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The effect of business accelerators on regional venture capital funding in the UK

El efecto de las aceleradoras de empresas sobre la financiación regional mediante capital riesgo en el Reino Unido

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Abstract
Over the past twenty years, numerous local governments in various countries have set up accelerators and incubators to fund start-ups and help transform their local economies. However, there is limited evidence regarding the impact of these programmes on the availability and supply of seed and early-stage venture capital in their regions. This study examines the effects of business accelerators on total venture funding in UK Local Enterprise Partnerships (LEPs) from 1998 to 2016. Multiple methods were employed to address concerns about reverse causality. The findings suggest that accelerators have a minimal to negligible impact on regional venture investment, particularly in large areas such as LEPs. Additionally, the results support the notion that regional characteristics moderate the relationship between venture capital and accelerator establishments.

Keywords: business accelerators; venture capital; regional development; information asymmetry; agency theory; proliferation paradox
JEL Classification:D82; G24; L26; M13; R11

Resumen
Durante los últimos veinte años, numerosos gobiernos locales de distintos países han creado aceleradoras e incubadoras para financiar empresas emergentes y contribuir a transformar sus economías locales. Sin embargo, existe evidencia limitada sobre el impacto de estos programas en la disponibilidad y oferta de capital riesgo en fases semilla e iniciales en sus regiones. Este estudio examina los efectos de las aceleradoras de empresas sobre la financiación total mediante capital riesgo en las Local Enterprise Partnerships (LEP) del Reino Unido entre 1998 y 2016. Se emplearon múltiples métodos para abordar los problemas de causalidad inversa. Los resultados sugieren que las aceleradoras tienen un impacto mínimo o insignificante sobre la inversión regional de capital riesgo, especialmente en áreas territoriales amplias como las LEP. Asimismo, los resultados respaldan la idea de que las características regionales moderan la relación entre el capital riesgo y el establecimiento de aceleradoras.

Palabras clave: aceleradoras de empresas; capital riesgo; desarrollo regional; asimetría de información; teoría de la agencia; paradoja de la proliferación
Clasificación JEL: D82; G24; L26; M13; R11

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1. Introduction

Business accelerators are widespread across the UK (Bone, Allen and Haley, 2017). The first were set up in London and the South East in the 1980s, and by 2016, most Local Enterprise Partnerships (LEPs) and regional economic areas had at least one, aiming to boost the local economy. Over 10,000 firms participate in accelerators, with new ones launching annually in the UK (Bone et al., 2019). From an academic point of view, there is a large literature that examines the impact of accelerators on a number of indicators, mostly the outcomes of enrolled start-ups. Studies in this tradition generally find that participating firms are more likely to secure subsequent venture capital investment, achieve higher valuations, and gain access to higher-status investors (Hallen, Cohen and Park, 2023; Carta, Danzo, Tenca and Di Biagi, 2025; Gonzalez-Uribe and Leatherbee, 2018).

However, there is limited evidence regarding the overall role and effectiveness of these programmes at the regional level. In other words, it is unclear whether these positive individual-level outcomes translate into aggregate regional-level benefits such as access to venture capital funding for the broader population of start-ups in a region. Literature suggests that accelerators can accelerate inflows of venture capital in a region by supporting local entrepreneurs (Blair, Khan, and Iftikhar, 2020) while simultaneosly reducing search costs for investors (Fehder and Hochberg, 2014). The empirical research by Fehder and Hochberg (2014) confirms these theoretical insights for the US; however, Bone et al. (2019) find that the positive effects on regional outcomes are mostly limited to high-tech sector venture capital. However, other research indicates that policies that appear effective for individual firms may have uncertain or even negative impacts on the broader regional economy (Davis, Haltiwanger, and Schuh, 1998). Factors such as regional industrial composition, which may not align with industries targeted by the accelerator, can diminish its impact on VC funding outside the accelerator's scope. For example, high-tech companies typically attract more venture capital (Shachmurove, 2007; Cruikshank, 2000; Keeble, 1994; Mason and Pierrakis, 2013) than other types of firms. Moreover, a lack of human capital in a region can reduce its appeal to VC funders. Other demand-related factors, including firm births (Karim, 2018) and the emergence of faster-growing firms (Mason, 1985), can also restrict VC investments in the area.

Against this background, the paper addresses a crucial research question: to what extent does establishing a business accelerator in a region increase venture capital funding for all local start-ups? This is an important question to answer as understanding how entrepreneurship initiatives affect regional outcomes is particularly vital for policymakers because regional VC is linked to the commercialisation of innovations (Kortum and Lerner, 1998) and to greater growth and performance of firms (Gompers and Lerner, 2002; Samila and Sorenson, 2011). Theoretically, we argue that two mechanisms may attenuate or negate the positive individual-level effects when viewed at the regional scale. First, drawing on agency theory and information economics (Van Osnabrugge, 2000), we propose that the proliferation of accelerators may create a 'lemon problem' at the aggregate level. When multiple accelerators compete to attract start-ups from a common pool, selection standards may deteriorate, and rather than acting as quality intermediaries that signal promising ventures to VCs, the abundance of accelerators becomes a source of noise in the investment environment (Hallen, Cohen and Park, 2023). Second, the characteristics of the regional environment moderate the relationship. In economically developed regions with mature VC ecosystems, investors have already established sophisticated screening mechanisms (e.g., extensive networks, due diligence capabilities, and track records) which render the incremental signalling value of accelerators largely redundant (Mayya and Huang, 2025).

The paper addresses three interrelated gaps in the literature. First, there is no systematic examination of the consequences of multiple accelerators operating simultaneously in a geographically limited area; existing studies treat accelerators as isolated programmes and evaluate them one at a time, overlooking the possibility that their aggregate presence may generate competitive dynamics (e.g., deteriorating selection standards and diluted signalling quality) that undermine rather than enhance VC activity across the region (Hallen, Cohen and Park, 2023). Second, the literature lacks a theoretical framework that explains why the positive firm-level effects of accelerators may fail to scale to the regional level; in particular, no prior study has applied agency theory and the 'market for lemons' logic (Akerlof, 1970; Van Osnabrugge, 2000) to model how accelerator proliferation can itself become a source of information noise for venture capitalists, rather than reducing information asymmetry. Third, there is insufficient understanding of how the characteristics of the regional environment, especially the maturity and resource-richness of the local VC, moderate the aggregate effect of accelerators. This paper addresses all three gaps by adopting a regional-level analytical framework grounded in agency theory and examining the UK context, where rapid accelerator proliferation across regions with highly uneven VC landscapes provides an ideal setting to test these arguments.

Evaluating whether accelerators influence the level and availability of VC funding regionally is complex, as there are no guaranteed exogenous sources of variation in accelerator locations, nor natural experiments to assist researchers. The main challenge is the non-random placement of accelerators, since regions with higher entrepreneurial activity are more likely to attract them, potentially confounding the results. In an OLS regression, increased venture funding might be incorrectly attributed to the accelerator, when it could actually be due to pre-existing entrepreneurial qualities. To mitigate reverse causality, we employ several methods. First, we match Local Enterprise Partnerships (LEPs) that have a treated accelerator with similar LEPs based on pre-treatment entrepreneurial trends. We then use Propensity Score Matching (PSM) to assess the impact of the accelerator on these LEPs. Second, we adopt a synthetic controls approach, constructing a counterfactual region without an accelerator—created by regressing pre-treatment venture investments and deals against untreated regions (donors) along with covariates. The difference in post-treatment venture investment and deals between the treated LEPs and their synthetic controls indicates the treatment effect (Abadie, Diamond and Hainmueller, 2010).

