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The Effect of Business Accelerators on Regional Venture Capital Funding in the UK

Abstract

Over the past two decades, numerous local governments in different countries have established accelerators to support start-ups and stimulate local economic transformation. However, the literature contains limited evidence regarding the impact of these programmes on the availability and supply of seed and early-stage venture capital (VC) within their regions. From a theoretical perspective, accelerators have been argued to positively influence regional VC markets by supporting local entrepreneurs and reducing investors' search costs. Drawing on agency theory as the principal theoretical framework, we argue that this relationship may no longer hold under certain conditions. Specifically, when public bodies invest in multiple competing accelerators, these organisations may become less effective at signalling venture quality to investors, thereby generating adverse selection dynamics akin to a 'market for lemons' that may negatively affect regional VC markets. We refer to this phenomenon as the 'proliferation paradox' and argue that it operates within the UK venture capital market, resulting in only limited effects of accelerators on regional VC flows. This paper examines this proposition by analysing the impact of business accelerators on regional VC funding across UK Local Enterprise Partnerships (LEPs) between 1998 and 2016. To address concerns regarding reverse causality, multiple methodological approaches are employed. The findings suggest that accelerators exert only a limited, and in some cases negligible, effect on regional VC investment, particularly in large territorial units such as LEPs. In addition, the results support the view that regional characteristics moderate the relationship between accelerators and VC investment.

1. Introduction

Business accelerators are now widespread across the UK (Bone et al., 2017). The first were established in London and the South East during the 1980s, and by 2016 most Local Enterprise Partnerships (LEPs) and regional economic areas hosted at least one accelerator aimed at stimulating local economic growth. More than 10,000 firms participate in accelerator programmes, and new accelerators continue to be launched annually across the UK (Bone et al., 2019). A substantial body of academic literature has examined the impact of accelerators on a range of indicators, focusing primarily on the outcomes of participating start-ups. Studies within this tradition generally find that firms enrolled in accelerator programmes are more likely to secure subsequent venture capital (VC) investment, achieve higher valuations, and gain access to higher-status investors (Hallen et al., 2023; Carta et al., 2025; Gonzalez-Uribe & Leatherbee, 2018).

However, there is limited evidence regarding the broader role and effectiveness of these programmes at the regional level. In other words, it remains unclear whether these positive firm-level outcomes translate into aggregate regional benefits, such as improved access to VC funding for the wider population of start-ups within a region. The literature suggests that accelerators may increase regional VC inflows by supporting local entrepreneurs (Blair et al., 2020) whilst simultaneously reducing investors' search costs (Fehder & Hochberg, 2014). Empirical research by Fehder and Hochberg (2014) supports these theoretical arguments in the US context; however, Bone et al. (2019) find that positive regional effects are largely confined to high-technology VC investment. Other studies suggest that policies that are effective at the firm level may have uncertain or even negative consequences for the wider regional economy (Davis et al., 1998). Regional industrial composition, for example, may reduce the impact of accelerators on VC investment if dominant local industries do not align with those targeted by the accelerator. High-technology firms, for instance, tend to attract greater levels of VC investment than firms in other sectors (Shachmurove, 2007; Cruikshank, 2000; Keeble, 1994; Mason & Pierrakis, 2013). In addition, shortages of human capital within a region may reduce its attractiveness to VC investors. Other demand-side factors, including rates of firm creation (Karim, 2018) and the emergence of high-growth firms (Mason, 1985), may also constrain regional VC investment.

Against this background, this paper addresses the following research question: to what extent does the establishment of a business accelerator within a region increase VC funding for the wider regional population of start-ups beyond those directly enrolled in the programme? Addressing this question is particularly important for policymakers, given that regional VC investment is associated with both the commercialisation of innovation (Kortum & Lerner, 1998) and the growth and performance of firms (Gompers & Lerner, 2002; Samila & Sorenson, 2011). Theoretically, we argue that two mechanisms may attenuate or even negate the positive firm-level effects of accelerators when considered at the regional scale. First, drawing on agency theory and information economics (Van Osnabrugge, 2000), we propose that the proliferation of accelerators may generate adverse selection dynamics akin to a 'market for lemons' at the aggregate level. When multiple accelerators compete to attract start-ups from the same pool of ventures, selection standards may weaken. As a result, rather than functioning as quality intermediaries that signal promising ventures to VC investors, the growing number of accelerators may instead dilute the informational value of accelerator signals within the investment environment (Hallen et al., 2023). Second, the characteristics of the regional environment may moderate this relationship. In economically developed regions with mature VC ecosystems, investors are more likely to possess sophisticated screening mechanisms, including extensive networks, due diligence capabilities, and established track records, which reduce the incremental signalling value provided by accelerators (Mayya & Huang, 2025).

This paper addresses three interrelated gaps in the literature. First, there has been no systematic examination of the consequences of multiple accelerators operating simultaneously within a geographically bounded area. Existing studies typically treat accelerators as isolated programmes and evaluate them individually, thereby overlooking the possibility that their aggregate presence may generate competitive dynamics—such as weakened selection standards and diluted signalling quality—that undermine, rather than enhance, regional VC activity (Hallen et al., 2023). Second, the literature lacks a theoretical framework explaining why the positive firm-level effects of accelerators may fail to translate to the regional level. In particular, no previous study has applied agency theory and the 'market for lemons' framework (Akerlof, 1970; Van Osnabrugge, 2000) to explain how accelerator proliferation may itself generate informational noise for VC investors, rather than reducing information asymmetry. Third, there is limited understanding of how regional characteristics—particularly the maturity and resource richness of the local VC ecosystem—moderate the aggregate effects of accelerators. This paper addresses these three gaps by adopting a regional-level analytical framework grounded in agency theory and by examining the UK context, where accelerators have proliferated across highly uneven regional VC landscapes, thereby providing an appropriate setting in which to test these arguments.

Evaluating whether accelerators influence the level and availability of regional VC funding is methodologically challenging, as there are no clearly exogenous determinants of accelerator location, nor natural experiments that can readily be exploited for causal identification. The principal challenge arises from the non-random placement of accelerators: regions with higher levels of entrepreneurial activity are more likely to attract such programmes, potentially confounding the estimated effects. Within an ordinary least squares (OLS) regression framework, increases in VC funding may therefore be incorrectly attributed to the presence of an accelerator when they may instead reflect pre-existing entrepreneurial characteristics of the region. To mitigate concerns regarding reverse causality, we employ several methodological approaches. First, we match LEPs hosting an accelerator (treated LEPs) with comparable LEPs on the basis of pre-treatment entrepreneurial trends and then apply Propensity Score Matching (PSM) to estimate the effects of accelerators on these regions. Second, we adopt a synthetic control approach, constructing a counterfactual region without an accelerator by modelling pre-treatment VC investment and deal activity using untreated regions (donor units) together with relevant covariates. The difference in post-treatment VC investment and deal activity between treated LEPs and their synthetic counterparts is then interpreted as the treatment effect (Abadie et al., 2010).

