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The Dynamics of Agglomeration: Evidence From Ireland and Portugal

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Abstract

This paper analyses and compares the dynamics of agglomeration in Portuguese and Irish manufacturing industries between 1985 and 1998 implementing Dumais, Ellison and Glaeser (2002)'s methodology. Using comparable and exhaustive micro-level data sets, we find that industries tend to be subject to strong geographical mobility despite little net aggregate changes in agglomeration in both countries. When the aggregate concentration changes are decomposed into portions attributable to the different stages of the plant life cycle, we discover that births consistently play a deagglomerating role, which continues at least into the early stages of the life cycle, whereas deaths have acted to reinforce agglomeration in both countries. Nevertheless, there are some differences across countries and industries.

Keywords: agglomeration, path dependence, plant's life cycle, Ireland, Portugal

JEL Classification: R11, R12, R32, L11

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1 Introduction

One of the most appealing message from the renewed economic geography literature is certainly the central place given to historical factors in order to explain the location of economic activities across space (see, for example, Arthur, 1986 and 1994, Krugman, 1991a, and Fujita et al., 1999). Accordingly, the geographic concentration of plants may well be initially determined by historical accidents or natural advantages due to favourable geographic conditions. As time goes on, plants belonging to the same or related industries may concentrate together in order to benefit from potential external economies, increasing in turn the size of the local market both in terms of intermediate inputs (and/or skilled labour) as well as final demand.[1] As this process is self-reinforcing, it could provide an explanation as to why industrial clusters last long after the initial conditions explaining their birth have vanished.[2] These arguments have been widely used to justify the existence of clusters such as the Sillicon Valley or the London Financial District or even to explain why wealth is unevenly distributed among countries, as, for example, Japan versus the rest of Southeast Asia (see Fujita and Thisse, 2002).

Although intellectually seducing, the idea that historical forces and positive feedback processes drive the rise of industrial clusters is likely to provide only part of the story. The main reason for this is that the geographic concentration of economic activities is also likely to be influenced by industry dynamics. For example, the empirical literature on employment flows generally indicates the existence of large employment turnover due to high birth and death rates, as well as the continuous adjustments by existing plants.[3] Since plants locating in different regions may

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[1] The external economies generally referred to in the literature are the existence of backward-forward linkages, the local availability of skilled workers, or the existence of more specific informational or technological spillovers (see Fujita and Thisse, 2002).

[2] Holmes (1999), in contrast, emphasizes that historical accidents may have less force than what the economic geography literature suggests. He argues that once a random economic event has selected a specific location, the industry can migrate for a superior location (e.g., a location with lower costs) even in the presence of important agglomeration benefits derived from better access to a wide variety of intermediated inputs. In a two-region two-sector agglomeration model, Ottaviano (1999) also shows that if a reduction in trade and migration costs resulting from the integration of these regions is large enough, there will be room for self-fulfilling expectations to reverse the lock-in effect of the historically inherited size advantage of the larger region.

[3] See, for example, the seminal paper by Davis and Haltiwanger (1992).

have different probabilities of success, the observed geographical concentration of economic activity may well be an artefact of heterogeneous plants being randomly distributed across space. Thus a plant's ability to survive or grow may not necessarily be linked to the potential external economies offered by its geographical environment. Using only the arguments proposed by the economic geography literature may hence not suffice to appropriately describe what drives the rise and fall of industrial clusters.

Importantly, Dumais et al. (2002) have proposed a simple and useful methodology that enables one to disentangle the forces of agglomeration into historical reasons and those due to pure randomness. More precisely, they develop a method to decompose changes in an index, similar to the commonly used Gini index of regional concentration of industries, into its mean reversion component, representing historical factors, and a random term. Applying this methodology to the US, the authors find that there is evidence of mean reversion and large amounts of randomness, thus suggesting the existence of substantial industry mobility. The degree to which these two countervailing forces occur suggests a surprising amount of industry mobility that is masked by relatively little net aggregate changes in geographic concentration and that historical accidents are unlikely to be driving locational patterns. The authors further investigate how this industry mobility is linked to the life cycle of plants by presenting another decomposition of the Ellison and Glaeser (1997) index using micro-level data, and unearth that new plant births and continuous plants generally tend to increase dispersion, while dying plants reinforce agglomerations.

Although the results generated by Dumais et al. (2002) have obvious important implications for both empirical and theoretical economic geography, they have yet to be confirmed to hold for countries other than the US.[4] The present paper constitutes the first attempt to address this paucity by studying the dynamics of geographic concentration of manufacturing plants in

[4] In a recent contribution, Barrios and Strobl (2003) applied part of the Dumais et al. (2002) methodology using country-industry and region-industry level data for the EU countries. While their results are in line with Dumais et al. (2002), their analysis is only limited to disentangling between the influence of historical factors and randomness in shaping EU economic geography and does not undertake the plant-level study carried out in the present paper. Devereux et al. (2003) have also investigated whether new entrants reinforce or act against agglomeration in the UK. Calculating the Maurel and Sedillot (1999) index over entrants, they find that, contrary to the US findings, the births of new firms in the UK do not lead to greater geographic mobility of agglomerated industries.

two European countries over a thirteen year period: Ireland and Portugal. We may expect the dynamics of geographic concentration to be different for Europe compared to the US for a number of reasons. Firstly, the US economy is characterized by quite different institutional features from those prevailing in Europe. For instance, the European labour market is marked by different regulations that have been shown to have repercussions for the relative turnover of firms and worker mobility (see Blanchard and Portugal, 2001), which may be an important determinant of agglomeration. In addition, labour mobility in Europe is much lower than in the US, thus influencing the way regional economies adjust to adverse shocks (see Decressin and Fatás, 1995) and possibly affecting the spatial distribution of economic activities (see Puga, 2002).

Another distinctive aspect of the countries investigated here is the importance of regional policy during the period considered and its possible influence on firms' location choice. Portugal and Ireland received significant amounts of EU structural funds, representing 6.5% and 5.5% of average GDP between 1985 and 1998. Indeed the tendency of economic activities to cluster together has often justified the need for the EU to intervene in order to foster economic development of disadvantaged regions that were likely to suffer from increased economic integration (see European Commission, 2000, and Boldrin and Canova, 2001). Active European regional policy, often consisting of large public funding awarded to certain objective regions, was consequently largely promoted under the idea that economic integration could worsen the development prospects of less advantaged areas in general and of peripheral regions in particular (see European Commission, 2000).[5] However, new economic geography models predict a more ambiguous relationship between some types of public intervention and the location of economic activities. In particular, given that space-related externalities are only partially understood, some authors have conjectured that public intervention may have positive as well as negative side effects in terms of spatial equity grounds (see Anas et al., 1998, and Martin, 1999). For instance, in terms of the effects of transport infrastructure on the growth prospects of the less developed regions, the new economic geography models show that lower transport costs from improved infrastructure are likely to give firms in the peripheral regions better access to inputs and markets of the more developed regions in the EU. But, they also make it easier for firms

[5] According to the European Commission (1990), Ireland and Portugal are both peripheral countries, that is, they are distant from mainland Europe where population concentration and income per capita are higher.

in the richer EU regions to supply the less developed regions at a distance, therefore harming their prospects of industrialization (see Puga, 2002).