Our findings from the Propensity Score Matching analysis show that establishing an accelerator in a LEP correlates with a 2.4% yearly increase in the number of VC deals in treated LEPs. However, the impact on deal values is not statistically significant. Similarly, the synthetic control analysis confirms that accelerators do not have a significant effect on VC funding across entire LEPs. Given that other studies have identified positive accelerator effects on VC funding at the local authority level (often a subset of LEPs) we conclude that the influence of accelerators tends to be very localised and primarily affects sectors targeted by specific programs.

This research contributes to the existing literature in a number of ways.Theoretically, it provides a theoretical framework that explains why the positive firm-level effects of accelerators may fail to scale to the regional level. By using the agency theory, we propose a “proliferation paradox” as a key argument to explain why multiple accelerators may not necessarily reduce information asymmetry. Empirically, the paper examines the impact of accelerators across all industries in the UK, not just the high-tech sector, removing the assumption that VC investment in some fields is unaffected by accelerators. This is an improvement upon Bone et al. (2019), who used a difference-in-difference approach to compare high-tech (affected) versus non-high-tech (unaffected) sectors. Also, our methodology is different from Fehder and Hochberg (2014) as we allow for unobservable factors to influence the probability of establishing an accelerator, rather than assuming it can be precisely estimated from observed regional characteristics.

The paper is organised as follows: Section 2 reviews relevant literature, Section 3 explains our methodology and data, Section 4 discusses the findings, and Section 5 presents concluding remarks.

2. Literature review

2.1 Theoretical framework: agency theory, information asymmetry, and accelerators as intermediaries

The venture capital investment process is fundamentally shaped by information asymmetries between entrepreneurs and investors (Van Osnabrugge, 2000). Entrepreneurs possess private information about their venture’s true quality, capabilities, and prospects, creating adverse selection risks for investors. As Van Osnabrugge (2000) demonstrates within an agency theory framework, venture capitalists mitigate these risks primarily through ex ante screening procedures, including due diligence, investment criteria assessment, and structured evaluation, whereas business angels rely more on ex post monitoring. The complexity of venture investment evaluation decisions is further underscored by Urban and Moreno (2022), who show that these decisions are influenced by a multiplicity of factors across the entrepreneurial process, including both individual and business investment criteria.

Within this agency-theoretic framework, accelerators can be understood as information intermediaries that may reduce adverse selection in two ways. First, through their competitive selection processes, accelerators screen start-ups, and graduation from a reputable programme serves as a quality signal to investors (Connelly et al., 2011; Mayya and Huang, 2025). Second, through mentorship and training, accelerators improve the actual quality of participating ventures, reducing the information gap between entrepreneurs and potential investors (Hallen, Cohen and Park, 2023; Gonzalez-Uribe and Leatherbee, 2018). Mayya and Huang (2025) provide evidence that accelerators function as credible information intermediaries for corporate venture capitalists, enabling them to invest in start-ups outside their core domain of expertise.

However, the effectiveness of this intermediary function is not uniform and may depend on regional-level conditions. Hallen, Cohen and Park (2023) demonstrate that while some top-tier accelerators act as ‘status springboards’ for start-ups, helping them access higher-status investors, many others have very limited or even negative signalling effects. Crucially, they identify a potential ‘market for lemons’ dynamic: if the highest-quality start-ups do not apply to accelerators (e.g., due to time costs, equity dilution, or concerns about what participation signals), this may lead to a recursive deterioration in accelerator quality, whereby accelerators are increasingly perceived as graduating lower-quality ventures. We extend this insight from the individual accelerator to the regional level: when multiple accelerators in a region compete for start-ups from the same pool, their collective signalling power may diminish. Rather than reducing information asymmetry for VCs, the proliferation of programmes itself becomes a source of noise in the environment, complicating rather than simplifying investor screening.

Furthermore, the regional environment moderates the value of accelerators as intermediaries. In regions with well-developed, resource-rich environments, investors have already developed sophisticated screening mechanisms and extensive networks that provide reliable information on start-up quality. In such environments, the marginal informational value added by accelerators is low, and their signalling effect becomes redundant. Conversely, in less developed regions, accelerators may be the primary source of information for investors, but they also face thinner pools of high-quality applicants, potentially exacerbating the lemon problem.

The UK context is particularly suited to examining these dynamics. While the ONS does not collect information on start-ups per se, their statistics suggest that between 2022 and 2023, 800000 new companies were established. London is the area with the largest number of new ventures in absolute terms, followed by the South-East. Fintech and AI are the sectors with the largest number of new ventures. UK start-ups face significant regional disparities in access to finance, with London and the South-East dominating the venture capital landscape (Mason and Harrison, 2002; Mason and Pierrakis, 2013). High-growth early-stage firms, which represent a small fraction of all new businesses, are the primary recipients of external equity finance yet face acute funding challenges (Van Osnabrugge, 2000). The rapid proliferation of accelerators is evident across UK regions. The estimates suggest that over 10,000 firms participate in and new programmes are launched annually (Bone et al., 2019), providing an ideal setting to test whether the aggregate regional effect of these programmes matches the positive individual-level effects documented in the literature.

2.2 Accelerators and regional venture capital: empirical evidence

Business accelerators are programs that support entrepreneurs by providing networking opportunities and mentorship. They often also offer incubation funding in exchange for equity (Bone et al., 2019). Accelerators in the UK tend to accept early-stage ventures mostly from the pre-startup stage onwards (Bone et al., 2017, 2019). Theoretical explanations for how accelerators boost regional venture capital are divided into demand-side and supply-side mechanisms. On the demand side, accelerators offer mentorship (Blair, Khan, and Iftikhar, 2020) and formal and informal education (Goswati, Mitchell, and Bhagavatula, 2018), helping startups grow and attract funding. Additionally, accelerators reduce entrepreneurs' search costs for services like networking, mentorship, education, and funding (Fehder and Hochberg, 2014). Since accelerators typically hold equity in startups, they may also conceal negative signals about startup quality, thereby certifying and increasing the value of the startups (Kim and Wagman, 2012). On the supply side, accelerators function as deal sorters and deal aggregators (Fehder and Hochberg, 2014). Deal sorting involves rigorous application processes to select high-potential startups, while deal aggregation entails organising investor events. Both activities lower search costs for investors, especially in smaller regions where such costs can be prohibitive.

