New Empirical Evidence on the Geographic Concentration of German Industries:

Do High-Tech Clusters Really Matter?

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Abstract

The agglomeration of industries has received much interest both in empirical and theoretical work in recent time. Especially in Germany politicians became inspired by the notion of high-technology industry clusters and German regional policy has seen a wave of initiatives aiming at the formation of such clusters. This papers explorers in a systematic way the geographic concentration of German manufacturing industries and relates it to industry characteristics and agglomeration forces proposed by theory. The main finding is that there is no general relationship between agglomeration and R&D or high-technology related business which suggests that hope put in the fast and effective development of ”high-tech” clusters might be disappointed.

1 Introduction

With the emergence of the New Economic Geography the issue of spatial concentration of economic activity has received much interest both in economic theory and empirical research. While the New Economic Geography—as well as longstanding concepts such as natural advantages in trade theory and external economies of scale already stressed by Marshall (1920)—has contributed much to our understanding of why firms may tend to cluster together there is still a lack of empirical evidence on the significance and determinants of geographical concentration and its actual relevance for economic policy. Further evidence is needed particularly on how much and why industries are actually concentrated and whether there are differences across industries. If there is indeed substantial concentration the question will be what forces drive agglomeration and what their relative impact is. Such an analysis may reveal important leverages for policy initiatives aiming at the promotion of business clusters for efficiency or equality reasons. If, on the other hand, no substantial concentration is found, then this would cast doubt on the effectiveness of such policy initiatives.

In fact, there has been a fundamental reorientation in regional policy in Germany, presumably being much inspired by qualitative work such as Porter (1991). The explicit aim of German regional policy has now become to promote the formation of high-technology industry clusters and to complement traditional policy measures that support the most backward regions. For example, the BioRegio contest set up in 1995 was an initiative that gave financial aid to the three most promising biotechnology clusters in Germany and the Inno Regio initiative launched in 1999 allocated funds to the least developed regions in East Germany in order to promote the emergence of business clusters.

In this paper we choose Ellison and Glaeser's (1997) index (EG index) to explore to what degree German manufacturing industries are agglomerated due to natural advantages or spillovers. Our work is different from previous research in so far as—to our knowledge—the EG index has not been applied to German industry data yet; in fact it has been applied to only a few countries comprising the US (Ellison/Glaeser, 1997), the UK (Devereux et al., 1999), France (Maurel/Sédillot, 1999), Spain (Callejón, 1997) and Austria (Mayerhofer/Palme, 2001). Lau (1996) and Keilbach (2002) have already investigated the geographic concentration of industries in Germany but have done so with a simpler measure; also, we have a more recent, more detailed and more comprehensive data set. In the following section we describe the agglomeration pattern of German manufacturing industries and in section 3 we relate our findings to theoretical agglomeration forces in a regression analysis.

2 Evidence on geographic concentration

2.1 The measures of concentration

Literature has established a variety of ways to measure concentration.[1] A measure that has been widely used is the spatial variant of the GINI coefficient introduced by Krugman. A severe disadvantage of the GINI coefficient is, however, that it measures concentration of economic activity both due to internal economies of scale, i.e. the "concentration" within a firm and due to natural advantages or external economies of scale, i.e. concentration stemming from the co-location of independent firms (or plants). In order to be able to distinguish between these two causes of concentration, we use two other measures instead. The first, and the one we put the focus on in this paper, has been proposed by Ellison and Glaeser (1997) and is derived from an explicit location decision model. The point of departure is the "raw concentration" of an industry defined as $G_i := \sum_i (s_{is} - x_i)^2$ where s_{is} is the portion of industry i's employment located in region s and x_s is the percentage of total employment in that region. Thus, G_i measures concentration relative to total employment which means that as long as an industry imitates the concentration pattern of aggregate employment it is not regarded as being concentrated.[2]

The advantage of defining concentration this way is that the overall distribution of employment (i.e. cities) and hence all location specific characteristics (population, commuting) are taken as given and that the benchmark is not an equal distribution of employment. EG show that—given their model of the firms' location decision—$E(G) = \left(1 - \sum_i x_i^2\right)(\gamma + (1 - \gamma)H)$ where γ is a combined measure of the strength of natural advantages and externalities between plants in a broad sense and H is the plant Herfindahl index. Rearranging then yields γ which is the measure of interest. A second advantage is that the model builds on a statistical distribution and allows one to test against the null of no concentration, i.e. plants choose their location in a pure random manner and independently from each other ("dartboard"). In this case, $\gamma = 0$ and $E(G) = \left(1 - \sum_i x_i^2\right) H =: G_{null}$.

Nevertheless, a weakness of this approach is that a world with natural advantages and

[1] For a survey see, for example, Devereux et al. (1999).

[2] Notice that there exists a range of suitable ways to define concentration, for example relative to an equal distribution or relative to population or land size.

one with externalities between plants are observationally equivalent. We try to overcome this limitation in section 3 where we relate concentration to agglomeration forces in a regression analysis.

Finally, note that while γ may be used for a variety of aspects of "concentration" we will use it to measure the concentration of firms belonging to the same industry. Thus, this paper examines the existence and impact of localisation economies as opposed to urbanisation economies which occur across industries. When we use the term "cluster" we refer to the agglomeration of an industry.

As one might worry that the EG index does not depict the reality of a firm's location decision process we choose a similar but simpler measure for comparison, namely a modified version of Devereux's et al. (1999) proposition. They define a measure $\alpha_i = G_i - M_i$ where $G_i = \left(\sum_s s_s^2\right) - \frac{1}{K_i^*}$, $K_i^* = \min(N; K_i)$, $M_i = H_i - \frac{1}{N_i}$, N_i is the number of plants in industry i and K is the number of geographic regions. G_i captures the geographic concentration of employment relative to the uniform share controlling for the maximum number of regions in which employment may be located given that there are (only) N_i plants. To be consistent with the EG index, which is relative to total employment, not to a uniform distribution, we use G_i instead of G_i. M measures the concentration of employment within firms (Herfindahl index) but relative to a uniform distribution. Then for any given geographic raw concentration G, the "internal" concentration of employment is subtracted while controlling for industry size (N). α is positive (but ≤ 1) whenever the distribution of employment (relative to total employment) across regions "exceeds" that across plants, it is zero whenever these are identical and it is negative (but ≥ -1) otherwise.

2.2 The data

The database we use provides the 1998 distribution of employment at the plant level across the 116 manufacturing industries (including extractive industries) and geographical areas (Kreise). While in their seminal paper EG focus on 4-digit industries and on states as the geographic unit of observation we are only able to use 3-digit industry data but at a much finer geographic level (440 Kreise as opposed to 51 U.S. states).

Our employment data are not classified (e.g. for confidentiality reasons) but instead contain precise figures for each plant regardless of its size. Therefore, no further improvement in the data

Figure 1: Descriptive statistics for manufacturing employment, 1998

Number of industries (NACE3)	116
Number of plants	216,545
Total employment	7,534,781
Employment per plant	34.8

is necessary and we directly compute the Herfindahl indices from it. However, the confidentiality of the data means that we are not able to aggregate plants to firms, i.e. determine whether plants are under common ownership. But according to EG's model plants of a firm are assumed to choose their location independently, anyway.[3] We are able to group total employment of a plant by education and by occupation (production, management, R&D etc.) which we will make use of when explaining concentration in section 3.

