Evaluating the Role of Tax-Incentivised Place-Based Policies in Enhancing Local Employment: Case Study Evidence from the 2017 UK Enterprise Zone Program

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Abstract

This paper investigates the local employment impact of place-based policies, specifically evaluating the 2017 Enterprise Zone (EZ) program in the UK as a tool for economic recovery. Using the Hertfordshire Enviro-tech Enterprise Zone as a case study, the study employs Propensity Score Matching (PSM) to construct a weighted counterfactual comparison group, and Difference-in-Differences (DiD) to estimate the causal effects of the EZ policy. Fixed effects models isolate the policy's impact by controlling for unobserved time-invariant heterogeneity across regions. The study defines three boundaries around the enterprise zone site location to identify the spatial impacts of the policy. In each boundary, analysis reveals significant positive effects of the program on local employment growth, with increases of 10.5% within 2km, 6.2% within 4km, and 3.3% within 10km of the zone. Therefore indicating a pattern of stronger employment boosts in closer proximity to the zone site location. This study also identifies positive spillover effects in peripheral regions, however further research is needed to disentangle these from potential displacement effects. This study contributes to the understanding of enterprise zones' efficacy by providing nuanced insights into their spatial effects and advocating for tax-incentivised place-based policies as a viable approach to employment generation. However, findings are constrained by single case study focus and a limited observation period. Future research should consider a multi-zone analysis over an extended period to yield a comprehensive understanding of the long-term impacts of enterprise zones on local labour markets.

1. Introduction

1.1 Motivations

The Covid-19 pandemic and the subsequent economic recession have accentuated the need for targeted policy measures aimed at employment generation and economic recovery. The OECD (2009) highlights the strategic importance of place-based policies in driving localised economic growth, a recommendation that gains urgency in the current context. This paper explores the effectiveness of such policies, specifically focusing on the local employment impact of the UK's 2017 Enterprise Zone program.

The pandemic has had profound impact on the UK labour market, increasing the unemployment rate to 5% by January 2021- marking the highest level observed since 2016. Whilst alarming, such national statistics only provide only begin to uncover the depth of the crisis, as they mask the varied spatial impacts of pandemic, which are expected to have significant long-term consequences for local economies across the UK (Work foundation, 2021). Against this backdrop, the UK's Levelling Up agenda, which advocates for the use of targeted interventions to alleviate regional disparities and promote economic growth, becomes particularly relevant. This study situates its analysis within this 'levelling up' framework, aiming to inform policymakers about the effectiveness of placed based policies in promoting economic growth. This is particularly pertinent given recent the introduction of the UK Freeports programme, representing a continued interest in place-based economic development approaches in the UK post pandemic.

1.2 Objectives

The core objective of this paper is to evaluate the effectiveness of place-based policies in driving local employment growth, focusing on the employment impact of the **2017 Enterprise Zone program**. Through detailed case study analysis, this study aims to address the fundamental question: *Did the designation of Enterprise Zone status successfully stimulate* ***local employment growth****, and to what extent does this change depending on proximity to the zone?*

Despite the extensive research on enterprise zones, from a policy standpoint, a notable gap persists in understanding whether enterprise zones effectively foster employment growth (Kolko & Neumark, 2010). This study aims to bridge this gap by quantifying the impacts of the UK Enterprise Zone policy on local labour markets, thereby contributing to the literature on place-based economic development strategies within the UK context.

1.3 Methodology and Contributions

In achieving its objectives, this paper will also contribute to academic literature in a variety of ways:

Firstly, this study employs a fixed effects difference-in-differences analysis to ascertain evidence of local employment increases in the selected case study areas. To aid this approach, propensity score matching is used to create a weighted counterfactual comparison group, a method increasingly recognised for 'assessing the causal effects of treatments on unique historical events' (Hollingsworth & Wing, 2022). To mitigate the impact of spillovers, the comparator areas selected for the propensity score matching, have been selected from a national wide pool of Lower Layer Super Output Areas (LSOAs).

Secondly, this study leverages the increased availability of local employment data at an LSOA level. Using GIS software, BRES employment microdata is matched to LSOAs within a 2km, 4km and a 10km boundary, the impacts of establishing these differing boundaries are twofold. firstly, the differing boundaries allows this research to capture the varied spatial employment impacts. Furthermore, this process also facilitates the creation of a panel dataset, specifically designed to enable the application of a "Within Group Fixed Effect (FE) model". Through structuring the data in this way, it becomes possible to control for unobserved time-invariant heterogeneity across areas, thus addressing a key challenge often present in the analysis of Enterprise Zones (Kolko & Neumark, 2010). Further rationale for the aforementioned contributions are detailed in the subsequent literature review.

Economic Theory and Literature review

The following chapter explores the existing literature on Enterprise zones and their effects on employment, focussing specifically on the presumed correlation between tax incentives and job creation. It begins with a summary of the historical context of enterprise zones in Britain, in order to provide a comprehensive understanding the political economy of the late 1980s from which the Zones emerged. By Using a detailed analysis of the current literature, the review will reveal a lack of clear consensus on the employment impacts of enterprise zones in both Britain and USA.

Following this, the review will examine methodologies commonly undertaken by economists in their analysis of enterprise zone efficacy; and will consider how these methods influenced their empirical findings.

Consequently, it becomes apparent that the use of different econometric models contributes to ongoing ambiguities around the efficiency of enterprise zones in stimulating job creation. The diversity of methods, theories and arguments presented by the established literature, provides scope for contributions presented in this study, in addition to highlighting the necessity for further comparative evaluations in this subject area.

1.4 Historical context and the case for enterprise zones in the UK

Since the mid-20thcentury, governments in Europe and North America have opted for the adoption of place-based policies in efforts stimulate economic growth in 'blighted' areas (Scavette, 2022). Broadly defined, place-based policies refer to government initiatives that seek to improve the economic performance of a given area, often resulting in both increased employment opportunities and wages. A practical example of this concept is evident in the designation of "enterprise zones", where a state will aim to incentivise increased private investment and business activity through the provision of tax concessions.

The seminal concept of enterprise zones is attributed to Peter Hall, a renowned British urban planning professor. Hall drew inspiration from the significant economic development observed in the "freeports" of Asia, noting the key driver of their economic success due to low taxation and minimal government intervention in markets. Building on these neoliberal principles, the newly elected Thatcher government introduced the first UK enterprise zones in 1981 (Palombo, 2015).

Economic theory proposes that reduced taxes and regulation incentivise businesses to operate in zones, minimising costs and maximising profits. This benefits the labour market as businesses expand production due to lower startup and operational costs. As a solution to the 'post-industrial inner-city crisis', the Thatcher government sought to use this policy to integrate unemployed inner-city residents into 'new jobs' (Potter & Moore, 2000). Expanding on this initiative, in 2017, a further 24 enterprise zones were introduced in the UK (Chaudhary & Potter, 2019).

1.5 Enterprise Zone Employment Impact Evidence

Empirical evaluations of enterprise zones employment effects present varied results. The following section will delve into the success of the enterprise zone policy within the UK in addition to briefly summarising the effectiveness of the policy in the USA.

In the UK, the initial successes of the programme are evident in Studies conducted by PACEC (1995), which examined employment levels over a 10-year period. Results indicate that due to the policy, there were over 4,300 companies operating within the designated zones, contributing to an estimated 'creation' of 63,300 jobs within zones by 1987. However, upon closer examination, subsequent studies reveal that the impact on job creation may not have been as straightforward as initially perceived. Sissons & Brown's (2011) evaluation of UK enterprise zones found that, of the 63,300 jobs created, only a small proportion (approximately 13,000) were truly 'new' and additional to the labour market. Further analysis using survey data indicated that about 25% of these jobs were genuinely new, whereas a significant portion, approximately 80%, were displaced from other areas, with 25% of these jobs displaced from within the same town that received the Enterprise designation (Sissons & Brown, 2011). These findings are in agreement with Papke's (1994) conclusion that the British zone program "did not achieve its goal of generating new industrial activity".