Empirical research summarises the impact of accelerators on regional VC funding in Table 1, Appendix A. Most studies are qualitative, with limited quantitative estimates from Fehder and Hochberg (2014) in the US and Bone et al. (2019) in the UK. Qualitative findings support a positive link between accelerators and the entrepreneurial ecosystem in Jordan (Al-Shamaileh, Saatci, and Eyamba, 2020) and India (Goswami, Mitchell, and Bhagavatula, 2018). However, the impact remains unclear for New Zealand (Blair, Khan, and Iftikhar, 2020). Several factors may influence the effect of accelerators on regional VC funding; for instance, the regional industrial composition plays a role, as high-tech firms tend to attract more venture capital (Shachmurove, 2007; Cruikshank, 2000; Keeble, 1994; Mason and Pierrakis, 2013). The proportion of Science, Technology, Engineering and Mathematics (STEM) students in a region can also indicate the availability of specialised human capital valued by VC investors (Martin, 1989). Other demand-side factors include GDP per capita, rates of firm births (Karim, 2018), and the emergence of high-growth companies (Mason, 1985), as such firms require more investment. Research also highlights factors such as the high cost and administrative burden of equity (Wray, 2012) and regional disparities in financial literacy (Mason and Harrison, 2002). The localised nature of VC deals and established financial ecosystems are also influential; VC investments often depend on trust and face-to-face contracts, which are more feasible with geographical proximity (Christensen, 2011).

Quantitative studies generally find a positive impact of accelerators on regional VC funding. A key issue is the potential reverse causality between VC funding levels and accelerator presence. Fehder and Hochberg (2014) addressed this by analyzing early-stage deals across US metropolitan areas, using a hazard model to match treated and untreated regions based on accelerator establishment probability. They then employed a difference-in-difference model with fixed effects and a triple-difference regression on this matched sample. Results showed a significant rise in venture deals: a 104.3% increase in early-stage deals and a 217% increase in early-stage software and IT investments compared to biotech.

Their approach has two main limitations. First, it predicts accelerator likelihood using only venture capital data without additional controls. Since the predictive power of the hazard model isn't reported, neglecting other economic or political factors could lead to biased estimates. Second, the assumption that biotech industries are unaffected by accelerators is questionable. As biotech firms also attract increased funding, the triple-difference estimate might be lower than the difference-in-difference estimate, indicating potential bias in the matching process using the hazard model. Bone et al. (2019) examined seed investments at the local authority level in the UK. Like the previous study, it assumes high-tech sectors are treated, with the rest of the non-high-tech sector serving as controls. Using a difference-in-difference approach, they found that funding in high-tech sectors increased by 114% after the accelerator compared to non-high-tech sectors. However, the assumption that accelerators do not impact the non-high-tech industries is questionable; even if a bias is not present, the effect could be underestimated because other sectors might also experience increased funding.

3. Model

3.1 Methodology

To quantify the impact of the presence of an accelerator on the regional level VC funding and identify the factors that moderate such an impact, we start by running a standard Ordinary Least Squares (OLS) regression with fixed effets for LEPs and year where the dependent variable is the regional level VC funding (proxied either by number of regional deals or by the deflated total monetary value of the regional deals). The main independent variable is a dummy variable that takes the value 1 for the presence of an accelerator in a region and 0 otherwise. Importantly, the dependent variable captures venture capital deals across all industries within each LEP-year observation, rather than restricting the analysis to a single sector. This all-industry approach is a deliberate methodological choice: previous studies (e.g., Bone et al., 2019; Fehder and Hochberg, 2014) assumed that only certain sectors (typically high-tech) are affected by accelerators, using unaffected sectors as controls. We argue that their assumption is questionable, as accelerator effects may spill over across sectors within a region. By including all industries, we capture the full regional effect without imposing untested assumptions about which sectors are or are not influenced by accelerators. Also, our analysis of accelerators across regions in the UK suggests that most do not impose any restrictions on the industry as part of their enrolment requirements.

Our basic model is as follows:

$$\text{VC deals}_{it} = \alpha_i\alpha + \beta D_{it} + x_{it} + t + u_{it} \qquad i=1,\ldots \quad t=1998\ldots2016 \qquad (1)$$

We also run a variation of (1) where the independent variable is the total number of accelerators by LEP in a given year.

3.1.2 Propensity Score Matching (PSM) and Synthetic controls estimators

As noted earlier, a key challenge in empirical studies measuring the impact of accelerators on outcome variables- whether at the regional or firm level- is the non-random placement of accelerators. They tend to be established in regions with high startup activity, and decisions to develop an accelerator in one area over another may be affected by temporary changes in a region’s attractiveness to investors. To address this, we use a Propensity Score Matching (PSM) estimator on our sample to create matched control and treated LEPs based on observable characteristics. We start by estimating a logit model where the probability of an accelerator being launched in a specific LEP in a given year depends on regional features and time trends. This model helps us estimate the likelihood of an accelerator being in a certain LEP based on current regional economic conditions. Next, we match each treated LEP with untreated LEPS that have the closest probability of establishing an accelerator in the same year, as long as the treated LEPS fall within the common support. We then calculate the Average Treatment Effect (ATE).

For the synthetic control estimator, we construct an artificial control LEP- termed a synthetic control- for each LEP with an accelerator, following Abadie, Diamond, and Hainmueller (2010). This synthetic control is a weighted average of non-treated areas that replicate the pre-treatment trend of the treated region. We focus on the treatment’s impact on venture funds invested and the number of venture deals, collectively called features. The treatment effect for an individual LEP i at time t, denoted τit, represents the difference between venture funds invested in the treated LEP (Yit(1)) and in the synthetic control (Yit(0)):

$$\tau_{it} \coloneqq Y_{it}(1) - Y_{it}(0) \qquad (2)$$

where each term is a 2x1 vector representing venture funds invested and the number of venture deals, τ_{it} is a vector of treatment effects for both features, $Y_{it}(1)$ is a vector of post-treatment features for a treated LEP, and $Y_{it}(0)$ is a vector of features for a synthetic control. Because there are multiple treated units, we also determine the average treatment effect on treated LEPs. This average is computed by taking the mean of the treatment effects for all N1 treated LEPs, as shown below:

$$\tau_t = \frac{1}{N_1}\sum_{j=1}^{N_1}\left(Y_{jt}(1) - Y_{jt}(0)\right) \quad (3)$$

where τ_t denotes the average treatment effect for the treated, $Y_{jt}(1)$ indicates the feature values for a treated region j at time t, $Y_{jt}(0)$ signifies the feature values for a synthetic control j at time t, and N_1 represents the number of treated regions.

A synthetic control estimator of $Y_{jt}(0)$ employs a weighted average of outcomes from untreated LEPs, where the weights are non-negative and sum to one. Since venture capital is volatile and outcomes for untreated LEPs can be influenced by various factors (Nanda and Rhodes-Kropf, 2016), some regions may not accurately predict venture capital, resulting in large standard errors. Therefore, covariates were included in the regression, as recommended by Abadie (2021). This allows us to determine the weights and coefficients for the control variables by minimising the following expression:

$$\hat{\beta} := \left(\widehat{\omega'}, \widehat{r'}\right) \in \arg\min_{\omega \in \mathcal{W}, r \in \mathcal{R}} \|(A - B\omega - Cr)'V(A - B\omega - Cr)\| \quad (4)$$

Where A is a matrix of pre-treatment features for treated units, B contains features of donor units, represents the weights assigned to donor units in a regression, C is a matrix of covariates, r indicates the coefficients for covariates in the regression, and V is the weighting matrix (assumed to be an identity matrix).

