POLICY PAPER

Local Multipliers: IDA Supported Companies in the Irish Regions

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Abstract: Global trends in foreign direct investment and trade have seen the Irish economy move from a high-tech manufacturing to a high-tech service driven foreign direct investment (FDI) model over recent decades. The nature of this investment has inevitably led to greater concentration of Industrial Development Authority (IDA) supported employment in a smaller number of urban cores. In this paper, we estimate the causal impact of local employment growth in IDA supported firms on local employment in firms in other sectors. To do so, we use a well-established instrumental variables method. In line with similar studies elsewhere this paper finds that the multiplier is significant. The results suggest that there are around three additional jobs created in a county for each job created in an IDA supported business in the same county. This suggests ongoing concentration of IDA supported employment will have significant implications for regional development.

I INTRODUCTION

Recent years have seen a well-documented shift in the sub-sectoral make-up of multinational (MNE) companies operating in Ireland (Barry and Bergin, 2012; Brady *et al.*, 2013; Breathnach *et al.*, 2015). Data from the Department of Business,

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Enterprise, and Innovation's "Survey of Economic Impact" show that as recently as 2007, there were only 50 jobs in Industrial Development Authority (IDA) supported services companies for every 100 in IDA supported manufacturing; by 2017 there were 95 (DBEI, 2016). Employment in IDA supported manufacturing in Ireland has fallen by a third (just under 39,000 jobs) since the turn of the century while services employment has risen by 79 per cent. Global (see Feenstra, 2010) as well as well as local trends have played a significant role in this,[1] and it is not unique to Ireland. Given that services FDI has traditionally been more likely to locate in urban centres by comparison to manufacturing this has important implications for regional policy. The ability of regional centres to attract FDI may have significant impacts on their future growth, it may also be increasingly difficult.

The impact of the parallel and related trends of structural change and regional concentration of FDI are clear. Between 1973 and 1997 the five counties of Cork, Dublin, Limerick, Galway and Clare (Shannon) accounted, on average, for 57 per cent of IDA supported employment in any given year. Shifts in the makeup of the sub-sectors of IDA supported activity over the course of the period between 1997 and 2007 – the period of the 'Celtic Tiger' – saw that ratio rise from 58 per cent to 68 per cent. Over the past decade the share of overall IDA supported employment in those counties has increased to 75 per cent on average.

This trend has, in recent years, been secular to the broader trends in private sector employment. In 2008, 66.3 per cent of overall non-IDA business employment was in Cork, Dublin, Limerick, Galway and Clare; by 2016 it was 67.9 per cent – a rise of only 1.5 percentage points. Over the same period the share of IDA supported employment in the three counties had increased by 7.8 percentage points. This is not just a relative phenomenon, 14 of the 26 counties outside Dublin[2] have seen an absolute decline in IDA supported employment in the last decade, as manufacturing has declined. Together the counties outside of the five main centres above now have the same absolute level of IDA supported employment as they did in 1997.

The IDA have recognised this trend of increased concentration, by making regional development a key focus of their most recent corporate strategy (IDA, 2015). The agency has set regional FDI project growth targets for each region for the first time. These amount to between 30 per cent and 40 per cent per region from 2015 to 2019.

Even if growth targets at a regional level are novel to IDA strategy, regional concerns were at the core of foreign direct investment strategies from the 1950s onward. For example, the Undeveloped Areas Act (1952) targeted several areas where employment in agriculture was declining quickly.[3] From its foundation

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[1] The rise of competition from cheaper manufacturing bases in Asia and upgrading of sectors domestically in Ireland, for example.
[2] Tipperary is divided into North and South.
[3] Sligo, Leitrim, Roscommon, Mayo, Galway, Clare, Donegal, Kerry and West Cork initially.

Figure 1: Employment in IDA Supported Companies, 1971 to 2017
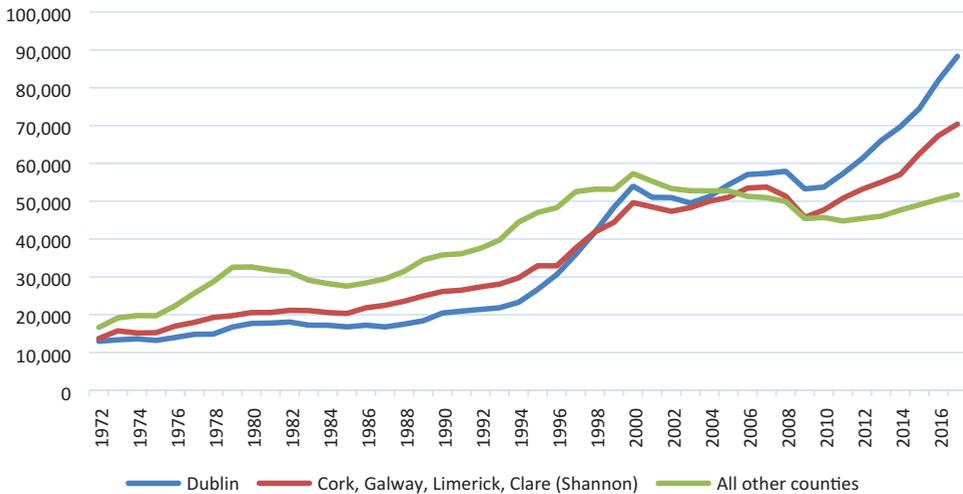
Source: Author's calculations using IDA data.

onward, the IDA gave more generous grants to facilities set up in undeveloped areas. This targeting of specific towns in more disadvantaged areas continued through the IDA strategies in the 1970s and early 1980s informed, partially, by the Buchanan report. NESC (1985) concluded:

> *Industrial location policy in Ireland has encouraged extensive dispersal of industrial projects. It has attempted, with great success, to bring jobs to the people rather than concentrating jobs in a few locations.*

However, the focus did shift over the intervening years to an industry rather than regional focus (see NESC, 1985, for discussion). The success of these earlier regional targets has been shown to have significant impacts on designated areas. Meyler and Strobl (2000) found that over one-quarter of employment growth in designated areas during the 1973 to 1982 period was driven by the explicit regional policy in IDA plans. They also noted, as we do above, that those trends seem to be going into reverse.

Why does the regional spread of IDA supported employment matter? The distribution of IDA supported employment has always played an important role in Irish industrial policy. Employment supported by the Industrial Development Authority (IDA) amounts to just under 18 per cent of total private sector employees in all counties outside of Dublin. It is, however, unevenly distributed between them. Some areas of the country are heavily reliant on IDA supported jobs. It amounts to as much as 30 per cent of business employment in Galway and as little as 1 per

cent of employees in Monaghan. In addition, wages paid in IDA supported employment tend to be higher and thus have a greater impact on local purchasing power and demand for goods and services. Employment is not the only benefit of a growing presence of IDA supported firms. Over the years between 2000 and 2016, wages made up only half of the total aggregate demand impact of IDA firms in the local economy. Purchases of goods and services from sub-suppliers made up around 50.5 per cent of all spending in the domestic economy by this group of companies. The scale of this purchasing power impact is likely to be greater in regions which are otherwise economically lagging.