Outside the UK context, research and academic discourse surrounding the employment impact of enterprise zones continues to present a history of conflicting evidence, this is particularly relevant in extensive research into the impacts of the policy in the USA. For instance, research by Boarnet and Bogart (1996) examined the employment impacts across seven enterprise zones in New Jersey, spanning from 1984 to 1996. The findings indicate that despite the provision of tax incentives, there were no significant changes observed in employment within the designated zones compared to regional employment trends. Similar conclusions are also apparent in Kolko & Neumark's (2010) study on California's enterprise zone program. Although researchers observed negligible short term employment increases (1-3%) within the zones, the overall evidence from the paper indicates that enterprise zones do not increase employment. Specific examples highlight instances where the policy has resulted in long-term reductions of employment by 1.2%. Therefore raising significant questions about the efficacy of the enterprise zone policy in achieving one of its intended goals of stimulating job growth.

In contrast, several US state program evaluations have reported significant employment benefits associated with the designation of enterprise zones status (Chaudhary & Potter, 2019). For instance, research by Leslie E. Papke (1994) used panel jurisdiction data to analyse the effects of Indiana's enterprise zone program on local employment. Papke's findings revealed a significant decrease of 19% in unemployment claims within the zone and its surrounding areas. Meanwhile additional research on Indiana's enterprise zone policy conducted by Rubin and Wilder (1989) also found that local employment levels increased by more than one-third. Additionally, both (Ham et al., 2011) and (Busso et al., 2013) evaluations of the US federal empowerment zone also corroborates with these findings, noting a 15% -34% local employment increase in their respective studies. Therefore showing that the designation of enterprise zone status can indeed have a positive impact on local employment levels as hypothesised by policymakers.

1.6 Quantifying Employment Impacts and Methodological Approaches

The third part of this literature review discusses varied approaches employed by empirical studies to assess the effectiveness of enterprise zones. It will then explore how sophisticated regression methods offer a robust solution to previous evaluative techniques, thus shaping the contribution of this paper's methodology to existing literature.

Assessing the extent to which enterprise zones stimulate employment growth is contingent on the methodological approach used. Typically, the task of many researchers interested in this subject area, is to both accurately measure and isolate the effects of the zone designation from the other influential "background effects". These include key local area characteristics such as wages, unemployment levels and economic stability. In other words, to truly determine the employment impact of enterprise zone, researchers must assess what would have happened in the absence of the zone (counterfactual). This entails evaluating whether the area of study would have witnessed employment changes with or without the presence of the enterprise zone (MN House Research, 2005).

Due to their inability to isolate zone-induced job growth, methodologies such as Survey Analysis and Shift Share Analysis are limited in their capacity to accurately depict this counterfactual scenario. This issue may in turn lead to biased empirical findings (MN House Research, 2005). Whereas regression analysis, offers a refined investigation into the effectiveness of enterprise zones by statistically assessing the impact of various factors on employment variables. Traditional comparative analysis methods, such as Difference-in-Differences (DiD), facilitate this analysis by comparing treated and control groups before and after the implementation of the policy.

However, despite the utility of these methods, they are not without limitations - particularly evident in enterprise zone research. Firstly, traditional DiD relies on the Parallel Trends assumption, which often fails to hold true in the context of enterprise zones. This challenge arises from the allocation of enterprise zones in economically distressed areas, where the identification of a realistic control group demonstrating similar economic characteristics and trends, proves challenging (MN House Research, 2005). This hindrance complicates the precise identification of policy treatment effects, thereby diminishing the reliability and prevalence of comparative evaluations within academic discussions focused on enterprise zones.

Secondly, as highlighted by Neumark & Young (2019), the use of traditional DiD in enterprise zone policy is also susceptible to the problem of “selection bias”. This issue acknowledges the potential bias arising from the non-random allocation of enterprise zones, which undermines exogeneity assumptions in addition to the validity of causal inference. Scavette’s analysis of New Jersey enterprise zones, reveals that this endogeneity issue may also violate the parallel trends assumption, as it can lead to a phenomenon known as ‘Ashenfelter’s Dip’, where these selected areas are likely to be subject to a negative trend in employment just before they receive zone status - in the pre-treatment period (Scavette, 2022).

To address these challenges, recent studies in enterprise zone research have embraced advanced econometric techniques, such as propensity score matching (PSM) and the adoption of synthetic controls. PSM matches treated and control units based on propensity scores, offering a more accurate estimation of the causal effects of the treatment. Similarly, the Synthetic Control Method (SCM) permits for a robust comparison through constructing a synthetic counterpart of treated units. This involves weighting variables and observations within the control group to create a suitable comparison group. Ferman & Pinto (2019) advocate for the use of such weighted counterfactual approaches to enhance causal effect estimates. As this method improves upon traditional evaluation techniques by incorporating the probability of receiving the treatment when selecting counterfactual groups.

Applying these methods, O'Keefe's (2003) evaluation of the Californian enterprise zone policy utilises a PSM approach and finds positive impacts on job growth providing evidence for zone designation stimulating an annual increase in employment growth by 3% during the first six years. Whereas J.Elvery's (2009) review of both Florida and Californias' enterprise zone policy finds no evidence for positive related employment growth due to the implementation of the zones.

Recognising the ambiguity in existing academic literature, Nidhi Chaudhary and Jonathan Potter (2019) advocate for more comparative evaluations of the enterprise zone policies. Highlighting the significance of these studies in strengthening confidence in evaluation findings through aligning treatment and control data more effectively. Responding to this imperative, the first contribution of this study involves establishing a weighted control group through the use of PSM, facilitating rigorous comparisons between control and treatment groups, enabling greater evaluation of treatment effects than traditional DiD methods. The adoption of PSM in this paper will also help to address the selection bias issue through matching treated units with controls areas with similar propensity scores. This contribution takes inspiration from Scavette (2022) adoption of a matched control to address this issue and increase comparability of control groups.

The second contribution of this paper is dedicated to addressing the endogeneity issue. Leveraging the increased availability of local employment data at an LSOA level, this study incorporates both panel data analysis and a Within Group Fixed Effect (FE) model to control for unobserved time-invariant heterogeneity. Through fixing the average effect of each area and focusing the regression on variations within groups over time, the FE model isolates the treatment's impact from other confounding factors (Wooldridge 2010). Therefore also helping to mitigate the effects of omitted variable bias. Previous studies on the local employment effect of enterprise zones have also adopted the use of FE models to address this endogeneity issue. Kolko & Neumark (2010) found that the use of FE models allowed for the effective control for variations among different treatment and control areas, in addition to permitting the researchers to account for potential the economic shocks affecting each EZ. Therefore providing a more precise estimate of zone induced employment changes at a local level.

The third advancement of this study is the use of LSOA data to measure local employment changes in enterprise zones. This approach is informed by the findings of O'Keefe (2004), who highlighted those empirical studies utilising detailed geographical analysis found "*significantly faster job growth*". LSOA data will also be used to analyse if the implementation of the policy had varying employment impacts across different geographical boundaries (2km & 10km).

2. Methodology & Data

2.1 Methodology Overview

This chapter will demonstrate the use of DiD and PSM to assess the impact of enterprise zones on employment, using data from the Hertfordshire Enviro-tech Enterprise zone, established in 2017[1]. The combination of Difference-in-Differences (DiD and Propensity Score Matching (PSM) is highlighted for its robustness in facilitating a robust estimation of the ATT effect within this research context. The combined outcomes of the econometric modelling, data and control methods presented in this chapter will attempt to address several epistemological gaps identified in the pervious chapter.

