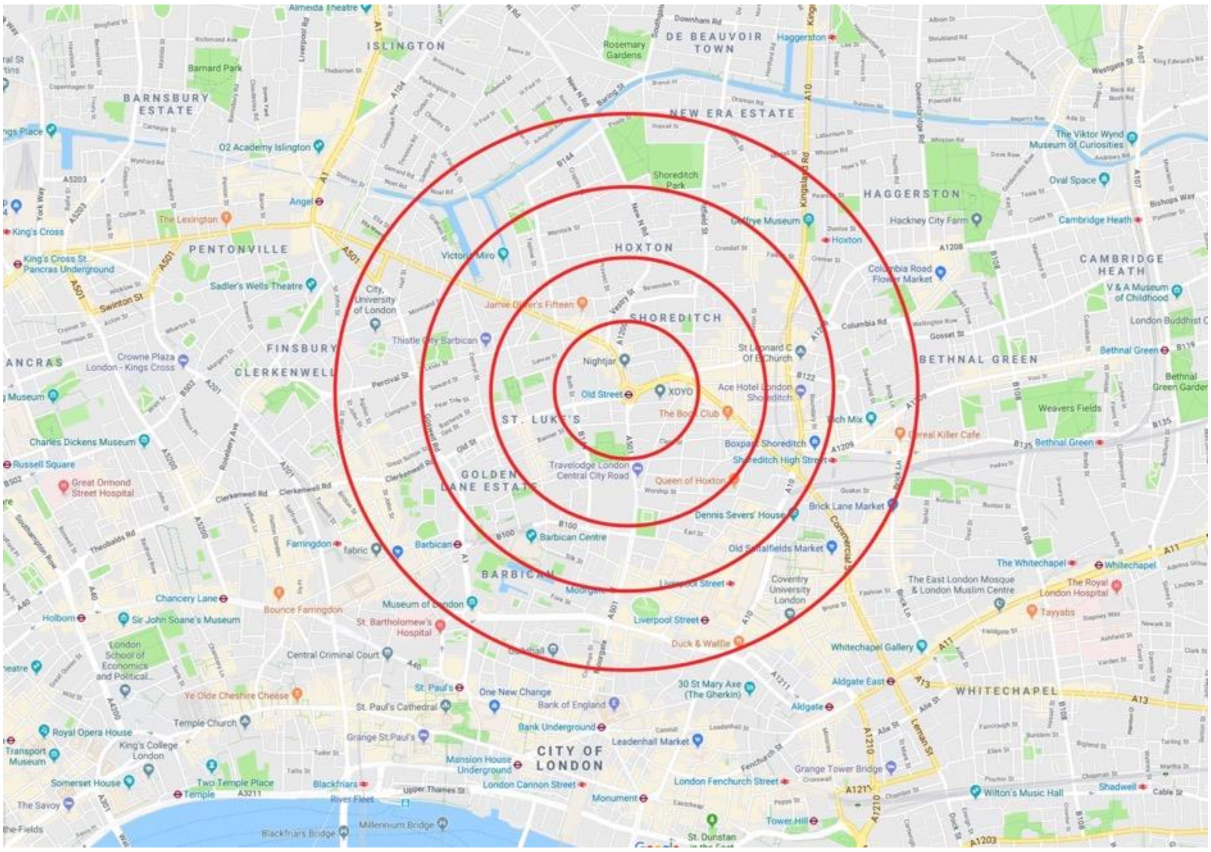
Figures and tables.

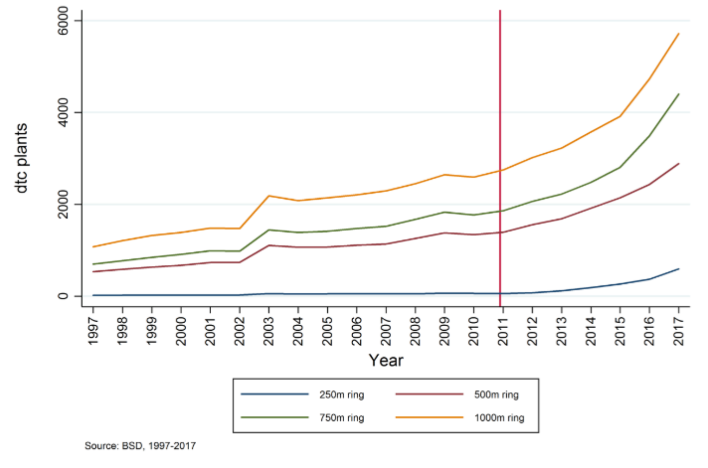
Figure 1. The Tech City area.



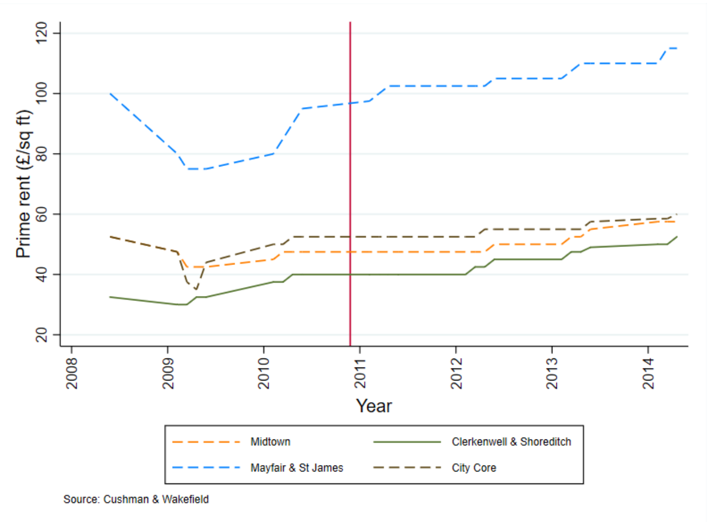
Source: Google Maps. Red circles show approx. 250m rings around Old St roundabout. The cluster zone is defined as the 1km ring from the roundabout.

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

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



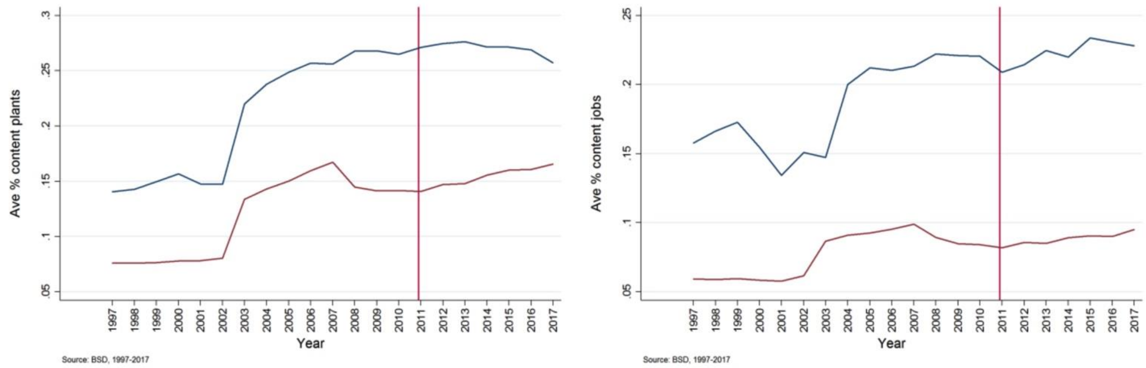
B. Prime rents for Clerkenwell and Shoreditch submarket, 2008-2014.



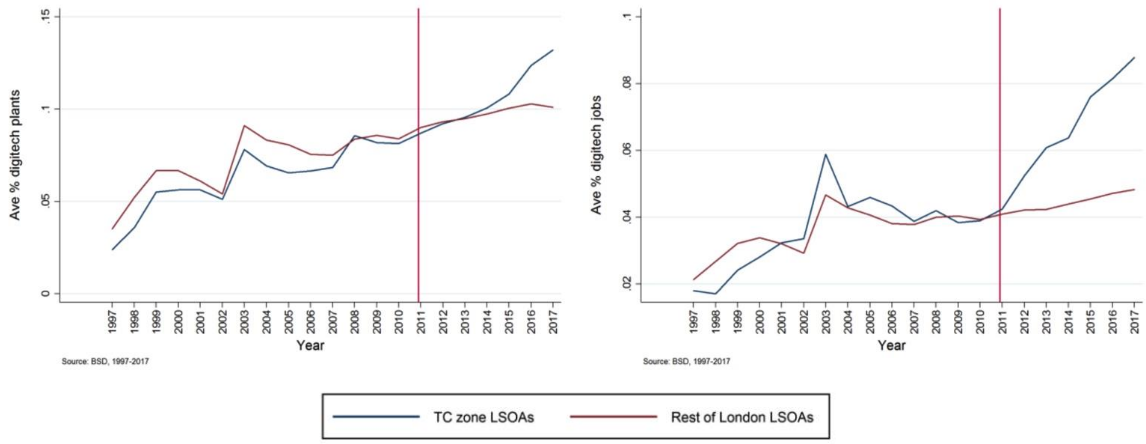
Source: BSD, Cushman & Wakefield. Prime rents for four Inner London C&W 'submarket geographies', Clerkenwell and Shoreditch, Mayfair and St James, Midtown (Holborn and Temple), City Core (City of London).

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



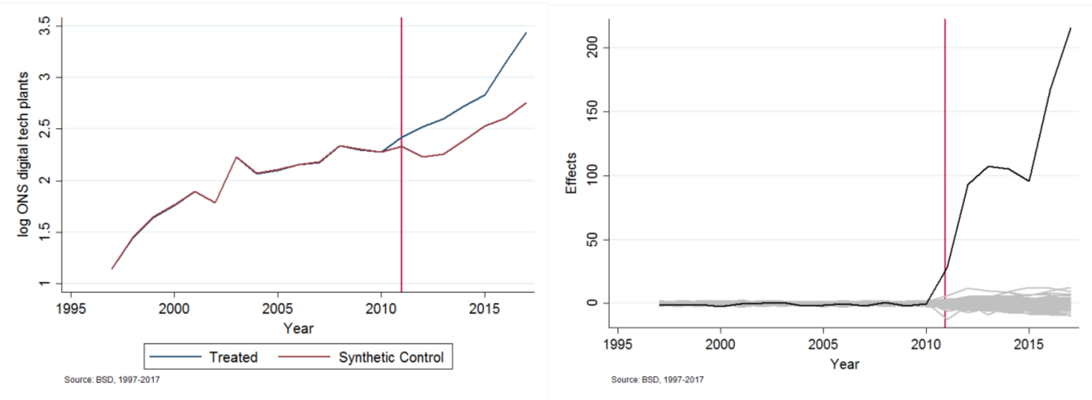
B. Digital technology. L: plants / all plants. R. jobs / all jobs



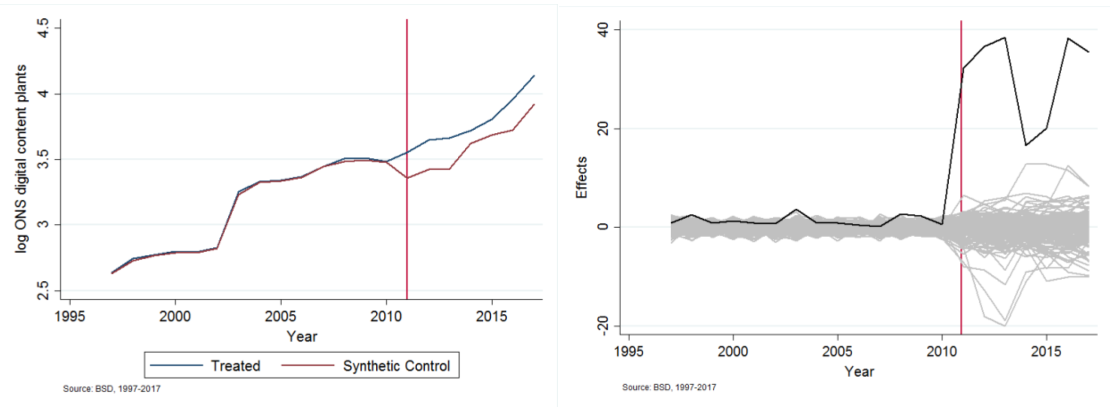
Graphs show % tech plants (jobs) as a share of all plants (jobs) in all industries, for average Tech City LSOA vs average rest of London LSOA. Top row: digital content. Bottom row: digital technology. Digital content activity includes advertising, media, design and web services Digital tech activity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

Figure 4. Cluster size analysis: Tech City vs. synthetic Tech City plants.

