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LOCALISED EMPLOYMENT SPILLOVERS

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This paper is the first to provide firm level estimates of the propagation rates of localised employment shocks through space and time. A spatial network of the universe of UK firms with near pinpoint location accuracy is used to estimate the firm-level employment adjustment to mass layoffs. Results show that firm level employment adjustment is highly localised and decays rapidly through space - the negative spillover effects halve approximately every kilometre further away from the event. Firm level adjustment is also highly persistent, with further localised employment losses continuing for at least five years after the event. The spillover effects are experienced by a wide range of local firms, but are strongest in non-tradeable sector firms, consistent with the presence of local product demand transmission mechanisms. The paper provides new supporting evidence to theories that sluggish firm level adjustment interacting with local agglomeration forces generate persistence in local labour market outcomes. Furthermore, the micro-level effects uncovered are extremely localised, and thus more standard analysis methods discretising space into regions will incur significant measurement costs.

Localised employment spillovers*

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Abstract

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Key words: local employment dynamics, spillover decay rates, agglomeration
JEL Classification: J23, J63, R12

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1 Introduction

There is substantial path dependence in local economic fortunes: economic inequalities between regions are highly persistent and, in some places, diverging over time.[1] These dynamics provide somewhat of a puzzle, as the traditional spatial equilibrium framework would suggest that localised shocks dissipate through factor adjustment and regions converge overtime. Focussing on the labour market, recent explanations have suggested that an initial labour demand shock is strengthened into a larger, more permanent shock (Amior and Manning, 2018). The conversion to a permanent shock may occur at the local firm level as sluggish firm adjustment interacts with local agglomeration forces (Dix-Carneiro and Kovak, 2017). To date, little is known about the strength through time and space of employment shock propagation at the firm level because the existing literature has approached the question of local employment dynamics by aggregating across firms, geography or both.

This paper provides the first firm level estimates of the propagation rates through space and time of localised employment shocks. Doing so demonstrates that an initial shock is indeed converted into a persistent shock as individual firms located in close proximity to an initial adverse employment shock continually reduce employment for many years after the event. The paper addresses 1) how localised are employment spillovers and how rapidly do these decay through space, as well as 2) what are the dynamics at the firm level of the shock propagation – do they exhibit continual employment adjustment or does the firm level shock dissipate overtime? The relevance and spatial scale of potential channels, including input-output links, local product demand, labour market spillovers, and within-industry knowledge spillovers are also considered.

The paper approaches the problem in a way novel to the established literature. The predominant approach when analysing spatial variation in any economic outcome is to discretise space into mutually exclusive and exhaustive units.[2] This may be due to data restrictions – observations are generally allocated an administrative unit rather than a precise location – or because spatial aggregation simplifies analysis. However, when the object of interest is spatial spillovers, any form of discretisation will not be innocuous. There is an inherent tradeoff in the scale of discretisation. If the unit size is too small, spillovers will extend into neighbouring units, contaminating control units. If set too large, the spillovers operate only in a small fraction of the unit and the estimates will likely average to near zero. The estimated result is therefore fundamentally dependent on the discretisation. Unfortunately, without knowledge of the underlying scale of the effects it is impossible to know where on the continuum one's analysis lies.

In contrast, this paper bypasses the inherent cost presented in standard methods by treating space

[1] Moretti (2011) provides a summary of the literature.

[2] See for example Dix-Carneiro and Kovak (2017); Amior and Manning (2018); Dube et al. (2010); Autor et al. (2013); Acemoglu et al. (2016), and many others, for a selection of applications.

as continuous. A spatial network of all firms in the UK is constructed using near pinpoint location accuracy from the Business Structure Database (BSD). The response of the firm level network to localised adverse employment shocks is then assessed. Mass layoffs, defined as more than 1,000 workers lost in a given year (with some caveats), are used as a localised employment shock event. Each non-masslayoff firm is linked to their closest masslayoff events in each year. The primary feature of interest is the relationship between geographic proximity to a masslayoff, measured in Euclidean distance, and subsequent firm level employment behaviour.

Employment spillovers from masslayoff events are strong and very highly localised. A firm located very close to a masslayoff loses, on average, approximately 7% of their employment. This employment loss exhibits strong spatial decay by abating rapidly with distance. The effect approximately halves for every kilometer further away from the events, becoming very small for firms located further than about 5 kilometers from a masslayoff.

The dynamic analysis finds that further firm level employment losses continue for at least five years after the masslayoff event. These subsequent effects also exhibit the strong spatial decay pattern. The annual effects compound over time such that the longer term firm level impact is much larger than the initial response to the shock. This provides firm-level microfounding evidence to support observations that the longer term effects exceed immediate effects at the regional level (Dix-Carneiro and Kovak, 2017).

A number of possible spillover channels to explain these effects are considered. In particular, I address several potential sources of agglomeration spillovers put forward by the literature. Firstly, I consider whether firms in similar industry, or similar labour markets, to nearby mass layoffs are more strongly affected by spillovers.[3] These two features are often through to indicate knowledge sharing, which in turn can generate productivity (and employment) spillovers following shocks. I also consider whether industries with input-output linkages to mass layoff firms might experience stronger spillovers. Lastly, I investigate the relevance of local product demand spillovers by testing for differences in responses between tradeable and non-tradeable firms.

Neither the spillovers nor their strong degree of localisation appear confined to a particular subset of firms or firm-masslayoff pairs. A wide range of firm types experience strong, localised enploymnent spillovers. However, firms in non-tradeable sectors experience stronger spillovers than the tradeable counterparts. The stronger non-tradeable response points to the relevance of local product demand spillovers following initial employment shocks.

The contributions of the paper are fourfold. Firstly, I provide the first direct estimates on the degree of localisation of negative employment spillovers - employment spillovers from adverse employment events, here taken to be masslayoffs, are highly localised. This pattern has not been directly uncovered to date as it requires the use of precise location data. The degree of localisation is stronger

[3]These features can also be referred to as 'industrial closeness' and 'labour market closeness' respectively.

than had been anticipated, either explicitly or implicitly in the employment spillovers literature. The results show that firm level employment spillovers are much like many other economic activities considered by other literatures; the micro effects are highly localised.[4]

Secondly, the paper sheds additional light on the dynamics behind localised employment adjustment. The firm level dynamic results provide the first empirical support to the theory that labour shocks are transmitted at the firm level, possibly through delayed firm adjustment interacting with agglomeration forces (as per Dix-Carneiro and Kovak (2017)).

Thirdly, the paper demonstrates the inherent costs of discretising space when attempting to measure effects that are continuous in nature. The use of discrete geographic units is near ubiquitous in spatial variation analysis, and yet is not an innocuous decision. Estimated results of zero may simply be because the spatial discretisation is at the wrong scale – in either direction – rather than due to genuinely absent effects. In short, the treatment of space is not a mere technicality but fundamental to the outcomes of interest. This lesson applies to a broader range of applications than just employment or agglomeration spillovers. Any research question using spatial variation must consider the issue carefully.

Lastly, the paper also provides an initial look into the spatial scale and strength of possible spillover mechanisms. I find evidence that supports the relevance of local product demand spillovers as a possible transmission mechanism.

The paper connects three strands of literature. Firstly, there is a large body of literature on regional dynamics following localised shocks. This paper extends the literature by looking at the micro level, in particular at the behaviour of individual firms and highly detailed spatial scales. Traditionally, the broader regional dynamics literature has followed the spatial equilibrium adjustment framework whereby regional outcomes converge overtime following shocks (surveyed in Moretti (2011)). A recent subset of the literature calls the validity of regional convergence into question. Papers have focussed on the strong persistence of shocks and, in particular, how the effects of shocks appear to exacerbate rather than mitigate overtime.[5] Amior and Manning (2018) argue that the deviation from spatial equilibrium adjustment is due to serial correlation in the labour demand shocks - in effect what may initially be temporary shocks are converted into persistent shocks. In a similar vein, Dix-Carneiro and Kovak (2017) show that the response of Brazilian regions exposed to trade shocks is twice as strong ten years after the shock than five years after the shock. They suggest that sluggish adjustment at the firm level interacting with local agglomeration forces may be generating the required serial correlation. However, given the regionally aggregated data, they are not able to

[4]For example, consumer and producer amenities in cities (Ahlfeldt et al., 2015), job search and commuting behaviour (Manning and Petrongolo, 2018; Hassink and Meekes, 2018), and export learning behaviour (Kamal and Sundaram, 2016; Bisztray et al., 2018) among others.

[5]Recent empirical research on regional dynamics following labour shocks include Topalova (2010), Autor et al. (2013), Kovak (2013), Dao et al. (2014), Hakobyan and McLaren (2016), Monte et al. (2018) and Meekes and Hassink (2019).

test their firm level hypothesis.

Secondly, the paper extends the agglomeration literature with dynamic, spatial analysis of negative employment shock spillovers across a broad range of firms and industries. Much of the agglomeration literature is focussed on the difficulty of identifying static agglomeration spillovers, as clean sources of exogenous variation approaches are difficult to come by (Moretti, 2011). Some use narrow policy discontinuities in a particular subset of areas or firms.[6] These have the advantage of clean event study approaches, but often lack external validity to other areas, policy designs or industries. At the other end of the spectrum, others use broad Bartik instrument approaches - they cover a wide range of possible shocks but are subject to well known identification concerns (Goldsmith-Pinkham et al., 2018). Gathmann et al. (2017) and others take a middle-ground approach, by pooling a wide-range of masslayoffs into multiple event studies. Gathmann et al. (2017) find substantial spillovers from masslayoffs at the German regional level. It is this identification approach that I follow here.

As well as measuring the magnitude of spillovers, the literature also concerns itself theoretically and empirically on possible sources of agglomeration. Since Marshall (1890), economists have identified the theoretical importance of labour market risk pooling, input-output linkages and knowledge spillovers as agglomeration sources. There is an amount of empirical work demonstrating that these agglomeration forces generate benefits to firms from the co-location of other firms.[7]. Conversely, these generate a negative impact on firms when nearby firms reduce operations, as quantified by Helm (2017) for German local employment shocks. Again, however, the data and empirical strategies used, including for Helm (2017) are aggregated so analysis is restricted to region-industry level.

The third literature stream focuses on the degree of localisation and the spatial scale involved in economic forces. As yet, detailed questions about the spatial scale and suitable analysis methods have not been applied to spillover effects of large, negative employment events. Micro level effects of other processes as diverse as job search, commuting, export learning behaviour, production spillovers and local consumption amenities are often found to be highly localised.[8] Such papers also explore the heterogeneity in spatial scales, in recognition that market size or spatial reach should not be imposed as constant across all applications. For example, Hassink and Meekes (2018) estimates a wide variety in local labour market sizes based on skill, gender and other individual characteristics. To analyse spatial scales in detail, the literature is required to use much more detailed geographic information and more complex analysis methods that move towards a continuous treatment of space (Manning and Petrongolo (2018) and Ahlfeldt et al. (2015) provide two examples).

The rest of the paper proceeds as follows. Section 2 outlines the conceptual framework, in particular

[6]Example research designs include using regions around the cutoff for regional funding grants and tax subsidies, or a new large plant. See for example Devereux et al. (2007), Greenstone et al. (2010), Kline and Moretti (2013) and Busso et al. (2013)

[7]See for example Krugman (1991), Harhoff (1999), Devereux et al. (2004), Graham et al. (2009) and Moretti (2010)

[8]Example work includes Manning and Petrongolo (2018); Hassink and Meekes (2018); Ahlfeldt et al. (2015); Kamal and Sundaram (2016); Bisztray et al. (2018). Spillovers often cascade into other areas so the macro effects may operate on larger spatial scales.

the treatment of space as a continuous concept, and the empirical strategy and data used. Section 3 presents the empirical results of the analysis of spillover spatial patterns on impact. Building on the impact results, Section 4 outlines the costs of more standard analysis methods by comparing the spillover spatial patterns with those using discretised geographic units. Next, Section 5 presents the analysis of the dynamic responses to mass layoffs. Section 6 evaluates possible spillover channels and Section 7 concludes with a discussion.

2 Framework and empirical strategy

The conceptual and empirical framework of the paper is based on treating space as continuous. Traditionally, analysis has discretised space by dividing areas up into mutually exclusive and exhaustive units. These may be arbitrary from an economic point of view (e.g. politically demarcated administrative regions) or have some economic principles defining them (e.g. commuting zones where a certain fraction of the population both reside and work in).[9] Either way, what is naturally a continuous concept is divided into indepedent units.

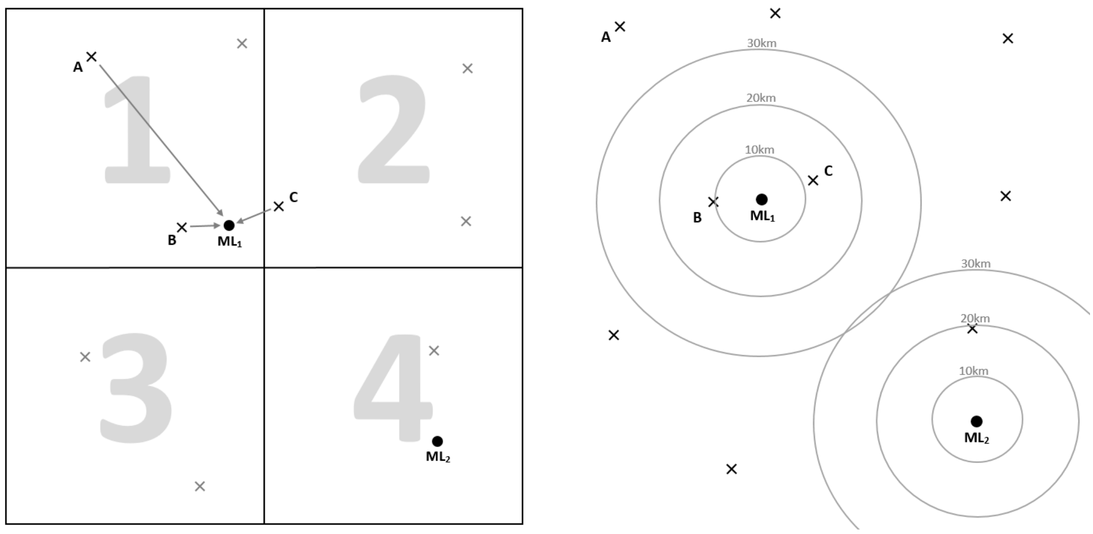
The most common approach to empirical analysis of local economies is quasi-experimental analysis of these discretised areas. For example, difference-in-differences can be used to compare discrete units that have experienced the event in question (e.g. a masslayoff, a rise in the minimum wage) to those that have not.

