

The spatial distribution of economic activities in the European Union¹

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Abstract: This paper considers the spatial distribution of economic activities in the European Union. It has three main aims. (i) To describe the data that is available in the EU and give some idea of the rich spatial data sets that are fast becoming available at the national level. (ii) To present descriptive evidence on the location of aggregate activity and particular industries and to consider how these location patterns are changing over time. (iii) To consider the nature of the agglomeration and dispersion forces that determine these patterns and to contrast them to forces acting elsewhere, in particular the US. Our survey suggests that much has been achieved in the wave of empirical work that has occurred in the past decade, but that much work remains to be done.

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1. Introduction

This chapter considers the location of economic activity across the European Union (EU). It complements the two chapters on North America (Holmes and Stevens) and ASEAN (Fujita, Mori, Kanemoto, and Henderson) in this volume.

From the chapter by Holmes and Stevens it is clear that, for North Americans, the titles of these three chapters hark back to an earlier period when economic geographers produced maps and studied the detailed location patterns of particular activities, and the detailed activity patterns of particular locations. For Europeans too, such titles evoke a rich history of area based studies from authors as diverse as Christaller (1933), Engels (1845) and Marshall (1890). However, in strong contrast to the North American experience, these titles also speak to a more recent period in which a distinct literature on spatial location in the EU pursuing broader objectives has re-emerged. This chapter surveys this literature.

Before proceeding, it is interesting to consider why European researchers seem to have taken such a different path from their North American colleagues. Our review of the literature points to three key factors. First, the ongoing process of EU integration and its likely impacts have made understanding the evolution of EU production patterns an important policy issue. Second, researchers in the EU have embraced models incorporating increasing returns to scale as the theoretical basis for understanding this evolution. With the development of the New Economic Geography, this has lead researchers to refocus on the spatial impact of continuing integration, and hence spatial location patterns more generally. But this combination of political impetus and theoretical development is not sufficient to explain why European economists have returned to area based approaches. Taken on its own, this only points to a renewed interest in location issues, but does not suggest a uniquely European perspective is necessary. The third factor which has pushed researchers towards a European area based approach is the feeling that the EU is somehow different from the US and that this urges caution in applying existing evidence (usually North American) to understanding European issues.

This brief discussion raises the question of how this EU area based approach should inform the development of regional and urban economics more generally. In an ideal world, the answer to this question would determine what papers appear in this chapter of the book and what papers should be dealt with elsewhere. The main bulk of this chapter would deal with *describing* the location of economic activity in the EU. Our *explanation* of these patterns could then draw widely on other chapters in the handbook, leaving us to consider in depth only material that helps us understand why things in the EU might be different. In reality, of course, things do not turn out to be that simple.

The first problem is that many papers that are basically area studies portray themselves as tests of theories of New Economic Geography or location theory more generally. The authors of these papers tend to be annoyed when the main body of regional and urban economics ignores their contributions in favour

of papers based on other areas (usually North America). Often this is portrayed as a form of cultural imperialism by our American colleagues. We consider these papers in some depth here with a view to doing two things. First, identifying exactly what they do tell us about the spatial distribution of economic activity in the EU. Second, arguing that they cannot tell us much about location theory more generally because data problems and methodological errors mean they are less informative about theory than papers published elsewhere. The second problem relates to a somewhat smaller body of literature and is in some ways the mirror image of the first. A number of papers use EU data in ways that do tell us things about location theory more generally, but then tend to be ignored because they get labelled as area based and are thus considered too specific for a broader audience. We also consider these papers here and try to spell out what a broader audience may learn from them. The reader should note that this focus tends to move us away from the more descriptive work in the two companion chapters and thus involves considerably more discussion of econometric issues than is found there.

Before outlining the structure of the paper, a comment on what we do not cover. We will not consider national or regional convergence in the EU, innovation, or FDI and trade as these literatures are considered elsewhere in this handbook, by Magrini and Quah, Audretsch and Feldman, and Head and Mayer, respectively. In addition, we only cover the EU as it now stands, with no consideration of the economic geographies of the 10 countries that will join the EU in the next two years.

Turning to what we do cover, the rest of the chapter is split in to three parts. In the first, we consider the main sources of data for studying EU location patterns. This survey is brief and less helpful than it could be reflecting the woeful state of pan-European national and sub-national data. The second part describes the location of economic activity in the EU. This focuses on three key aspects. First, the pattern of overall agglomeration as reflected in differences in regional GDP and GDP per capita. Next we consider the specialization patterns of particular areas and the concentration patterns of particular activities at both the national and sub-national level. We also consider the characteristics of spatially concentrated industries. Finally, we show how micro-geographic data may be used to compare spatial patterns in the US and the EU. The third part of our survey considers the literature that seeks to explain location patterns in the EU. After a very brief theoretical survey, we focus, in turn, on spatial inequalities in terms of industrial localization, labour productivity, wages, and growth.

1. Data for studying the spatial distribution of economic activity in the European Union

In this section, we consider the data that are available for studying the spatial distribution of economic activity in the EU. After reviewing the literature, and given our first hand knowledge, the only conclusion that we are able to reach is that the European data are a mess. It is not clear where blame for this situation lies. It is clear that part of the problem stems from the institutional framework within which most EU

governmental statistical agencies work. In particular, the fact that they often have no mandate to facilitate the re-use of data collected to fulfil their institution roles. Even where they do have a mandate, data are often expensive and incentives to ensure efficient delivery appear to be limited. It is clear that these barriers could be removed, but this would require political support across the EU. Even if this support were forthcoming, variations in collection policies, access and pricing conditions, confidentiality requirements and legal frameworks would still hamper unified data provision. These problems clearly present considerable barriers for Eurostat, the EU's statistical office, in delivering on its mission "to provide the European Union with a high quality statistical information service". However, it is probably fair to say that the delivery itself leaves something to be desired. Informal discussions suggest that two of the biggest frustrations for academic researchers are poor documentation and the inconsistency across different versions of the same datasets. For example, paper copies will have different coverage from the electronic copies and coverage will change over time (not necessarily expand). There is usually little or no discussion of why these differences occur. Even the names of data sets can change frequently over time, a problem that is clearly illustrated below. As this brief discussion makes clear, the pan-European data situation is not a happy one. In this section, we will discuss the major data sources, giving some idea of their coverage and the main problems associated with using them.

We start with data that allows us to assess overall agglomeration patterns. REGIO is Eurostat's regional database. It provides data on GDP and GDP per capita on a comparable basis for regions across the EU 15.⁴ The coverage of regions is based on Eurostat's Nomenclature of Territorial Units for Statistics (NUTS). NUTS is a hierarchical classification dividing each country into a number of NUTS 1, with each NUTS 1 divided into a number of NUTS 2 and so on down to NUTS 5. There are 78 NUTS 1 regions, 210 NUTS 2 regions, 1092 NUTS 3 regions. NUTS 4 is only defined for a limited number of countries.⁵ There are 98,433 NUTS 5 regions corresponding to communes or their equivalent. The classification is based primarily on existing institutional divisions and thus, to the extent national systems differ, meets no consistent requirements across the EU. Areas for instance may significantly differ for a given level of NUTS. REGIO usually provides data at the NUTS 2 or NUTS 3 level. Theoretically, data are available for GDP, population, employment and wages. In reality, a complete GDP series for the entire EU 15 at approximately NUTS 2 is only available from 1995 onwards. NUTS 2 GDP data for the EU 12 is generally available from 1980 onwards⁶, although the accounting system and the NUTS classification changed in 1996 and 1998, respectively. Population and employment data have slightly better coverage while wage data coverage is extremely variable and generally quite poor.

⁴ The EU 15 is used to designate all 15 current member states: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden and the UK. The EU 12 consists of the EU 15 less the three 1990s entrants: Austria, Finland and Sweden.

⁵ Finland, Greece, Ireland, Luxembourg, Portugal and the UK.

⁶ Data for the UK, Denmark, Ireland and Luxembourg are at NUTS 1.