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



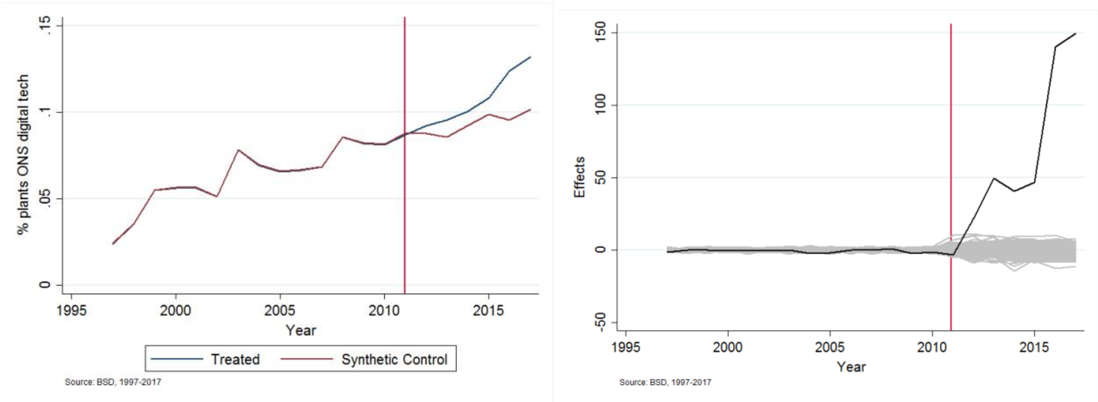
B. Log digital content plants: treatment vs control (L); weighted effect sizes (R)



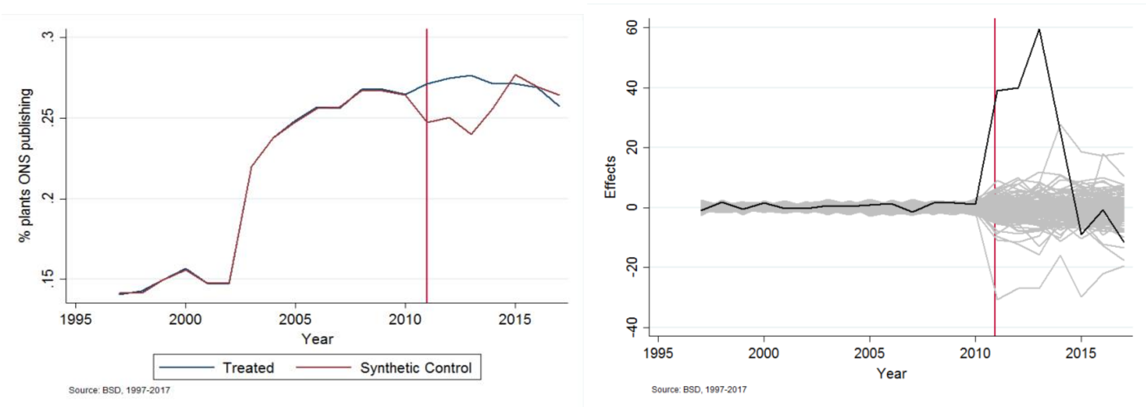
The left column shows outcomes for Tech City versus synthetic Tech City. The right column shows relative/weighted effect sizes for Tech City (bold line) versus placebo tests for 185 units in the donor pool. Effect sizes are weighted by pre-treatment RMSPE as in Galiani and Quistorff (2016).

Figure 5. Cluster density analysis: Tech City vs. synthetic Tech City plants.

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



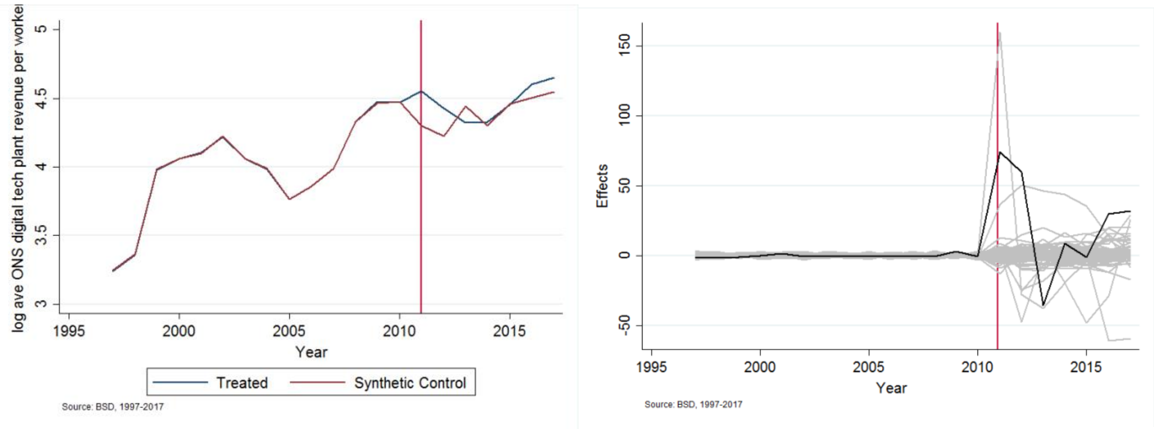
B. % digital content plants: treatment vs control (L); weighted effect sizes (R)



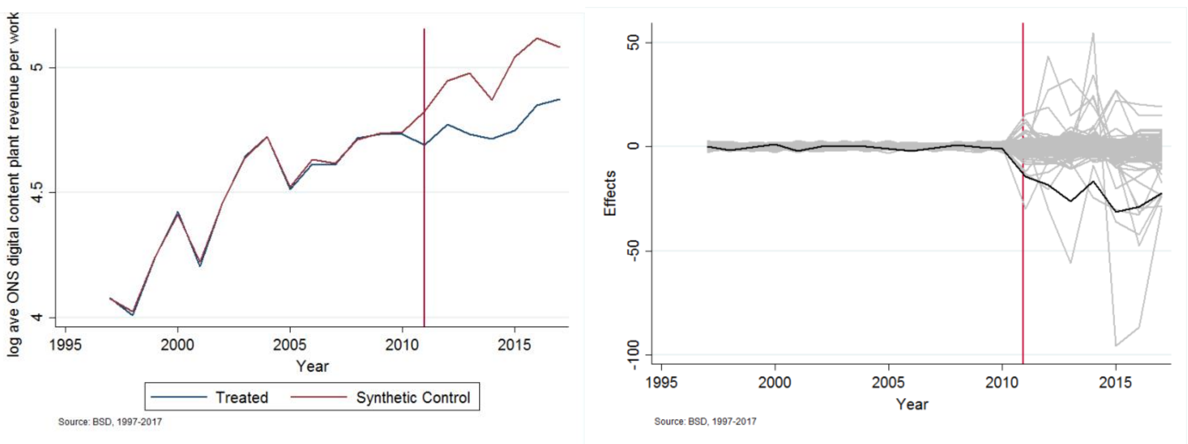
The left column shows outcomes for Tech City versus synthetic Tech City. The right column shows relative/weighted effect sizes for Tech City (bold line) versus placebo tests for 185 units in the donor pool. Effect sizes are weighted by pre-treatment RMSPE as in Galiani and Quistorff (2016).

Figure 6. Cluster firm performance: Tech City vs. synthetic Tech City.

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



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



The left column shows outcomes for Tech City versus synthetic Tech City. The right column shows relative/weighted effect sizes for Tech City (bold line) versus placebo tests for 185 units in the donor pool. Effect sizes are weighted by pre-treatment RMSPE as in Galiani and Quistorff (2016).

Table 1. Mean characteristics for Tech City LSOAs versus rest of Greater London LSOAs, 1997-2010.

Variable	TC unit	ROGL unit
LSOA total plant entry	3.500	0.963
ONS digital tech plant entry	0.251	0.088
ONS digital content plant entry	0.689	0.112
ONS digitech & content plant entry	0.929	0.197
GI tech plant entry	1.300	0.347
ONS plant count	X	X
ONS digital tech plant count	15.854	4.297
ONS content plant count	57.503	9.620
ONS digitech & content plant count	72.406	13.616
GI tech plant count	103.826	26.952
% plants ONS digital tech	0.063	0.071
% plants ONS digital content	0.208	0.118
% plants ONS digital tech & content	0.267	0.184
% plants GI tech	0.359	0.361
LSOA total employment	4199.506	796.347
ONS digital tech employment	172.100	21.944
ONS content plant employment	928.866	76.554
ONS digitech & content plant employment	1070.226	96.179
GI tech plant employment	1941.463	291.417
% employment ONS digital tech	0.036	0.036
% employment ONS digital content	0.185	0.077
% employment ONS digital tech & content	0.218	0.109
% employment GI tech	0.357	0.329
LSOA total revenue per worker	1.35e+05	17763.513
Total ONS digital tech revenue	1816.104	429.743
Total ONS content plant revenue	8931.765	1440.213
Total ONS digitech & content plant revenue	10654.802	1838.854
GI tech plant revenue	1.01e+05	8019.650
LSOA mean plant revenue per worker	274.280	110.875
mean ONS digital tech revenue per worker	86.051	83.444
mean ONS content revenue per worker	145.584	101.966
mean ONS digitech & content revenue per worker	142.313	92.411
Mean GI tech revenue per worker	409.367	104.468
Observations	*350*	*67144*

Source: BSD. Table compares pre-2011 means for an LSOA in the Tech City zone (23 LSOAs) for an LSOA in the rest of Greater London (c. 4800 LSOAs).

