Entrepreneurial Risk and the Geographical Concentration of Industries: UK 1996

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Abstract:

This paper provides a sketch of the effects that conditions of imperfect information and irreversibility of investment exert on location decisions, and produces some empirical evidence in support of those theoretical results, by looking into the concentration of manufacturing industries in the UK. We argue that the existence of an industry in a locality signals a "good" matching between industry-specific needs and local endowments; as a consequence, the expected level of profits conditional on the locality being "active" will be higher than the unconditional. The difference is bigger the higher the variability of industry profits. Agents will thus have an incentive to locate on "active" locales, which is stronger the higher the level of entrepreneurial risk of the industry. Our main prediction is that high-risk industries will be more concentrated geographically, *ceteris paribus*. We test this hypothesis on the geographical distribution of manufacturing activity in the UK, by running a series of OLS regressions of 217 NACE Rev.1 4-digit industries' Ellison and Glaeser's gammas on a measure of entrepreneurial risk, after controlling for transport costs, natural resource intensity and Marshallian economies of agglomeration. Our results confirm that high-risk industries are more concentrated geographically. As an additional contribution, a new proxy for vertical linkages is introduced.

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1. Introduction

The observation that economic activity is unevenly distributed across space is hardly new, and has attracted a great deal of attention from various fields of enquiry, from Sociology to International Trade Theory, from Complexity Theory to Geography. Since the seminal works of Von Thuenen and of Marshall, a substantial body of scientific activity has aimed at identifying the nature and scope of the forces at the origin of this phenomenon, and at defining their effect on the evolution of economic systems. Despite the wide variety of such contributions, fairly little interest has been devoted to analysing the decisional processes that lay at the basis of the emergence of agglomerations, and in particular at the effect that imperfect information and irreversibility of investments have on location decisions. Location theorists haven't shown much interest in the interaction between the two and its effect on location decisions, either. If, in fact, decision-making is at the very heart of location theory, and indeed the significance of investment irreversibility has been, more or less explicitly, recognized at least from the works of Hotelling on (Hotelling 1929), the issue of imperfect information has remained fairly marginal in the discipline. Notable exceptions are Pred's behavioural matrix (Pred 1967), which conceptualises a location decision as a point on a plane defined by availability of information and ability to process it, and the works of the followers of the so-called behavioural approach to location (see e.g. Lloyd and Dicken 1977). In contrast with the substantial lack of interest of location theorists, the literature in business sciences (Scharfstein and Stein 1990) and a host of empirical works on the location of foreign direct investment (Head et al. 1995) show that information incompleteness is remarkably pervasive in location decisions, and propose an intriguing view of sequential location decisions as interacting through the information channel (Kinoshita and Mody).

The objective of this paper is to draw a sketch of the effect that conditions of imperfect information and irreversibility of investment exert on location decisions, and consequently provide some preliminary empirical evidence on this relationship, by looking into the patterns of concentration of manufacturing industries in the UK. The plan of the paper is as follows: Section 2 analyses the relationship between entrepreneurial risk and location decisions in an imperfect information environment and outlines the effects that this interdependence has on the geographical concentration of industries. Section 3 provides some preliminary evidence of the relationships uncovered theoretically, by analysing the geographical concentration of 216 NACE Rev.1 4-digit manufacturing industries in the UK in the year 1996 as a function of a measure of entrepreneurial risk. Section 4 summarises our main findings and concludes.

2. Entrepreneurial risk and location decisions

Entrepreneurial risk can be defined as the characteristic of an economic venture to produce a stream of profits or losses whose amount cannot be determined ex-ante. A key feature of a risky investment is that it can produce losses;[1] in order for this to be possible, two necessary conditions must hold: prices must be uncertain, and investment must be at least partly irreversible[2].

Considerable attention has been devoted to investigating the nature of risk and its consequences on the organisation of economic activity since its first systematic definition, due to Cantillon 1755. Having no ambition to enter the depths of such a long-standing debate (see Schmidt 1996 for an account of the main contributions), we concentrate here on a specific aspect that has been somewhat ignored in the literature so far: that of the interaction between entrepreneurial risk and the geographical concentration of economic activity[3]. Our interest for such a relationship emerges out of two sets of considerations: on the one hand, a growing body of empirical work in Industrial Organisation shows the importance of entrepreneurial risk as a shaping force of the economic landscape (Disney et al. 2003; Dunne et al. 1989a; Dunne et al.1989b); Dunne, Roberts and Samuelson 1988, for example, found that 61% of manufacturing plants in the US ceased to exist within five years of their appearance; a figure that leaves little doubt on the pervasiveness of failure for economic ventures, and a finding that is hardly

[1] Here a loss is correctly defined as an opportunity cost, i.e. a profit that is lower than the one of the best alternative riskless investment.

[2] It is worth noting here that an investment whose monetary value is entirely recoverable but only at a subsequent point in time, still implies some irreversibility, represented by the interest that is foregone on the monetary value of the investment for the period of installation.

[3] To the best of our knowledge, only Webber 1972 attempts a systematic analysis of the effect demand uncertainty has on the geographical concentration of economic activity. As will become clear in the following, his risk-diminishing effect of agglomeration rests on completely different grounds than our analysis.

reconcilable with the persistence of geographical concentration in economic activity using the kind of tools Economic Geography theory provides, but rather indicates that the relatively stable levels of geographical concentration of industries over time is the outcome of a dynamic process of continual entry and exit of plants, often times with extremely short life spans[4]. On the other hand, the Business Studies literature has stressed the quantity, variety and complexity of the information necessary to make a location decision, and the high costs and the difficulties involved in gathering such information (see e.g. Schmenner 1982), and has clearly shown that the appropriate framework for the analysis of location decisions is one of imperfect information.

While a fruitful debate on the effect of profit uncertainty on entry decisions has been going on over the past decades (see Wu and Knott 2005 for a recent account), the substantial neglect for the fact that an entry decision is always, explicitly or implicitly, also a location decision has distracted researchers from analysing the interaction between the two levels of uncertainty. By interpreting location as a problem of decision under uncertainty, we are going to show how agents can exploit this interaction to produce better location decisions.

An optimal location decision can be defined as one that maximises the expected profit from an investment over the available pool of locales. Assuming we can identify all the local features that affect the profitability of an investment, which we shall refer to as local endowments, then an optimal location decision is one that best matches production requirements with local endowments[5]. A crucial problem in making a location decision is that information on local endowments is usually unavailable to the decision maker. It may not exist at all, as not all the couples industry/location are always observed, or, when it does exist, the agents with better access to it, the active producers, may not be willing to share it with their potential competitors. Potential entrants therefore need to estimate such characteristics on the basis of the information that is available to them independently of active agents' cooperation. We argue that the existence of an industry in a locality[6] affects both the availability of such information and the estimation process. Activity signals to non-informed agents that the matching between industry-specific needs and local endowments is good enough to produce non-negative profits, thus cutting the left tail off their ex-ante subjective probability

[4] Dunne et al. 1989a, for example, find that more than 50% of manufacturing plants in their sample appear in only one census.

[5] Notice that in this framework we consider market proximity, as captured for example by a measure of market potential, as part of the local endowments.

