Transport Research & Information Note

Evidence on the link between Productivity and Agglomeration for Ireland: Estimated Parameters for Wider Economic Benefit Calculations

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1 Introduction

1.1. Cost Benefit Analysis (CBA) is commonly used to assess the ex-ante economic case for transport schemes. CBA helps inform decision makers about the relative magnitude of cost and benefits, from where they are sourced, and how they play out over time. It has been used to good effect in making value for money comparisons across different types of scheme and in prioritising investments to achieve strategic objectives (e.g. Eddington 2006).

1.2. CBA uses concepts from economic theory to calculate the benefits and costs of a scheme in monetary values and produces summary measures of value for money such as the net present value of the scheme and the benefit cost ratio. In so doing, it adopts the concept of "social-welfare" as a measure of the benefits that accrue to society net of costs. Benefits and costs are measured by approximating change in consumers' surplus. An increase in net welfare is regarded as a positive outcome (for a recent review of CBA see Mackie et al. 2012).

1.3. The consumer surplus based calculation of conventional CBA capture potential benefits of transport schemes that are generated for both new and existing users of the transport system. These can arise via changes in the generalised cost of travel (e.g. in time and fare/operating costs) or in the quality of transport services. These are the so-called Direct User Benefits (DUBs) of a scheme and they typically constitute the largest component of benefits within conventional CBA calculations.

1.4. From theory, we know that under conditions of perfect competition, constant returns to scale, and in the absence of market failures; DUBs will capture all economic impacts of a transport improvement. In practice, however, market failures and scale economies tend to be prevalent in the spatial economy and this has led to developments in CBA methodology to capture what are referred to as Wider Economic Benefits (WEBs) (e.g. Venables 2007, Mackie et al. 2012, Venables et al. 2014, DfT 2014). These are benefits that are additional to conventional user benefits precisely because they arise from sources of market failure. In current UK CBA practice three categories of WEBs are recognised:

i. **Imperfect competition** - transport improvements can cause a decrease in the costs of interacting in the spatial economy, thus potentially allowing firms to profitably expand output. Output expansion yields a welfare gain in monopolistic markets when willingness to pay for the increased output exceeds the cost of producing it.

ii. **Tax revenues arising from labour market impacts** - the decisions that firms and workers make about where to locate is influenced by the accessibility offered through transport systems. If accessibility improves and causes firms / workers to move to more productive locations or have greater participation in labour markets, this will result in a tangible financial gain (i.e. higher wages or productivity). Most of this gain is captured in the consumer surplus based calculations of user benefits, but not the resulting change in tax revenue to the government (i.e. income tax, national insurance, and corporation tax).

iii. **Agglomeration economies** - transport improvements can increase the potential scale of economic interactions available in the economy, with implications for the relative level of agglomeration experienced by firms. Essentially, improved transportation increases accessibility to economic mass and this yield scale economies of agglomeration.

1.5. Of the three defined sources of WEBs, most attention has focused on productivity effects that arise via agglomeration economies, because these are thought be by far the largest source of WEBs and because they can be quantified with a reasonable degree of accuracy via established econometric methods (e.g. Graham 2005, 2006, 2007b, Graham et al. 2009, Mare and Graham 2009, 2013). The key parameters require to calculate WEBs of agglomeration are elasticities of productivity with respect to agglomeration. Graham and Gibbons (2018) provide a comprehensive up-to-date survey of the evidence and methods required to evaluate agglomeration elasticities for use within transport appraisal.

1.6. In this report we present empirical work undertaken to estimate agglomeration elasticities for Ireland. The report is structured as follows. Section 2 reviews international empirical estimates of urban agglomeration elasticities to provide some context on the magnitude of these effects. Section 3 describes the data available to estimate agglomeration elasticities for Ireland. Section 4 describes the methods and econometric models use for estimation. Results are presented in section 5. Finally, section 6 concludes with a summary of the main findings of the report.

2 Review of Estimates of Urban Agglomeration Economies

Estimates from the International Academic Literature

2.1. The spatial distribution of economic activity exhibits tendencies towards spatial concentration, or *agglomeration*. We observe this tendency at the level of cities, which contain vast concentrations of economic activity despite high land prices, rents and other costs. We can also observe forces of agglomeration at an industrial level, for instance in the spatial concentration of financial sectors in Wall Street or the City of London; or in the co-location of information technology firms found around Silicon Valley.

2.2 In this section we review empirical evidence on the productivity effects of urban agglomeration obtained for different countries throughout the world. Empirical studies of agglomeration measure represent productivity in one of two ways: i) as total factor productivity (TFP) within a production function framework; or ii) as labour productivity within a wage equation by invoking the assumption that workers are paid the value of their marginal product.

2.3. Economic theory states that the process of agglomeration is driven by the presence of productive advantages offered through concentration. These include improved opportunities for labour market pooling, knowledge interactions, specialisation, and the sharing of inputs and outputs (e.g. Duranton and Puga 2004). These ‘mechanisms’ or ‘sources’ of agglomeration economies are thought to result in higher productivity and lower average costs for firms. Furthermore, due to increasing returns, the larger the scale of agglomeration the greater the productivity benefits that accrue.

2.4. Accordingly, empirical work on agglomeration has sought to estimate the relationship between productivity and measures of spatial economic mass. Evidence of a positive relationship is viewed as consistent with the existence of agglomeration economies. Agglomeration has typically been measured by city size (via population or employment) or via a variable measuring the accessibility to economic mass. Productivity has been represented by wages or by Total Factor Productivity (TFP).

2.5. Key international empirical evidence on urban agglomeration economies is shown in Table 1, which reproduces estimated elasticities from relevant papers. The table shows the number of elasticity estimates collected from each study, the mean elasticity value, the median elasticity value, and the range of estimated elasticity values. Figure 1 provides a histogram of the values shown in the table.

2.6. The general consensus we can draw from the literature is that agglomeration economies exist and that they induce higher productivity for firms and workers. Estimates vary between -0.800 and 0.658 and have unweighted mean equal to 0.046. An elasticity of 0.046 implies an increase of 0.46% in productivity levels for a 10% increase in the level of agglomeration.

2.7. Figure 1 also shows that there is considerable variation in the size-distribution of the elasticity values, even within the sub-sample of positive estimates. Melo et al. (2009) conduct a meta-analysis of the empirical literature on urban agglomeration economies to investigate differences in size of the estimates. They find large differences in estimates across countries reflecting differences in the particular nature of economies and their urban systems.