Finally, the cases of Ireland and Portugal are particularly interesting because these two countries have experienced rapid structural changes characterized by a pronounced catching-up with respect to the rest of the EU over the period considered. For example, the Irish (Portuguese) annual growth rate was 5.5% (3.7%) while the EU annual rate was 2.6% between 1985 and 1998. In addition, the European Single Market Program (SMP) was implemented during this period provoking a strong need for modernization and adaptation to increased competition in both countries. Such factors may have very well manifested themselves in the dynamics of agglomeration in the two countries over the period.

Our first main result is that both Portuguese and Irish industries tend to be geographically very mobile, even if the aggregate levels of agglomeration remained stable. This coincides with what was found by Dumais et al. (2002) for the US economy, despite the obvious differences between their respective institutional settings. Such empirical regularities provide support for the idea that, contrary to the argument generally put forward by the renewed economic geography literature, the industry level of agglomeration is essentially an equilibrium phenomenon without any dominant role reserved for historical accidents.

The second main result is related to the relationship between agglomeration and the plant life cycle. We find, as has been confirmed for the US, that new plants are more likely to be born way from Portuguese and Irish industry centers and this, in turn, favours the dispersion of economic activities. This effect tends to be compensated by deaths that are also more likely to occur in the Portuguese and Irish periphery which, in turn, favours the agglomeration of economic activities. Our results by age indicate, however, that the dispersion effects of job expansions of plant's start-ups outweigh the increased probability of job contraction in the early part of the life cycle of a plant in both countries. This suggests that, as argued by Jacobs (1969), important knowledge transfers may be inter-sectoral, at least in the early stages of the firm's life-cycle. In contrast, the agglomerating effects of job destruction of mature plants outweigh the dispersion effects of job creation in both countries. That is, job destruction of mature plants is less likely to occur in industry centers, suggesting that mature plants benefit from being in industry centers.

The rest of the paper is organized as follows. Our data sources are presented in Section

2. Section 3 outlines some trends in agglomeration. The Dumais et al. (2002) decomposition of changes in the raw concentration index and results of employing it to the data are given in Section 4. This is followed by the presentation of the methodology and results for the link between agglomeration and the plant life cycle in Section 5. Section 6 concludes and discusses some policy implications.

2 Data

The data used in this paper has been obtained from an annual survey conducted by the Portuguese Ministry of Employment (Quadros de Pessoal, hereafter QP) and from the Irish Forfàs Employment Survey for Portugal and Ireland, respectively. Several distinctive features make these two data sets particularly suited for our study. First, they essentially cover all existing establishments in the countries considered here. Second, they have a longitudinal dimension, i.e., the establishments are identified by a unique code, which allows them to be followed over time, and thus through their life cycle. Given the coverage of both data sets, we are able to define a common longitudinal dimension of 1985 to 1998.

2.1 Portugal

The QP is a survey that records, among other information, the location, sector of activity, and number of employees of all the existing establishments employing paid labour that operate in Portugal as taken from an annual questionnaire conducted in March (October since 1994). Limiting the analysis to manufacturing industries, the data covers more than 37,000 establishments each year over the sample period. Newly created establishments in a given year are all those establishments that appeared for the first time in the QP database after 1985 (newly created companies and establishments of existing companies). The QP has, however, some coding errors, with temporary exits occurring simply because establishments fail to return the survey form on time. In order to deal with this issue, establishments that were in the files in years $t-1$ and $t+1$ were considered to be active in year t even if they were not actually in the file. The establishments' record was amended for that year, employment being imputed as the average of employment in years $t-1$ and $t+1$. These establishments were then added to the category of existing establishments in period t. For exits we required an establishment to be absent from the file for the rest of the period in order to be classified as a closure. Since for Ireland the regional and sectoral classification for an establishment is only given for the last year it is observed, thus ignoring any changes in these during a plant's life time, we also assumed for the QP that the regional and sectoral classification of a plant was constant during a plant's life time, as measured in the last year which is observed in the data set.[6]

Portuguese industries are aggregated to the ISIC Rev.1 4-digit level, which includes 85 industry groups.[7] Location in the QP, reflecting the spatial units used, is measured at the district level. The Portuguese mainland is divided into eighteen districts, with an average area of 4,800 sq. km. These districts are administrative areas centered generally around one medium to large city. This breakdown is geographically equivalent to splitting the United States territory into 2,060 geographical units. We, therefore, have 1,530 district-industry units of analysis in each period. The choice of using districts rather than more/less aggregated units was based on the fact that this level of spatial unit is most comparable to those available for the Irish data.

2.2 Ireland

The Forfàs Employment Survey is an annual establishment-level survey collected by Forfàs since 1972, the policy and advisory board for industrial development in Ireland. The response

[6] Another problem in the QP concerns the change of the industry codes in 1994, going from the ISIC-Rev.1 to the NACE-Rev.1 system (but everything else remained equal). The equivalence between the two industry codes was done meticulously in order to ensure that industry classification is consistent over time. As a first step, we merge the 1994 and the 1995 files using the unique establishment code in order to retain only the establishments common to both years. For these common establishments, we simply replace the ISIC system by the corresponding NACE system. (The same procedure was used for 1996, 1997 and 1998). This exercise also enables us to create a table of correspondence between the ISIC system and NACE system. Accordingly, each branch of the NACE system has its counterpart in the ISIC system according to the maximum number of observations. Using this table of correspondence, we can attribute to establishments created in 1995, 1996, 1997 and 1998 the ISIC Rev.1 classification

[7] The sample consists of all manufacturing industries except ISIC's 2100 (Coal and mining), 2200 (Extraction of petroleum and natural gas), 2902 (Minerals for chemical), 3845 (Building and repairing of aircrafts), 3118 (Production and processing of sugar), 4102 (Production and distribution of gas), 3530 (Petroleum refining) and 3849 (Other transport equipment). The first three of these were omitted because they were not present in the entire period. The last five of these were excluded because of a major discontinuity in employment over time, which might be due to recoding errors.

rate to this survey is argued by Forfàs to essentially be 100 %, i.e., it can be seen as including virtually the whole population of manufacturing establishments in Ireland. Information at the establishment level includes time invariant variables such as the sector of production, detailed regional location of each establishment, as well as the level of employment in each year. Restricting our attention to manufacturing industries, more than 5,000 establishments have positive employment each year over the period 1985-1998.

As for the QP, newly created establishments in a given year are all those establishments that appeared for the first time in the Forfàs database in any year after 1985 (newly created companies and establishments of existing companies). For exits, we also required an establishment be absent from the file for the rest of the period in order to be classified as a closure. Existing establishments in period t are also all those establishments active in years $t+1$ and $t-1$. Problems of falsely recording exits are generally not a feature of the Irish data.

Since the industrial coding in the Irish data is based on the 4-digit NACE Rev.1 System, we manually changed these to correspond to the ISIC Rev.1 classification system of the Portuguese data. Industries are aggregated to the 4-digit level ISIC Rev.1 System, which includes 67 industry groups. Geographical location is observed at the county level in Ireland, which is divided into its 27 counties, each having on average a size of 2,600 sq. km. Similar to Portuguese districts Irish counties are administrative areas generally centered around one medium to large city. This breakdown is equivalent to splitting the United States territory into 3,800 geographical units. We, therefore, have 1,742 county-industry units of analysis in each period.