For sectoral activity, our primary interest is in getting data for manufacturing and services⁷. Unfortunately, EU wide data is only available for very aggregate sectoral classifications. The OECD provides the best two sources for comparable services data: Services: Statistics on Value Added and Employment and Structural Statistics for Industry and Services. Experience with the data suggests that availability will allow the study of employment in five service sectors from the early 1980s onwards.⁸ More detailed sectoral coverage does exist for individual countries, but using it for EU wide studies would involve too much missing data. Manufacturing data is available from the OECD STAN Database for Industrial Analysis (see OECD (2001) for details). Until 2001, STAN was based on the International Standard Industrial Classification (ISIC) revision 2 and covered 36 manufacturing sectors for 14 EU countries (the EU 15 excluding Ireland). This data can be supplemented with data for Ireland from the United Nations UNIDO National Accounts Statistics Database. This gives a dataset for manufacturing covering 36 sectors for the time period 1970-1999. Around 7% of this data is missing. The most recent version of STAN has extended industrial coverage to non-manufacturing sectors and now includes information on both agriculture and services.⁹ At the national level, Eurostat provides industrial survey data as theme 4 in the New Cronos database. The name applied to this theme 4 data seems to change regularly. Chronologically these data were first known as VISA, then DEBA then DAISIE and now as European Production and Market Statistics (or EUROPROMS). SBS (Structural Business Statistics) and ISBI (Industrial Structural Business Indicators) also appear to cover some aspects of theme 4 data. VISA covers the EU 12 (not the EU 15) for the period 1976 to 1995. Sectoral coverage is according to the old General Industrial Classification of Economic Activities within the European Communities (NACE) covering 113 manufacturing sectors. DEBA superseded VISA in the mid-1990s and had become DAISIE by (at the latest) 1998. DEBA/DAISIE data covered 100 manufacturing sectors for most EU countries for the time period 1985-1997. Unfortunately, much of the data is missing. For the period 1985-1990 approximately 30% of the data is missing. For the period 1991-1997 approximately 20% of the data is missing. Our feeling is that 25% missing data is probably not acceptable for most purposes. Researchers wishing to use this kind of industrial data might be better off trying to obtain VISA which reportedly has less missing data. It appears that DAISIE/DEBA has now been superseded by EUROPROM. Eurostat claims that this will cover 4,400 industrial sectors¹⁰ for most European countries for the time period 1993-1998. Enquiries to Eurostat suggest that a CD-rom actually covering 1995-2000 can be purchased for around €2000, with 2001 data expected shortly. Unfortunately, Table 1 shows that a lot of this data will be missing or confidential and so not available to researchers.

⁷ Factors explaining the location of agriculture and extraction are downplayed in recent economic geography models.

⁸ Wholesale and Retailing; Restaurants and Hotels; Transport; Communication; Financial Services, Insurance, Real Estate and Business Services; Non-market services.

⁹ Effectively, this new STAN has been derived by merging the old STAN with the OECD International Sectoral Database (ISDB) which is no longer updated.

¹⁰ Although the data used to calculate Table 1 suggests that there are in fact 5009 headings (some of these may be totals).

Table 1: Percent of headings with value data

Country	Available and not confidential	Not available	Confidential
Belgium	52%	3%	42%
France	54%	22%	21%
Austria	59%	0%	40%
Italy	60%	27%	10%
Netherlands	61%	0%	38%
Ireland	66%	0%	33%
Spain	70%	0%	28%
Germany	71%	2%	25%
Greece	73%	2%	22%
Portugal	76%	0%	23%
UK	79%	0%	19%
Denmark	87%	8%	3%
Luxembourg	94%	0%	6%
Sweden	96%	1%	1%
Finland	99%	0%	1%

Note: Table provided by EUROSTAT. Rows do not sum to 100% in original data.

Things are worse at the regional level. REGIO does provide regional sectoral data. Sectoral disaggregation is according to NACE 17, which uses 17 sectors to classify activity as agricultural, mining, manufacturing or services. Manufacturing is subdivided in to 9 categories, services in to 6 categories. Data coverage is very variable both with respect to regional and industrial classification. For example, most German data is provided for Länder, i.e. NUTS 1 rather than NUTS 2 and for NACE 3 (agriculture, manufacturing, services) rather than NACE 17. A number of papers have tried to correct for the missing data from other sources. Hallet (2000), for example, has broken down the German production data to NACE 17 using information on employment by Land. While improving the data is clearly moving us in the right direction, it would be fair to say that no widely available, suitably detailed EU regional data set has yet emerged.

The situation is much simpler at the urban level. There is no consistent, publicly available, EU wide data on cities. The situation is often not better at the national level. This said, some countries do provide very good sub-national data. We will refer to some of this data when we cover individual papers below. However, one problem remains - it is often impossible for any but a limited number of national researchers to get access to these data sources.

To summarise, the data situation is not good at the national, regional, or urban levels in the EU, although individual countries may provide excellent data sources. In the rest of this chapter we consider what this data can tell us about location in the EU and how it should inform location theory more generally.

2. Facts about the spatial distribution of economic activity in the European Union

In this section we describe what we know about the spatial distribution of economic activity in the EU. We start by considering the spatial distribution of total production across EU regions. We then turn to the sectoral composition of economic activities. We consider how we should go about describing EU location patterns and detail the pros and cons of a number of the standard measures employed. In light of this discussion, we then look at the location of economic activity at both the national and sub-national level. The section ends by showing how micro-geographic data might help in making comparisons between the EU and the US.

2.1. Aggregate economic activity and the EU core-periphery pattern

In this section we highlight a number of facts about the spatial distribution of aggregate economic activity in the EU:

- Regional incomes in the EU follow a clear pattern. We can identify a rich core of regions that have high GDP per capita and are located close to one another and a poor peripheral set of regions located away from the core. Although marked, this EU wide core periphery pattern has declined slightly since the mid-1980s as the income of EU countries has converged. In contrast, core-periphery patterns within EU countries have remained stable.
- Core regions with high GDP per capita have good access to EU markets. Closer integration is improving the accessibility of all regions in the EU, but it is improving the accessibility of the core regions relatively faster than regions in the periphery.

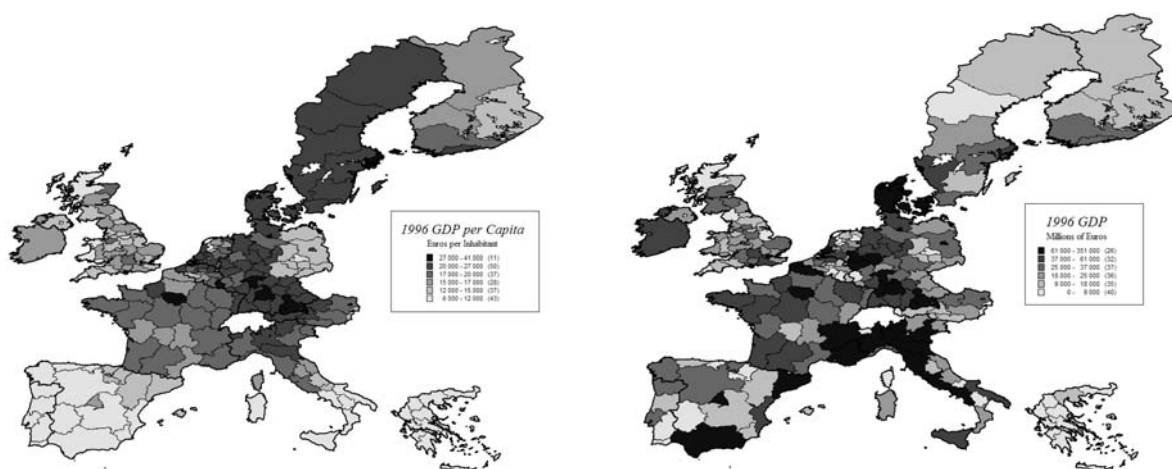
2.1.1. Regional incomes

The two maps in Figure 1 highlight the key stylised facts concerning the spatial distribution of aggregate activity across regions in the EU. The left hand map plots GDP per capita data from 1996 for NUTS 2 regions using data from Eurostat's REGIO database. The darker the colour, the higher the GDP per capita. The map clearly demonstrates the strong core periphery pattern which sees rich regions located on a "blue banana" running from the South East of the UK through Holland, West Germany and then curving round (hence the banana) through Austria and in to Northern Italy.¹¹ Denmark and the capital city regions of Paris, Stockholm and Helsinki show up as clear outliers. Maps of wages and employment

¹¹ The "blue" comes from the fact that the name initially reflected an observation, not about economic activity, but about the light emitted from these cities at night. Viewed from space by cosmonauts, or photographed by satellite, the banana appeared as a blue glowing X-ray cutting across the EU.

would show similar patterns, although recent work by Overman and Puga (2002) suggests that this pattern may not be so marked in terms of unemployment outcomes.