[6] And its size, if we allow for idiosyncratic differences in firms efficiency.

distribution of profitability for the locale. It would only be natural then, in absence of private information, that potential entrants would prefer to locate in an active locale; it can also be shown that this effect is comparatively stronger for higher risk industries[7]. It is important to stress here that were investment fully recoverable, profit variability would have no effect on the geographical distribution of economic activity, as firms could move instantly (and at no cost) to a new location whenever their first choice was not optimal. Sunk costs act as a price firms have to pay whenever they choose a location, and therefore they make it costly to engage in a trial and error process of this kind.[8]

In the following we build a framework for the analysis of entry decisions as location decisions in an uncertain environment, with the objective to unravel the relationship between entrepreneurial risk and geographical concentration. We address two fundamental questions: how does entrepreneurial risk affect location decisions? And how does this effect, in turn, interact with the geography of production? In order to do so, we first set up the decisional problem of entry in a market characterised by entrepreneurial risk, and then introduce a location decision in it, to highlight how the interaction between entrepreneurial risk and imperfect information on locales' endowments changes the decision-making process.

A rational agent will embark in a risky investment project only when the expected present value of profits is positive[9]. As such, an informed decision must be based on the estimation of the flow of profits the investment will produce over its economic life. Let's recall here that entrepreneurial risk has two components: uncertainty about future profits and irreversibility of investment. The effect of uncertainty is immediately clear: agents are unable to produce an accurate prediction of future profits, but can at best produce an estimate of their probability distribution. The effect of irreversibility is slightly subtler: assume that a share S of the initial investment is sunk. If after a decision to invest is made market conditions turn out to be bad, and thus the investment is abandoned, the agent will have to face a loss equal to S, even if production never starts.[10] It is thus crucial for the potential entrant to accurately estimate future profits before an entry decision is made. This in turn requires the estimation of future prices and consequently the analysis of the interaction of market supply and demand.

[7] We subscribe to Theory of Decision's analytical definition of risk based on the concept of mean-preserving spreads.
[8] The evidence in support of the existence of sunk costs is quite clear despite the difficulties involved in their measurement (see Asplund 2000; Guiso & Parigi 1999).
[9] We can assume investors to be risk-neutral here without loss of generality.
[10] With no sunk costs, in fact, we could imagine that agents would enter the market at every period, in the hope of making positive profits, and exit immediately every time market conditions turn out to be bad.

Let us assume, for simplicity, that uncertainty about future profits derives exclusively from randomness in future demand. Consider a demand function that is subject to a random shock in every period; the shocks are serially independent and distributed according to a density function that is known to all agents. Ex-ante demand is thus a family of functions identified by the value of the random parameter.

On the supply side of the market we want to avoid the degenerate solution of monopoly which is not interesting for our purposes. We thus need to introduce some assumption that can limit the size of individual firms as compared to the market. This can be a binding capacity constraint, for example, or we can assume the average cost function to be increasing for reasonably small levels of output. It does not matter for our immediate purposes what type of constraint is introduced, as long as individual plants are bound to be small and we can consider agents to behave as price-takers.

Given the shape of the supply and demand functions, market equilibrium at time t is contingent on the realisation of the demand shock. In particular, once the shock is realised, each firm will know their selling price, and can thus decide whether to stay in the market or leave. In equilibrium there will be a price threshold below which the discounted value of expected profits becomes negative[11]: if market price falls below such threshold, the firm will exit, otherwise it will produce.

The presence of entrepreneurial risk has a series of far reaching effects on market equilibrium: first of all it makes it possible for firms to make losses from their ventures; secondly, the actual duration of the investment is aleatory also when plants have infinite economic life, and depends on the actual realisation of the demand shock in every period. Therefore, the kind of equilibrium we will be looking at is dynamic in nature: entry and exit can occur at any period, depending on the realisation of demand shocks and on the agents' expectations on future profits. Another peculiarity of the equilibrium of a market characterized by entrepreneurial risk is the phenomenon of hysteresis, i.e. the existence of a wedge between entry and exit-trigger prices (Dixit 1989) between which market price can move without causing entry or exit of firms.

Let us analyse the decisional problem of a firm that upon entering a market of the kind described above has to choose a location for its production plant. First of all we need to introduce some type of asymmetry between locales that can justify the need for a location

[11] If such probability is equal to zero, entry will occur at every level of S, as there will always be positive profits to make.

decision. We assume that a plant's marginal cost function is affected by its location in such a way that locales can be ordered in terms of their suitability for investment; we can imagine firms to have access to a technology characterised by a marginal cost function with an intercept that is dependent on local characteristics. We shall also assume that such local characteristics are unobservable and that only their probability distribution over locales is known. In order to identify the effect of entrepreneurial risk on location choices we need to introduce a series of additional assumptions on both geography and technology that allow us to isolate the location decision from all locational factors that can overshadow our relationship of interest. We assume, in particular, that all available sites are at the same distance from a market centre, where all exchanges take place, and that they all have identical natural endowments. Moreover, we assume that there are no external economies or diseconomies of scale, so that production costs are not influenced by the presence of other plants in the locale. Effectively, all locales look identical to potential investors, except they can observe where active plants in the industry are located, but this alone, in absence of external (dis)economies does not affect the assessment of the locale's suitability for investment.

All information that is available on the supply-side of the market is the shape of the marginal cost function, the probability distribution over locales of the parameters that determine its intercept, and the location of active plants. The cost function is thus not completely identified a-priori; rather, the potential entrant faces a family of cost functions, the actual realisation of which will be disclosed only after a location has been chosen, and the initial investment made. Given the peculiar structure of the supply side of the market, at any point in time the shape of the supply curve is contingent on the number of active plants and on their location, and is consequently dependent on previous periods' entry and exit decisions.

The timeline of investment looks as follows: at time 0 the firm decides whether to enter the market, based on expected future profits, chooses a location and makes an irreversible investment S; only then the actual marginal cost function is disclosed. At the beginning of time 1 the demand shock is realised, the firm observes prices, and hence decides whether to produce or leave the market. The decision described in time 1 is repeated for every subsequent period, until exit occurs. Upon exit the plant is scrapped.

We argue that an active producer's decision to stay in the market generates an informational externality potential entrants can exploit to make a better location decision. The reasoning is as follows: since the entrant has no direct information on the single locales, her optimal choice is to enter the market whenever the present value of expected profits, computed at the expected value of marginal costs over locales, is positive[12], and pick a location at random. Entry will continue until the discounted expected value of profits from the investment is exactly equal to the entry cost S. If the range of variation of the demand shock is wide enough[13], at this equilibrium there will be a non-empty subset of locales for which the probability of price to fall below the exit threshold is positive. If such a subset exists, then choosing a location at random from the whole pool is not rational, in the sense that it does not make full use of all available information. Observing the location of active plants introduces an asymmetry in the pool of available locations, in terms of their expected level of marginal costs: for each level of local marginal costs, in fact, there exists a price below which the expected value of staying in the market becomes negative. In general, the probability of price to fall below the exit-trigger value is, given the variance of equilibrium price and the level of sunk costs, an increasing function of marginal costs. If this is the case, then it follows that the probability of a locale to be "active" is in each period a negative function of its level of marginal costs, and therefore that the expected value of marginal costs on the subset of "active" locales is strictly lower than the unrestricted value. A rational agent will therefore always choose to locate in an "active" locale, in absence of better information. This effect is stronger the higher the variability of demand. Higher variability of demand, in fact, implies a higher probability of prices to fall below the exit trigger for each level of marginal costs, and thus the probability density function of costs conditional on activity will be more skewed towards the left, with respect to the unconditional.