Table 2. Control units: results of propensity score matching on treatment status, 1997-2010.

Variable	Pre-treatment means			T-test		$V_e(T)/V_e(C)$
	Treated	Control	%bias	*t*	*p>t*	
# plant entry ONS digitech & content	0.953	0.504	32.5	3.32	0.001	0.60*
mean revenue ONS digitech & content	1484.6	2071.1	-15.5	-1.11	0.269	0.14**
mean revenue/worker ONS digitech & content	142.31	152.77	-2.9	-0.24	0.81	0.23**
% plants ONS digital tech and content	0.274	0.272	1.9	0.23	0.82	0.71*
% employment ONS digital tech and content	0.224	0.232	-5.7	-0.58	0.562	0.67*
Herfindahl Index	0.147	0.141	13.4	1.92	0.055	0.74*
% cafes and restaurants	0.028	0.029	-4.9	-0.64	0.524	0.62*
% bars cafes and clubs	0.016	0.019	-16.3	-1.58	0.115	0.31**
% coworking and shared offices	0.007	0.008	-5.1	-0.65	0.517	0.77*
% galleries and museums	0.002	0.002	-2.2	-0.2	0.842	0.55*
% libraries	0.001	0.001	1.4	0.18	0.86	0.19**
% other accommodation	0.000	0.000	0.3	0.11	0.914	0.94
% artists and performers	0.043	0.040	5.6	0.73	0.463	0.43**
% arts and arts support facilities	0.001	0.001	3.3	0.42	0.673	0.87
% universities and colleges	0.003	0.003	-0.2	-0.02	0.98	0.31**
count of TFL stations	0.123	0.135	-3.3	-0.34	0.733	0.35**
Summary stats	*MeanBias*	*MedBias*	*B*	*R*	*%concern*	*%bad*
	7.2	*4.1*	*38.4**	*0.89*	*41*	*41*

Source: BSD 1997-2010, 1991/2001/2011 Census, ONS mid-year population estimates, TFL. Probit regression where dependent variable = LSOA is in the Tech City Zone. Nearest neighbour matching when nn = 1. I impose the common support condition and keep the LSOAs with the 25% highest propensity scores, leaving 185 matched control units. Variance ratio (V_eT / V_eC) should equal 1 if matched group is perfectly balanced with treatment group. * = variance ratio is 'of concern', i.e. variance ratio in [0.5, 0.8) or (1.25, 2]. ** = variance ratio is 'bad', i.e. variance ratio <0.5 or >2. 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 3. 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)	1.321	1.321	0.713
Log digitech plants (1998)	1.557	1.564	1.054
Log digitech plants (1999)	1.769	1.771	1.310
Log digitech plants (2000)	1.930	1.942	1.291
Log digitech plants (2001)	2.198	2.177	1.277
Log digitech plants (2002)	2.056	2.045	1.172
Log digitech plants (2003)	2.537	2.521	1.695
Log digitech plants (2004)	2.372	2.385	1.646
Log digitech plants (2005)	2.402	2.402	1.596
Log digitech plants (2006)	2.473	2.471	1.583
Log digitech plants (2007)	2.492	2.502	1.623
Log digitech plants (2008)	2.560	2.551	1.767
Log digitech plants (2009)	2.599	2.609	1.774
Log digitech plants (2010)	2.572	2.559	1.716
Plant entry	3.714	3.486	2.190
Revenue / worker	220.701	220.347	129.752
Herfindahl Index	0.135	0.136	0.144
LSOA total cafes and restaurants	8.332	7.821	6.239
LSOA total bars pubs and clubs	3.411	3.584	2.214
LSOA total coworking spaces	1.700	2.055	1.835
LSOA total museums and galleries	0.204	0.201	0.190
LSOA total libraries	0.289	0.287	0.145
LSOA total other accommodation	0.071	0.071	0.092
LSOA total arts and arts support activities	12.943	12.835	7.884
LSOA total supporting arts orgs	0.271	0.285	0.331
LSOA total HEIs	0.593	0.607	0.498
LSOA count of TFL stations	0.139	0.140	0.124
LA share of non-UK born	0.308	0.309	0.327
LA share of residents aged 18-29	0.230	0.230	0.211

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

Table 4. Effects on cluster size: synthetic control / DID estimates

	Log tech plants		**Log tech jobs**	
	Digitech	**Content**	**Digitech**	**Content**
Synthetic control ATT	0.367***	0.191***	1.062***	0.377***
p-value	0.005	0.005	0.005	0.005
Number of placebos	185	185	185	185
Pre-treatment RMSPE	0.003	0.006	0.014	0.011
% placebo > treated RSMPSE	100	100	100	100
Diff-in-diff ATT	*0.35****	*0.16***	*0.51****	*0.48****
	(0.120)	*(0.074)*	*(0.140)*	*(0.134)*
Observations	*3913*	*4025*	*3912*	*4021*
R^2	*0.81*	*0.93*	*0.81*	*0.89*
Pre-treatment LSOA mean	15.854	57.50	172.10	928.87

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%.

Table 5. Effects on cluster density: synthetic control and DID estimates.

	% tech plants		% tech jobs	
	Digitech	**Content**	**Digitech**	**Content**
Synthetic control ATT	0.013***	0.012***	0.021***	0.016***
p-value	0.005	0.005	0.005	0.005
Number of placebos	185	185	185	185
Pre-treatment RMSPE	0	0.001	0	0.002
% placebo > treated RSMPSE	100	100	100	100
Diff-in-diff ATT	*0.03****	*0.02**	*0.02***	*0.05***
	(0.009)	*(0.009)*	*(0.009)*	*(0.021)*
Observations	*4100*	*4100*	*4100*	*4100*
R^2	*0.57*	*0.72*	*0.49*	*0.60*
Pre-treatment LSOA mean	0.063	0.208	0.036	0.185

Notes as in Table 4.

Table 6. Effects on tech firm performance: synthetic control and DID estimates.

	Log ave rev/worker	
	Digitech	**Content**
Synthetic control ATT	0.080**	-0.211**
p-value	0.011	0.016
Number of placebos	185	185
Pre-treatment RMSPE	0.003	0.009
% placebo > treated RSMPSE	100	99.5
Diff-in-diff ATT	*0.06*	*-0.09*
	(0.063)	*(0.074)*
Observations	*3911*	*3783*
R^2	*0.40*	*0.59*
Pre-treatment LSOA mean	86.051	145.584

Notes as in Table 4.

Table 7. Tech City policy effects: timing / falsification tests.

	Plants		Jobs		% plants		% jobs		Ave rev/worker	
	Digitech	**Content**	**Digitech**	**Content**	**Digitech**	**Content**	**Digitech**	**Content**	**Digitech**	**Content**
Synthetic control ATT	0.367***	0.191***	1.062***	0.377***	0.013***	0.012***	0.021***	0.016***	0.080**	-0.211**
p-value	*0.005*	*0.005*	*0.005*	*0.005*	*0.005*	*0.005*	*0.005*	*0.005*	*0.011*	*0.016*
RMSPE	*0.003*	*0.006*	*0.014*	*0.011*	*0*	*0.001*	*0*	*0.002*	*0.003*	*0.009*
Start treatment in 2008	0.258***	0.324**	0.705**	0.530***	0.013***	0.050***	0.014***	0.041***	0.146***	0.04
	0.005	*0.011*	*0.016*	*0.005*	*0.005*	*0.005*	*0.005*	*0.005*	*0.005*	*0.054*
	0.009	*0.007*	*0.023*	*0.011*	*0.000*	*0.000*	*0.000*	*0.001*	*0.001*	*0.004*
Start treatment in 2008, end in 2010	0.043**	0.142**	0.033*	0.347**	-0.002**	0.046***	-0.002**	0.046***	0.007***	0.131**
	0.043	*0.011*	*0.081*	*0.022*	*0.011*	*0.005*	*0.07*	*0.005*	*0.005*	*0.038*
	0.009	*0.007*	*0.023*	*0.011*	*0.000*	*0.000*	*0.000*	*0.001*	*0.001*	*0.004*
End treatment in 2014	0.201***	0.145**	0.823***	0.136	0.012***	0.034**	0.012***	-0.005**	0.016**	-0.059**
	0.005	*0.027*	*0.005*	*0.113*	*0.005*	*0.016*	*0.005*	*0.016*	*0.011*	*0.032*
	0.011	*0.019*	*0.029*	*0.03*	*0.000*	*0.002*	*0.000*	*0.002*	*0.001*	*0.004*
Effect size / year, 2011-2017	*0.052*	*0.027*	*0.152*	*0.054*	*0.002*	*0.002*	*0.003*	*0.002*	*0.011*	*-0.030*
Effect size / year, 2008-2010	*0.014*	*0.047*	*0.011*	*0.116*	*-0.001*	*0.015*	*-0.001*	*0.015*	*0.002*	*0.044*
Effect size / year, 2011-2014	*0.067*	*0.048*	*0.274*	*0.045*	*0.004*	*0.011*	*0.004*	*-0.002*	*0.005*	*-0.020*

Notes as in Table 4.

Table 8. Churn in the cluster: tech plant entry, exit and movement.

	2009 - 2010		2013 - 2014		2016 - 2017	
	count	**%**	**count**	**%**	**count**	**%**
UK tech plants	1,273,436		1,376,168		1,581,100	
Tech City tech plants	3,059		3,889		6,253	
Present in both years	1,844	60.2	2,202	56.6	3,460	55.3
Present in last year of pair only	607	19.8	977	58.1	2,082	33.3
Of which						
Movers from rest of London	*150*	*24.7*	*178*	*18.2*	*481*	*23.1*
Movers from rest of UK	*32*	*5.3*	*65*	*6.7*	*130*	*6.2*
New / new in BSD	*425*	*70*	*734*	*75.1*	*1,471*	*70.6*
Present in first year of pair only	608	19.9	710	18.3	711	11.4
Of which						
Moved to rest of London	*142*	*23.4*	*213*	*30*	*303*	*42.6*
Moved to rest of UK	*43*	*7.1*	*34*	*4.8*	*79*	*11.1*
Died / left BSD	*423*	*69.5*	*463*	*65.2*	*329*	*46.3*

Source: BSD.

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 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.

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.

This version of the BSD shows a gradual increase in the UK stock of live plants over time, with a decline after the Great Financial Crisis, from 2009 - 2012. This pattern is broadly mirrored in Greater London, although the post-crash decline is shorter and gentler, in line with secondary studies.[18] By contrast, the raw plant counts (before cleaning for dead plants, duplicates etc.) show much more volatility (Table A1).

[18] Gordon IR. (2016) Quantitative easing of an international financial centre: how central London came so well out of the post-2007 crisis. Cambridge Journal of Regions, Economy and Society 9: 335-353.

Table A1. Basic panel shapes: raw plant-level data.