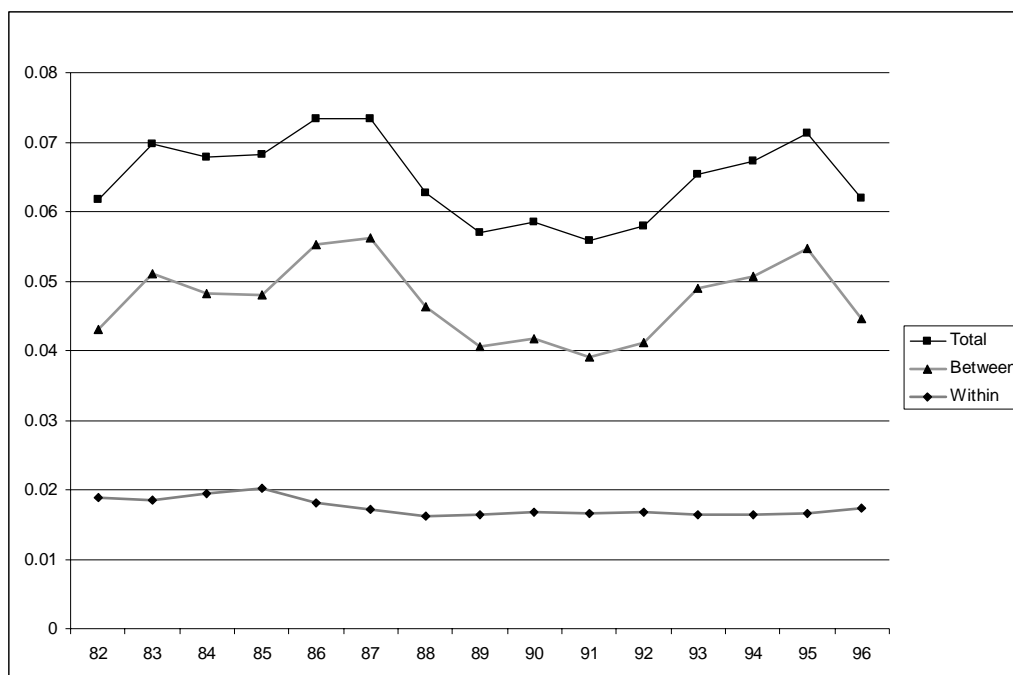
Figure 1: Per capita (left) and total (right) GDP in European NUTS 2 regions



The right hand map also plots data for 1996, but now for total GDP rather than GDP per capita. Comparing these two maps we see that the core-periphery pattern is much less marked when it comes to total GDP. This comparison neatly demonstrates another key stylised fact about the spatial distribution of economic activity in the EU. Population (and hence aggregate activity) remains quite spread out in the EU, despite very large differences in GDP per capita across EU regions.

There is some evidence that this core-periphery pattern in GDP per capita may be weakening between countries, while stable within countries. To highlight this, Figure 2 plots a Theil index for regional inequalities in the EU12 between 1982 and 1996. The figure also decomposes this Theil index in to its between country and within country components. The overall Theil index rose until 1987, then fell until 1992 and has been increasing since. Over the whole period, inequalities are fairly stable. As is also clear from the figure, this pattern is driven mainly by between country inequality. Within country differences have remained stable.

Figure 2: Theil Index for regional GDP per capita (EU12)



Two key questions emerge. First, what drives this strong EU-wide core-periphery pattern and the changes that we are seeing over time? Second, are the changes that we are seeing related to deeper EU integration? Researchers seeking to address these two questions have turned to the idea of accessibility as a key driver of these patterns. It is to this issue that we now turn.

2.1.2. Accessibility

Since Harris (1954) researchers have used the idea of market potential to measure the accessibility of different locations to national markets. According to Harris a region's market potential could be measured as a distance weighted sum of economic activity in all other locations:

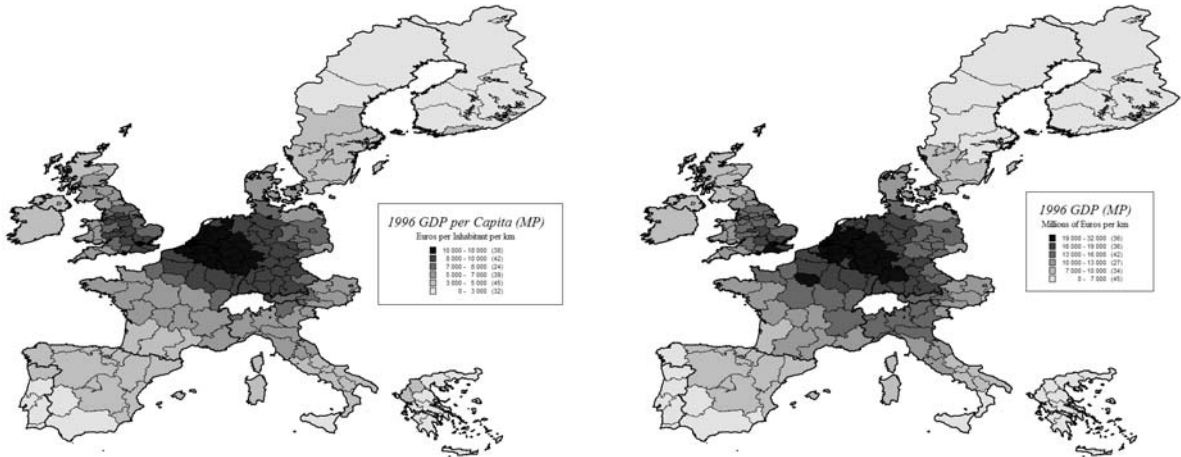
$$MP_i = \sum_j \frac{x_j}{d_{ij}}$$

where x_j is some measure of economic activity in location j and d_{ij} is the distance between location i and j . In the EU, the issue of market potential remains an area of interest to both academics and policy makers. This partly reflects the fact that people believe that accessibility explains the core-periphery pattern in terms of GDP per capita. That the two are correlated is plain to see from Figure 3 which plots basic market potential calculated on the same GDP per capita and total GDP data used above.¹² Again,

¹²For our calculations x_j is region j GDP or GDP per capita, d_{ij} is the distance between the geographic centres of region i and region j . The internal distance (of region i from itself) is computed as two-third of the square of the ratio of area over π .

darker colours signify higher values. The core-periphery pattern is clear for both market potentials, although the pattern is again stronger when considering GDP per capita.

Figure 3: Market potential of per capita (left) and total (right) GDP in European NUTS2 regions



The interest in market potential also reflects the impact of integration in encouraging particular dimensions of the EU area studies. Economic geography models tell us that accessibility can matter and integration explicitly changes accessibility. Hence the interest in describing what is happening to accessibility in the EU. The stylised fact that emerges from this literature, is that integration is associated with improving accessibility of all locations in the EU, but the accessibility of the core regions is improving relatively faster than regions in the periphery. This finding is reversed if we consider travel cost indicators rather, than market potential à la Harris (1954): In contrast to accessibility, travel cost indicators have actually fallen fastest in the periphery. A non-exhaustive list of articles with further discussion includes: Keeble et al. (1982, 1988), Lutter (1993), Spiekermann and Wegener (1994, 1996), Chatelus and Ulied (1995), Gutiérrez and Urbano (1996), Copus (1997), Vikerman et al. (1999), Schürmann and Talaat (2000), Schürmann et al. (2001).¹³

The entire burgeoning literature revolves around a number of controversies relating to exactly how the formula should be applied. Many variants have been suggested as regards the way the centre of locations are defined; the way distance between the centres should be measured; the way distance within the region should be measured (and whether this component should be included); and how economic mass at each location should be measured. Different answers to these questions generally deliver different measures of regional accessibility. See Copus (1997), Head and Mayer (2002) and Combes and Lafourcade (2003) for discussion.

Economists coming back to this issue in light of the New Economic Geography often find this list of controversies somewhat puzzling because they fail to address two fundamental questions. What does

¹³ The list only includes cross European studies. There is a vast literature studying accessibility at the national level.

theory tell us about why and how we should be calculating accessibility? These two questions are intimately linked and will determine how we then use accessibility to explain location patterns. Traditionally, geographers have limited themselves to fairly simple correlations between outcomes and accessibility. Economists have recently begun to take a very different approach using market potential estimated on the basis of functional forms that are clearly related to theory. (See Hanson (2002) and Redding and Venables (2002)). This literature has had very little impact on how the area-based literature has approached this issue for the EU.

2.2. Concentration and specialization in the EU.

In this section, we turn from the distribution of total production to the sectoral composition of economic activities. We document a number of stylised facts:

- Although production structures differ across EU countries we can identify groups of countries with similar structures. Differences in structure have slowly increased between the 1970s and the 1990s as EU countries became more specialised.
- EU regions show a much more mixed pattern. Between the 1980s and the 1990s approximately 50% of EU regions have become more specialised, while the remaining 50% have become less specialised. Overall changes in specialisation are small however.
- The extent of industrial concentration varies widely by industry. Most studies find that high tech, increasing returns to scale activities are more spatially concentrated. Results are less clear on resource intensive activities and activities that have strong linkages with other sectors. Changes over time show a mixed pattern. Between the 1970s and the 1990s roughly one third of EU industries became more concentrated, while the rest became more dispersed.