Our PSM results indicate that the establishment of an accelerator within an LEP is associated with a 2.4% annual increase in the number of VC deals in treated LEPs. However, the effect on deal values is not statistically significant. The synthetic control analysis similarly suggests that accelerators do not exert a statistically significant effect on VC funding across LEPs as a whole. Given that previous studies have identified positive effects of accelerators on VC funding at the local authority level—often within subregions of LEPs—we conclude that the influence of accelerators is likely to be highly localised and concentrated primarily within sectors targeted by specific programmes.

This research makes several contributions to the literature. Theoretically, the paper develops a framework explaining why the positive firm-level effects of accelerators may fail to translate to the regional level. Drawing on agency theory, we propose the 'proliferation paradox' as a key mechanism explaining why the presence of multiple accelerators may not necessarily reduce information asymmetry. Empirically, the paper examines the impact of accelerators across all industries in the UK, rather than focusing exclusively on high-technology sectors, thereby avoiding the assumption that VC investment in certain industries is unaffected by accelerators. In this respect, the study extends the work of Bone et al. (2019), who employed a difference-in-differences approach comparing high-technology sectors (treated) with non-high-technology sectors (untreated). Our methodological approach also differs from that of Fehder and Hochberg (2014) by allowing unobservable factors to influence the probability of accelerator establishment, rather than assuming that this probability can be fully estimated from observed regional characteristics.

The paper is organised as follows. Section 2 reviews the relevant literature, Section 3 outlines the methodology and data, Section 4 presents the empirical findings, and Section 5 discusses the findings and concludes.

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 regarding the true quality, capabilities, and prospects of their ventures, thereby creating adverse selection risks for investors. Drawing on agency theory, Van Osnabrugge (2000) argues that venture capitalists mitigate these risks primarily through *ex ante* screening procedures, including due diligence, the assessment of investment criteria, and structured evaluation processes, whereas business angels rely more heavily on *ex post* monitoring. The complexity of venture investment decisions is further highlighted by Urban and Moreno (2022), who demonstrate that such decisions are influenced by multiple factors across the entrepreneurial process, encompassing both individual- and firm-level investment criteria.

Within this agency-theoretic framework, accelerators can be understood as information intermediaries that may reduce adverse selection in two ways. First, through competitive selection processes, accelerators screen start-ups, and participation in or graduation from a reputable programme serves as a quality signal to investors (Connelly et al., 2011; Mayya & Huang, 2025). Second, through mentorship and training, accelerators enhance the quality of participating ventures, thereby reducing the information gap between entrepreneurs and potential investors (Hallen et al., 2023; Gonzalez-Uribe & 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 domains of expertise.

However, the effectiveness of this intermediary function is not uniform and may depend on regional conditions. Hallen et al. (2023) demonstrate that whilst some top-tier accelerators act as ‘status springboards’ for start-ups—helping them gain access to higher-status investors—many others exhibit only limited, or even negative, signalling effects. Crucially, they identify a potential ‘market for lemons’ dynamic: if the highest-quality start-ups choose not to apply to accelerators, whether because of time costs, equity dilution, or concerns regarding the signals associated with participation, this may trigger a recursive deterioration in accelerator quality, whereby accelerators become increasingly associated with lower-quality ventures. We extend this insight from the level of the individual accelerator to the regional scale. When multiple accelerators within a region compete for start-ups drawn from the same pool, their collective signalling capacity may weaken. Rather than reducing information asymmetry for VC investors, the proliferation of programmes may itself generate informational noise within the investment environment, thereby complicating, rather than simplifying, investor screening.

Furthermore, the regional environment moderates the value of accelerators as intermediaries. In regions with well-developed and resource-rich VC ecosystems, investors are likely to possess sophisticated screening mechanisms and extensive networks that provide reliable information regarding start-up quality. In such environments, the marginal informational value provided by accelerators is limited, and their signalling function becomes largely redundant. Conversely, in less developed regions, accelerators may constitute one of the primary sources of information available to investors. However, these regions may also contain smaller pools of high-quality start-ups, potentially exacerbating the ‘market for lemons’ dynamic.

The UK context is particularly well suited to examining these dynamics. Although the ONS does not collect data specifically on start-ups, its statistics indicate that approximately 800,000 new companies were established in the UK between 2022 and 2023, illustrating the contemporary scale of new company formation. London recorded the highest number of new ventures in absolute terms, followed by the South East, whilst fintech and artificial intelligence (AI) were among the sectors exhibiting the greatest concentration of new activity. UK start-ups also face significant regional disparities in access to finance, with London and the South East continuing to dominate the VC landscape (Mason & Harrison, 2002; Mason & Pierrakis, 2013). High-growth early-stage firms—which represent only a small proportion of newly established businesses—are the primary recipients of external equity finance, yet they continue to face substantial funding constraints (Van Osnabrugge, 2000). The rapid proliferation of accelerators across UK regions further reinforces the suitability of the UK as a setting for this analysis. Estimates suggest that more than 10,000 firms participate in accelerator programmes annually, whilst new programmes continue to be launched each year (Bone et al., 2019). Together, these conditions make the UK a particularly suitable setting for examining whether the aggregate regional impact of accelerator programmes replicates the positive firm-level outcomes documented in the literature.

2.2 Accelerators and Regional Venture Capital: Empirical Evidence

Business accelerators are programmes designed to support entrepreneurs by providing networking opportunities, mentorship, and, in many cases, seed funding in exchange for equity stakes (Bone et al., 2019). In the UK, accelerators tend to accept early-stage ventures, primarily from the pre-start-up stage onwards (Bone et al., 2017, 2019). Theoretical explanations for how accelerators may stimulate regional VC activity can be divided into demand-side and supply-side mechanisms. On the demand side, accelerators provide mentorship (Blair et al., 2020) as well as formal and informal education (Goswami et al., 2018), thereby helping start-ups grow and attract investment. In addition, accelerators reduce entrepreneurs' search costs for services such as networking, mentorship, education, and funding (Fehder & Hochberg, 2014). Given that accelerators typically hold equity stakes in participating ventures, they may also mitigate negative signals regarding start-up quality, thereby certifying and enhancing the perceived value of the ventures they support (Kim & Wagman, 2012). On the supply side, accelerators function as both deal sorters and deal aggregators (Fehder & Hochberg, 2014). Deal sorting involves rigorous selection processes designed to identify high-potential start-ups, whereas deal aggregation entails organising investor events that connect ventures with potential investors. Both activities reduce investors' search costs, particularly in smaller regions where such costs may otherwise be prohibitive.