2.2 Propensity Score Matching (PSM) and Differences-in-Differences (DID) Approach

This study combines DiD with PSM to robustly model the ATT effect. Recognising the limitations inherent to both DiD and PSM when used independently, this methodology draws inspiration from the work of Becker and Hvide (2013)[2] to innovatively integrate these two techniques. The approach leverages PSM to construct a weighted control group for both pre-treatment and post-treatment periods. The creation of this counterfactual improves the precision and reliability of the causal inference by building on traditional DiD analysis in the following ways:

Firstly, the use of a weighted control group increases the probability of satisfying the parallel trends assumption, that is crucial for DiD analysis. This assumption suggests that prior to intervention, the treated and control groups exhibit similar trajectories. Through the

[1] https://enterprisezones.communities.gov.uk/ez-data-release-april-2018-t-b-c/

application of PSM (nearest neighbour matching), I increase the likelihood for parallel trends holding true.

Additionally, the integration of PSM into the DiD framework also helps to mitigate selection bias. Selection bias occurs when there are differences between treated and control groups that may influence the outcome of interest, independent from the treatment itself. Through matching treated units with control units that have similar propensity scores, the impact of this bias is reduced (Tucker 2011)[3]. Therefore ensuring that the observed change is attributable to the treatment rather than pre-existing differences between the groups.

2.3 Data

To facilitate this approach, I construct a panel dataset of LSOAs spanning from 2015 to 2022, utilising data sourced from the Office of National Statistics (ONS).

2.4 Identifying Variables

Dependant variable: Annual employment data, at the LSOA level has been sourced from Business Register and Employment Survey (BRES). For each case study zone, employment data have been logarithmically transformed aligning with methodologies used by O'Keefe (2003) and Kolko & Neumark (2010) to stabilise variance and normalise distributions. Evidence of the logarithmic transformation to improve the normality of residuals can be seen in annex B.

Explanatory variables: To qualify for an enterprise zone designation, legislation states that areas must meet specific criteria, including **high poverty** and **unemployment rates** (Scavette, 2022). Based on these criteria, the following explanatory variables were selected:

- Indices of Multiple Deprivation (IMD): Sourced from the ONS, the IMD serves as a holistic measure of poverty and education levels within an area. It is utilised as a covariate to ensure that both the PSM and DiD analysis adequately reflect the economic conditions of the observed areas. This was influenced by works of both (Scavette, 2022) and J. Elvery (2009), who use poverty rates and education levels in their counterfactual matching process.

- Claimant Count: Addressing the legislative requirement for high unemployment rates, this variable, quantifies the unemployment levels within both treated and control LSOAs.
- Gross value Added: This serves as holistic indicator for an area's economic outputs, helping to improve robustness of the counterfactual matching process.

	Count	Max	Mean	Min	Range	Std	Skewness	Kurtosis
Employment	2568.00	46000.00	890.31	0.00	46000.00	2401.45	8.67	117.04
GVA	2247.00	2127.16	40.26	2.57	2124.59	121.65	11.41	160.79
Claimant Count	2568.00	190.00	26.56	0.00	190.00	25.54	1.91	4.48
Treated Units	54.00	--	--	--	--	--	--	--
Control Units	267.00	--	--	--	--	--	--	--

Table 1 - Hertfordshire Enviro-tech 2km Boundary

	Count	Max	Mean	Min	Range	Std	Skewness	Kurtosis
Employment	3416.00	21000.00	645.44	10.00	20990.00	1342.59	6.13	51.44
GVA	2989.00	1440.52	42.03	2.00	1438.52	93.60	7.26	74.84
Claimant Count	3416.00	335.00	27.06	0.00	335.00	27.44	3.07	17.61
Treated Units	72.00	--	--	--	--	--	--	--
Control Units	355.00	--	--	--	--	--	--	--

Table 2 - Hertfordshire Enviro-tech 4km Boundary

	Count	Max	Mean	Min	Range	Std	Skewness	Kurtosis
Employment	17232.00	391000.00	1062.91	0.00	391000.00	7723.97	41.02	1843.89
GVA	15078.00	55925.37	73.21	1.68	55923.69	1119.61	44.02	2015.10
Claimant Count	17232.00	485.00	28.76	0.00	485.00	29.76	2.73	14.32
Treated Units	368.00	--	--	--	--	--	--	--
Control Units	1786.00	--	--	--	--	--	--	--

Table 3 - Hertfordshire Enviro-tech 10km Boundary

2.5 Defining Boundaries and Treatment Assignment

Spatial economic theory: Urban and regional economics literature suggests that the spatial effects of place-based policies are influenced by the commuting patterns within labour markets. To provide a standardised approach, Urban economists have introduced "travel-to-work" areas to effectively account for these commuting patterns in spatial studies. Inspired by this framework, this study adopts 2km, 4km and 10km around the enterprise zone site location to capture the varying impacts of zones based on proximity.

Immediate Zone Effects (IZE): A 2km boundary surrounding each enterprise zone site is established to evaluate the direct impacts on employment within the local LSOAs. This 2km boundary has been included as a control measure to accurately capture employment data where Zone site locations spread across LSOA boundaries.

Peripheral Zone Effects (PZE): Kolko & Neumark (2010) highlight that enterprise zones have the potential to influence the employment of areas beyond the immediate zone boundaries. To capture the employment spillover into these adjacent areas, a 4km boundary zone is introduced.

Wider Zone Effects (WZE): Ladd (1994) acknowledges that zone induced employment growth can be driven by the displacement of businesses and jobs from neighbouring areas. To capture these negative spillovers, a 10km boundaries is used. This boundary roughly correlates to a 30-minute free-flow drive time from enterprise zone site locations, aiming to capture potential displacement from LSOAs within the travel-to-work catchment.

Consequently, this paper makes use of QGIS, a geoprocessing tool, to select LSOAs within the specified boundaries according to drive time and distance criteria. The categorisation of LSOAs into treatment groups is based on their proximity to the enterprise zone sites, which is determined using the population-weighted centroids (PWCs) of each output area. For each case study, LSOAs whose centroids fall within either the 2km, 4km or 10km catchments are then included in the treatment group during PSM and DiD analysis. A visual representation of this analysis is evident on the Map below.