Given the path-dependent nature of equilibrium, we cannot infer a deterministic relationship between entrepreneurial risk and geographical concentration; what we can identify is a tendency for newcomers in the industry to replicate their forerunners' location decisions, which is stronger the higher the level of entrepreneurial risk of the industry. We thus expect higher-risk industries to be *on average* more geographically concentrated, as a consequence of both the selection process triggered by the sheer existence of entrepreneurial risk, and of the concentration of new plant births.

[12] In computing the expected value of profits we need to consider that in every period there is a positive probability of exit q. Therefore the expected value of profits in every period will be equal to the difference between expected value of price subject to the price being above the exit threshold, minus the expected value of costs, multiplied by quantity, all multiplied by the probability of price being above the exit threshold.

[13] In comparison to the range of variation of local characteristics.

3. The geographical concentration of UK manufacturing industries

This section examines empirically the relationship between entrepreneurial risk and the geographical concentration of industries.

Our theoretical analysis suggests that firms have a stronger incentive to agglomerate spatially in higher risk industries. If this is the case, in equilibrium, higher risk industries will display a higher degree of geographical concentration, *ceteris paribus*. We test this hypothesis on the geographical distribution of manufacturing activity in the UK in 1996. For this year we are able to obtain the Ellison-Glaeser gammas (E-G 1997) for 216 4-digit industries (NACE Rev.1) within the manufacturing sector, computed over postcode areas. [14]

The Ellison –Glaeser gamma of the i^{th} industry looks as follows:

$$\gamma_i = \frac{G_i - (1 - \sum_l x_l^2) H_i}{(1 - \sum_l x_l^2)(1 - H_i)},$$

where H_i is the industry's Herfindall index: $H_i = \Sigma_s z_{is}^2$, z_{is} being the s^{th} plant's share in industry i's the total employment; G_i is the spatial Gini coefficient: $G_i = \Sigma_l (x_l - s_{il})^2$, where x_l is location l's share in total employment and s_{il} its share in industry i's employment.

The main advantage of the Ellison-Glaeser gamma over alternative measures of geographical concentration is that it accounts for the level of industrial concentration by adjusting for the industry's Hirschman-Herfindall index.[15] Gamma will thus assume a value of zero when the industry's geographical concentration is compatible with a random allocation of plants to spatial units, given the size distribution of plants, and therefore is not "real" agglomeration.

Table 3.1 and 3.2 show the UK's 20 most and least geographically concentrated industries in 1996. As we can see from the tables, industries do vary substantially in their level of geographical concentration.[16] The most concentrated industry, *Manufacture of coke oven products*, has a gamma over 60 times as high as the median value of the sample, while 22

[14] The E-G gammas are built from plant-level data contained in the ONS's Annual Respondent Database. Source: Duranton & Overman 2005.

[15] A feature it shares with the Maurel-Sedillot index (M. & S. 1999)

[16] The coefficient of variation over our sample is 2.2.

industries display a gamma smaller than one tenth of such value. Thirteen industries have negative gammas.

Looking at the 20 most concentrated industries in the UK (Table 3.1) doesn't reveal any surprises: 8 out of 20 industries belong to the textile sector, traditionally geographically concentrated in Britain, as are the production of bicycles, wallpaper and ceramic goods (see Devereux et al. 2004). We then find industries that are consistently amongst the most concentrated in country studies, such as the branches of the food and beverage industries with low-perishability outputs and the production of basic chemicals.

The 20 least geographically concentrated industries (Table 3.2) don't reveal any surprises either; we find low value/mass ratio products: mortars, ready-mixed concrete, paper stationary, starches, as well as perishable goods such as ice-cream, cocoa, chocolate and sugar confectionary.

Table 3.1: The UK's 20 most concentrated industries in 1996.

NACE Rev.1	Industry	Gamma E-G
df2310	Manufacture of coke oven products	0.6764235
di2621	Manufacture of ceramic household and ornamental articles	0.4868832
db1771	Manufacture of knitted and crocheted hosiery	0.3063018
db1723	Worsted type weaving	0.1993559
db1721	Cotton type weaving	0.1616460
da1591	Manufacture of distilled potable alcoholic beverages	0.1566419
db1713	Preparation and spinning of worsted-type fibres	0.1404961
db1725	Other textile weaving	0.1387996
dm3542	Manufacture of bicycles	0.1332697
db1712	Preparation and spinning of woollen-type fibres	0.1278669
db1810	Manufacture of leather clothes	0.1176941
db1772	Manuf. of knitted and crocheted pullovers, cardigans and similar articles	0.1109296
da1532	Manufacture of fruit and vegetable juice	0.1097321
db1711	Preparation and spinning of cotton-type fibres	0.1070678
da1520	Processing and preserving of fish and fish products	0.0977008
da1588	Manufacture of homogenised food preparations and dietetic food	0.0972404
dg2414	Manufacture of other organic basic chemicals	0.0966347
de2124	Manufacture of wallpaper	0.0957056
dk2951	Manufacture of machinery for metallurgy	0.0918688
dc1930	Manufacture of footwear	0.0885854
Median		0.010746

Table 3.2: The UK's 20 least concentrated industries in 1996.

NACE Rev.1	Industry	Gamma E-G
dg2462	Manufacture of glues and gelatine	0.000639
dd2051	Manufacture of other products of wood	0.0006193
dn3612	Manufacture of other office and shop furniture	0.0005463
di2663	Manufacture of ready-mixed concrete	0.0005349
da1589	Manufacture of other foods products not elsewhere specified	0.000517
dk2922	Manufacture of lifting and handling equipment	0.000264
dn3662	Manufacture of brooms and brushes	4.73E-06
de2123	Manufacture of paper stationery	-0.0001452
da1584	Manufacture of cocoa; chocolate and sugar confectionary	-0.0013349
da1586	Processing of tea and coffee	-0.0017489
dn3630	Manufacture of musical instruments	-0.0018725
da1552	Manufacture of ice cream	-0.0019657
dk2960	Manufacture of weapons and ammunition	-0.00239
di2664	Manufacture of mortars	-0.002707
dl3161	Manufacture of electrical equipment for engines and vehicles n.e.c.	-0.0040379
da1562	Manufacture of starches and starch products	-0.0048348
dm3541	Manufacture of motorcycles	-0.0057457
dm3543	Manufacture of invalid carriages	-0.0107654
dn3621	Striking of coins and medals	-0.0111023
dh2511	Manufacture of rubber tyres and tubes	-0.0158617
Median		0.010746

Simply looking at these two charts we can't envisage a single force that could cause the agglomeration/dispersion of industries so different from one-another. Rather we can imagine that a multiplicity of factors drive the geographical concentration or dispersion of different industries: e.g. pooling of specialised but relatively unskilled workers for textiles, perishability of inputs or outputs for the food and beverage industries, high unit transport costs for mortars and concrete.

In trying to explain the overall distribution of the Ellison-Glaeser gammas as a product of the industries' intrinsic risk level, we will need to account for all such industry-location specific features: transport costs, resource endowment, economies of agglomeration. After controlling for all these determinants of geographical concentration, we expect the coefficient on our proxy for entrepreneurial risk to be positive.