Empirical research examining the impact of accelerators on regional VC funding is summarised in Table A1 in Appendix A. Most existing studies are qualitative in nature, and only a limited number provide quantitative estimates, most notably Fehder and Hochberg (2014) for the US and Bone et al. (2019) for the UK. Qualitative evidence suggests a positive relationship between accelerators and entrepreneurial ecosystems in Jordan (Al-Shamaileh et al., 2020) and India (Goswami et al., 2018), although the effects remain less clear in New Zealand (Blair et al., 2020). Several factors may moderate the impact of accelerators on regional VC funding. Regional industrial composition, for example, is important because high-technology firms tend to attract greater levels of VC investment (Shachmurove, 2007; Cruikshank, 2000; Keeble, 1994; Mason & Pierrakis, 2013). The proportion of students enrolled in Science, Technology, Engineering, and Mathematics (STEM) disciplines within a region may also indicate the availability of specialised human capital valued by VC investors (Martin, 1989). Other demand-side factors include GVA per capita, rates of firm creation (Karim, 2018), and the emergence of high-growth ventures (Mason, 1985), since such ventures typically require greater levels of investment. Previous research also highlights the high costs and administrative burdens associated with equity finance (Wray, 2012), as well as regional disparities in financial literacy (Mason & Harrison, 2002). In addition, the localised nature of VC transactions and the presence of established financial ecosystems appear to play an important role. VC investments often depend on trust and face-to-face interaction, both of which are facilitated by geographical proximity (Christensen, 2011).

Quantitative studies generally report a positive relationship between accelerators and regional VC funding. A key methodological concern in this literature is the potential for reverse causality between VC funding levels and accelerator presence. Fehder and Hochberg (2014) addressed this issue by analysing early-stage investment deals across US metropolitan areas. They first used a hazard model to match treated and untreated regions on the basis of the probability of accelerator establishment and subsequently employed a difference-in-differences model with fixed effects, together with a triple-difference regression applied to the matched sample. Their findings indicate a substantial increase in venture investment activity following accelerator establishment, including a 104.3% rise in early-stage deals and a 217% increase in early-stage software and IT investments relative to biotech investments.

This approach has two principal limitations. First, the probability of accelerator establishment is predicted using only VC-related data, without the inclusion of additional control variables. Because the predictive performance of the hazard model is not reported, the omission of broader economic or political factors may result in biased estimates. Second, the assumption that biotech industries remain unaffected by accelerators is open to question. Since biotech firms may also experience increased investment following accelerator establishment, the triple-difference estimate may be smaller than the corresponding difference-in-differences estimate, thereby suggesting potential bias in the matching procedure. Bone et al. (2019) examined seed investment at the local authority level in the UK and similarly assumed that high-technology sectors were treated, whilst non-high-technology sectors served as controls. Using a difference-in-differences approach, they found that funding in high-technology sectors increased by 114% following accelerator establishment relative to non-high-technology sectors. However, the assumption that accelerators do not affect non-high-technology industries is likewise open to question. Even in the absence of such bias, the estimated effect may still be understated, since firms in other sectors may also experience increased funding.

3. Data and Methodology

3.1 Methodology

To quantify the impact of accelerator presence on regional VC funding and identify the factors that moderate this relationship, we begin by estimating a standard ordinary least squares (OLS) regression with fixed effects for both LEPs and years. The dependent variable is regional VC funding, proxied either by the number of VC deals within a region or by the deflated total monetary value of those deals. The principal independent variable is a binary indicator equal to 1 when an accelerator is present within a given region–year observation and 0 otherwise. Importantly, the dependent variable captures VC deals across all industries within each LEP–year observation, rather than restricting the analysis to a specific sector. This all-industry approach represents a deliberate methodological choice. Previous studies (e.g., Bone et al., 2019; Fehder & Hochberg, 2014) assumed that accelerator effects are confined to certain sectors, typically high-technology industries, whilst unaffected sectors serve as controls. We argue that this assumption is problematic, since the effects of accelerators may spill over across sectors within a region. By including all industries, we seek to capture the full regional effect without imposing untested assumptions regarding which sectors are, or are not, influenced by accelerators. Furthermore, our analysis of accelerators across UK regions indicates that most programmes do not impose industry-specific restrictions as part of their enrolment criteria.

Our baseline specification is as follows:

$$Y_{it} = \alpha_i + \beta D_{it} + X'_{it}\gamma + \lambda_t + u_{it}, \text{ where } i = 1, \ldots, N \text{ and } t = 1998, \ldots, 2016 \qquad (1)$$

where Y_{it} is the dependent variable for LEP i at time t (proxied either by the number of VC deals or by the deflated total value of VC deals); D_{it} is a binary indicator equal to 1 if an accelerator is present in LEP i at time t and 0 otherwise; X'_{it} is a vector of time-varying regional covariates with associated coefficient vector γ; λ_t denotes year fixed effects; α_i denotes LEP fixed effects; and u_{it} is the error term.

We also estimate a variant of Equation 1 in which the key independent variable is the total number of accelerators operating within each LEP in a given year.

3.1.1 Propensity Score Matching (PSM) and Synthetic Control Estimators

As noted earlier, a central challenge in empirical studies examining the impact of accelerators on outcome variables—whether at the regional or firm level—is the non-random placement of accelerators. Accelerators tend to be established in regions with high levels of start-up activity, and decisions to establish an accelerator in one area rather than another may also be influenced by temporary changes in regional attractiveness to investors. To address this issue, we apply a Propensity Score Matching (PSM) estimator to construct matched treated and control LEPs based on observable characteristics. Specifically, we first estimate a logit model in which the probability of accelerator establishment within a particular LEP–year observation depends on regional characteristics and time trends. This allows us to estimate the likelihood of accelerator establishment conditional on prevailing regional economic conditions. Each treated LEP is subsequently matched with untreated LEPs exhibiting the closest estimated probability of accelerator establishment in the same year, provided that the treated observations fall within the region of common support. We then estimate the Average Treatment Effect (ATE).

For the synthetic control estimator, we construct an artificial control LEP—referred to as a synthetic control—for each LEP hosting an accelerator, following the approach developed by Abadie et al. (2010). This synthetic control consists of a weighted combination of untreated areas designed to replicate the pre-treatment trajectory of the treated region. We focus on the impact of treatment on both the value of VC funding invested and the number of VC deals, which are collectively treated as outcome measures. The treatment effect for an individual LEP *i* at time *t* is defined as the difference between venture funding in the treated LEP, $Y_{it}(1)$, and venture funding in the corresponding synthetic control, $Y_{it}(0)$:

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

where each term is a 2×1 vector representing the value of venture funding invested and the number of venture deals; τ_{it} is the vector of treatment effects for both outcome measures; $Y_{it}(1)$ is the vector of post-treatment outcomes for a treated LEP; and $Y_{it}(0)$ is the vector of outcomes for the corresponding synthetic control. Because the analysis includes multiple treated units, we also estimate the average treatment effect across treated LEPs, calculated as the mean treatment effect across all N_1 treated LEPs:

$$\tau_t = 1/N_1 \sum_{j=1}^{N_1} (Y_{jt}(1) - Y_{jt}(0)) \tag{3}$$

where τ_t denotes the average treatment effect for the treated; $Y_{jt}(1)$ represents the outcome values for treated region *j* at time *t*; $Y_{jt}(0)$ denotes the outcome values for the corresponding synthetic control 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. Because VC activity is highly volatile and outcomes in untreated LEPs may be influenced by a range of external factors (Nanda & Rhodes-Kropf, 2016), some donor regions may provide poor approximations of VC trends, thereby increasing estimation uncertainty. Covariates are therefore incorporated into the model, following the recommendation of

Abadie (2021), enabling the estimation of weights and coefficients for the control variables by minimising the following expression:

$$\hat{\beta} \coloneqq (\hat{\omega}', \hat{r}') \in \arg\min_{\omega \in W,\, r \in R} \|(A - B\omega - Cr)'V(A - B\omega - Cr)\| \tag{4}$$

where A is a matrix of pre-treatment outcome measures for treated units; B contains the corresponding outcome measures for donor units; ω represents the weights assigned to donor units; C is a matrix of covariates; r denotes the coefficients associated with the covariates; and V is the weighting matrix, assumed here to be an identity matrix.