Table 1: International Estimates of Urban Agglomeration Elasticities

study	country	period	data	aggregation	obs.	mean	median	Range
Aaberg (1973)	Sweden	1965-68	CS	regions	4	0.017	0.018	[0.014, 0.019]
Ahlfeldt et al. (2015)	Germany	1936-1986-2006	PD	regions	3	0.062	0.066	[0.045, 0.074]
Au and Henderson (2006)	China	1997	CS	regions	2	0.013	0.013	[-0.007, 0.033]
Baldwin et al. (2007)	Canada	1999	CS	plant	8	0.061	0.071	[-0.008, 0.104]
Baldwin et al. (2008)	Canada	1989-1999	PD	plant	6	-0.088	-0.130	[-0.310, 0.300]
Brulhart and Mathys (2008)	Europe	1980-2003	PD	regions	14	-0.080	0.055	[-0.800, 0.280]
Ciccone (2002)	Europe	1992	CS	regions	7	0.047	0.045	[0.044, 0.051]
Ciccone and Hall (1996)	US	1988	CS	regions	8	0.053	0.049	[0.035, 0.084]
Cingano and Schivardi (2004)	Italy	1992	CS	regions	13	0.054	0.064	[0.019, 0.073]
Combes et al. (2010)	France	1988	PD	worker	43	0.035	0.037	[0.012, 0.054]
Combes et al. (2008)	France	1988	PD	zone	11	0.052	0.035	[0.024, 0.143]
Combes et al. (2012)	France	1994-2002	PD	plant	17	0.090	0.070	[0.040, 0.190]
Davis and Weinstein (2003)	Japan	1985	CS	regions	11	0.027	0.028	[0.010, 0.057]
DiAddario and Patacchini (2008)	Italy	1995-2002	PD	worker	1	0.010	0.010	[0.010, 0.010]
Fingleton (2003)	UK/GB	1999-2000	CS	regions	3	0.017	0.016	[0.016, 0.018]
Fingleton (2006)	UK/GB	2000	CS	regions	7	0.025	0.018	[0.014, 0.049]
Graham (2000)	UK/GB	1984	CS	regions	22	-0.006	-0.001	[-0.168, 0.141]
Graham (2005)	UK/GB	1998-2002	PD	firm	36	0.193	0.171	[-0.037, 0.503]
Graham (2007b)	UK/GB	1995-2004	PD	firm	28	0.110	0.098	[-0.191, 0.382]
Graham (2007a)	UK/GB	1995-2004	PD	firm	18	0.194	0.195	[0.041, 0.399]
Graham (2009)	UK/GB	1995-2004	PD	firm	108	0.097	0.083	[-0.277, 0.491]
Graham and Kim (2008)	UK/GB	1995-2004	PD	firm	18	0.079	0.049	[-0.13, 0.306]
Graham et al. (2009)	UK/GB	2000-2006	PD	plant	5	0.041	0.034	[0.021, 0.083]
Graham and Van Dender (2011)	UK/GB	1995-2004	PD	firm	6	0.072	0.061	[0.009, 0.134]
Henderson (1986)	Brazil	1970-72	CS	regions	52	0.010	0.018	[-0.366, 0.18]
Henderson (2003)	US	1982	PD	firm	4	0.024	0.017	[-0.127, 0.189]
Hensher et al. (2012)	Australia	2006	CS	zone	39	0.071	0.051	[-0.049,406]
Holl (2012)	Spain	1991-2005	PD	firm	23	0.089	0.047	[-0.079, 0.827]
Kanemoto et al. (1996)	Japan	1985	CS	regions	9	0.089	0.070	[0.010, 0.250]
Lall et al. (2004)	India	1991	CS	plant	18	0.017	0.007	[-0.204, 0.658]
Mare (2016)	NZ	2001-2012	PD	plant	31	0.075	0.075	[0.0405, 0.116]
Mare and Graham (2013)	NZ	1999-2007	PD	plant	114	0.043	0.048	[-0.13, 0.222]
Marrocu et al. (2013)	Europe	1996-2007	CS	regions	5	0.036	0.041	[0.027, 0.040]
Martin et al. (2011)	France	1996-2004	PD	plant	8	0.011	0.010	[-0.06, 0.066]
Melo and Graham (2009)	UK/GB	2002-2006	PD	worker	64	0.029	0.020	[-0.13, 0.114]
Mion and Naticchioni (2005)	Italy	1995	PD	worker	30	0.034	0.022	[0.002, 0.109]
Moomaw (1981)	US	1967	CS	regions	18	0.060	0.032	[0.006, 0.319]
Moomaw (1983)	US	1977	CS	regions	26	0.038	0.034	[-0.052, 0.182]
Moomaw (1985)	US	1972	PD	regions	36	0.040	0.036	[-0.104, 0.27]
Morikawa (2011)	Japan	2002-2005	PD	firm	4	0.110	0.110	[0.070, 0.150]
Nakamura (1985)	Japan	1979	CS	cities	38	0.026	0.022	[-0.037, 0.081]
Rice et al. (2006)	UK/GB	1998-2000	CS	regions	14	0.026	0.024	[-0.005, 0.07]
Rosenthal and Strange (2008)	US	2000	CS	worker	9	0.042	0.046	[0.025, 0.058]
Sveikauskas et al. (1988)	US	1977	CS	regions	6	0.013	0.014	[0.007, 0.017]
Sveikauskas (1975)	US	1967	CS	regions	42	0.057	0.054	[0.012, 0.124]
Tabuchi (1986)	Japan	1980	CS	regions	57	0.060	0.056	[-0.079, 0.300]
Wheeler (2001)	US	1980	CS	worker	3	0.017	0.020	[0.000, 0.030]
Average					1043	0.046	0.043	[-0.800, 0.658]

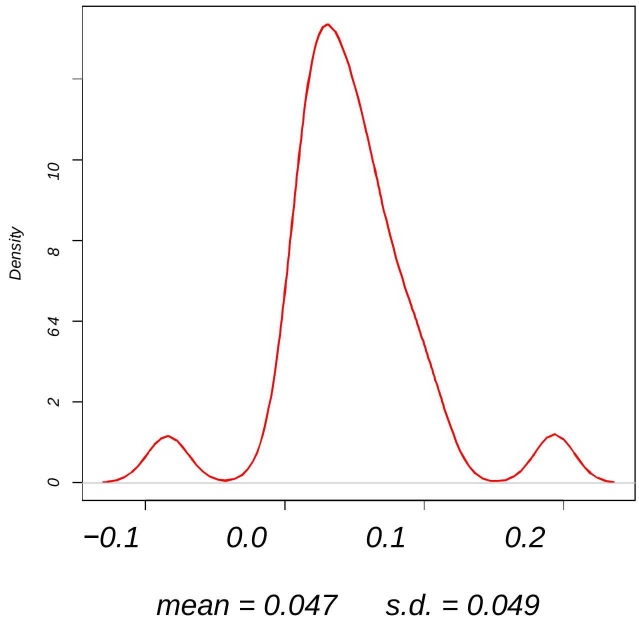

Figure 1: Histogram of Urban Agglomeration Elasticities.