This approach employs a separate synthetic controls methodology. Pooled or partially pooled synthetic control methods, as outlined in Ben-Michael, Feller, and Rothstein (2021), were considered but dismissed due to significant differences among VC ecosystems across regions. Constraints include Lasso (L1) and ridge (L2) penalties, as suggested by Doudchenko and Imbens (2016). Trend and constant terms are incorporated for deal values and deal numbers. No time-fixed effects are used, aligning with Cattaneo et al. (2023) and Abadie, Diamond, and Hainmueller (2014), because exchangeable shocks within a particular year are reflected in the venture deals of donor regions, inherently accounting for common shocks for each year. Uncertainty estimates follow the methods in Cattaneo, Feng, and Titiunik (2021), utilising simulation-based techniques for in-sample uncertainty and sub-Gaussian bounds for out-of-sample uncertainty. The methodology is implemented in Python using the scpi package, as described in Cattaneo et al. (2023).

3.2 Data

LEPs were selected as regional units of analysis because they are partnerships that promote local economic growth (Local Government Association, 2023). England has 38 LEPs. Since Scotland and Wales do not have LEPs, the analysis used 9 economic regions (ERs), as defined by the Office for National Statistics (ONS). Northern Ireland was excluded due to its distinct environment. The full list of LEPs and ERs along with treatment years is shown in Figure 1. Three regions—The Borderlands Partnership, Mid and South West Wales Economic Region, and Cumbria—were removed from the sample as they do not host any accelerator. Only 11 of the 139 accelerators in the sample have some local government funding, while most are funded by other corporate, public, or educational entities. LEPs sharing borders were excluded because they were treated before the period studied; these include Stoke-on-Trent and Staffordshire, Greater Birmingham and Solihull, and Worcestershire. The main variable of interest is VC investment, but detailed aggregate venture capital data for UK regions from 1998-2016 is unavailable from the ONS. Therefore, the dataset was created from microeconomic deal data sourced from CapitalIQ Pro. To identify venture capital transactions, ‘Early Stage’ (angel, pre-seed, seed funding) and ‘Venture’ (for companies under five years old) types were selected. After excluding deals from Northern Ireland, 36,898 deals remained. Deals were then grouped by region and year. A program matched company postcodes to LEPs via findthatpostcode.com API. In England, deals were aggregated by LEPs across years. For Wales and Scotland (which do not host LEPs), the same API assigned deals to local authorities, which were then grouped into ONS-defined Economic Regions (ERs).

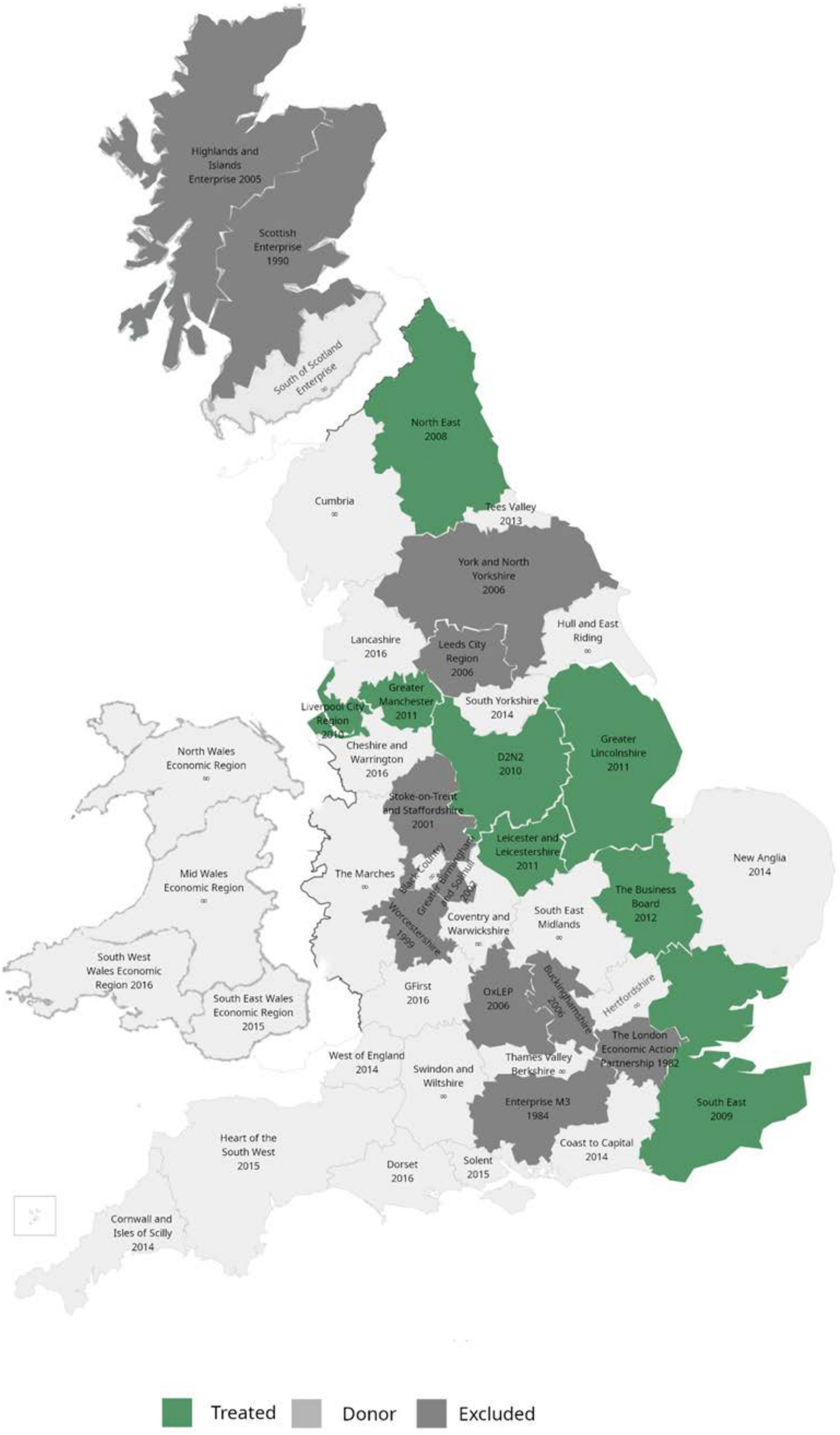

Figure 1. Incubator Landscape in the UK

Of the initial deals, 5,920 lacked a postcode. These were matched to LEPs when city names were available. For deals missing postcodes with a company registration number (CRN), postcodes were retrieved via the Companies House API. After these steps, only 1,272 deals remained unassigned to any LEP. The total number of deals was 36,898, with 26,385 disclosed values adjusted to 2021 prices using the ONS Gross Value Added (GVA) deflator. A challenge with microeconomic data aggregation is the incomplete nature of deal disclosures—some deals remain undisclosed, although this is likely a minority of cases. For instance, evidence from Hamm et al. (2021) shows that nearly half of publicly listed US firms do not disclose their corporate venture activities.

Data on accelerators were sourced from the NESTA dataset (2017), focusing on those that offer direct funding, such as equity or loans. This yielded 144 accelerators, matched to LEPs and ERs using the same methods as for deals. The UK accelerator landscape in 2016—the last year of available data—shows that London's Economic Action Partnership received £4,929m, Scottish Enterprise received £758m, and The Business Board received £447m in venture capital investments (values in 2021 prices). This aligns with the literature, which identifies London, the South-East, and Scotland as regions with the most mature VC ecosystems (Mason and Harrison, 2002). Figure 1 shows London, surrounding regions, and Scotland among the earliest to establish accelerators, paralleling VC trends. Notably, The Business Board area, including Cambridge, did not have an accelerator until 2012.