Panel A of Figure 1 demonstrates this approach using the issue of masslayoff spillovers. Firms, denoted by a cross, are scattered across a space which is divided up into four regions. Regions 1 and 4 on the diagonal experience a masslayoff (ML) while regions 2 and 3 on the off-diagonal do not. The outcomes of firms located in regions 1 and 4 are compared to firms in regions 2 and 3.

Such an approach is prone to bias. Firstly, if the economic forces of interest operate on a much more local scale than the unit of analysis, it is likely that they will be undermeasured and potentially not identified at all. For example, if only firms very close to the masslayoff (e.g. Firm B) are affected, while further away firms (e.g. Firm A) are not, the estimate will provide some average of the two. Implicitly, all firms within region 1 are assumed to be equally treated.

Secondly, the approach assumes that the spillover effects do not cross the unit borders. All firms within regions 2 and 3 are assumed to be entirely unaffected by the masslayoffs. This will be violated if an event occurs near the border (e.g. firm C is affected by the first masslayoff) or if the spillovers operate on a larger scale than the geographic units used. In either case, regions 2 and 3 cannot be

[9]It should be noted that there are substantial linkages between any commonly used local labour market definition. For example, there are 320 travel to work areas (TTWAs) in the UK defined as having at least 75% of the working residents work in the area and at least 75% of the workers also live in the area. That means up to 25% flow across the boundaries for work every day. These cannot be thought of fully separate geographic entities in any sense. Manning and Petrongolo (2018) further discusses the limitations of discrete local labour market measures.



(a) Discretised space (b) Continuous space

Figure 1: Measurement of spillovers across space

used as ‘controls’ in empirical analysis.

The approach here avoids artificially discretising space. As I have individual firm locations, I am able to retain the spatial structure. I can then use the masslayoff as the centre of the treatment, and analyse how firms of varying distances are affected. Panel B of Figure 1 demonstrates this approach. This approach allows for Firms B and C to be approximately equally affected by the first masslayoff, and Firm A to be unaffected.

2.1 The spillover distance function

The analysis uses masslayoffs as a localised employment shock. A masslayoff will generate spillovers to nearby firms if a firm’s productivity is related to local economic activity. Phrased differently, in the presence of local agglomeration forces, a decrease in local employment will reduce the productivity, hence output and employment, of other nearby firms.

Consider a simple price taking, profit maximising firm i with Cobb-Douglas production choosing their optimal level of inputs. In the short run, capital, $K = \bar{K}$ is fixed and only labour L is chosen:

$$\max_{L} \left\{ A_i L^{\alpha} \bar{K}^{\beta} - wL - r\bar{K} \right\} \tag{1}$$

Wages are denoted w, capital prices r, and output prices are normalised to $p = 1$. Labour is chosen such that the marginal product of labour equals the prevailing wage $w = MPL = \alpha A_i L^{\alpha-1} \bar{K}^{\beta}$. The optimal level of labour, in logs, is therefore:

$$\ln L^* = \underbrace{\frac{1}{1-\alpha}\ln A_i}_{\text{object of interest}} + \frac{1}{1-\alpha}\left[\ln\alpha + \beta\ln\bar{K} - \ln w\right] \tag{2}$$

Spillovers occur when a firm's log productivity $\ln A_i$ is a function of local employment - this empirical fact is well documented.[10] The analysis here is particularly interested in whether $\ln A_i$ is a function of distance-weighted employment, and in particular what that distance function is.

Consider firm productivity as a function of distance-weighted local employment, and all other productivity characteristics unrelated to distance $\bar{A}_i$: $A_i = \bar{A}_i e^{f(\text{distance weighted employment})}$. I assume the distance weighted local employment function sums across all nearby firms, j. Inside the sum, the contribution of nearby firm j to firm i's productivity is some function, f, of the distance between i and j, d_{ij}, multiplied by some function, g, of j's employment size E_j.

$$\ln A_i = \ln\bar{A}_i + \sum_j f(d_{ij}).g(E_j) \tag{3}$$

The current set up places no restriction on the function form of the distance function to each nearby firm - and this distance function is the key function of interest. The direct impact of the employment size of j is not constrained. However, the set up does assume that the impact of distance is multiplicatively separable to the employment size effect.

A masslayoff is a large change to the employment of some nearby firm, k. This will affect the productivity of nearby firm i:

$$\Delta\ln A_i = f(d_{ik}).\underbrace{\Delta g(E_k)}_{\text{masslayoff} = 1} + \sum_{j\neq k} f(d_{ij}).\Delta g(E_j) \tag{4}$$

I can use the variation in distance to this masslayoff to identify the distance function. As productivity itself is not observable, I revert back to the observed short run employment change of firm i. Combining equation 4 with equation 2, I get a more estimable equation for short run log employment changes:

$$\Delta\ln L_i = \underbrace{f(d_{ik}).\text{masslayoff}_k}_{\text{masslayoff distance effect}} + \underbrace{\sum_{j\neq k}\frac{1}{1-\alpha}f(d_{ij}).\Delta g(E_j)}_{\text{other local employment changes}} - \underbrace{\frac{1}{1-\alpha}\Delta\ln w}_{\text{local wage adjustment}} \tag{5}$$

[10] The spillovers and agglomeration literature discussed earlier documents the empirical evidence.

$g(E_k)$ is not of direct interest here, so $\Delta g(E_k) * \frac{1}{1-\alpha}$ is replaced with a binary variable for a masslayoff in nearby firm k.

2.2 Empirical strategy

The analysis uses an event study approach based around localised mass layoffs. As stated in more detail in Section 2.3, a masslayoff is defined as a single plant losing 1000 or more workers in a year which is not associated with regularly fluctuating employment or an ownership change. The masslayoff provides a shock to nearby employment for all local firms.

I follow the extensive masslayoff literature with the identifying assumption that large employment losses are unrelated to local factors, hence are exogenous to the local area. They are assumed to be driven by national or international forces such as trade shocks or industrial decline. Non-tradeable, locally consumed goods that respond to local events are, in general, produced by firms too small to generate a 1,000 person masslayoff. Such events are usually restricted to tradeable services, manufacturing etc. The local exogeneity justification is a very standard chain of logic, but one that does not come without its critics.

In this context, I have the added advantage of highly detailed firm level microdata; much of the literature relies on aggregated data. These data mean I am able to control for annual industry shocks up to the five digit level, leaving only sub-national industry variation for all non-masslayoff firms. This removes concern that other firms in the local area are laying off staff in response to the same industry trend that generated the masslayoff. I am also able to control for general local shocks, which could include local policy shifts or broad spending shocks to hit the local economy. What remains is therefore sub-national, local industry variation, primarily in distance to the masslayoff event.

Given the masslayoff event construction, I then construct distance measures for each firm to the masslayoffs. As a result, each firm is linked to their closest masslayoffs and key data on those masslayoffs, such as industry and employment size.

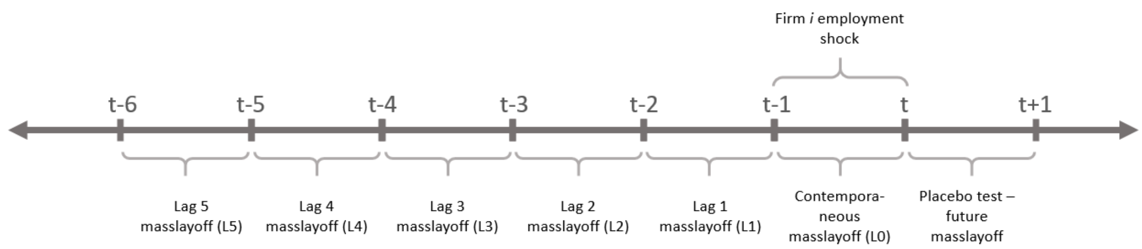


Figure 2: Timing of event study estimation strategy

I then estimate the relationship between employment changes in each non-masslayoff firm and distance to the nearby masslayoffs, considering in turn contemporaneous masslayoffs and masslayoffs that occured in the previous years. Figure 2 demonstrates the timing of the event study approach. Our dependent variable is some measure of employment change for firm i (local plant) between time $t-1$ and t. The event generating the shock is the closest masslayoff in the period of interest. A contemporaneous (lag 0) event would be a masslayoff that also occurs between $t-1$ and t: i.e. a local firm sheds at least 1,000 workers in the time period. Lagged masslayoffs occur in preceeding time periods, as demonstrated in the figure (2).

Using the event study approach and motivated by equation 5, the baseline estimating equation is of the following form:

$$\Delta \ln L_{ijlt} = \alpha + \beta f(d_{ik}).\text{masslayoff}_k + \gamma X_{ijlt} + c_j + c_t + c_l + \epsilon_{ijlt} \tag{6}$$

Where $\Delta \ln L_{ijrt}$ is the change in log employment at firm i in industry j at location l between time t and time $t-1$ and, as standard, can be approximated as percentage changes. For firms that shut down over the period, $\Delta \ln L_{ijrt}$ is simply $-\ln L_{ijr,t-1}$.[11] $f(dist_{ik})$ is a function of the distance to the closest masslayoff, k. X_{ijlt} are relevant factors or controls such as the number of masslayoffs within a certain distance during the year in question, or the distance of the second closest masslayoff. A variety of fixed effects are used, including industry, time and location, as well as industry-time and location-time fixed effects. Errors are primarily clustered at the two digit industry level, although a variety of spatial and industry-spatial errors structures are investigated.

The primary features of interest are the functional form of distance, $f(dist_{ik})$, and the strength and direction of the effects, β. Instead of imposing functional forms on f, the baseline results take a non-parametric approach to estimating the distance function. f is estimated using a collection of mutually exclusive dummy variables of distance to the closest masslayoff, for example:

$$\begin{aligned}\Delta \ln L_{ijlt} =& \alpha + \beta_0 dist_{ik}^{0-1} + \beta_1 dist_{ik}^{1-2} + \beta_2 dist_{ik}^{2-3} + \beta_3 dist_{ik}^{3-4} + \beta_4 dist_{ik}^{4-5} + \\ & \beta_5 dist_{ik}^{5-10} + \beta_{10} dist_{ik}^{10-20} + \beta_{20} dist_{ik}^{20-40} + \gamma X_{ijlt} + c_j + c_t + c_l + \epsilon_{ijlt}\end{aligned} \tag{7}$$

The dummy variable $dist_{ik}^{x-y}$ equals 1 if the distance from firm i to the closest masslayoff k lies between x and y kilometers. For firms who are not located near any masslayoff - i.e. the closest masslayoff is further than the maximum distance dummy - will have all dummy variables equal to

[11] Numerically, this is equivalent to the firm shedding all but its final employee. This is a reasonable approximation of log employment loss for larger firms. As we see later, smaller firms on whom the approximation might make a material impact are not the primary drivers of the result. Therefore the assumption is unlikely to be particularly influential.

zero. They are therefore the baseline case, and the β coefficients $(\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_{10}, \beta_{20})$ plot non-parametric estimates of the distance function.

It should be noted that two key terms in equation 5 are not included in the estimating equations, 6 and 7. Firstly, the adjustment of local wages will in part determine firm i's short run employment adjustment. Local wages are notoriously downwardly rigid empirically, but nonetheless analysis in section 3 confirms their zero response here.

Secondly, the responses of other non-masslayoff firms in the local area are not included. Undoubtedly, they too will respond directly to the masslayoff, and their responses will generate a standard reflection issue. The β coefficients should therefore be interpreted as a sum of firm i's direct adjustment to the closest masslayoff, and the indirect adjustments to other nearby firms' own adjustments to the masslayoff. The inability to separate direct and indirect effects is a matter of results interpretation, rather than fundamental to the approach. Provided the masslayoff event itself is exogenous to the local area (the earlier identifying assumption), other sources of local firm changes should be independent of the masslayoff and not cause endogeneity problems.

Appendix B outlines the variety of robustness check undertaken. Standard event study checks such as a placebo check for anticipation effects are included. Setting specific concerns around spatial sorting, the Global Financial Crisis and spatial clustering of multiple masslayoffs, among others, are also addressed.

2.3 Data

The primary dataset used for analysis is the annual UK Business Structure Database (BSD) from 1997-2017. The BSD encompasses almost the entire universe of business entities in the UK, encorporating 99% of economic activity in the UK. All firms in the UK who employ at least one staff member registered for PAYE tax collection and/or are eligible for Value Added Tax (VAT) are included in the BSD. The BSD is available at both the parent company level (Enterprise Unit - EU) and local plant level (Local Unit - LU). Each level provides birth and death dates, tax information, five digit industry codes and employment counts. The EU level dataset provides turnover of the company. I use the LU, plant level information as the topics of concern relate to highly localised employment.

Crucially, extremely detailed location information down to the postcode level is available for both the EU and LU. There are around 1.8million postcodes in the UK for a population of approximately 66 million, with the average postcode covering five properties.[12] Postcodes therefore provide an almost exact pin-point location. The postcodes are mapped to northings and eastings using the Office for National Statistics Postcode Database, resulting in precise coordinates matched to every plant and firm in the UK.

[12] Details from BPH postcodes https://www.bph-postcodes.co.uk/guidetopc.cgi

I exclude public sector employment entities and retain all companies, sole proprietors and partnerships in the BSD. Due to the requirement for VAT registration and/or at least one PAYE enrolled employee, the smallest of sole proprietors are not included in the dataset. What remains is effectively the near-entirety of the UK private sector, with an average of X plant observations annually totalling Y observations overall.

I then define and identify every local mass layoff event in the UK from 1997-2017. These are defined as a plant shedding at least 1000 net employees in a given year. This can occur through either a plant of 1000 or more employees shutting down or a larger plant firing 1000 workers and remaining active with a smaller employment count. To avoid capturing seasonal workers or other types of highly fluctuating employment, I exclude those firms which rehire 1000 workers in the subsequent few years, and those who hire 1000 workers in the previous year. I also check that the plant has not simply changed ownership, name or ID code by using the demographic event information available in the dataset; a masslayoff through plant death has to coincide with the BSD labelling the event as death too (as opposed to merger, acquisition etc). Appendix A presents key descriptive statistics for the firm and masslayoff data.