They also find substantial differences in the magnitude of agglomeration economies across industry sectors, with service industries tending to derive considerably larger benefits from urban agglomeration than manufacturing.

2.8. In addition to these broad contextual factors, the methodological approaches used to estimate elasticities can also have a large influence on results. This is evident both between and within studies. In particular, the magnitude of agglomeration estimates is strongly influenced by the manner in which studies have, or have not, attempted to correct for potential sources of 'endogeneity'.

2.9. In summary, there is a great deal of empirical evidence indicating that a positive causal relationship exists between agglomeration and productivity, and this finding is consistent with key insights from urban economic theory. The literature also shows that the data and methods used to estimate the relationship between agglomeration and productivity matter for the results obtained. In particular, in order to obtain causal inference on productivity-agglomeration effects, it is necessary to adjust for potential sources of endogeneity. This issue is discussed further in the methods section below.

Agglomeration Parameter Values Used in WebTAG

2.10. CBA practice in the UK applies estimates of agglomeration elasticities to quantify the WEBs of transport schemes. The agglomeration parameter values used for appraisal in the UK were estimated by Graham et al. (2009). They use ONS firm level micro panel data, from the Annual Respondents Database (ARD), to estimate TFP within a Cobb- Douglas production function model. They adopt a panel control function approach for estimation to addresses potential sources of endogeneity arising from unobserved productivity, including via heterogeneity in input quality.

2.11. To represent agglomeration, they use an ED measure of the form:

$$n\rho_i^D = \sum_{j=1}^{n} \frac{m_j}{d_{ij}^{\alpha}}$$

Agglomeration elasticities are estimated separately for four broad sectors of the economy: manufacturing, construction, consumer services and business services.

2.12. The results from this study yield an overall agglomeration elasticity of 0.04 across all sectors of the economy. For manufacturing and consumer services they estimate an elasticity of 0.02, for construction 0.03, and for business services 0.08. The distance decay parameter is found to be approximately 1.0 for manufacturing, but around 1.8 for consumer and business service sectors and 1.6 for construction. This implies that the effects of agglomeration diminish more rapidly with distance from source for service industries than for manufacturing. The relative impact of agglomeration on productivity is, however, larger for services than it is for manufacturing.

2.13. The key empirical results of their research are summarised in Table 2.

Table 2: Summary of UK Agglomeration Elasticity Parameters Estimated by Graham et al. (2009)

	SIC	*Agglomeration Elasticity*	α
Manufacturing	*15-40*	*0.024*	*1.122*
		(0.002)	*(0.127)*
Construction	*45*	*0.034*	*1.562*
		(0.003)	*(0.159)*
Consumer services	*50-64*	*0.024*	*1.818*
		(0.003)	*(0.190)*
Business services	*65-75*	*0.083*	*1.746*
		(0.007)	*(0.144)*
Economy (weight aver.)	*15-75*	*0.044*	*1.659*

3. Data

3.1. The literature reviewed in section 2 has made substantial progress in understanding the conditions required to obtain valid inference on agglomeration effects. In particular, recent empirical work has demonstrated the considerable superiority of models based on disaggregate micro-level panel data, over aggregate cross-sectional models. This arises for the following reasons.

1. Micro panel data allow for application of sophisticated methodologies capable of producing robust measures of productivity.
2. Micro panel models can allow dynamics and adjustment in behaviour (i.e. lagged effects) to be studied.
3. The precision of estimation can be increased by using both between unit and within unit variation.
4. The behavioural assumptions inherent in economic theory (i.e. profit maximisation, cost minimisation, competitive equilibrium) have micro foundations and it is thus most appropriate to test theory at a micro level.

3.2. To estimate elasticities of productivity with respect to agglomeration for Ireland we therefore seek to construct a micro panel data set that allow us to represent.

1. Spatial variance in levels of agglomeration within Ireland and over time; and
2. Spatial variance in micro-productivity across Ireland and over time.

3.3. In this section of the report we discuss the data used to represent these phenomena.

Measuring Agglomeration

3.4. To capture variance in the level of agglomeration within Ireland, and over time, we use a mean effective density (MED) connectivity metric. MED values measure the level of agglomeration in terms of access to economic mass (ATEM). We construct this metric at the level of electoral divisions within Ireland, of which there are 3,440.

3.5. Indexing electoral divisions, or units, by *i*, i = (1, ...n), or j, j = (1, ...n), the MED for unit i, which we denote ρ_i is calculated as;

$$\rho_i = \frac{1}{n}\sum_{j=1}^{n}\frac{E_j}{d_{ij}^{\alpha}}$$

where E_j is total workplace-based employment at unit j, d_{ij} is the Euclidean distance from the centroid of unit i to the centroid of unit j as calculated from geographic coordinate using Pythagoras theorem, and α is a distance decay parameter to be determined (though often assumed to be 1.0).

3.6. The employment data used to calculate MEDs have been supplied by Edgar Morgenroth. These are panel data for electoral divisions over the period 2006-2016. Interpolation was required to produce values between major census years.

3.7. Summary statistics for MED values calculated using these employment data (with α value set to 1.0) are shown in Table 3 below.