This paper uses a well-established method similar to that used in previous papers, by Moretti (2010), Moretti and Thulin (2013), Van Dijk (2015), Faggio and Overman (2014) and Card (2007), to estimate the local impact of net additions to IDA supported employment (a proxy for activity in the area) on employment in the non-FDI sectors of the economy. Each of these papers uses a two-stage least squares approach to attempt to establish causation. The instrument is based on Bartik's (1991) widely used approach to identifying demand shocks in regional economies. From this the implications of our findings for the future of Ireland's regional development are discussed.

This paper contributes to the existing literature in two ways. Firstly, it is the first time that the size of local economy multipliers has been estimated for FDI activity in Ireland. This builds on earlier estimates for FDI activity at a national level (IDA, 2015; Department of Finance, 2014) based on Input-Output methods. What is more, it is the first time any local multipliers for FDI employment have been estimated ex-post rather than ex-ante. That is, these estimates are the first attempt to measure changes in local employment because of actual FDI activity rather than predicting the impact of changes in FDI activity before it occurs.

This study has the added advantage of being the first to estimate multipliers without relying on the problematic assumptions inherent in Input-Output analysis. Input-Output models traditionally assume that prices are fixed and pay little attention to general equilibrium constraints. It is possible, for example, that the impact of FDI in a locality may attract other firms due to agglomeration externalities and thus have larger impacts on local employment than regional Input-Output models would predict. For example, firms in sub-supply of FDI companies may move to the local area to continue to provide services locally. On the other hand, an increase in FDI employment in a region with a thin labour market may result in an increase in labour costs and result in a loss of competitiveness for other companies in the tradeable sector. The method used in this paper allows for the reallocation of factors and adjustment of prices which is not possible in Input-Output models (Moretti, 2010).

The scale of the local multiplier effect is important for the future of both regional and industrial policy. The estimates provided in this paper help us understand both the impact of attracting FDI to the regions and the impact of

regional concentration of FDI on overall regional inequality. From this, we can try and understand the scale of the social and political challenges which might occur if the trend in regional concentration of FDI continues. These estimates may also help those trying to gauge whether additional efforts and incentives to attract FDI employment to the regions might constitute good 'value for money'.

The rest of this paper is structured as follows. Section II presents the conceptual framework utilised in this paper in the context of other similar studies. Section III presents the methodology used. Section IV contains a description of the data we use and discusses the strengths and weaknesses of our approach. In Section V we present econometric estimates of employment multipliers for IDA assisted firms. Finally, in Section VI we present the conclusions of our findings, discuss the strengths and weaknesses of our approach and their relevance for policy.

II THE IMPACT OF FDI EMPLOYMENT ON LOCAL EMPLOYMENT

The conceptual underpinnings of this paper are similar to those of earlier studies, notably Moretti (2010), Moretti and Thulin (2013), Van Dijk (2015) and Faggio and Overman (2014). Of those papers the underpinnings are closest to Moretti (2010), Van Dijk (2015) and Moretti and Thulin (2013). All three papers estimated the employment multiplier of the tradeable sector in the local areas on the non-tradeable sector in the same area.

In an adaption of Moretti (2010; 2011), Van Dijk (2015) and Faggio and Overman (2014), this paper takes the approach that assumes that each Irish county is a local economy which produces a globally traded good whose price is exogenous, and a locally traded good whose price is determined locally. Labour is assumed to be mobile across sectors and local labour supply is upward sloping – that is more workers will supply hours as wages increase. The slope of labour supply depends on a resident's preference for leisure over work, the elasticity of local housing supply and the degree of labour mobility in and to the region.

In such a scenario, new IDA investment in a county either from a new or existing firm will result in a direct increase in employment in the IDA supported industries in the county. The level of local demand increases both because there are more workers and an aggregate increase in wages. It may also increase because of increases in purchases from local suppliers. Unless local labour supply is infinitely elastic (which is unlikely given the factors above) then the general equilibrium effect of the investment is also likely to increase local wages.

The aggregate increase in demand, from the factors above, increases demand for locally produced services in other sectors such as retail, hospitality, and construction. This demand then has a knock-on effect on employment in the non-tradeable sector both reducing local unemployment and attracting new workers to

the county. The size of this impact is determined by several factors such as the type of IDA supported employment, the size of the local unit, the scale of purchasing by the company from local suppliers and the preferences of the new employees for living in the area. If the wage differential between the new IDA supported jobs over local jobs is higher, then the multiplier will be larger. We expect this to be the case given that in Ireland, the average wage in IDA supported firms nationally is 1.9 times that of domestic firms in both the tradeable and non-tradeable sector (DBEI, 2015). If the sector of the investment is both labour intensive and highly paid, then the multiplier will be higher again. In addition, if the firm makes efforts to include local firms in its sub-supply the multiplier will increase. If the IDA company purchases more from local, rather than international suppliers the multiplier will be higher. There may also be other agglomeration impacts such as productivity spill-overs for local firms. The evidence on this in Ireland has tended to be mixed (Ruane and Ugur, 2005; Haller, 2014; Di Ubaldo *et al.*, 2018).

On the other hand, we assume the decision of workers to live in the county of their work, rather than commute from elsewhere is based on idiosyncratic preferences, the net local wage and the cost of local housing. As such, higher housing costs or changes in preferences will reduce the number of workers co-locating with their work and decrease the multiplier for non-tradeable sectors. In addition, if the general equilibrium effects of the investment on local prices and wages crowds out other tradeable or non-tradeable firms then the supply from those firms will fall and partially offset the benefits of the investment. This in turn depends on the elasticity of local labour supply.

As Moretti (2010) shows this simple framework is an improvement on the Input-Output methods which have previously been used in an Irish context for two reasons. Firstly, given the approach does not assume away price adjustments and general equilibrium effects; the method captures the employment impact of IDA supported investment on the local non-tradeable sector. Second, for the same reason this method allows for negative impacts of rising costs on the local tradable sector and positive impacts from local agglomeration economies. It is also worth noting that the local multipliers obtained in the coming sections are also conceptually different from national multipliers due to the differences in scale, such as differences in the slope of the labour supply curve in local areas and at national levels.