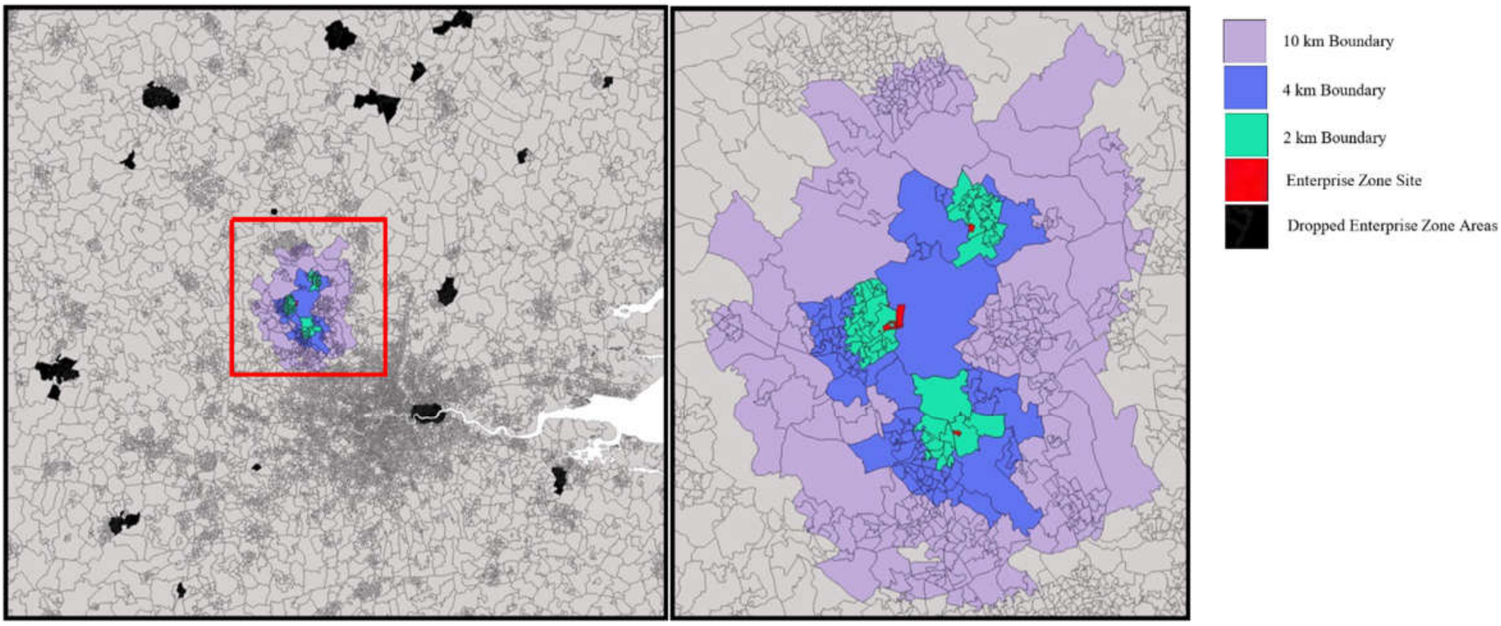

Figure 1 - GIS Map Detailing Case Study Boundaries

2.6 Identifying Counterfactuals Through Propensity Score Matching

As aforementioned, PSM was employed to refine each control group for the purpose of DiD analysis. By conducting PSM, a bespoke weighted counterfactual could be defined for each boundary (immediate, periphery and wider zone). Each counterfactual zone is comprised of comparable LSOAs that did not receive enterprise zone status. These counterfactuals were created by matching treated and control zones using propensity scores, which reflect the similar ex-ante probability of treatment based on their pre-treatment attributes – consistent with Rosenbaum and Rubin's (1983)[4] method. To estimate the propensity scores, I run a logistic regression model with pre-intervention characteristics, deriving scores for both the treatment and control groups. The details of the PSM logistic model are as follows:

$$P(similar\ to\ treated\ case\ study\ enterprise\ zone\ |X = x) = \alpha + \beta xi + \varepsilon i$$

- x - is a vector of variables that includes Employment (2015), GVA (2015), IMD (2015), and Claimant Count (2015)[5]

[5] 2015 has been selected as the Year to conduct PSM as this reflects two years before the implementation of the treatment. The weights calculated from this exercise are then applied consistently to the subsequent years in the panel for each of the matched LSOAs (2016-2022)

- α - represents the intercept or the average probability of treatment when all observable variables (x) are zero
- β - is a vector of coefficients related to the observable variables (x), indicating the expected change in the probability of treatment for each unit change in x.
- εi - is the error term.

Matching Algorithm (Nearest neighbour)

Propensity scores were derived using an R matching algorithm, specifically the "MatchIt" package, which is widely recognised for its effectiveness in nonparametric estimation of propensity scores. This package facilitates the creation of weighted control groups through nearest neighbour matching. Specifically, nearest neighbour matching identifies the most similar control unit (non-treated LSOA) for each treated LSOA based on pre-intervention characteristics that influence the probability of an area being designated as an enterprise zone. This technique ensures that each treated LSOA within the enterprise zone boundary is paired with a highly similar non-treated LSOAs, creating a robust comparison.

Matching Controls

Ratios and Callipers: Caliper matching, *a refined version of nearest neighbour matching*, has been used to improve the quality of matches (Cochran and Rubin, 1973)[6]. Specifically, I use a caliper of 0.05, ensuring precise pairing between treated and untreated LSOAs within enterprise zones. Additionally, as a further control to enhance match quality, I implement a 1:5 matching ratio. This allows one treated LSOA to be matched with up to five untreated LSOAs. This targeted selection process leads to a matched sample that forms the basis of the subsequent weighting and DiD analysis.

Propensity Score Weighting

Following this matching process, I then assign weights to each of the matched LSOAs using stratification method in R. This method takes inspiration from the weighting method available in Greifer, N. (2023) *Matching with sampling weights*. Observations were sorted into these strata based on their propensity scores, each with a range between zero and one (Rosenbaum and Rubin's (1983). Depending on the propensity score, some strata had more (or less) observations, to account for this and have a balanced representation, weights were assigned according to which strata the observations were found in.

Once calculated, the weights for each counterfactual LSOA are integrated into the panel data regression model for each of the subsequent years (2016 onwards). This is done to ensure that across the panel, each LSOA's contribution is proportional to the balance calculated through the stratification process. The DiD estimation is then adjusted for these weights to measure the causal impact of the treatment.

GIS Matching

It is critical to specify that the UK hosts an additional 48 enterprise zones in addition to that presented by this analysis. To delineate the comparison group for the PSM analysis accurately, GIS software has been used to identify where these Enterprise zones are located and subsequently exclude LSOAs containing these zones. This exclusion safeguards this analysis against potential biases by ensuring that the counterfactual LSOAs used to calculate the relevant weights are not confounded by other treated areas. Additionally, when examining the immediate zone area effects, LSOAs within a 4km and 10km radius of any enterprise zone are excluded to mitigate potential spillover effects. Defining the studies control group through this rigorous process therefore helps to enhance the integrity and accuracy of the PSM matching process, ensuring that the control LSOAs genuinely reflect non-treated areas. The jitter plots below illustrate a substantial overlap in propensity scores between treated and control groups within both the immediate and wider enterprise zone boundaries, indicating effective matching by the PSM algorithm. Notably, the scores cluster at the lower end, which suggests the possibility of omitted covariates or the need to refine the matching process. Although the current match provides a solid basis for the subsequent DiD analysis, future research should investigate potential additional covariates or model adjustments to strengthen the findings.

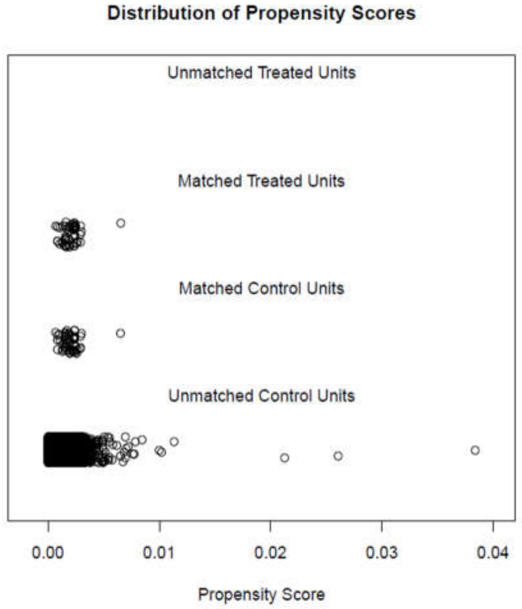

Figure 2 - Distribution of Propensity Scores (2km Boundary)