Additional covariates were included in the regression to improve predictive accuracy and account for regional differences. GVA per capita was deflated using regional GVA inflation from ONS and logged, to control for regional economic activity. Firm births data from ONS controlled for new venture creation. The share of STEM undergraduates, from the Higher Education Statistics Agency (HESA) (as in Fehder and Hochberg, 2014), served as a proxy for specialized human capital. These covariates are summarized in Table 1, alongside descriptive statistics revealing considerable variation in venture capital across the UK. Investment averages range from about £1.39m for Greater Lincolnshire to £178.2m for The Business Board, with large standard deviations mainly due to high-value hubs like Cambridge.

Table 1. Descriptive Statistics

Variable	Mean	Std Dev	Source
Deal value (£m)	69.15	119.03	*Capital IQ Pro*
Number of deals	16.99	17.08	*Capital IQ Pro*
GDP per capita (£)	24743.15	3153.19	*ONS*
Firm births	6295.40	4690.7	*ONS / BERR*
STEM share	0.43	0.090	*HESA*

Because the NESTA accelerators data only goes to 2016 and regional GDP data is available from 1998, the analysis covers 1998-2016. In our models using PSM and Synthetic controls estimators, regions treated between 2008 and 2012 were included, allowing for sufficient pre-treatment periods for synthetic control creation and post-treatment periods to observe effects. Regions treated before 2008 were excluded, while those treated after 2012 served as the donor group. In Figure 1, treated regions are marked in green, donors in light grey, and excluded regions in dark grey.

4. Results

This section presents the empirical findings, starting with the initial OLS regression models before moving to the more robust Propensity Score Matching and Synthetic Control estimators designed to account for potential reverse causality.

4.1 OLS

We begin by exploring the relationship between accelerator presence and venture capital funding using OLS and Poisson models with fixed effects for both LEPs and years. The results, presented in Tables 2a and 2b, offer initial insights into these dynamics.

As shown in Table 2a, the mere presence of at least one accelerator (the dummy variable) is not significantly associated with the value of VC deals within a LEP (column 1). However, it does show a small but statistically significant positive correlation with the number of deals in the Poisson model (column 2). This suggests that an accelerator's initial presence may be more related to the quantity of small-scale investment activities than to the total capital invested.

A more telling relationship emerges when we consider the total number of accelerators in a region (columns 4-6). Here, a greater concentration of accelerators is significantly and positively correlated with both the total value of VC deals and the number of deals. This implies that while a single accelerator may have a limited impact, a thriving ecosystem with multiple accelerators is associated with a more vibrant regional VC market.

Table 2a. Regression model estimates for the main effect – OLS and Poisson estimators

	Log Deals value by LEP (deflated) (a)	**No of deals by LEP (b)**	**Log Deals value by LEP (deflated) /No of deals by LEP (a)**	**Log Deals value by LEP (deflated) (a)**	**No of deals by LEP (b)**	**Log Deal value (deflated) by LEP / No deals by LEP (a)**
Dummy variable (=1 if the LEP has an accelerator or incubator in any given year)	0.23 (1.33)	0.25** (2.57)	0.19 (1.16)			
Total number of incubators and accelerator (by LEP)				0.0080** (2.20)	0.006*** (6.75)	-0.0006 (0.19)
Firm births (log)	1.58*** (3.68)	1.06*** (16.13)	-1.01 (-1.34)	1.49*** (3.16)	0.91*** (17.78)	0.86** (2.13)
STEM graduates share	-1.30 (0.53)	1.73*** (5.85)	0.87** (2.42)	-1.08 (-1.11)	1.77*** (7.19)	-0.8 (-0.88)
GDP per capita (log and deflated)	-0.68 (0.53)	1.75*** (8.52)	1.36 (1.15)	0.87 (0.52)	1.46*** (8.21)	1.59 (1.04)
Constant	-16.84 (-1.33)	-25.52*** (-13.80)	-20.37 (-1.72)	-18.11 (-1.09)	-21.08*** (-13.22)	-22.69 (-1.47)
Year FE	YES	YES	YES	YES	YES	YES
LEP FE	YES	YES	YES	YES	YES	YES
N	635	744	635	635	744	635

Note: Robust Standard Errors. t-ratios are in parentheses. LEP fixed effects and time dummies are included. (a) OLS estimator; (b) Poisson estimator.

In Table 2b, the analysis of interaction effects reveals a more nuanced picture. The interaction term between the STEM graduates share and the total number of accelerators is positive and significant (column 2). This indicates that the positive effect of accelerators on the number of venture capital deals is amplified in regions with a greater concentration of specialised human capital. Conversely, the interaction term between GDP per capita and the number of accelerators is negative and significant (column 5) when explaining the number of deals. This suggests a potential diminishing returns effect, where the marginal impact of an additional accelerator on the number of VC deals is weaker in regions that are already more economically developed. However, if we focus on the OLS estimates, we can see that the coefficients associated to either GDP or the STEM graduates share is positive. In this case we can calculate the total effect of GDP per capita and STEM graduate share on the value of deals. Indeed, as GDP per capita increases, each additional accelerator in a LEP is associated with an increase of the number of deals by a factor ranging between 0.00048 and 0.0012; while in the case of the STEM graduates share, the factor ranges between 0.95 and 1.10 as the share of STEM graduates in a LEP increases.

Table 2b. Regression model estimates for the interaction effects – OLS and Poisson estimators

	Log Deal value by LEP (deflated) (a)	No of deals by LEP (b)	Log Deal value (deflated) / No of deals by LEP (a)	Log Deal value by LEP (deflated) (a)	No of deals by LEP (b)	Log Deal value (deflated) / No of deals by LEP (a)
Total number of incubators and accelerator (by LEP)	-0.05 (-0.64)	-0.05** (-2.32)	0.05 (0.77)	1.39** (2.59)	0.85*** (4.64)	1.09** (2.25)
Firm births (log)	1.47*** (3.16)	0.90*** (17.11)	0.85*** (2.11)	1.20** (2.52)	0.76*** (11.58)	0.64 (1.54)
STEM graduates share	1.16 (-1.19)	1.43*** (6.03)	-0.88 (-0.96)	-1.04 (-1.08)	1.80*** (7.68)	-0.78 (-0.85)
GDP per capita (log and deflated)	0.77 (0.46)	1.45*** (8.03)	1.50 (0.97)	1.49 (0.88)	1.87*** (10.26)	2.08 (1.34)
Interaction between STEM graduates share and Total number of incubators and accelerator (by LEP)	0.13 (0.74)	0.15** (2.57)	0.12 (0.76)			
Interaction between GDP per capita and Total number of incubators and accelerator (by LEP)				-0.12** (-2.5)	-0.774*** (-4.62)	-0.10** (-2.25)
Constant	-16.84 (-1.01)	-20.73*** (-12.50)	-21.52 (-1.39)	-22.29 (-1.36)	-24.18*** (15.52)	-25.99 (-1.69)
Year FE	YES	YES	YES	YES	YES	YES
LEP FE	YES	YES	YES	YES	YES	YES
N	635	744	635	635	744	635

Note: Robust Standard Errors. t-ratios are in parentheses. LEP fixed effects and time dummies are included. (a) OLS estimator; (b) Poisson estimator.