The first two sets of facts consider what particular locations do and how this changes over time. The interest in *changes* clearly reflects the influence of EU integration in shaping the debate. Our major focus is the third set of facts on where particular activities locate. Again, the role of integration in motivating the literature is obvious. However, just because integration is the motivating factor does not mean that we necessarily have to learn nothing about location theory more generally from studying European data. We will return to this issue below.

2.2.1. Standard methodology

The literature uses a variety of measures to describe the spatial location of economic activity in the EU. Most papers also include a discussion of why some measures are better than others when it comes to examining location patterns. However, there has been no systematic attempt to outline the criteria by which we should be assessing these measures. Thus, it seems appropriate to begin our survey by the consideration of some baseline criteria. Our philosophy in developing these criteria, has been to allow for the strong theoretical tradition in the location literature by incorporating theoretical considerations

directly in to the criteria, rather than adopting the first principles (axiomatic) approach that has tended to form the basis of the income inequality literature.¹⁴ We outline the criteria focusing on measures of concentration (i.e. for the geographical concentration of particular activities). It should be obvious how to develop very similar criteria for measuring industrial specialisation of given locations, an issue to which we return briefly below.

1. Measures should be comparable across activities. This criteria is important for two reasons. First, it allows us to make meaningful statements about whether (say) broad sectors are more concentrated than specific sub-sectors. Second, it allows us to consider the extent of concentration at (say) the three digit level after controlling for the extent of concentration at the two digit level. This second example actually implies a somewhat stronger criteria - that measures should be additive across spatial scales. Most standard measures do allow some comparisons across activities if correctly implemented. It turns out, however, that these indices may fail on this condition once we consider our third criteria.
2. Measures should be comparable across spatial scales. This is often assumed for existing indices but never explicitly discussed. It is the mirror image of the first criteria and matters for similar reasons. First, it allows us to make meaningful statements about whether (say) activity is more concentrated at the national than the regional level, or more concentrated in the US than the EU. Second, it allows us to consider the extent of concentration at (say) the county level after controlling for the extent of concentration at the regional level. This second example actually implies a somewhat stronger criteria - that measures should be additive across spatial scales.
3. The measure should take a unique (known) value under the 'null hypothesis' that there is no systematic component to the location of the activity. We may need to think of this from both a deterministic and stochastic perspective and allow for the fact that the systematic component will often be identified by theory. To give an example, Ellison and Glaeser (1997) point out that industrial concentration can lead to geographical concentration even when activities are randomly located due to the 'lumpiness' of individual establishments. They develop a measure of concentration by defining random location as the patterns that would emerge by throwing darts at a map. The darts differ in mass (to allow for industrial concentration), are thrown randomly (a stochastic component) and their probability of landing in any given region is proportional to the amount of overall activity in that region (a deterministic component). While data limitations rule out the use of the Ellison and Glaeser index for EU wide studies (calculating industrial concentration needs information on plant sizes), careful consideration of this criteria may still rule out some of the measures that have been used. Notice that much of the debate over absolute versus

¹⁴ Kaplow (2002) argues for a far great role for theory in deriving useful descriptive measures of income inequality. This clearly goes against the idea of a-priori principles as emphasised in the existing literature. Our feeling is that location theorists should be pursuing the theory route in their descriptive work if they want to make anything but the most basic claims about theory.

relative measures (see Haaland et al., 1999) is basically about this issue, although the criteria itself is much broader than just that consideration.

4. The significance of the results should be reported where appropriate (i.e. when statements about concentration are probabilistic as a result of meeting criteria 3).
5. Measures should be unbiased with respect to arbitrary changes to the spatial classification. Nearly all existing measures take points on a map and allocate them to units in a box. The importance of this criterion comes from recognising that these boxes are then treated as separate units. As a result, bias with respect to spatial classification has two origins. First, clusters of industries may cut the boundaries of these boxes. Therefore, changing the boundaries changes the measure even for a given number and size of sub-units. Next, activity in neighbouring spatial units is treated in exactly the same way as activity at opposite ends of the country. In other words, the distance between sub-units is not taken into account and again, very different spatial configurations may end up with the same value. Duranton and Overman (2002) discuss the issues in some depth and propose a measure that satisfies the criteria by using data reported on continuous space. Again, data limitations prevent implementation of this measure for EU wide studies, but that does not reduce the importance of the criterion for assessing the performance of existing measures.
6. Measures should be unbiased with respect to arbitrary changes to industrial classification. This is the mirror image of the fifth criteria. There the problems occurred because spatial classifications discretise continuous space in to boxes. Here problems occur because industrial classification discretises the activities of firms in to a given number of boxes and again, these boxes are then treated as separate units. Bias can occur for exactly the same reasons. This is a particular problem if the level of disaggregation varies systematically with activity types. For example, if sectoral disaggregation is finer for manufacturing than it is for services, then changes in the composition of output towards services may change measures of concentration even if the location patterns of firms remain unchanged.
7. If we want to make any statements about theory, then we should understand the way the measure behaves under the alternative hypothesis suggested by theory. That is, our choice of measure should reflect a consideration of both the null of random/non-systematic location and the alternative of what forces should drive systematic location patterns.

Applying these criteria to measuring specialisation involves straightforward extension, although some criteria have received more attention, and some criteria (not necessarily the same ones) are clearly more important than others. For example criteria 2 and 5 (regarding issues of spatial scale), tend to be downplayed for specialisation indices, often because criteria 7 (theory) has played a strong role in deciding the spatial scale at which such measures should be imposed. Criteria 3 and 4 (on the null hypothesis and significance) have probably received less attention than they should have done. For

example it would be of interest to know how much specialisation remains to be explained after conditioning out the effects of industrial concentration. We have seen no consideration of this sort of issue.

No measure currently meets all of these criteria. The measure proposed by Ellison and Glaeser (1997) satisfies criteria 1, 3 and 4. That of Duranton and Overman (2002) satisfies criteria 1 to 5 but is demanding in terms of data. Little progress has been made in satisfying criteria 6 although Rosenthal and Strange discuss the issue in a different context (the measurement of location externalities) in their chapter in this volume. There has also been very little progress on criteria 7. This is an issue to which we return below when we consider the characteristics of spatially concentrated industries. We note in passing, that even once we have such a measure, taking it to real world data will involve resolving a number of issues. Presumably we are trying to pick up structural change rather than the business cycle so we may need to time average data, for example. We should also understand how the measure behaves when there are missing data. Finally, if the measure does satisfy criteria 7, then following Kim (1995), we presumably want the industrial classification to group activities that are similar in terms of the impact of location forces and define regions that are similar in terms of location attributes.

Although these two measures meet most of the criteria, the measures that are applied when considering EU wide location patterns tend not to. For our current purposes spelling out these criteria is aimed at meeting two goals. First, they should be in the back of our mind as we review the existing evidence to avoid misinterpretations of empirical findings. Second, progress on meeting these criteria should be a key research goal if we want to take the descriptive literature forward. In this spirit, we use these criteria (referenced as C1 to C7) to help assess the descriptive work that we outline in the next section. Before doing this, we briefly consider the Gini coefficient and Krugman index, the two most common measures of concentration and specialisation used in descriptive work.

Start with a measurement of the activity level of industry k in location i , and call this x_i^k .¹⁵ This measurement may be based on employment, value added, gross output or any other activity measure. If results change according to the units of measurement, then we need to consider which measure best captures structural changes and whether theory tells us anything about which measure is preferable for distinguishing between the null and alternative (C3 and C7). All the measures we consider express activity as a share, either of total EU activity in the industry (s_i^k), or activity in a given location (v_i^k). That is:

$$s_i^k = x_i^k / \bar{x}^k \quad \text{and} \quad v_i^k = x_i^k / \bar{x}_i,$$

¹⁵ The exposition here closely follows Midelfart-Knarvik et al. (2002). For simplicity we ignore time.

where $\bar{x}^k = \sum_i x_i^k$ is total EU activity in industry k and $\bar{x}_i = \sum_k x_i^k$ is total activity in location i . The most frequently used measures are the Gini coefficients of concentration and specialisation based on the ‘Location Quotient’, or ‘Balassa Index’:

$$LQ_i^k = s_i^k / \bar{s}_i = v_i^k / \bar{v}^k,$$

where $\bar{s}_i \equiv \sum_k x_i^k / \sum_i \sum_k x_i^k$ is the share of location i in overall EU activity and $\bar{v}^k \equiv \sum_i x_i^k / \sum_k \sum_i x_i^k$ is the share of the same industry in total EU activity¹⁶. The Lorenz curve associated with the Gini coefficient of concentration of industry k ranks LQ_i^k across regions in ascending order and plots cumulated values of s_i^k on the vertical axis against cumulated values of \bar{s}_i on the horizontal. The Gini is equal to the area between the Lorenz curve and the 45° line. The Lorenz curve corresponding to the Gini coefficient of specialization is calculated similarly for a given region by ranking LQ_i^k across industries and plotting cumulated values of v_i^k against cumulated values of \bar{v}^k . The implied null hypothesis for both indices is that each location should just be a scaled version of the average “representative” EU region. Comparisons across locations, industries or time can be problematic. For instance, calculations from Midelfart-Knarvik et al. (2003) suggested that the associated Lorenz curves cross for at least 50% of changes over time. This happens when industry shares are declining simultaneously in both low and high share regions. Clearly, the first change increases concentration, while the second decreases it making statements about global changes dependent on which effect dominates.