Table 1 summarises the results of other studies which have adopted this framework. There are clear divergences between the results, attributed to the elasticity of labour supply, the 'wage premium' for those working in the tradeable sector (i.e. the inequality between wages in the tradeable and non-tradeable sectors), and the specifications used. Particularly there is a sensitivity in specification of the dependent variable to 'all employment' or just that in the private sector. The results can be read as the number of jobs in the non-tradeable sector created by an increase of one job in the tradeable sector.

Table 1: Estimated Local Economic Multipliers in Similar Studies

Study	Country	Overall tradeable multiplier	High-tech job multipliers
Moretti (2010)	US	1.6	4.90
Moretti and Thulin (2013)	Sweden	0.75	2.79
De Blasio and Menon (2011)	Italy	0	0
Malgouyres (2016)	France	1.5	–
Van Dijk (2017)	US	1.7	2.3
Goos *et al.* (2018)	European Regions	–	4.75

There are large differences in the overall tradeable multiplier between the US studies and those in Sweden and Italy. In Moretti and Thulin (2013) they explain this disparity as being down to differences in labour supply elasticity (higher unemployment benefits and lower labour mobility in Sweden) and a lower tradeable sector wage premium. De Blasio and Menon (2011) explain the Italian differential by attributing it to low labour mobility, strict centralised nominal wage setting and heavy regulation of non-tradeable firms. Given Ireland's level of product market regulation and earnings inequality by comparison we would expect the multiplier to be higher for Ireland than other European countries but lower than that of the US.

For results focused on high-tech or high-skill tradeable sectors only, the employment multiplier is found to be larger. These high skilled multipliers may be a better baseline with which to compare our results given that IDA-supported employment tends to be at the higher level of the technological distribution within the overall tradeable sector in Ireland. In addition, other studies tend to exclude tradeable services and concentrate only on tradeable manufacturing. Using IDA assisted employment avoids that issue and should more fully capture the impact of the sector. Goos *et al.'s* (2018) results are potentially of interest for us given that they focus solely on the multiplier for high-tech tradeable jobs. This, in effect, is what we are doing by focusing on IDA supported employment. The ICT, Biotech and Medical Device industries make up just over three-quarters of IDA supported employment in our sample. Goos *et al.* (2018) also show that multipliers are larger in regions with higher immigration, an abundance of less-skilled workers, and lower gross output per capita. This could reflect many of the Irish counties over the time period we study.

From a policy point of view, it is important to note that the overall level of IDA supported employment is concentrated in a small number of counties. Figure 1 shows the Herfindahl-Hirschman Index (HHI),[4] a commonly used measure of

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[4] The HHI is the sum of the square root of the shares of IDA supported employment in each county and can range from close to 0 to 10,000 at its maximum.

Figure 2: Herfindahl-Hirschman Index of IDA Supported Employment Across Irish Counties
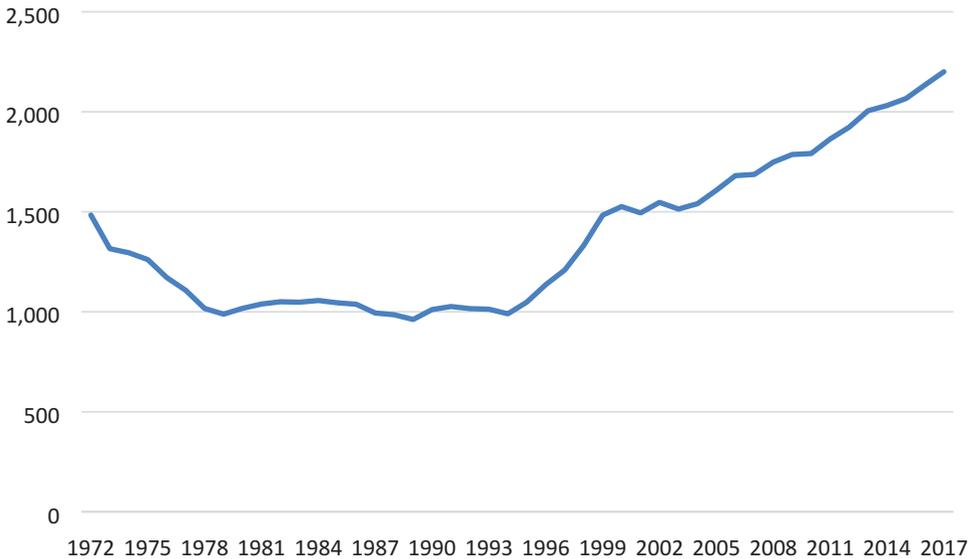
Source: Author's calculations.

market concentration shows that the concentration of IDA activity has been growing since the 1990s. It reached a reading of 2,200 in 2017 and has risen by about 60 points per year since 2010.[5]

Table 2: Internal Labour Mobility in Ireland

Census year	*1971*	*1981*	*1986*	*1991*	*1996*	*2002*	*2006*	*2011*	*2016*
% of persons who had moved within the country during the past year	0.9%	0.8%	0.5%	1.1%	1.1%	2.0%	3.0%	1.2%	1.8%

Source: Census data.

If multipliers in our study are as large as those found elsewhere then the structural changes outlined in Section I, and evident in Table 2, will have significant impacts on the Irish regions outside Dublin. A higher multiplier suggests that the cost of growing regional concentration may be high for many local areas. If labour mobility

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[5] By way of comparison the Horizontal Merger Guidelines of the US Department of Justice and Federal Trade Commission tend to see any market with a HHI above 2,500 as a highly concentrated.

in Ireland falls as elsewhere in the EU and US and there is a high multiplier, or if we put greater value on the welfare of those who cannot move from one region to another, then efforts to alter structural trends at the margin may be more cost effective than previously thought (Rodríguez-Pose, 2017; Austin *et al.*, 2018).

III METHODOLOGY

Our econometric specification is quite straightforward and an extension of Card (2007) and Faggio and Overman (2014). We can write the sum of employment in County E at time t as E_t. That employment is the sum of IDA supported employment X_t and other local employment in both the tradeable and non-tradeable sectors S_t. As such we can decompose the change in employment in County E at any given period between the IDA and non-IDA sectors by:

$$\frac{E_t - E_{t-1}}{E_{t-1}} = \frac{X_t - X_{t-1}}{E_{t-1}} + \frac{S_t - S_{t-1}}{E_{t-1}} \qquad (1)$$

However, to isolate the impact of changes in X on the other sectors we must estimate a version of the model:

$$\frac{S_t - S_{t-1}}{S_{t-1}} = \alpha + \beta \left(\frac{X_t - X_{t-1}}{X_{t-1}} \right) + y + e \qquad (2)$$

Where $\dfrac{S_t - S_{t-1}}{S_{t-1}}$ is the change over time in the log of employment in the local sector in each Irish county and $\dfrac{X_t - X_{t-1}}{X_{t-1}}$ is the change over time in the log of employment in IDA supported firms in each Irish county. y is a time dummy controlling for national shocks to employment in the non-tradable sector. The error term e is assumed to consist of unobservable region-specific fixed effects, represented by μ, and a truly random component, v. β is the elasticity of employment in the local non-IDA sectors to changes in employment in local IDA supported employment. Given that the number of jobs locally in the non-IDA sector is a multiple of the number of jobs in the IDA sector we find the employment multiplier for each additional IDA job by multiplying β by the ratio of non-IDA to IDA jobs.