This approach employs a separate synthetic control methodology for each treated unit. Pooled and partially pooled synthetic control methods, as proposed by Ben-Michael et al. (2021), were considered but ultimately rejected owing to the substantial heterogeneity of VC ecosystems across regions. The estimation procedure incorporates both Lasso (L1) and ridge (L2) regularisation penalties, following Doudchenko and Imbens (2016). Trend and intercept terms are included for both deal values and numbers of deals. Time-fixed effects are not incorporated, consistent with the recommendations of Cattaneo et al. (2023) and Abadie et al. (2014), because common year-level shocks are already reflected in the VC outcomes of donor regions and are therefore implicitly captured within the synthetic control framework. Uncertainty estimates follow the procedures outlined by Cattaneo et al. (2021), employing simulation-based methods for in-sample uncertainty and sub-Gaussian bounds for out-of-sample uncertainty. The analysis is implemented in Python using the scpi package described by Cattaneo et al. (2023).

3.2 Data

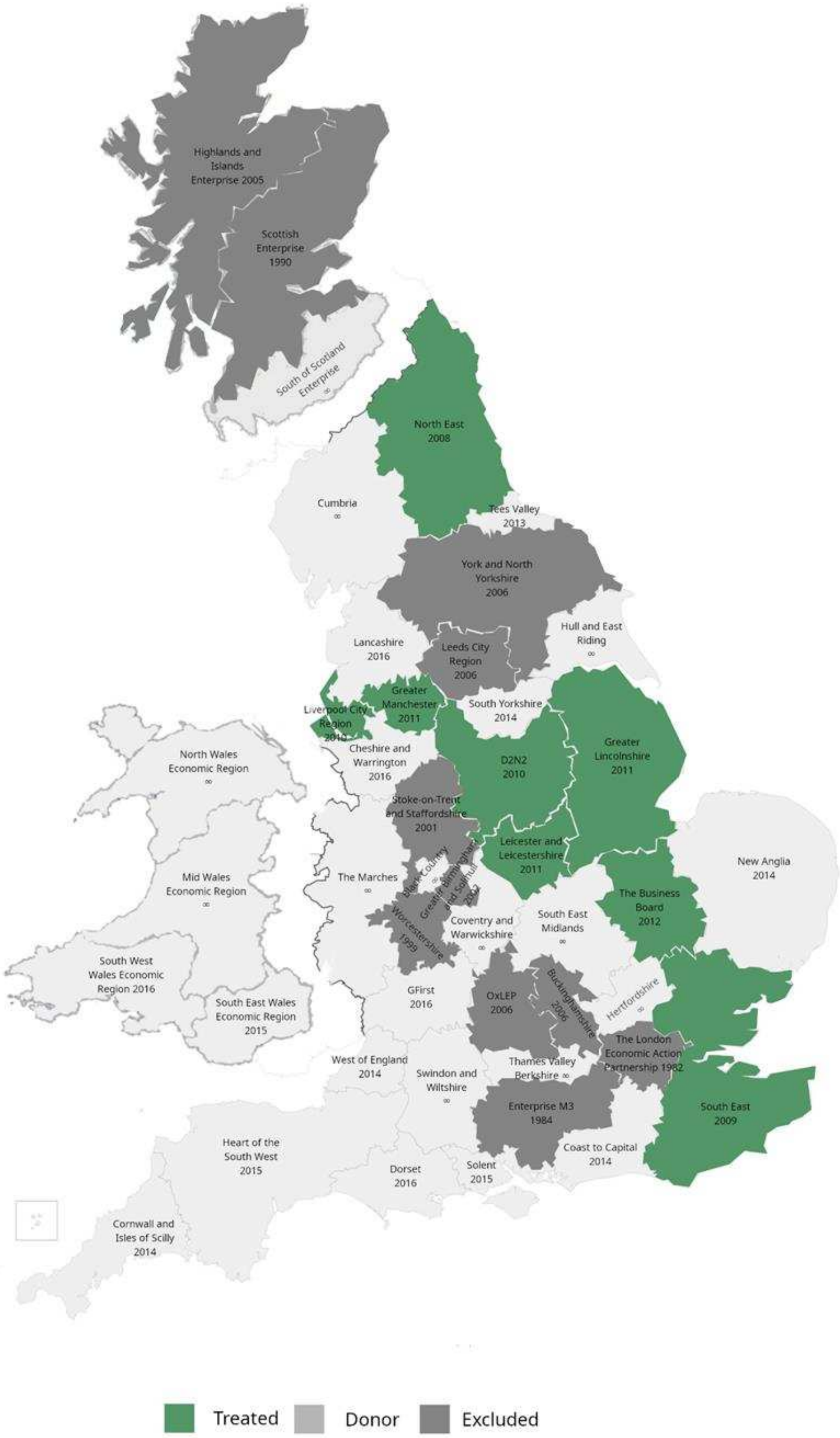
LEPs were selected as the regional units of analysis because they are partnerships established to promote local economic growth (Local Government Association, 2023).

England contains 38 LEPs. Because Scotland and Wales do not have LEPs, nine economic regions (ERs), as defined by the Office for National Statistics (ONS), were used for these nations. Northern Ireland was excluded owing to its distinct economic environment. The full list of LEPs and ERs, together with their corresponding treatment years, is presented in Figure 1. Three regions—the Borderlands Partnership, the Mid and South West Wales Economic Region, and Cumbria—were removed from the sample because none hosted an accelerator during the study period. Of the 139 accelerators included in the sample, only 11 received some form of local government funding; the majority were funded by corporate, public, or educational organisations. Several LEPs whose treatment occurred before the study window were also excluded, namely Stoke-on-Trent and Staffordshire, Greater Birmingham and Solihull, and Worcestershire.

The principal variable of interest is VC investment. However, detailed aggregate VC data for UK regions covering the period from 1998 to 2016 are not available from the ONS. The dataset was therefore constructed using micro-level deal data obtained from Capital IQ Pro. To identify venture capital transactions, the deal categories 'Early Stage' (including angel, pre-seed, and seed funding) and 'Venture' (restricted to companies less than five years old) were selected. After excluding transactions from Northern Ireland, 36,898 deals remained and were subsequently aggregated by region and year. A custom programme was used to match company postcodes to LEPs through the findthatpostcode.com API. In England, deals were aggregated at the LEP level across years. For Wales and Scotland, the same API was used to assign deals to local authorities, which were subsequently grouped into ONS-defined ERs.