Haaland et al. (1999) have argued for the use of Gini coefficients based on absolute shares rather than relative shares. The Lorenz curve associated with this absolute Gini of concentration (specialisation) ranks s_i^k (v_i^k), instead of LQ_i^k , and then plots cumulated shares against cumulated values of $1/N$ where N is the number of locations (industries). The implied null hypothesis is rather odd: Each location has an identical share in each industry independent of the locations overall size. It is hard to think of a random location model that would produce such a distribution. Unfortunately under the null that each location should just be a scaled version of the average “representative” EU region the value of this index depends on the distribution of overall activity across locations, again making comparisons difficult. This index does have the distinct advantage, however, that the level of concentration for a particular industry does not depend on the size of the country in which the industry is concentrated.

Another frequently used index was proposed by Krugman (1991a) to measure specialization:

$$KS_k = \sum_i |v_i^k - \bar{v}^k|.$$

The index takes value zero if location i has an industrial structure identical to that of the rest of the EU and has an upper bound of 2.¹⁷ A similar index can be constructed for concentration if we instead sum across locations relative to the share of each location in overall EU activity:

$$KC_i = \sum_k |s_i^k - \bar{s}_i^k|.$$

The implied null for both indices is that each location should just be a scaled version of the average “representative” EU region. The index can be difficult to interpret when some industries are growing faster than others because magnification of existing initial differences changes the value of the index. It does, however, have the nice property that it can be used for bilateral comparisons of locations or industries.

Applications of these indices to EU wide data suffer from a number of generic problems. First, given the data available, the measures used can take no account of industrial concentration as a driver of location and hence concentration or specialisation (C3). If we think this is important then these measures are not strictly comparable across industries or locations (C1). Second, the significance of results is often not reported (C4), often because there has been no explicit consideration of what random location would look like (C3). Third, the indices are not comparable across spatial scales or unbiased with respect to spatial scale (C2 and C5) because they take no account of the relative position of locations after we divide the EU in to a set of countries or regions. Fourth, as should be clear from our discussion in Section 1, the level of detail in the industrial classification varies systematically for EU data depending on whether the activity is classified as manufacturing or services (C6). Finally, and importantly, theories of location actually tell us very little, if anything, about how any of these measures should change with trade and integration so these descriptive statistics can tell us very little about theory (C7). In addition, to these problems with the measures used, most studies fail to time average the data meaning that we cannot distinguish between temporary and structural changes and many studies are based on data which does not cover all industries or all locations, but there is no discussion of how completing the data would affect the results.

Other descriptive measures have been proposed and used in the literature. For instance, Greenway and Hine (1991) use the mean of the Finger-Kreinin for production and export data. Brühlhart and Traeger

¹⁶ Midelfart-Knarvik et al. (2002) suggest making this share country specific by only considering the share of the same industry in all other countries (i.e. $\bar{v}^k \equiv \sum_{j \neq i} x_j^k / \sum_k \sum_{j \neq i} x_j^k$). This can help ensure the index is comparable across different locations (C1) if the locations differ greatly in size but it is not then clear what is the null hypothesis (C3).

¹⁷ A point which seems to have gone unnoticed in the literature is that the maximum value for the Krugman localisation index is not known. To see why consider a two region, two industry situation. For industry one to be completely concentrated (i.e. KL=2) it would need to be located in a region which had no share in overall manufacturing. Clearly this is not possible. The upper bound for any given industry approaches two as the industry becomes infinitely small with respect to overall manufacturing.

(2002) study the generic family of entropy indices. Herfindhal indices, based on the sum of squares of industry shares in local activity have also been quite widely used. The reader can assess for themselves which criteria these measures fulfil, but problems are in general similar to those encountered with the Gini and Krugman indices.

2.2.2. Specialisation patterns across EU countries

In describing the specialisation patterns of EU countries, we will refer exclusively to the group of papers that consider overall patterns for a majority of the countries in the EU. Earlier studies for individual countries exist, see for example Henner (1976) for France or Hine (1989) for Spain. However, we feel that a focus on pan-European papers is warranted given our interest in location patterns across the EU as a whole. We come back to the role of individual country studies in Section 2.3 below.

Table 2: Specialisation patterns in the EU

Country	1970-73	1980-83	1988-91	1994-97
Austria	0.314	0.275	0.281	0.348
Belgium	0.327	0.353	0.380	0.451
Denmark	0.562	0.553	0.585	0.586
Spain	0.441	0.289	0.333	0.338
Finland	0.598	0.510	0.528	0.592
France	0.204	0.188	0.207	0.201
Great Britain	0.231	0.190	0.221	0.206
Germany	0.319	0.309	0.354	0.370
Greece	0.531	0.580	0.661	0.703
Ireland	0.701	0.623	0.659	0.779
Italy	0.351	0.353	0.357	0.442
Netherlands	0.508	0.567	0.547	0.517
Portugal	0.536	0.478	0.588	0.566
Sweden	0.424	0.393	0.402	0.497
Weighted average	0.326	0.302	0.33	0.351

Note: Minimum values for each country in bold font. Calculations based on four year averages at the dates indicated.

Table 2, taken from Midelfart-Knarvik et al. (2002) reports Krugman specialisation coefficients for 14 EU countries based on data from the OECD STAN database for 36 industries covering the period 1970 to 1997. Minimum values for each country are highlighted in bold. From the table, it is clear that the UK and France are the least specialised of the EU 15 countries. For these two countries, only roughly 10% of industrial activity would have to switch industry to bring them in to line with the rest of the EU.¹⁸ Ireland and Greece are the most specialised. For Ireland, 39% of industrial activity would have to switch industry to bring it in to line. We can roughly identify four groups of countries in terms of specialisation patterns. The big core countries (France, Germany, and the UK) tend to be least specialised. Small core countries tend to be slightly more specialised (Austria, Belgium, the Netherlands). Scandinavian countries are more

¹⁸ The rest of the EU is calculated excluding the country in question (see our earlier discussion). The amount of industry that would have to move is calculated as the Krugman index divided by 2, because the measure counts both positive and negative deviations.

specialised still (Sweden, Denmark, Finland). Finally cohesion countries tend to be most specialised (Greece, Ireland and Portugal).¹⁹ Of course, these groups have fuzzy boundaries and overlap somewhat. Spain and Italy are outliers from this classification. Italy is a big core country with specialisation patterns roughly similar to the smaller core countries. Spain is a cohesion country with remarkably low levels of specialisation.

Further results from Midelfart-Knarvik et al. (2003) on bilateral comparisons and the type of industries in which a country specializes helps understand these differences. The French and UK economies are very similar to one another and quite similar to Germany. Of course, because of their size, any two of these countries have a heavy weight when calculating the production structure for the rest of the EU and this tends to reduce the specialisation measures. All three countries tend to specialise in high tech, high skill industries. In contrast, France, the UK and Germany are most dissimilar to Greece and Ireland and fairly dissimilar to Portugal explaining the high specialisation of these three countries. The least specialised of the cohesion countries, Spain, is relatively similar to the big three. In terms of the types of industries in which the Cohesion four are specialising, Ireland is the clear outlier. Greece and Portugal are tending to specialise in low tech, low skill industries, Spain in medium tech, medium skill while Ireland has focused on high tech, high skill industry. Patterns in terms of the other two groups are also mixed. Of the three small core countries, Austria and Belgium are fairly similar in terms of both production structure and the type of industry (medium skill, medium tech). The Netherlands is the outlier of that group, both in terms of production structure and the type of industry (higher skill, but lower tech). Amongst the Scandinavian's Finland and Sweden have similar production structures although Sweden's is slightly higher tech. Denmark's production structure is quite different to both these countries focusing on industries that are medium skill and medium tech making it more similar to Austria and Belgium. The reader is referred to Midelfart-Knarvik et al. (2003) for more details.