Year	All plants	Live plants	London live plants
1997	2,800,732	2,397,130	361,709
1998	3,203,902	2,477,372	376,612
1999	3,181,018	2,512,861	384,445
2000	3,196,472	2,491,759	386,746
2001	3,293,706	2,533,109	392,443
2002	3,388,364	2,544,367	392,070
2003	3,809,199	2,436,439	383,666
2004	3,868,854	2,609,750	386,411
2005	3,866,165	2,659,510	392,682
2006	4,266,324	2,716,299	399,082
2007	4,711,449	2,799,470	414,735
2008	5,119,814	2,802,056	416,553
2009	5,069,402	2,763,255	425,678
2010	5,445,415	2,691,489	417,468
2011	4,027,312	2,644,698	416,090
2012	3,570,326	2,731,916	446,350
2013	3,563,183	2,747,326	458,922
2014	3,642,049	2,858,588	490,055
2015	3,718,352	2,950,831	519,095
2016	3,823,996	3,054,766	550,684
2017	3,973,101	3,179,814	580,940

Source: BSD. london_live_plants gives the underlying number of observations used to build the LSOA*year cells. raw_plants and live_plants are comparator panels built for the whole of the UK.

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 A2. 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. Mean tech plant and job counts for Tech City LSOAs versus rest of Greater London LSOAs, 1997-2017.

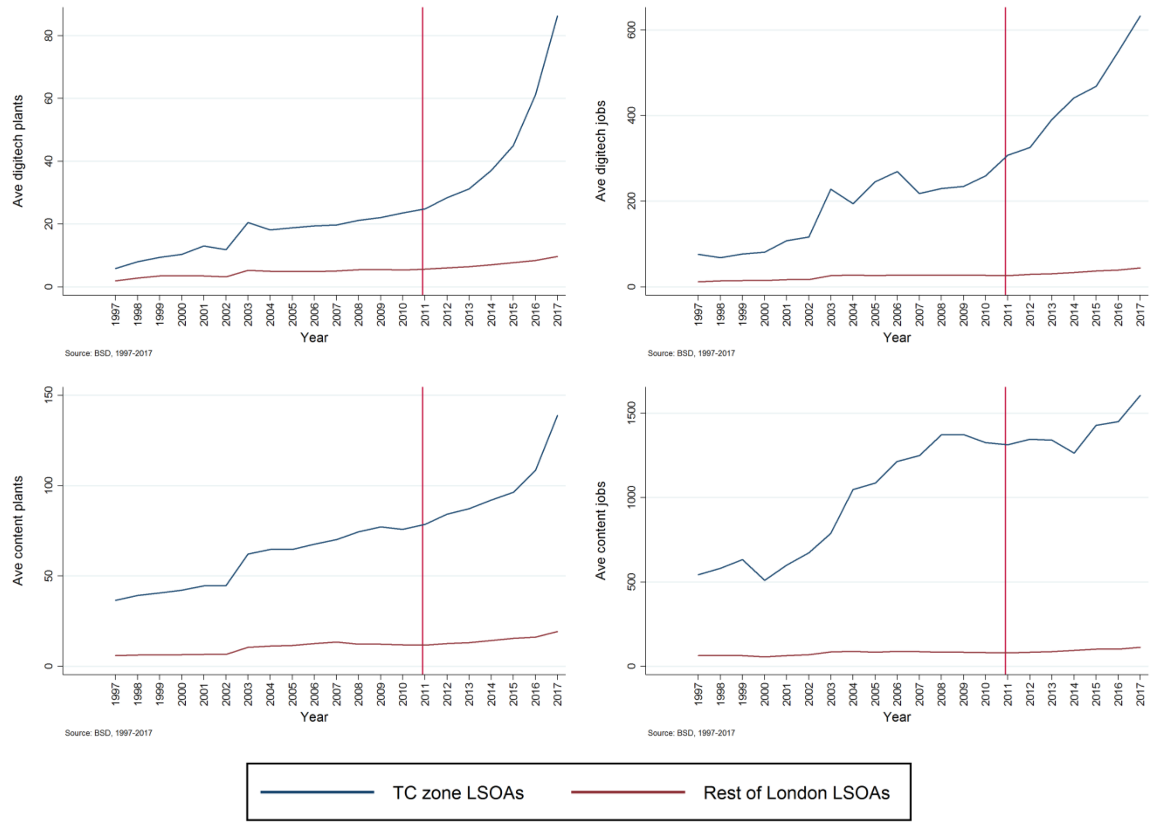


Figure B2. Mean tech plant revenue per worker for Tech City LSOAs versus rest of Greater London LSOAs, 1997-2017.

Digital tech firms. Digital content firms.

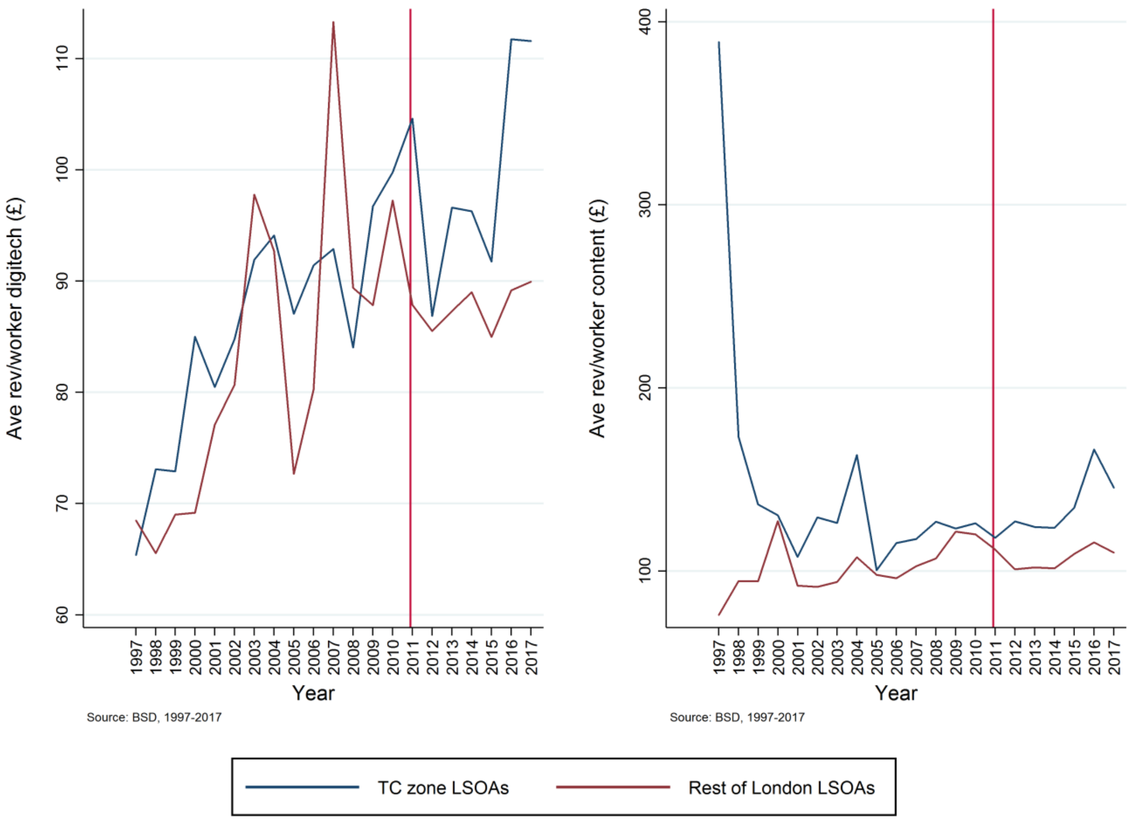
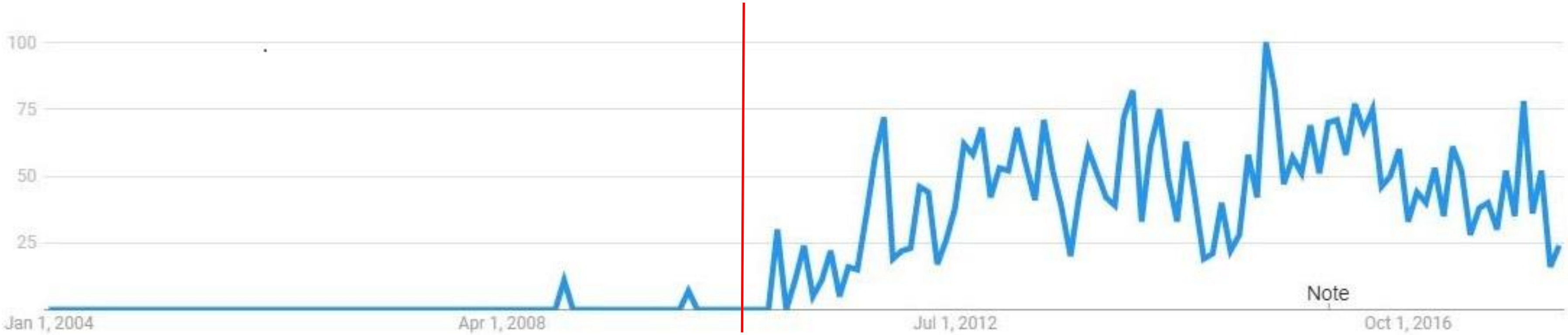


Figure B3. Google Trends analysis.

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.