Figure 1

Accelerator Landscape in the UK



Of the initial set of deals, 5,920 lacked postcode information. Where city names were available, these observations were manually matched to LEPs. For deals missing postcodes but containing a company registration number (CRN), postcode data were retrieved via the Companies House API. Following these procedures, only 1,272 deals remained unassigned. The final dataset contained 36,898 deals, of which 26,385 disclosed transaction values; these values were adjusted to 2021 prices using the ONS Gross Value Added (GVA) deflator. One challenge associated with aggregating micro-level deal data is the incomplete disclosure of transaction information, since some deals remain undisclosed, although this is likely to affect only a minority of observations. For example, Hamm et al. (2021) report that nearly half of publicly listed US firms do not disclose their corporate venture capital activities.

Data on accelerators were obtained from the Nesta dataset (2017), focusing specifically on programmes offering direct funding in the form of equity investment or loans. This initially identified a sample of 144 accelerators, which were matched to LEPs and ERs using the same procedures applied to the deal-level data. After applying the regional exclusions described above, 139 accelerators remained in the analytical sample. The UK accelerator landscape in 2016—the final year for which data are available—indicates that London's Economic Action Partnership received £4,929 million in VC investment, Scottish Enterprise received £758 million, and The Business Board received £447 million (all values expressed in 2021 prices). These patterns are consistent with the existing literature, which identifies London, the South East, and Scotland as regions possessing the most mature VC ecosystems (Mason & Harrison, 2002). Figure 1 shows that London, the surrounding regions, and Scotland were among the first areas to establish accelerators, a pattern that closely parallels broader VC investment trends. Notably, the area covered by The Business Board, which includes Cambridge, did not host an accelerator until 2012.

Additional covariates were incorporated into the regression models to improve predictive accuracy and account for regional heterogeneity. Gross Value Added (GVA) per capita was deflated using the regional GVA deflator provided by the ONS and subsequently log-transformed to control for differences in regional economic activity. ONS firm birth data were included to account for new venture creation. The proportion of Science, Technology, Engineering, and Mathematics (STEM) undergraduates, sourced from the Higher Education Statistics Agency (HESA) and following the approach adopted by Fehder and Hochberg (2014), was used as a proxy for specialised human capital. These covariates are summarised in Table 1 alongside descriptive statistics, which reveal substantial variation in VC activity across UK regions. Mean regional investment ranges from approximately £1.39 million in Greater Lincolnshire to £178.2 million in The Business Board area, with large standard deviations driven primarily by high-investment hubs such as Cambridge.

Table 1

Descriptive Statistics

Variable	Mean	SD	Source
Deal value (£m)	69.15	119.03	Capital IQ Pro
Number of deals	16.99	17.08	Capital IQ Pro
GVA per capita (£)	24,743.15	3,153.19	ONS
Firm births	6,295.40	4,690.70	ONS / BERR
STEM graduate share	0.43	0.09	HESA

Note. Statistics are at the LEP–year level. Deal values are deflated to 2021 prices using the ONS GVA deflator. ONS = Office for National Statistics; BERR = Department for Business, Enterprise and Regulatory Reform; HESA = Higher Education Statistics Agency.

Because the Nesta accelerator dataset extends only to 2016 and regional GVA data are available from 1998 onwards, the analysis covers the period from 1998 to 2016. In the PSM and synthetic control models, only regions treated between 2008 and 2012 were included. This ensured a sufficient number of pre-treatment observations for synthetic control construction, as well as an adequate post-treatment period in which to observe treatment effects. Regions treated before 2008 were excluded, whereas regions treated after 2012 were used as donor units. In Figure 1, treated regions are shown in green, donor regions in light grey, and excluded regions in dark grey.

4. Results

This section presents the empirical findings, beginning with the baseline OLS regression models before turning to the more robust PSM and synthetic control estimators designed to address potential reverse causality.

4.1 OLS Results

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

As shown in Table 2a, the presence of at least one accelerator (captured by the dummy variable) is not significantly associated with the value of VC deals within an LEP (column 1). However, it is significantly and positively associated with the number of deals in the Poisson model (column 2), albeit the magnitude of the effect is small. This finding suggests that accelerator presence is more closely related to the number of investment deals than to the total volume of capital invested.

A more informative pattern emerges when the analysis considers the total number of accelerators within a region (columns 4–6). In the baseline OLS specifications, a higher concentration of accelerators is significantly and positively associated with both the total value of VC deals and the number of deals. This suggests that, whilst the presence of a single accelerator may exert only a limited effect, regions hosting multiple accelerators also tend to exhibit more active VC markets.

Table 2a

Regression Model Estimates for the Main Effect: OLS and Poisson Estimators

	Log deal value per LEP (deflated) (a)	**No. of deals per LEP (b)**	**Log deal value per LEP (deflated) / No. of deals per LEP (a)**	**Log deal value per LEP (deflated) (a)**	**No. of deals per LEP (b)**	**Log deal value per LEP (deflated) / No. of deals per LEP (a)**
Accelerator dummy (= 1 if LEP hosts an accelerator in a given year)	0.23 (1.33)	0.25** (2.57)	0.19 (1.16)			
Total number of accelerators per 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 graduate share	−1.30 (−0.53)	1.73*** (5.85)	0.87** (2.42)	−1.08 (−1.11)	1.77*** (7.19)	−0.80 (−0.88)
GVA per capita (log, 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 in parentheses. LEP and year fixed effects included in all models. (a) OLS estimator. (b) Poisson estimator. *$p < .05$. **$p < .01$. ***$p < .001$.

Table 2b presents the interaction effects analysis and reveals a more nuanced pattern of relationships. The interaction term between the STEM graduate share and the total number of accelerators is positive and statistically significant (column 2), indicating that the positive association between accelerators and the number of VC deals is stronger in regions with a higher concentration of specialised human capital. Conversely, the interaction term between GVA per capita and the number of accelerators is negative and statistically significant (column 5) when the number of deals is the dependent variable. This finding suggests a diminishing returns effect, whereby the marginal impact of an additional accelerator on the number of VC deals weakens in regions that are already more economically developed.

Turning to the main-effect coefficients, the estimated effects of GVA per capita and the STEM graduate share vary across model specifications. Considered alongside the interaction effects, the estimates suggest that the relationship between accelerator concentration and VC activity is moderated by regional economic conditions and human capital. As GVA per capita increases, the estimated marginal effect of an additional accelerator on the number of deals remains small but positive, ranging between 0.00048 and 0.0012. Similarly, as the STEM graduate share increases, the corresponding estimated effect ranges between 0.95 and 1.10.