Table 3: Summary of MED values for Ireland

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
mean	8.76	9.26	9.38	8.78	8.53	8.47	8.41	8.62	8.80	9.11	9.44
median	5.68	6.07	6.20	5.72	5.52	5.47	5.42	5.54	5.67	5.86	6.06
std. dev.	9.82	10.24	10.23	9.80	9.63	9.55	9.53	9.81	9.98	10.32	10.76
max	90.63	94.74	94.80	90.86	89.42	88.89	88.64	91.11	92.57	95.68	99.79
min	2.47	2.61	2.65	2.45	2.37	2.36	2.34	2.40	2.45	2.54	2.62
skewness	3.62	3.61	3.60	3.62	3.64	3.65	3.65	3.65	3.64	3.64	3.65

The summary statistics indicate that MED values for Ireland follow a highly skewed distribution. Mean MED values are in the range 8.5 to 9.5, while maximum values fall in the range 90.0 to 100.0.

This skewed distribution is illustrated in Figure 2 in the form of a kernel density plot.

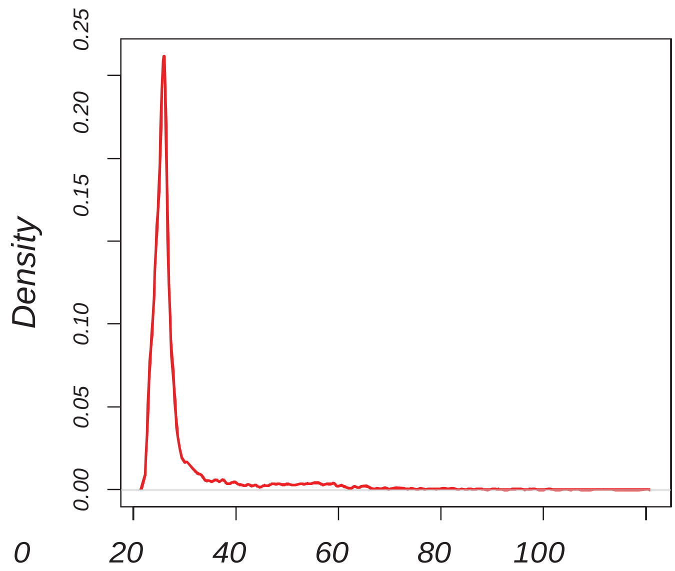

Figure 2: Kernel Density Plot of 2016 MED Values for Ireland

3.8. The plot shows that the vast majority of MED values fall in the range 0 to 20. In fact, very large values tend to be concentrated in and around the Dublin metropolitan area. The spatial distribution of Irish MED values is shown in Figure 3 below. Map (a) show a plot of the full spatial distribution of MED values while plot (b) shows a plot of MED values in the range 0 to 20.

3.9 The dominance of Dublin in terms of agglomeration is clearly evident. Restricting the range of MED values to a maximum of 20, as in plot (b), allows us to see the influence of other important settlements including Kilkenny, Cork, Limerick and Galway.

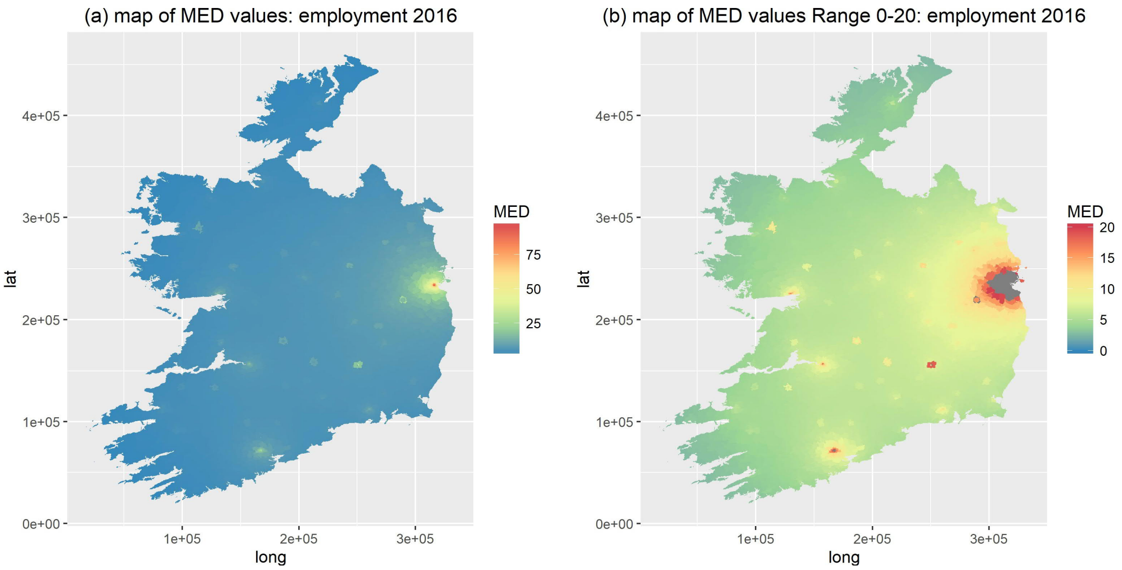

Figure 3: MED values for Ireland with Total Employment as Mass

Distance Decay

3.10. The impedance function of the MED measure of agglomeration typically includes an exponent on distance, denoted α, which is used in appraisal calculations to model the decay of agglomeration with distance from source. This is a key parameter that determines the sensitivity of the agglomeration index to changes in impedance. The higher the value of α, the more sensitive the measure of agglomeration to reductions in impedance (i.e. transport cost reductions) (for a comprehensive discussion see Graham and Gibbons 2018). Figure 4 and Table 4 show MEDs for Irish zones calculated using different values of the distance decay parameter α.

Table 4: Summary statistics for MED values for Irish Zones with Different Distance Decay Values

α	*0.50*	*0.75*	*1.00*	*1.25*	*1.50*
min	*34.99*	*9.16*	*2.47*	*0.70*	*0.21*
median	*51.80*	*16.83*	*5.68*	*2.00*	*0.74*
mean	*55.84*	*20.53*	*8.76*	*4.55*	*2.92*
max	*140.08*	*103.19*	*90.63*	*89.53*	*95.75*
sd	*17.14*	*12.91*	*9.82*	*7.93*	*6.96*
sd/mean	*0.31*	*0.63*	*1.12*	*1.74*	*2.39*

3.11. The data show that by increasing α, the mean of the MED values falls, but the distribution becomes more skewed and the coefficient of variation increases. In effect, when the value of α is increased, the influence of the mass of outlying zones on the MED value diminishes in relative terms while that of proximate zones increases. In other words, higher values of α imply a higher degree of localisation of agglomeration effects. Note that the value of α can vary by industry, as is the case in the set of parameter values used for transport appraisal in the UK (see Table 2 above).