An important implicit assumption we make when estimating β is that IDA supported employment in a local area is exogenously determined. This is quite possible, given that investment decisions are often made by corporate headquarters

with no ties to the local area. In addition, demand from the local non-FDI sector is unlikely to materially increase employment in local IDA supported companies. However, one of the issues which may be raised in our analysis is the possibility that non-IDA supported employment is impacted by some unobserved factor (captured in our error term e) which may also impact on IDA supported employment in the area. Where this is a possibility, estimating Equation 1 using a simple OLS model may result in inconsistent parameter estimates. For example, there may be changes in the local economy which impact on the labour supply curve such as a shift in the number or quality of graduates, a deterioration of local amenities or some other factor which makes people prefer the area less. This would then change the slope of the labour supply curve and bias our estimates.

To account for this endogeneity, in so much as that is possible, we estimate a two-stage least squares instrumental variable regression of Equation (2) (Greene, 2008). We estimate (2) using two separate instruments over two separate time periods. For our first instrument, over the period 1971 to 2016, we attempt to isolate exogenous shifts in local investment in IDA supported firms using a shift-share instrumental variable based on Bartik (1991). All the studies mentioned in Table 1 use some variation of this instrument but it has been applied in the broader literature by Card (2007) when looking at the impact of immigration on local labour markets and Faggio and Overman (2014) when estimating the employment multiplier of public sector employment.

Our instrument uses initial shares of employment in IDA supported firms and the national trend in IDA supported employment to predict the growth in local employment in the absence of an area-specific shock. That is, we assume that in the absence of area-specific shocks, the increasing tendency of IDA firms to co-locate and agglomerate would have seen an increase in county level IDA supported employment in proportion to national employment growth in IDA supported firms, and its initial share of IDA supported employment. Intuitively, our instrument should capture exogenous changes in local labour demand because the national changes do not reflect local economic conditions. In line with Faggio and Overman (2014) we exclude own county employment in the construction of our instrument. As such the national changes in IDA supported employment affect different counties differently because of their share in the base year.

There are some drawbacks to this econometric approach in that it assumes that the impact of changes in one county on another are captured by reporting standard errors that account for clustering on a county level. This may not be the whole picture as it may not capture fully the way units are dependent on one another.

The alternative to this approach would be to use some form of spatial weights matrix to control for the relationships between counties either based on contiguity (i.e. non-zero between neighbouring regions) or distance between regions (based on the location of their population centre). There are drawbacks to this approach

also. Namely, imposing a spatial weights matrix would require us to assume a given spatial structure 'W' for the impact of IDA firms *a priori*. That is, we would be assuming that increases in aggregate demand or general equilibrium effects of rising IDA employment in each county are more likely to impact those counties closest to them rather than, for example, more distant regions with similar industrial structures. For example, it would require us to assume that an increase in activity in a medical device plant in Galway has a larger impact (through rising demand for goods, competition for staff etc.) on unrelated firms in a neighbouring region (Mayo) than related firms (sub-suppliers, same industry) in a region further away (Cork).

These complications in applying valid weights is common in the literature and discussed at length in Harris *et al.* (2011). As Harris *et al.* (2011) point out distance as a concept is more complicated to measure when there are multiple competing complex processes at play. Distance may be best measured by proximity, alternatively it may be best measured by transport times, technological proximity, differences in absorptive capacity or distances based on exchange of goods between regions (Harris *et al.*, 2011).

There is significant debate in the literature on the various approaches – see Gibbons and Overman (2012) and Partridge *et al.* (2012) for example. In our case, while it may be possible to impose an ad hoc restriction through a spatial weight matrix, in the absence of better data identifying linkages between counties directly, we cannot choose one which we know is well founded. If the choice of weight is invalid, then so is our identification strategy.

In these situations, Gibbons and Overman (2012) propose adopting a reduced form approach focusing on credibly exogenous sources of variation. By using an instrument which seeks to isolate exogenous variation in local labour demand we seek to identify the causal process at work. For a cross-check we report the results of Samples 1 and 2, with Dublin included in the sample in the Appendix. We use an instrument based on IDA site visits for Sample 2 and report OLS results for Sample 1. We also construct a spatial weights matrix based on inverse distance and use this to cross-check the strength of any potential spatial correlation in our samples – reporting Moran's I and Geary's C for each sample. Finally, we report the results of spatially weighted models for each of our samples. All our results suggest that spatial correlation as measured by traditional distance has little impact on our multiplier estimates – even in cases where it clearly present. Indeed, a few of our specifications suggest that there may be significant additional indirect multipliers over the long run.

We set out in the next section the complications, in greater detail, we face in this paper. Future research will be needed to obtain better information on the spatial structure of the impact of IDA firms. With that data it may be possible to create better estimates for 'W' such as those outlined in Harris *et al.* (2011).

IV DATA

The data in our first sample (1971-2016) include nine observations per county and 26 counties (234 observations in total). The periods of the observations correspond to each national census release since 1971. Tipperary is split into North Riding and South Riding and we exclude the four Dublin local authorities. Dublin's exclusion is for two reasons, firstly the analysis is primarily interested in IDA supported employment outside the capital. Secondly, Moretti and Thulin (2013) exclude Stockholm from their analysis of Sweden due to its scale relative to other local areas. Dublin has the same effect. Our strategy seeks to isolate the variation in local employment coming from national changes in IDA supported employment. It is difficult to think of national changes which are not changed by what happens in Dublin, and which thus would invalidate our instrument. This may have implications for our analysis – in particular for the relevance of our results for those counties closest to Dublin where intra county commuting flows are higher. In the Appendix, we include an alternative specification. In this we use a different instrument (IDA site visits) which does not necessitate the exclusion of Dublin from our data. The results are very similar to our results later in this piece, albeit at the higher end.

In our second sample (2010 to 2016) we focus purely on the impact of IDA supported employment changes on private sector employment in private business. Given the impact of the financial crash we exclude the years 2008 and 2009 along with the construction sector. The data for our dependent variable is taken from the CSO's Business Demography survey and has 175 observations (25 counties over seven years). Again, we exclude Dublin as it would invalidate our instrument.