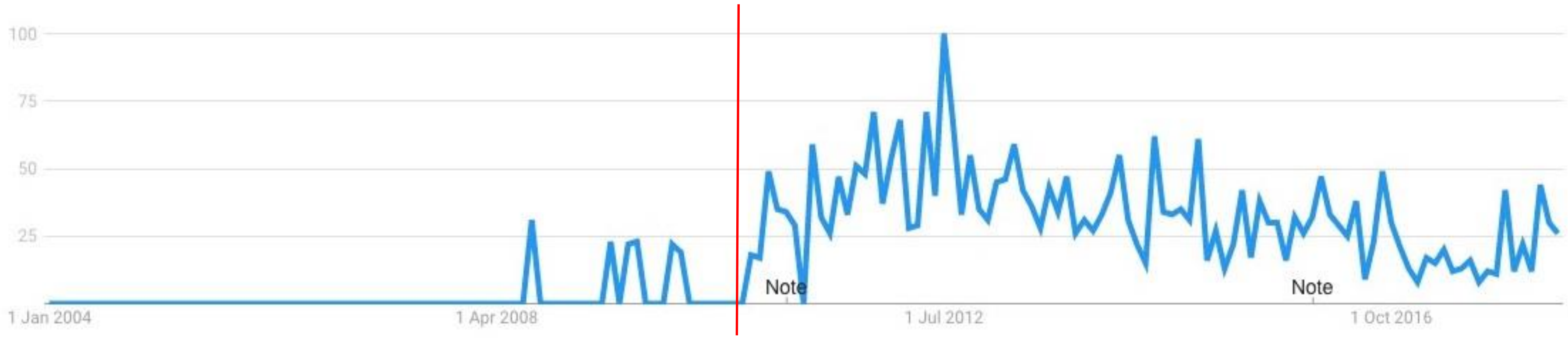
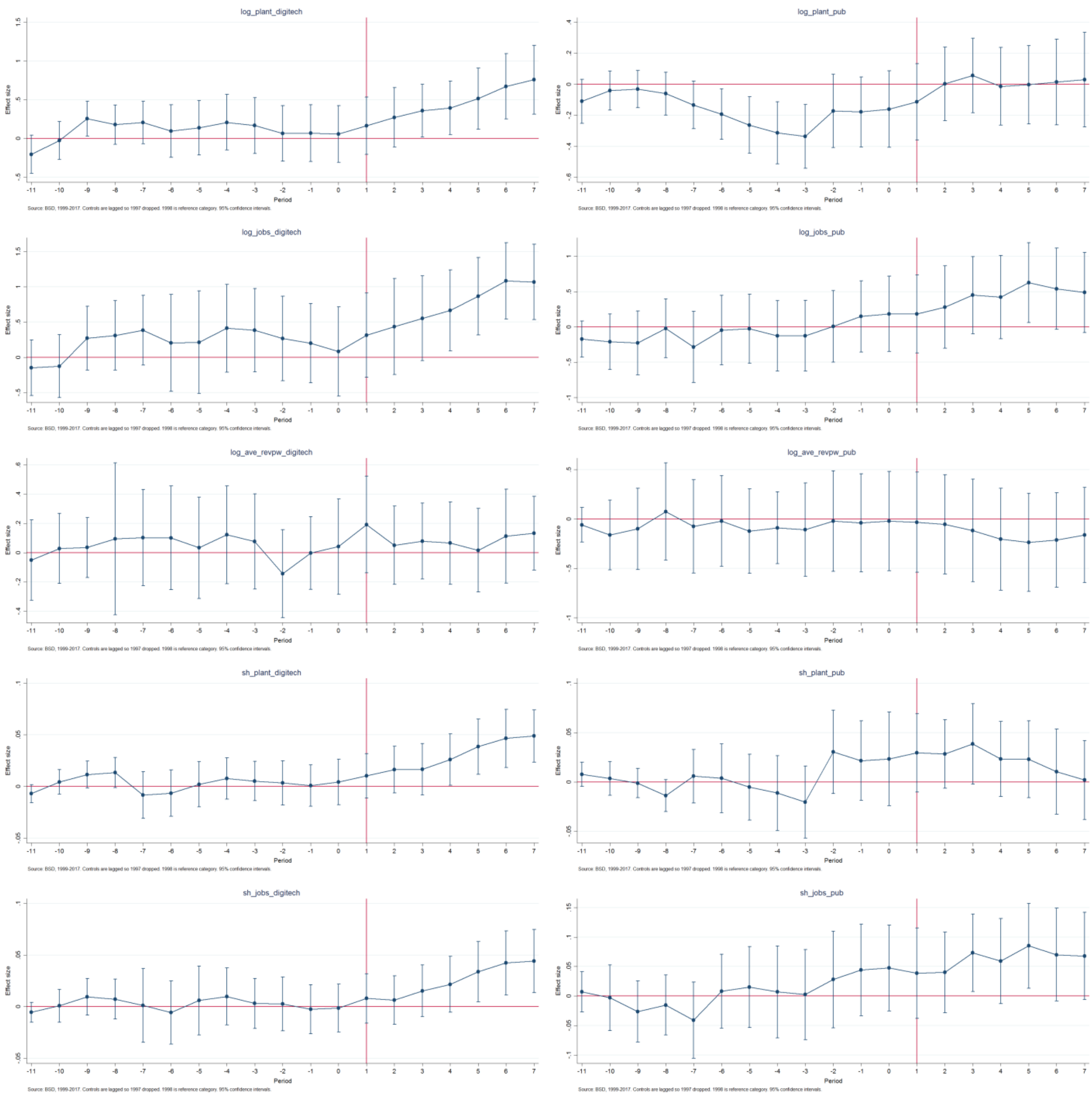


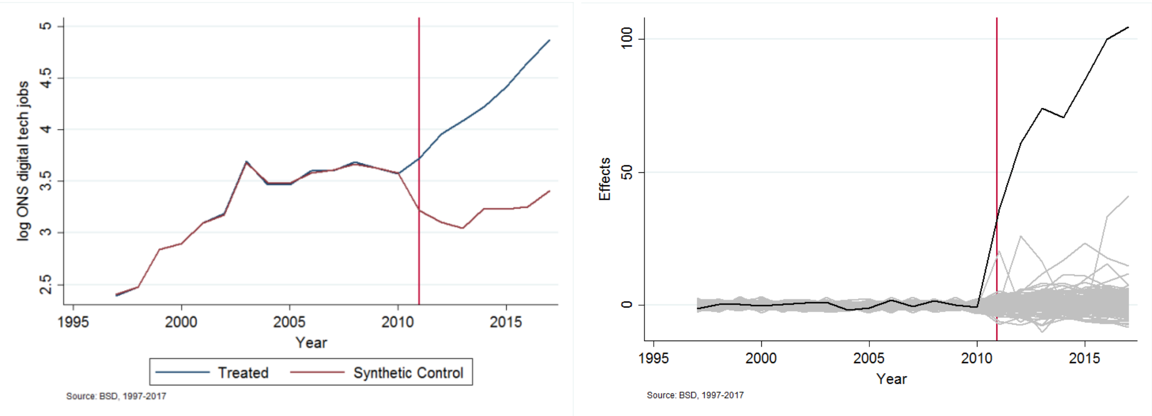
Figure B4. Balancing regressions for Tech City zone vs. matched sample of control LSOAs, 1999-2017.



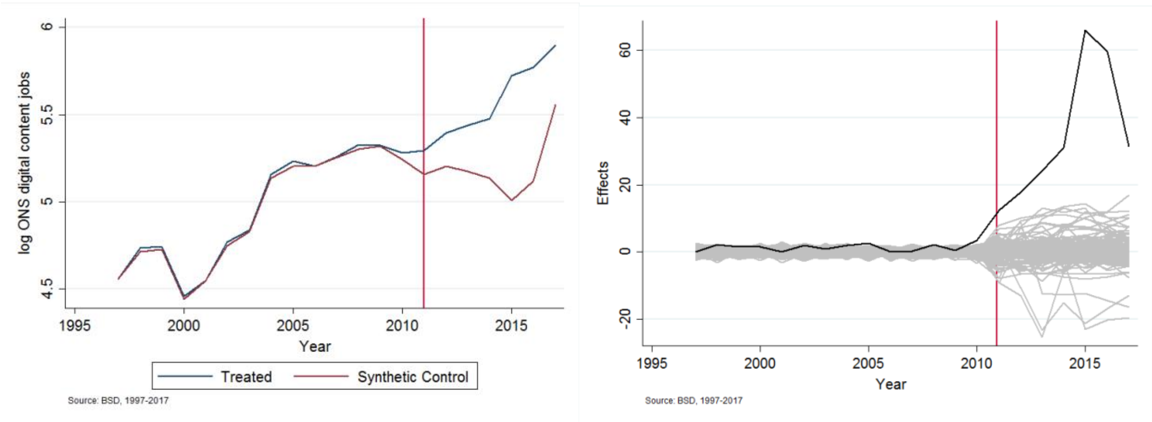
Source: BSD, Census, ONS mid-year population estimates, TFL. 95% confidence intervals. 1998 is reference category, 1997 dropped via lags. All regressions fit LSOA and year dummies. Time-varying controls fitted are one-year lags of LSOA all-sector plant entry, LSOA all-sector revenue/worker, LSOA Herfindahl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

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



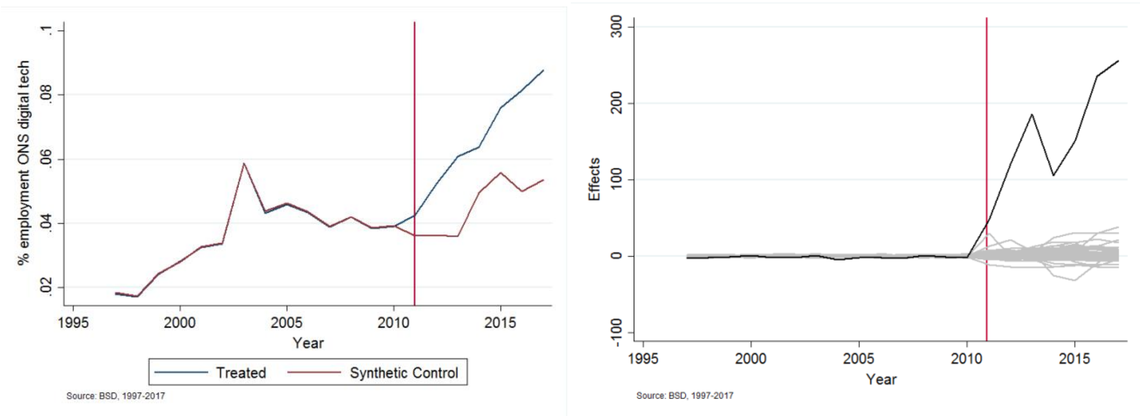
B. Log digital content jobs: treatment vs control (L); weighted effect sizes (R)



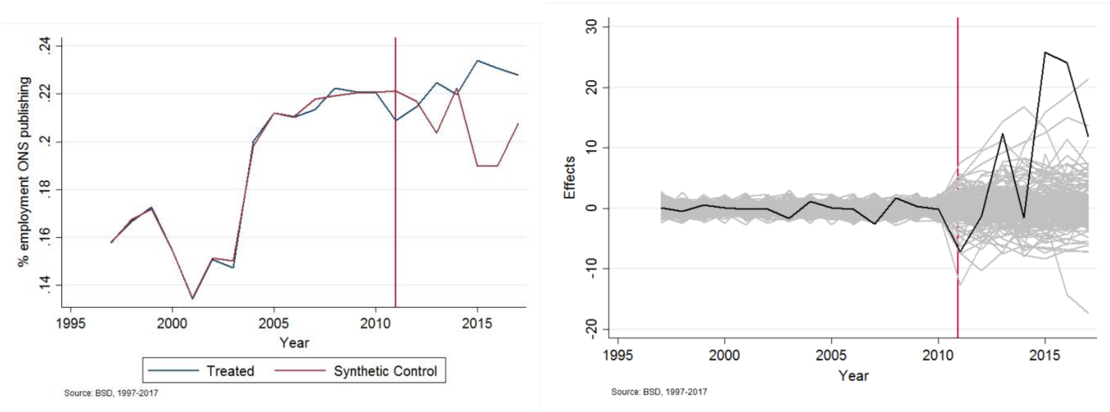
The left column shows outcomes for Tech City versus synthetic Tech City. The right column shows relative/weighted effect sizes for Tech City (bold line) versus placebo tests for 185 units in the donor pool. Effect sizes are weighted by pre-treatment RMSPE as in Galiani and Quistorff (2016).

Figure B6. Cluster density analysis: Tech City vs. synthetic Tech City jobs.