3 Portuguese and Irish agglomeration trends

In order to first investigate the evolution of agglomeration in Ireland and Portugal over our sample period we make use of Ellison and Glaeser (1997)'s (hereafter, EG) index. This index measures the degree to which an industry is geographically concentrated conditional on its industrial concentration. The EG index of the degree to which an industry i is geographically concentrated at time t is given by

$$\gamma_{it} = \frac{\frac{G_{it}}{1-\sum_s S_{st}^2} - H_{it}}{1 - H_{it}},$$

where S_{ist} is the share of industry i's time t employment located in area s, $G_{it} \equiv \sum_s (S_{ist} - S_{st})^2$ is the sum of squared deviations of the industry shares S_{ist} from a measure, S_{st}, of the area's share employment in the average industry and $H_{it} \equiv e_{ikt}/\left(\sum_k e_{ikt}\right)^2$ is the Herfindhal index, with e_{ikt} being the level of employment in the kth plant in industry i at time t. The subtraction of H_{it} is a correction that accounts for the fact that the raw geographic concentration of employment in an industry, G_{it}, would be expected to be larger in industries consisting of fewer larger plants if locations were chosen completely at random. The EG index has thus the distinctive feature of being comparable across industries, across countries, and over time regardless of plants' size distribution. It must, however, also be noted that the EG index suffers from two major drawbacks: firstly, it cannot distinguish between spillovers and natural advantages to explain why plants agglomerate; secondly, it treats the spatial units symmetrically, i.e., plants in neighbouring spatial units are treated exactly the same as plants at opposite ends of a country.

The first row of tables 1 and 2 reports the mean across 4-digit manufacturing industries of the EG index.

Insert tables 1 and 2

As can be seen, the concentration level of the mean industry is much larger in Portugal than in Ireland, a result that is mainly due to substantial differences in the Herfindhal index values and that is in line with previous findings (see Barrios et al., 2003). Also, the level of concentration of the mean industry has remained fairly constant between 1985 and 1998 in Portugal, decreasing only by 5%. In contrast, while the concentration of the Irish mean industry has also remained fairly stable between 1985 and 1990, it fell by about 15 % between 1990 and 1994 and then stabilised between 1995 and 1998. The second and third rows of tables 1 and 2 show that both the raw concentration and Herfindhal indices remained relatively constant in Portugal while they decreased in Ireland. Moreover, the decline in the EG index in Ireland is associated mainly with a decrease in raw concentration rather than a change in the plant size distribution. In practice, as noted by Dumais et al. (2002), changes in the value of the EG index over time are well approximated by changes in the difference between the raw geographic concentration of employment in an industry (G_{it}) and its industrial concentration (H_{it}).

Table 3 shows that the correlation of EG indices between 1985 and 1998 is 0.69 for Portugal.

A closer look at the top 20 most agglomerated industries in 1998 reveals that 16 of these were also in the top 20 most agglomerated industries in 1985. Hence, despite the dynamic nature of employment across industries, differences in concentration across industries were persistent in Portugal.

Insert tables 3 and 4

According to Table 4, the changes of spatial concentration across industries are substantially greater in Ireland than in Portugal. Indeed, the correlation of EG indices between 1985 and 1998 is only 0.41. Nevertheless, 15 of the top 20 most agglomerated industries in 1985 were also among the top 20 in 1998.

4 Geographic concentration and industry mobility

It is important to point out that despite the relatively constant aggregate trends in geographic concentration, both Irish and Portuguese manufacturing experience, as do other countries, a considerable amount of employment turnover per year. For example, 56% (33%) of all manufacturing employees in 1998 were working in plants that had not yet existed as of 1985 and 73% (51%) of the plants that existed in 1985 closed over the next thirteen years in Portugal (Ireland). There have been also employment changes at existing establishments, even if it is more pronounced in Ireland than in Portugal: the mean annual job turnover rates over the period are 29.35 % and 23.95 % for existing Irish and Portuguese establishments, respectively.

The existence of such large employment turnover can be reconciled with the constancy of agglomeration in two ways. First, the turnover of employment at the establishment level simply does not change the area-industry employment level because new establishments are built next to the old ones they replace and employment growth at continuing plants may come at the expense of competitors "in the same street". Alternatively, there may be a lot of movement of industries, with old centers dying while new ones emerge, also leaving the EG index unchanged because it treats the spatial units symmetrically. In the first case, a rejection of path dependence story put forward by the renewed economic geography literature is not justified. However, in the second case agglomeration is essentially an equilibrium phenomenon without any dominant role for historical accidents. Disentangling changes in geographic concentration over time due to systematic growth/contraction of old industry centers and randomness in growth rates is then a critical issue for the realm of the economic geography literature.

To disentangle the importance of these two possibilities we implement the decomposition of the simple geographic concentration index proposed by Dumais et al. (2002). Accordingly, we consider a simple regression in which the change in area-industry employment share is a function of the growth of the area's average employment share and the difference between initial area-industry share and the area's average employment share:

$$S_{ist+1} - S_{ist} = \hat{\alpha} + \hat{\beta}(S_{ist} - S_{st}) + \hat{\gamma}(S_{st+1} - S_{st}) + \hat{\epsilon}_{ist}, \tag{1}$$

where S_{ist} is the share of industry i's employment in area s at time t, S_{st} is the average of this variable for area s across industries and $\hat{\alpha}$, $\hat{\beta}$ and $\hat{\gamma}$ are estimated coefficients, and $\hat{\epsilon}_{ist}$ is an estimated error term which is, by construction, orthogonal to each of the regressors. This regression is specified so that each variable has mean zero and so that the two regressors are orthogonal. As a result, under OLS estimation it will always be that $\hat{\alpha} = 0$ and $\hat{\gamma} = 1$.

Writing $G_t \equiv (1/I)\sum G_{it}$ for the mean of the raw concentration across industries, Dumais et al. (2002) show that the changes in G_t can be written as follows:[8]

$$G_{t+1} - G_t = (2\hat{\beta} + \hat{\beta}^2)G_t + 1/I\sum_{is}(\hat{\epsilon}_{ist})^2.$$

This equation decomposes changes in raw concentration into the sum of two terms: the mean reversion and the randomness term. The first term depends on the extent to which net changes in employment are correlated with the initial gap between the area-industry share and the area's share of employment in the average industry. When $\hat{\beta}$ is negative, current centers of industry are declining in importance and/or employment is tending to increase in areas where industry was initially underrepresented. In this case, the area-industry employment shares display mean reversion, and the first term represents a decrease in raw concentration that is attributable to this tendency. Conversely, when $\hat{\beta}$ is positive and industry centers are growing, the first term reflects a subsequent increase in raw concentration that is attributable to this tendency. The second term in the decomposition, $\sum_{is}(\hat{\epsilon}_{ist})^2$, captures the effect of randomness in the growth in area-industry employment shares. It is positive by definition and

[8] Since the trends in the raw concentration and the EG index are fairly similar, we, as Dumais et al. (2002), can focus for the moment on the raw concentration (G_{it}) rather on the EG index to describe changes in agglomeration.

its magnitude reflects the degree of heterogeneity in the experience of areas that initially have similar concentrations of employment in a given industry. One might expect it to be larger the more diverse the experiences across industry centers are, i.e., if some fail while others succeed, or if some regions are more successful in attracting new plants than others. One should, however, note that this decomposition implicitly assumes that the $\hat{\beta}$'s are constant across regions and industries. Part of the size of the second term may thus very well be due to differences in different rates of adjustment across area's industry shares. It is also important to point out that this methodology cannot separate traditional trade and economic geography theories. Indeed, current industrial location patterns may be related to historical ones not because of externalities but because of persistent local comparative advantages.