3.1 The determinants of agglomeration

The present section describes the data and the processes used in building the variables on the right-hand side of our regressions. We begin with our main regressor, entrepreneurial risk, and its components, variability of profits and sunkness of fixed costs. We then move on to describe the controls for the forces that have been identified in the literature as possible causes of geographical concentration of industries: natural advantage, transport costs and Marshallian agglomeration forces.

3.1.1 Entrepreneurial Risk

In order to capture entrepreneurial risk, we need to interact a measure of industry profits' variability with an indicator of the "sunkness" of fixed costs.

Industry-level profits are available at the 4-digit level for the years 1996 to 2002 in the Annual Detailed Enterprise Statistics dataset published by Eurostat as *Gross Operating Surplus*. From the industry time-series we compute the linear trend of profits over the period using simple least squares. We then compute an index of the variability of realized profits around this trend as the coefficient of variation:

$$VP_i = \sqrt{\frac{\sum_t \left((Y_{it} - \hat{Y}_{it}) / \hat{Y}_{it} \right)^2}{n}} ,$$

where Y_{it} is industry i's profits at time t, $\hat{Y}_{it}$ is their estimated value on the linear trend, and n is the number of time points, in our case 6.

The choice of an indicator for sunkness of fixed costs is more problematic, both on a theoretical and on a practical level, because the degree of sunkness of fixed costs is not observable. We construct a proxy based on the recognition that the sunkness of physical investment depends essentially on its specificity, and that different categories of capital goods have different levels of specificity. Machinery and equipment, in particular, tend to be more industry-specific than the other components of the fixed capital stock (Kessides 1990a). We thus use the share of machinery and equipment in the industry's fixed capital stock as a proxy for “sunkness”. The actual construction of this proxy presents some technical difficulties: the Office of National Statistics produces data on the detailed composition of capital stocks only at the 2-digit level. We thus need to build our own estimate of capital stocks starting from data on investment. These are available in Eurostat’s Detailed Enterprise Statistics (DES, from now on) for the years 1996-2001. Investment in tangible goods, as measured in DES, is broken down into 4 categories: land, buildings and structure (2), and machinery and equipment. A fifth category can be built residually by subtracting the sum of all the categories from the total expenditure on investment goods, also published in the same dataset.

We use a capitalisation method to build estimates of capital stocks from data on investment flows. For each industry we compute the average annual level of investment in each category of capital stock as a percentage of sales. We then multiply these values by the appropriate capitalisation factor, to account for differences in the economic lives of the different categories of capital goods, to obtain capital stocks.[17] Our method only provides an approximation of real stocks. Accurate figures could be obtained with a Perpetual Inventory Method, using data on the actual flows of investment in capital goods for all periods prior to the period of interest[18], but unfortunately such data are not available at a usable definition. We don’t consider this to be too much of a problem for our regressions, as we would expect inter-industry differences in capital composition to be reasonably stable over such a short period of time.

A number of alternative measures have been proposed in the Industrial Organization literature:

Kessides proposed three measures based on the incidence of rented capital goods on total capital, depreciation rates of physical capital, and expenditure on used capital goods on total investment (Kessides 1990b; Ghosal 2002). We build a close proxy of the first of such measures, as the average over the period 1996-2001 of the ratio of *Value of tangible goods acquired through financial leasing* (from DES) to total fixed capital. Data on depreciation rates at the 4-digit level are not publicly available for the UK, nor are data on the origin of capital goods, therefore we can’t build either of the other indicators.

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[17] The capitalisation factors are defined as: $\frac{1}{2}$ (service life + 1), which is consistent with a linear depreciation function. Service lives of different capital goods in different industries are obtained from the OECD report “Methods used by OECD countries to measure stocks of fixed capital”.

[18] We only have data for the period 1996-2001, while PIM would require data since at least 1971; earlier if we were to include land in capital stock.

Sutton proposed an estimate based on the concept of Minimum Efficiency Scale, built from the size of the median plant in the industry (Sutton 1991). Although this measure can approximate the level of barriers to entry in a market, it does not necessarily capture the losses incurred with exit, which is the kind of sunkness in which we are interested the most, when capital composition differs across industries (Sutton 1991, p.94). Imagine an industry characterised by positive returns to scale, but low specificity of assets: in this case median plant size would be bigger for purely technological reasons, while barriers to exit may be relatively low. We can't build such a measure since we do not have access to the data on individual plant size.

The two components of our main regressor, *variability of profits* and *sunkness of fixed costs,* are interesting in their own right as regressors, as they can help shed some light on the processes behind the observed levels of agglomeration, and in particular on the balance between exits, entry and growth in determining them. Sunkness of fixed costs, in fact, is expected to be negatively correlated with exit rates (Caves & Porter 1977). When a higher portion of fixed costs are sunk, the scrap value of installed capital decreases, and thus the monetary value of the exit option is reduced. Therefore, higher sunk cost industries will be expected to have lower exit rates, *ceteris paribus* (Gschwandtner & Lambson 2006 provide some empirical evidence on such negative relationship). On the contrary, higher variability of profits implies higher exit rates, as it increases the probability of profits to fall below the exit threshold in every period (Dixit 1989).[19]

We can use these relationships as an indicator of the turnover of plants in an industry, of exit rates, in particular. A positive sign on sunkness of fixed costs would suggest that industries with lower exit rates tend to be more concentrated, and consequently that exit is not likely to be the dominant force in shaping the observed pattern of concentration, but entry and growth are. A negative sign, on the contrary, will hint towards a significant effect of exit. A positive sign on variability of profits, indicating higher concentration for industries with higher probability of exit, will suggest a dominant effect of exits, and a comparatively lower importance of

[19]The condition holds strictly only if agents are impatient. If agents are not impatient and their expectations consistent, low profits in period 0 will necessarily imply higher expected profits in future periods, and thus the incentive to exit is offset by the expectations of higher profits in the future.

entries[20] and of growth. A negative sign will hint towards a comparatively more important role of entries and growth.

Dumais et al. explore this relationship directly on US data. They find an unambiguous positive effect of exits on agglomeration, and a negative effect of entries and growth. They also find, though, that entries are more likely to occur in locations where an industry is already concentrated, but the increase is less than one for one (Dumais et al. 2002). They also present some evidence of inter-industry differences in such effects, but do not explore the causes of such differences.[21]

3.1.2 Natural Resources, Water and Energy

A well-recognized determinant of the location of industries is the spatial distribution of natural resources. In a positive transport costs environment industries that rely on inputs that are unevenly distributed across space will show a tendency to locate closer to where these can be found. Ellison and Glaser show that even in an advanced economy such as the United States natural advantage alone explains about 20% of the observed concentration of industries (Ellison and Glaeser 1999).

We proxy for the importance of natural resource endowment to the location of manufacturing establishments through an indicator that captures the importance of natural resources to an industry's production. The underlying assumption is that industries that are more intensive in the use of natural resources will also have, *ceteris paribus,* a higher incentive to locate where those resources are found (or shipped in). We build our measure from the Office of National Statistics' I-O Analytical Tables, as the sum of the industry's input coefficients on the seven I-O primary industries: Agriculture, Forestry and Fishing (industries 1, 2 and 3), and Mining and Quarrying (industries 4, 5, 6 and 7). I-O tables break up the manufacturing sector into 77 industries. These are compatible with NACE Rev.1 and generally correspond to NACE 3-digit. We bridge the gap between the 216 NACE industries in our sample and the 77 data points in the I-O tables by assigning the same coefficient to all the

[20]If we assume agents not to be risk-loving, otherwise higher variability of profits will be associated with both higher entry and higher exit rates, and the sign on variability of profits can't help discriminating between them as causes of agglomeration.