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

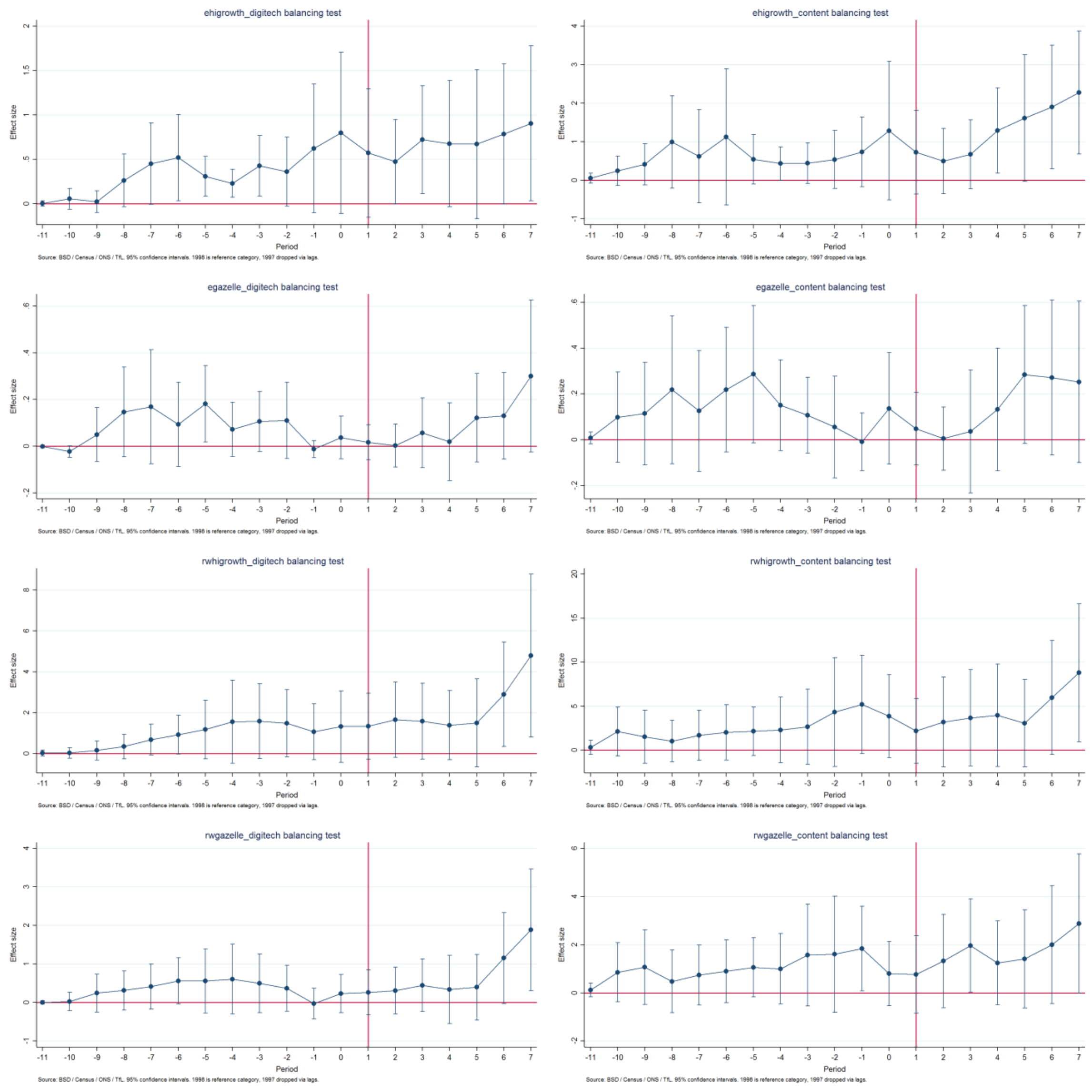


B. % digital content jobs: treatment vs control (L); weighted effect sizes (R)



The left column shows outcomes for Tech City versus synthetic Tech City. The right column shows relative/weighted effect sizes for Tech City (bold line) versus placebo tests for 185 units in the donor pool. Effect sizes are weighted by pre-treatment RMSPE as in Galiani and Quistorff (2016).

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 and LA characteristics for Tech City LSOAs versus rest of Greater London LSOAs, 1997-2010: amenities and demographics.

Variable	TC unit	ROGL unit
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 galleries and museums	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 (23 LSOAs) for an LSOA in the rest of Greater London (c. 4800 LSOAs).

Table B2. Tech city control areas: 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 content plants (1997)	3.034	3.043	1.745
Log content plants (1998)	3.152	3.138	1.770
Log content plants (1999)	3.192	3.166	1.825
Log content plants (2000)	3.184	3.170	1.811
Log content plants (2001)	3.227	3.233	1.851
Log content plants (2002)	3.223	3.242	1.865
Log content plants (2003)	3.647	3.611	2.281
Log content plants (2004)	3.713	3.709	2.410
Log content plants (2005)	3.700	3.698	2.468
Log content plants (2006)	3.735	3.754	2.559
Log content plants (2007)	3.799	3.819	2.629
Log content plants (2008)	3.891	3.850	2.539
Log content plants (2009)	3.915	3.904	2.530
Log content plants (2010)	3.908	3.900	2.498
Plant entry	3.714	3.498	2.190
Revenue / worker	220.701	220.627	129.752
Herfindahl Index	0.135	0.135	0.144
LSOA total cafes and restaurants	8.332	8.292	6.239
LSOA total bars pubs and clubs	3.411	3.437	2.214
LSOA total coworking spaces	1.700	1.959	1.835
LSOA total museums and galleries	0.204	0.217	0.190
LSOA total libraries	0.289	0.286	0.145
LSOA total other accommodation	0.071	0.072	0.092
LSOA total arts and arts support activities	12.943	12.946	7.884
LSOA total supporting arts orgs	0.271	0.286	0.331
LSOA total HEIs	0.593	0.596	0.498
LSOA count of TFL stations	0.139	0.139	0.124
LA share of non-UK born	0.308	0.308	0.327
LA share of residents aged 18-29	0.230	0.230	0.211

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

Underlying cell counts: Tech City = 23 LSOAs * 13 years. Synthetic Tech City = single observation weighted from 181 LSOAs * 13 years. Matched sample = 181 LSOAs * 13 years.

Table B2 continued.

Variable	Tech City	Synthetic Tech City	Matched sample
Log digitech jobs (1997)	2.818	2.829	1.460
Log digitech jobs (1998)	2.775	2.785	1.722
Log digitech jobs (1999)	3.139	3.130	2.015
Log digitech jobs (2000)	3.189	3.190	2.000
Log digitech jobs (2001)	3.560	3.555	1.999
Log digitech jobs (2002)	3.595	3.573	1.953
Log digitech jobs (2003)	4.226	4.191	2.609
Log digitech jobs (2004)	3.948	3.983	2.522
Log digitech jobs (2005)	3.932	3.979	2.464
Log digitech jobs (2006)	4.097	4.048	2.430
Log digitech jobs (2007)	4.105	4.097	2.442
Log digitech jobs (2008)	4.085	4.042	2.506
Log digitech jobs (2009)	4.089	4.115	2.552
Log digitech jobs (2010)	3.962	3.995	2.497
Plant entry	3.714	3.403	2.190
Revenue / worker	220.701	220.443	129.752
Herfindahl Index	0.135	0.135	0.144
LSOA total cafes and restaurants	8.332	8.461	6.239
LSOA total bars pubs and clubs	3.411	3.535	2.214
LSOA total coworking spaces	1.700	2.178	1.835
LSOA total museums and galleries	0.204	0.215	0.190
LSOA total libraries	0.289	0.287	0.145
LSOA total other accommodation	0.071	0.071	0.092
LSOA total arts and arts support activities	12.943	12.615	7.884
LSOA total supporting arts orgs	0.271	0.302	0.331
LSOA total HEIs	0.593	0.581	0.498
LSOA count of TFL stations	0.139	0.137	0.124
LA share of non-UK born	0.308	0.309	0.327
LA share of residents aged 18-29	0.230	0.230	0.211

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

Underlying cell counts: Tech City = 23 LSOAs * 13 years. Synthetic Tech City = single observation weighted from 181 LSOAs * 13 years. Matched sample = 181 LSOAs * 13 years.

Table B2 continued.

Variable	Tech City	Synthetic Tech City	Matched sample
Log content jobs (1997)	5.07	5.10	3.214
Log content jobs (1998)	5.29	5.25	3.327
Log content jobs (1999)	5.29	5.29	3.331
Log content jobs (2000)	5.02	5.00	3.193
Log content jobs (2001)	5.01	5.04	3.226
Log content jobs (2002)	5.24	5.25	3.296
Log content jobs (2003)	5.38	5.39	3.578
Log content jobs (2004)	5.74	5.71	3.728
Log content jobs (2005)	5.83	5.79	3.806
Log content jobs (2006)	5.80	5.84	3.901
Log content jobs (2007)	5.86	5.90	3.939
Log content jobs (2008)	5.97	5.94	3.875
Log content jobs (2009)	6.02	6.00	3.772
Log content jobs (2010)	5.98	5.92	3.706
Plant entry	3.71	3.37	2.190
Revenue / worker	220.70	219.67	129.752
Herfindahl Index	0.14	0.14	0.144
LSOA total cafes and restaurants	8.33	7.88	6.239
LSOA total bars pubs and clubs	3.41	3.54	2.214
LSOA total coworking spaces	1.70	2.10	1.835
LSOA total museums and galleries	0.20	0.21	0.190
LSOA total libraries	0.29	0.29	0.145
LSOA total other accommodation	0.07	0.07	0.092
LSOA total arts and arts support activities	12.94	13.05	7.884
LSOA total supporting arts orgs	0.27	0.28	0.331
LSOA total HEIs	0.59	0.60	0.498
LSOA count of TFL stations	0.14	0.14	0.124
LA share of non-UK born	0.31	0.31	0.327
LA share of residents aged 18-29	0.23	0.23	0.211

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

Underlying cell counts: Tech City = 23 LSOAs * 13 years. Synthetic Tech City = single observation weighted from 181 LSOAs * 13 years. Matched sample = 181 LSOAs * 13 years.

Table B2 continued.

Variable	Tech City	Synthetic Tech City	Matched sample
share digitech plants (1997)	0.028	0.028	0.044
share digitech plants (1998)	0.032	0.032	0.065
share digitech plants (1999)	0.042	0.042	0.081
share digitech plants (2000)	0.048	0.048	0.076
share digitech plants (2001)	0.056	0.056	0.077
share digitech plants (2002)	0.050	0.050	0.068
share digitech plants (2003)	0.082	0.082	0.123
share digitech plants (2004)	0.070	0.071	0.112
share digitech plants (2005)	0.073	0.073	0.104
share digitech plants (2006)	0.074	0.074	0.100
share digitech plants (2007)	0.072	0.072	0.099
share digitech plants (2008)	0.079	0.078	0.108
share digitech plants (2009)	0.080	0.080	0.109
share digitech plants (2010)	0.082	0.081	0.106
Plant entry	3.714	3.523	2.190
Revenue / worker	220.701	221.152	129.752
Herfindahl Index	0.135	0.136	0.144
LSOA total cafes and restaurants	8.332	8.493	6.239
LSOA total bars pubs and clubs	3.411	3.444	2.214
LSOA total coworking spaces	1.700	1.913	1.835
LSOA total museums and galleries	0.204	0.204	0.190
LSOA total libraries	0.289	0.289	0.145
LSOA total other accommodation	0.071	0.071	0.092
LSOA total arts and arts support activities	12.943	12.862	7.884
LSOA total supporting arts orgs	0.271	0.273	0.331
LSOA total HEIs	0.593	0.587	0.498
LSOA count of TFL stations	0.139	0.139	0.124
LA share of non-UK born	0.308	0.309	0.327
LA share of residents aged 18-29	0.230	0.230	0.211

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

Table B2 continued.