Statistically significant coefficients for the control variables are scarce across the models that estimate the value of the deals (whether in absolute value or divided by the number of deals). The only exception is the share of new firms established in the LEPs where the estimates indicate a positive relationship between firm births and early-stage funding activities. Viceversa, the control variables are all significant and positive in the Poisson models where the total number of deals appears as the dependent variable. While these OLS results are informative, they do not establish causality. Accelerators are often established in regions that already have strong entrepreneurial characteristics, a classic endogeneity problem that can bias estimates. Therefore, we turn to methods designed to mitigate this issue.

4.2 PSM and SYNTHETIC CONTROL ESTIMATOR

To address the non-random placement of accelerators, we employ Propensity Score Matching (PSM) and the Synthetic Control Method. Table 3 presents the Propensity Score Matching estimates, indicating an increase in the number of early-stage venture deals following the creation of an accelerator in the LEP. However, in the case of VC deal values, there is no significant difference between treated and untreated LEPs.

Table 3. Propensity Score Matching Estimates

	Deal value (deflated)	Number of deals
ATE	8.07** (2.29)	-13.17 (-0.34)
N	836	836

Regarding the Synthetic Control estimators, Figures 2-4 display venture funding in the treated regions (black lines) compared to their synthetic controls (blue lines). Figure 2 shows the prediction intervals for each treated unit, while Figure 3 zooms in to illustrate how the algorithm matches synthetic controls. Finally, Figure 4 presents the prediction intervals for the average treatment effect on the treated.

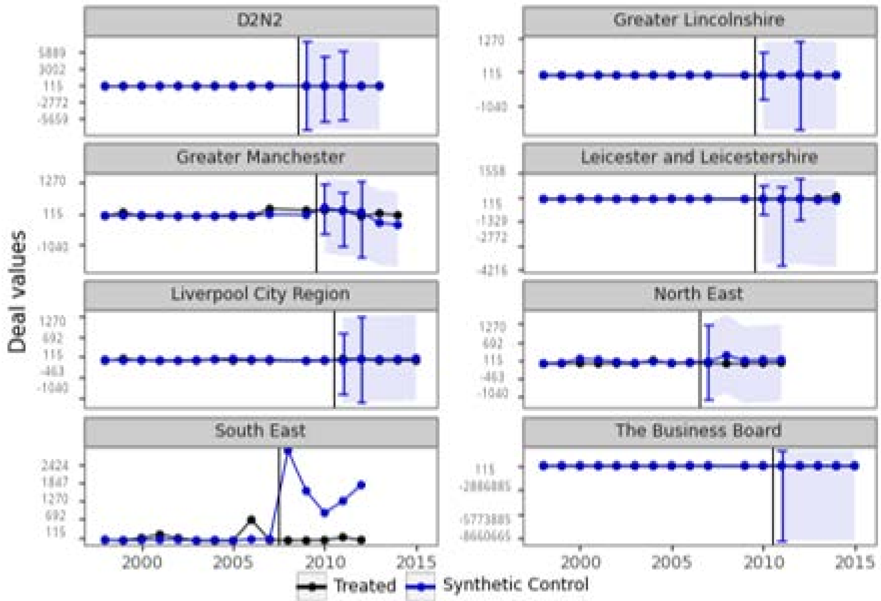

Figure 2. Prediction interval for single treatment effect

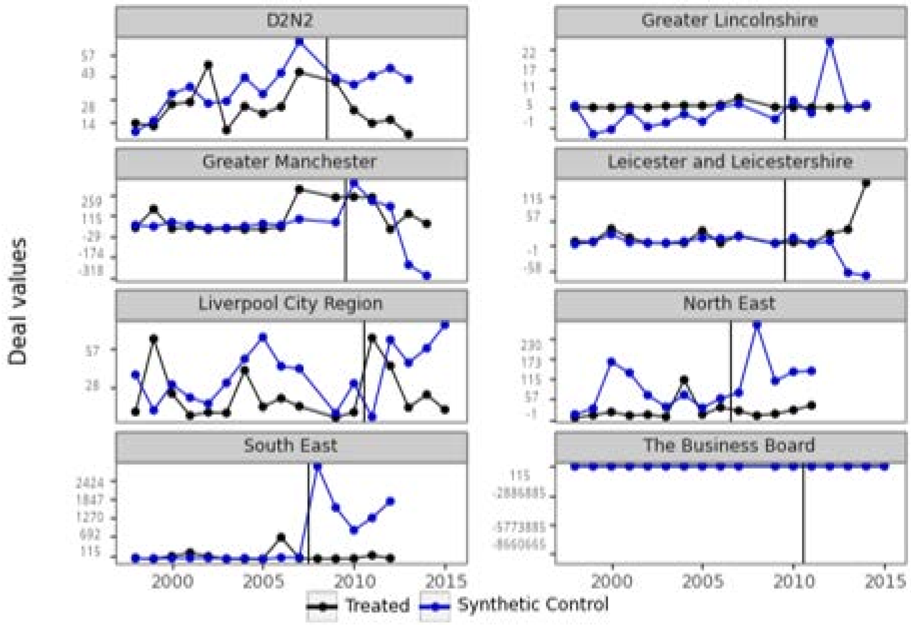

Figure 3. Fitted trends for single treatment effect

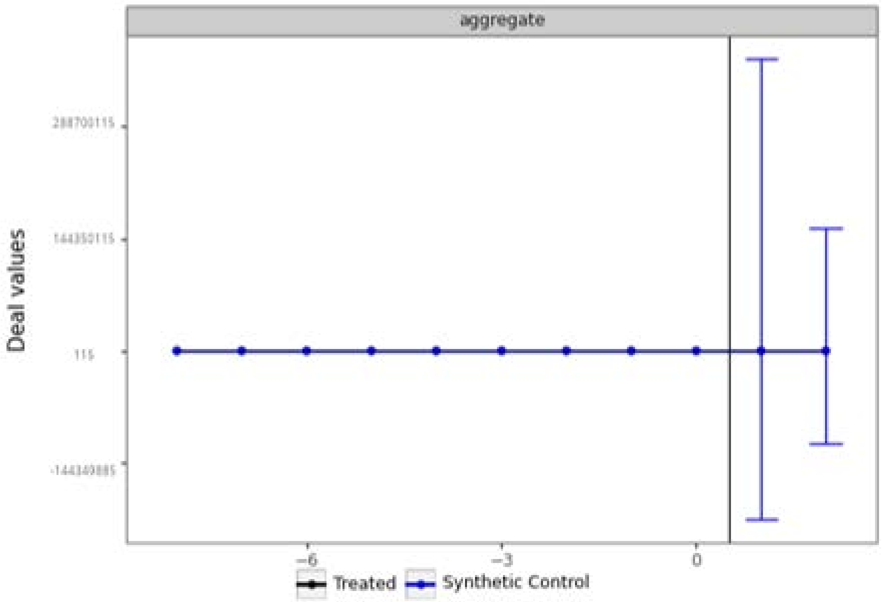

Figure 4. Prediction intervals for ATT

In Figure 3, we anticipate a well-aligned pre-treatment trend since synthetic controls are used to predict venture investment in treated units (Abadie, 2021). We also expect a positive gap after treatment between funds invested in a treated region and its synthetic control, attributable to the establishment of an accelerator. Figures 2 and 4 present a larger scale, and we expect the increase in venture funds invested to be significant enough to lie outside the prediction intervals.