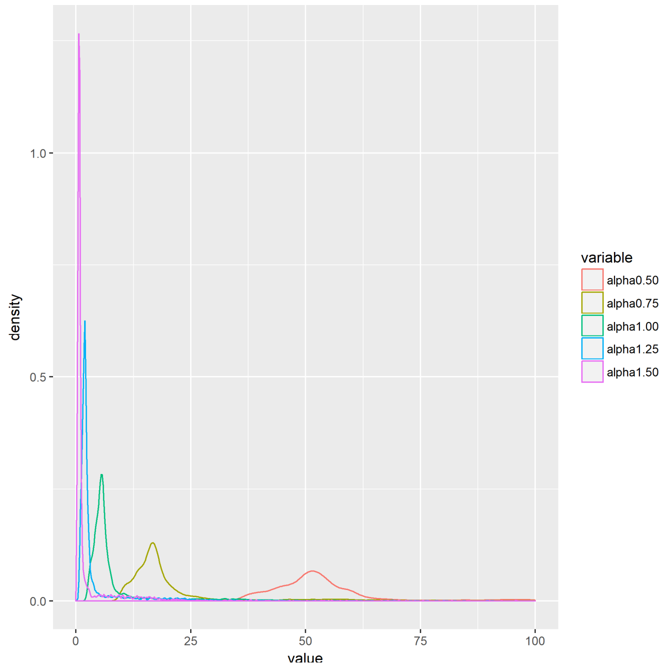

Figure 4: Densities for MEDs with Different Distance Decay Values

Measuring Productivity

3.12. To represent spatial variance in productivity across Ireland, and over time, we have constructed a panel firm level dataset from Companies House records available through the on-line database Financial Analysis Made Easy (FAME). From the FAME data we have derived an unbalanced panel of over 20,000 Irish single plant companies over the period 2008-2017. Postcode information for firms has been used to derive GIS co-ordinates. Figure 5 shows the geographic distribution of firms obtained from the FAME data.

3.13. By superimposing an electoral district GIS layer on top of the firm coordinate layer we can assign the relevant zone level MED measures to each firm, thus linking our production data set to our agglomeration measures.

3.14. The geo-coded FAME and MED data allow us to develop an empirical representation of a production function of the form:

$$y_{it} = g(\rho_{it}, Z_{it})f(x_{it}),$$

where y_{it} measures the output of firm i at time t, x_{it} is a vector of factor inputs, ρ_i is the MED value for the zone in which firm i resides at time t, and Z_{it} represents other time-varying or time invariant factors that determine firm TFP.

3.15. For firm output we use a measure of turnover as reported in the Companies house data. We define three factor inputs in the production function:

1. Labour - measured as the number of employees per firms,
2. Capital - measured as the value of fixed assets per firms, and
3. Materials (or intermediates) - measured as the value of current assets per firms.

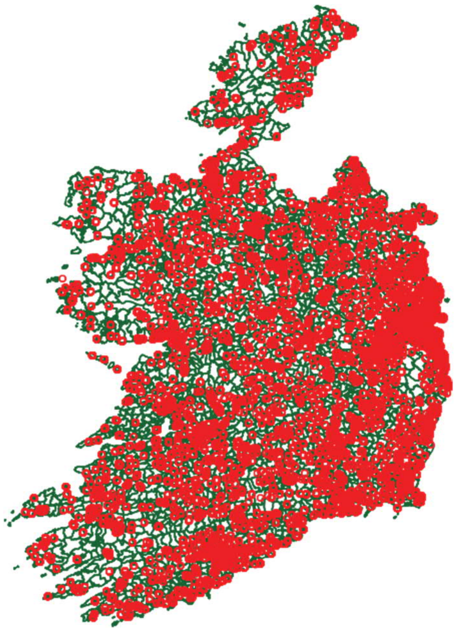

Figure 5: Distribution of firms from the FAME data

3.16. We disaggregate our analysis of agglomeration by industry, according to the following classification based on the Standard Industrial Classification (SIC) 2007.

Table 5: Industrial Sectors for Analysis of Agglomeration

	Sector	Code	SIC Divisions
1	Manufacturing	MAN	10-33
2	Construction	CON	41-43
3	Wholesale & Distribution	WAD	45-47
4	Transport	TRA	49-56
5	Information & Communication Technology	ICT	58-63
6	Financial & Business services	FIN	64-74

Similar to the UK evidence, we do not analyse agglomeration effects for primary industries or public services since the case for urban agglomeration economies in these sectors is not straightforward.

4 Methods

Estimation Strategy

4.1. As mentioned above, the data available for estimation allow us to model production functions of the form:

$$y_{it} = g(\rho_{it}, Z_{it})f(x_{it}).$$

4.2. Estimation of the production function allows us to isolate the determinants of total factor productivity (TFP) for each observation, which we denote $\omega_{it} = g(\rho_{it}, Z_{it})$. TFP is a measure of the efficiency of production given the use of all defined factors or production.

4.3. We are particularly interested in the effect of agglomeration on TFP. Specifically, our target of inference is the elasticity of TFP with respect to agglomeration.

$$\delta^s = \partial \log \omega^s / \partial \log \rho.$$

We estimate this quantity separately for each of the six sector s = (1, ..., 6) of interest.

4.4. To be suitable for use in transport appraisal our estimates of δ^s should capture the causal effect of agglomeration on productivity as distinct from an associational effect. In other words, as far as possible, we want to measure how an actual change in agglomeration directly affects productivity, net of other potentially spurious influences (i.e. Z_{it}). The main challenges that have to be addressed to obtain valid causal inference relate to potential sources of endogeneity in estimation. These are as follows:

1. **Endogeneity via unobserved productivity** - the relationship between inputs and outputs is imperfectly observed because factors such as input quality and technology are not measured. Furthermore, the production function inputs themselves cannot be treated as truly exogenous because inputs are chosen by the producer in the knowledge of some expected level of productivity (e.g. Griliches and Mairesse 1995, Van Beveren 2012). This implies the existence of a productivity component that is unobserved but important to TFP, and which may be determined in various ways by local technology factors such as agglomeration. If ignored, unobserved productivity can induce bias and inconsistency in estimation of TFP.