4.1 Full sample of industries

Tables 5 and 6 report the parameter estimates of regression (1) for the area-industry employment changes and other summary statistics for the full sample of industries for Portugal and Ireland.

Insert tables 5 and 6

From the estimates of the coefficient $\hat{\beta}$, it is apparent that both Ireland and Portugal, as was found for the US, experience mean reversion rather than mean diversion. Comparing the size of the coefficient, we discover that the rate of mean reversion is, however, substantially higher for Ireland (-0.43) than for Portugal (-0.23). Hence, areas in which an industry was initially underrepresented experience a rise in their share by 43% in Ireland compared to 23% in Portugal over the thirteen-year period.

As evidenced from the sixth and the seventh columns of Tables 5 and 6, the Portuguese economy is characterized by lower convergence and smaller random shocks than its Irish counterpart. The overall picture is one where the mean reversion effect is sufficiently strong to produce by itself a 41% decrease in agglomeration in Portugal and a 67% decrease in agglomeration in Ireland over the period. But the random shocks in Portugal (Ireland) were almost as strong to counteract this mean reversion with a 39% (56%) increase in agglomeration. The final result is a slight decrease in raw concentration of 1.77% for Portugal and a larger decrease in the raw concentration of 13.4% for Ireland. We should note that the slight net changes of geographic concentration in both countries could have very well also been driven by very small mean reversion and randomness effects. The fact that these are, as in the US, two very large countervailing forces suggest that considerable amounts of industry mobility, some due to randomness and some due to mean reversion, are netted out on aggregate. Such large geographical mobility of industries, together with the stability in the aggregated agglomeration levels, suggests that agglomeration is an equilibrium phenomenon without any dominant role reserved for historical accidents as often proposed by the renewed economic geography literature. The amplitude of the mean reversion rates and the length of the time period used suggest that there is more industrial mobility in these two European countries than in the US (Dumais et al., 2002, found a mean reversion of 25% for a twenty-year period), and the correlation between each area's share of each industry's employment in 1985 to that in 1998 (0.47 for Portugal, 0.41 for Ireland and 0.86 for the US) seems to confirm this result. We must note, however, that the US study uses states, i.e., geographic areas that are often substantially greater than the two countries themselves and generally contain several large metropolitan areas. Given this, we thus focus on qualititative rather than quantitative comparisons to the US.

We also calculated the raw concentration over sub-periods in Tables 7 and 8, which report the decomposition of the change in the raw concentration into mean reversion and randomness contributions over time.

Insert tables 7 and 8

Accordingly, the raw concentration index declined slightly in all three periods in Portugal. For Ireland, the change in the concentration level was more pronounced, being negative in the first two periods and positive in the last one. Interestingly, the mean reversion dominates the randomness effect in the three periods in Portugal and in the first two for Ireland. In the third period, however, the mean reversion effect was smaller than the randomness effect in Ireland.

4.2 Subsamples of industries

The analysis of different groups of industries may provide further insight given the different predictions for different types of industries suggested by the economic geography literature. In light of the model-based EG index, for example, industries with a high geographic concentration level are subject to strong agglomerating (or natural advantages) forces and, consequently, should experience a lower mean reversion effect than the non-concentrated industries. Among these agglomerated industries, it may be insightful to analyze textiles and footwear industries because they are found to be highly agglomerated in many economies.[9] Besides, some of these industries (for example, the carpet industry) have been used to show the importance of accidents of history and agglomeration economies in the current location of economic activities (see Krugman, 1991c). The high technology industries compose another group of interest since these industries are usually referred to as being intensive in knowledge spillovers and this characteristic may affect the rate of mean reversion. Because the cost of transferring knowledge rises with distance, those industries for which knowledge is of primary importance should tend to cluster more than other industries. However, although the idea that knowledge spillovers tend to favour the spatial clustering of economic activities with a high innovative content is not new, supportive evidence of it remains relatively scant and inconclusive.[10] As a matter of fact, recent theoretical papers by Bottazzi (2003) and Combes and Duranton (2002) show that the spatial concentration of this kind of industry need not to be considered as a general rule.

Insert tables 9 and 10

The third column of tables 9 and 10 reports the parameter estimates of regression (1) for the area-industry employment changes for different samples of industries for Portugal and Ireland. We should note that in all our industry specific calculations we used only the sub-sample of industries that belong to the group in question, thus assuming that agglomeration is measured relative to agglomeration patterns within that group. Our results show that the more agglomerated industries in 1985 (first quartile) in Portugal have an estimated $\hat{\beta}$ that is greater than that of the low-concentration subsample industries (fourth quartile). The estimated $\hat{\beta}$ for the less (more) agglomerated industries is -0.46 (-0.16), indicating that, on average, areas in which an industry was overrepresented saw their excess employment reduced by 46% (16%) over the entire period. The randomness in the growth process in this subsample (measured by σ) is also

[9] See Devereux et al., 2003, for UK, Barrios et al., 2003, for Portugal, Ireland and Belgium, Maurel and Sedillot, 1999, for France, Ellison and Glaeser, 1997, for the US.

[10] For example, Jaffe et al.'s (1993), Feldman's (1994), and Audretsch and Feldman's (1996) findinds suggest that for the US we observe a higher concentration of R&D and knowledge intensive activities. In contrast, recent evidence provided by Devereux et al. (2003) for the UK and by Barrios et al. (2003) for Belgium, Ireland and Portugal shows no clear pattern of geographical concentration for high technology industries.

stronger than that of the more agglomerated industries subsample. The fact that in Portugal the low-concentration industries are subject to a stronger mean reversion and randomness process than the more agglomerated industries seems to be in line with some theoretical predictions. However, the Irish case is quite different. Here, the estimated $\hat{\beta}$ for the less agglomerated industries in 1985 is greater than that for the more agglomerated industries. Specifically, the estimated $\hat{\beta}$ for the less (more) agglomerated industries is -0.27 (-0.34), indicating that, on average, areas in which an industry was overrepresented saw their excess employment reduced by 27% (34%) over the entire period. The randomness in the growth process in the less agglomerated industries subsample is very similar to that of the more agglomerated industries subsample. Interestingly, and somewhat surprisingly, the concentrated Irish industries are more geographically mobile than the non-concentrated industries.

The high technology subsample also exhibits a noteworthy pattern.[11] For Portugal the estimated $\hat{\beta}$ is -0.31, indicating that, on average, areas in which an industry was overrepresented saw their excess employment reduced by 31% over the entire period, while for Ireland, the corresponding figure is 68%. On average, the high technology industries have a greater mean reversion than other industries in the two countries. In addition, these industries are also subject to a substantial random growth process. Taking together, both effects suggest that these industries exhibit strong geographical mobility (in particular in the Irish case). Thus, these results seem to cast some doubt on the role of knowledge spillovers being a major driving force in industry agglomeration in the two countries. These findings confirm some recent results showing no clear pattern of geographical concentration for high technology industries (see, e.g., Devereux et al., 2003 and Barrios et al., 2003).