[21] The percentage change in gamma attributable to new entries, in particular, ranges from 0 for unconcentrated industries to -4.3 for concentrated crafts.

NACE 4-digit industries grouped under a single I-O heading. This should not hinder the effectiveness of our proxies as controls, given that the NACE 4-digit industries aggregated under a single I-O heading are generally technologically similar, and that on average less than 3 NACE 4-digit industries are grouped in one I-O class.

Water and energy are arguably ubiquitous inputs in an advanced economy such as the UK. The need to introduce controls for them derives from the peculiar market structure the sectors assumed when they were privatised at the turn of the nineties. The distribution of water and electricity was handed over to region-based private monopolists, who could set their prices up to a limit established by the regulator so as to assure them with a fair return on their assets.[22] This structure is still in place in the water market and persisted in the electricity market until full liberalisation was introduced, between 1990 and 1999. As a result of such a system appreciable differences in water prices between regions emerged. The effect on electricity prices is not clear since regional data on electricity prices are not published.[23] In the gas market, although full competition in supply was in place by the end of 1995, distribution was divided amongst 12 local distribution zones, with potential effects on end-user prices.[24]

In line with our treatment of natural resources we proxy for the importance of water and energy as location factors through industries' intensity in their use. For water, we only have data for the 77 I-O industries, and we assign their input coefficient on industry 87: "Collection, purification and distribution of water", to all NACE 4-digit industries under the same I-O heading. Energy use data are available at the NACE 4-digit level in Eurostat's DES. We compute the ratio value of energy products purchased to total production value to have a measure homogeneous with the ones we use for water and natural resources; we then take its average over the period 1996-2001, to get a measure that captures the technological component of energy use, not the effects of energy products' price variation.

[22] Details on the price-capping system can be found in Pollitt 1999.
[23]Data on electricity prices for domestic use are, and these show a difference between the highest (Belfast) and the lowest (Brighton) of around 35% in 1995 (source: DTI 1996). Prices for water for a sample manufacturing plant are published by OFWAT for 1997/98. Here the difference between the highest price (West Kent) and the lowest (Cambridge) exceeds 112% (source: OFWAT 1998)
[24] Figures for industrial use are not available. Figures for domestic use show some regional divergence immediately after liberalisation. Starting from identical prices across Britain in 1995, the price spread was up to circa 3.5% by 1999.

3.1.3 Marshallian Forces

The third set of controls is meant to capture the so-called Marshallian agglomeration forces: labour pooling, knowledge spillovers, input sharing.

The theory of labour pooling states that firms in the same industry benefit from locating close to one-another, as this enhances their access to a pool of labourers with industry-specific skills. Direct measures of such skills or that capture the sensitivity of an industry to labour pooling as a location factor are generally unavailable; therefore proxies are needed that capture their effect on the dynamics of the local labour markets or on the composition of an industry's labour force.[25]

Within the second strand, we try to get to labour pooling through a measure that captures the importance of labour as an input for an industry: the incidence of labour costs on total costs. Eurostat provides data on both at the 4-digit level for the years 1996-2001. Here again we use the average computed over the whole period, to capture the structural component of labour demand as closely as possible.

Empirical studies that have relied on industry-specific proxies have used indicators such as the level of education of the labour force, labour productivity, and share of non-production workers. Following those studies, we also employ two measures of labour productivity: *Gross Value Added per Person Employed,* available from Eurostat for the years 1996-2001, and *Gross Value Added per Hour Worked,* available from the same source for the year 2001 only. Since we don't know the actual location of plants, and thus can't match them with their local labour market, we can't use any proxy that relies on local labour market dynamics.

The proxy for knowledge spillovers has the highest degree of arbitrariness. The problem is, to use Paul Krugman's words, that knowledge spillovers don't leave paper trails (Krugman 1991). Indirect measures are needed to assess their importance in different industries. We try to get to the importance of knowledge spillovers indirectly, using the importance attached to innovation in an industry, as captured by investment in Research and Development. In particular, we use the ratio of R&D employment on total employment and the share of R&D expenditure in value added as proxies for the importance attached to innovative activity by the decision makers. A drawback of our proxies is that the appropriation of knowledge spillovers

[25] Ellison and Glaeser 1999, produce a series of measures that couple the two, interacting indicators of the two.

and internal R&D activity are, to some extent, substitutes. We still think, though, that industries for which innovation is important will have a higher tendency to invest in R&D, as compared to industries where innovation is not crucial. Such indicators are readily available from Eurostat as *Share of R&D Employment in the Number of Persons Employed* and *Share of R&D Expenditure in Value Added.* Data are published for the years 1998-2001. Unfortunately their coverage is not complete: only 169 industries out of the 216 in our sample have data for R&D employment, and 162 out of 216 for expenditure. We fill in the gaps using, where possible, the 3-digit datum to substitute for the missing 4-digits. By doing so we increase the coverage of the two measures to 210 and 208 data points, respectively.

Several alternative measures have been proposed to capture knowledge spillovers, such as patent citations (Jaffe et al. 1993) or new products advertised (Audretsch and Feldman 1996), to cite but the most famous. Although those measures appear indeed fit to detect knowledge spillovers, which is what they were built for, they don't tell us much on their importance for location. For this we need a measure that is comparable across industries, and that is an object of decision for firms, like the one we propose. [26]

The proxy for vertical linkages is theoretically the most straightforward to build. The immediate choice is to compute the industry's input coefficient on total purchases of goods and services, i.e. the ratio of total purchases of goods and services to production value, both measures available from Eurostat for the years 1996-2001. We use the average of this ratio over the period, for the same reasons explained in discussing the proxy for labour pooling. Eurostat's DES does not distinguish between purchases of goods and of services, but only provide the total. Although theoretically this shouldn't be a problem, as both effects are expected to be positive, empirical analyses have sometimes found opposite effects for the two subsets of inputs (R&S 2001). This suggests that it could be useful to construct two distinct indicators for the two types of vertical linkages, so as to avoid the two effects cancelling out one-another. We build such indicators from I-O data. We use the sum of the input coefficients on industries 8 to 84 for manufactured inputs, and the sum of the coefficients on industries 107 to 115 and 118 to 123 for the non-manufactured. The same methodology and caveats apply as explained in Section 3.1.2.

[26] Such an indicator is generally rejected in those studies as it represents an input rather than an output of innovative activity, but this is exactly what we need it to proxy for, here.

In recognition of the fact that the incentive to locate closer to input suppliers is more likely to cause an industry to agglomerate when the input suppliers are geographically concentrated themselves, we propose a new measure to proxy for vertical linkages, that couples input intensity with the geographical concentration of input suppliers. We do so by weighing the input coefficient on each manufacturing industry by the industry's E-G gamma, before summation. The practical implementation of the measure on our data is slightly more complicated, due to the differences between the I-O classification and NACE. We first build the matrix of each industry's input coefficients on all other manufacturing industries[27], we then compute a vector of approximate E-G gammas for the 77 I-O industries, as the average of the gammas of the NACE 4-digit industries under the same I-O heading, weighted by employment. We multiply matrix and vector thus built, and finally convert the resulting 77 data-points back to 216, by assigning the same value to all the NACE 4-digit industries comprised under each I-O heading.