Variable	Tech City	Synthetic Tech City	Matched sample
share content plants (1997)	0.161	0.162	0.125
share content plants (1998)	0.164	0.163	0.119
share content plants (1999)	0.174	0.172	0.121
share content plants (2000)	0.168	0.168	0.119
share content plants (2001)	0.165	0.164	0.121
share content plants (2002)	0.162	0.167	0.125
share content plants (2003)	0.242	0.240	0.188
share content plants (2004)	0.256	0.257	0.209
share content plants (2005)	0.258	0.258	0.217
share content plants (2006)	0.266	0.268	0.231
share content plants (2007)	0.268	0.272	0.240
share content plants (2008)	0.291	0.286	0.212
share content plants (2009)	0.291	0.290	0.214
share content plants (2010)	0.295	0.293	0.215
Plant entry	3.714	3.348	2.190
Revenue / worker	220.701	219.054	129.752
Herfindahl Index	0.135	0.137	0.144
LSOA total cafes and restaurants	8.332	8.172	6.239
LSOA total bars pubs and clubs	3.411	3.596	2.214
LSOA total coworking spaces	1.700	2.297	1.835
LSOA total museums and galleries	0.204	0.210	0.190
LSOA total libraries	0.289	0.286	0.145
LSOA total other accommodation	0.071	0.071	0.092
LSOA total arts and arts support activities	12.943	12.301	7.884
LSOA total supporting arts orgs	0.271	0.279	0.331
LSOA total HEIs	0.593	0.619	0.498
LSOA count of TFL stations	0.139	0.161	0.124
LA share of non-UK born	0.308	0.311	0.327
LA share of residents aged 18-29	0.230	0.230	0.211

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

Table B2 continued.

Variable	Tech City	Synthetic Tech City	Matched sample
share digitech jobs (1997)	0.022	0.022	0.042
share digitech jobs (1998)	0.018	0.018	0.046
share digitech jobs (1999)	0.023	0.023	0.055
share digitech jobs (2000)	0.029	0.029	0.053
share digitech jobs (2001)	0.038	0.038	0.055
share digitech jobs (2002)	0.037	0.036	0.055
share digitech jobs (2003)	0.070	0.071	0.096
share digitech jobs (2004)	0.051	0.052	0.084
share digitech jobs (2005)	0.055	0.055	0.077
share digitech jobs (2006)	0.052	0.051	0.070
share digitech jobs (2007)	0.045	0.046	0.070
share digitech jobs (2008)	0.047	0.047	0.072
share digitech jobs (2009)	0.044	0.044	0.072
share digitech jobs (2010)	0.042	0.042	0.069
Plant entry	3.714	3.573	2.190
Revenue / worker	220.701	220.956	129.752
Herfindahl Index	0.135	0.136	0.144
LSOA total cafes and restaurants	8.332	8.683	6.239
LSOA total bars pubs and clubs	3.411	3.451	2.214
LSOA total coworking spaces	1.700	1.896	1.835
LSOA total museums and galleries	0.204	0.207	0.190
LSOA total libraries	0.289	0.290	0.145
LSOA total other accommodation	0.071	0.072	0.092
LSOA total arts and arts support activities	12.943	13.058	7.884
LSOA total supporting arts orgs	0.271	0.279	0.331
LSOA total HEIs	0.593	0.609	0.498
LSOA count of TFL stations	0.139	0.141	0.124
LA share of non-UK born	0.308	0.309	0.327
LA share of residents aged 18-29	0.230	0.230	0.211

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

Table B2 continued.

Variable	Tech City	Synthetic Tech City	Matched sample
share content jobs (1997)	0.179	0.179	0.141
share content jobs (1998)	0.189	0.191	0.150
share content jobs (1999)	0.199	0.198	0.152
share content jobs (2000)	0.181	0.180	0.143
share content jobs (2001)	0.155	0.155	0.144
share content jobs (2002)	0.172	0.172	0.148
share content jobs (2003)	0.173	0.175	0.176
share content jobs (2004)	0.236	0.235	0.196
share content jobs (2005)	0.251	0.252	0.202
share content jobs (2006)	0.251	0.251	0.211
share content jobs (2007)	0.258	0.261	0.220
share content jobs (2008)	0.269	0.266	0.204
share content jobs (2009)	0.268	0.268	0.184
share content jobs (2010)	0.268	0.268	0.181
Plant entry	3.714	3.392	2.190
Revenue / worker	220.701	220.363	129.752
Herfindahl Index	0.135	0.136	0.144
LSOA total cafes and restaurants	8.332	8.251	6.239
LSOA total bars pubs and clubs	3.411	3.527	2.214
LSOA total coworking spaces	1.700	2.125	1.835
LSOA total museums and galleries	0.204	0.208	0.190
LSOA total libraries	0.289	0.288	0.145
LSOA total other accommodation	0.071	0.071	0.092
LSOA total arts and arts support activities	12.943	12.779	7.884
LSOA total supporting arts orgs	0.271	0.296	0.331
LSOA total HEIs	0.593	0.598	0.498
LSOA count of TFL stations	0.139	0.140	0.124
LA share of non-UK born	0.308	0.309	0.327
LA share of residents aged 18-29	0.230	0.230	0.211

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

Table B2 continued.

Variable	Tech City	Synthetic Tech City	Matched sample
Log digitech revenue/worker (1997)	3.688	3.695	3.172
Log digitech revenue/worker (1998)	3.570	3.579	3.641
Log digitech revenue/worker (1999)	3.955	3.964	3.810
Log digitech revenue/worker (2000)	4.099	4.107	3.783
Log digitech revenue/worker (2001)	4.137	4.144	3.899
Log digitech revenue/worker (2002)	4.236	4.246	3.782
Log digitech revenue/worker (2003)	4.272	4.280	4.122
Log digitech revenue/worker (2004)	4.221	4.230	4.143
Log digitech revenue/worker (2005)	4.136	4.146	4.061
Log digitech revenue/worker (2006)	4.220	4.229	4.053
Log digitech revenue/worker (2007)	4.223	4.234	4.104
Log digitech revenue/worker (2008)	4.350	4.359	4.160
Log digitech revenue/worker (2009)	4.458	4.465	4.240
Log digitech revenue/worker (2010)	4.545	4.552	4.201
Plant entry	3.714	3.533	2.190
Revenue / worker	220.701	220.506	129.752
Herfindahl Index	0.135	0.136	0.144
LSOA total cafes and restaurants	8.332	8.564	6.239
LSOA total bars pubs and clubs	3.411	3.480	2.214
LSOA total coworking spaces	1.700	1.938	1.835
LSOA total museums and galleries	0.204	0.204	0.190
LSOA total libraries	0.289	0.288	0.145
LSOA total other accommodation	0.071	0.071	0.092
LSOA total arts and arts support activities	12.943	12.982	7.884
LSOA total supporting arts orgs	0.271	0.281	0.331
LSOA total HEIs	0.593	0.588	0.498
LSOA count of TFL stations	0.139	0.141	0.124
LA share of non-UK born	0.308	0.309	0.327
LA share of residents aged 18-29	0.230	0.231	0.211

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

Table B2 continued.

Variable	Tech City	Synthetic Tech City	Matched sample
Log content revenue/worker (1997)	4.479	4.477	3.877
Log content revenue/worker (1998)	4.363	4.365	4.051
Log content revenue/worker (1999)	4.608	4.604	4.064
Log content revenue/worker (2000)	4.436	4.431	4.157
Log content revenue/worker (2001)	4.406	4.415	4.123
Log content revenue/worker (2002)	4.522	4.520	4.176
Log content revenue/worker (2003)	4.643	4.644	4.274
Log content revenue/worker (2004)	4.772	4.767	4.404
Log content revenue/worker (2005)	4.605	4.604	4.363
Log content revenue/worker (2006)	4.716	4.721	4.487
Log content revenue/worker (2007)	4.725	4.722	4.499
Log content revenue/worker (2008)	4.854	4.847	4.488
Log content revenue/worker (2009)	4.843	4.839	4.496
Log content revenue/worker (2010)	4.862	4.860	4.548
Plant entry	3.714	3.393	2.190
Revenue / worker	220.701	219.621	129.752
Herfindahl Index	0.135	0.135	0.144
LSOA total cafes and restaurants	8.332	8.200	6.239
LSOA total bars pubs and clubs	3.411	3.540	2.214
LSOA total coworking spaces	1.700	2.088	1.835
LSOA total museums and galleries	0.204	0.203	0.190
LSOA total libraries	0.289	0.289	0.145
LSOA total other accommodation	0.071	0.071	0.092
LSOA total arts and arts support activities	12.943	12.742	7.884
LSOA total supporting arts orgs	0.271	0.280	0.331
LSOA total HEIs	0.593	0.600	0.498
LSOA count of TFL stations	0.139	0.143	0.124
LA share of non-UK born	0.308	0.309	0.327
LA share of residents aged 18-29	0.230	0.230	0.211

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

Table B3. Synthetic control: LSOAs used and weights assigned, by outcome.

Digitech plants		Content plants		Digitech jobs		Content jobs		Digitech revenue/worker	
lsoa	weight	lsoa	weight	lsoa	weight	lsoa	weight	lsoa	weight
4	0.045	19	0.018	2	0.057	2	0.04	2	0.049
8	0.027	23	0.008	8	0.044	16	0.042	8	0.074
16	0.064	24	0.033	11	0.023	31	0.026	12	0.001
24	0.039	25	0.004	16	0.059	47	0.052	24	0.023
25	0.005	31	0.012	24	0.008	48	0.002	25	0.007
48	0.03	44	0.085	25	0.005	54	0.005	30	0.002
54	0.02	48	0.005	31	0.019	55	0.002	39	0.008
69	0.01	58	0.025	47	0.038	69	0.07	42	0.004
75	0.205	69	0.024	69	0.051	72	0.039	48	0.004
80	0.023	72	0.014	72	0.025	75	0.166	58	0.013
96	0.037	75	0.186	74	0.077	84	0.071	69	0.041
104	0.053	95	0.01	75	0.103	87	0.019	75	0.054
106	0.06	104	0.058	79	0.031	95	0.016	76	0.081
109	0.007	105	0.052	90	0.016	97	0.066	104	0.09
110	0.013	106	0.074	103	0.012	104	0.078	106	0.035
131	0.017	115	0.079	104	0.088	105	0.027	110	0.143
132	0.007	131	0.001	107	0.022	129	0.032	112	0.025
138	0.031	133	0.008	109	0.048	133	0.014	115	0.042
154	0.01	134	0.003	131	0.031	134	0.09	117	0.01
159	0.044	138	0.029	138	0.07	138	0.044	137	0.016
165	0.11	147	0.005	152	0.017	163	0.01	138	0.102
175	0.098	159	0.063	157	0.069	165	0.045	154	0.03
188	0.028	165	0.08	165	0.018	173	0.01	169	0.059
194	0.017	173	0.112	175	0.057	175	0.008	171	0.044
		194	0.011	194	0.013	193	0.001	193	0.001
						194	0.011	194	0.013
						205	0.013	205	0.031

Source: BSD / Census / ONS / TfL.