The subsample of agglomerated and traditional Portuguese textiles and footwear industries is an exception to the general pattern. This subsample has an estimated $\hat{\beta}$ of 0.005, suggesting no mean reversion, while the randomness in the growth process is modest. Taken together, both effects imply little geographical mobility for Portuguese textiles industries (a similar pattern

[11] Definition of high-tech sectors stems from Hatzichronoglou (1997). The high-tech industries consists of SIC's 3511 (Basic Chemicals), 3512 (Pesticides And Fertilizers), 3521 (Paints And Varnish), 3522 (drugs and medicines), 3523 (Perfumes And Cosmetics), 3529 (Other Chemical Products), 3559 (Rubber Products), 3560 (Plastic Articles), 3825 (Computers And Office Machines), 3831 (Industrial Electronics), 3832 (Radio, Television And Telecommunications), 3839 (Other Electric Material), 3851 (Instruments And Appliances For Measuring), 3852 (Optical Instruments And Photographic Equipment), and 3853 (Watches).

was also found for U.S. textiles). In contrast, the same industries experienced clear mean reversion and a strong randomness in Ireland, which imply extensive geographical mobility.

All in all, results on the subsamples of industries show some interesting similarities/dissimilarities across industries and across countries. Even if some of these results raise more questions than answers, our evidence concerning the tendency for high technology industries to disperse in both countries suggests that agglomerating forces may not always be strong enough to compensate for the influence exerted by dispersion forces as some theoretical papers have shown (see, for instance, Combes and Duranton, 2002). On the other hand, the fact that some low technology industries as textiles industries can experience different geographic dynamics in one economy but not in the other suggests that different agglomerating mechanisms are at work in different countries. Finally, the fact that agglomerated industries exhibit stronger geographical mobility than the non-agglomerated industries in Ireland is a striking finding that might be explained by the drastic structural changes that this country has experienced during this period.

5 Geographic concentration and the plant life cycle

Changes in the geographic concentration can come from a combination of four different elements: job creation due to entries, job creation due to expansion in continuing establishments, job destruction due to exits and job destruction due to contraction in continuing establishment), where we summarize these categories of events by the index j (i.e., j = births, expansions, contractions and deaths). We should note that if we are focusing on the impact of a plant's life cycle on changes in geographic concentration, changes in the plant Herfindhal index cannot be ignored if we intend to decompose the concentration changes into portions attributable to various life cycle stages. Even if the overall distribution of plant size has not changed much over the period, events like plant births clearly tend to reduce the Herfindhal index, while plant deaths tend to increase it. As Dumais et al. (2002) note, the effects of births or deaths may be very different for the raw concentration than for the EG index. Thus, we use, following Dumais et al. (2002), a measure of agglomeration, $\tilde{\gamma}_{it}$, approximating the EG index to obtain a more tractable decomposition:

$$\tilde{\gamma}_{it} = \frac{G_{it}}{1 - \sum_s s_t^2} - H_{it}.$$

Writing $G_t \equiv (1/I) \sum G_{it}$ for the average raw concentration across industries, it is possible to decompose the aggregate change in raw concentration into portions attributable to each j event: $G_{t+1} - G_t = \sum_{j=1}^{J} \Delta G_t^j$. The same is true for the decomposition of changes in the average plant Herfindhal: $H_{t+1} - H_t = \sum_{j=1}^{J} \Delta H_t^j$. Finally, the change in the index $\tilde{\gamma}_t \equiv 1/I \sum_i \tilde{\gamma}_{it}$attributable to the jth stage of the life cycle is just[12]

$$\Delta \tilde{\gamma}_{it}^j = \frac{\Delta G_{it}^j}{1 - \sum_s S_{st}^2} - \Delta H_{it}^j.$$

We can define Δs_{sit}^j as the portion of the change in area s's share of employment in industry i that is due to the jth event

$$\Delta s_{sit}^j \equiv \frac{\Delta E_{ist}^j - s_{sit} \Delta E_{it}^j}{E_{it+1}},$$

where E_{ist} is the employment level of industry i in area s at time t, and ΔE_{ist}^j is the change due to the event of type j.[13] The Δs_{sit}^j is expressed as follows:

$$\Delta S_{sit}^j = \hat{\alpha}_j + \hat{\beta}_j (S_{ist} - S_{st}) + \hat{\gamma}_j (S_{st+1} - S_{st}) + \hat{\epsilon}_{ist}^j. \tag{2}$$

Estimating regression (2) under OLS implies that $\sum_j \hat{\beta}_j = \hat{\beta}$, $\sum_j \hat{\gamma}_j = \hat{\gamma}$ and $\sum_j \hat{\epsilon}_{sit}^j = \hat{\epsilon}_{sit}$, where $\hat{\beta}$, $\hat{\gamma}$ and $\hat{\epsilon}$ are estimates from regression (1).

The aggregate change in raw concentration is related to the parameters of these regressions by:

$$\Delta G_t^j \equiv \hat{\beta}_j (2 + \hat{\beta}) G_t + \frac{1}{I} \sum_{is} \hat{\epsilon}_{sit}^j \hat{\epsilon}_{sit}.$$

The decomposition of changes in the plant Herfindhal index into portions due to events at different stages of the life cycle is made in an analogous way. Let $z_{ikt} \equiv e_{ikt} / \sum_k e_{ikt}$ be the kth plant employment share within its industry, where e_{ikt} is the employment level in the kth plant in industry i at time t. Defining the portion of the change in each plant's share of employment to events in each category, then

$$\Delta z_{ikt}^j \equiv \frac{\Delta e_{ikt}^j - z_{ikt} \Delta E_{it}^j}{E_{it+1}}.$$

This definition again yields an allocation of share changes across the categories, that is, $z_{ikt+1} - z_{ikt+1} = \sum_j \Delta z_{ikt}^j$. For each j the following regression is then run:

[12]The definition of $\Delta \tilde{\gamma}_{it}$ ignores the effect on measured concentration due to changes in the denominator. Hence, the sum of $\Delta \tilde{\gamma}_{it}^j$ will not be exactly equal to $\tilde{\gamma}_{it+1} - \tilde{\gamma}_{it}$. This difference is very small because the area size, $\sum_s S_{st}^2$, does not change much over time.

[13]If the jth event in an industry occurred proportionally to the initial area-industry employments, the value of Δs_{sit}^j would be zero (if there are no differences in the size of births across areas).

$$\Delta z_{ikt}^{j}{=}\hat{\alpha}_{j}{+}\hat{\beta}_{j}\tilde{z}_{ikt}{+}\hat{\epsilon}_{ikt,}^{j} \tag{3}$$

where $\tilde{z}_{ikt} \equiv z_{ikt} - \frac{1}{N_i}$, for N_i, the number of plants that operate in the industry either in period t or in period $t+1$. The aggregate change in the Herfindhal index is related to the parameters of these regressions by

$$\Delta H_t^j \equiv (2\hat{\beta}_j + \hat{\beta}\hat{\beta}_j)(H_t - \frac{1}{I}\sum_i \frac{1}{N_i}) + \frac{1}{I}\sum_{ik}(\hat{\epsilon}_{ikt}^j)^2 + \frac{1}{I}\sum_{ik}\hat{\epsilon}_{ikt}^j(\sum_{l\neq j}\hat{\epsilon}_{ikt}^l).$$

5.1 Full sample of industries

Tables 11 and 12 report the coefficient estimates from regressing each component of employment change, Δs_{sit}^j, on the initial excess concentration of the industry in the area, $S_{ist} - S_{st}$, and the overall growth of the area , $S_{st+1} - S_{st}$, as in regression (2). For the births regression, the $\hat{\beta}$ coefficient is statistically negative for both countries, as was also found for the US, tough more negatively pronounced in Ireland than in Portugal. This indicates that there is mean reversion in employment shares: employment in new plants increases less than one-for-one with the area-industry employment or, similarly, births are more likely to start away from current areas of the industry. In contrast, but similar as in the US, the coefficient on the initial excess employment is statistically positive in the deaths regression in both economies, indicating that plants are less likely to close and/or are smaller in areas that have a higher that expected share of industry's employment (the dependent variable is negative is this regression). For expansions, the $\hat{\beta}$ coefficient is also significantly negative for both economies, which indicates that growth rates are lower in areas with a high initial concentration in the industry. For contractions, the $\hat{\beta}$ coefficient is similarly significantly negative for both economies indicating that plants are more likely to contract in areas that have a higher than expected share of industry's employment (the dependent variable is negative in this regression).