2.3 How much are industries concentrated?

In EG's simple dartboard model without any spillovers and natural advantages the plants of an industry choose their location randomly. In this case we would have $\gamma = 0$ and $E(G) = G_{null}$. In a first step we test whether $E(G)$ is significantly different from G_{null} and to our knowledge this is the first formal test for the statistical significance of the agglomeration of German industries. The mean values of G and G_{null} are 0.057 and 0.040, respectively, with their difference being highly significant.[4] More precisely, 91 out of the 116 manufacturing industries are significantly more (or less) geographically concentrated than what one would expect if location decisions were pure random.[5] Accordingly, for 25 industries the hypothesis of a pure random location decision cannot be rejected. This is in line with the results of EG who find that most but not all industries in the US are statistically concentrated in excess.

Figure 7 in the appendix shows the distribution of γ at the 3-digit industry level. It is skewed with mean 0.018 and median 0.006. A striking observation is the large number of industries (75%) that have a γ lower than 0.02 which—as argued in Ellison and Glaeser—can be interpreted as low concentration.[6] We find that only about 10% of all industries have a γ greater than 0.05

[3] Devereux et al. (1999) aggregate plants that are under common ownership and that are located in the same geographic region. If one assumes that the location of each plant is chosen independently and that a firm may well choose to locate its plants in different places then this procedure seems inconsistent.

[4] The difference is nearly three times larger than the average standard deviation of G.

[5] For these industries the difference between G and G_{null} is larger than 1.96 times the standard deviation of G.

[6] See Ellison and Glaeser (1997), p. 903.

Figure 2: Raw concentration attributable to spillovers and/or natural advantage

Range of ϕ	Manufacturing Industries	High-G Industries
0.00	7%	14%
0.25	28%	28%
0.50	30%	34%
0.75	24%	14%
1.00	11%	10%

and these are highly signi…cant. We conclude that in Germany slight concentration (at the Kreis level) is widespread while strong concentration is found only in a small subset of industries.

Besides, one can interpret Á := $\frac{G ¡ Gnull}{G}$ as the fraction of raw concentration attributable to some form of spillovers/natural advantage rather than randomness.[7] In Germany, for more than 60% of all industries randomness is at least as important for raw concentration as actual agglomeration of plants (Figure 2); in the sub-sample of high-G industries (upper quartile consisting of 29 industries) this share amounts even 75%. Put di¤erently, for less than half of all industries—and for only few industries with a high raw concentration—natural advantages and/or spillovers play a dominant role in agglomeration. In total, randomness seems to have a bit stronger in‡uence on observed agglomeration than agglomeration forces themselves.

Figure 8 in the appendix shows the most and least concentrated industries. Note that the negative gamma of the 15 least concentrated industries is insigni…cant, i.e. it is presumably zero. What is striking is that "high-tech" and "medium-tech" industries are not among the top most concentrated.[8] Rather, high- and medium technology industries lie in the middle …eld or even at the lower end of the ranking as Figure 9 in the appendix demonstrates. This is much in line with the …ndings of Devereux et al. (1999) for the UK.

Obviously, resource extractive industries dominate the top group and ® produces fairly the same ranking as ° with the notable exception of Kokerei and Uran- und Thoriumbergbau (NACE 231, 120).[9] These two industries consist of only 6 and 2 plants, respectively, each of which is located in a di¤erent location so that there is no agglomeration of plants. Hence these industries must be underrepresented in the majority of the regions which leads to such a high raw concentration. While the ° indicates that this particular concentration pattern may well

[7] Note that Ellison and Glaeser (1997), p. 909, use a slightly di¤erent expression.

[8] We use a common classi…cation developed by Grupp et al. (2000).

[9] If the resource related industries are excluded three out of the nine high-tech industries jump up into the top 15 but one of them still has an insigni…cant °.

be the outcome of pure random, α is much more responsive to the high raw concentration and ranks them on position 4 and 1 despite their high internal concentration.

2.4 Industrial scope of agglomeration

As we find concentration within industries an interesting question is if we can also identify concentration at a more aggregated industry level, i.e. at the NACE2 level. Is the concentration of industry groups due merely to the concentration of its (sub)industries which would imply that natural advantages and spillovers are industry-specific or is there a common effect on the industries of a NACE2 group? In order to explore this issue we calculate in a first step the degree of concentration at the NACE2 level for the 25 industry groups that contain more than one sub-industry using EG's γ^c.[10] It reflects how much the location decisions of firms that belong to an industry group are correlated; $\gamma^c = 0$ would indicate that there is no correlation across industries and hence no more agglomeration in the industry group than simply that resulting from the concentration of its sub-industries. Figure 3 compares our measures at the two industry levels.

Figure 3: Concentration at the NACE2 level

	H	G			γ			α		
		min	av.	max	min	av.	max	min	av.	max
NACE2	0.040	0.001	0.050	0.648	-0.003	0.004	0.051	0.000	0.014	0.075
NACE3	0.040	0.001	0.057	0.648	-0.010	0.018	0.263	-0.001	0.029	0.493

When moving from the aggregate to the finer industry definition raw concentration remains nearly unchanged while γ and α more than double. Since the magnitude of the co-agglomeration index for industry groups can be interpreted in the same way as the index for industries we conclude that geographic concentration at the NACE2 level is weaker than at the NACE3 level. Figure 10 in the appendix presents the results for all NACE2 industry groups.

At the NACE2 level there is no concentration in traditional industry groups like automobiles, communication technology, furniture, machinery and rubber which is in line with EG's findings for the US. Also similarly to the US, there is some co-agglomeration in the textile, metal,

[10] EG extend the model to the co-location of whole industries proposing a measure

$$\gamma^c := \frac{[G/(1-\sum x_i^2)] - H - \sum_{j=1} \gamma_j w_j^2 (1-H_j)}{1-\sum_{j=1} w_j^2}.$$

Figure 4: Distribution of λ

Range	Frequency	
-0.1	2	8%
0.0	2	16%
0.1	2	24%
0.2	4	40%
0.3	4	56%
0.4	4	72%
0.5	1	76%
0.6	3	88%
0.7	1	92%
0.8	1	96%
0.9	0	96%
1.0	0	96%
1.1	1	100.0%

lumber and paper industry. However, in absolute terms Germany's manufacturing industry groups exhibit only little concentration at the Kreis level if one takes 0.05 and 0.02 as an upper and lower benchmark, again.[11]

In a second step we calculate $\lambda := \frac{\gamma^c}{\sum w_j \gamma_j}$ which expresses the agglomeration of the group as a fraction of the weighted average of its industries. It indicates that there is no agglomeration attributable to the group as a whole if it is zero and that natural advantages and spillovers are completely group-specific rather than (sub)industry-specific if it is greater than 1. Figure 7 shows the distribution of λ.