Table 3 shows our data and sources. Our independent variable is the number of IDA supported jobs located in the county and comes from the IDA's client surveys which have been conducted by Forfás and more recently the Strategic Policy Division of the Department of Jobs, Enterprise and Innovation with the assistance of IDA Ireland's regional offices. Our other variables are all taken from the CSO's population Census or Business Demography data.

The major challenge in our data is the proper geographical unit of analysis. As outlined in Section II we are trying to capture a number of effects.

1) Firstly, we are trying to capture demand shocks in to the local economy from the local purchases of workers.
2) Secondly, we are trying to capture demand impact in the local economy from purchases of the IDA supported firms from firms in the same county.
3) Finally, we are also trying to capture the general equilibrium impacts on the local labour market and other firms.

This makes finding an appropriate unit of analysis difficult. The 'area of impact' of (1), and thus interest, may be based on both working and living patterns of workers.

Table 3: Variables and Measures

Variable	Measure	Spatial level	Period	Source
IDA supported employment	Employment in IDA supported jobs	County of work	1971-2016	IDA Ireland
Employment in non-IDA companies (1)	Total employment excluding IDA supported employment, agriculture, mining and public administration	County of residence	1971-2016	CSO Ireland, Census
Employment in non-IDA companies (2)	Total employment in private businesses excluding construction	County of work	2010-2016	CSO Ireland, Business Demography
Public sector employment	Number of persons living in the county in in employment in public administration	County of residence	1971-2016	CSO Ireland, Census
Year	Period Dummy	–		–

In addition, over the years between 2000 and 2016 wages made up less than half of the direct aggregate demand impact of IDA firms in the local economy. As such our geographical unit of analysis must be consistent with (2) also, in so far as that is practicable. It must also allow for the local interactions of the firm in terms of both aggregate demand from wages and purchases by the firm. Finally, it cannot be so large as to be completely absent of internal homogeneity.

We could for example focus on the town in which the firm was located only, or on a set of electoral divisions based on employment density, population density or commuting patterns. However, constructing the correct unit is difficult in the absence of *a priori* knowledge of the spatial spillover from IDA firms. For example, it is highly unlikely the additional local demand created by employees of the IDA firms would be restricted to just their town of work, or residence, alone. In peri-rural areas, for example, workers may visit local amenities (e.g. restaurants, bars etc.), purchase services (e.g. plumbers, tradesmen) and purchase goods (e.g. groceries) in areas based outside those two locations. An IDA investment in a smaller town, for example, may have just as significant an impact on demand in a larger local 'county' or 'market' town which has more choice in retail than where the IDA supported employees either live or work. This is complicated by the fact that budgets are often shared within households, so the same patterns matter for their spouse or dependents too.

There is an added complication of how the firm procures locally and how it interacts with local firms. Between 2000 and 2016 payroll costs before tax

accounted for only 49.5 per cent of total direct expenditure in the Irish economy from IDA supported companies. Thus, the direct impact on aggregate demand nationally from purchases of goods and services is likely to be larger than that for wages. We do not know, however, how much of these goods and services were spent on local suppliers versus specialist suppliers in other regions of the country. For example, services such as utilities, insurance and transport make up a large proportion of non-wage costs of business. Most of those services are likely to be procured from national providers. When it comes to specialist services such as advertising, legal or accountancy there is little reason to believe firms close by would be especially favoured by large companies.

There are alternative boundaries that one could adopt, for example; travel to work patterns (Van Egeraat *et al.*, 2013), or using agglomerations of firms in sub-supply sectors. But to do this we would need to know more about the nature of spatial properties of sub-supply linkages of multinationals. Given the data available it is unlikely we can define a 'field' which easily catches the impact of these firms. Indeed, mis-specifying the fields (i.e. creating fields based on the wrong indicator) could generate further bias.

Using administrative counties also allows for a longer period to be covered within the confines of the data available to us. Definitions of administrative towns and any areas delineated by other variables (commuting, density etc.) are likely to introduce bias over long periods as they are inconsistent across time. For example, town boundaries have expanded, and commuting patterns have changed significantly over recent decades. There is a clear trade-off between more granular analysis and a longer period of analysis.

As such, we use the administrative county as our level of analysis. It is unlikely, like any potential spatial variables, that county boundaries capture a full natural area of impact for each firm. We must acknowledge that this is a weakness of our approach and a route for further research. While this paper is a first attempt to estimate IDA multipliers in a general equilibrium setting, it is likely significant further research will be needed to find a unit of analysis which is optimal for this kind of analysis.

A further challenge in our data is that our measure of employment in IDA firms is based on the place of work, whereas our data on non-IDA supported employment in Sample 1 are based on place of residence. Other studies (see Table 4) have tended to focus on using both dependent and independent variables based on place of residence. This has the advantage of being consistent but also requires an inherent assumption that there is little bias introduced by persons living in location 'C' but both working and procuring goods or services elsewhere. The last time-use survey for Ireland (McGinnity *et al.*, 2005), for example, showed that for those working full-time, over half their time was spent working or travelling during the week. Focusing on place of residence alone at too granular a spatial level will miss the impact of purchases people make during those hours, or in their leisure time outside

Table 4: Comparison of Geographical Unit of Analysis with Other Studies

Study	Level of geographical analysis	Basis
Moretti (2010)	Metropolitan areas	Population density, commuting patterns
Moretti and Thulin (2013)	Functional regions	Overlap of the residing and the working population
De Blasio and Menon (2011)	Local labour market	Overlap of the residing and the working population
Malgouyres (2016)	Employment zone	Overlap of the residing and the working population
Van Dijk (2017)	Metropolitan areas	Population density, commuting
Goos *et al.* (2018)	NUTS 2 regions	Administrative
Faggio and Overman (2014)	Local Authorities areas (LAs)	Administrative

the home. In addition, if there are large interregional commuting flows out of 'C' then measuring employment based on people living in 'C' only may not be fully reliable.

Other studies (see Table 4) have tended, similarly, to use either administrative boundaries as a geographical basis or focus on 'functional areas' based on the overlap of place of work and place of residence. To overcome the issues above, the unit of spatial analysis must be defined by some level of cohesion between people's place of work and home. In 2016, for example, 86 per cent of Irish workers in the counties included in our sample both lived and worked in the same county. This however varies across counties, with the ratio falling below 70 per cent in eight of 25 counties in the Dublin commuter belt.