Insert tables 11 and 12

Hence, the conditions that favour new Portuguese and Irish business development seem to be in line with the Jacobs (1969) view suggesting that start-up activity may be far way from industry centers to benefit from more important knowledge transfers that come outside the own sector. However, the conditions that favour existing Portuguese and Irish business seem to follow the Marshall, Arrow and Romer view emphasizing that plants benefit from being located in industry centers because deaths are more likely to occur and/or are smaller away from industry centers. The results about plant deaths are also in line with a new, richer portrait of the plant shutdown decision process recently proposed by Bernard and Bradford Jensen (2002). Indeed, Bernard and Bradford Jensen (2002) find that the manufacturing plant deaths within and across industries in the U.S. are significantly related to regional specialization (negatively) and to regional diversity (positively) after controlling for a richer set of industry and plant characteristics.

Tables 13 and 14 report the portions of change in the EG index attributed to each life-cycle stage. These changes are listed as a percentage of the initial concentration in the set of industries, i.e., $100\Delta\tilde{\gamma}_t^j/\tilde{\gamma}_t$.

Insert tables 13 and 14

As can be seen, births consistently have the effect of reducing the degree to which industries are agglomerated in both countries, as was also found for the US. On its own, the deagglomerating effect of births would increase more than 11 (6) times the observed decline in the geographic concentration over the period in Portugal (Ireland). Deaths have, in contrast, but similar as in the US, the effect of increasing the degree to which industries agglomerated in both countries. On its own, the agglomerating effect of deaths would be 11 (5) times more than the observed decline in the geographic concentration over the period in Portugal (Ireland). We also find that expansions have contributed to the decrease in the degree to which industries are agglomerated in both countries. The magnitude of this deagglomerating effect is substantially smaller than that of births: on its own, the deagglomerating effect of expansions would increase more than 1.6 (1.4) times the observed decline in the geographic concentration over the period in Portugal (Ireland). Finally, contractions contribute to the increase in the degree to which industries are agglomerated in both countries (except in the first period in Portugal). This finding seems to be somewhat inconsistent with our previous result that contractions are higher in areas with an excess of employment in an industry. However, when changes in the Herfindhal index are taken into account, the two findings can be reconciled: the reduction in the Herfindhal index more than compensates for that of the raw concentration index. The magnitude of this agglomerating effect is, however, substantially smaller than that of deaths: on its own, the agglomerating effect of contractions would be 0.9 (1.5) times more than the observed decline in the geographic concentration over the period in Portugal (Ireland).

5.2 The plant life cycle events by age class

The similar amplitude of the effect of births and deaths is a striking feature that raises a natural question: do most births in less agglomerated areas exit after a short period of time? If this is the case, the deagglomeration effect of births would simply be compensated by the agglomerating effect of deaths and we are just capturing short-run plant turnover without any substantial implications for economic geography patterns. We assess the net effect of employment changes of these possibilities by decomposing the plant life cycle events into job creation (the sum of expansions and births) and job destruction (the sum of contractions and deaths) events and further classify these event groups by age category according to regressions (2) and (3). Our choice of age groups is limited by the fact that we have no information on the start-up year for incumbent plants in the Portuguese data - that is, while we can follow new plant start-ups within our sample period, we know of those plants that are incumbent to the data in 1985 only that they are at least five years of age by 1990. Thus, for both countries, we classified plants into two groups - those less than, and those at least five years of age - and necessarily truncated our sample period to start in 1990 rather than 1985.

Insert tables 15 and 16

The results of our age decomposition are given in Tables 15 and 16. Accordingly, total net job creation by young Portuguese and Irish plants (less than 5 years) or mature Portuguese and Irish plants (more (or equal to) than 5 years) have a deagglomerating effect. However, the deagglomerating effect of the expansion of young survival plants is three times more than that of mature plants in both countries. In contrast, the total job destruction by young Portuguese and Irish plants or mature Portuguese and Irish plants have an agglomerating effect, and the differences between the two age groups is not as stark as for the case with job creation. More importantly, one should note that job creation clearly dominates job destruction by young plants in both countries. As these plants tend to locate more in the less concentrated areas (a significantly negative $\hat{\beta}$ was found in regression (2) for the regression of the net job creation of young plants) for both countries, the effect of this net job creation is to reduce agglomeration. Hence, the deagglomerating effect of births is not simply a temporary phenomenon. In contrast, job destruction clearly dominates job creation in mature plants in both countries. As these mature plants mainly located in the more concentrated Portuguese and Irish areas (a significantly positive $\hat{\beta}$ was found in regression (2) for the regression of the net job destruction of mature plants (the dependent variable of this regression is negative)), the effect of this net job creation is to increase agglomeration.

If it were the case that a region with a small concentration of an industry was also more diversied across industries, then these findings can be related to the "nursery city" argument in Duranton and Puga (2002). Indeed, according to the "nursery city" argument plants are first set up in more diversified areas but then, once they have found their ideal of production process, they mainly locate in more specialized areas. The fact that net job creation by young plants is favoured by a low industry concentration in an area but that the net job destruction in mature plants is less likely to occur in industry concentrated areas in both countries seems to be supportive, at least to a certain extent, of this argument.

5.3 Subsamples of industries

Tables 17 and 18 report the results of performing the life cycle decomposition calculation on the same subset of industries, assuming that agglomeration is measured relative to agglomeration patterns within that group as for the industry mobility decomposition presented earlier.

Insert tables 17 and 18

A richer pattern appears in examining these different subsets. Accordingly, the main difference in the life cycle pattern of the location between the concentrated and unconcentrated industries is the role played by contractions. In both countries, there seems to be a greater difference between contraction rates in industry centers in these subsamples. Such contractions seem to explain why the aggregate level of geographic agglomeration has increased only in the non-localised industries in Ireland. Distinctive features also characterize the life cycle pattern of the location in the high technology subsample industries. First, both countries display impressive birth-related deagglomerating and death-related agglomerating effects in this subsample. While in Portugal the deaths' agglomerating effects more than compensate for the births' deagglomerating effect, in Ireland we have the opposite situation. There also seems to be a greater difference between contraction rates in industry centers in both countries: contractions have a strong agglomerating effect in Ireland but a relatively weak deagglomerating effect in Portugal. Expansions are similarly quite different across countries, having an agglomerating effect in Ireland and a deagglomerating effect in Portugal. In aggregate, the level of geographic agglomeration in the high technology subsample increases only in Portugal. The textiles and footwear industries stand out for being geographically more concentrated over the period in the two countries (in particular in Portugal), as was found for the US. In Portugal, all components of the plant's life cycle except births play in favour of agglomeration. This particular pattern was also found for the US. In Ireland, however, only death played in favour of agglomeration. This effect, however, was sufficiently strong to compensate all the others.