We observe that for nearly all industry-groups there is some degree of co-agglomeration but with about 70% of them having a λ smaller than 0.5. This means that for the majority group-concentration accounts for less than half of the weighted industry-concentration. In contrast, Recycling, Papers and Automobiles seem to share natural advantages or inter-industry spillovers to a high degree but they are not much (or even negatively) concentrated in absolute terms (see again Figure 10 in the appendix).

Another way to quantify the relative strength of industry-specific and group-specific agglomeration has been proposed by Maurel and Sédillot (1999). They remark that the concentration of a whole industry group measured by the "simple γ" of the group can be written as the weighted average of the γ's of the group members ("intra-industry concentration") and some group-specific component ("inter-industry concentration"). Thus, in addition to comparing agglomerative (γ_j) and co-agglomerative forces (γ^c) one can also express intra-industry agglom-

[11] Note, however, that a comparison of the EG index across countries is not possible because it is standardised neither with respect to the area covered by the geographic unit used nor to the number of regions under study.

eration (γ_j) as a fraction of the group's total concentration (γ^{group}). This ratio ranges from as low as -2% to 134% (see column 7 in Figure 10). A fraction of intra-industry concentration greater than 100% corresponds to a negative contribution of the inter-industry component. Communications engineering (NACE 32) on rank 22, for example, is a group whose industries themselves are significantly concentrated but taken together they are rather dispersed.

In general, there seems to be no relationship between the degree of group-concentration (γ^c) and its magnitude relative to the weighted average of its components (λ_j); the spearman rank correlation is 0.40 and the standard correlation is 0.07. An implication of this is that one may always want to look at absolute concentration and its source at the same time.

One might worry that the NACE classification misrepresents plants which are difficult to be assigned a single and meaningful industry code. This is most problematic in the field of high-technology related activities where traditional industry codes do not appropriately cover completely new fields of economic activity.[12] Therefore, we compile by hand a high-tech and medium-tech industry group which do not exist under the NACE2 classification in order to examine if they—instead—are agglomerated (see Figure 5).[13]

Figure 5: Agglomeration of special industry groups

Group	Industries contained	G	H	γ^c	Weighted average γ	λ
High-tech	233, 242, 244, 296, 300, 321, 322, 333, 353	0.006	0.004	0.001	0.009	0.092
Medium-tech	241, 243, 246, 291, 293, 294, 295, 311, 314, 315, 316, 323, 331, 334, 341, 343, 352	0.002	0.003	-0.001	0.002	-0.646

The result is in contrast to what common wisdom about inter-firm spillovers in the high-technology area suggests. First, both groups have a γ^c close to zero and that of the medium-tech group is even negative. Secondly, they rank only very modestly compared to the standard NACE2 manufacturing groups.

We conclude, first, that there is some inter-industry concentration in German manufacturing industries which implies that industries share the benefits of natural advantages and/or spillovers to some degree. But for the very majority agglomeration within industries is stronger than across industries. Secondly, in the high- and medium-tech area not only industries but also industry

[12] Especially Germany's "new economy" characterised by a wave of start-up activity and a boom of the information- and communication industry is a challenge for the traditional industry classification system.

[13] Again, we use the classification by Grupp et al. (2000).

groups are not agglomerated much in absolute and relative terms.

2.5 Geographic scope of agglomeration

The EG index has the property that its expected value is independent of the geographic level provided spillovers are of an all-or-nothing type and natural advantages are not correlated across regions.[14] If spillovers decline with distance and thus work beyond regions, however, γ reflects the additional probability with which plants locate in the same location. In order to explore whether agglomeration forces exist at a higher geographic level and to account for the fact that administrative boundaries are not necessarily economically relevant we aggregate the 440 Kreis to 97 Raumordnungsregionen (ROR) which represent functional and self-contained regions with regard to commuting patterns.

A comparison of Figure 6 with Figure 3 shows that raw concentration and γ increase drastically on average while α does not change much. The overall ranking, especially the top group, remains fairly unchanged with the notable exception that Coking (NACE 231), which was on rank 113 and had no statistically significant concentration before, jumps on the very top of the ranking. But more industries than at the Kreis level are agglomerated only insignificantly. In fact, there is no rule about how agglomeration changes at a higher geographic level in general. Depending on the way the data are aggregated, the degree of concentration and the ranking can alter substantially.

Figure 6: Concentration at the ROR level

	H	G			γ			α		
		min	av.	max	min	av.	max	min	av.	max
Nace2	0.039	0.013	0.073	0.666	-0.286	0.033	0.182	-0.007	0.007	0.074
Nace3	0.040	0.002	0.072	0.667	-0.019	0.036	0.564	0.000	0.039	0.410

Dividing the γ's at the Kreis level by that of the ROR level and taking the median gives us a value of 0.517. This means that about 50% of the excess concentration at the ROR level stems from the tendency of plants to locate in the same Kreis. First, since a ROR on average consists of more than 2 Kreise we conclude—as EG did for the US—that agglomeration forces within Kreise are stronger than between Kreise. Secondly, if we take 0.975 as a benchmark we find

[14] Spatial correlation means that there is a tendency of neighbouring regions to have the same natural endowment.

that in only five cases concentration at the Kreis level is equal to that at the ROR level. For all other industries concentration is higher at the ROR level which means that agglomeration forces operate beyond Kreise.

3 Explaining concentration

The EG index is an appropriate way to measure concentration with regard to many aspects but it cannot distinguish between the various forces that may drive agglomeration: as noted, any gamma is consistent with a world only with natural advantages, only with spillovers or both. Furthermore, the index captures spillovers in a very broad sense. In a final step we want to determine what forces are actually at work. We do so by regressing the EG index on a variety of controls. While natural advantages can well be a reason for agglomeration they are clearly not of much intellectual interest. Rather, we are interested in the existence and magnitude of external effects spurring agglomeration. Based on the considerations of Marshall (1920) literature has established three types of externalities: (1) a pooled market for specialised labour, (2) a pooled market for specialised input services (input sharing) and (3) knowledge spillovers (for empirical evidence see Jaffe et al. 1993, Anselin et al. 1997, Harhoff 1999).

3.1 Controls for Marshallian forces

Input sharing. In a world with fixed costs specialisation of firms can lead to a cumulative process of concentration. The more customers an industry producing a non-tradable service has, the more it can specialise and exploit increasing returns to scale due to fixed costs. This increases productivity and/or the variety of the products which in turn benefits the purchasing industry which is assumed to like variety à la Dixit/Stiglitz (1977). This mechanism may eventually lead to the formation of a cluster both of specialised input producers and specialised purchasing industries.[15] We employ the portion of technical and industrial services and the portion of manufactured inputs in total shipments as an indicator of how specialised these are and hence how large gains from sharing inputs could be. All cost data are taken from the 1998 collection of the cost structure in German manufacturing industries carried out by the German census bureau. Services are likely to be very industry-specific with the largest potential for scale economies and manufactured inputs much less special so that we expect a positive sign for both

[15] For a formal model of this mechanism see Abdel-Rahman and Fujita (1990).

but a much stronger impact of the former.[16]

Labour market pooling. If an industry needs workers with industry specific skills it benefits from locating in an area where the supply of such labour is high because this increases the probability of finding capable personnel. Conversely, specialised workers reduce the probability of being unemployed by moving where the demand for their skills is relatively high.[17] With the assumption that low-skilled workers are relatively immobile and do not need to be much mobile because they find a job everywhere, it becomes possible to reveal the effect of the need for specific skills.