Our last control is the input coefficient of an industry on itself. This is meant to control for vertical disintegration within the same industry, which our previous control does not account for. Input coefficients are obtained directly from the I-O tables. The conversion procedure from I-O industries to NACE 4-digit is the same as described above.

3.1.4 Transport Costs

Accounting for the effect of transport costs on location is a complex business. It is well recognized that due to the endogeneity of transport costs to location, their observed level does not capture fully their effect on location decisions. Realised transport costs are in fact the equilibrium result of the decisional trade-off between maximising locational advantage, and minimising transport costs to the market[28]: higher unit transport costs produce a higher incentive to locate closer to the market, and thus reduce shipment length; the final effect of such countervailing forces on realized transport costs is ambiguous.

[27] We substitute the coefficients on the main diagonal with zeroes to avoid endogeneity when we multiply it by the vector of e-g gammas.

[28] We refer here to transport-to-market costs, because being c.i.f. pricing normally used in manufacturing, input transport cost will be reflected in input prices. This, in turn, will be accounted for by the proxy for vertical linkages.

Rosenthal and Strange put forward a proxy for inverse transport costs based on the average level of inventories per shipment (R&S 2001). The rationale for such a proxy lies in the observation that industries that produce perishable goods face higher unit transport costs, and at the same time cannot store their products for long. This, in turn, results in a lower stock to shipment ratio. Inventory to shipment ratios are readily available at the NACE 4-digit level in the Annual Detailed Enterprise Statistics on manufacturing, as *Ratio of stocks of finished products and work in progress to production value*. Data are available for the years 1996 to 2001. Considering that we need a measure that captures as closely as possible the systematic component of transport costs and not the effect of the economic cycle on the evolution of stocks, we use the average on the whole time series as our proxy, like we did for energy.[29]

We are not entirely satisfied with the stock to shipment ratio as a proxy for transport costs for two main reasons: first we find the link between transport costs and stock ratio quite weak; secondly we are not entirely convinced that the sign of its relationship with transport costs is unambiguously negative. If, in fact, we consider holding stocks as an alternative to frequent shippings, as the logistics cost approach to location does (McCann 1996), we would expect industries with higher unit transport costs to hold more stocks, *ceteris paribus*, so as to minimise the number shipments, and thus transport costs. We would then have a negative relationship with realised transport costs (holding unit costs constant), but a positive relationship with unit transport costs, and it is the latter that determine location decisions, not the former. If this is the case, the sign of the relationship could go either way, depending on which effect is stronger in each industry. We thus decide to introduce two more proxies for transport costs, one for realised transport costs and one for unit costs.

The first measure is the average ratio of expenditure on transport services to total output. We obtain it from the I-O tables as the average over the years 1996-2002 of the sum of the input coefficients on the I-O industries 93 to 97. There are a number of problems involved with using this measure, on top of the endogeneity issue already discussed: the manufacturing sector

[29] One caveat in using this proxy is that it can also capture the effect of the variability of demand on location. We could imagine, in fact, that in industries with high variability of demand, firms could run a higher stocks to shipments ratio, in order to be able to face peaks in demand. On the other hand, it is also possible that firms will react to higher variability of demand through a closer stock management, in order to reduce the risk of being stuck with an expensively high level of stocks. The overall effect of variability of demand on the stocks to shipment ratio is thus ambiguous. We test it empirically and find almost no linear correlation between this proxy and the variability of turnover, while its correlation with the variability of surplus is negative (-0.37) and significant. The correlation is low enough not to pose any problem for our regressions, but it is highly significant, and this must be kept in mind when interpreting the coefficient obtained on transport costs through this proxy, if variability of profits is not controlled for.

is broken down into only 77 industries in the I-O tables, and we therefore do not have a single data point for each of the 216 4-digit industries we use. Also, this measure captures only the cost of transport services acquired on the market, ignoring the cost of transport services internally produced. This could underestimate the impact of transport costs for those industries in which internal provision is more wide-spread, which, incidentally, are likely to be the more transport-intensive, so much so as to allow the achievement of an efficient scale of activity internally.

Our second proxy is the value-mass ratio. Value-mass ratios offer a measure that is negatively correlated with the incidence of transport costs, being unit transport costs generally dependent on weight of the goods to be shipped, and that is also independent on distance, and thus on location. We obtain such a measure from the UK export data published by HM Revenue & Customs.[30] Trade data are classified according to the Standard International Trade Classification (SITC). They therefore need to be converted into NACE, before we can use them. Unfortunately, SITC is not entirely compatible with NACE, in that there is not in general a univocal correspondence between the two classifications in either direction. We therefore build a correspondence table between SITC and NACE[31], starting from the conversion table provided by HM Customs[32]. Typically each NACE 4-digit industry has several corresponding SITC 5-digit classes; in a few cases discriminating amongst those results is straightforward as the majority of them are patently not representative of the NACE industry of interest, and we can thus narrow down our selection to a single result. In most cases, though, the decision is subtler as there are several plausible candidates. In this case we proceed in two ways depending on the results obtained from the conversion table: when all the results fall in the same SITC 3-digit class, we typically use that class altogether, to avoid any arbitrary selection. When, on the contrary, the results belong to different SITC 3-digit classes, and there is no obvious best candidate amongst them, we opt for the SITC 3-digit class that is closer to the counterparts of the closest NACE industries (typically those in the same NACE 2-digit group). Finally, for a considerable number of industries (71 out of the 237 NACE 4-digit industries in the conversion table), we obtain all the SITC 5-digit classes included in one SITC 4-digit class. In this case we

[30] We are indebted to Prof. Ian Gordon for suggesting the use of value/mass ratios.
[31] Conversion table available upon request.
[32] A web-base conversion tool is available at: http://www.uktradeinfo.co.uk/index.cfm?task=nomcorrelation

compute the unweighted average of such classes, to produce an approximate 4-digit SITC class measure.[33]

Table 3.3 shows the coefficients of linear correlation between the three proxies for transport costs we compute. As we can immediately notice, while the linear correlation between value/mass ratio and expenditure on transport services has the expected negative sign (highly significant), the stock to shipments ratio is almost uncorrelated with the other two measures.[34] Although the signs of the linear correlation coefficients seem to support McCann's interpretation rather than Rosenthal & Strange's, their level of significance is too low for this to be considered as evidence in favour of either. We'll return on the issue in Section 3.2, to try and get a better understanding in the light of our regression results.

Table 3.3: Coefficients of linear correlation between transport cost proxies

	Stock/shipment ratio	Transport services	Value/mass
Stock/shipment ratio (inverse)	1		
Transport services (direct)	0.0883 0.2101	1	
Value/mass (inverse)	-0.0843 0.2317	-0.6281 0.000	1

Significance levels are shown below ρ.

[33] Data on the SITC 4-digit classes are not available when data for the include 5-digit classes are published.
[34] So we would expect if transport costs are endogenous.

3.2 Determinants of Geographical concentration in the UK

We start by estimating a base-line regression of the Ellison-Glaeser gamma for industry i (γ_i) as a function of entrepreneurial risk, variability of profits and level of sunk costs, of the form:

$$\gamma_i = \beta_{Risk}\, Risk_i + \beta_{VP} VP_i + \beta_{Sunk}\, Sunk_i + \varepsilon_i \,,$$

where $Risk_i$ is industry i's level entrepreneurial risk, VP_i is the coefficient of variation of profits around their linear trend and $Sunk_i$ the degree of sunkness of fixed costs, as described in Section 2.1.1.