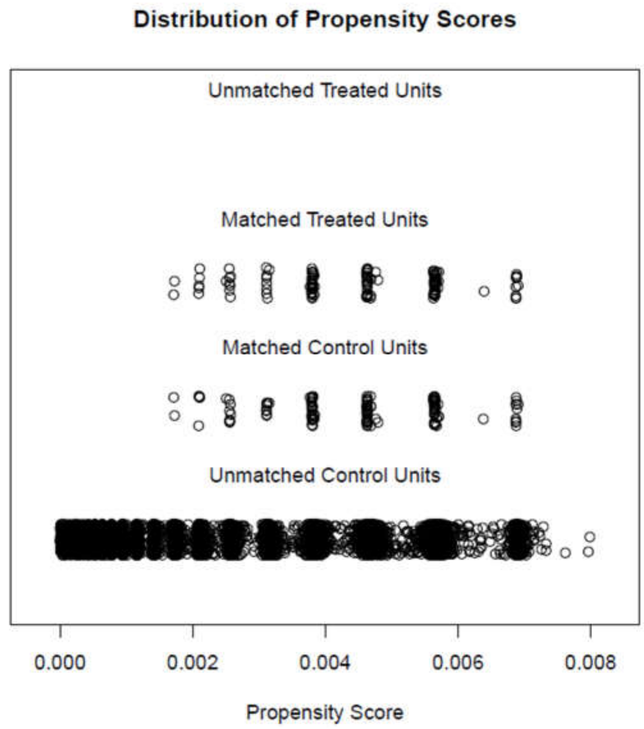

Figure 3 - Distribution of Propensity Scores (4km Boundary)

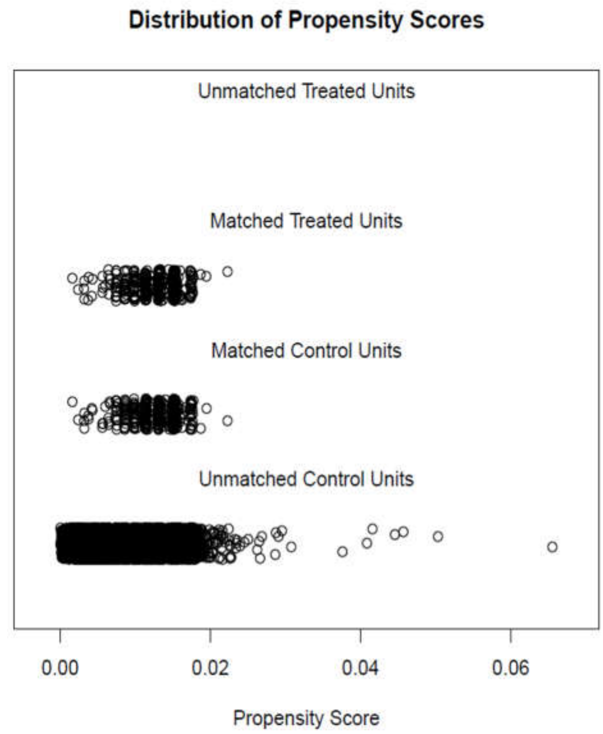

Figure 4 - Distribution of Propensity Scores (10km Boundary)

2.7 Hypothesis

Hypothesis 1 (H1):

Null Hypothesis (H1_0): Enterprise Zones have no significant impact on local employment levels.

Alternative Hypothesis (H1_A): Within the boundary, Enterprise Zones significantly increase local employment levels.

Hypothesis 2 (H2):

Null Hypothesis (H2_0): The impact of Enterprise Zones on employment is uniform across different spatial boundaries.

Alternative Hypothesis (H2_A): The impact of Enterprise Zones on employment diminishes with increasing distance from the zone.

2.8 Model Specification

The DiD model is used to compare the outcomes between the treated and control groups, this helps to answer the counterfactual question of the employment outcome in the absence of the intervention. A more detailed review of the specification and assumptions of the DiD model is given below:

Preferred Model Specification:

$$\ln Employment_{it} = \beta_1 + \beta_2 Treated_i + \beta_3 post_t + \beta_4 Treated * Post + \beta_5 X_{it} + FE_i + e_{it}$$

Where:

- $Employment_{it}$ – is the natural log of the employment outcome for unit i at time t.
- $Treated_i$ – is a binary variable indicating whether unit i is in the treated group.
- $Post_t$ – is a binary variable indicating the post intervention period (2017 – onwards).
- $Treated * Post$ – captures the treatment effect by representing the interaction between being in the treatment group and the post intervention period.
- X_{it} - represents other control variables that vary across units and over time.
- FE_i - represents fixed effects for each unit that does not vary over time.
- e_{it} - is the error term.

Testing for Parallel trends:

Figures 5-7 below, presents a graphical examination of the parallel trends assumption for each of the difference-in-differences estimations (immediate, periphery and wider zone boundaries). From a visual inspection, it is evident that the employment trends in for both boundaries were consistent with the parallel trends assumption prior to the treatment year

(2017). This consistency supports proceeding with the DiD analysis, as it suggests that differences in employment post-intervention can be attributed to the treatment effect.

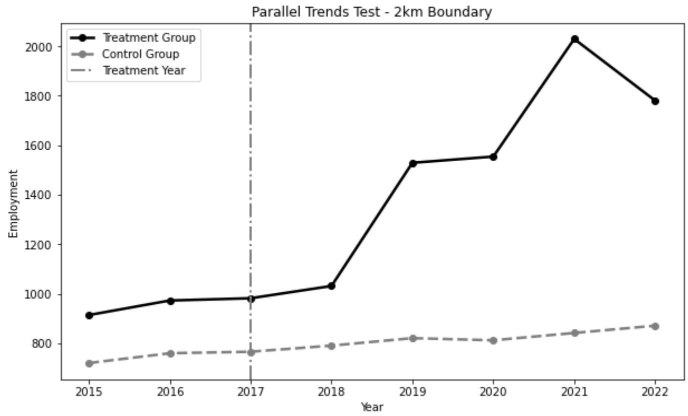

Figure 4 - Parallel Trends Test (2km): Employment Variable

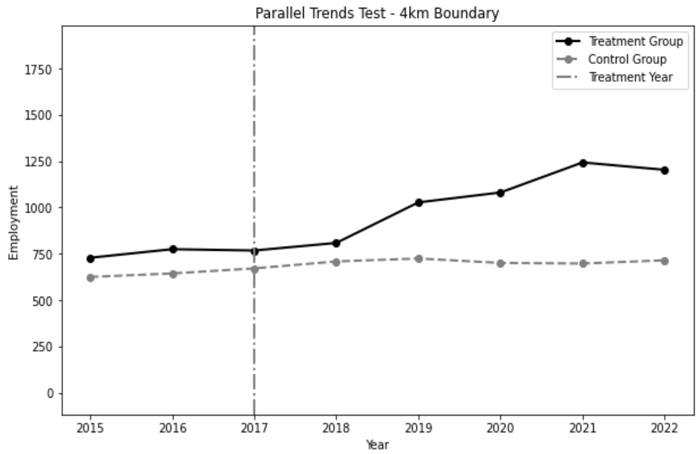

Figure 6 - Parallel Trends Test (4km): Employment Variable

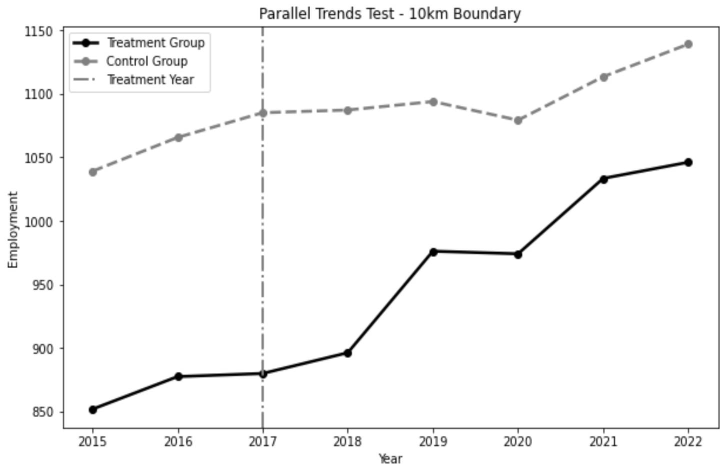

Figure 7 - Parallel Trends Test (10km): Employment Variable

Panel and Fixed Effects (Within-group estimator)

To estimate the coefficients of the preferred model, I use of a within-group fixed effects (FE) estimator to control for unobserved heterogeneity. Specifically, this removes unit-specific fixed effects and focuses on the time-varying components of the model. This has been done to robustly capture the unique time-invariant characteristics of each LSOA that may otherwise influence employment outcomes. By ‘fixing’ the average effect of LSOA, I aim to isolate the treatment impact from other confounding factors. Thereby enhancing the accuracy of the causal effect estimation by forcing the regression to focus on within group variation across time. In doing so, I help this mitigate the effects of omitted variable bias, as demonstrated from the demeaned model specification below.