We use three alternative measures for the specificity of an industry's skills. The first is an industry's share of employees with a highly specialised occupation. We follow the common definition of "secondary services" which includes management, supervision, teaching and R&D (as opposed to primary services: trading, security, office and general duties).[18] The data are taken from our employment database. The second measure accounts for employees' education. We are able to split up total employment into three groups: no vocational training, vocational training and university degree. In terms of education the discriminatory power will be highest if we take the first and the third because employees with no vocational training at all are very unlikely to have a high school degree while those with a university degree must have one. People with a vocational training in contrast, may have very diverse educational backgrounds in real life. We expect a positive coefficient for the university proxy and a zero for the no training proxy if labour market pooling of specialised skills drives agglomeration. Thirdly, we estimate an industry's labour specificity by its deviation from the national average labour composition:

$$Skilldev_i = \sum_o (x_{io} - \bar{x}_o)^2$$

where x_{io} is the percentage of industry i's workforce with occupation o and $\bar{x}_o$ the national average percentage.[19]

The externality we are most interested in is knowledge spillovers. Knowledge spillovers imply the idea that when knowledge is created (i.e. research) a significant fraction of it cannot be appropriated but leaks out of a firm. If this knowledge is tacit (which means it cannot be

[16] Note that Rosenthal and Strange (2003) argue that manufactured inputs are more specialised than services.
[17] For a formal model see Helsley and Strange (1990).
[18] This classification scheme of occupations is used by the Bundesanstalt für Arbeit.
[19] This measure has been used already by Dumais et al. (1997).

codi…ed) it cannot spread over long distances but requires personal contact and spatial proximity to be transmitted. By their very nature knowledge spillovers are hard to measure directly. We assume that if spatially bounded knowledge spillovers exist between plants then they render a single plant and consequently the respective industry as a whole the more innovative the more concentrated it is. Accordingly, we can expect …rms to optimise the location of their plants with respect to spillovers to the extent that innovative capacity is crucial for their industry. Unfortunately, reliable and consistent data are available neither for the number of patents nor innovations.[20] We proxy the importance of innovation in three other ways. First, we employ Peneder's (1999) dummies specifying whether in an industry is R&D intensive and whether it has a strong or only few competitive advantages. Secondly, we use a high-tech and medium-tech dummy according to the above de…nition of the special industry groups. Finally, we use an industry's R&D intensity de…ned as R&D personnel divided by total employment.[21] If knowledge spillovers are an agglomeration force then they should have a positive impact on our concentration measures.

3.2 Other controls

Transportation costs. The more costly it is to transport a good the more likely a plant cannot exploit the idiosyncratic bene…ts of a particular location (including those from agglomeration externalities) but has to locate optimally between suppliers and customers to minimise transportation costs (Marshall, 1920). It is important to note that in principle the colocation of trade partners can render an industry agglomerated or dispersed. Since we are interested in localisation economies only we limit our analysis to industries with …nal goods and ask whether they in fact tend to disperse the higher transportation costs are.[22] Essentially, this is a test for the centrifugal force of transportation costs as modelled by the New Economic Geography (see, for example, Krugman 1991b). We proxy the average transportation cost of an industry by the inverse of its unit value. From trade data containing both the total weight (tons)

[20] Patent data are not available for the NACE industry classi…cation system and data on innovations are available from panel surveys and only at a highly aggregated level.

[21] A problem is that it is correlated with the proxy vocational training + university degree (labour market pooling) which is plausible as R&D is usually carried out by highly educated employees while not all educated employees work in R&D. If one assumes instead that labour market pooling and knowledge spillovers should be independent and do not exhibit any correlation in reality, a regression including the two (somewhat correlated) proxies is subject to classical measurement error. However, employees' education and a …rm's share of R&D personnel are a good proxy each and there are no appropriate instruments available for them.

[22] Note that literature is often not precise on these distinct e¤ects. Relatively higher transportation costs of inputs (shipments) induce plants to locate more close to their suppliers (customers). But this implies coagglomeration of trade partners and has to be distinguished from the agglomeration of a single industry.

and value of goods imported and exported we calculate an average reciprocal unit value as $\frac{1}{UV} = \frac{\text{weight imports+exports}}{\text{value imports+exports}}$.[23]

In principle one needs to account for the possibility that industries are geographically concentrated just because they rely on natural resources such as water or energy sources that are distributed unevenly in space. However, compared to the U.S. for example, Germany is a small country with a relatively even distribution of regional and local power stations so that access to electricity and gas should be fairly the same in all regions. Furthermore, Germany is poor in natural resources and consequently extractive industries are small. In sum, natural advantages should be relevant for only very few industries and we control for them with the help of a resource extractive dummy which is assigned to the industries with NACE codes 101 - 145 and 152 (Fish processing).

For any given geographic space a larger but otherwise identical industry will find it more difficult to agglomerate if there are congestion effects. We want to make sure that we capture this effect and consequently control for the size of an industry in terms of total employment.

Finally, traditional and therefore most presumably heavy industries may be located the way they are just because of historical (chance) events and/or because they are not footloose.[24] As an indicator of the importance of history and the degree of bondage we use the share of depreciation on assets in total shipments. First, traditional industries are very likely to be older and use relatively more fixed assets which should be reflected by a higher share of capital depreciation in output. Secondly, if a new plant of such an industry chooses its location, idiosyncratic location preferences are likely to be stronger and more diverse than in other industries for the following reason. The higher the share of depreciation the more important are tangible assets for production, the higher is presumably the share of fixed costs and hence the more receptive is a plant for site-related factors such as commercial rents, tax breaks or subsidies.[25] For these reasons we anticipate depreciation to have a negative impact on industry agglomeration.

[23] The portion of actual transportation cost in output (the importance of transportation cost) $\frac{\frac{c}{t}\text{weight}}{\text{output}}$ is then proportional to the reciprocal unit value with $\frac{c}{t}$ assumed to be a constant independent of the industry.

[24] Examples comprise Siemens AG, Munich, and Bayer AG, Leverkusen, each of which became the centre of an industrial cluster. The location of their headquarter was determined by the Allied occupation authorities after World War II.

[25] Take, for example, BWM, DaimlerChrysler and VW all of which looked for a place for a new plant in recent time. In each case the investment involved and the number of jobs to be created were substantial and several places all over the world were shortlisted. Ultimately, all three companies went to East Germany (though different counties) after federal subsidies of more than Euro 490 mil. in total had been promised.