Once we turn to changes in specialisation, we can draw on a wider literature. In an early paper, Helg et al. (1995) present specialisation figures for the EU 12 countries based on the OECD Indicators for Industrial Activity for eight, 1-digit ISIC industries. Their results suggest that all countries, except France, Portugal and Spain become more specialised between 1975 and 1995. Their results are hard to interpret however as they are purely based on the shares of output of each industry in each country. Changes in the composition of output that are common across EU countries (say a move from textiles in to chemicals) will show up as increased specialisation. Thus, these numbers capture both the change in individual countries relative to the rest of the EU and the change in the EU relative to the rest of the world. More recent studies have tended to focus on shifts in countries specialisation patterns relative to the rest of the EU as the key variable of interest. Amiti (1999), Brülhart (1998a,b, 2001a,b), Brülhart and Torstensson

¹⁹ The "Cohesion countries" is often used to describe the four poorest members of the EU15: Greece, Ireland, Portugal and Spain. The name reflects the fact that all four receive Cohesion Fund money from the EU aimed at increasing economic convergence with the rest of the EU.

(1996), CEPII (1997), OECD (1999), WIFO (1999) Midelfart-Knarvik et al. (2002, 2003) and Storper et al. (2002) all present results on specialisation for EU nations. Some differences arise due to differences in data, time periods and measurement techniques. However, the results from Midelfart-Knarvik et al. (2002) reported in Table 2 tell the basic story. Most countries were least specialised at the beginning of the 1980s, although four countries had already reached their minimum in the 1970s. Subsequent changes led all countries to become more specialised. Findings from WIFO (1999) using the more detailed industrial classification available for the DAISIE database are similar (although the exact timings differ slightly). Midelfart-Knarvik et al. (2003) also report bilateral comparisons using the same data. Of 91 distinct pairs, 71 exhibit increasing difference between the early 1980s and the 1990s.

Our feeling is that this sort of study has now hit fairly rapidly decreasing returns. As outlined in Section 3.1 attempts to collapse the entire structure of industrial production down to one number that can be compared across time and across countries are fraught with many difficulties and these studies suffer from a number of problems. These descriptive pieces epitomize the area based approach we discussed in the introduction. They are useful for generating some stylised facts about location and integration in the EU, but they can tell us very little about what is causing those patterns or about location theory more generally. To summarize the key stylised finding that does emerge – the degree of specialisation varies substantially across the EU and the bulk of the evidence suggests that EU countries are slowly becoming more specialized.

2.2.3. A mixed picture for regional specialisation

Following our discussion in Section 1, it should be clear that data availability means making statements about economic activity in the EU at the regional level is much more difficult than making comparisons at the country level. Again, individual country studies exist, for example Smith (1975) for the UK, or Paluzie et al. (2001) for Spain, but there are relatively few studies taking an EU wide perspective.

Molle (1997) provides the longest historical perspective that we can find. He reports Krugman coefficients of specialisation for 96 EU regions providing figures every 10 years from 1950 to 1990. Data limitations mean that he considers NUTS 2 regions for France, Spain and Italy, NUTS 1 regions for the UK and Germany, and country data for Sweden, Finland, Denmark, Ireland, Portugal and Greece.²⁰ He identifies three groups of regions. The overwhelming majority saw specialisation fall continuously throughout the period. A much smaller number saw a small rise in the 1950s, but a fall since. Finally, another small group saw no change, but these regions tended to have low specialisation coefficients to begin with. This is hardly the mixed picture to which the title of this subsection alludes. However, on close inspection, the numbers turn out to be quite hard to interpret. The calculations are based on

²⁰ It is not clear how the paper deals with the three Benelux countries.

Eurostat's NACE 17 industrial classification dividing employment into 17 branches. As we saw in Section 1 six of these branches cover service sectors. Of these service branches, five are market service branches and a sixth is non-market services. Between them these service sectors count for nearly 70% of employment by 1990. Arguably, the composition effects from the growth in services²¹, the tendency for some of the services (such as catering) to closely mirror population, the non-market nature of non-market services, and the rather aggregate regional classification mean that any changes in specialisation patterns are likely to be obscured. More recent work suggests that all of these concerns may be relevant.

Hallet (2000) suggests that even small increases in the number of regions tend to give a more mixed picture. Using the same NACE 17 industrial classification, but 119 regions instead of 96, he finds that between 1980 and 1995, 34 regions became more specialised, while 85 regions became less specialised. In contrast to Molle (1997), Hallet (2000) does discuss the fact that the changing composition of output from industry (where the NACE 17 classification is finer) to services (where it is more aggregate) will artificially reduce measures of specialisation, but does not then present figures just for the nine industrial branches. Midelfart-Knarvik and Overman (2002) do just that. Just focusing on industrial branches, they find a much more mixed picture. Now, a majority of regions (53%) become more specialised, with the remainder showing either a decrease or no change. On average, however, increases in regional specialisation are small.

Given the problems with EU data at the regional level, it could be useful to look at individual country data to get a richer picture. Unfortunately, these papers usually suffer from all the same problems as the EU wide papers and are nearly always written from a national perspective. To take a good example, Paluzie et al. (2001) consider specialisation for 50 Spanish provinces (NUTS 3) for 30 manufacturing sectors over the time period 1979-1992. They find that 16 out of the 50 provinces show very small increases in specialisation while the rest show moderate decreases in specialisation. However, results from Table 2 suggest that Spain became more specialised relative to other EU countries. So, the fact that Spanish regions did not change much with respect to one another does not mean that Spanish regions did not become more specialised relative to the rest of the EU. Of course, which of these questions is more interesting may well depend on the theoretical model that you have in mind (C7). This brief discussion also suggests decomposing changes into within and between nations although we do not know of any study that does this.

All of this suggests the need for considerable caution in reaching conclusions at the regional level. Problems with getting regional data, composition effects and the lack of good detailed disaggregate data makes it difficult to reach broad conclusions for the EU's regions. The pattern appears mixed, but it is

²¹ The classification for industrial activity is much finer relative to the overall industrial employment than the classification for services (9 industrial classifications to cover 30% of employment versus 6 industrial classifications to cover 70%). Thus as activity switches from several manufacturing branches into fewer service branches we get a statistical reduction in specialisation.

clear that more careful analysis and better data seem to be pushing us in the direction of finding slightly more regional specialisation than we initially thought.

2.2.4. A mixed pattern for industrial concentration

Overall manufacturing activity is concentrated in the four biggest countries of the EU. In the mid 1990s Germany accounted for roughly 30% of total output, France 15%, Italy 14.5% and the UK 14%. Patterns in terms of overall manufacturing share are remarkably stable between 1970 and the mid-1990s at the national level. France and the UK have been the biggest losers with roughly a 2 and 3 percentage point decline respectively. Italy has been the biggest gainer, increasing its share from 12.5% to 14.5% (Midelfart-Knarvik et al., 2003). The picture is different at the regional level where overall concentration (as measured by the coefficient of variation) has increased considerably, at least from 1980 onwards.

As for regional specialisation, when we turn to looking at the distribution of individual industries across locations the pattern is again mixed. There are marked differences across industries in the degree to which they are concentrated. In terms of changes over time, some industries are becoming increasingly geographically concentrated, others are becoming less concentrated. We first deal briefly with the changes over time, before considering the characteristics of spatially concentrated industries in some detail in section 2.2.5.

Midelfart-Knarvik et al. (2003) use production data from the OECD STAN database to calculate absolute Gini coefficients of concentration for 36 manufacturing sectors based on four year averages (1970-73, 1980-83, 1990-93, and 1994-97). They find that concentration is increasing for 12 industries and decreasing for the remaining 24 industries. There is considerable variation over time. In the 1970s, 11 industries became increasingly concentrated, while 25 became less so. This pattern was reversed in the 1980s, with increasing concentration the norm (23 industries relative to 13 industries) before reversing again in the 1990s (15 industries increasing relative to 21). Table 3 shows the Gini coefficients for the 1970s, the 1990s and the change between those two periods. The industries are sorted from most to least concentrated according to how concentrated they were in the 1990s. The results broadly agree with those of Amiti (1999) using UNIDO production data for 27 manufacturing sectors for 10 EU countries.²²

²² They differ somewhat from Brühlhart (2001a) who conducts a similar exercise using employment data for 12 of the EU 15 countries. Brühlhart's results are hard to interpret, however. First, he excludes Belgium, Ireland and Luxembourg due to data availability. Second, he fails to time average the data, instead presenting the change between 1996 and 1972. It is thus difficult to know whether his findings are driven by structural differences, or just differences in the business cycle across countries.