One issue with the construction of the masslayoff variable is that it also captures large, local employment outsourcing. For example, a large firm that restructures its labour force by shifting many support jobs to external providers will be included in the events. If the external providers are in close proximity geographically, this is not a local negative employment shock in any sense. Unfortunately, the occurrence of such events cannot be measured with the data available. If such events are not negligible in number, they will provide an attenuation bias in the estimated treatment effect by mixing the pool of events into true treatments and false treatments.

In section 3, the adjustment of local wages are considered. For this, I use the UK Annual Survey of Hours and Earnings (ASHE), as the BSD does not contain the required wage information. The ASHE is a one percent sample of UK workers, based on national insurance (tax) numbers. It is compulsorily employer reported from payroll information so is considered highly accurate relative to workers' self-reported earnings. Sampled individuals are included in the dataset for each year they are employed, even if changing employers. From the ASHE, I construct an annual worker panel that includes hourly wages and employment postcode. For individuals with multiple jobs in any given year, I take their reported main job. The required postcode information is only reliably provided from 2004, so the panel spans 2004-2017.

3 Spatial distribution of effects on impact

3.1 Baseline

The baseline results follow equation 7 by regressing employment change at the non-masslayoff firm level on distance to the closest masslayoff in the same year. Collections of mutually exclusive dummy variables are used as the non-parametric distance function. These are labelled by the distance they refer to: for example, 'dist 2-3km' equals one if the closest masslayoff in the current year is between 2 and 3km from the plant in question. Industry (2 digit SIC), postcode (2 digit) and year dummies are included in each regression as fixed-effect controls. All standard errors are clustered at the two digit SIC industry level.

In all three specifications of Table 1 we find that plants located close to a masslayoff experience substantial employment loss, and this mitigates as the distance increases. The preferred specification is column three as it includes the most detail for the closer distances. The coefficients on the distance dummies in column three uncover strong but very localised employment spillovers. As we see, the employment loss rapidly decays within a few kilometers; the impact on firms between two and three kilometers from the event is approximately half that of those between one and two kilometers, which in turn is half that of those located within one kilometer. Employment losses become insignificant at approximately the twenty kilometer mark.

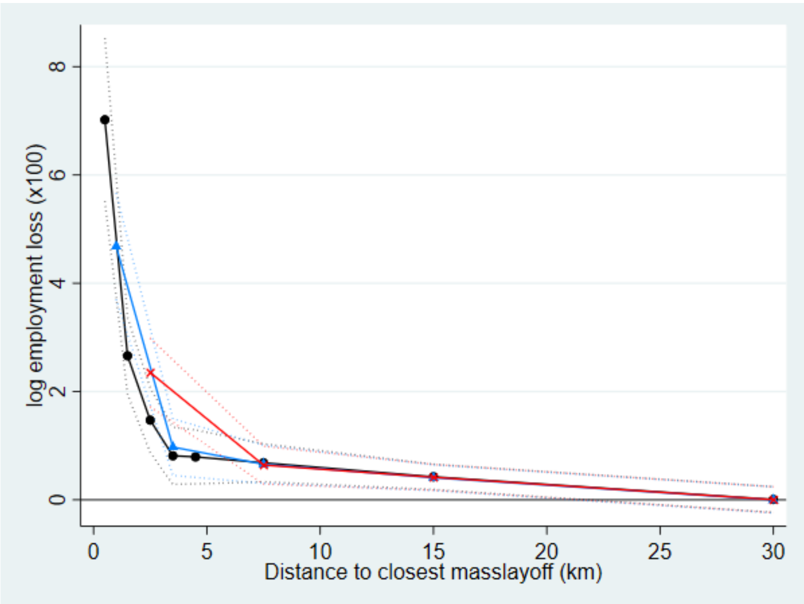


Figure 3: Employment loss estimates from Table 1, contemporaneous masslayoff

Figure 3 plots the coefficients from Table 1 along with 95 percent confidence intervals. Column

Table 1: Baseline estimates of spatial effects on impact

	(1) $\Delta log(L)$	(2) $\Delta log(L)$	(3) $\Delta log(L)$
dist 0-5km	-0.0235***		
	(0.00323)		
dist 0-2km		-0.0468***	
		(0.00500)	
dist 2-5km		-0.00973***	
		(0.00267)	
dist 0-1km			-0.0702***
			(0.00769)
dist 1-2km			-0.0266***
			(0.00362)
dist 2-3km			-0.0147***
			(0.00305)
dist 3-4km			-0.00813**
			(0.00269)
dist 4-5km			-0.00792**
			(0.00254)
dist 5-10km	-0.00641***	-0.00656***	-0.00683***
	(0.00178)	(0.00179)	(0.00179)
dist 10-20km	-0.00415**	-0.00407**	-0.00424***
	(0.00121)	(0.00121)	(0.00119)
dist 20-40km	-0.0000138	0.0000272	-0.0000507
	(0.00122)	(0.00123)	(0.00121)
Cons	-0.0434***	-0.0427***	-0.0426***
	(0.00642)	(0.00648)	(0.00641)
Controls	Yes	Yes	Yes
N	66,014,522	66,014,522	66,014,522
R^2	0.023	0.023	0.023

Standard errors in parentheses, clustered on 2 digit industry. Variables are a set of dummies indicating distance to closest masslayoff. Fixed effects are 2 digit SIC industry, 2 digit post-code, and year. Years included are 1997-2017.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

three is plotted in black with circular points, column two is plotted in blue with triangular points and column one is plotted in red with cross points. The initial coefficient points are lower for the blue (Column 2) and red (Column 1) specifications as the less detailed dummies provide weighted estimates for the smaller distances.

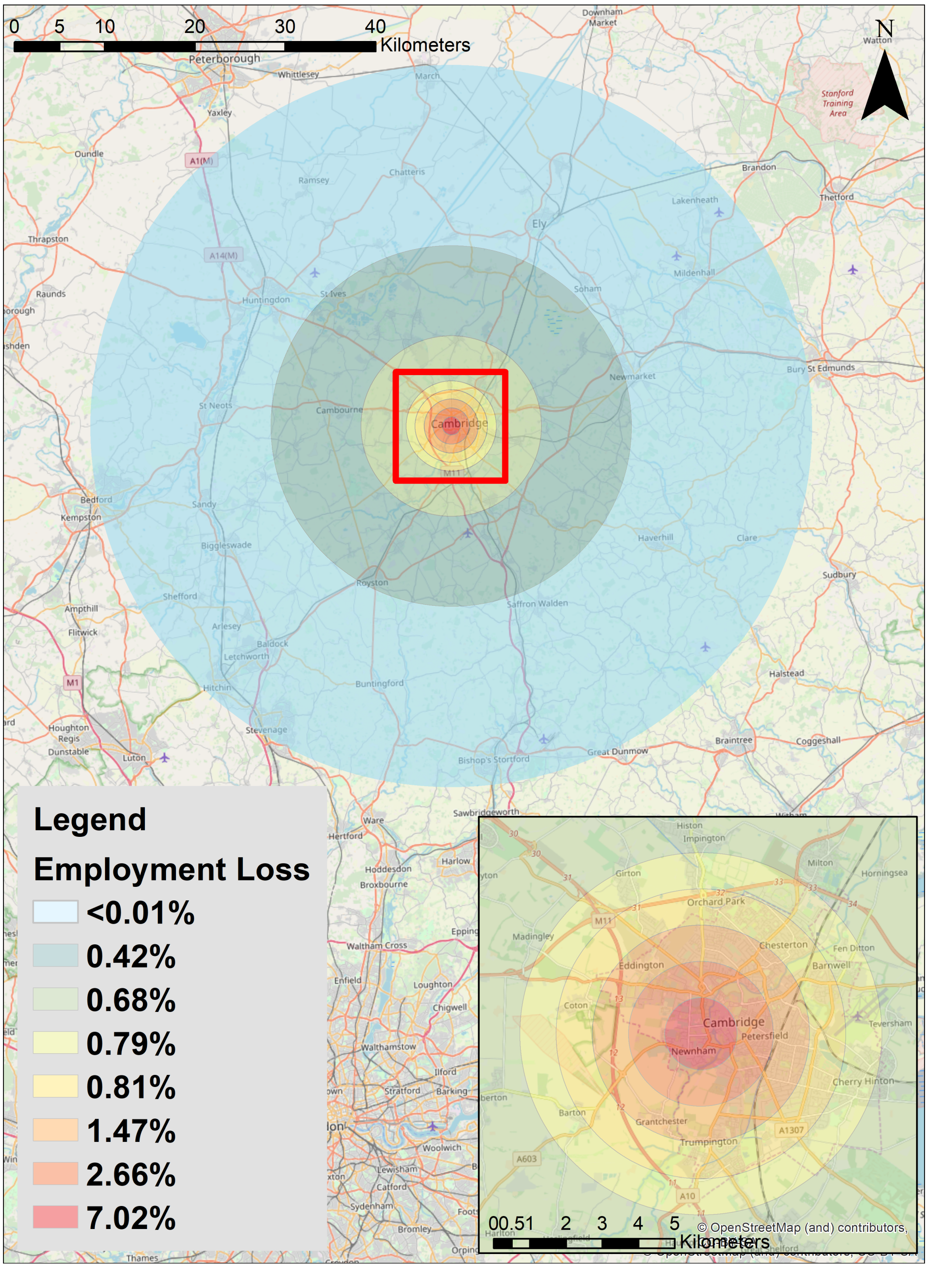


Figure 4: Map of predicted employment impacts from a hypothetical masslayoff in Cambridge, UK

Figure 4 maps the predicted employment impacts of a hypothetical masslayoff centred in Cambridge, UK, using the decay estimates from the baseline regressions.[13] The map is a visual display of the high degree of localisation. Cambridge is a very small city with a dense population of around 120,000 individuals. The substantial employment spillovers would only be experienced by a subset of the city area, before rapidly decaying further out.

These non-parametric estimates accurately demonstrate the magnitude and speed at which localised spillovers propagate spatially. They suggest that employment spillovers are highly localised, affecting very close firms most strongly. At least at the local firm level, they become negligible at fairly conservative distances, approximately ten kilometers.

The rapid spatial decay patterns have several implications. In terms of measurement, they mean that firm-level spillovers are highly localised. Standard estimation strategies relying on larger administrative areas may therefore fail to pick them up. As the more geographically aggregated specifications in Figure 3 show, larger geographic units provide a weighted average of the spillovers within the area. Averaging across an administrative area ten or twenty kilometers around a masslayoff would provide very small, potentially insignificant results given the coefficients above.

Economically, the results also show that the firm-to-firm transmission mechanisms must be highly localised in nature. A high degree of localisation is consistent with much of the urban economics agglomeration literature - many economic linkages from productivity spillovers to consumption amenity spillovers appear to operate in a very localised way.[14] The degree of localisation in these employment spillovers can help elucidate the mechanisms at hand. Many have been discussed hypothetically in the literature, and these results give more weight to those that operate very locally around the masslayoff event. Section 6 continues down this chain of logic further.

3.2 Impact on local wages

The baseline analysis has so far ignored impacts on local wages; implicitly I have ignored price adjustments in favour of quantity adjustments for labour. As touched on in Section 2, equation 5 demonstrates that local employment adjustment will partly depend on the response of local wages to a masslayoff. One might expect that a large reduction in local labour demand will depress local wages. Wage adjustments exclusion from the picture has so far been driven by the extensive literature finding strongly downwardly rigid wages.[15]

[13] The masslayoff is centred over the Faculty of Economics which is located next to the Faculty of Law at the University of Cambridge. The hypothetical scenario is therefore at least 1,000 economists (and/or lawyers) being laid off. This may well be a net positive boost to the local Cambridge economy, however I abstract from such a discussion by imposing the baseline estimates.

[14] See for example Ahlfeldt et al. (2015), Manning and Petrongolo (2018) and Hassink and Meekes (2018).

[15] See Bewley (2009), Kahn (1997), Altonji and Devereux (1999) and Elsby (2009) for general analysis of the downwardly rigid wage phenomenon. Kaur (2019) and de Ridder and Pfajfar (2017) address downwardly rigid wages at the local level.

However, the same logic applied to the employment spillover analysis can be applied to the local wage phenomenon. Perhaps existing results that find no effect on local wages are driven by a mis-specification of distance. Wage analysis will also suffer from the costs of discretising space, and the zero results may derive from discretisation rather than genuinely zero effects.

Table 2: Wage changes as a function of the distance to the closest masslayoff

	(1) $\Delta log(W_1)$	(2) $\Delta log(W_2)$
dist 0-1km	0.0862	0.0861
	(0.0912)	(0.0913)
dist 1-2km	0.00521	0.00532
	(0.0192)	(0.0190)
dist 2-3km	-0.00133	-0.00174
	(0.0224)	(0.0223)
dist 3-4km	-0.0180	-0.0182
	(0.0199)	(0.0198)
dist 4-5km	-0.0162	-0.0160
	(0.0167)	(0.0166)
dist 5-10km	0.0161	0.0159
	(0.0144)	(0.0144)
dist 10-20km	0.00632	0.00613
	(0.0103)	(0.0103)
dist 20-40km	-0.00694	-0.00693
	(0.00799)	(0.00799)
Cons	6.826***	6.818***
	(0.0992)	(0.0994)
Controls	Yes	Yes
N	2,256,208	2,256,021
R^2	0.148	0.147

Standard errors in parentheses, clustered on 2 digit occupation. Variables are a set of dummies indicating distance to closest masslayoff. Controls are 2 digit occupation codes, 2 digit postcode, and year fixed effects. Years included are 2004-2017.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

I estimate the impact of a masslayoff on local wages using the same methodology as for employment adjustments. The ASHE worker panel provides the required hourly wage information. I use both hourly wages excluding overtime and hourly wages including overtime to allow for possible impacts through changes in overtime employment. The change in the individual worker level log wage,

$\Delta \ln(w_{it})$, is regressed on the distance to the closest masslayoff.[16] Occupation, location and year dummy control variables are included to keep the analysis consistent with the firm level employment analysis. Standard errors are clustered at the 2-digit occupation level.