Table 2b

Regression Model Estimates for the Interaction Effects: OLS and Poisson Estimators

	Log deal value per LEP (deflated) (a)	**No. of deals per LEP (b)**	**Log deal value per LEP (deflated) / No. of deals per LEP (a)**	**Log deal value per LEP (deflated) (a)**	**No. of deals per LEP (b)**	**Log deal value per LEP (deflated) / No. of deals per LEP (a)**
Total number of accelerators per 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 graduate 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)
GVA per capita (log, 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)
STEM graduate share × total no. of accelerators per LEP	0.13 (0.74)	0.15** (2.57)	0.12 (0.76)			
GVA per capita × total no. of accelerators per LEP				−0.12** (−2.50)	−0.074*** (−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 in parentheses. LEP and year fixed effects included in all models. (a) OLS estimator. (b) Poisson estimator. **p* < .05. ***p* < .01. ****p* < .001.

Statistically significant coefficients for the control variables are relatively limited across the models estimating deal values, whether measured in absolute terms or normalised by the number of deals. The principal exception is the share of new firms established within LEPs, for which the estimates indicate a positive association between firm births and early-stage funding activity. By contrast, the control variables are consistently positive and statistically significant in the Poisson models in which the total number of deals serves as the dependent variable.

Although these OLS results are informative, they do not establish causality. Accelerators are frequently established in regions that already possess strong entrepreneurial characteristics, giving rise to a classic endogeneity problem that may bias the estimated coefficients. We therefore turn to alternative methods designed to mitigate this issue.

4.2 PSM and Synthetic Controls Estimators

To address the non-random placement of accelerators, we employ both Propensity Score Matching (PSM) and the synthetic control method. Table 3 presents the PSM estimates, which indicate an increase in the number of early-stage venture deals following the establishment of an accelerator within an LEP. However, no statistically significant difference is observed between treated and untreated LEPs with respect to the value of VC deals.

Table 3

Propensity Score Matching Estimates

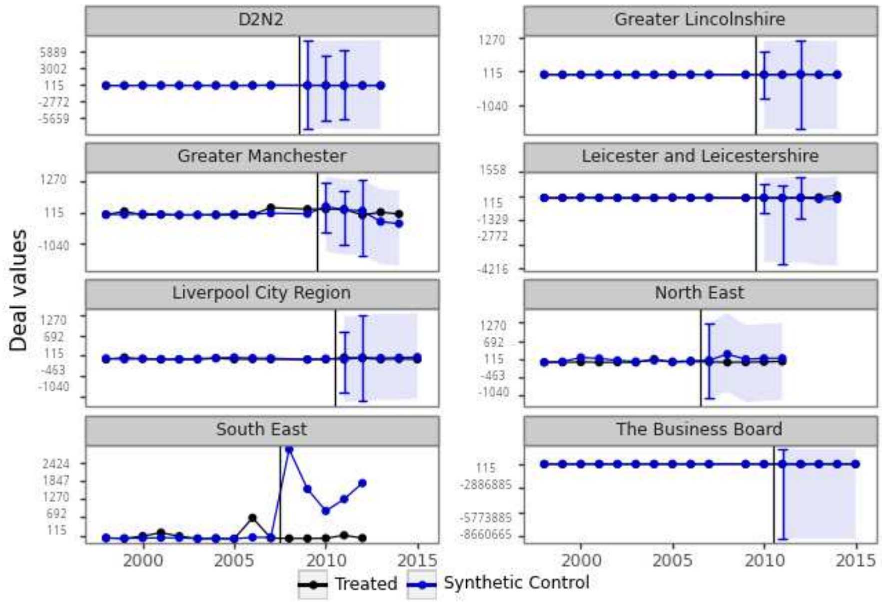
	Deal value (deflated)	**Number of deals**
ATE	−13.17 (−0.34)	8.07** (2.29)
N	836	836

Note. Robust standard errors. *t*-ratios in parentheses. ATE = average treatment effect. ***p* < .01.

Turning to the synthetic control estimators, Figures 2–4 compare venture funding trajectories in the treated regions (black lines) with those of their corresponding synthetic controls (blue lines). Figure 2 presents the prediction intervals for each treated unit, whilst Figure 3 provides a more detailed view of how the algorithm constructs the synthetic controls. Figure 4 then displays the prediction intervals for the average treatment effect on the treated (ATT).

Figure 2

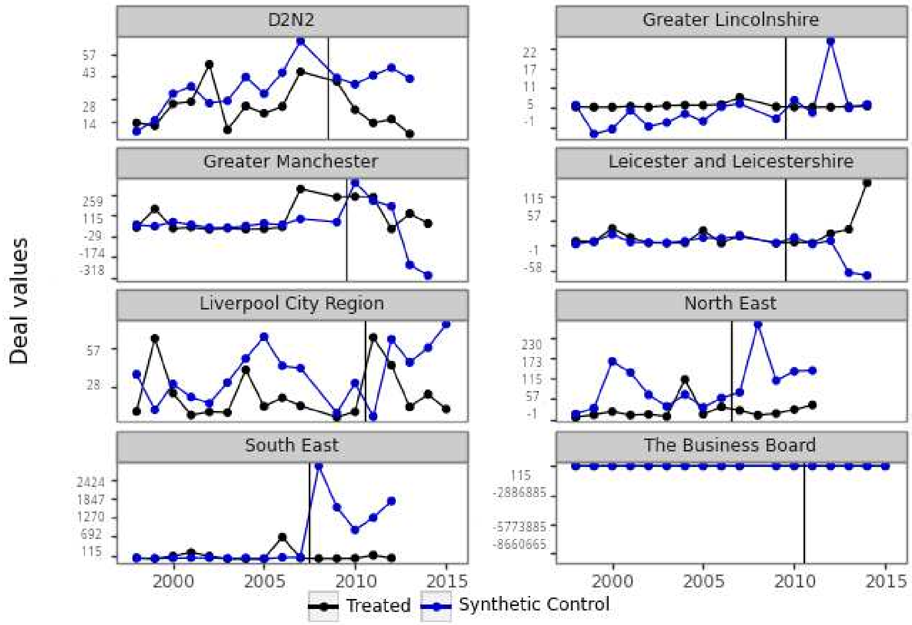
Prediction Intervals for Individual Treatment Effects



Note. Deal values are in £m, deflated to 2021 prices. Black circles = treated LEP; blue circles = synthetic control. The vertical line marks the treatment year.