6 Conclusion

An intrinsic feature of recent economic geography models is their multiple equilibria and path dependency. That is, once random economic events have selected a specific location, centripetal forces guarantee a reinforcement of this initial advantage. Despite the supposed importance of the path dependence in the location of activities - for instance, P. Krugman notes that "if there is one single area of economics in which path dependence is unmistakable, it is in economic geography" (Krugman, p.21, 1991b) -, empirical tests of its relevance have been rare. We bring further new evidence to this field by considering the case of two European countries: Ireland and Portugal.

Our first main result is that the extensive geographical mobility of industries alongside with their relatively stable level of agglomeration suggests that agglomeration is essentially an equilibrium phenomenon without any dominant role reserved for historical accidents. This finding contrasts with the emphasis of the renewed economic geography literature on the historical accidents. Although some of this may be due to active regional policy in these two countries, similar results for the US, where regional policy is limited, suggest that at least some of the mean reversion is due to non-policy related factors. This finding is in line with the conclusions drawn from recent evidence questioning the effectiveness of EU regional policy (see, for instance, Midelfart-Knarvik and Overman, 2002) in dispersing industrial activity. In particular, mean reversion, rather than mean diversion, implies a relatively less role for public incentives in order to favor location in disadvantaged areas. However, we must nevertheless note that regional policy may itself be driving these results.

Apart from the possible influence of regional policy, our results can also be considered within the context of the strong structural changes that occurred in Portugal and Ireland during the period, including the setting-up of the European Single Market Program, and, for Portugal, the increased competition related with the accession to the European Community. All of these factors may have had some effect on agglomeration dynamics. In particular, the large size of the randomness term, which was similarly found for the US, suggests that much of the underlying process driving geographical concentration of economic activity is not well understood. This would then make it especially difficult to predict the potential effects of regional policy.

The second main finding deals with the relationship between agglomeration and the plant life cycle. We show that that new Portuguese and Irish plant start-ups tend to be born away from industry centers and this, in turn, favours the dispersion of economic activities. Such a feature may arguably provide at least a partial rationale for policy intervention if market failures, such as poor access to risk capital markets, are preventing an efficient number of start-ups in peripheral regions. This, of course, would not be the case if the start-ups in the disadvantaged regions were the driving factors behind why plant deaths act to concentrate economic activities. However, our results by plant age indicate that, at least for the first few years, the dispersing effects of birth of plants' start-ups outweighs the increased probability of exit in the early part of the life cycle of a plant in both countries.

Finally, our evidence concerning the tendency for high technology industries to disperse suggests that knowledge externalities may not always be strong enough to compensate for the influence exerted by dispersion forces. Further empirical analysis should try to explain why, even within a group of industries where agglomeration forces are expected to be so important, one observes no clear pattern of geographical concentration.

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Table 1: Mean levels of geographic concentration for Portugal

	1985	1990	1994	1998
EG index (γ)	0.081	0.080	0.079	0.077
Raw concentration (G)	0.159	0.158	0.157	0.156
Plant Herfindhal (H)	0.086	0.086	0.086	0.087
Employment weighted mean γ	0.101	0.098	0.096	0.095

The table reports means (across 85 Portuguese ISIC four-digit industries) of the EG index and the two components: the simpler raw geographic concentration measure and a Herfindhal measure of plant-level concentration.

Table 2: Mean levels of geographic concentration for Ireland

	1985	1990	1994	1998
EG index (γ)	0.032	0.031	0.027	0.027
Raw concentration (G)	0.170	0.160	0.142	0.147
Plant Herfindhal (H)	0.155	0.152	0.132	0.140
Employment weighted mean γ	0.043	0.043	0.040	0.042

The table reports means (across 67 Irish ISIC four-digit industries) of the EG index and the two components: the simpler raw geographic concentration measure and a Herfindhal measure of plant-level concentration.

Table 3-Correlations of EG index over time for Portugal

	1985	1990	1994
1990	0,871		
1994	0,812	0,912	
1998	0,687	0,822	0,901

The table gives the correlation between the values of the EG index when computed using data from different years for Portugal.

Table 4-Correlations of EG index over time for Ireland

	1985	1990	1994
1990	0.788		
1994	0.615	0.888	
1998	0.409	0.753	0.856

The table gives the correlation between the values of the EG index when computed using data from different years for Ireland.

Table 5 - Pattern of raw concentration changes across industries for Portugal

Set of Industries	Mean γ (1985)	Correlation area shares 1998-1985	Estimates		Total percentage change in Raw concentration		
			β	σ	Total	Mean reversion	Dispersion
Full sample	0.081	0.47	-0.230 (0.017)	0.070	-1.77	-40.74	38.97

The column (1) gives the mean EG index for the set of the industries in 1985.The column (2) reports the average correlation between each district's share of the industry's employment in 1985 and 1998. Columns (3) and (4) present a coefficient estimate and the estimated residual standard deviation from regression (1). Columns (5), (6) and (7) report the average percentage change in raw concentration attributed to the mean reversion and dispersion as described in the text.

Table 6 - Pattern of raw concentration changes across industries for Ireland

Set of Industries	Mean γ (1985)	Correlation area shares 1998-1985	Estimates		Total percentage change in Raw concentration		
			β	σ	Total	Mean reversion	Dispersion
Full sample	0.032	0.409	-0.427 (0.020)	0.091	-13.39	-67.16	56.26

The column (1) gives the mean EG index for the set of the industries in 1985.The column (2) reports the average correlation between each county's share of the industry's employment in 1985 and 1998. Columns (3) and (4) present a coefficient estimate and the estimated residual standard deviation from regression (1). Columns (5), (6) and (7) report the average percentage change in raw concentration attributed to the mean reversion and dispersion as described in the text

Table 7: Raw Concentration changes and industry movement over time for Portugal

Time period	Percentage Change in Raw concentration		
	Total	Mean reversion	Dispersion
1990-1985	-0.78	-16.48	15.71
1994-1990	-0.25	-15.24	14.99
1998-1994	-0.76	-13.38	12.62

The table presents the decomposition of changes in raw concentration as described in the text for different periods of time

Table 8: Raw Concentration changes and industry movement over time for Ireland

Time period	Percentage Change in Raw concentration		
	Total	Mean reversion	Dispersion
1990-1985	-6.20	-51.88	45.68
1994-1990	-10.83	-33.68	22.85
1998-1994	3.55	-20.62	24.17

The table presents the decomposition of changes in raw concentration as described in the text for different periods of time

Table 9 - Pattern of raw concentration changes across industries for Portugal

Set of Industries	Mean γ (1985)	Correlation area shares 1998-1985	Estimates		Total percentage change in Raw concentration		
			β	σ	Total	Mean reversion	Dispersion
Less concentrated	0.001	0.49	-0.457 (0.058)	0.107	35.29	-70.52	105.81
More concentrated	0.165	0.60	-0.157 (0.026)	0.065	-8.37	-28.86	20.49
High tech	0.060	0.71	-0.312 (0.045)	0.074	-5.18	-52.73	47.55
Textiles & Footwear	0.143	0.46	0.005 (0.045)	0.034	22.27	0.97	21.29

The column (1) gives the mean EG index for the set of the industries in 1985.The column (2) reports the average correlation between each district's share of the industry's employment in 1985 and 1998. Columns (3) and (4) present a coefficient estimate and the estimated residual standard deviation from regression (1). Columns (5), (6) and (7) report the average percentage change in raw concentration attributed to the mean reversion and dispersion as described in the text.