Table 2 displays the estimated wage impacts. Column 1 uses hourly wages excluding overtime, denoted W_1, and Column 2 uses hourly wages including overtime, denoted W_2. As can be observed, at no distance are there significant effects on wages from masslayoffs. The results here confirm the presence of strong downward rigidities in wages. It appears that employment adjustment following localised shocks occurs through the quantity of labour employed rather than the price of labour.

3.3 Heterogeneity by firm type and location

I investigate heterogeneity by firm and location observables. These help deepen the picture about features of the spatial spillovers and help assuage concerns that the results are purely down to detailed spatial sorting and associated spatial autocorrelation in shocks.

A natural starting point is to identify which firms are driving the spillover results. Are smaller firms located near to mass layoffs more susceptible to employment spillovers, or are their larger counterparts the primary drivers of spillover employment loss?

To do so, I segment the sample into larger and smaller non-mass layoff firms using an employment cut-off of either 20 or 50 employees. I repeat the baseline regressions on each sample in turn. I also pool the entire firm sample and include the firm size variables both as a level term and as an interaction with the distance function. Both approaches shed light on whether small or larger firms receive stronger spillovers, and what the distance decay function for each is.

The results, displayed in Table 13 in Appendix C, demonstrate that all firm sizes experience employment spillovers if located in close proximity to a masslayoff and all firm sizes exhibit a similar spatial decay rate. However, larger firms (those with more than 20 or 50) employees do have proportionately stronger responses. It appears that small firms respond less strongly but still exhibit employment losses.

I next evaluate the specific role of the manufacturing industry. The advantage of the data and empirical approach used here are that they are able to capture a broader range of industries. However, much of the existing local spillovers literature has restricted focus to the manufacturing sector so it is of value to see how important the distinction is.

I broadly classify a firm (including a masslayoff firm) as in the manufacturing sector if their 2 digit SIC codes are in the range 15-34 (based on the UK Data Service SIC coding). The analysis that

[16] Recorded changes will include an individual receiving a pay change from their existing firm, and individuals switching firms. For individuals laid off, their change in log wages is recorded as $-\ln(w_{i,t-1})$. For workers who have just entered employment, their change in log wages is recorded as $\ln(w_{it})$

follows is in two parts; assessing the role of a manufacturing mass layoff event (manufacturing is the 'generating' firm) and assessing the response of nearby non-mass layoff manufacturing firms to any mass layoff event (manufacturing is the 'receiving' firm).

Results are similar to the firm size results and are displayed in Table 14 in Appendix C. Manufacturing firms incur larger employment losses from being located very near (any) masslayoff. Non-manufacturing firms still have a loss function that decays, but it is smaller in magnitude across all distances. This may be inextricably tied up with the firm size results. Manufacturing firms tend to be larger and as larger firms have larger losses (even proportionately) it is unclear whether the key driver is firm size, manufacturing or some omitted covariate.

Whether or not the masslayoff itself is from a manufacturing plant does not seem to meaningfully affect the spatial spillovers. Segmenting the sample into firms located closest to a manufacturing masslayoff and those located closest to a non-manufacturing masslayoff give similar results. If anything, the non-manufacturing masslayoffs seem to generate slightly stronger spillover results.

I also consider whether a location's employment density matters for the observed spillovers. If a firm is located in a dense area economically, the presence of a lot of additional economic activity may either amplify or mitigate the shock. The latter would imply that density provides some insurance value against shocks to a single large nearby employer.

The economic density each non-masslayoff firm's location is measured at the employment per square kilometer of a 3km by 3km grid around each firm. For meaningful interpretation, this employment density measure is standardised. Results, displayed in Tables 15 and 16 in Appendix C suggest that a one standard deviation increase in employment density has a very small level effect on employment changes overall. However, there is a positive interaction term with the distance function, suggesting that density somewhat mitigates the firm level employment loss associated with locating very near a masslayoff. The insurance value this provides is in the order of two percentage points less employment loss for a firm located immediately next to a masslayoff.

Of course, these results are all for the individual firm's employment loss. There may be less employment loss at the firm level in a dense environment, but a denser environment is associated with more firms. Once aggregating over all nearby firms, it may still be the case that denser areas lose more employment overall from a masslayoff, even if individual firms are somewhat insured.

4 The costs of discretising space versus a continuous measure

The analysis so far has used continuous measures of distance to analyse the spatial scale of masslayoff employment spillovers. The approach used is novel in part because it relies on precise location data that are rarely available.

The more standard method for analysing spatial features is to discretise space into mutually exclusive and exhaustive units. A difference-in-differences style approach is typically used to compare those units that have experienced an event to those that have not. As discussed in Section 2, such an approach will suffer from two potential sources of bias. If the area affected by the spillovers exceeds the geographic unit size used, control units will become contaminated. If the spillover area is much smaller than the geographic unit size used, estimated results will average out close to zero. Both can cause estimates that are biased towards zero.

To demonstrate these costs more fully, I now shift to estimating spillovers using discrete spatial methods. I begin by dividing the space spanned by the UK landmass into grids of set unit sizes. In effect, I take the approach displayed in Panel a) of Figure 1. The smallest discretisation of space divides the entire UK up into 1km by 1km grid squares. The largest divides the UK up into 40km by 40km grid squares. A range of intermediate grid sizes are constructed as well.

Table 3: Discretising space into units: count of masslayoffs in unit

	(1)	(2)	(3)	(4)	(5)
	$\Delta log(L)$	$\Delta log(L)$	$\Delta log(L)$	$\Delta log(L)$	$\Delta log(L)$
Unit size	1x1km	2x2km	3x3km	4x4km	5x5km
# ML in unit	-0.0249***	-0.00935***	-0.00589***	-0.00449***	-0.00298***
	(0.00392)	(0.00251)	(0.00119)	(0.000893)	(0.000523)
Constant	-0.0476***	-0.0475***	-0.0471***	-0.0469***	-0.0468***
	(0.00662)	(0.00657)	(0.00659)	(0.00661)	(0.00664)
Controls	Yes	Yes	Yes	Yes	Yes
N	66,014,522	66,014,522	66,014,522	66,014,522	66,014,522
R^2	0.023	0.023	0.023	0.023	0.023

	(6)	(7)	(8)	(9)	(10)
	$\Delta log(L)$	$\Delta log(L)$	$\Delta log(L)$	$\Delta log(L)$	$\Delta log(L)$
Unit size	10x10km	15x15km	20x20km	25x25km	30x30km
# ML in unit	-0.00112**	-0.000758**	-0.000124	-0.000148	0.000101
	(0.000329)	(0.000248)	(0.000223)	(0.000203)	(0.000173)
Constant	-0.0471***	-0.0472***	-0.0478***	-0.0477***	-0.0483***
	(0.00662)	(0.00664)	(0.00660)	(0.00660)	(0.00662)
Controls	Yes	Yes	Yes	Yes	Yes
N	66,014,522	66,014,522	66,014,522	66,014,522	66,014,522
R^2	0.022	0.022	0.022	0.022	0.022

Standard errors in parentheses, clustered at 2 digit industry level. Controls are 2 digit SIC industry, 2 digit postcode, and year. Years included are 1997-2017.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

For each grid square (of a given size), I sum up the number of masslayoffs occuring in the grid square in the year in question. This equals zero for squares with no masslayoff - the majority - and one for those that include a masslayoff.[17] I then regress the change in firm level log employment on the presence of a masslayoff in the firm's grid square. This is standard difference-in-differences; comparing the change of a firm in a unit that has experienced a masslayoff to the change of a firm in a unit that has not. For consistency with the continuous results, the same controls are used (controls for industry, year fixed effects and two digit postcode fixed effects) and standard errors remain clustered at the 2 digit industry level.

It should be noted that the grid square sizes are not directly comparable to the analogous distance dummies in the continuous analysis. The continuous analysis effectively draws concentric circles centred around the masslayoff. The discrete approach says nothing about where in the grid square the masslayoff occurs, which is an inherent problem in the method. If the masslayoff is directly centred in the square of size xx$x$km, other firms in the same grid square will be located anywhere between 0 and $\sqrt{(\frac{x}{2})^2 + (\frac{x}{2})^2}$ km from the masslayoff. But if the masslayoff is near the corner of the grid square, a firm could be located up to $\sqrt{x^2 + x^2}$km from the masslayoff. Naturally, a firm located immediately across the border in an adjacent grid square will be closer.

The results illuminate the discretisation costs. For grid squares of very small sizes (e.g. 1x1km, 2x2km), significant effects on firms within the same unit are found. However, the magnitudes are much smaller than the continuous methods would suggest because the effects 'spillover' into nearby units, contaminating the controls. As the grid size is increased, the magnitude of the effects declines rapidly. Once grid sizes of around 10-20km are used, the point estimates are tiny and statistically insignificant.

In effect, estimates of the spillovers to nearby firms are zero. As the continuous method shows, strong spillovers are in operation and will be experienced by many firms within the 'treated' grid square. However, averaging across too large an area means they fail to be picked up by the difference-in-differences methodology.

Interestingly, the point at which the results become statistically insignificant - around 10x10km or 20x20km - is comparable in size to many administrative units or commuting zone units used in typical analyses.

5 Dynamics in the spatial distribution of effects

One of the motivations for the analysis is the (recently documented) phenomenon that very local shocks tend to generate larger impacts overtime as the effects strengthen. The classic spatial equi-

[17] Very occasionally, more than one masslayoff occurs within a grid square in a given year. This is slightly more common when larger units (e.g. 30-40km are used). As a robustness check, I also turn the masslayoff count into an indicator variable that equals zero if no masslayoff occurs, and one if one or more occurs.

librium adjustment process whereby the impact of shocks dissipates overtime is called into question. This section considers the dynamic effects at the firm level. In particular, I investigate the magnitude of the current firm level responses to masslayoff shocks that occurred in the past, and the spatial distribution of these.

To do so, I repeat the analysis of Section 3 using lagged masslayoff events. For each firm in time t, I calculate their change in log employment since $t-1$. I estimate a relationship between this current employment change and proximity to a masslayoff occurring at some $t-s$, where $s>1$. The results displayed here are for the non-parametric distance function approach of equation 7, using a mutually exclusive set of dummies for the distance to the closest (lagged) masslayoff. The distance is the euclidean distance in kilometers between firm i (at time t) and the closest masslayoff at time $t-s$. Again, time, industry and postcode fixed effects are included, and errors are clustered at the 2 digit industry level. The full regression estimates are presented in Appendix D. Figure 5 summarises the distance coefficients for one to five lags of masslayoffs, and includes the contemporaneous results from Table 1 as T0 for comparison.

As we see, significant negative employments impacts are present for firms located close to a masslayoff event that occurred for all lags. The magnitude does decline from the initial shock (T0) to the firm level impacts five years later (T5). The spatial decay patterns are also remarkably persistent. The meaningful impacts occur for firms within 5km of the event, and particularly so for those within one or two kilometers.

A few points should be considered when interpreting these results. Each set of time results is for an annual firm level change ($t-1$ to t) and the proximity to an event that occurred in the past ($t-s$, with $1<s<5$). Some firms will therefore have been born since the event, particularly for the further back lagged events. This is not conceptually problematic: the current impact on firms of a lagged event is the question at hand.

More of concern is the weakening of a clean event study approach once further lags are considered. Iterative spillovers (i.e. reflection) between other nearby firms subsequently reducing their employment counts will be present. These are likely to become more pronounced overtime. The total annual changes estimated will therefore be a combination of the direct impacts from the masslayoff event and the indirect, iterative spillovers from other firms adjusting their employment in response. The method used here is unable to decompose the total effect into the direct and indirect spillovers, and so the final figures should be read as a combination of the direct and indirect effects.

A back of the envelope calculation is possible to calculate the cumulative change, aggregating the initial impact and subsequent lagged impacts. The change in log employment can be approximated with percentages, and multiplied out over the five lags. Figure 6 displays the results this approximation. The black line with circular points is the cumulative impact at the firm level after five years. The dotted grey lines are the earlier cumulative impacts starting from the initial impact (lowest

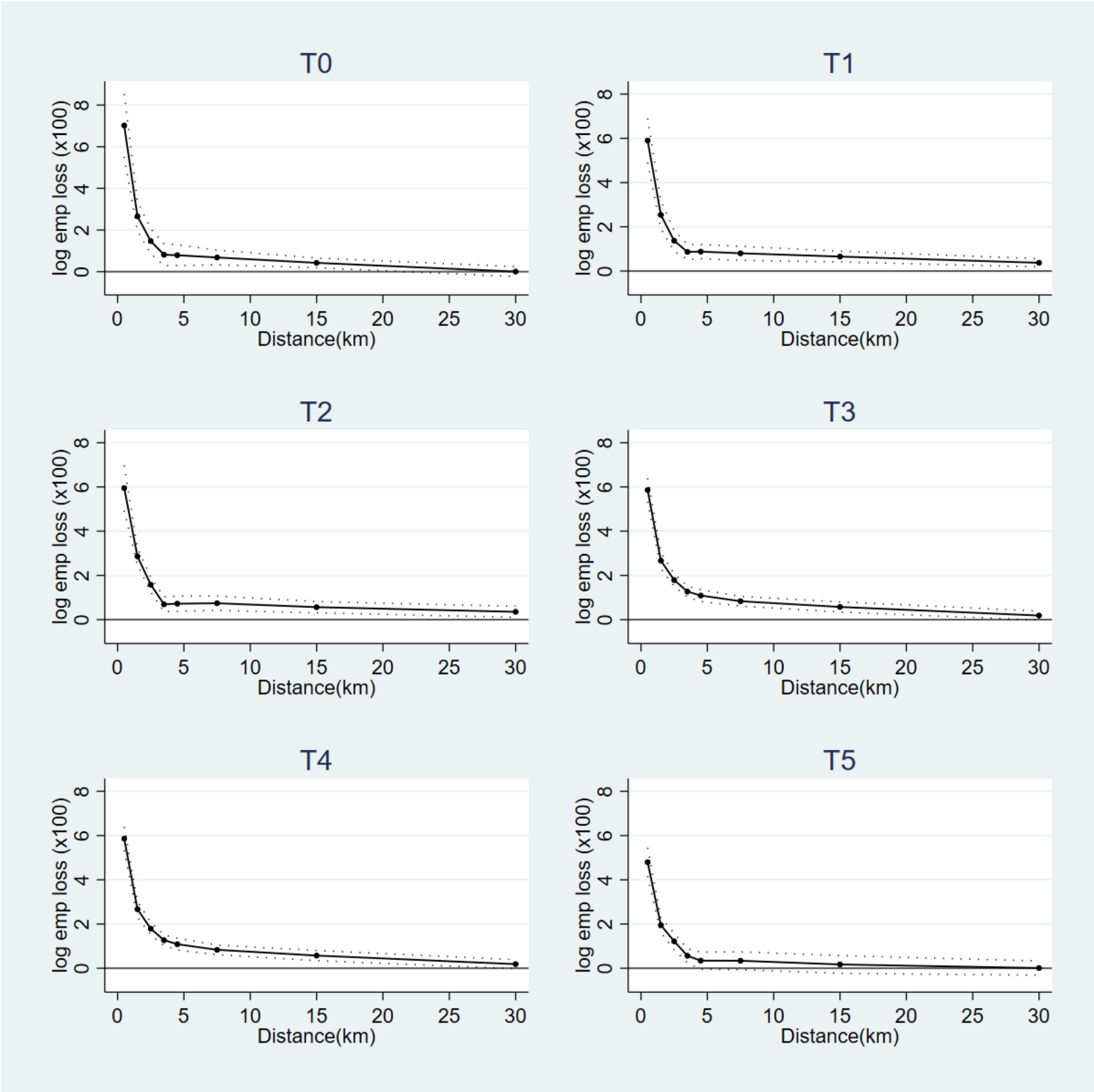


Figure 5: Year-to-year employment changes by distance to closest masslayoff in T0

line) and building up through the lags.