We acknowledge the issues discussed above as a weakness of our data and approach. As such, we must carefully interpret our coefficient estimates from Sample 1. We also seek to control for any bias introduced by separately using a dependent variable based on place of work in Sample 2. If our estimates across both models are consistent this suggests that there is not much significant bias introduced by the issue of inter-regional commuting outlined above. As a final control, we directly test the size and significance of spatial autocorrelation in the Appendix. Our results from tests of Moran's I, Geary's C and spatial lag models on data from both samples all suggest the issue does not significantly impact on our identification strategy.

In effect, we intend to measure in β the impact of a rise in the number of persons working in IDA supported employment within the county on demand for labour of people living in the same county *only* for Sample 1. As we acknowledge in Section II this means that we assume the decision of workers to live in the county of their work, rather than commute from elsewhere is based on idiosyncratic preferences, the net local wage and the cost of local housing. As such, higher housing costs or changes in preferences will reduce the number of workers co-locating[6] and will decrease the multiplier for the IDA supported sectors in our analysis. In Sample 2, we intend to measure in the impact of a rise in the number of persons working in IDA supported employment within the county on demand for labour of people working in the same county *only.*

V EMPIRICAL ANALYSIS

Table 5 contains our estimation results for Sample 1. The specification in Model (1) reports two-stage least squares estimates. Our dependent variable is measured as total employment in the county excluding agriculture, public administration, and the extractive industries in line with Moretti (2010). Our independent variable of interest is employment in IDA supported companies in the county. Model (2) repeats this approach using the alternative approach of a two-stage generalised least squares random effects model. Model 3 then additionally controls for shocks to local demand from changes in public sector employment.

The Bartik (1991) shift-share instrument described in the previous section is used in each model. Both the dependent and independent variable of interest (along with public sector employment control) are in their logarithmic form. In line with Moretti (2010) and Moretti and Thulin (2013) we also include a time-dummy to control for national shocks to employment in the non-tradable sector and results are presented with standard errors clustered at the county level (for Model 1).

Although not reported below, the OLS estimate of β (the coefficient on the IDA supported employment on growth in other tradable sectors) is 0.40. This implies that for every 1 per cent rise in IDA supported employment over the period in each county, employment of persons living locally has risen by about 0.4 per cent. However, we again need to be conscious of the possibility that both IDA supported employment and employment in the local sector in each county are endogenous.

We perform several tests to test the strength and appropriateness of our instrument. If tests signifying endogeneity are not statistically significant, it is appropriate to report our OLS estimation of (1) only, as using instrumental variable estimates when they are not necessary can create more problems than they solve (Bound *et al.,* 1995). As we have clustered standard errors by county, Wooldridge's

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[6] That is, both living and working in the same county.

(1995) robust regression-based test is our best test of exogeneity. The test statistic is highly significant at a 99 per cent level, as such we reject the null of exogeneity. As such this suggests our two-stage least squared estimates are more appropriate.[7]

It is now important to test the strength of our instrument using the first stage of our two-stage least squares equation. The results show an R^2 of 40 per cent on the first stage our two-stage least squares equation which does suggest a strong instrument, given that the instrument is relatively strongly correlated with the endogenous variable. Our F-statistic testing the explanatory power of our shift-share variable after accounting for our endogenous variable is highly significant also, and at more than 27, suggesting again that we have a strong instrument. Stock and Yogo (2005) suggest that the F-statistic should exceed 10 for inference based on the 2SLS estimator to be reliable when there is one endogenous regressor.

As we have an issue with endogeneity and a strong instrument we report our IV results only.

The two-stage least squares estimate of β (the coefficient on the IDA supported employment on growth in other tradeable sectors) is 0.63 in Model 1. This implies that for every 1 per cent rise in IDA supported employment over the period in each county, local employment has risen by about 0.63 per cent. Using a two-stage least squares random effects model alters this only slightly to 0.6 per cent.

The estimate from our best performing model of β can be found in Model 3. This model also controls for a contemporaneous demand shock from rising public sector employment in the county over the period. This is our preferred specification for several reasons. Firstly, public sector and its growth has not been uniform throughout the country due to the nature of the decentralisation of the 1980s and 2000s. From our point of view, however, the unplanned nature also means that unlike other potential control variables such as local income levels it is likely to represent an exogenous source of demand. It is also the case that those public sector jobs are better paid on average than local jobs and thus may have a significant local economic impact. Or, as Faggio and Overman (2014) find, have significant offsetting impacts on the private sector which are worth controlling for.

The coefficient on the IDA supported employment on growth in other tradeable sectors in Model 3 is 0.45. This implies that for every 1 per cent rise in IDA supported employment over the period in each county, local employment has risen by about 0.45 per cent.

The difference between these results and our smaller OLS estimates[8] suggests that our OLS estimates were biased downward. There are several reasons why this may be the case. For example, it is entirely plausible that efforts to attract IDA supported employment to a county may have occurred to attempt to overcome

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[7] We test this again, without clustered standard errors in the equation and both Durbin and Wu-Hausman tests of endogeneity result in a similar outcome. Although a Breusch-Pagan test suggests that our model may suffer from heteroskedasticity, as such clustered standard errors are appropriate.

[8] 0.4 when public employment was not controlled for and 0.31 when it was controlled for.

Table 5: Estimation of the Full Sample 1

Variable	Model 1	Model 2	Model3
Method	2SLS	G2SLS, RE	G2SLS, RE
IDA supported employment	0.63 ***	0.60***	0.45***
	(0.08)	(0.19)	(0.21)
Public sector employment	–	–	0.36**
			(0.20)
Time Dummies (base period 1971-1981)			
1981-1986	–0.34 ***	–0.31 *	–0.33 *
	(0.12)	(0.19)	(0.13)
1986-1991	–0.34 **	–0.32 *	–0.37 ***
	(0.11)	(0.18)	(0.11)
1991-1996	–0.43 **	–0.40 *	–0.46 ***
	(0.12)	(0.23)	(0.15)
1996-2002	–0.37 ***	–0.33	–0.38 *
	(0.13)	(0.26)	(0.18)
2002-2006	–0.069	–0.03	–0.04
	(0.16)	(0.27)	(0.14)
2006-2011	0.20	0.24	–0.26
	(0.16)	(0.26)	(0.11)
2011-2016	0.23	0.27	0.051
	(0.18)	(0.20)	(0.12)
Cons	3.1***	5.4***	4.1***
Obs	233	233	233
Prob>F	0.00	0.00	0.00
R2	0.507	0.6	0.75
		(Overall)	(Overall)
RMSE	.509		–

Source: Author's calculations

Note: Robust standard errors are reported in parentheses; *, **, *** indicate significance at the 10 per cent, 5 per cent and 1 per cent levels, respectively. Hausman tests for Model 3 and 4 indicate random effects are appropriate.

weaknesses in existing sectors of the economy in that county. For example, IDA (1972; 1979; 2015) development plans in the 1970s and 1980s were focused on drawing industrial capacity to less developed areas of the counties in the West and Midlands with grants and 'advanced' factory development. This priority of regional development remains in existence with the most recent plans outlined in Section 1. Data limitations prevent us from drilling deeper into regional or temporal variations in the data which may shed more light on this.