Figure 3

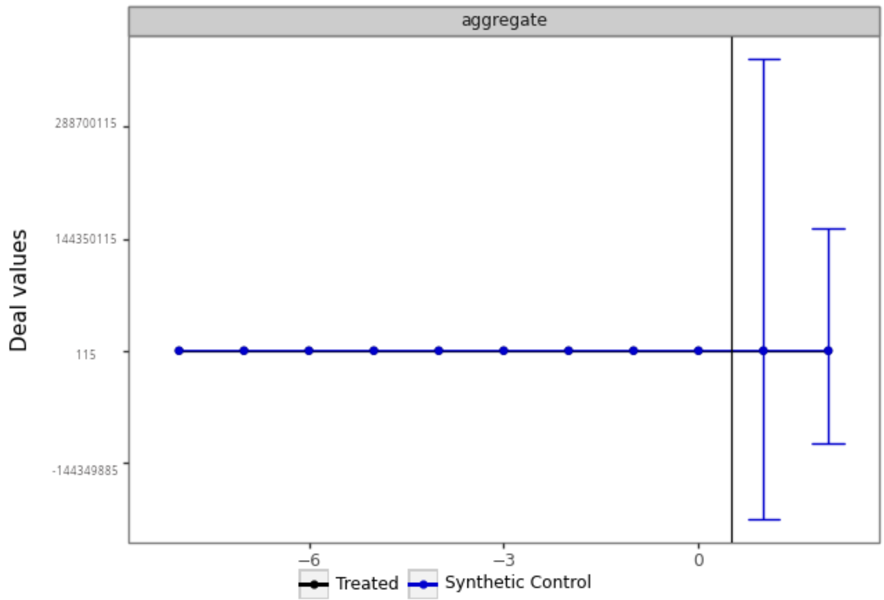
Fitted Pre- and Post-Treatment Trends



Note. Deal values are in £m, deflated to 2021 prices. Black circles = treated LEP; blue circles = synthetic control. The vertical line marks the treatment year.

Figure 4

Prediction Intervals for the Average Treatment Effect on the Treated (ATT)



Note. Deal values are in £m, deflated to 2021 prices. Black circles = treated LEPs (mean); blue circles = synthetic controls (mean). The x-axis indicates years relative to the treatment year (0 = treatment year).

In Figure 3, we expect to observe a close alignment in pre-treatment trends, since synthetic controls are specifically constructed to predict venture investment trajectories in treated units (Abadie, 2021). We also expect a positive post-treatment gap between venture funding in a treated region and in its corresponding synthetic control following the establishment of an accelerator. Figures 2 and 4 present the results on a broader scale, where any increase in venture funding attributable to accelerator establishment would be expected to fall outside the prediction intervals if statistically significant.

Figure 3 shows that the synthetic controls generally provide imperfect fits for venture funding trends in treated regions, with the exception of Leicester and Leicestershire. Nevertheless, the treated and synthetic series follow broadly similar trajectories, suggesting that the pre-treatment values are reasonably well predicted. The weakest fit is observed for The Business Board area, which is unsurprising given that previous research has linked early-stage investment primarily to high-technology clusters, such as the Cambridge cluster located within The Business Board region (Mason, 2007). Figure 3 further indicates that only Greater Manchester and Leicester and Leicestershire exhibit higher post-treatment venture investment relative to their synthetic controls; however, Figure 2 suggests that these differences are not statistically significant.

Moreover, in cases where accelerators appeared to exert a positive effect, the synthetic controls generated negative predicted investment values. Because accelerators do not exert a statistically significant effect across LEPs as a whole, Figure 4 provides no evidence of an average treatment effect on the treated (ATT), as the black line remains within the prediction intervals and coincides with the blue line. Given the well-documented volatility of regional VC investment (Nanda & Rhodes-Kropf, 2016), accurately predicting venture investment at the LEP level is inherently challenging, and any modest effect associated with a single accelerator may remain within the prediction intervals. However, this interpretation is undermined by the fact that regions in which the first accelerator was established (D2N2 and Leicester and Leicestershire) do not exhibit even a small positive post-treatment gap in Figure 3.

We now turn to the economic mechanisms that may explain why accelerators appear to exert positive effects at the local authority level but not at the LEP level. Bone et al. (2019) demonstrate that accelerators generate spillover benefits within local authorities that extend beyond participating firms themselves. Two possible explanations may account for these geographical differences. First, accelerators may function as deal aggregators primarily within their host local authority, attracting firms from that locality rather than from elsewhere within the same LEP. Investors may similarly prefer to concentrate their search activities within a single local authority, thereby reducing the availability of VC investment in other parts of the LEP. In addition, firms seeking VC funding may relocate to local authorities hosting accelerators; however, previous research suggests that other factors play a more important role in start-up relocation decisions (Colombo et al., 2021). Taken together, a reduced supply of VC and weaker demand for VC within areas of the treated LEP outside the specific local authority may offset any positive accelerator effects, thereby resulting in a negligible overall impact on regional venture funding.

4.3 Analysis of Donor Weights and Covariates

To assess the plausibility of the synthetic controls, we examine both the donor weights and the influence of regional covariates. Table 4 reports donor-unit weights equal to or greater than 0.05 for the regression associated with each treated unit. Geographical proximity to London and regional industrial composition are used to evaluate the similarity between donor and treated regions. Regions located near London are classified as core regions, whereas all others are classified as peripheral regions, as indicated in Table 4.

To measure similarity in industrial composition, we compute the Krugman index by comparing sectoral employment shares between pairs of regions in 2016, the final year for which data are available. The index captures differences in sectoral employment shares and summarises these deviations in a single indicator: a value of 0 indicates highly similar industrial structures, whereas a value of 2 indicates entirely dissimilar structures. Owing to data limitations in the Nomis dataset, the index could only be calculated for LEPs in England; Welsh regions are therefore marked 'N/A' in the final column. To contextualise the index values, we compare the Krugman indices of treated regions with the corresponding index value for London, which exhibits a distinctly different industrial structure. The lowest Krugman index observed for any treated region relative to London is 0.35 (Greater Manchester); values below this threshold therefore indicate relatively similar industrial structures.

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	0.270
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

Note. Only donor units with a weight ≥ 0.05 are shown. The Krugman index measures dissimilarity in industrial composition; higher values indicate greater dissimilarity. Regions classified as core are those in proximity to London. N/A indicates that data were unavailable for Welsh economic regions owing to Nomis data limitations.

A plausible synthetic control should be constructed from donor regions that are economically similar to the treated region. For example, Greater Manchester, a major peripheral city-region, is matched primarily with Dorset (69%), another peripheral region, together with the core regions of Hertfordshire and South East Midlands. The low Krugman index values (below 0.3) for these pairings indicate broadly similar industrial structures, suggesting that the algorithm has identified plausible economic comparators and thereby strengthening the credibility of the counterfactual scenario.

Table 5

Coefficients on Covariates

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

Note. Coefficients are from the synthetic controls regression (Equation 4). Only treated units and covariates with non-zero coefficients are shown. GVA per capita is log-transformed and deflated to 2021 prices. STEM graduate share is the proportion of STEM undergraduates in the region. Greater Lincolnshire is absent as no covariate coefficients exceeded zero in that model.

Furthermore, the covariate coefficients used in constructing the synthetic controls, presented in Table 5, illustrate how different regional characteristics shape VC funding trends, thereby highlighting substantial regional heterogeneity. For example, in Greater Manchester and the North East, a higher share of STEM graduates is associated with increased VC funding (with coefficients of 0.57 and 0.14, respectively). By contrast, this relationship is strongly negative in the South East and The Business Board area (−3.79 and −0.17, respectively). These findings support the view that the determinants of VC investment are not uniform across regions. In mature ecosystems such as the South East, factors beyond the simple availability of STEM talent may play a more important role. Similarly, the effect of firm births varies across regions, functioning as a strong positive predictor in the North East and South East, but as a negative predictor in Greater Manchester and The Business Board area.