2. **Endogeneity via spatial sorting / functional self-selection** - firms within the same industry are typically engaged in different activities across different types of locations. This is due to spatial self-selection of labour, with high quality workers self-selecting into zones that contain the highest quality jobs. This is sometimes referred to as a people versus place distinction, in which the 'place' based effects of agglomeration are obscured by the 'people' based effects of sorting.

3. **Reverse causality** - the relationship between agglomeration and productivity is likely bi-directional since higher productivity locations may attract a greater level of private investment over time leading to larger economic mass. This increase in mass can 'feedback' in the form of higher productivity.

4. **Endogeneity via output price heterogeneity** - because GVA is a price-based measure firms that exist in local markets with higher prices may have seemingly higher productivity, even in the absence of superior efficiency.

5. **Endogeneity via confounding / omitted variables** - the 'pure' effect of agglomeration may be just one element of local technology that could affect productivity.

4.5. Following Graham et al. (2009) and Mare and Graham (2013) we address these methodological challenges using a panel data control function (CF) approach for TFP estimation. Under this approach, structural assumptions concerning firm behaviour are used to derive a proxy for unobserved productivity resulting from endogeneity. The proxy function, which must be very highly correlated with the endogenous unobserved productivity, is introduced into the production function as an additional model component to obtain consistent parameter estimates (for an extensive review of the CF approach see Van Beveren 2012).

4.6. There are a variety of different procedures that have been used to derive the function that proxies for unobserved productivity. Olley and Pakes (1996) (OP) used the firm's long run profit maximisation problem to drive an expression for unobserved productivity as a function of investment and capital stock. Levinsohn and Petrin (2003) (LP) criticised the assumption of a monotonic relationships between investment and productivity inherent in OPs model, and instead used the firm's short run profit maximisation problem to derive a proxy function with intermediate inputs and capital as arguments. More recently, Ackerberg et al. (2015) have cited problems of multicollinearity between factor inputs in the OP and LP approaches as a hindrance to identification, and have instead proposed a proxy function based on invertibility of an input demand function with labour choice conditional on the choice of intermediates.

4.7. We adopt a CF approach, and model the effects of agglomeration on TFP using both a one-step or two-step procedure.

1. **One step procedure** - we include a measure of the log of agglomeration within the production function itself as a 'state variable'. Classification as a state variable implies that the firm's choice of agglomeration is determined in a past period, and therefore, that the level of this variable is unaffected by contemporaneous idiosyncratic shocks to productivity. The other state variable is capital, labour is defined as 'free variable' and intermediates is defined as our proxy variable. We include two-digit industry-year dummies as control variables.

   The one-step CF approach yields estimates of the effect of agglomeration on productivity that are conditional on unobserved productivity effects arising from firm specific technology, thus giving us the partial derivatives $\partial \log \omega s / \partial \log \rho$.

2. **Two-step procedure** - first, TFP is estimated from the production function in a first stage model similar to the one-step procedure but without agglomeration as a state variable. Second, the predicted values of TFP are then used as the dependent variable in a second stage regression on agglomeration and other relevant control variables. The TFP estimate produce from the first stage regression is an estimate of $\omega it = g(\rho it, Zit)$.

   The merits of the two-step approach are that it permits flexibility in modelling the relationship between agglomeration and productivity, and it allows us test some specific hypothesis about the underlying nature of unobserved productivity and the influence of controls on agglomeration estimates.

Econometric Models

4.8. For the one-step procedure we estimate the production function using the Ackerberg et al. (2007) (ACF) CF approach. The estimated model is

$$\log y_{it} = \omega'_{it} + \delta \log \rho_{it} + \beta_L \log L_{it} + \beta_M \log M_{it} + \beta_K \log K_{it} + \gamma_{dt} + u_{it}$$

where $\omega'_{it} = \beta_0 + f(Z_{it})$ is unobserved productivity due to non-agglomeration related factors, K is capital stock for firm i at time t, L is labour, M is intermediate inputs, and γ_{dt} is a set of two-digit industry-year fixed effects which capture temporal industry shocks and adjust for inflation. u_{it} is a zero mean error term. For the construction sector, which has only 3 two-digit industries defined, we use year dummies rather an industry year interaction.

4.9. For the two-step CF procedure our first stage regressions involve estimation of Cobb-Douglas production functions of the form

$$\log y_{it} = \omega_{it} + \beta_L \log L_{it} + \beta_M \log M_{it} + \beta_K \log K_{it} + \gamma_{dt} + c_{it}$$

where the error term $c_{it}$is an idiosyncratic shock distributed as white noise error. Again, we apply the ACF CF approach in these first stage regressions.

4.10. TFP is captured by the term $\omega_{it} = \beta_0 + f(\rho_{it}, Z_{it})$, which comprises a term β_0 that measures the mean efficiency across firms and over time; and a second term $f(\rho_{it}, Z_{it})$, which represents deviation from this mean due to unobserved productivity that may be time-varying or time invariant and may arise from the 'technology' of the firm it-self or from the environment in which the firm is located, including via the level of agglomeration (i.e. ρ_{it}).

4.11. CF estimation yields consistent estimates of the output elasticities of the production function. Having obtained estimates of $\hat{\beta}_L, \hat{\beta}_M$, and $\hat{\beta}_K$, we estimate firm specific TFP via:

$$\hat{\omega}_{it} = \log y_{it} - \hat{\beta}_L \log L_{it} - \hat{\beta}_M \log M_{it} - \hat{\beta}_K \log K_{it} - \hat{\gamma}_{dt}.$$

Note that our estimates of ωˆit are conditional on fixed 2-digit industry year effects. In the second stage, we use estimates of ωit in models of the form:

$$\hat{\omega}_{it} = \alpha + \delta \log \rho_{it} + \tau Z_{it} + \varepsilon_{it}$$

where in addition to variables already defined $\varepsilon_{it} \sim N(0, \sigma_\varepsilon)$ is a random error.

5 Results

One-step Estimation

Estimates Assuming Unitary Distance Decay

5.1. We first consider estimates obtained by constraining the distance decay parameters of the MED variables to equal 1.0. These results provide a useful comparison to the international literature on productivity-agglomeration effects as summarised in Table 1, which has also in general assumed unitary distance decay.

5.2. Results from regression based on an ACF CF approach for production function estimation with agglomeration included as a state variable are shown in Table 6 below.