As is seen, the large annual impacts within one and two kilometers reinforce each other substantially overtime. The cumulative impacts are very large in close proximity to the event and decay very rapidly. The calculations are rough approximations and should be viewed in a critical light. I am multiplying out firm level impacts calculated for firms alive at each subsequent time period. As the stock of firms exhibits churn year to year, I am not using the same set of firms for each annual

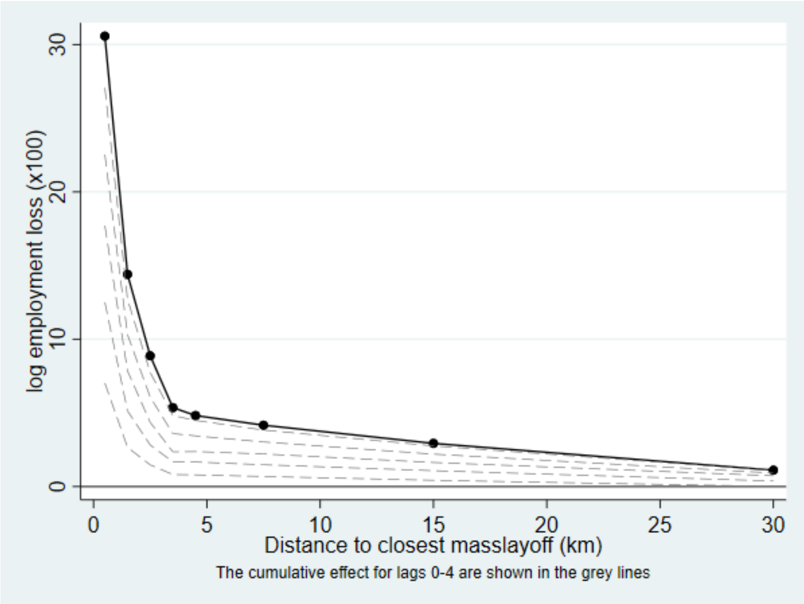


Figure 6: Cumulative firm level employment loss overtime, calculated from dynamic estimates

calculation. Therefore the results are not necessarily representative of a firm that is present for the full five lags. Measurement error and the aforementioned issues with reflection are also likely to be magnified with such a calculation. Nonetheless Figure 6 provides an interesting visual approximation of the amplified firm level effects overtime and their rapid decay rate.

6 Potential spillover channels

I now turn to considering some possible channels through which spillovers operate. The sources investigated here are industrial closeness, labour market closeness, industry input-output linkages and local demand spillovers.

6.1 Potential channel: Industrial closeness

I asses the degree to which industrial similarity matters for masslayoff spillovers. If a nearby non-masslayoff firm shares the same industry as the closest masslayoff, we might expect firm level employment spillovers to be stronger. This would occur if knowledge sharing agglomeration was an important driver behind spillovers, and if knowledge sharing is strongest between firms in similar industries.

Table 4: Industry of closest masslayoff

	(1) $\Delta log(L)$	(2) $\Delta log(L)$	(3) $\Delta log(L)$	(4) $\Delta log(L)$
exp(-dist)	-0.114***	-0.114***	-0.112***	-0.110***
	(0.0110)	(0.0109)	(0.0108)	(0.0109)
1D match	-0.00579**			
	(0.00176)			
exp(-dist) * 1D match	-0.00885			
	(0.0174)			
2D match		-0.00802		
		(0.00454)		
exp(-dist) * 2D match		-0.0129		
		(0.0320)		
3D match			-0.0220	
			(0.0117)	
exp(-dist) * 3D match			-0.0885	
			(0.0676)	
4D match				-0.0402*
				(0.0194)
exp(-dist) * 4D match				-0.201**
				(0.0750)
Cons	-0.0440***	-0.0439***	-0.0440***	-0.0439***
	(0.00652)	(0.00656)	(0.00661)	(0.00665)
Controls	Yes	Yes	Yes	Yes
N	66,014,522	66,014,522	66,014,522	66,014,522
R^2	0.023	0.023	0.023	0.023

Standard errors in parentheses, clustered on 2 digit industry. Exp(-dist) is the exponential of the negative distance to the closest masslayoff. XD match is a dummy equal to one if plant SIC matches closest masslayoff SIC to the X digit level. Fixed effects are 2 digit SIC industry, 2 digit postcode, and year. Years included are 1997-2017.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

To unpick this phenomenon, for each firm in the dataset I construct a set of dummies equal to one if the firm's closest masslayoff shares the same industry SIC code to the one, two, three or four digit level. These are included in turn as both level controls and interaction terms with a distance function. Using the full set of non-parametric dummies and four different levels of industry gradation would be difficult to interpret. To more succinctly capture the issue, I use an exponential decay function (the exponential of the negative euclidean distance to the closest masslayoff). This does place an imperfect parametric form on the distance relationship, but nonetheless shows whether those firms close to the mass layoff ($\exp(-dist) \approx 1$) have different spillovers to those further away ($\exp(-dist) \approx 0$). The results are displayed in Table 4.

As can be seen, the point estimates for both the level and interaction are negative but very rarely significant. It appears that whether or not firms are industrially related to the closest masslayoff is not a key determinant of spillovers. Proximity dominates regardless of industrial closeness.

Only once the firm in question and its closest masslayoff share a four digit SIC code - extremely closely related - do we see any significant and meaningful impact. Extremely closely related firms that are also located very close to the mass layoff appear to suffer additional employment loss. However, this is a very small and specific subset of firms and so the result should not be interpreted as substantial. The main message from the analysis appears to be that industrial closeness is not a key determinant of the degree of spatial spillovers.

6.2 Potential channel: Labour market closeness

Similarly, one might expect knowledge spillovers to operate through the labour market. Firms in industries that share similar labour forces as the masslayoff may be more exposed to knowledge agglomeration externalities and therefore more negatively affected by masslayoffs.

To measure the degree to which a firm shares labour markets with its closest masslayoffs, I use the UK Annual Survey of Hours and Earnings (ASHE). The ASHE provides employer reported wage information for a 1% sample of UK workers, selected based on National Insurance Numbers (tax identification numbers). Using the worker panel dynamics of the ASHE, I construct a matrix of employment flows between 2-digit industry codes (SIC07 codes). If a firm of industry A is located closest to a masslayoff of industry B, I construct a measure of labour sharing as the maximum of:

- The percentage of industry A's employment that flows to industry B (labour outflows) and;
- The percentage of industry A's employment that originates from industry B (labour inflows)

The maximum of these percentages is a measure of the firm's (industry A) reliance on the masslayoff's (industry B) labour market. I then merge these maximum flow measures back into the BSD employment-masslayoff panel. The sample of firms is then segmented based on firm percentiles of the labour market closeness measure. Three thresholds are used; the 50th percentile (top 50% of firms), the 75th percentile (top 25% of firms) and the 90th percentile (top 10% of firms) of labour market closeness. Firm's are deemed to share the masslayoff market to a 'high degree' if they are above the relevant percentile cutoff, and to a 'lower degree' if below.

Table 5: Segmenting sample on the 'high' degree of labour market closeness

	(1)	(2)	(3)	(4)
	$\Delta log(L)$	$\Delta log(L)$	$\Delta log(L)$	$\Delta log(L)$
Sample:	50% most related	25% most related	10% most related	Remaining 90 %
dist 0-1km	-0.0740***	-0.0777***	-0.0714***	-0.0685***
	(0.0105)	(0.0131)	(0.0159)	(0.00650)
dist 1-2km	-0.0282***	-0.0272***	-0.0212*	-0.0265***
	(0.00585)	(0.00600)	(0.00865)	(0.00335)
dist 2-3km	-0.0148**	-0.0133*	-0.00783	-0.0148***
	(0.00545)	(0.00601)	(0.00879)	(0.00275)
dist 3-4km	-0.00794	-0.00637	-0.000412	-0.00825**
	(0.00493)	(0.00557)	(0.0100)	(0.00264)
dist 4-5km	-0.00738	-0.00523	-0.000967	-0.00789**
	(0.00465)	(0.00457)	(0.00748)	(0.00257)
dist 5-10km	-0.00651	-0.00489	0.000670	-0.00705***
	(0.00415)	(0.00417)	(0.00674)	(0.00179)
dist 10-20km	-0.00297	-0.00158	0.00146	-0.00414***
	(0.00376)	(0.00336)	(0.00614)	(0.00118)
dist 20-40km	-0.000580	-0.000261	0.00151	0.000445
	(0.00324)	(0.00257)	(0.00542)	(0.00166)
Cons	-0.0380***	-0.0447***	-0.0470**	-0.0434***
	(0.00597)	(0.0128)	(0.0158)	(0.00653)
Controls	Yes	Yes	Yes	Yes
N	31,883,890	16,041,175	6,286,332	59,694,725
R^2	0.022	0.025	0.028	0.023

Standard errors in parentheses, clustered on 2 digit industry. Variables are a set of dummies indicating distance to closest masslayoff. Controls are 2 digit SIC industry, 2 digit postcode, and year. Years included are 1997-2017.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results are displayed in table 5. The distance estimates of spillover effects do not vary significantly with the sample segmentation. Firms sharing labour markets with their closest mass layoff are not more strongly affected by spillovers than other firms. Labour market closeness, and the theorised knowledge spillovers, do not appear to be operating strongly here.

6.3 Potential channel: Input-output related industries

Another commonly cited source of local agglomeration and employment spillovers is vertical linkages between firms. Perhaps the employment spillovers found in this analysis are down to input-output linkages between mass layoffs and very local firms. Already the degree of localisation suggests this may not be the case as it is unlikely that primary suppliers or buyers are located within a couple of kilometers.

I repeat a similar analysis based on the degree of input-output linkages between a firm's industry (industry A) and the industry of their closest masslayoff (industry B). To do use, I use the ONS input-output tables available at the 2 digit industry level. From the 2006 industry I-O tables, I calculate the following percentages:

- Upstream degree: the percentage of an industry A's output that is sold to industry B. This is flow from A to B divided by the total output of A (final demand of A).
- Downstream degree: the percentage of industry's A's intermediate inputs that are sourced from industry B. This is the flow from B to A divided by the total intermediate purchases by industry A.

These percentages are then merged back into the BSD firm panel using the 2 digit industry codes of the firm (industry A) and their closest masslayoff (industry B). Similar to the labour market closeness analysis, I then use firm percentile cutoffs to segment firms into those that are 'highly upstream', 'highly downstream' or 'neither highly upstream nor highly downstream' to their closest masslayoff.

Table 6 displays the non-parametric estimates of employment spillovers for different input-output linked firms. Column one estimates the spillovers of the 25% of firms in industries with the highest upstream linkages to their closest masslayoff's industry. (The firm's industry sells a large proportion of their output to the masslayoff's industry). Column two estimates the spillovers for the 25% of firms in industries with the highest downstream linkages to their closest masslayoff's industry. (The firm's industry sources a large proportion of their inputs from the masslayoff's industry). For comparison, column three presents the estimates for firms that are neither in the 25% upstream or 25% downstream samples, and column four presents the pooled estimates across all firms.

Again, the results find no statistically different spillover measures between these subsets of firms. The patterns are repeated when we restrict the cutoffs further by comparing the top 10% of upstream and downstream firms with the remainder. It would appear that industry input-output linkages are not driving the strong, localised employment spillovers.