Figure 3 shows mostly imperfect fits for venture fund trends in treated regions, except for Leicester and Leicestershire. Nonetheless, they exhibit similar trajectories and suggest good predictions of pre-treatment values. The poorest fit is seen in The Business Board, which is expected since only high-tech clusters - like the Cambridge cluster in The Business Board - have been linked to early-stage investments in earlier research (Mason, 2007). From Figure 3, only Greater Manchester, Leicester, and Leicestershire display increased post-treatment venture investments compared to controls, but Figure 2 indicates these differences are not statistically significant. Additionally, when accelerators positively impacted these regions, the counterfactual venture investment predicted by a synthetic control was negative. Since accelerators do not have a statistically significant effect among the LEPs, Figure 4 likely shows no evidence of an average treatment effect on the treated, as the black line falls within prediction intervals and overlaps with the blue line. Given the volatility of regional VC investment (Nanda and Rhodes-Kropf, 2016), accurately predicting it at the LEP level can be difficult, so a small effect from one accelerator may be within the prediction intervals. However, this is rejected because regions with funding from any first accelerator (D2N2 and Leicester and Leicestershire) do not necessarily show even a small positive gap in Figure 3.

Let us now examine the economic reasons behind why accelerators positively impact local authorities but not LEPs. Bone et al. (2019) demonstrate that accelerators generate spillover benefits at the local authority level, extending beyond the participants themselves. Two possible explanations exist for these geographical effects. First, accelerators might serve as deal aggregators solely for their local authorities, meaning they may not draw firms from outside their own authority but within the same LEP. Investors might also prefer to focus their search within a single local authority, reducing venture capital availability in other parts of the LEP. Additionally, firms seeking venture capital may relocate to a local authority with an accelerator; however, research suggests that other factors are more influential in startup relocations (Colombo, Adda, and Quas, 2021). Overall, there may be a diminished supply and demand for venture capital within a treated LEP outside the specific local authority, neutralising any accelerator effect and resulting in an insignificant impact on venture funding.

4.3 Analysis of Donor Weights and Covariates

To ensure the plausibility of our synthetic controls, we examine the donor weights and the influence of regional covariates. Table 4 reports weights of donor units that are larger or equal to 0.05 in a regression for separate treated units. Proximity to London and industrial makeup are used to evaluate how similar donor and treated regions are. Regions near London are labelled as core, while others are called peripheral, as shown in Table 4. To measure similarity in industrial composition, we compute the Krugman index by comparing employment shares in each industry between region pairs in 2016, the final year of data. The index measures the difference in employment shares across sectors and summarises all deviations. A Krugman index of zero indicates very similar industrial profiles, while a value of 2 indicates entirely different ones. Due to limited data from Nomis, the index is only available for LEPs in England; Welsh regions are marked "N/A" in the last column. To interpret the index values, we compare Krugman indices of treated regions with London's, which has a different industrial profile. The lowest Krugman index for any treated region with London is 0.35 (Greater Manchester). Thus, indices below 0.35 suggest similar industrial compositions.

Table 4. Weights of donor units

Treated region	Donor region	Weight	Treated location	Donor location	Krugman index
D2N2	New Anglia	0.21	Periphery	Core	0.144
D2N2	North Wales Economic Region	0.19	Periphery	Periphery	N/A
D2N2	Thames Valley Berkshire	0.05	Periphery	Core	0.405
D2N2	The Marches	0.53	Periphery	Periphery	0.126
Greater Lincolnshire	Black Country	0.14	Periphery	Periphery	0.174
Greater Lincolnshire	Dorset	0.29	Periphery	Periphery	0.257
Greater Lincolnshire	Lancashire	0.08	Periphery	Periphery	0.181
Greater Lincolnshire	Mid Wales Economic Region	0.17	Periphery	Periphery	N/A
Greater Lincolnshire	South East Midlands	0.16	Periphery	Core	0.304
Greater Lincolnshire	South West Wales Economic Region	0.10	Periphery	Periphery	N/A
Greater Manchester	Dorset	0.69	Periphery	Periphery	0.237
Greater Manchester	Hertfordshire	0.17	Periphery	Core	0.295
Greater Manchester	South East Midlands	0.14	Periphery	Core	0.176
Leicester and Leicestershire	Cheshire and Warrington	0.56	Periphery	Periphery	0.232
Leicester and Leicestershire	Heart of the South West	0.21	Periphery	Periphery	0.267
Leicester and Leicestershire	South East Midlands	0.12	Periphery	Core	0.197
Leicester and Leicestershire	South West Wales Economic Region	0.11	Periphery	Periphery	N/A
Liverpool City Region	South East Midlands	0.33	Periphery	Core	0.27
Liverpool City Region	Swindon and Wiltshire	0.39	Periphery	Periphery	0.261
Liverpool City Region	Solent	0.27	Periphery	Periphery	0.164
North East	Swindon and Wiltshire	0.34	Periphery	Periphery	0.251
North East	Thames Valley Berkshire	0.19	Periphery	Core	0.205
South East	Lancashire	0.25	Periphery	Periphery	0.217
The Business Board	Cheshire and Warrington	0.75	Core	Periphery	0.306
The Business Board	Hertfordshire	0.25	Core	Core	0.228

A plausible synthetic control should be formed from donor regions that are economically similar. For example, Greater Manchester, a major peripheral city-region, is primarily matched with Dorset (69%), another peripheral region, and the core regions of Hertfordshire and South East Midlands. The low Krugman indices (<0.3) for these pairings indicate a similar industrial structure, confirming that the algorithm has identified reasonable economic peers. This lends credibility to the counterfactual scenario.

Table 5. Coefficients on covariates

Treated Unit	Covariate	Coefficient
D2N2	Firm births	−0.46
D2N2	STEM share	−0.10
Greater Manchester	GDP per capita	−1.02
Greater Manchester	Firm births	−4.51
Greater Manchester	STEM share	0.57
Leicester and Leicestershire	GDP per capita	−0.05
Leicester and Leicestershire	Firm births	−0.74
Leicester and Leicestershire	STEM share	0.05
Liverpool City Region	GDP per capita	0.05
Liverpool City Region	Firm births	0.69
North East	GDP per capita	−0.09
North East	Firm births	1.16
North East	STEM share	0.14
South East	Trend	0.39
South East	GDP per capita	0.31
South East	Firm births	10.40
South East	STEM share	−3.79
The Business Board	GDP per capita	0.15
The Business Board	Firm births	−1.80
The Business Board	STEM share	−0.17

Furthermore, the coefficients of the covariates used to construct the synthetic controls, shown in Table 5, reveal how different regional characteristics predict VC funding trends. The results highlight significant regional heterogeneity. For instance, in Greater Manchester and the North East, a higher share of STEM graduates is a positive predictor of VC funding (coefficients of 0.57 and 0.14, respectively). Conversely, for the South East and The Business Board, this relationship is strongly negative (-3.79 and -0.17). This supports the notion that the drivers of VC investment are not uniform; in mature ecosystems like the South East, other factors beyond the simple supply of STEM talent may be more decisive. Similarly, the effect of firm births varies, being a strong positive predictor in the North East and South East but a negative predictor in Greater Manchester and The Business Board.