Table 6: Production Function Estimated using the Ackerberg et al. (2007) Control Function Approach with Agglomeration as a state variable: α = 1.0

	MAN	CON	WAD	TRA	ICT	FIN
log(L)	0.106	0.411	0.497	0.388	0.303	0.416
	(461.29)	(52.94)	(31.40)	(4.74)	(62.46)	(21.63)
log(K)	0.064	0.139	0.084	0.043	0.055	0.065
	(52.98)	(7.80)	(6.21)	(1.09)	(2.29)	(3.07)
log(M)	0.767	0.473	0.579	0.575	0.698	0.553
	(365.92)	(19.67)	(16.20)	(15.87)	(67.35)	(23.08)
log(ρ)	0.219	0.065	-0.046	0.108	-0.002	0.078
	(500.68)	(2.80)	(-0.85)	(5.65)	(-0.13)	(6.81)
α	1.00	1.00	1.00	1.00	1.00	1.00
RTS	0.937	1.023	1.160	1.006	1.056	1.034
N	415	238	1432	354	930	3982

5.3. As mentioned previously, agglomeration enters the production function as a state variable and the resulting estimates of δ therefore in theory capture the conditional effect of agglomeration on productivity (i.e. net of unobserved productivity effects arising from firm specific technology).

5.4. The estimated output elasticities are significant (Z-statistics are shown in parentheses) and overall, they look plausible. Estimates of returns to scale (RTS) are close to 1.0 in all cases, which indicates that given the standard errors, most sectors appear to operate under constant returns to scale.

5.5. We obtain positive estimates of urban agglomeration economies for four of the six sectors listed in the table: manufacturing (0.219), construction (0.065), transport (0.108) and financial & business services (0.078). We do not find significant effects for wholesale and distribution or information & communications technologies.

5.6. In general, the order of magnitude of these estimated agglomeration elasticities appears high in relation to evidence from the existing literature (see Table 1) or to that obtained for the UK (see Table 2). These elasticities, however, are generated under the restrictive assumption of unitary distance decay, which we now relax in the next subsection.

Estimates Over Varying Values of Distance Decay

5.7. To relax the assumption of unitary distance decay we repeatedly estimated the ACF CF models using different values for the distance decay parameter α. Values are selected in the range 0.5 to 2.5 in steps of 0.25. 'Preferred models' are then chosen using the Z-statistics for the agglomeration covariate (i.e. log(ρ)). Where results exhibit instability across different values of α, we neglect estimates inconsistent with theory (i.e. of implausible magnitude) and choose the most statistically significant estimates close to the α value of 1.0.

5.8. Again, agglomeration is specified as a state variable in the ACF CF models. Results are shown in Table 7.

Table 7: Production Function Estimated using the Ackerberg et al. (2007) Control Function Approach with Agglomeration as a state variable: optimum values of α

	MAN	*CON*	*WAD*	*TRA*	*ICT*	*FIN*
log(L)	*0.133*	*0.411*	*0.497*	*0.407*	*0.317*	*0.419*
	(0.000)	*(0.008)*	*(0.016)*	*(0.006)*	*(0.027)*	*(0.013)*
log(K)	*0.066*	*0.139*	*0.084*	*0.050*	*0.045*	*0.068*
	(0.001)	*(0.018)*	*(0.013)*	*(0.078)*	*(0.012)*	*(0.021)*
log(M)	*0.749*	*0.473*	*0.579*	*0.579*	*0.694*	*0.555*
	(0.000)	*(0.024)*	*(0.036)*	*(0.088)*	*(0.032)*	*(0.083)*
log(ρ)	*0.015*	*0.065*	*-0.046*	*0.092*	*0.018*	*0.058*
	(0.000)	*(0.023)*	*(0.054)*	*(0.022)*	*(0.012)*	*(0.010)*
α	*1.25*	*1.00*	*1.00*	*1.25*	*1.50*	*1.50*
RTS	*0.948*	*1.023*	*1.160*	*1.036*	*1.056*	*1.042*
N	*415*	*238*	*1432*	*354*	*930*	*3982*

Again, we find positive and significant agglomeration economies for four of the six sectors: manufacturing (0.015), construction (0.065), transport (0.022) and financial & business services (0.058). Note the substantial shift in the magnitude of the elasticity estimates that is induced by selecting an optimal value of α.

5.9. We do not find a significant effect for information & communications technologies and we find a small significant negative effect for wholesale and distribution. Results for these two sectors are fairly consistent across different values of α. We obtain agglomeration elasticities that look more plausible relative to the international empirical evidence.

5.10. The results in table also compare reasonably well to the WebTAG parameters used in the UK. We find that the distance decay parameter for financial & business services is somewhat larger than that of manufacturing or construction. Our estimated elasticity for manufacturing is 0.015 compared to 0.024 for the UK, and for financial & business services 0.058 compared to 0.083 for the UK.

5.11. However, it also should be noted that we do find instability of estimates across different decay parameter values. For sectors with relatively small samples, such as manufacturing and construction, this instability can be quite considerable. The reasons underpinning this effect are poorly understood in the existing literature but are the subject of ongoing research in the UK (see Graham and Gibbons 2018)

Two-step Estimation

5.12. The one-step TFP approach gives estimates of productivity-agglomeration effects that are conditional on unobserved productivity as captured using the Ackerberg et al. (2007) Control Function Approach. Alternatively, as mentioned above, we can omit the agglomeration variable from the first stage TFP model, and then conduct second stage regressions of estimated TFP on agglomeration to obtain productivity-agglomeration elasticities.

5.13. Estimates of TFP that we obtain from the first stage regression capture unobserved productivity at the firm level, for instance arising from differences in input quality, as well as local technology factors arising from agglomeration or other sources. The advantage of the two-step approach is that we can test some specific hypothesis about the underlying nature of unobserved productivity and the influence of controls on agglomeration estimates.

5.14. Following Mare and Graham (2013) we consider three models to gauge the impacts of alternative controls for firm heterogeneity and the sorting of input quality across locations and industries.