Table 10 - Pattern of raw concentration changes across industries for Ireland

Set of Industries	Mean γ (1985)	Correlation area shares 1998-1985	Estimates		Total percentage change in Raw concentration		
			β	σ	Total	Mean reversion	Dispersion
Less concentrated	-0.016	0.279	-0.270 (0.043)	0.023	4.02	-46.73	50.74
More concentrated	0.165	0.004	-0.343 (0.034)	0.023	-19.86	-56.83	36.98
High tech	-0.021	0.070	-0.683 (0.041)	0.024	-33.68	-89.95	56.26
Textile & Footwear	0.05	0.80	-0.261 (0.062)	0.074	25.45	-45.32	70.77

The column (1) gives the mean EG index for the set of the industries in 1985.The column (2) reports the average correlation between each county's share of the industry's employment in 1985 and 1998. Columns (3) and (4) present a coefficient estimate and the estimated residual standard deviation from regression (1). Columns (5), (6) and (7) report the average percentage change in raw concentration attributed to the mean reversion and dispersion as described in the text

Table 11 – Employment changes at various life cycle stages for Portugal

Independent Variable	Δs^j_{ist}				
	Total	Expansions	Contractions	Births	Deaths
$s_{ist} - s_{st}$	-0.230	-0.014	-0.035	-0.184	0.002
	(0.174)	(0.006)	(0.013)	(0.0134)	(0.014)
$s_{st+1} - s_{st}$	1	0.115	0.165	0.628	0.092
	(0.092)	(0.031)	(0.069)	(0.071)	(0.074)
R^2	0.184	0.014	0.069	0.17	0.01

The table presents estimates from regression (2). The column (1), the change in the district's share of industry employment is regressed on the excess share of employment in the industry in the district in the initial year and a measure of district growth. The next four columns report similar regressions for dependent variables that are the portion of the total change attributed to events at each of four stages of the plant life cycle. Standard errors are in parenthesis.

Table 12 – Employment changes at various life cycle stages for Ireland

Independent Variable	Δs^j_{ist}				
	Total	Expansions	Contractions	Births	Deaths
$s_{ist} - s_{st}$	-0.427	-0.044	-0.031	-0.397	0.045
	(0.012)	(0.008)	(0.009)	(0.017)	(0.009)
$s_{st+1} - s_{st}$	1	0.342	0.097	0.481	0.079
	(0.130)	(0.054)	(0.049)	(0.108)	(0.059)
R^2	0.277	0.05	0.016	0.302	0.019

The table presents estimates from regression (2). The column (1), the change in the county's share of industry employment is regressed on the excess share of employment in the industry in the county in the initial year and a measure of district growth. The next four columns report similar regressions for dependent variables that are the portion of the total change attributed to events at each of four stages of the plant life cycle. Standard errors are in parenthesis.

Table 13 : Life cycle decomposition of changes in geographic concentration for Portugal

		Percentage Change in γ_t attributed to:			
Time period	Percentage Change in γ_t	Expansions	Contractions	Births	Deaths
1990-1985	-1.07	-12.66	-3.13	-24.25	38.89
1994-1990	-1.03	-9.59	12.10	-38.99	35.56
1998-1994	-3.16	-7.53	2.97	-29.31	30.77
Total Period	-5.18	-8.51	4.31	-57.71	56.76

Column (1) reports the percentage change over each period of the average (across the 85 four-digit industries) of the γ_t . The final four columns decompose these changes into partitions attributable to events at various stages of the plant life cycle as described in the text.

Table 14 : Life cycle decomposition of changes in geographic concentration for Ireland

		Percentage Change in γ_t attributed to:			
Time period	Percentage Change in γ_t	Expansions	Contractions	Births	Deaths
1990-1985	-23.20	-32.19	28.46	-88.78	69.31
1994-1990	1.46	-47.93	54.61	-73.92	68.70
1998-1994	-7.96	-64.65	43.86	-28.57	41.41
Total Period	-27.80	-40.02	43.39	-167.21	136.03

Column (1) reports the percentage change over each period of the average (across the 67 four-digit industries) of the γ_t . The final four columns decompose these changes into partitions attributable to events at various stages of the plant life cycle as described in the text.

Table 15 – Life cycle decomposition of changes in geographic concentration by age class for Portugal

	Percentage	Expansions		Contractions		Net Effect	
Time period	change in γ_t	0-5 years	+5 years	0-5 years	+5 years	0-5 year	+5 years
1994-1990	-1.02	-40.41	-8.18	29.22	18.39	-11.18	10.21
1998-1994	-3.16	-30.09	-6.74	17.19	16.54	-12.90	9.80

Column (1) reports the percentage change over each period of the average (across the 85 four-digit industries) of the γ_t . Columns (2) to (5) decompose these changes into partitions attributable to expansions and contractions by classes of age. Columns (6) and (7) give the net effect.

Table 16 – Life cycle decomposition of changes in geographic concentration by age class for Ireland

	Percentage	Expansions		Contractions		Net Effect	
Time period	change in γ_t	0-5 years	+5 years	0-5 years	+5 years	0-5 year	+5 years
1994-1990	1,46	-90,61	-31,24	58,48	64,83	-32,13	33,59
1998-1994	-7,96	-45,25	-47,98	8,66	76,60	-36.59	28,62

Column (1) reports the percentage change over each period of the average (across the 67 four-digit industries) of the γ_t . Columns (2) to (5) decompose these changes into partitions attributable to expansions and contractions by classes of age. Columns (6) and (7) give the net effect.

Table 17: Life Cycle decomposition for Portugal

Set of industries	Percentage change in γ_t	Percentage Change in γ_t attributed to:			
		Expansions	Contractions	Births	Deaths
More concentrated	-17.9	-4.25	4.63	-39.77	21.43
Less concentrated	69.84	-11.17	29.28	-40.12	150.52
High tech	8.97	-25.15	-15.79	-134.73	186.29
Textiles & Footwear	23.95	4.72	3.02	-12.40	28.65

The table gives the decomposition of percentage changes in γ_t into portions attributable to events at various stages of the plant life cycle for different subsets of industries.

Table 18 : Life Cycle decomposition for Ireland

Set of industries	Percentage change in γ_t	Percentage Change in γ_t attributed to:			
		Expansions	Contractions	Births	Deaths
More concentrated	-58.95	-29.28	-14.29	-63.60	48.22
Less concentrate	91.04	-8.20	116.18	-102.68	85.74
High tech	-54.70	64.59	288.87	-939.92	531.77
Textiles & Footwear	0.99	-150.2	-31.3	-119.02	202.3

The table gives the decomposition of percentage changes in γ_t into portions attributable to events at various stages of the plant life cycle for different subsets of industries.