Table 3: Industrial concentration across EU countries

Industry	Gini	Change	Industry	Gini	Change
Motor Vehicles	0.703	0.009	Furniture & Fixtures	0.596	0.028
Pottery & China	0.695	0.071	Machinery & Equipment nec	0.592	-0.071
Aircraft	0.693	0.016	Tobacco	0.592	-0.07
Leather & Products	0.685	0.138	Railroad Equipment	0.591	-0.048
Petroleum & Coal Products	0.682	0.009	Communication equipment	0.589	-0.065
Motorcycles & Bicycles	0.671	0.029	Glass & Products	0.569	-0.047
Footwear	0.669	0.075	Metal Products	0.567	-0.009
Electrical Apparatus nec	0.645	-0.023	Textiles	0.566	0.012
Transport Equipment nec	0.628	0.077	Beverages	0.557	-0.09
Rubber Products	0.624	0.005	Other Manufacturing	0.552	-0.025
Non-Ferrous Metals	0.623	0.042	Industrial Chemicals	0.546	-0.067
Chemical Products nec	0.622	-0.036	Non-Metallic minerals nec	0.542	-0.034
Petroleum refineries	0.621	-0.01	Pharmaceuticals	0.519	-0.078
Wearing Apparel	0.613	0.038	Printing & Publishing	0.515	-0.024
Iron & Steel	0.611	-0.014	Wood Products	0.498	-0.035
Office & Computing Machinery	0.608	-0.072	Paper & Products	0.479	-0.025
Plastic Products	0.6	-0.002	Food	0.46	-0.043
Professional Instruments	0.597	-0.068	Shipbuilding & Repairing	0.445	-0.022

Turning to the regional level, we are again hampered by data availability. As for specialisation, Molle (1997) provides the longest historical study we can find looking at changes in industrial concentration from 1950 to 1990. The paper uses the Krugman index of concentration. The data and regional definition are the same as for his study of regional specialisation. The results show that most sectors experience a decrease in concentration. Only Agriculture and Textiles show an increase, while Mining, and Food, Beverages and Tobacco show no clear pattern. However, as for specialisation, the inclusion of service sectors makes the results very hard to interpret due to the compositional changes over the time period. To see the problem, consider one particular manufacturing sector such as transport equipment. Imagine that, relative to manufacturing the concentration of transport equipment remained unchanged. What happens to the index will now be driven purely by the relationship between changes in regional manufacturing shares and changes in shares in other activities. Again, whether this makes sense will depend on the null hypothesis (C3) and theory (C7) one has in mind.

We have little additional evidence. In a recent paper, Brühlhart and Traeger (2002) consider changes in regional specialisation using data for NUTS 2 regions disaggregating employment in to eight sectors covering the full range of economic activities. They decompose concentration in to what they call topographic and relative components. Topographic concentration considers the degree to which sectors are concentrated in geographical space, relative concentration the degree to which sectors are concentrated relative to overall activity. Although preliminary, their results suggest that the topographic distribution of total employment is stable. Broad sectors show conflicting movements, with agriculture becoming more topographically concentrated and manufacturing less. For individual sectors however, only transport and communication services and non-market services show significant decreases, while the

four remaining sectors remain unchanged. This overall stability is increasingly driven by between country considerations rather than within country considerations. Turning to relative concentration, they find that there has been a monotonic increase in the relative concentration of manufacturing. Further, their evidence suggests that these increases are significant. In contrast, Transport and communications and Non-market services have seen significant reductions in their relative concentration.

2.2.5. The characteristics of spatially concentrated industries

In the introduction, we suggested that in an ideal world, this chapter would need to do two things. First, spend a lot of time describing the location of economic activity in the EU. Second, explain these patterns drawing widely on other chapters in the handbook, leaving us to consider in depth only material that helps us understand why things in the EU might be different. Obviously, this second stage would require us to clearly identify the differences between the EU and the US. Data quality and conceptual issues mean this has proved difficult to do, so the literature has taken a different route. This area-based descriptive work has now spawned a new set of area-based explanatory pieces using methodologies that allow for the limited amount of data available in the EU.

In this section we consider the characteristics of concentrated industries by looking at what we think of as this “first generation” of area-based studies. These follow Kim (1995) in examining the determinants of concentration by considering the correlation between spatial concentration and industry characteristics. We review this literature in depth here. We conclude that, for a number of reasons, this work often ends up telling us very little about what explains the economic geography of Europe. While the authors often claim that these papers represent tests of various economic geography models, we believe that they are purely descriptive in nature.

Two early papers, Brülhart and Torstensson (1996) and Brülhart (1998b) use employment data to compute rank correlations between Gini indices of spatial concentration and returns to scale and to consider whether concentrated industries are found in core or peripheral locations. They do this for two years, 1980 and 1990, for 11 countries (EU 12 minus Luxembourg) and 18 manufacturing industries. Data is from EUROSTAT and the OECD. Returns to scale are based on Pratten (1988). Core and peripheral locations are defined using a simple market potential based on GDP and geodesic distances. Brülhart (1998b) extends this work by further classifying industries according to their labour and resource intensity, whether they are science based, and whether goods are highly differentiated. His classification is taken from OECD (1987). Both papers also study the impact of these determinants on intra-industry trade using a Grubel-Lloyd index for six points between 1961 and 1990.

In contrast to Kim (1995), neither paper uses time varying explanatory factors ruling out the use of industry fixed effects. This is unfortunate as industry fixed effects could control for some of the problems with both the concentration measure and the explanatory variables. In particular, in line with the discussion of C3 in Section 2.2.1, fixed effects can partly account for the fact that the Gini index

does not control for the degree of industrial concentration. Note, however, that industry fixed effects cannot totally control for industrial concentration in the way suggested by Ellison and Glaeser (1997) because the Herfindahl enters their index non-linearly. Fixed effects also control for omitted variables, such as the nature of competition, if these characteristics are time-invariant. Interpretation of the intra-industry trade results is also difficult because as Brülhart (1998a) himself notes, the link between intra-industry trade and spatial concentration is complex and non-monotonic. Cross sectional differences in intra-industry trade tell us little about spatial concentration if we cannot control for all the other determinants of trade. Even for a given industry more concentration does not necessarily imply less intra-industry trade if global volumes of trade have changed.

Amiti (1999) moves beyond simple correlations making her paper closest in spirit to Kim (1995). Using Eurostat data, she computes Gini indices of production and employment concentration across 5 EU countries for 65 manufacturing industries between 1976 and 1989. She captures Heckscher-Ohlin effects through the share of labour in value added and uses the cost of intermediate inputs divided by value-added to proxy for demand and cost linkages arguing that high intermediate input usage should encourage concentration near intermediate suppliers. Plant size is used as a proxy for increasing returns. Results on these variables should be interpreted with caution, however. Labour intensity only considers one type of factor while inputs include raw materials, so the intermediate input variable actually confounds Heckscher-Ohlin and linkages effects. Average plant size is only a good proxy for increasing returns under strong conditions.²³ Some of these problems are mitigated by the fact that estimations allow for time and industry fixed effects.

Haaland et al. (1999) extend Amiti (1999) to consider more countries (EU 15 apart from Luxembourg and Ireland) at the cost of a more aggregated industrial classification (35 industries from STAN) and less time series coverage (data is only available for 1985 and 1992, which prevents them from using fixed effects). As discussed in Section 3, they calculate both an absolute and relative Gini coefficient of concentration. Their explanatory variables capture labour intensity, human capital intensity, technology level, returns to scale, non-tariff trade barriers and concentration of final demand.²⁴

This brief survey of papers is not exhaustive. Other studies providing simple correlations include Brülhart (2001a) and Brülhart (2001b) covering 32 manufacturing sectors from 1972-1996. Midelfart-Knarvik et al. (2003) consider additional characteristics including capital intensity, within and between

²³ It assumes that the industry is in long run equilibrium so that firm numbers have adjusted to ensure zero profit. Further, if firms behave strategically or products are differentiated, firm size can differ across industries with the same degree of economies of scale unless strategic behaviour and the degree of product differentiation are identical across sectors. Other considerations can also break the link between plant size and returns to scale. In particular in some models firm size is codetermined with spatial concentration meaning this variable may be endogenous as well as a bad proxy for returns to scale.