Table 6 contains our estimation results for Sample 2. Again, we run a series of tests for our preferred model. The outcome from Durbin and Wu-Hausman tests of

endogeneity result in a similar outcome as our Woolridge robust regression test. All suggest an IV approach is appropriate. The specification in Model (1) reports two-stage least squares estimates. Model (2) repeats this approach using the alternative approach of a two-stage generalised least squares random effects model.[9]

The instrument is again based on the Bartik (1991) shift-share method. Both the dependent and independent variable of interest are in their logarithmic form. In line with Moretti (2010) and Moretti and Thulin (2013) we also include a time dummy to control for national shocks to employment in the non-tradable sector and results are presented with standard errors clustered at the county level (for Model 1).

The 2SLS estimate of β in Model 4 is 0.48. This implies that for every 1 per cent rise in IDA supported employment over the period in each county, employment of persons living locally has risen by about 0.48 per cent. The same figure is 0.30 per cent in Model 5. Overall these are consistent with our estimation from Model 1. The consistency of results between Sample 1 and 2 gives us some comfort given the variation in time period, data sources and focus on place of work versus place of residence.

By way of comparison, the elasticities reported by Moretti (2010) were between 0.33 and 0.55 for all tradeable sectors (both high and low tech) in the US. This rises to over 0.9 for high-tech employment. Goos *et al.* (2018) finds results of 0.54 in their preferred specification for high-tech[10] only jobs across European regions. In this context our results of 0.45 for IDA supported employment seems reasonable – particularly given that three-quarters of IDA supported employment in 2016 is in the ICT, Biotech and Medical device sectors.

Table 7 converts our elasticity estimates to multiplier estimates. Over the total period of our analysis, both between 1971 and 2016 and between 2008 and 2016, there have been just over six jobs in the non-IDA private business sectors of the economy for every job in the job supported directly by the IDA. As such our estimates imply that every additional IDA supported job created over that period has resulted in somewhere between 1.8 and 3.8 jobs elsewhere in the local private sector in the same county. Given that we categorise IDA supported employment as being high-tech, these estimates are within a range of those reported previously. Notably they are somewhere between those reported for the US high-tech sectors in Moretti (2010) of 4.9, and of Moretti and Thulin (2013) for Sweden of 2.8. Our results would seem to follow from our conceptual underpinnings as reported in Section II. Primarily, the impact of these sectors on local employment in Ireland is somewhere between Sweden with higher product market regulation, lower labour mobility and lower wage inequality, and the US which typifies the inverse of those.

[9] We perform the same battery of tests of instrument quality and again it appears we have a strong instrument. Our Hausman test for Model 2 suggests random effects are a more appropriate estimator.
[11] Goos et al. (2018) define high tech as all workers in NACE sectors 24.4, 30, 32, 33, 35.3,64,72 and 73 plus workers in other sectors from STEM occupations (ISCO 211,221,321,212,213,312,214,311).

Table 6: Estimation of the Full Sample 2

Variable	Model 4	Model 5
Method	2SLS	G2SLS, RE
IDA supported employment	0.48 ***	0.30 **
	(0.08)	(0.15)
Time Dummies (base year 2010)		
2011	−0.09	0.07
	(0.01)	−(0.02)
2012	−0.02	−0.02
	(0.02)	(0.02)
2013	−0.26 **	−0.02
	(0.03)	(0.02)
2014	−0.01	−0.01
	(0.03)	(0.02)
2015	0.03	0.05 **
	(0.04)	(0.02)
2016	0.05	0.08 ***
	(0.04)	(0.03)
Cons	6.0 ***	7.4 ***
Obs	175	175
Prob>F	0.00	0.00
R2	0.57	0.59
		(overall)
RMSE	0.42	–

Source: Author's calculations.

Table 7: Estimated Multiplier of IDA Supported Employment

	Model 1	Model 2	Model 3	Model 4	Model 5
	3.8***	3.6***	2.8***	2.9***	1.8**
	(0.48)	(1.1)	(1.2)	(0.48)	(0.9)
Time period	1971–2016	1971–2016	1971–2016	2008–2016	2008–2016
Obs	233	233	233	175	175

Source: Author's calculations.
Note: Robust standard errors are reported in parentheses; *, **, *** indicate significance at the 10 per cent, 5 per cent and 1 per cent levels, respectively.

VI CONCLUSION

This paper has provided a first study of the size of local multipliers for IDA supported companies in a general equilibrium framework. The results of this paper suggest several observations which are new to literature on the Irish labour market; chief among which is that the addition of an IDA supported job to an Irish county outside of Dublin typically creates around three jobs in other non-IDA supported sectors in that county. This local multiplier represents the upper bound of the national multiplier. This finding supports our hypothesis that the wage premium for IDA supported companies combined with high labour mobility has contributed to a high return to local areas which have been able to attract IDA supported employment.

The strengths of this study lie chiefly in its originality in an Irish context and the use of a methodology which is both commonly used and broadly comparable across countries. In addition, this paper represents the first time any multipliers for FDI employment have been estimated ex-post rather than ex-ante. This study is also the first using Irish data to estimate multipliers without relying on the problematic assumptions inherent in Input-Output analysis. As such we allow for effects like agglomeration externalities and general equilibrium impacts on prices and wages to be accounted for. These estimates may also help policymakers trying to gauge whether additional efforts and incentives to attract FDI employment to the regions might constitute good 'value for money'.

There are also a number of limitations to our study which mean that this will have to be a first attempt to shed light on this subject. Our choice of administrative counties as our unit of spatial analysis has issues like all other available options. This can be improved upon in future research by developing better understand of linkages of IDA firms with their local areas. This must be not just through the commuting patterns of their workers but also through linkages with sub-suppliers and other general equilibrium effects.

There are also some drawbacks to our econometric approach in that it assumes that the impact of changes in one county on another are captured by reporting standard errors that account for clustering on a county level. This may not be the whole picture as it may not capture fully the manner in which units are dependent on one another. We test the impact of spatial autocorrelation directly through a number of methods. Our results suggest this does not significantly impact on our identification strategy. Future research will be needed to provide more appropriate definitions of 'distance' which are appropriate when trying to understand the impact of IDA companies and their spillover impacts on neighbouring and non-neighbouring regions. Such measures of distance could include measures of proximity, alternatively it may be best measured by transport-times, technological proximity, differences in absorptive capacity or distances based on exchange of goods between regions (Harris *et al.*, 2011). The importance of this question is not limited to this study alone.