Demeaned specification

$$\ln(\widetilde{Employment_{it}}) = \beta_3 \widetilde{post}_t + \beta_4 (Treated * Post) + \beta_5 \tilde{X}_{it} + \tilde{e}_{it}$$

Hausman Test

A Hausman test was employed to assess the appropriateness of fixed effects versus Random effects (RE) modelling. Although the test showed a slight preference for the RE model, the decision to proceed with the fixed effects model was driven by its capacity to control for unobserved time-invariant factors in the LSOAs, such as historical economic conditions. This approach is supported by the similarity in results between the FE and RE models, as discussed in Table 4. This consistency across model results, provides additional confidence in the robustness of the fixed effects approach and the validity of paper findings.

Table 4 - Hausman Test Outputs

Hausman Test Results	2KM	4KM	10KM
Chi-Square Statistic	0.82039	1.4882	7.5431
p-value	0.8446	0.685	0.05646
Alternative Hypothesis	One model is inconsistent	One model is inconsistent	One model is inconsistent
Interpretation	Random effects model is preferred (high p-value, insignificant difference)	Random effects model is preferred (high p-value, insignificant difference)	Fixed effects model is preferred (low p-value, significant difference)

3. Results

Significance codes: **0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1**	**Immediate Zone Effects (2km)** Inc. Robust standard Errors	**Immediate Zone Effects (2km)**	**Peripheral Zone Effects (4km)** Inc. Robust standard Errors	**Peripheral Zone Effects (4km)**	**Wider Zone Effects (10km)** inc. Robust standard Errors	**Wider Zone Effects (10km)**
Post	0.014976 (0.45474)	0.01734 (0.2233)	0.023040* (0.03633)	0.024146** (0.00171)	0.014348* (0.02249)	0.015629** (0.0005404)
	(0.02003) Std. Error	(0.01423) Std. Error	(0.044160) Std. Error	(0.007696) Std. Error	(0.00628) Std. Error	(0.004.51) Std. Error
Treated: Post	0.10540* (0.01708)	0.10317** (0.0029)	0.061892* (0.01449)	0.06082** (0.001171)	0.03255* (0.02544)	0.031273** (0.0041975)
	(0.04416) Std. Error	(0.03461) Std. Error	(0.025306) Std. Error	(0.018726) Std. Error	(0.01457) Std. Error	0.010921 Std. Error
GVA	-0.00018 (0.54070)	-0.00021 (0.5969)	0.000381 (0.38063)	0.000375* (0.018723)	<0.0001 0.47909	<0.0001 0.47909
	(0.00029) Std. Error	(0.00039) Std. Error	(0.00045) Std. Error	0.00015954 Std. Error	(0.00001) Std. Error	(0.00001) Std. Error
Within R-Squared	0.0079889	0.0079752	0.0092396	0.0092356	0.0025195	0.0025235
F-Test	0.022936	0.001172	0.00010361	<0.0001	<0.0001	0.0003326
Durbin-Watson Test for Autocorrelation *H_0 - No first-order autocorrelation*	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
Breusch-Pagan Test for heteroskedasticity	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001

Table 5 - Within Group Estimator Results

Significance codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1**	**Immediate Zone Effects (2km)** Inc. Robust standard Errors	**Immediate Zone Effects (2km)**	**Peripheral Zone Effects (4km)** Inc. Robust standard Errors	**Peripheral Zone Effects (4km)**	**Wider Zone Effects (10km)** inc. Robust standard Errors	**Wider Zone Effects (10km)**
(Intercept)	5.68160*** (<0.0001)	5.68160*** (<0.0001)	5.579954*** (<0.0001)	5.57995*** (<0.0001)	5.895700*** (<0.0001)	5.895700*** (<0.0001)
	(0.079764) Std. Error	(0.082167) Std. Error	(0.04747) Std. Error	(0.047948) Std. Error	(0.029148) Std. Error	(0.028701) Std. Error
Treated	0.056152 (0.7676)	0.056152 (0.7770)	0.121968 (0.29669)	0.121968 (0.29360)	0.056069 (0.41400)	0.056069 (0.419162)
	(0.18998) Std. Error	(0.19830) Std. Error	(0.116864) Std. Error	(0.11613) Std. Error	(0.068636) Std. Error	(0.069403 Std. Error
post	0.014426 (0.4694)	0.014426 (0.3118)	0.02286* (0.03699)	0.022863** (0.0029191)	0.014139* (0.02451)	0.014139** (0.001749)
	(0.019936) Std. Error	(0.01426) Std. Error	(0.01096) Std. Error	(0.007682) Std. Error	(0.0062862) Std. Error	(0.0045175) Std. Error
GVA	<0.0001 (0.9858)	<0.0001 (0.9838)	0.00044373 (0.28058)	0.000444** (0.003114)	0.000032. (0.06438)	0.000032* (0.013950)
	(0.00037) Std. Error	(0.000329) Std. Error	(0.00041) Std. Error	(0.00015) Std. Error	(0.00002) Std. Error	(0.00001) Std. Error
Treated: Post	0.104920* (0.0176)	0.104920** (0.0025)	0.06171* (0.01479)	0.06170919*** (0.0009632)	0.032596* (0.02523)	0.032596** (0.002852)
	(0.0441650) Std. Error	(0.0347) Std. Error	(0.02531) Std. Error	(0.0186938) Std. Error	(0.014565) Std. Error	(0.010926) Std. Error
R-Squared	0.006959	0.0069594	0.0089157	0.0089157	0.0026339	0.0026339
Chi squared	0.04544	0.0034304	<0.0001	<0.0001	0.00011094	<0.0001
Durbin-Watson Test for Autocorrelation *H_0 - No first-order autocorrelation*	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
Breusch-Pagan Test for heteroskedasticity	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001

Table 6 - Random Effects Model Results

This section presents the results of the localised employment impact of enterprise zones, Utilising both Fixed Effects with and Random Effects Model (REM) model outputs. Specifically focusing on the "Treated:Post" interaction variable, I quantify the ATT through isolating the impact of the policy's introduction in the Hertfordshire area. The ATT reflects the additional employment changes attributable to the policy within each specified boundary, compared to what would have occurred in its absence, thereby providing an evaluation of the policy's effectiveness.

To further validate these findings, sensitivity analyses were performed. These analyses include varied model specifications and adjusted geographical boundaries (2km, 4km, and 10km), to assess the varying employment impacts of the policy on LSOAs within the selected travel-to-work areas.

Robustness tests & Diagnostics.

The model diagnostics reveal relatively low R-squared values (0.003 – 0.008), indicating a limited capacity to capture all variation in the employment data. Despite this, both FE and REM models display highly significant F-test statistic (0.00 – 0.003) and Chi-squared values (p-values: 0.00 - 0.003) respectively. Therefore indicating that the included independent variables collectively have a meaningful effect on the dependent variable.