3.3 Regression results

Before we present our regression results there are two things to note. First, agglomeration theory predicts that plants sensitive to specialised labour, specialised inputs or innovation tend to agglomerate because this will reduce production costs. Especially where we proxy "sensitivity" by cost shares there raises the question of identi…cation. A high share of costs of—say—manufactured inputs indicates susceptibility to sharing inputs and thus a propensity to agglomerate. But this in turn should lower these costs and hence their portion in output. Consequently, what we observe is the equilibrium relationship between industry characteristics and agglomeration which tends to push the regression coe¢cients towards zero. If we …nd an insigni…cant relationship in equilibrium we cannot rule out the possibility that in fact there exists one. On the other hand, if we …nd a signi…cant relationship we can expect it to be even stronger.[26]

Secondly, an analysis of our data reveals that there are two extreme outliers that lead to a very poor …t of the regression and a distribution of residuals that is almost certainly not normal. Therefore, we exclude Watches (NACE3 335) and Jewellery (362) with rank 3 and 4. Both industries are very small (0.08% and 0.23% of manufacturing employment) and are characterised by family-owned, small-scale handcrafts for which the location decision is presumably dominated by family tradition and history and for which our cost proxies do not take e¤ect. After excluding all industries with missing data we are left with 98 observations.

We estimate the model gamma = ® + ¯X + " where X is a vector of the industry characteristics. Since we use alternative proxies for knowledge spillovers and labour market pooling we run 9 regressions in total.

First of all, our control for industry size is highly signi…cant and has the anticipated negative sign in all regressions, that is, bigger industries are less geographically concentrated.[27] The resource dummy is positive and always highly signi…cant and in fact it contributes substantially to the goodness of the regression. Depreciation on assets is always signi…cantly negative indicating that age and history of an industry reduce industry agglomeration.

Transportation costs associated with …nal good industries are unexpectedly positive but never signi…cant and the …nal good dummy by itself has mostly a negative sign which is a rather inconsistent result. However, when we do not restrict transportation costs to …nal good

[26] See also Rosenthal and Strange (2003).

[27] Size is not to be confused with average plant size which is already accounted for by °.

industries but instead include it for all industries, it becomes highly signi…cant with a negative coe¢cient in all regressions. Moreover, when we experiment with the speci…cation of the regression it turns out to be one of the most robust explanatory variables. We conclude that transportation costs tend to reduce agglomeration in general. This does not contradict Marshall's argument about the colocation of trade partners but is ultimately consistent with our previous …ndings, namely that German industries exhibit only little concentration in general. Individual plants may well choose to locate close to suppliers and/or customers in order to minimise transportation costs but since industries as a whole are not much concentrated there must exist such a negative relationship. Using input/output data at the NACE2 level we con…rm in an additional analysis omitted here that transportation costs increase the proximity to customers/suppliers and that proximity in turn has a signi…cant but slightly negative impact on industry concentration.

Technical and industrial services has the anticipated sign, is always highly signi…cant and is the most robust variable. Manufactured inputs is mostly signi…cant and—somewhat surprisingly—even reduces agglomeration. We conclude that industries that use a higher share of input services tend to agglomerate as theory predicts while the usage of manufactured inputs reduces agglomeration.

The results for labour market pooling are less pronounced. Our proxy for specialised occupations is positive but not signi…cant while those for education (no vocational training, university degree) are almost always signi…cant both with a positive sign. As low-skilled workers prove to be very immobile we conclude that …rms that need them relatively much locate where they are. Apart from that, we note that both workers with no vocational training and those with a university represent only a minority of total manufacturing employment (21% and 8%). Based on this one could argue that unemployment insurance is well an issue for the very low skilled, too. We can support this additional argument by replacing the two variables by the industry's share of workers with a medium education (vocational training). It is signi…cantly negative implying that those with an average level of education indeed do not need geographic concentration.

The deviation of the national labour mix has the anticipated sign but is only marginally signi…cant. In sum, we interpret this as weak evidence for labour market pooling whereby in the case of low skilled workers it is …rms that locate where (immobile) labour supply resides.

Concerning knowledge spillovers our results are disillusioning. While we found in the previous section that "high-tech" industries belong to the least concentrated industries we now find that even when controlling for other factors, all of the different measures of susceptibility to spillovers are insignificant, which is consistent with that result. In the majority of the regressions the measures are even associated with a negative sign. Especially in the case of our most reliable proxies, namely share of R&D employees and the technology dummies, this is striking.

Before concluding, we want to spend a few comments on agglomeration at the higher geographic level. We noted above that when moving to more aggregate geographic levels there is no rule for the changes in the concentration measure and for Germany we found a higher concentration at the ROR level for the majority of the industries. Unlike Rosenthal and Strange (2003) we find that the concentration pattern at the higher level remains almost the same with the resource dummy explaining almost half of the variation. In particular, all measures of R&D/high-tech remain insignificant and nearly always have a negative sign.

4 Conclusion

This paper has explored the geographic concentration of German manufacturing industries with the help of Ellison and Glaeser's (1997) concentration index for the first time. Thereby we add to previous empirical work dealing with the concentration in other European countries. The questions we ask is (i) how much plants of an industry are agglomerated and (ii) what factors determine concentration, i.e. we are interested in the pattern and magnitude of localisation economies. The focus is on high-technology related industries motivated by the observation that the idea of "high-tech clusters" is en vogue at the moment and has inspired many policy initiatives.

Concerning the first question we find that 80% of the 116 industries are statistically significantly more concentrated than what would result if location decisions were pure random. However, the degree of concentration is rather low and randomness accounts for almost half of it; only resource related industries exhibit strong concentration and they dominate the group of the top 15. In particular, high-/medium-tech industries and industry groups are only little concentrated, partly even not significantly so, and rank medium or even lowest. This result does not change when we use an alternative and simpler concentration measure or when we take a more aggregate geographic level.

To answer the second question, we have related concentration to a variety of industry measures that shall re‡ect theoretical agglomeration forces in a regression analysis. We …nd that transportation costs associated with …nal good industries have no signi…cant impact which is at odd with the new economic geography arguing for a centrifugal e¤ect. Rather they signi…cantly reduce agglomeration in all industries. The history/age of an industry has a strong negative and its size a slight negative impact on concentration indicating that congestion e¤ects exist.

Concerning Marshall's (1920) agglomeration forces we …nd strong evidence for inputs sharing (specialised service inputs), weak evidence for labour market pooling and no evidence for knowledge spillovers. Neither of our alternative proxies for high-technology or research intensity produces a signi…cant and positive relationship. Either such spillovers are not limited to knowledge intensive activities but instead are much more general than has been assumed so far or they simply do not spur agglomeration. Shaver and Flyer (2000), for example, address the latter point and argue that heterogeneity among …rms can lead to asymmetric contributions and bene…ts from agglomeration externalities and that …rms' location choice becomes strategic then. They give empirical evidence that …rms with superior technologies, human capital or suppliers have the incentive to locate distant from other …rms, especially from …rms within their industry, i.e. from direct rivals. Our systematic analysis of manufacturing industries gives some support to their …rm-level study. Orlando (2002) …nds that R&D spillovers between …rms in the U.S. exist and that they are stronger within an industry than across industries but that unlike inter-industry spillovers intra-industry spillovers do not attenuate by distance. If this is true there is no need for an industry to agglomerate in order to bene…t from knowledge spillovers. As Germany is a relatively small country with every major city within one-day travel distance, spatial proximity might actually be a poor proxy for the importance of personal contact, trust etc. An additional caveat is that we do not include in our analysis the proximity to public research facilities.