Table B3 continued.

Content revenue/worker		% digitech plants		% content plants		% digitech jobs		% content jobs	
lsoa	weight	lsoa	weight	lsoa	weight	lsoa	weight	lsoa	weight
2	0.037	2	0.016	9	0.032	7	0.013	8	0.027
14	0.062	6	0.021	14	0.035	11	0.04	14	0.011
23	0.012	24	0.025	16	0.016	14	0.009	28	0.019
48	0.042	25	0.005	23	0.032	16	0.041	47	0.1
49	0.02	48	0.027	24	0.013	17	0.003	48	0.034
73	0.028	68	0.058	25	0.001	18	0.003	69	0.029
75	0.127	75	0.179	28	0.066	24	0.008	72	0.034
77	0.03	79	0.072	31	0.018	25	0.007	77	0.022
79	0.016	83	0.014	33	0.15	48	0.032	79	0.003
91	0.005	92	0.02	47	0.005	52	0.052	88	0.04
104	0.054	104	0.07	68	0.034	54	0.018	97	0.049
106	0.125	105	0.021	74	0.028	68	0.107	103	0.025
110	0.085	106	0.064	75	0.011	75	0.164	104	0.069
115	0.035	110	0.073	104	0.099	79	0.016	105	0.007
120	0.031	113	0.066	105	0.113	91	0.001	106	0.012
129	0.034	115	0.046	133	0.003	92	0.002	110	0.161
133	0.006	133	0.004	134	0.07	104	0.076	129	0.017
138	0.004	138	0.061	138	0.071	105	0.007	133	0.002
152	0.009	139	0.008	141	0.049	106	0.047	138	0.032
158	0.029	154	0.033	149	0.118	109	0.035	152	0.037
165	0.05	159	0.008	165	0.009	110	0.145	158	0.042
175	0.004	165	0.058	168	0.009	125	0.003	165	0.026
179	0.078	175	0.013	193	0.005	138	0.079	173	0.105
185	0.007	178	0.013	194	0.015	152	0.023	175	0.01
190	0.009	189	0.009			165	0.025	177	0.006
191	0.028	193	0.005			173	0.022	193	0.007
193	0.012	194	0.012			193	0.007	194	0.021
194	0.02					194	0.016	196	0.054

Source: BSD / Census / ONS / TfL.

Table B4. 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	*0.35****	*0.16***	*0.51****	*0.48****	*0.03****	*0.02**	*0.02***	*0.05***	*0.06*	*-0.09*
	(0.120)	*(0.074)*	*(0.140)*	*(0.134)*	*(0.009)*	*(0.009)*	*(0.009)*	*(0.021)*	*(0.063)*	*(0.074)*
Synthetic control ATT	0.367***	0.191***	1.062***	0.377***	0.013***	0.012***	0.021***	0.016***	0.080**	-0.211**
p-value	*0.005*	*0.005*	*0.005*	*0.005*	*0.005*	*0.005*	*0.005*	*0.005*	*0.011*	*0.016*
RMSPE	*0.003*	*0.006*	*0.014*	*0.011*	*0*	*0.001*	*0*	*0.002*	*0.003*	*0.009*
75% lagged outcomes + covariates + ID V	0.347***	0.380**	0.816**	0.552*	0.019***	0.056	0.024***	0.023	0.228	-0.003
	0.005	*0.011*	*0.016*	*0.091*	*0.005*	*0.274*	*0.005*	*0.118*	*0.285*	*0.597*
	0.024	*0.052*	*0.151*	*0.161*	*0.003*	*0.023*	*0.002*	*0.010*	*0.160*	*0.083*
50% lagged outcomes + covariates + ID V	0.427***	0.431**	0.897**	0.870	0.027***	0.045*	0.031*	0.045	0.045	-0.064
	0.005	*0.011*	*0.016*	*0.134*	*0.005*	*0.065*	*0.054*	*0.398*	*0.909*	*0.941*
	0.065	*0.062*	*0.212*	*0.379*	*0.006*	*0.015*	*0.010*	*0.042*	*0.247*	*0.253*
Covariates + ID V	0.378**	0.655**	1.003**	0.944**	0.007*	0.070**	0.027**	0.048*	0.021	-0.042
	0.016	*0.011*	*0.016*	*0.022*	*0.081*	*0.048*	*0.038*	*0.097*	*0.935*	*0.758*
	0.183	*0.260*	*0.347*	*0.423*	*0.011*	*0.030*	*0.012*	*0.039*	*0.382*	*0.255*
All lagged outcomes, data-driven V	0.399***	0.135**	0.654**	0.328*	0.023***	0.023*	0.027*	0.018**	0.165	0.009
	0.005	*0.03*	*0.032*	*0.054*	*0.005*	*0.091*	*0.054*	*0.048*	*0.151*	*0.118*
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*

Notes as in Table 6, main paper. Red = non-significant result. . = does not compile.

Table B4 continued.

	Plants		Jobs		% plants		% jobs		Ave rev/worker	
	Digitech	**Content**	**Digitech**	**Content**	**Digitech**	**Content**	**Digitech**	**Content**	**Digitech**	**Content**
Diff in diff ATT	*0.35****	*0.16***	*0.51****	*0.48****	*0.03****	*0.02**	*0.02***	*0.05***	*0.06*	*-0.09*
	(0.120)	*(0.074)*	*(0.140)*	*(0.134)*	*(0.009)*	*(0.009)*	*(0.009)*	*(0.021)*	*(0.063)*	*(0.074)*
Synthetic control ATT	0.367***	0.191***	1.062***	0.377***	0.013***	0.012***	0.021***	0.016***	0.080**	-0.211**
p-value	*0.005*	*0.005*	*0.005*	*0.005*	*0.005*	*0.005*	*0.005*	*0.005*	*0.011*	*0.016*
RMSPE	*0.003*	*0.006*	*0.014*	*0.011*	*0*	*0.001*	*0*	*0.002*	*0.003*	*0.009*
75% lagged outcomes + cov + cross-vali V	0.508***	0.432*	0.696**	0.631	0.013	0.066	0.019*	-0.002	0.261	-0.195
	0.005	*0.086*	0.027	*0.226*	*0.102*	*0.237*	0.054	*0.253*	*0.263*	*0.285*
	0.040	*0.085*	0.091	*0.2*	*0.005*	*0.022*	0.003	*0.009*	*0.117*	*0.095*
50% lagged outcomes + cov + cross-vali V	0.360**	0.412**	0.862**	0.907	0.01	0.041	0.025**	0.065	0.179	-0.210
	0.027	*0.022*	*0.011*	*0.204*	*0.253*	*0.194*	*0.038*	*0.226*	*0.629*	*0.640*
	0.089	*0.07*	*0.150*	*0.387*	*0.007*	*0.018*	*0.008*	*0.034*	*0.236*	*0.209*
Long difference 1997-2010, outcomes + cov + ID V	0.863	1.092	1.665*	1.971	0.006	0.038	0.014	0.051	0.242*	0.126
	0.108	0.286	*0.087*	*0.215*	*0.724*	*0.254*	*0.353*	*0.108*	*0.071*	*0.288*
	0.471	0.922	*1.078*	*1.737*	*0.023*	*0.029*	*0.023*	*0.035*	*0.165*	*0.269*
First differences, coutcomes + covariates + ID V	0.706	0.713	1.692	1.463	0.013	0.034	0.027	0.086	.	0.175
	0.108	*0.328*	*0.151*	*0.263*	*0.177*	*0.452*	*0.188*	*0.237*	.	*0.301*
	0.355	*0.608*	*0.921*	*1.089*	*0.011*	*0.027*	*0.021*	*0.066*	.	*0.135*

Notes as in Table 4, main paper. Red = non-significant result. . = does not compile.

Table B5. 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	*0.35**** *(0.120)*	*0.16*** *(0.074)*	*0.51**** *(0.140)*	*0.48**** *(0.134)*	*0.03**** *(0.009)*	*0.02** *(0.009)*	*0.02*** *(0.009)*	*0.05*** *(0.021)*	*0.06* *(0.063)*	*-0.09* *(0.074)*
Roundabout + 250m	0.91*** (0.074)	0.60*** (0.098)	0.59*** (0.155)	-0.08 (0.205)	0.01 (0.012)	-0.05*** (0.009)	-0.01 (0.013)	-0.06* (0.037)	-0.20** (0.098)	-0.56*** (0.090)
Roundabout + 500m	0.01 (0.304)	-0.10 (0.144)	0.13 (0.323)	0.12 (0.259)	0.02 (0.021)	0.01 (0.010)	0.00 (0.026)	-0.03 (0.057)	-0.01 (0.113)	0.25 (0.195)
Roundabout + 750m	0.03 (0.340)	-0.04 (0.149)	-0.09 (0.357)	-0.44** (0.225)	-0.00 (0.020)	-0.03** (0.015)	0.02 (0.026)	0.01 (0.052)	0.01 (0.118)	-0.25 (0.188)
Roundabout + 1000m	0.19 (0.155)	0.13 (0.103)	0.29 (0.202)	0.45*** (0.166)	0.01 (0.010)	0.03** (0.015)	0.00 (0.009)	0.04 (0.028)	-0.03 (0.108)	-0.06 (0.088)
Observations	4005	4079	4001	4078	4140	4140	4140	4140	4000	4077
R^2	0.81	0.93	0.81	0.90	0.62	0.72	0.54	0.64	0.38	0.56

Source: BSD / Census / ONS / TfL. 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, LSOA and year dummies. Standard errors clustered on LSOA. * significant at 10%, ** 5%, *** 1%.

Table B6. Scaling analysis: # high-growth and gazelle events, 1999-2010. 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 B7. Scaling analysis: synthetic control results.

	# High-growth episodes: revenue/worker		# High-growth episodes: jobs	
	digitech	**digitech**	**digitech**	**content**
Synthetic control ATT	0.283**	0.435	0.435	0.178
p-value	0.011	0.290	0.290	0.145
Number of placebos	185	185	185	185
Pre-treatment RMSPE	0.016	0.078	0.078	0.117
Average pre-treatment quality	0.989	0.178	0.178	0.827
Pre-treatment mean	*36.1*	*8.857*	*8.857*	*47.8*

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%.