1. Base Model - no controls included, other than via the two-digit industry-year fixed effects included in the first stage TFP regressions.
2. Within Local Industry - adds two-digit industry-county fixed effects to the Base Model. There are 34 counties within Ireland. We specify the within local industry model to account for the possibility that higher quality factor inputs sort into higher-density regions.
3. Within Enterprise - this specification adds a firm level fixed effect to the Base Model, allowing for firm specific effects that are correlated with TFP and with the level of agglomeration. This model will correct for bias when firms with high idiosyncratic productivity are disproportionately located in high density areas. However, since our measure of agglomeration is highly persistent over time, the within firm panel approach can effectively remove much of the cross-sectional identifying variance, possibly leading to attenuation bias and inefficiency (for a discussion see Mare and Graham 2013)

5.15. In the first stage of our two-step procedure we use a ACF CF approach to obtain consistent estimates of the output elasticities of the production function. Results from these first stage regression are shown in Table 8 below.

Table 8: Production Function Estimated using the Ackerberg et al. (2007) Control Function Approach

	MAN	*CON*	*WAD*	*TRA*	*ICT*	*FIN*
log(L)	*0.119*	*0.404*	*0.460*	*0.347*	*0.284*	*0.401*
	(0.000)	*(0.053)*	*(0.044)*	*(0.045)*	*(0.029)*	*(0.008)*
log(M)	*0.797*	*0.664*	*0.542*	*0.592*	*0.696*	*0.559*
	(0.001)	*(0.113)*	*(0.054)*	*(0.057)*	*(0.009)*	*(0.020)*
log(K)	*0.0738*	*-0.0755*	*0.0759*	*0.0749*	*0.0658*	*0.0629*
	(0.002)	*(0.014)*	*(0.018)*	*(0.078)*	*(0.028)*	*(0.025)*
RTS	*0.9898*	*0.9925*	*1.0779*	*1.0139*	*1.0458*	*1.0229*
N	*446*	*248*	*1528*	*358*	*969*	*4305*

The output elasticities are significant and overall they look plausible, with the possible exception of the capital output elasticity for the construction sector. Estimates of returns to scale (RTS) are close to 1.0 in all cases, which indicates that given the standard errors, most sectors appear to operate under constant returns to scale.

Base Models

5.16. The results from our base models are shown in Table 9 below. The distance decay parameter values selected match those fitted in the one-step models.

Table 9: Two stage TFP Base Model Estimates of Elasticities of Productivity w.r.t Agglomeration

	MAN	*CON*	*WAD*	*TRA*	*ITC*	*FIN*
log(ρ)	*0.108*	*0.174*	*-0.033*	*0.043*	*-0.021*	*0.049*
	(0.038)	*(0.065)*	*(0.021)*	*(0.033)*	*(0.034)*	*(0.011)*
α	*1.25*	*1.00*	*1.00*	*1.25*	*1.50*	*1.50*
N	*415*	*238*	*1432*	*354*	*930*	*3982*
adj-R2	*0.017*	*0.025*	*0.001*	*0.002*	*3.92E-04*	*0.005*

From the base models we obtain positive estimates of urban agglomeration economies for three of the six sectors listed in the table: manufacturing (0.108), construction (0.174) and financial & business services (0.049). Note that these unconditional elasticity estimates are higher than the one-stage conditional estimates, other than for financial & business services for which the estimate is of a comparable order of magnitude.

Within Local Industry Models

5.17. The results from the Within Local Industry models are shown in Table 10 below.

Under this model specification we find evidence of positive urban agglomeration economies for financial & business services (0.063) only.

Table 10: Two stage TFP Within Local Industry Model Estimates of Elasticities of Productivity w.r.t Agglomeration

	MAN	CON	WAD	TRA	ITC	FIN
log(ρ)	0.233	-0.867	0.046	0.010	0.098	0.063
	(0.218)	(0.276)	(0.094)	(0.112)	(0.092)	(0.033)
α	1.25	1.00	1.00	1.25	1.50	1.50
N	415	238	1432	354	930	3982
adj-R2	0.624	0.241	0.134	0.172	0.172	0.085

Within Enterprise Models

5.18. The results from the Within Enterprise models are shown in Table 11 below.

Table 11: Two stage TFP Within Enterprise Model Estimates of Elasticities of Productivity w.r.t Agglomeration

	MAN	CON	WAD	TRA	ITC	FIN
log(ρ)	0.118	-0.591	-0.454	-0.089	0.595	0.109
	(0.681)	(1.548)	(0.388)	(0.286)	(0.655)	(0.246)
α	1.25	1.00	1.00	1.25	1.50	1.50
N	415	111	897	193	505	2600
adj-R2	0.000	0.001	0.002	0.001	1.63E-03	0.000

The within enterprise model specification does not indicate significant urban agglomeration economies for any economic sector. Note also that the R^2 values for the within estimator are very low.

Summary of the Two-Step Estimation Models

5.19. Overall, results from the two-step estimation models seem less convincing than those of the one-step models. There appear to be three key problems. First, the R^2values are generally low indicating that there are substantial influences on spatial variation in TFP that are not represented in our models. Second, agglomeration estimates from the base models, while sometimes statistically significant, are not conditional on unobserved firm productivity, and are therefore potentially subject to bias from unobserved firm heterogeneity and the sorting of input quality across space. Third, for the conditional models (i.e. within local industry and within enterprise), our samples do not in general appear to offer enough identifying variation to produce reliable elasticity estimates, other than for financial & business services, for which we have a large sample and consequently a satisfactory degree of stability across model estimates.

5.20. The two-step models would likely benefit from an instrumental variables (IV) approach to reduce reliance on the assumption of strict exogeneity and purge any residual correlation between covariates and the error term.

6 Conclusions

6.1 This report has presented empirical work conducted to estimate elasticities of productivity with respect to agglomeration for Ireland that can be used to assess WEBs within transport appraisal. We constructed a micro level firm panel data set and applied a variety of different one-step and two-step TFP estimation approaches to analyse the effect of agglomeration on productivity.

6.2 Our preferred estimates are from one-step TFP models estimated using different distance decay values for agglomeration. These estimates are summarised below in Table 12 with corresponding distance decay parameter values and standard errors in parentheses.

Table 12: Summary of Preferred Agglomeration Elasticity Parameters for Ireland

	SIC code	*Decay Parameter*	*Elasticity*
Manufacturing	*10-33*	*1.25*	*0.015*
			(0.000)
Construction	*41-43*	*1.00*	*0.065*
			(0.023)
Wholesale & Retail	*45-47*	*1.00*	-
			-
Transport	*49-56*	*1.25*	*0.092*
			(0.022)
Inf. & Comm. Tech.	*58-63*	*1.50*	-
			-
Fin. & Bus. services	*64-74*	*1.50*	*0.058*
			(0.010)

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