In addition the consistency of our estimates between Sample 1 and Sample 2, along with our alternative specification in the Appendix, would suggest the impact of these factors does not invalidate our results but does leave significant questions. We acknowledge it as a weakness of the data and focus on carefully interpreting our coefficients. Testing these results further using localised administrative data or by isolating changes at a local level using plant openings and closures may be a direction for future research.

From a policy point of view the size of local multipliers is important for the future of both regional development and industrial policy. The estimates provided in this paper help us understand the impact of attracting FDI to the regions on overall regional economic wellbeing. In line with previous research, the impact of high-tech jobs in otherwise poor regions is substantial. In this context, the IDA regional strategy into the future will have a significant impact on overall regional strategy and the delivering the ambitious economic rebalancing aspired to in the National Planning Framework. As we discussed in Sections I and II the drive toward services FDI may have significant impacts on the concentration of economic opportunity both in the IDA supported firms but also in other sectors of the economy.

Our analysis clearly shows that there are underlying structural changes in the sector and location of IDA supported employment in Ireland. These changes will make the old model of a 'factory for every town', and policies based on same, much more difficult to deliver. If labour mobility slows as our population ages, that could present significant challenges to regional standards of living. The ongoing structural change in IDA supported employment and multiplier estimates provided in our analysis may help us understand the scale of the social and political challenges which might occur if the trend in regional concentration of FDI continues. It is worth bearing in mind Autor *et al.* (2016) and Rodrik (2018) argue that areas which have been prone to shocks from shifting patterns in globalised manufacturing and trade have been more prone to political extremism both in the US and elsewhere. Our analysis raises considerable questions for Irish politics in this context; although it is not the purpose of this paper to speculate on them it is worth bearing in mind when considering the costs and benefits of regional industrial policy into the future.

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APPENDIX
ALTERNATIVE ESTIMATION OF SAMPLES 1 AND 2

Table A.1 displays the results of our alternative specifications both of which include County Dublin in the analysis. Both Models 6 and 7 presented in Table A.1 use an alternative instrument, being IDA site visits to the county. Model 8 resorts to OLS in order to include Dublin, thus invalidating our instrument used in the body of this paper. The dependent variable is total private sector business employment – excluding the construction sector. Given the number of private sector jobs for every IDA job in the sample over the period, the multiplier implied by these estimates is between 4.2 and 4.6.

Table A.1: Re-estimation of the Full Samples 1 and 2

Variable	Model 6	Model 7	Model 8
Method	2SLS	G2SLS, RE	OLS
Sample	2	2	1
IDA supported employment	0.66 ***	0.67 ***	0.54 ***
	(0.04)	(0.03)	(0.03)
Time dummies included	Y	Y	Y
Cons	5.1 ***	5.2 ***	6.0 ***
Obs	234	234	242
Prob>F	0.00	0.00	0.00
R2	0.57	0.75 (overall)	0.69
RMSE	0.59	–	0.49

Source: Author's analysis.

To test for global spatial auto-correlation we construct an inverse distance-based weights matrix based on the location (DMS latitude-longitude coordinates) of Irish county towns. This does have an advantage over contiguity based matrices in that it meets Toblers first law of geography: "Everything is related to everything else, but near things are more related than distant things". Our p-value and negative z-statistic on our test of Moran's I for Sample 2 suggests that we may reject the null hypothesis although the spatial autocorrelation present is very weak (measures closer to +1 or -1 would suggest strong positive or negative autocorrelation). The spatial distribution of IDA employment is more spatially dispersed than would be expected if underlying spatial processes were random. Similarly we have a statistically significant value on Geary's C but with a value of 1.05 (range of 0 to 2) this again suggests that the spatial autocorrelation is extremely weak.

Table A.2: Test of Spatial Autocorrelation – IDA Employment Sample 2

	I/C	E(I/C)	sd(I/C)	z	p-value
Moran's I	−0.028	−0.004	0.004	−6.546	0.00***
Geary's C	1.051	1.000	0.035	1.426	0.07*

Source: Author's analysis.

When it comes to Sample 1. Again similar results emerge with little sign of spatial autocorrelation. In Sample 1 Geary's C test is not significant and Moran's I is again close to zero in effect.

Table A.3: Test of Spatial Autocorrelation – IDA Employment Sample 1

	I/C	E(I/C)	sd(I/C)	z	p-value
Moran's I	−0.023	−0.004	0.004	−4.86	0.00***
Geary's C	1.036	1.000	0.050	0.75	0.237

Source: Author's analysis.

Finally, we look at the Anselin-Morans local I. At a local level the only counties with significant p-values in Sample 1 are Dublin, Cork, Wicklow, Louth and Longford. All have low values of I suggesting weak spatial correlation. The first four have negative z-statistics with the largest being in Cork and Dublin. In Sample 1, the only counties are again Dublin and Cork along with Kildare and Wicklow.

Finally, we perform a spatially weighted regression on Samples 1 and 2. For Sample 1 we have a temporally unbalanced panel which introduces issues in spatial panel data if it is non-random. We report a pooled spatial lag model in Model 9. Although the spatial coefficient is significant it does not have a strong impact on our coefficient of interest. Model 9 suggests a multiplier of around 3, in line with our other results.

In Model 11 we have a strongly balanced panel and thus can report a straightforward Spatial Durbin fixed effects model. From this we can also asses the direct and indirect impact of rising IDA employment in line with LeSage and Pace (2008). Again, our spatial lag coefficient is significant suggesting spillover effects are present between counties. Our spatial autoregressive coefficient, however, is not statistically significant. Again, our coefficient of interest suggests a multiplier of about 3.8 in line with our other estimates. When it comes to our long-run effects estimates, our direct effect estimates are similar to our initial multiplier estimates suggesting that the impact of investments hold over time. In addition, our results suggest significant long-term indirect positive multiplier for neighbouring counties. Further exploration of these long-term impacts may be a fruitful line for future research.

Table A.4: Spatially Weighted Regression

Variable	*Model 9*	*Model 10*
Method	Spatial lag model, pooled	Spatial Durbin model, fe
Sample	1	2
IDA supported employment	0.51***	0.63***
	(0.03)	(0.02)
Spatial lag coefficient (rho)	0.34*	0.43***
	(0.22)	(0.04)
Spatial autoregressive coefficient (lambda)	–	–0.3
		(0.25)
Long-run Direct effects	–	0.64***
		(0.02)
Long-run Indirect effects	–	0.48***
		(0.09)
Long-run Total effects	–	1.12***
		(0.09)
Year dummies included	Y	N
Cons	–26.88***	–
Obs	243	234
R2 overall	–	0.74

Source: Author's analysis.