We conclude that among German manufacturing industries there is no general relationship between agglomeration and R&D or high-technology related business which means that these characteristics do not make industries agglomerate naturally. This suggests that German regional policy in which much hope is currently put in the fast and e¤ective development of high-tech clusters might see some disappointments.

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6 Appendix

Figure 7: Distribution of ° and ®

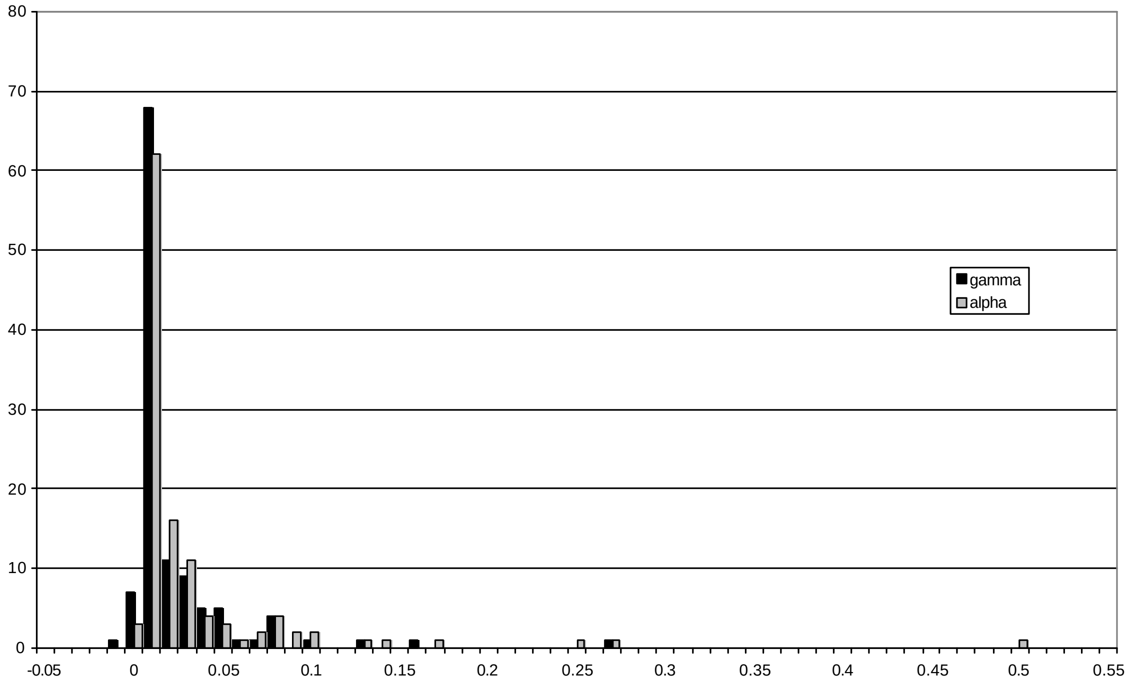

Figure 8: The most and least concentrated NACE3 manufacturing industries

Rank	NACE	γ	H	G	α		T	Sign.	Rank α
1	112	0.263	0.070	0.314	0.268	Erbringung von Dienstleistungen bei der Gewinnung von Erdöl und			2
2	131	0.156	0.204	0.327	0.248	Eisenerzbergbau			3
3	335	0.124	0.027	0.147	0.125	Herstellung von Uhren			6
4	362	0.096	0.010	0.105	0.096	Herstellung von Schmuck u.ä. Erzeugnissen			7
5	101	0.077	0.045	0.118	0.087	Steinkohlenbergbau und –brikettherstellung			10
6	143	0.074	0.097	0.163	0.087	Bergbau auf chemische und Düngemittelminerale			9
7	132	0.072	0.177	0.235	0.094	NE-Metallerzbergbau (ohne Uran- und Thoriumerze)			8
8	152	0.070	0.026	0.093	0.072	Fischverarbeitung			14
9	103	0.069	0.044	0.109	0.075	Torfgewinnung und –veredlung			13
10	263	0.060	0.098	0.151	0.076	Herstellung von keramischen Wand- und Bodenfliesen und -platten			11
11	111	0.049	0.069	0.115	0.060	Gewinnung von Erdöl und Erdgas			16
12	176	0.047	0.012	0.058	0.048	Herstellung von gewirktem und gestricktem Stoff			18
13	160	0.041	0.072	0.110	0.056	Tabakverarbeitung			17
14	232	0.041	0.039	0.078	0.045	Mineralölverarbeitung			19
15	102	0.041	0.050	0.088	0.063	Braunkohlenbergbau und –brikettherstellung			15
102	222	0.001	0.001	0.002	0.002	Druckgewerbe			107
103	281	0.001	0.001	0.002	0.002	Stahl- und Leichtmetallbau			108
104	292	0.001	0.002	0.003	0.002	Herstellung von sonstigen Maschinen für unspezifische Verwendung			109
105	158	0.001	0.001	0.001	0.001	Sonstiges Ernährungsgewerbe (ohne Getränkeherstellung)			112
106	204	0.001	0.009	0.010	0.002	Herstellung von Verpackungsmitteln und Lagerbehältern aus Holz		no	100
107	159	0.001	0.003	0.003	0.001	Getränkeherstellung			111
108	342	0.000	0.008	0.008	0.001	Herstellung von Karosserien, Aufbauten, Anhängern		no	113
109	343	0.000	0.014	0.014	0.001	Herstellung von Teilen und Zubehör für Kraftwagen und	MT	no	110
110	311	-0.001	0.057	0.056	-0.001	Herstellung von Elektromotoren, Generatoren und Transformatoren	MT	no	115
111	316	-0.001	0.021	0.019	-0.001	Herstellung von elektrischen Ausrüstungen a. n. g.	MT	no	116
112	354	-0.001	0.182	0.180	0.003	Herstellung von Krafträdern, Fahrrädern und Behindertenfahrzeugen		no	97
113	231	-0.002	0.263	0.260	0.164	Kokerei		no	4
114	341	-0.004	0.046	0.042	0.000	Herstellung von Kraftwagen und Kraftwagenmotoren	MT	no	114
115	242	-0.005	0.186	0.182	0.034	Herstellung von Schädlingsbekämpfungs- und Pflanzenschutzmitteln	HT	no	23
116	120	-0.010	0.654	0.648	0.493	Bergbau auf Uran- und Thoriumerze		no	1