We then add the controls for natural resources, transport costs and marshallian forces sequentially, to check for the robustness of our first findings to different specifications. Our final specification has the form:

$$\gamma_i = \beta_{Risk}\, Risk_i + \beta_{VP} VP_i + \beta_{Sunk}\, Sunk_i + \Sigma_n\, \beta_n C_{ni} + \varepsilon_i \,,$$

where C_{ni} is the n^{th} control variable for industry i.

A caveat is necessary before we proceed to interpret the results of our regressions: all the proxies for the Marshallian forces and the two measures for transport stock to shipment ratio and expenditure on transport services are endogenous. It is theory itself to tell us that they should be, as they are linked to geographical concentration by a circular causation mechanism. We don't have a straightforward way to solve the problem, and given that the data we use to build our regressors are all more recent than E-G's we can't use lagged variables, either. For this reason, although we use OLS, our coefficients cannot be interpreted in the usual way, as the impact effect on the regressand of a unit increase in the value of the associated regressor. Rather they describe an equilibrium relationship between agglomeration forces and geographical concentration (see R&S 2001, p.206 for a discussion).

Table 3.4 shows the results of the estimation of our base line regression together with those of the different specifications we obtain by adding the controls for agglomeration forces sequentially. Table 3.5 reports the results of the complete regression when different measures of transport costs are used.

In our final specification we choose to use the Machinery and equipment to total fixed capital ratio as a proxy for sunkness of costs. We also tried the proxy based on the share of leased capital goods we describe in Section 3.1.1, but it performed quite poorly in our regressions. Consequently, the measure of entrepreneurial risk we use in our final specification is the product of variability of profits and the share of machinery and equipment on total fixed capital.

Looking at Table 3.4, the first thing to notice is that the coefficient on our proxy for entrepreneurial risk is positive and significant in all regressions. We thus find some robust empirical backing for our theoretical proposition that the level of entrepreneurial risk of an industry should be positively correlated with geographical concentration. What we cannot infer from our regressions, though, is whether this correlation emerges out of the "Darwinian" selection process described in Section 2, or out of a convergence in the location choices of the newcomers to the industry

Some hints on the processes at work behind the observed patterns of concentration can be found by looking at the signs of the coefficients on our proxies for "sunkness" and variability of profits. Variability of profits is, *ceteris paribus,* positively correlated with exit and negatively with entry. Obtaining a negative sign on it, although not very significant, would suggest that industry with higher exit rates are less geographically concentrated, and thus that the "Darwinian" selection process shouldn't be the main driver of geographical concentration. The positive, although scarcely significant, residual effect of "sunkness" on geographical concentration, is consistent with such interpretation (see Section 3.1.1). The kind of evidence produced here does not allow us to draw a final conclusion; detailed data on the geographical location of entries and exit in industries would be needed to investigate such processes, but we don't have such data in our availability. These results are robust to the alternative specification of transport costs discussed in Section 3.1.3, as shown in Table 3.5.

Table 3.4: Ordinary Least Square Regressions of industry E-G gammas on Entrepreneurial Risk, under different sets of controls.

Gamma E-G OLS Regression				
	1	2	3	4
Risk	0.049*	0.070***	0.073***	0.063***
	(0.025)	(0.022)	(0.022)	(0.023)
Variability of profits	-0.037	-0.0531***	-0.0561***	-0.047**
	(0.022)	(0.020)	(0.020)	(0.021)
Sunk costs (Mach.+Eq./Capital)	0.029***	0.013**	0.004	0.021
	(0.006)	(0.005)	(0.008)	(0.020)
Natural Resources			0.105***	0.150***
			(0.038)	(0.048)
Water			6.167	2.875
			(4.301)	(4.344)
Energy			-0.314	-0.243
			(0.237)	(0.233)
Labour Pooling (Labour cost in production)				0.054*
				(0.029)
Knowledge Sp. (R&D expenditure)				-0.035
				(0.026)
Vertical Linkages 1: Manufactured Inputs				1.610***
				(0.562)
Vertical Linkages 2: Services				-0.390**
				(0.163)
Vertical Linkages 3: Same-industry input				-0.037
				(0.039)
Transport cost inverse (stock/shipment ratio)		-0.005***	-0.004***	-0.004***
		(0.001)	(0.001)	(0.001)
R^2	0.2580	0.4357	0.4636	0.5471
Adjusted R^2	0.2472	0.4247	0.4451	0.5181
Number of Observations	210	210	210	200[a]

Standard errors in parentheses
Significance levels: * = 10%; ** = 5%; *** = 1%
a) Observations on R&D expenditure are available only for 200 industries, due to mismatching with the coverage of the main regressors.

Table 3.5: Ordinary Least Square Regressions of industry E-G gammas on Entrepreneurial Risk: Alternative specifications for transport costs.

Gamma E-G OLS Regression			
	Inverse tr. Costs	Two	Three
Risk	0.063***	0.051**	0.057**
	(0.023)	(0.024)	(0.025)
Variability of profits	-0.047**	-0.0355	-0.040*
	(0.021)	(0.022)	(0.023)
Sunk costs (Mach.+Eq./Capital)	0.021	0.033	0.031
	(0.020)	(0.021)	(0.022)
Natural Resources	0.150***	0.174***	0.178***
	(0.048)	(0.049)	(0.050)
Water	2.875	5.164	5.444
	(4.344)	(4.471)	(4.741)
Energy	-0.243	-0.161	-0.091
	(0.233)	(0.235)	(0.263)
Labour Pooling (Labour cost in production)	0.054*	0.050*	0.054*
	(0.029)	(0.028)	(0.030)
Knowledge Sp. (R&D expenditure)	-0.035	-0.042	-0.048*
	(0.026)	(0.026)	(0.028)
Vertical Linkages 1: Manufactured Inputs	1.610***	1.364**	1.346**
	(0.562)	(0.572)	(0.593)
Vertical Linkages 2: Services	-0.390**	-0.353**	-0.336**
	(0.163)	(0.163)	(0.170)
Vertical Linkages 3: Same-industry input	-0.037	-0.051	-0.046
	(0.039)	(0.039)	(0.042)
Transport cost inverse (stock-shipment ratio)	-0.004***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)
Transport costs (transport services expenditure)		-0.450*	-0.572**
		(0.001)	(0.264)
Inverse unit transport costs (value/mass ratio)			0.0002
			(0.0002)
R^2	0.5471	0.5560	0.5619
Adjusted R^2	0.5181	0.5251	0.5267
Number of Observations	200	200	188[a]

Standard errors in parentheses

Significance levels: * = 10%; ** = 5%; *** = 1%

a) The HM Customs tables on value/mass allow us to produce an observation only for 188 industries in our sample.

The proxy for natural resources has the expected positive sign and is highly significant. Natural resources seem to be playing a crucial role in location decisions, also in an advanced economy like the UK. A result that is consistent with what previous studies have found for the US (E-G 1999; R&S 2001).