Breusch-Pagan (p-value = 0.00) Durbin-Watson (p-value = 0.00) test outputs highlight the presence of heteroscedasticity and autocorrelation in model estimations. Despite employing robust standard errors to mitigate these issues, the potential for reduced efficiency of estimators and biased standard errors persists. The presence of autocorrelation suggests that error terms within groups are correlated across time, potentially impacting the precision of the estimated coefficients. Whereas the presence heteroscedasticity, increases the potential for narrower (or wider) confidence intervals due to inaccurate representations of standard errors, thus impacting the precision of the results.

Additionally, it is important to recognise that while the logarithmic transformation of the employment helps improve the normality of residuals, it does fully satisfy the assumption of normality. Therefore increasing the potential for bias in the reported results. Given these limitations, it is suggested that these findings be considered as indicative rather than definitive, particularly in the context of policy recommendations.

2km Boundary

- **Treated:Post (** Coefficient - 0.11**)**: The immediate zone boundary shows a significant employment increase of approximately 10.5% (p-value = 0.02), with consistent results across FE and REM models. This supports the rejection of the null hypothesis (H1_0) at the 95% confidence level, affirming the policy's effectiveness in stimulating increased employment within this boundary.
- **Post (**Coefficient - 0.01)**:** The post-treatment period's coefficient suggests a 1.5% average growth rate across both treatment and control areas. However this is statistically insignificant across models (p-value= 0.45-0.31), indicating uncertainty about the true impact of time alone on employment changes.

4km Boundary

- **Treated:Post** (Coefficient - 0.06): Consistent with the 2km results, FE and REM models at the indicate a 6.2% rise in employment for LSOAs within a 4km catchment of the enterprise zone sight. Model outputs conclusively reject the null hypothesis (H1_0) at the 99% confidence level.
- **Post** (Coefficient - 0.02): The post-treatment period's coefficient is statistically significant at the 95% confidence level, suggesting a 2.31% uplift in employment following the treatment. This reflects a general positive trend in employment over time, applicable to both treated and control zones.

10km Boundary

- **Treated:Post** (Coefficient - 0.03): At this extended boundary, the interaction term remains significant (p-value < 0.03), translating to an estimated 3.26% increase in employment. Therefore providing evidence for the alterative hypothesis (H1_A) for LSOAs within a 10km boundary of the enterprise zone site.
- **Post** (Coefficient - 0.01): The period post-intervention shows a statistically significant increase in employment by 1.41% (p-value = 0.00), suggesting a general increase in employment following the implementation of the policy across both treatment and control areas.
-

Discussion

The findings support economic theories suggesting that the introduction of enterprise zones stimulates increased levels of local employment growth. In regard to hypothesis 2, results indicate that the effects are notably stronger at closer proximities to the enterprise zone site location. This is highly likely due to the tax exemptions offered within the immediate zone sites (2km), that are not otherwise available to firms situated in the wider enterprise zone boundaries (4km, 10km). This therefore suggests that although the employment effects remain positive at greater distances, there is a noticeable decrease in these benefits as distance from the zone boundary increases, evidenced by the reduction in employment impact from 10.5% at 2km to 6.2% at 4km, and 3% at 10km.

Spillovers and Displacement

Positive employment growth of 6.2% in the peripheral zone boundary (4km) provides evidence for positive spillovers in this case study. This finding is consistent with the positive spillover theory described in Kolko & Neumark's (2010) paper. This growth could be attributed to changes in the labour market dynamics of these adjacent areas, that may witness an increase in business activity and employment to support immediate zone actives. This may manifest itself through an increase in service sector activities such as retail and hospitality activity.

However, contrary to academic literature, this study also finds increased employment growth (3%) at the wider spatial boundary (10km). This observation provides further insight to the existing literature that found significant job displacement (negative spillovers) from neighbouring areas, as evident in papers by PACEC (1995) and Hanson and Rohlin (2011, 2013). However this evidence is not yet definitive. This positive employment growth could be attributed to the relatively close proximity of the "wider" area in this study's design. To further validate these conclusions, it is recommended to conduct extended boundary analysis at a more granular level. For example, observing employment changes at 1km increments at boundaries beyond the predefined travel-to-work areas utilised in this analysis (10km and beyond). This approach will offer a more definitive understanding of potential displacement effects associated with enterprise zones.

When interpreting these findings, considerations regarding the precision and reliability of the observed spatial impacts is necessary. As illustrated by annex A, between each boundary there is a degree of overlap in the 'treated:post' confidence intervals. This may initially suggest reduced confidence in the statistical significance of the varied employment impacts by boundary. However insights from Cumming and Finch (2005) reveal that the presence of overlapping confidence intervals do not necessarily imply the absence of statistically significant differences between groups. This is particularly relevant to this paper's findings in which each 'treated:post' interaction term, maintains statistical significance across each of the specified boundaries. This suggests that even with some degree of overlap, the observed differences in impacts across the 2km, 4km, and 10km boundaries remain statistically significant. To further clarify these distinctions, Goldstein and Healy (1995) propose the use of alternative confidence levels (83%) as opposed to the conventional 95%. This adjustment could be potentially considered in further analyses in which researchers aim to better delineate the employment impacts at different spatial boundaries.

Given these considerations to the observed spatial effect, Policymakers should consider the impacts of such placed based policies within a 2-4km radius to maximise economic impacts, as the effects appear to diminish with distance. Complementary initiatives to the enterprise zone programme, such as investment in local infrastructure links, or labour upskilling services may in turn increase the level employment growth to the wider boundaries. These findings are particularly pertinent in the current UK context in which tax incentivised placed based policies are being extended across the UK in attempts to stimulate economic growth, as evident in the recent Freeports extension programmes.

4. Model limitations.

Further to the modelling limitations, it is also key to acknowledge the limitations of this paper's methodology answering the broader question of local employment impacts of enterprise zones within the UK. While the DiD approach is a robust quasi-experimental method for estimating the causal effect of a policy intervention, the use of a single case study zone raises concerns about the generalisability of the findings.

Specifically, the employment impacts observed in this case study may be influenced by other contextual factors unique to that location. For example, as noted by Scavette (2022) and Kolko & Neumark (2020), zone impacts can vary across firm sizes, capital-intensive or labour-intensive industries, which are not explicitly considered in this method. As a result, the findings may not be representative of the broader population of enterprise zones, limiting the external validity of the study.

Additionally, the boundary analysis applied in this methodology is limited in its capacity to account for spatial heterogeneity across enterprise zones. The Periphery and Wider boundary methodology may not be as applicable to denser or more rural areas with differing transport links, given that the commuting patterns are likely to be different. Therefore potentially capturing too much noise in urban areas with good transport networks while underestimating the impacts in less dense, larger rural areas.

To address these concerns, it would have been preferable to include multiple enterprise zones in the analysis, capturing different geographic regions and diverse economic characteristics. This approach could have leveraged the variation across multiple treatment sites, potentially revealing patterns and heterogeneities that are not evident from a single case study. Thereby strengthening the generalisability of the findings and provided a more comprehensive understanding of the employment impacts of enterprise zones for the purpose of policy recommendations.

Restricted by the availability of BRES Employment LSOA (2015 onwards), this analysis might not comprehensively capture the long-term effects of enterprise zones. Enterprise zones are structured to support long-term economic growth and job creation, which often require prolonged periods of time to fully materialise. This is due to the associated time lag of business set up and site development works. It may be the case that the chosen time period is too short, potentially limiting the study’s ability to capture the complete effects of the policy intervention, thus underestimating or misrepresenting the true impact.

Given the limitations above caution should be exercised when extrapolating these findings to broader contexts without additional analyses over a longer time period. Policymakers should consider additional research to explore how the dynamics observed in this study manifest.