Figure 9: The ranking of high- and medium-tech industries

Rank	NACE	γ	H	G	α		Sign.	Rank α
						High-technology industries		
16	296	0.037	0.072	0.105	0.044	Herstellung von Waffen und Munition		20
19	233	0.032	0.263	0.285	0.133	Herstellung und Verarbeitung von Spalt- und Brutstoffen	no	5
23	353	0.027	0.050	0.076	0.029	Luft- und Raumfahrzeugbau		25
51	300	0.007	0.035	0.041	0.008	Herstellung von Büromaschinen, Datenverarbeitungsgeräten und-Einrichtungen		59
54	322	0.007	0.019	0.025	0.008	Herstellung von nachrichtentechnischen Geräten und Einrichtungen		61
59	333	0.006	0.124	0.128	0.007	Herstellung von industriellen Prozeßsteuerungsanlagen	no	64
73	321	0.004	0.012	0.016	0.005	Herstellung von elektronischen Bauelementen		81
84	244	0.003	0.018	0.020	0.004	Herstellung von pharmazeutischen Erzeugnissen	no	90
						Medium-technology industries		
32	334	0.015	0.020	0.035	0.015	Herstellung von optischen und fotografischen Geräten		41
38	352	0.011	0.042	0.052	0.016	Schienenfahrzeugbau		37
43	315	0.009	0.034	0.042	0.010	Herstellung von elektrischen Lampen und Leuchten		52
49	246	0.007	0.010	0.017	0.008	Herstellung von sonstigen chemischen Erzeugnissen		56
50	314	0.007	0.046	0.052	0.014	Herstellung von Akkumulatoren und Batterien	no	42
57	291	0.006	0.006	0.013	0.007	Herstellung von Maschinen für die Erzeugung und Nutzung von		66
62	323	0.005	0.020	0.025	0.007	Herstellung von Rundfunk- und Fernsehgeräten sowie phono- und		70
68	293	0.005	0.009	0.013	0.005	Herstellung von land- und forstwirtschaftlichen Maschinen		82
72	243	0.004	0.014	0.018	0.006	Herstellung von Anstrichmitteln, Druckfarben und Kitten		76
76	294	0.004	0.002	0.006	0.005	Herstellung von Werkzeugmaschinen		85
82	331	0.003	0.002	0.005	0.003	Herstellung von medizinischen Geräten und orthopädischen		93
97	241	0.002	0.071	0.073	0.002	Herstellung von chemischen Grundstoffen	no	98
101	295	0.002	0.002	0.004	0.002	Herstellung von Maschinen für sonstige bestimmte Wirtschaftszweige		106
109	343	0.000	0.014	0.014	0.001	Herstellung von Teilen und Zubehör für Kraftwagen und	no	110
111	316	-0.001	0.021	0.019	-0.001	Herstellung von elektrischen Ausrüstungen a. n. g.	no	116
110	311	-0.001	0.057	0.056	-0.001	Herstellung von Elektromotoren, Generatoren und Transformatoren	no	115
114	341	-0.004	0.046	0.042	0.000	Herstellung von Kraftwagen und Kraftwagenmotoren	no	114
115	242	-0.005	0.186	0.182	0.034	Herstellung von Schädlingsbekämpfungs- und Pflanzenschutzmitteln	no	23

Figure 10: The coagglomeration of manufacturing industries

Rank γ^c	NACE2	γ^c	λ	Rank λ	Rank α	Intra-industry concentration as % of group's concentration	NACE2	# industries
1	11	0.051	0.402	7	1	68%	Gewinnung von Erdöl und Erdgas, Erbringung damit ver	2
2	23	0.015	0.382	9	4	93%	Kokerei, Mineralölverarbeitung, Herstellung von Brutstof	3
3	17	0.007	0.387	8	9	33%	Textilgewerbe	7
4	35	0.005	0.319	11	6	55%	sonstiger Fahrzeugbau	5
5	27	0.003	0.274	12	11	56%	Metallerzeugung und-Bearbeitung	5
6	20	0.003	0.575	5	22	37%	Holzgewerbe (ohne Herstellung von Möbeln)	5
7	22	0.003	0.584	4	10	60%	Verlags-, Druckgewerbe, Vervielfältigung	3
8	21	0.003	0.748	2	16	57%	Papiergewerbe	2
9	37	0.003	1.046	1	21	64%	Recycling	2
10	14	0.002	0.137	18	23	65%	Gewinnung von Steinen und Erden, sonstiger Bergbau	5
11	24	0.002	0.513	6	15	30%	chemische Industrie	7
12	26	0.002	0.208	15	26	49%	Glasgewerbe, Keramik, Verarbeitung von Steinen und E	8
13	18	0.002	0.322	10	13	97%	Bekleidungsgewerbe	3
14	19	0.002	0.061	21	7	93%	Ledergewerbe	3
15	28	0.002	0.235	14	19	49%	Herstellung von Metallerzeugnissen	7
16	36	0.001	0.080	20	17	89%	Herstellung von Möbeln, Schmuck, Musikinstrumenten u	6
17	33	0.001	0.166	16	18	65%	Medizin-, Meß-, Steuer-und Regelungstechnik, Optik	5
18	15	0.001	0.237	13	27	43%	Ernährungsgewerbe	9
19	25	0.000	0.157	17	25	91%	Herstellung von Gummi-und Kunststoffwaren	2
20	29	0.000	0.136	19	24	62%	Maschinenbau	7
21	31	0.000	-0.143	24	14	-2%	Herstellung von Geräten der Elektrizitätserzeugung, -Ve	6
22	32	-0.001	-0.149	25	12	134%	Rundfunk-, Fernseh-und Nachrichtentechnik	3
23	34	-0.002	0.666	3	20	65%	Herstellung von Kraftwagen und Kraftwagenteilen	3
24	13	-0.002	-0.027	22	3	101%	Erzbergbau	2
25	10	-0.003	-0.038	23	5	103%	Kohlenbergbau, Torfgewinnung	3

Figure 11: Regression 1

Variable	Coefficient	Std.Error	t-Statistic	Prob.
CONSTANT	0.021109	0.004863	4.340700	0.0000
SIZE	-4.91E-05	1.61E-05	-3.054190	0.0030
DEPREC	-0.183674	0.067018	-2.740664	0.0074
RESOURCE	0.030717	0.005661	5.426097	0.0000
FINALGOOD	-0.002175	0.003561	-0.610564	0.5430
FINALGOOD*TC	0.000706	0.003259	0.216572	0.8290
MANUFINP	-0.033235	0.022366	-1.485998	0.1408
SERVICEINP	0.096265	0.028234	3.409539	0.0010
RDINTENS	-0.060293	0.055706	-1.082353	0.2820
SECSERVICE	0.046416	0.045858	1.012180	0.3142
R-squared	0.513503	Meandependentvar		0.012708
AdjustedR-squared	0.464307	S.D.dependentvar		0.017375

Figure 12: Regression 2

Variable	Coefficient	Std.Error	t-Statistic	Prob.
CONSTANT	0.022355	0.004795	4.662469	0.0000
SIZE	-4.71E-05	1.61E-05	-2.929759	0.0043
DEPREC	-0.187364	0.066713	-2.808497	0.0061
RESOURCE	0.032172	0.005413	5.943592	0.0000
FINALGOOD	-0.002378	0.003555	-0.669019	0.5052
FINALGOOD*TC	0.000504	0.003247	0.155314	0.8769
MANUFINP	-0.033497	0.022263	-1.504627	0.1360
SERVICEINP	0.105855	0.026981	3.923280	0.0002
RDINTENS	-0.055400	0.042732	-1.296450	0.1982
UNIVERSITY	0.068950	0.054625	1.262249	0.2102
R-squared	0.516558	Meandependentvar		0.012708
Adjusted R-squared	0.467670	S.D. dependentvar		0.017375