5. Discussion and Conclusions

This paper investigates whether establishing a business accelerator increases venture capital funding across a wider region, using UK LEPs as the unit of analysis. Our analysis, which employs multiple methods to account for the non-random placement of accelerators, yields three main findings. First, it shows that accelerators have an insignificant impact on regional venture investment, contrasting with earlier studies by Fehder and Hochberg (2014) and Bone et al. (2019), which analysed local authorities as units. We conclude that the economic benefits of accelerators, such as deal aggregation and investor networking, are highly localized and do not generate significant spillovers to the wider region. Second, it supports Shachmurove' s (2007) notion that venture capital's relationship with an area's industrial composition can differ. As shown in our analysis of the synthetic control covariates (Table 5), factors like the share of STEM graduates and the rate of firm births can be positive predictors of VC funding in some LEPs but negative in others. This heterogeneity underscores that a one-size-fits-all approach to entrepreneurship policy is unlikely to succeed. Third, it offers new insights into the link between venture capital, firm births, and regional GDP per capita. While previous studies highlight positive and negative relationships, this research finds that these relationships vary depending on regional characteristics.

These findings are consistent with our theoretical framework grounded in agency theory and information economics. At the individual programme level, accelerators can function as effective information intermediaries that reduce adverse selection by signalling start-up quality to investors (Van Osnabrugge, 2000; Mayya and Huang, 2025). However, at the regional aggregate level, the proliferation of accelerators introduces a 'lemon problem' (Hallen, Cohen and Park, 2023). When multiple programmes compete for start-ups from a common pool, the overall quality of the signal they transmit to investors is diluted. Rather than acting as reliable intermediaries that reduce information asymmetry, the abundance of accelerators becomes itself a source of noise in the investment environment, complicating rather than simplifying the screening task for VCs.

The role of regional characteristics in moderating accelerator effects deserves particular attention. Our finding that the interaction between GDP per capita and accelerator count is negative and significant (Table 2b) is directly explained by the redundancy mechanism: in resource-rich regions, investors possess established screening mechanisms, such as peer benchmarks and informal networks for due diligence, that render the informational value of accelerators largely redundant. This is consistent with Mayya and Huang (2025), who show that the benefits of accelerators are greatest for investors lacking domain expertise. Conversely, the positive interaction between STEM graduate share and accelerator count suggests that regions with strong human capital are replete with higher numbers of potentially qualified (commercialisable) ideas that make the average pool of high quality ventures higher than other regions. In this environment, accelerators can play a more meaningful intermediary role by connecting a richer pool of technically capable ventures with investors.

An important consideration when interpreting our results is the distinction between the UK and other contexts, such as the US (the most highly scrutinised context). Fehder and Hochberg (2014) examined 38 US metropolitan areas using Census data, whereas our study covers UK LEPs and economic regions using deal-level data from CapitalIQ Pro. Several contextual differences caution against direct generalisation. First, US metropolitan areas are typically more self-contained economic units than UK LEPs, which vary greatly in size, industrial composition, and VC market maturity. Second, the US has a more geographically distributed VC market compared to the UK, where London and the South-East account for a disproportionate share of venture activity (Mason and Harrison, 2002; Mason and Pierrakis, 2013). Third, national differences in cultural and institutional contexts give rise to distinct entrepreneurial ecosystems (Dheer, 2017), each with subtle yet meaningful variations that yield country-specific insights, limiting the generalisability of US-based findings to the UK setting. Similarly, recent research highlights that start-ups frequently participate in accelerator programmes outside their home region (Kuebart, Santini and Forrer, 2025), suggesting that accelerator effects may leak across regional boundaries. Such a trans-local dynamic that further explains why measuring impact at the LEP level is inherently challenging.

For regions with less developed start-up infrastructure, our analysis suggests a dual challenge. On the one hand, accelerators in such regions may be the primary vehicle for supporting nascent ventures and attracting investor attention (Fehder and Hochberg, 2014). On the other hand, the limited pool of high-quality start-ups in these areas may force accelerators to lower selection thresholds to fill cohorts, further exacerbating the adverse selection problem (Yu, 2020). This tension implies that the policy prescription is not simply to establish more accelerators, but rather to ensure that those established maintain rigorous selection standards and operate within a broader ecosystem of complementary support mechanisms. The heterogeneity among accelerator types, including the emerging category of ‘ecosystem builder’ accelerators that emphasise corporate partnerships over pure financial returns (Carta et al., 2025; Prexl et al., 2018), further underscores that a differentiated approach to accelerator policy is needed rather than a one-size-fits-all model.

Taken together, our findings directly address the three gaps identified in the introduction. First, by examining the collective regional consequences of multiple accelerators operating within the same area, we provide evidence that their aggregate presence does not translate into increased VC activity at the LEP level. This finding supports our argument that competitive dynamics among proliferating programmes generate noise rather than a clear quality signal for investors. Second, we offer the first empirical test of an agency-theoretic framework applied to accelerator proliferation at the regional level: the ‘market for lemons’ logic (Van Osnabrugge, 2000) explains why positive individual-level effects documented by Hallen et al. (2023) and Carta et al. (2025) fail to scale upward, as the cumulative signal from many accelerators erodes rather than reinforces investors’ confidence. Third, our interaction analyses confirm that the regional environment matters: the negative moderation by GDP per capita and the positive moderation by STEM graduate share demonstrate that the signalling value of accelerators is contingent on the existing resource endowment of the region. The proliferation of accelerators becomes redundant where VCs already possess sophisticated screening mechanisms (Mayya and Huang, 2025), but potentially valuable where human capital concentrations provide a richer pool of investable ventures.

This study has some limitations. First, the synthetic control method only assesses the effect of establishing the first accelerator in a region, viewed as the treatment event. Second, due to the volatile and confidential nature of venture capital data, this approach is better suited for larger areas like LEPs than smaller local authorities. Some local authorities require many years of venture deals for meaningful analysis, which makes matching pre- treatment trends challenging. As a result, the findings may be less comparable to previous research at the local authority level, such as Bone et al. (2019). Third, analysing the separate demand- and supply- side effects of accelerators is beyond this paper’ s scope.

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Appendix A

Table 1: Determinants of regional VC funding

Study	Determinant	Expected relationship with VC
Shachmurove (2007)	Industrial composition	Varies for different industries
Cruikshank (2000)	Concentration of tech firms	Positive
Keeble (1994)	Concentration of tech firms	Positive
Mason and Pierrakis (1994)	Concentration of tech firms	Positive
Karim (2018)	Firm births	Positive
Mason (1985)	Growth rate of firms	Positive
Andriani et al. (2005)	R&D spending	Positive
Christensen (2011)	Proximity of investors	Positive
Martin (1989)	Availability of professional labour	Positive
Mason (2007)	Strong financial sector	Positive
Fehder and Hochberg (2014)	STEM graduate share	No relationship
Fehder and Hochberg (2014)	Income per capita	Negative
Ning, Wang and Yu (2014)	GDP per capita	Positive
Gompers and Lerner (1998)	GDP per capita	Positive
Pires and Gulamhssen (2012)	GDP per capita	Positive