5. Conclusion

This paper evaluated the UK's 2017 Enterprise Zone (EZ) program's effectiveness in stimulating local employment growth, using detailed case study analysis. The findings provide evidence that the designation of Enterprise Zone status successfully increased employment levels within each boundary, with a 10.5% increase within the 2 km zone, followed by a 6% increase within 4 km and a 3.26% increase within 10 km boundaries. Thereby revealing that while zones can stimulate employment spillovers in neighbouring areas, their influence tends to dissipate with increasing distance from the zone site.

This analysis contributes to the literature through the use of robust quasi-experimental methods, including difference-in-differences with propensity score matching, to establish causal estimates of the policy's impact. Additionally, by leveraging granular employment data at the LSOA level, this study provides insights into the spatial heterogeneity of enterprise zone effects. The findings are insightful and provide nuance to the ongoing discussion on enterprise efficacy; however, the reliance on a single case study limits broader applicability of findings to other zones with different characteristics. Furthermore, the chosen time period may not fully capture the long-term impacts due to the lag time needed for business to become fully operational.

Despite this, the positive local employment effects observed in this study provides supporting evidence for the continued use of tax-incentivised place-based policies as part of the UK's Levelling Up agenda and economic recovery efforts. Future research should aim to explore the impacts across multiple enterprise zones and over extended time periods to provide a more comprehensive understanding of these policies' effectiveness, thus permitting policymakers to make more informed decisions about the local employment effects of placed based polices in the UK.

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Annex A

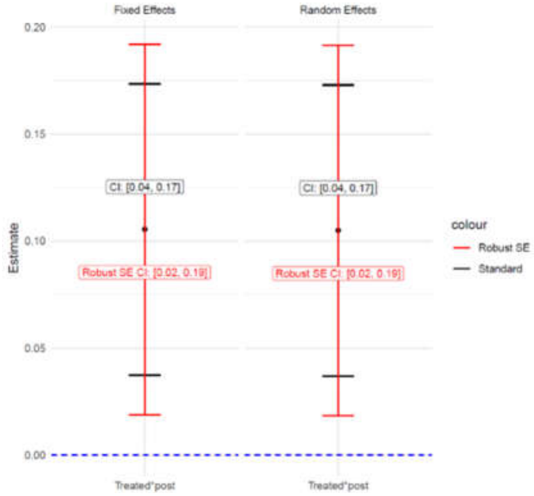

Figure 7 – 2km Confidence intervals.

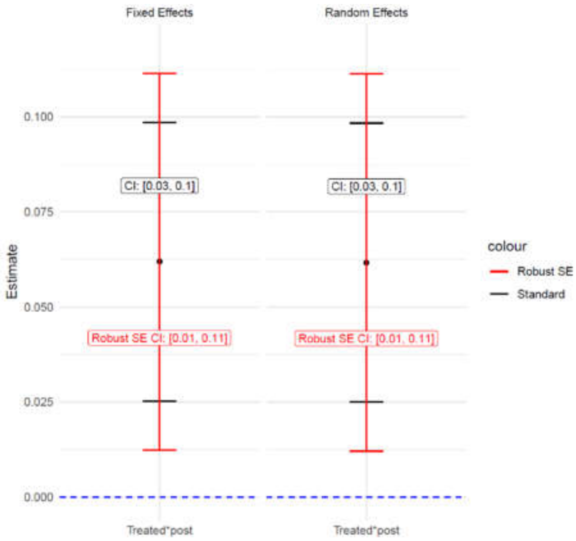

Figure 8 - 4km Confidence Intervals.

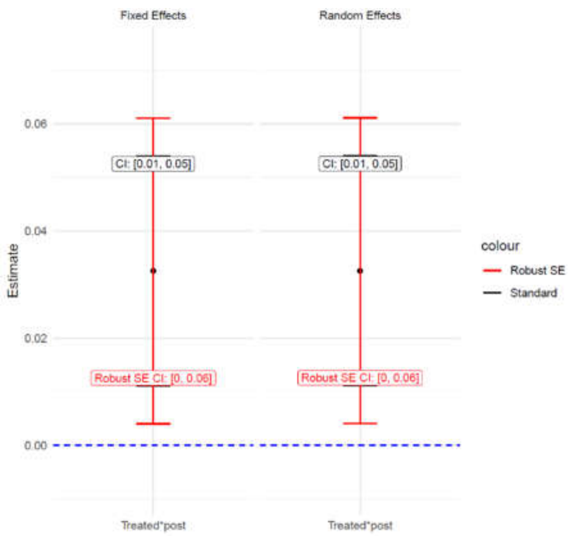

Figure 5 - 10km Confidence Intervals

Annex B (Within Group Model – Robust Standard Errors)

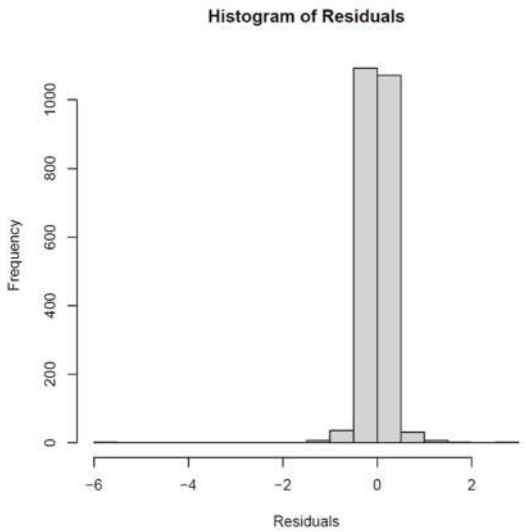

Figure 10 - 2km Residual Plot

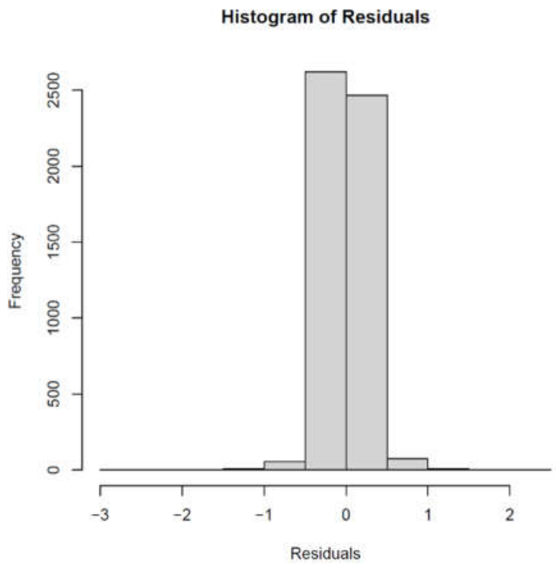

Figure 6 - 4km Residual Plot

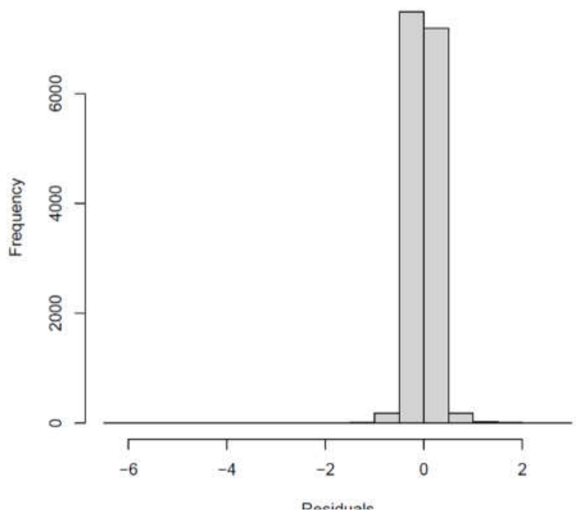

Figure 12 - 10km Residual Plot