Figure 13: Regression 3

Variable	Coefficient	Std.Error	t-Statistic	Prob.
CONSTANT	0.020656	0.004823	4.283005	0.0000
SIZE	-5.12E-05	1.60E-05	-3.203559	0.0019
DEPREC	-0.172355	0.067030	-2.571324	0.0118
RESOURCE	0.028714	0.005847	4.911085	0.0000
FINALGOOD	-0.001511	0.003461	-0.436585	0.6635
FINALGOOD*TC	5.07E-05	0.003246	0.015615	0.9876
MANUFINP	-0.033664	0.022135	-1.520871	0.1318
SERVICEINP	0.094166	0.027592	3.412782	0.0010
RDINTENS	-0.006246	0.019769	-0.315961	0.7528
SKILLDEV	0.032124	0.020192	1.590879	0.1152
R-squared	0.521510			
Adjusted R-squared	0.473123			

Figure 14: Regression 4

Variable	Coefficient	Std.Error	t-Statistic	Prob.
CONSTANT	0.021660	0.005098	4.248970	0.0001
SIZE	-4.63E-05	1.71E-05	-2.712988	0.0080
DEPREC	-0.193172	0.068010	-2.840339	0.0056
RESOURCE	0.032953	0.005695	5.786444	0.0000
FINALGOOD*TC	0.000579	0.003288	0.176124	0.8606
FINALGOOD	-0.001275	0.003441	-0.370499	0.7119
MANUFINP	-0.034476	0.023152	-1.489107	0.1400
SERVICEINP	0.105549	0.027856	3.789038	0.0003
HIGHT	0.003749	0.006531	0.574055	0.5674
MEDIUMT	-0.001274	0.004252	-0.299679	0.7651
SECSERVICE	-0.005183	0.021310	-0.243216	0.8084
R-squared	0.510573			
Adjusted R-squared	0.454956			

Figure 15: Regression 5

Variable	Coefficient	Std.Error	t-Statistic	Prob.
CONSTANT	0.020948	0.004770	4.391998	0.0000
SIZE	-4.66E-05	1.70E-05	-2.736447	0.0075
DEPREC	-0.192052	0.067963	-2.825835	0.0058
RESOURCE	0.032642	0.005598	5.831420	0.0000
FINALGOOD	-0.001081	0.003409	-0.317202	0.7518
FINALGOOD*TC	0.000573	0.003291	0.174125	0.8622
MANUFINP	-0.034214	0.023160	-1.477273	0.1432
SERVICEINP	0.104149	0.027313	3.813131	0.0003
HIGHT	0.002697	0.006748	0.399663	0.6904
MEDIUMT	-0.001712	0.004226	-0.405003	0.6865
UNIVERSITY	0.000746	0.033969	0.021966	0.9825
R-squared	0.510247			
Adjusted R-squared	0.454593			

Figure 16: Regression 6

Variable	Coefficient	Std.Error	t-Statistic	Prob.
CONSTANT	0.020004	0.004303	4.649129	0.0000
SIZE	-4.98E-05	1.70E-05	-2.936981	0.0042
DEPREC	-0.175678	0.068019	-2.582764	0.0115
RESOURCE	0.029026	0.006032	4.812349	0.0000
FINALGOOD	-0.001222	0.003321	-0.367909	0.7138
FINALGOOD*TC	7.27E-05	0.003268	0.022258	0.9823
MANUFINP	-0.033275	0.022872	-1.454844	0.1493
SERVICEINP	0.094346	0.027786	3.395425	0.0010
HIGHT	0.001256	0.005255	0.238954	0.8117
MEDIUMT	-0.001126	0.003889	-0.289474	0.7729
SKILLDEV	0.030534	0.020875	1.462711	0.1471
R-squared	0.521869			
Adjusted R-squared	0.467536			

Figure 17: Regression 7

Variable	Coefficient	Std.Error	t-Statistic	Prob.
CONSTANT	0.021874	0.005496	3.979964	0.0001
SIZE	-5.40E-05	1.63E-05	-3.310483	0.0014
DEPREC	-0.191591	0.069617	-2.752063	0.0072
RESOURCE	0.035221	0.006007	5.863685	0.0000
FINALGOOD	-0.000544	0.003433	-0.158548	0.8744
FINALGOOD*TC	0.000914	0.003266	0.279910	0.7802
MANUFINP	-0.040722	0.023401	-1.740164	0.0853
SERVICEINP	0.107674	0.027490	3.916901	0.0002
RD1	0.005476	0.003745	1.462423	0.1472
RD2	0.004906	0.005504	0.891197	0.3753
SECSERVICE	-0.015528	0.022421	-0.692528	0.4904
R-squared	0.519146			
Adjusted R-squared	0.464504			

Figure 18: Regression 8

Variable	Coefficient	Std.Error	t-Statistic	Prob.
CONSTANT	-0.000815	0.007627	-0.106875	0.9151
SIZE	-4.08E-05	1.59E-05	-2.568857	0.0119
DEPREC	-0.184083	0.065175	-2.824457	0.0059
RESOURCE	0.036200	0.005491	6.592989	0.0000
FINALGOOD	-0.000561	0.003190	-0.175968	0.8607
FINALGOOD*TC	0.001530	0.003082	0.496344	0.6209
MANUFINP	-0.046401	0.022094	-2.100211	0.0386
SERVICEINP	0.099665	0.025467	3.913436	0.0002
RD1	0.003137	0.003542	0.885709	0.3782
RD2	0.001737	0.005113	0.339797	0.7348
NOTRAIN	0.064618	0.018089	3.572256	0.0006
UNIVERSITY	0.060876	0.038046	1.600050	0.1132
R-squared	0.578924			
Adjusted R-squared	0.525685			

Figure 19: Regression 9

Variable	Coefficient	Std.Error	t-Statistic	Prob.
CONSTANT	0.018642	0.004443	4.195790	0.0001
SIZE	-5.51E-05	1.62E-05	-3.403580	0.0010
DEPREC	-0.167045	0.068661	-2.432894	0.0170
RESOURCE	0.030030	0.006180	4.859403	0.0000
FINALGOOD*TC	0.000304	0.003253	0.093508	0.9257
FINALGOOD	-0.000224	0.003297	-0.067828	0.9461
MANUFINP	-0.035642	0.023000	-1.549638	0.1248
SERVICEINP	0.094568	0.027538	3.434076	0.0009
RD1	0.004040	0.003452	1.170498	0.2450
RD2	0.001431	0.004052	0.353178	0.7248
SKILLDEV	0.030243	0.020391	1.483193	0.1416
R-squared	0.528317			
Adjusted R-squared	0.474716			