Table 6: Segmenting the sample based on degree of upstream and downstream relationship to closest masslayoff

Sample	(1) $\Delta log(L)$ 25% most upstream	(2) $\Delta log(L)$ 25% most downstream	(3) $\Delta log(L)$ Neither upstream nor downstream	(4) $\Delta log(L)$ All firms
dist 0-1km	-0.0613***	-0.0737***	-0.0700***	-0.0702***
	(0.00854)	(0.0150)	(0.00678)	(0.00769)
dist 1-2km	-0.0231***	-0.0240**	-0.0262***	-0.0266***
	(0.00573)	(0.00713)	(0.00345)	(0.00362)
dist 2-3km	-0.00748	-0.0109	-0.0174***	-0.0147***
	(0.00510)	(0.00644)	(0.00309)	(0.00305)
dist 3-4km	-0.000153	-0.00484	-0.0107***	-0.00813**
	(0.00449)	(0.00635)	(0.00287)	(0.00269)
dist 4-5km	-0.000973	-0.00500	-0.00892**	-0.00792**
	(0.00455)	(0.00559)	(0.00297)	(0.00254)
dist 5-10km	-0.000749	-0.00369	-0.00802***	-0.00683***
	(0.00401)	(0.00478)	(0.00207)	(0.00179)
dist 10-20km	0.000886	-0.00225	-0.00413**	-0.00424***
	(0.00393)	(0.00415)	(0.00125)	(0.00119)
dist 20-40km	0.00371	-0.000457	0.000655	-0.0000507
	(0.00240)	(0.00372)	(0.00189)	(0.00121)
Cons	-0.0328***	-0.0198**	-0.0468***	-0.0426***
	(0.00593)	(0.00578)	(0.00633)	(0.00641)
Controls	Yes	Yes	Yes	Yes
N	14,838,080	14,451,151	38,779,548	66,014,522
R^2	0.020	0.022	0.024	0.023

Standard errors in parentheses, clustered on 2 digit industry. Variables are a set of dummies indicating distance to closest masslayoff. Controls are 2 digit SIC industry, 2 digit postcode, and year. Years included are 1997-2017.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Highly non-tradeable vs not highly non-tradeable industries

Sample	(1) $\Delta log(L)$ 50% least tradeable	(2) $\Delta log(L)$ 25% least tradeable	(3) $\Delta log(L)$ 10% least tradeable	(4) $\Delta log(L)$ Remaining firms
dist 0-1km	-0.0704***	-0.0701***	-0.116***	-0.0668***
	(0.0118)	(0.0165)	(0.00307)	(0.00721)
dist 1-2km	-0.0227***	-0.0201*	-0.0353***	-0.0255***
	(0.00529)	(0.00816)	(0.00208)	(0.00390)
dist 2-3km	-0.00982**	-0.00836	-0.0157*	-0.0147***
	(0.00353)	(0.00393)	(0.000811)	(0.00353)
dist 3-4km	-0.00515*	-0.00490*	-0.00717	-0.00833**
	(0.00236)	(0.00169)	(0.00391)	(0.00320)
dist 4-5km	-0.00500**	-0.00466***	-0.00511	-0.00825**
	(0.00170)	(0.000963)	(0.000603)	(0.00306)
dist 5-10km	-0.00312*	-0.00227*	-0.00217	-0.00747***
	(0.00129)	(0.000894)	(0.000548)	(0.00212)
dist 10-20km	-0.00330***	-0.00289***	-0.00351	-0.00438***
	(0.000699)	(0.000564)	(0.000660)	(0.00146)
dist 20-40km	-0.00129*	-0.00123	0.00142	-0.0000346
	(0.000468)	(0.000658)	(0.000855)	(0.00138)
Cons	-0.0424***	-0.201***	-0.181***	-0.0442***
	(0.00669)	(0.00941)	(0.00486)	(0.00698)
Controls	Yes	Yes	Yes	Yes
N	33,290,051	18,359,195	7,481,532	57,748,254
R^2	0.022	0.020	0.019	0.023

Standard errors in parentheses, clustered on 2 digit industry. Variables are a set of dummies indicating distance to closest masslayoff. Controls are 2 digit SIC industry, 2 digit postcode, and year. Years included are 1997-2017.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6.4 Potential channel: Local product demand spillovers

Finally, I look at whether or not firms in non-tradeable industries experience stronger employment spillovers from masslayoffs. Non-tradeable goods are the most responsive to local consumer spending. In turn, local consumer spending is likely to be hit following a masslayoff as the newly laid off workers reduce their consumption. Therefore, if firms in non-tradeable industries experience more negative spillovers from masslayoffs, this would point towards local spending as a transmission channel.

I calculate the degree of tradeability for industry A using the same two digit input-output tables from the ONS. In short, the degree of tradeability measure captures the international integration of each industry. The index measure is the maximum of:

- Export fraction: the fraction of industry A's total output that is exported (rather than sold/consumed domestically).
- Import fraction: the fraction of industry A's total intermediate inputs that is sourced from imports (rather than domestic sources).

The measure is then merged back into the BSD firm panel using the firms' 2 digit industry codes. I segment the set of firms in the same way according to percentile fractions. Firms above percentile cutoffs are considered in 'tradeable' industries, and firms below are considered in 'non-tradeable' industries.

Results are displayed in Table 7. As we see, the 10% of firms in the least tradeable industries experience the strongest spillovers, particularly at the closest distances to the mass layoff. Non-tradeable firms still exhibit employment spillovers but to a lesser extent. Local demand channels are therefore likely to be one channel contributing to the observed spillovers.

7 Conclusion

The paper has provided the first estimates of employment spillover decay rates over space and time of masslayoffs. Spillovers on nearby firms are strongly negative but very highly localised. They are also very persistent, despite the one-off nature of the masslayoff shock. Individual firms in close proximity continue to reduce their employment year-on-year for at least five years after the event.

The degree of localisation matters both for the measurement of the spillovers and for policy targeting. As to the measurement issue, Section 4 explicitly addresses the costs of measuring spillovers over large discrete units. With the spillovers as localised as they are, averaging over large administrative or commuting zone units, as is the common approach in spatial labour market analysis, will tend towards estimating no spillover effects. This is clearly not the case as the zero results stem from looking at a misleading area.

The localisation and their dynamics are important for policy responses too. We do observe a large initial shock generating persistently negative local spillovers. If a policy maker wishes to mitigate the negative 'snowball effect' the results would imply that any intervention, such as support to nearby firms or workers at the outset of the shock, should be very local in nature. Intervention over a broader area would be more costly and poorly targeted. Beyond this observation, I leave the evaluation of any particular policy intervention's effectiveness to other discussions.

Section 6 considers possible local firm linkages that could be contributing to the local spillovers. No support is found for input-output spillovers, shared labour market spillovers (which would indicate possible knowledge agglomeration spillovers), or within-industry productivity spillovers. It should be noted that the first two were only able to be measured at the two-digit industry level for data availability reasons. The lack of findings must therefore be interpreted in this light.

The results do however find some evidence of local product demand spillovers as non-tradeable firms reduce their employment more strongly than their tradeable counterparts. These local demand effects are found around the masslayoff, therefore around the place of work of laid off workers. However, households are likely to spend a large fraction of their income around their place of residence. An interesting corollary of the local demand results would be to investigate whether non-tradeable firms in residential areas are affected by local residents experiencing a mass layoff. The data available do include place of residence from 2004 so such an extension can be feasibly implemented.

Bibliography

Acemoglu, D., Autor, D., Dorn, D., Hanson, G. H., and Price, B. (2016). Import competition and the great us employment sag of the 2000s. *Journal of Labor Economics*, 34(S1):S141–S198.

Ahlfeldt, G. M., Redding, S. J., Sturm, D. M., and Wolf, N. (2015). The economics of density: Evidence from the berlin wall. *Econometrica*, 83(6):2127–2189.

Altonji, J. G. and Devereux, P. J. (1999). The extent and consequences of downward nominal wage rigidity. *NBER Working Paper*, (7236).

Amior, M. and Manning, A. (2018). The persistence of local joblessness. *American Economic Review*, 108(7):1942–70.

Autor, D., Dorn, D., and Hanson, G. H. (2013). The china syndrome: Local labor market effects of import competition in the united states. *American Economic Review*, 103(6):2121–68.

Bewley, T. F. (2009). *Why wages don't fall during a recession.* Harvard University Press.

Bisztray, M., Koren, M., and Szeidl, A. (2018). Learning to import from your peers. *Journal of International Economics*, 115:242–258.

Busso, M., Gregory, J., and Kline, P. (2013). Assessing the incidence and efficiency of a prominent place based policy. *American Economic Review*, 103(2):897–947.

Dao, M., Furceri, D., and Loungani, M. P. (2014). *Regional labor market adjustments in the United States.* Number 14-211. International Monetary Fund.

de Ridder, M. and Pfajfar, D. (2017). Policy shocks and wage rigidities: empirical evidence from regional effects of national shocks. *Cambridge Working Papers in Economics*, (1717).

Devereux, M. P., Griffith, R., and Simpson, H. (2004). The geographic distribution of production activity in the uk. *Regional science and urban economics*, 34(5):533–564.

Devereux, M. P., Griffith, R., and Simpson, H. (2007). Firm location decisions, regional grants and agglomeration externalities. *Journal of public economics*, 91(3-4):413–435.

Dix-Carneiro, R. and Kovak, B. K. (2017). Trade liberalization and regional dynamics. *American Economic Review*, 107(10):2908–46.

Dube, A., Lester, T. W., and Reich, M. (2010). Minimum wage effects across state borders: Estimates using contiguous counties. *The review of economics and statistics*, 92(4):945–964.

Elsby, M. W. (2009). Evaluating the economic significance of downward nominal wage rigidity. *Journal of Monetary Economics*, 56(2):154–169.

Gathmann, C., Helm, I., and Schönberg, U. (2017). Spillover effects of mass layoffs. *Journal of the European Economic Association*.

Goldsmith-Pinkham, P., Sorkin, I., and Swift, H. (2018). Bartik instruments: What, when, why, and how. Technical report, National Bureau of Economic Research.

Graham, D. J., Melo, P. C., and Noland, R. B. (2009). A meta-analysis of estimates of urban agglomeration economies. *Regional Science and Urban Economics*, 39(3):332–342.

Greenstone, M., Hornbeck, R., and Moretti, E. (2010). Identifying agglomeration spillovers: Evidence from winners and losers of large plant openings. *Journal of Political Economy*, 118(3):536–598.

Hakobyan, S. and McLaren, J. (2016). Looking for local labor market effects of nafta. *Review of Economics and Statistics*, 98(4):728–741.

Harhoff, D. (1999). Firm formation and regional spillovers-evidence from germany. *Economics of Innovation and New Technology*, 8(1-2):27–55.

Hassink, W. H. and Meekes, J. (2018). Endogenous local labour markets, regional aggregation and agglomeration economies. *USE Working Paper series*, 18(03).

Helm, I. (2017). National industry trade shocks, local labor markets, and agglomeration spillovers.

Kahn, S. (1997). Evidence of nominal wage stickiness from microdata. *The American Economic Review*, 87(5):993–1008.

Kamal, F. and Sundaram, A. (2016). Buyer–seller relationships in international trade: Do your neighbors matter? *Journal of International Economics*, 102:128–140.

Kaur, S. (2019). Nominal wage rigidity in village labor markets. *American Economic Review*, 109(10):3585–3616.

Kline, P. and Moretti, E. (2013). Local economic development, agglomeration economies, and the big push: 100 years of evidence from the tennessee valley authority. *The Quarterly Journal of Economics*, 129(1):275–331.

Kovak, B. K. (2013). Regional effects of trade reform: What is the correct measure of liberalization? *American Economic Review*, 103(5):1960–76.

Krugman, P. (1991). Increasing returns and economic geography. *Journal of political economy*, 99(3):483–499.

Manning, A. and Petrongolo, B. (2018). How 'local' are local labour markets? Technical report, Centre for Economic Performance, LSE.

Marshall, A. (1890). *Principles of economics. Vol. 1.*

Meekes, J. and Hassink, W. H. (2019). The role of the housing market in workers′ resilience to job displacement after firm bankruptcy. *Journal of Urban Economics*, 109:41–65.

Monte, F., Redding, S. J., and Rossi-Hansberg, E. (2018). Commuting, migration, and local employment elasticities. *American Economic Review*, 108(12):3855–90.

Moretti, E. (2010). Local labor markets. Technical report, National Bureau of Economic Research.

Moretti, E. (2011). Local labor markets. In *Handbook of labor economics*, volume 4, pages 1237–1313. Elsevier.

Topalova, P. (2010). Factor immobility and regional impacts of trade liberalization: Evidence on poverty from india. *American Economic Journal: Applied Economics*, 2(4):1–41.

Data citations:

Office for National Statistics. (2019). Business Structure Database, 1997-2018: Secure Access. [data collection]. 10th Edition. UK Data Service. SN: 6697, http://doi.org/10.5255/UKDA-SN-6697-10

Office for National Statistics. (2019). Annual Survey of Hours and Earnings, 1997-2018: Secure Access. [data collection]. 14th Edition. UK Data Service. SN: 6689,
http://doi.org/10.5255/UKDA-SN-6689-13

A Descriptive statistics

Table 8 displays basic descriptive statistics for the Business Structure Database firm (plant) level dataset used. Key variables displayed include the plant level employment, number of masslayoffs within 20km of the plant, distance to the closest mass layoff in the year in question (if there exists a mass layoff within 50km), the number of firms not located within 50km of a mass layoff, and the employment change at the firm level.

Table 8: Descriptive statistics: firms (plants)

Firm Variable	Mean	Std. Dev.	p25	p50	p75	N
Employment	7.679	83.243	1	2	5	71,128,244
# ML within 20km	5.136	11.2371	0	1	4	71,128,248
Dist to closest ML if $<$50km	15.689	13.134	4.7	11.9	24.2	58,755,900
No ML within 50km	-	-	-	-	-	12,372,348
Employment change	-.699	41.479	0	0	0	67,482,554

ML refers to mass layoff in the year in question. Sample is 1997-2017 of the BSD

Table 9 displays descriptive statistics for the sample of mass layoffs. On average, there are 100 mass layoffs of more than 1,000 workers per year over the sampled period. These are spread across a range of industries, as displayed by the 1 digit industry percentage counts.

Table 9: Descriptive statistics: masslayoffs

Masslayoff Variable	Mean	Std. Dev.	p25	p50	p75	N
Employment change	-2732	5567	-1200	-1500	-2300	2,009

1 digit industry	Count	Percent
0-1	72	3.58%
2	140	6.97%
3	104	5.18 %
4	123	6.12%
5	305	15.18%
6	496	24.69%
7	662	32.95%
8	21	1.05%
9	86	4.28%

B Robustness checks

I build up the analysis using a variety of fixed effects, eliminating sources of variation one-by-one to assuage some concerns about endogeneity. The baseline formulation uses 2 digit SIC industry, 2 digit postcode and time fixed effects. This removes industry trends, location fixed effects and non-parametric time-specific shocks shared by all firms. The variation driving the results remains proximity to masslayoffs, absent all these fixed effects.

Concern remains that individual industries or regions may have time varying shocks, correlated with proximity, that are driving these results. I therefore add industry-year interactions, to control for national industry shocks in each year. This would remove endogeneity stemming from masslayoff and non-masslayoff firms spatially sorting close together based on industry. The employment loss observed would be from correlated shocks, rather than true proximity spillovers. The results remain robust to this. The apparent lack of concern with industrial spatial sorting is consistent with the industrial closeness results of section 6.1 - all industries, whether close or not, appear to be affected by spatial spillovers.