5. Discussion and Conclusion

This paper investigates whether the establishment of a business accelerator increases venture capital funding across a broader region, using UK LEPs as the unit of analysis. Our study, which employs multiple methods to address the non-random placement of accelerators, yields three principal findings. First, accelerators appear to exert only a limited effect on aggregate regional venture investment, contrasting with earlier studies by Fehder and Hochberg (2014) and Bone et al. (2019), which used local authorities as the units of analysis. We conclude that the economic benefits associated with accelerators—including deal aggregation and investor networking—are highly localised and do not generate substantial spillover effects across the wider region.

Second, the analysis supports the view that the relationship between venture capital and regional industrial composition is not uniform (Shachmurove, 2007). As demonstrated in the synthetic control covariate analysis (Table 5), factors such as the STEM graduate share and the rate of firm births may function as positive predictors of VC funding in some LEPs but as negative predictors in others. This heterogeneity underscores the difficulty of applying a uniform entrepreneurship policy framework across regions.

Third, the analysis provides new insights into the relationships between venture capital, firm births, and regional GVA per capita, showing that these relationships vary according to regional characteristics rather than being uniformly positive or negative, as suggested in some earlier studies.

These findings are consistent with our theoretical framework grounded in agency theory and information economics. At the level of individual programmes, accelerators may function as effective information intermediaries that reduce adverse selection by signalling start-up quality to investors (Van Osnabrugge, 2000; Mayya & Huang, 2025). However, at the aggregate regional level, the proliferation of accelerators may generate adverse selection dynamics akin to a 'market for lemons' (Hallen et al., 2023). When multiple programmes compete for start-ups drawn from the same pool, the informational value of accelerator signals may become diluted. Rather than functioning as reliable intermediaries that reduce information asymmetry, the proliferation of accelerators may itself generate informational noise within the investment environment, thereby complicating, rather than simplifying, the screening process for VC investors.

The role of regional characteristics in moderating accelerator effects deserves particular attention. Our finding that the interaction between GVA per capita and accelerator count is negative and statistically significant (Table 2b) is consistent with the redundancy mechanism: in resource-rich regions, investors possess established screening mechanisms—such as peer benchmarks and informal due diligence networks—that render the informational value of accelerators largely redundant. This interpretation aligns with the findings of Mayya and Huang (2025), who demonstrate that the benefits of accelerators are greatest for investors lacking domain-specific expertise. Conversely, the positive interaction between the STEM graduate share and accelerator count suggests that regions with strong human capital possess a larger pool of potentially commercialisable ideas, thereby increasing the average quality of ventures relative to other regions. In such environments, accelerators may play a more meaningful intermediary role by connecting a richer pool of technically capable ventures with investors.

An important consideration in interpreting our results is the distinction between the UK context and other national contexts, most notably the US. Fehder and Hochberg (2014) examined 38 US metropolitan areas using Census data, whereas the present study analyses UK LEPs and economic regions using deal-level data from Capital IQ Pro. Several contextual differences caution against direct generalisation of the findings. First, US metropolitan areas are typically more self-contained economic units than UK LEPs, which vary substantially in size, industrial composition, and VC market maturity. Second, the US possesses a more geographically dispersed VC market than the UK, where London and the South East account for a disproportionate share of venture activity (Mason & Harrison, 2002; Mason & Pierrakis, 2013). Third, national differences in institutional and cultural contexts give rise to distinct entrepreneurial ecosystems (Dheer, 2017), each characterised by meaningful structural differences that generate country-specific dynamics, thereby limiting the generalisability of US-based findings to the UK context.

In addition, recent research highlights that start-ups frequently participate in accelerator programmes outside their home region (Kuebart et al., 2025), suggesting that accelerator effects may spill across regional boundaries. This trans-local dynamic further explains why measuring accelerator impacts 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 represent the primary mechanism for supporting nascent ventures and attracting investor attention (Fehder & Hochberg, 2014). On the other hand, the limited pool of high-quality start-ups in these areas may compel accelerators to lower their selection thresholds in order to fill programme cohorts, thereby further exacerbating adverse selection dynamics (Yu, 2020). This tension suggests that the appropriate policy response 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, which emphasise corporate partnerships over purely financial returns (Carta et al., 2025; Prexl et al., 2018)—further underscores the need for a differentiated approach to accelerator policy rather than a uniform, 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 supports our argument that competitive dynamics among proliferating programmes may dilute rather than reinforce the informational value of accelerator signals for investors. Second, we provide one of the first empirical applications of an agency-theoretic framework to accelerator proliferation at the regional level. Specifically, the 'market for lemons' logic (Van Osnabrugge, 2000) helps explain why the positive firm-level effects documented by Hallen et al. (2023) and Carta et al. (2025) may fail to scale to the regional level. As multiple accelerators proliferate within the same environment, their cumulative signalling effects may erode rather than reinforce investor confidence.

Third, our interaction analyses confirm the importance of the regional environment. The negative moderating effect of GVA per capita and the positive moderating effect of the STEM graduate share demonstrate that the signalling value of accelerators is contingent on the existing resource endowment of a region. Accelerator proliferation may become redundant in contexts where VC investors already possess sophisticated screening mechanisms (Mayya & Huang, 2025) but may remain valuable in regions where concentrations of human capital provide a richer pool of investable ventures.

This study has several limitations. First, the synthetic control method assesses only the effect of establishing the first accelerator within a region, which constitutes the treatment event in the analysis. Second, owing to the volatile and confidential nature of venture capital data, this approach is more suitable for larger regional units such as LEPs than for smaller local authorities, where the limited number of venture deals per year makes accurate matching of pre-treatment trends difficult. Consequently, the findings may not be directly comparable with previous studies conducted at the local authority level, such as Bone et al. (2019). Third, a separate analysis of the demand- and supply-side effects of accelerators falls outside the scope of this paper.

Appendix A

Table A1

Determinants of Regional VC Funding

Study	Determinant	Expected relationship with VC
Shachmurove (2007)	Industrial composition	Varies by industry
Cruikshank (2000)	Concentration of tech firms	Positive
Keeble (1994)	Concentration of tech firms	Positive
Mason & Pierrakis (2013)	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 & Hochberg (2014)	STEM graduate share	No relationship
Fehder & Hochberg (2014)	Income per capita	Negative[a]
Ning et al. (2014)	GDP per capita	Positive
Gompers & Lerner (1998)	GDP per capita	Positive
Pires & Gulamhussen (2012)	GDP per capita	Positive

Note. This table summarises the determinants of regional VC funding identified in the literature and their expected directional relationship with VC investment. [a] The negative relationship reported by Fehder and Hochberg (2014) reflects a conditional effect within their hazard model specification and should not be interpreted as a general negative association between income per capita and regional VC investment.