On the contrary, the proxies for energy and water are never significant in our regressions. In the case of water, this could be partially due to the poor coverage of our data. In the case of energy we suspect that the low significance of the coefficient may depend on low spatial variability of energy prices in the UK, but we haven't got the data to support this view. We can only observe that the spread in electricity prices for domestic use was lower than 20% (1995) and that of gas lower than 4% (1999)[35], and since manufacturing plants are freer in their location choices than households, we would expect energy prices for industrial use to vary less than those spatially. Therefore, we may not expect a dramatic effect of energy intensity on location. A relatively unimportant effect of energy on location is also consistent with the findings of R&S for the US.

The proxy for labour pooling based on labour costs shows the expected positive sign. In our preliminary regressions we have also tried the proxies based on labour productivity described in Section 3.1.4. We decide not to use them in our final specification because they don't seem to effectively capture labour pooling, as they consistently show an implausible negative sign. We suspect that such a poor performance may be due to the sensitivity of labour productivity to capital intensity. We test this hypothesis empirically, and we find a strong positive correlation between both measures of labour productivity and a number of measures of capital intensity.[36] The proxy based on labour costs, on the contrary, tends to overestimate the importance of labour pooling for the labour intensive industries that rely on unskilled labour. This should be less problematic, though, when analysing manufacturing employment in an advanced economy, where we would not expect labour-intensive industries to be dominant. The case would be different if we were to apply such a proxy to the service sector or in the study of a less developed country.

[35]These figures exclude Northern Ireland. See footnotes 10 and 11 for more details.
[36] Value added per person employed displays a coefficient of linear correlation of 0.30 with the capital/turnover ratio, and of 0.34 with capital/turnover from industrial activity. Both are significant at the 99%. For value added per hour work, the coefficients are, respectively, 0.15, significant at 95%, and 0.18, significant at 99%.

Contrary to what theory would predict, we find a negative coefficient on knowledge spillovers, too. A plausible explanation could be quite simply the inadequacy of our proxies to capture such effects, if the "substitution effect" between in-house R&D and knowledge spillovers appropriation described in Section 3.1.4 were dominant. Cross-checking with the closest empirical experiment of this kind, Rosenthal and Strange 2001, it emerges that also there the proxy for knowledge spillovers, number of innovations, has a negative sign (R&S p.217). A possible reason why the signs on both such proxies are negative is that knowledge spillovers act more through urbanisation externalities, rather than localisation (Jacobs 1969). In this case only an analysis of cross-industry co-location would capture these effects directly. We also run all regressions using R&D employment instead of expenditure, with identical results in terms of signs and significance. R&D employment, though, performs marginally better in terms of explanatory power. The regressions run using the originally available 162 data points produce very similar results.

The Proxy for vertical linkages based on the interaction between input intensity and the geographical concentration of upstream industries shows the expected positive sign and is significant at the 1% confidence level. This is comparatively a much better performance than the alternative measures employed in similar studies (R&S 2001). The measure based on service-intensity is also significant, but with an unexpected negative sign. This could be due to the higher degree of immateriality of services, which may render physical proximity to service providers unnecessary. Such a result is consistent with previous empirical findings, as we discuss in Section 3.1.4. We also try running the same regressions using the sum of the input coefficients on manufacturing industries directly, without weighting for geographical concentration. The results are very poor in terms of significance, and the signs are very sensitive to specification. Since the coverage of the two indicators, weighted and unweighted, is the same (the 77 I-O industries), we consider such a difference in performance to be an indicator of the fitness of our proposed measure as a proxy for vertical linkages. The proxy based on total purchases of goods and services is never significant in our regressions, despite its better coverage, and we thus discard it. The control for industry vertical disintegration is also never significant.

The negative sign on the proxy for inverse transport costs based on the stock/shipment ratio is to some extent surprising, too; it would imply, in fact, a positive correlation between transport costs and agglomeration. A surprising finding, but not implausible when interpreted through the lenses of NEG's "Bell-shaped curve" (Krugman and Venables 1995): it could simply mean that Britain is on the upward-sloping side of the curve, i.e. in the range of transport costs where diseconomies of agglomeration (labour market congestion, higher land prices, etc.) increase faster than agglomeration economies, as transport costs fall. This would be consistent with Britain having very low transport costs and high congestion costs. Both seem plausible if we consider that Britain has a well-developed transport system, and that it does show very high land prices and some congestion on the labour market, especially in the Southeast. We cannot infer that this is the case, though, just by looking at cross-section data. We would need to follow the same industry over time, and observe some changes in transport costs to apply the "bell-shaped curve" framework. Although it is possible that something in the line of the above might be happening, this is not the only plausible interpretation of the negative sign we obtain, as it is not clearly established that the stock/shipment ratio should be inversely correlated with unit transport costs. Looking at the result shown in last two columns of Table 3.5 can help shed some light on the relationship between transport cost and geographical concentration. The signs of the two coefficients that are significant, that on Stock/shipment ratio and that on expenditure on transport services imply opposite effects of transport costs on the geographical concentration of industries. It is possible that the internalisation effect discussed in Section 3.1.3 could explain partly the negative sign on expenditure on transport services, but it seems quite unlikely that something of that kind may be happening here, given the very high level of significance of our estimates and the size of our sample. An alternative explanation, one that is also supported by the results shown in Table 3.3, is that the dominating force behind the correlation between stock/shipment ratios and transport cost is the opportunity cost effect described by McCann (McCann 1996) and not the perishability effect of R&S. If this is the case, stock/shipment ratios would proxy direct transport costs, and the interpretation of our results would be reversed: transport costs would be negatively correlated with geographical concentration, and, to use the NEG framework again, the UK would be on the downward-sloping side of the bell-shaped curve. We do not have enough empirical grounds here to discriminate unambiguously between the two possibilities, but our empirical results are more supportive of the view that the Stock/shipment ratio is a direct proxy for transport costs, and thus the relationship between transport costs and geographical concentration be inverse, as expected.

4. Conclusions

We have presented some theoretical ideas on the effect imperfect information, irreversibility of investment costs and uncertainty of future profits have on the location of new manufacturing plants. Our main hypothesis was that when agents don't know a-priori all the relevant characteristics of available locations, observing the location of existing plants in the same industry can provide them with precious information on the suitability of the locales for investment. In Section 2 we have shown how this phenomenon is expected to have an effect on the outcome of new plants' location decisions, and in particular that higher variability of profits and irreversibility of investments should increase the geographical concentration of plant births in an industry. This in turn would affect the equilibrium level of geographical concentration of industries, in each period, *ceteris paribus*.

In Section 3 we tested the last hypothesis directly on the concentration of manufacturing industries in the UK in 1996. We did so by running a series of OLS regressions of the E-G gammas for 216 NACE 4-digit industries on a measure of entrepreneurial risk, after controlling for all the agglomeration forces identified in the literature. Our results support the view of a positive effect of entrepreneurial risk on the level of geographical concentration of industries. The signs we find for the residual effect of variability of profits (negative) and sunkness of fixed costs (negative), give some indirect support to the idea that a "Darwinian" selection process can't fully explain the observed correlation between entrepreneurial risk and geographical concentration.

The question of what exactly is the mechanism behind the emergence of such an outcome, and in particular the role that entry, exit and growth play in it, remains open. We can't provide a definitive answer as to whether the observed levels of geographical concentration are the result of selective exit or if convergence of entries has a role in it, as we haven't got data on entries and exits in our availability. Our results seem nonetheless to suggest that the geographical concentration of entries play a determinant role.

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