Furthermore, I add location-year interactions. However, as 2 digit postcode locations cover a several kilometer radius these remove a lot of the year-to-year variation I am interested in. The results, unsurprisingly, are therefore substantially weakened.

Next, I check for robustness around other mass layoffs. Table 10 displays several robustness checks. Column 1 controls for serial correlation in the mass layoff treatment variable, by controlling for the distance to the closest mass layoff in the previous year. For simplicity of display, the parametric form $\exp(-dist)$ is used for the lagged mass layoff, which is approximately one for very close firms and approximately zero for far away firms. The negative coefficient implies negative employment spillovers that decay with distance - as expected. Importantly, the spillover distance estimates for the current year's closest mass layoff are not significantly altered.

Columns 2 and 3 control for other mass layoffs in the same year. Column two controls for the distance to the second closest mass layoff, again using the parametric form $\exp(-dist)$. A negative coefficient implies negative but decaying employment spillovers from the second closest, but the estimated impact of the first closest is only very slightly weakened. Column three controls for the number of mass layoffs within 20km - checking for the possibility that the estimates are contaminated by spatial clustering of mass layoffs. The employment spillover distance decay estimates are unaffected.

Lastly, column four displays a standard placebo check - the analogue of the parallel trends assumption used in difference-in-differences approaches. The distance dummies are replaced by the distance to the closest mass layoff one period in the future. Significant results would call into question the event study approach - either by demonstrating anticipation effects or indicating that the shocks may not be as exogenous as hoped. We see no significant estimates, assuaging endogeneity concerns.

Table 10: Controlling for other mass layoffs in the spatial distribution of effects on impact

	(1)	(2)	(3)	(4)
Extra controls:	ML Lag 1	2nd closest ML	# ML in 20km	Placebo
Dep. var.	$\Delta \log(L)$	$\Delta \log(L)$	$\Delta \log(L)$	$\Delta \log(L)$
dist 0-1km	-0.0696***	-0.0521***	-0.0716***	0.00127
	(0.00769)	(0.00615)	(0.00739)	(0.000981)
dist 1-2km	-0.0260***	-0.0237***	-0.0270***	0.000728
	(0.00357)	(0.00338)	(0.00354)	(0.000665)
dist 2-3km	-0.0140***	-0.0154***	-0.0152***	0.000256
	(0.00298)	(0.00304)	(0.00296)	(0.000369)
dist 3-4km	-0.00740**	-0.00984***	-0.00860**	0.000473
	(0.00263)	(0.00270)	(0.00264)	(0.000518)
dist 4-5km	-0.00718**	-0.00985***	-0.00787**	-0.0000525
	(0.00250)	(0.00256)	(0.00267)	(0.000398)
dist 5-10km	-0.00606***	-0.00839***	-0.00630**	-0.0000811
	(0.00171)	(0.00180)	(0.00201)	(0.000401)
dist 10-20km	-0.00349**	-0.00490***	-0.00351*	-0.000233
	(0.00117)	(0.00118)	(0.00145)	(0.000376)
dist 20-40km	0.000539	-0.000310	0.000589	-0.000539*
	(0.00120)	(0.00119)	(0.00136)	(0.000241)
exp(-dist) lagged	-0.00594***			
	(0.00122)			
exp(-dist) 2nd closest		-0.0999***		
		(0.0162)		
# ML in 20km			0.000385*	
			(0.000170)	
Constant	-0.0410***	-0.0425***	-0.0439***	-4.155***
	(0.00659)	(0.00643)	(0.00645)	(0.405)
Controls	Yes	Yes	Yes	Yes
Observations	66,014,522	66,014,522	66,014,522	54,990,618
R^2	0.023	0.023	0.023	0.001

Standard errors in parentheses, clustered at 2 digit industry level. Controls are 2 digit SIC industry, 2 digit postcode, and year, plus the additional mass layoff controls displayed. Column 1 controls for the distance to the closest mass layoff in the previous year, column 2 for the distance to the second closest in the current year and column 3 for the number of mass layoffs within 20km in the current year. Column 4 is a placebo regression, where the distance dummies are the distance to the closest mass layoff one year in the future. Years included are 1997-2017.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

There may also be concern that the Global Financial Crisis (GFC) was the driving force behind the results. The sampled period of 1997-2017 includes the timeframe, and the pooled results may simply be an average of large GFC effects and zero effects at other times. Table 11 segments the sample into different time periods and runs separate regressions on each. We see that negative employment spillovers in close proximity to mass layoffs were somewhat stronger in the GFC year (approximately 2007-2012) but present and significant during all time periods.

Table 11: Global Financial Crisis segmentation

	(1)	(2)	(3)	(4)
Years:	< 2007	≥ 2007	2007-2012	2013-2017
Dep. var.	$\Delta \log(L)$	$\Delta \log(L)$	$\Delta \log(L)$	$\Delta \log(L)$
dist 0-1km	-0.0585***	-0.0795***	-0.0905***	-0.0564***
	(0.00455)	(0.0109)	(0.0140)	(0.00606)
dist 1-2km	-0.0251***	-0.0284***	-0.0227***	-0.0329***
	(0.00275)	(0.00460)	(0.00654)	(0.00313)
dist 2-3km	-0.0134***	-0.0163***	-0.0178**	-0.0128***
	(0.00290)	(0.00380)	(0.00587)	(0.00201)
dist 3-4km	-0.0117***	-0.00584	-0.00736	-0.00133
	(0.00273)	(0.00331)	(0.00542)	(0.00157)
dist 4-5km	-0.0110***	-0.00582	-0.00576	-0.00328
	(0.00277)	(0.00308)	(0.00499)	(0.00177)
dist 5-10km	-0.0102***	-0.00461*	-0.00549	-0.000438
	(0.00256)	(0.00201)	(0.00320)	(0.00155)
dist 10-20km	-0.00753***	-0.00167	-0.000474	-0.00183
	(0.00217)	(0.00135)	(0.00191)	(0.00194)
dist 20-40km	-0.00335*	0.00269	0.00523	-0.000128
	(0.00139)	(0.00208)	(0.00302)	(0.00150)
Constant	-0.0503***	0.0422***	0.0488***	-0.0387***
	(0.00624)	(0.00901)	(0.00950)	(0.00465)
Controls	Yes	Yes	Yes	Yes
Observations	27,759,558	38,254,964	21,671,828	16,583,136
R^2	0.017	0.028	0.040	0.010

Standard errors in parentheses, clustered at 2 digit industry level. Controls are 2 digit SIC industry, 2 digit postcode, and year. Full sample is 1997-2017, subsamples indicated in column headers.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Lastly, I also consider a variety of alternative corrections for non-spherical errors. Results remain significant in all instances. Table 12 displays some of the forms: clustered errors at the two digit industry level (allowing for national shocks correlated across related industries), at the regional level (allowing for shocks correlated within regions) and at the industry-regional interaction level.

Table 12: Various error clustering: industry, region, industry-region two way

	(1)	(2)	(3)
Clustering:	Industry	Region	Ind-Reg
Dep. var:	$\Delta \log(L)$	$\Delta \log(L)$	$\Delta \log(L)$
dist 0-1km	-0.0702***	-0.0702***	-0.0702***
	(0.00769)	(0.00559)	(0.00316)
dist 1-2km	-0.0266***	-0.0266***	-0.0266***
	(0.00362)	(0.00300)	(0.00201)
dist 2-3km	-0.0147***	-0.0147***	-0.0147***
	(0.00305)	(0.00269)	(0.00182)
dist 3-4km	-0.00813**	-0.00813**	-0.00813***
	(0.00269)	(0.00278)	(0.00177)
dist 4-5km	-0.00792**	-0.00792**	-0.00792***
	(0.00254)	(0.00264)	(0.00181)
dist 5-10km	-0.00683***	-0.00683**	-0.00683***
	(0.00179)	(0.00261)	(0.00160)
dist 10-20km	-0.00424***	-0.00424	-0.00424**
	(0.00119)	(0.00264)	(0.00142)
dist 20-40km	-0.0000507	-0.0000507	-0.0000507
	(0.00121)	(0.00187)	(0.00129)
Constant	-0.0426***	-0.0426***	-0.0426***
	(0.00641)	(0.00912)	(0.00904)
Controls	Yes	Yes	Yes
Observations	66,014,522	66,014,522	66,014,522
R^2	0.023	0.023	0.023

Standard errors in parentheses. Column 1 clusters the errors at 2 digit industry level, column 2 at the 2 digit region level (the letters only for UK postcodes - effectively a small-medium sized city + hinterland), and column three at the 2 digit industry-region interaction level. Controls are 2 digit SIC industry, 2 digit postcode, and year. Years included are 1997-2017.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C Additional results for section 3: spatial results on impact

C.1 Comparing baseline results to parametric functions

Much of the spatial literature (e.g. Ahlfeldt et al. (2015)) use exponential decay functions to capture the effects of distance. Figure 7 overlays two candidate exponential decay functions to the graphed non-parametric estimates. As can be observed, a single exponential decay function cannot accurately capture the spatial spillovers: the effects decay far more rapidly at short distances than they do at further distances. The rapid decay patterns, up to about 4km in distance, can be roughly captured by the red line which plots a scale parameter of 10 and a decay parameter of -0.75. After about 5km from the masslayoff, the decay rate is much less rapid, albeit the magnitude of the effects are much smaller. A scale parameter of 1.5 and a much slower decay parameter of -0.1 provide a better fit.

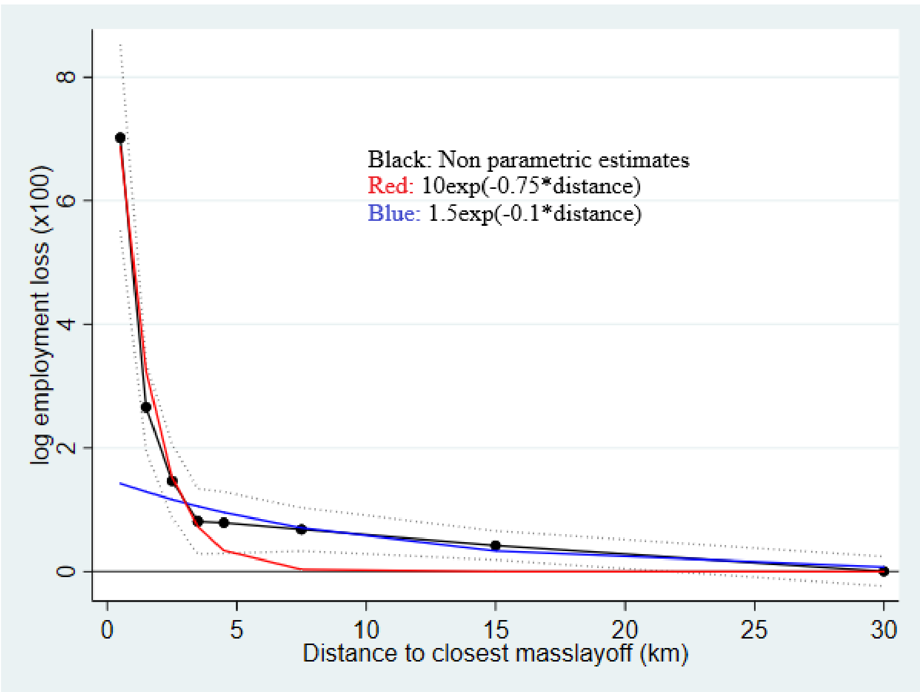


Figure 7: Exponential decay functions versus non parametric estimates.
The black line plots the column three non-parametric estimates from Table 1, including 95% confidence intervals. The red line overlays an exponential decay function of the form $10\exp(-0.75 * dist)$. The blue line overlays a second exponential decay function of the form $1.5\exp(-0.1 * dist)$

C.2 Firm type heterogeneity tables

Table 13: Partitioning the sample based on firm size (employment count)

	(1)	(2)	(3)	(4)	(5)
Firm size:	< 10	< 20	> 50	> 100	20-50
Dep. Var	$\Delta \log(L)$	$\Delta \log(L)$	$\Delta \log(L)$	$\Delta \log(L)$	$\Delta \log(L)$
dist 0-1km	-0.0229***	-0.0391***	-0.134***	-0.151**	-0.0902***
	(0.00461)	(0.00576)	(0.0383)	(0.0480)	(0.0233)
dist 1-2km	-0.00734**	-0.0139***	-0.0654***	-0.0812**	-0.0321***
	(0.00220)	(0.00276)	(0.0166)	(0.0255)	(0.00800)
dist 2-3km	-0.00496*	-0.00844***	-0.0261*	-0.0354	-0.0186*
	(0.00201)	(0.00242)	(0.0127)	(0.0186)	(0.00840)
dist 3-4km	-0.00323	-0.00500*	-0.00391	-0.0102	-0.00248
	(0.00203)	(0.00234)	(0.0121)	(0.0178)	(0.00599)
dist 4-5km	-0.00352	-0.00469*	-0.0102	-0.0267	-0.0131**
	(0.00199)	(0.00229)	(0.00788)	(0.0134)	(0.00464)
dist 5-10km	-0.00354*	-0.00454**	-0.00416	-0.0166	-0.00615
	(0.00145)	(0.00162)	(0.00619)	(0.00837)	(0.00680)
dist 10-20km	-0.00284**	-0.00323**	-0.00335	-0.0106	-0.00473
	(0.00102)	(0.00111)	(0.00564)	(0.00806)	(0.00395)
dist 20-40km	-0.000455	-0.000168	0.00484	0.000681	0.00206
	(0.00112)	(0.00125)	(0.00401)	(0.00609)	(0.00351)
Constant	-0.0242***	-0.0320***	-0.606***	-0.735***	-0.376***
	(0.00430)	(0.00500)	(0.0302)	(0.0438)	(0.0137)
Controls	Yes	Yes	Yes	Yes	Yes
N	57,353,827	61,900,460	1,403,569	613,127	2,710,493
R^2	0.023	0.024	0.048	0.050	0.043

Standard errors in parentheses, clustered at 2 digit industry level. Controls are 2 digit SIC industry, 2 digit postcode, and year fixed effects. Years included are 1997-2017.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: Partitioning sample based on whether firm or closest masslayoff was in the manufacturing industry

	(1)	(2)	(3)	(4)
Type:	Man ML	Non-man ML	Man firm	Non-man firm
Dep. var	$\Delta \log(L)$	$\Delta \log(L)$	$\Delta \log(L)$	$\Delta \log(L)$
dist 0-1km	-0.0508***	-0.0721***	-0.120***	-0.0672***
	(0.0129)	(0.00733)	(0.0154)	(0.00740)
dist 1-2km	-0.0168*	-0.0275***	-0.0300***	-0.0261***
	(0.00767)	(0.00343)	(0.00419)	(0.00376)
dist 2-3km	-0.0124	-0.0147***	-0.0235***	-0.0140***
	(0.00740)	(0.00287)	(0.00358)	(0.00312)
dist 3-4km	-0.00844	-0.00793**	-0.0117***	-0.00776**
	(0.00788)	(0.00245)	(0.00205)	(0.00279)
dist 4-5km	-0.00633	-0.00758***	-0.0131***	-0.00737**
	(0.0105)	(0.00217)	(0.00229)	(0.00260)
dist 5-10km	-0.00687	-0.00642***	-0.0103***	-0.00645**
	(0.00660)	(0.00178)	(0.00266)	(0.00185)
dist 10-20km	-0.000360	-0.00422**	-0.00508*	-0.00413**
	(0.00465)	(0.00143)	(0.00187)	(0.00127)
dist 20-40km	0.00410	0.0000103	0.00225	-0.000347
	(0.00356)	(0.00148)	(0.00153)	(0.00131)
Constant	-0.0548***	-0.0421***	-0.380***	-0.0393***
	(0.00902)	(0.00668)	(0.0164)	(0.00625)
Controls	Yes	Yes	Yes	Yes
N	10,072,080	55,909,683	4,125,366	61,889,156
R^2	0.029	0.022	0.026	0.023

Standard errors in parentheses, clustered at 2 digit industry level. Controls are 2 digit SIC industry, 2 digit postcode, and year fixed effects. Years included are 1997-2017.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: Employment density around the firm

	(1)	(2)	(3)	(4)
	$\Delta log(L)$	$\Delta log(L)$	$\Delta log(L)$	$\Delta log(L)$
	Impact	Lag 1	Impact	Lag 1
exp(-dist)	-0.101***	-0.0717***	-0.112***	-0.0847***
	(0.000606)	(0.000607)	(0.000627)	(0.000635)
Dens	-0.00664***	-0.00909***	-0.0158***	-0.0173***
	(0.000112)	(0.000111)	(0.000174)	(0.000162)
exp(-dist) * Dens			0.0208***	0.0210***
			(0.000300)	(0.000300)
Cons	-0.0464***	-0.0492***	-0.0486***	-0.0514***
	(0.000813)	(0.000813)	(0.000813)	(0.000813)
FEs	Yes	Yes	Yes	Yes
N	66,016,397	66,016,397	66,016,397	66,016,397
R^2	0.023	0.023	0.023	0.023

Standard errors in parentheses, clustered on 2 digit industry. Exp(-dist) is the exponential of the negative distance to the closest masslayoff. Dens is the standardised employment per square km in a 3by3km grid around the plant. Controls are 2 digit SIC industry, 2 digit postcode, and year fixed effects. Years included are 1997-2017.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16: Partitioning the firm sample based on employment density

	(1)	(2)	(3)	(4)
Emp. density	Top 50%	Bottom 50%	Top 25%	Bottom 25%
Dep. var	$\Delta \log(L)$	$\Delta \log(L)$	$\Delta \log(L)$	$\Delta \log(L)$
dist 0-1km	-0.0515***	-0.0420***	-0.0465***	-0.0271**
	(0.00645)	(0.00529)	(0.00671)	(0.00980)
dist 1-2km	-0.0113***	-0.0102**	-0.00834	-0.00482
	(0.00298)	(0.00324)	(0.00429)	(0.00537)
dist 2-3km	-0.00162	-0.00701*	-0.000987	-0.00829*
	(0.00234)	(0.00311)	(0.00387)	(0.00352)
dist 3-4km	0.00372*	-0.00588*	0.00451	-0.00270
	(0.00175)	(0.00285)	(0.00310)	(0.00275)
dist 4-5km	0.00134	-0.00500	-0.00104	-0.00472
	(0.00200)	(0.00276)	(0.00381)	(0.00321)
dist 5-10km	-0.00305	-0.00438	-0.00932**	-0.00438
	(0.00160)	(0.00231)	(0.00295)	(0.00249)
dist 10-20km	-0.00666***	-0.00298*	-0.0140***	-0.00321*
	(0.00143)	(0.00141)	(0.00284)	(0.00153)
dist 20-40km	-0.000199	-0.000912	0.00291	-0.00115
	(0.00280)	(0.000601)	(0.00553)	(0.000832)
Constant	-0.0834***	-0.0320***	-0.0971***	-0.0282***
	(0.00974)	(0.00489)	(0.0100)	(0.00466)
Controls	Yes	Yes	Yes	Yes
N	32,794,533	33,219,989	16,267,241	16,665,832
R^2	0.024	0.021	0.026	0.021

Standard errors in parentheses, clustered on 2 digit industry. Sample is segmented based on the standardised employment per square kilometer in a 3km-by-3km grid around the plant. Controls are 2 digit SIC industry, 2 digit postcode, and year fixed effects. Years included are 1997-2017.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

D Dynamic results table

Table 17: Estimates for the dynamic impacts of mass layoffs: up to five time periods after the event

	(1) T1 $\Delta \log(L)$	(2) T2 $\Delta \log(L)$	(3) T3 $\Delta \log(L)$	(4) T4 $\Delta \log(L)$	(5) T5 $\Delta \log(L)$
dist 0-1km	-0.0590***	-0.0595***	-0.0586***	-0.0586***	-0.0480***
	(0.00510)	(0.00520)	(0.00270)	(0.00270)	(0.00326)
dist 1-2km	-0.0254***	-0.0286***	-0.0267***	-0.0267***	-0.0195***
	(0.00321)	(0.00197)	(0.00186)	(0.00186)	(0.00173)
dist 2-3km	-0.0137***	-0.0158***	-0.0179***	-0.0179***	-0.0122***
	(0.00236)	(0.00173)	(0.00143)	(0.00143)	(0.00188)
dist 3-4km	-0.00866***	-0.00694***	-0.0127***	-0.0127***	-0.00566***
	(0.00171)	(0.00168)	(0.00123)	(0.00123)	(0.00159)
dist 4-5km	-0.00878***	-0.00723***	-0.0109***	-0.0109***	-0.00344
	(0.00165)	(0.00176)	(0.00137)	(0.00137)	(0.00197)
dist 5-10km	-0.00802***	-0.00742***	-0.00834***	-0.00834***	-0.00340
	(0.00161)	(0.00164)	(0.00111)	(0.00111)	(0.00206)
dist 10-20km	-0.00654***	-0.00565***	-0.00574***	-0.00574***	-0.00173
	(0.00124)	(0.00130)	(0.00117)	(0.00117)	(0.00204)
dist 20-40km	-0.00372***	-0.00355**	-0.00186	-0.00186	-0.000112
	(0.000938)	(0.00128)	(0.00102)	(0.00102)	(0.00164)
Constant	-0.0447***	-0.0561***	-0.0641***	-0.0641***	-0.0454**
	(0.00681)	(0.00763)	(0.00750)	(0.00750)	(0.0155)
Controls	Yes	Yes	Yes	Yes	Yes
N	66,014,522	63,245,479	60,450,337	60,450,337	54,824,033
R^2	0.023	0.023	0.024	0.024	0.026

Years included are 1998-2017 for T1, 1999-2017 for T2, 2000-2017 for T3, 2001-2017 for T4, 2002-2017 for T5. Standard errors in parentheses, clustered on 2 digit industry. Variables are a set of dummies indicating distance to closest masslayoff. Fixed effects are 2 digit SIC industry, 2 digit postcode, and year. The estimates are plotted in figure 5 in section 5.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

E Firm churn and aggregate local impacts

The analysis so far estimates the employment response of existing firms to a nearby masslayoff. We see existing firms in close proximity to a mass layoff reduce their employment substantially. However, a related margin of adjustment is the impact on firm churn. Firm churn may be a large part of local adjustment to masslayoffs - some firms may shut down while new firms may establish in their place. Another way of phrasing this is that firm dynamism may rise in response to masslayoffs. Here, I estimate the direct impact on firm birth and death of mass layoff proximity.[18]

Table 18 displays estimates of the impact on firm birth and death. Columns 1 and 2 are linear probability models where the dependent variable equals one if the life event (birth or death respectively) occurred and zero if it did not (i.e. the firm existed in both $t-1$ and t). We see that both birth rates and death rates are higher in close proximity to a mass layoff. However, the increase in death rates is relatively larger - approximately four times the increase in birth rates for firms located within 1 kilometre of the mass layoff. In short, churn increases, but the increase in firm death outweighs firm birth.

Column 3 extends the baseline analysis by including firms born implicitly in the analysis. The dependent variable, $\Delta \log L_t = (\log L_t - \log L_{t-1})$ is set to $(\log L_t)$ for those firms born between $t-1$ and t. In effect, this sets their lagged employment to 1 to avoid the $\log 0$ issue. We see that the overall firm level employment effect close to mass layoffs is still negative, but weakened once firm birth is included in the picture.

The baseline analysis estimates firm level adjustment, not regional or aggregate level adjustment. Regional or aggregate estimates would require aggregation, and therefore the firm level estimates to be weighted by firm size. Table 19 therefore weights the firm level changes in a variety of ways. Column 1 is the baseline, unweighted estimates, column 2 weights the baseline estimates by firm employment levels, and columns 3 and 4 weight the firms by their log employment. Columns 1-3 are the baseline samples, including only those firms alive at the start of the period. Column 4 adds in firms born during the time period. The weighted regressions have more negative point estimates than their unweighted counterparts. This is consistent with earlier estimates that larger firms respond more strongly.

[18] Existing firms that die during the time period in question are included implicitly in the baseline analysis. Those firms have their $\Delta \log L_t = (\log L_t - \log L_{t-1})$ set to $(-\log L_{t-1})$, i.e. $\log L_t = 0$. In effect, this assumes that all but one of their employees leave the firm, so as to avoid the $\log 0$ issue. However, the direct effect on firm death is not estimated, while firm birth has been entirely abstracted from so far.

Table 18: Firm churn: the impact on firm birth and death

	(1)	(2)	(3)
Dep var:	Birth	Death	$\Delta \log(L)$
dist 0-1km	0.00527***	0.0200***	-0.0243***
	(0.00119)	(0.00411)	(0.00589)
dist 1-2km	0.00682***	0.00748**	-0.00310
	(0.00163)	(0.00220)	(0.00272)
dist 2-3km	0.00489**	0.00287	-0.00370
	(0.00143)	(0.00191)	(0.00227)
dist 3-4km	0.00455**	0.00129	-0.000548
	(0.00135)	(0.00178)	(0.00166)
dist 4-5km	0.00314*	0.00194	-0.00184
	(0.00122)	(0.00149)	(0.00135)
dist 5-10km	0.00250**	0.000380	-0.00173
	(0.000907)	(0.00140)	(0.001000)
dist 10-20km	0.00336	-0.00150	-0.000901
	(0.00250)	(0.00107)	(0.000912)
dist 20-40km	0.00107	0.000373	0.00109
	(0.00101)	(0.00126)	(0.000768)
Constant	0.0742***	0.0627***	-0.0102
	(0.00865)	(0.00429)	(0.00600)
Controls	Yes	Yes	Yes
Observations	76,505,519	76,505,519	74,739,307
R^2	0.014	0.064	0.009

Standard errors in parentheses, clustered at 2 digit industry level. Controls are 2 digit SIC industry, 2 digit postcode, and year fixed effects. Years included are 1997-2017. Columns 1 and 2 are linear probability models for the probability of firm birth and death respectively, in the year of the mass layoff. Column 3 is the combined effect on the change in $\log(L)$ including firm birth and death.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 19: Weighted firm level employment regressions

	(1)	(3)	(5)	(6)
Dep. Var	$\Delta \log(L)$	$\Delta \log(L)$	$\Delta \log(L)$	$\Delta \log(L)$
Weighting:	None	L	$\log(L)$	$\log(L)$
Firm birth	No	No	No	Yes
dist 0-1km	-0.0702***	-0.174***	-0.113***	-0.0484***
	(0.00769)	(0.0401)	(0.0166)	(0.0127)
dist 1-2km	-0.0266***	-0.0762***	-0.0462***	-0.00994
	(0.00362)	(0.0177)	(0.00752)	(0.00545)
dist 2-3km	-0.0147***	-0.0513*	-0.0251***	-0.00837
	(0.00305)	(0.0230)	(0.00530)	(0.00522)
dist 3-4km	-0.00813**	0.0153	-0.0124***	-0.000274
	(0.00269)	(0.0179)	(0.00333)	(0.00353)
dist 4-5km	-0.00792**	-0.0221	-0.0130***	-0.00210
	(0.00254)	(0.0176)	(0.00270)	(0.00257)
dist 5-10km	-0.00683***	-0.0125	-0.00778***	0.000131
	(0.00179)	(0.0153)	(0.00221)	(0.00216)
dist 10-20km	-0.00424***	-0.0280	-0.00230	0.00180
	(0.00119)	(0.0221)	(0.00199)	(0.00214)
dist 20-40km	-0.0000507	0.00165	0.00309**	0.00434***
	(0.00121)	(0.00945)	(0.00115)	(0.00114)
Constant	-0.0426***	-0.337***	-0.146***	-0.0825***
	(0.00641)	(0.0688)	(0.00949)	(0.0122)
Controls	Yes	Yes	Yes	Yes
Observations	66,014,522	66,014,522	42,470,811	47,214,972
R^2)	0.023	0.045	0.031	0.016

Standard errors in parentheses, clustered at 2 digit industry level. Controls are 2 digit SIC industry, 2 digit postcode, and year. Years included are 1997-2017. Columns 1,2 and 3 include only firms alive at the start of the period, column 4 also includes firms born during the period.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$