²⁴ Returns to scale are based on Cawley and Davenport (1988) which basically transforms Pratten's (1988) ordinal rankings in to a continuous variable. Factor and input intensities are calculated from Eurostat input-output tables and the OECD (1994). The final demand variable is based on final expenditure data. This last variable is potentially endogenous and is instrumented using lagged values when necessary although the suitability of lagged values as an instrument is not tested.

industry linkages, agricultural inputs, and final demand bias for 36 industries for 14 EU countries for 1970 to 1997 using data from OECD STAN.

If we take their results at face value what do we learn about the spatial concentration of EU industries from this series of papers?

Labour, capital, and resource intensity: The papers find little evidence that labour, capital or resource intensive activities tend to be more concentrated. Amiti (1999) finds no correlation with labour intensity. Haaland et al. (1999) find a weak positive correlation with labour intensity in 1992, but not 1985, and the reverse for human capital intensity. This is supported by Midelfart-Knarvik et al. (2003) whose simple correlations suggest a positive effect of skill intensity only in the 1970s and no effect of capital intensity for any period. Brühlhart (1998a) finds that both labour and resources intensive industries are more dispersed across space than the average. The high intra-industry trade observed in labour intensive industries leads to a similar conclusion although these trade volumes are low for resource intensive industries.

Technology: Technology intensive and science based industries are more concentrated than average according to both Brühlhart (1998a) and Haaland et al. (1999) although both studies detect a decline of spatial concentration in these sectors.

Increasing returns to scale: All papers except Haaland et al. (1999) find a positive correlation between increasing returns to scale and spatial concentration.

Demand and cost linkages: Evidence on the role of demand and cost linkages are mixed. Brühlhart (1998a) finds that concentration takes places in high market potential areas. Amiti (1999) finds a positive correlation for the intermediate input cost variable, while the own input variable of Haaland et al. (1999) is associated with increased absolute, but not relative, concentration. In contrast, Midelfart-Knarvik et al. (2003) find no significant correlation with intra or inter industry inputs. Nor do they find any correlation with final demand.

Trade barriers and trade liberalization: Results on transactions costs are inconclusive and somewhat contradictory. Non-tariff barriers are not correlated with relative concentration, (Haaland et al. (1999)), nor intra-industry trade (Brühlhart (1998a)). On the other hand, Haaland et al. (1999) show that absolute concentration is associated with high trade barriers.

For comparison, we briefly review what this approach tells us about the spatial concentration of activities in the US. Kim (1995) has data on employment for 20 industries across 9 regions at 5 points in time, 1880, 1914, 1947, 1967 and 1987. He uses this data to calculate a Gini index of employment concentration across regions. He assumes two variables can explain variations across industries and time - the share of raw material in value added and average plant size in the industry to capture differences in

the degree of increasing returns to scale. As for the EU, Kim (1995) finds positive effects of increasing returns to scale, but in contrast to the EU, he also finds a positive significant effect for raw materials. Taken at face value, this suggests an important difference between EU countries and US regions. In the EU, transaction costs have prevented countries from specialising according to their comparative advantage.

At first glance, the results presented in this section seem to paint a fairly rich picture, even if they are not always consistent with one another. Overall though, we feel that the methodological problems are such that despite the claims of the authors an acceptable *explanation* of EU location patterns cannot, and will not, be based on the kind of evidence that we have considered here. One can even question their validity as useful descriptions of the industry characteristics associated with spatial concentration.

From an econometric point of view, we can identify a number of serious problems with regressions based on indices and industry characteristics. (i) Differences in spatial concentration are captured using summary measures of the kind we described in Section 2.2.1. As such, they suffer from all the problems that we outlined in detail there; (ii) The number of explanatory variables in these studies is low (often less than three) compared to the complexity of the phenomenon that is studied, and it is sometimes difficult to link the way some variables are computed and the effects they are supposed to capture; (iii) Dealing with omitted variable problems that we know are present requires at least introducing industry fixed effects, which in turn requires industry characteristics to vary over time. A similar observation can be made with regard to country fixed effects; (iv) Explanatory variables may be endogenous and simultaneously determined in a complex way suggesting the need for instrumenting; (v) We need to take account of spatial autocorrelation and other sources of heterogeneity.

Of course, many of these criticisms reflect data problems. However, there are two key conceptual issues here. First, given the state of the art, theory tells us nothing about the relationship between these indices and industry characteristics when the number of regions is larger than two. Second, as pointed out by Midelfart-Knarvik et al. (2000), working on concentration indices (and other summary statistics) wastes information on the location of industries across space. If concentration indices can be computed, then data on industry shares are available and can be used as dependent variable. Why not use this information instead of calculating one summary statistic? This is not just a question of throwing away information. Ellison and Glaeser (1999), Midelfart-Knarvik et al. (2000), Gagné et al. (2002), and Combes and Lafourcade (2001) all develop theoretical models that make predictions about industry shares. We believe that understanding the determinants of economic location in the EU requires an approach which explicitly builds on theory and which uses the existing data in the most efficient way to assess these theories. We consider this issue further in Section 3.

Where does this leave us with respect to industrial concentration? First given the quality of available data it is clear that making further progress at the national level will be difficult. Brülhart and Traeger

(2002) suggest that some limited progress could be made at the regional level. However, our feeling is that without significant improvement in the quality of EU regional data, this sort of approach is also going to run in to decreasing returns to scale very soon. We now turn to outline a more positive research agenda.

2.3. Comparing the EU and the US: A role for micro-geographical data?

To avoid some of the problems underlined in the previous section, we also need to use the limited amount of data that we have more effectively. In Section 3, we outline some explanatory work that begins to do this. Before that, however, we want to outline how a different approach to descriptive work might also help. Krugman (1991a) introduced the idea that activity in the US may be more concentrated than in the EU by comparing employment data for four US regions (Northeast, Midwest, South and West) with four large European countries (Germany, France, the UK and Italy). The comparison is interesting if we can think of the US as a large integrated economy that may act as a benchmark for where an integrating Europe might be heading. Of course, certain features of the economic geography literature argue caution in undertaking such an exercise. For example, in formal models, whether agglomeration occurs depends on the share of the increasing returns to scale, transport intensive good in consumption. This share may have changed over time. Coupled with the path dependant nature of economic geography models, it is unclear to what extent the US is a good benchmark for the future of the EU. With this caution in mind, we still believe that such a comparison would be useful.

Unfortunately, a more rigorous comparison, has not been forthcoming. The key problem is that the US and Europe are differently sized and shaped. This introduces problems if concentration measures are not comparable across spatial scales (C2) and are biased with respect to spatial scale (C5). Given that most existing measures do not meet these criteria, comparing levels of these concentration measures is non-informative (although comparing changes over time may be). As discussed in Section 2.2.1, this is not just a matter of having the same number of spatial units, or the same size spatial units, but a more fundamental one about making comparisons between geographical areas on the basis of discretising continuous space.²⁵ Midelfart-Knarvik et al. (2003) come the closest to addressing this issue by proposing a spatial separation index which takes in to account the distance between spatial units (in their case countries). This allows them to distinguish between industries that may appear equally geographically concentrated using standard measures, while one is predominantly located in two neighbouring locations and the other split between (say) Finland and Portugal. To compare concentration in the EU and the US, they propose calculating a conditional spatial separation index as the spatial separation index for each industry divided by that for manufacturing as a whole. This controls for the greater geographical size by making all statements conditional on the distribution of overall manufacturing. They calculate this conditional measure for 21 industries in the mid 1990s and compare EU countries with US states. They

²⁵ This point is still misunderstood. For example, Aiginger and Leitner (2002) emphasise the importance of getting data for an approximately comparable number of regions in the USA and Europe. But this does not resolve the issue.

find that in 15 out of 21 industries, the location of activity is more concentrated in the EU than the US. This finding is evocative, but we think that a more careful analysis is needed before a clear conclusion can be reached.

It seems to us that too little of the existing literature confronts this key question head on. In what ways does the EU differ from the US? It should be clear from the discussion above that we have not reached a conclusion about this based on studying pan-European data. Indeed, the quality of the EU data is the fundamental barrier to reaching such a conclusion. It is also clear that we are unlikely to see a significant improvement in this pan-European data in the near future. This is, of course, unfortunate, because we would like to know (say) if labour immobility in Europe leads to EU activity being more dispersed and we can probably only answer this question with better pan-European data. However, some key questions can be answered now using the micro-geographic data that is beginning to emerge in countries across the EU.²⁶

These micro-geographic data sets allow us to calculate indices which come close to meeting the criteria that we outlined in Section 2.2.1. Further, they allow us to do this for fairly detailed industrial classifications. There are, of course, problems with making precise comparisons across countries due to the fact that industrial classifications differ. But the results do allow us to begin to identify some of the detailed differences between EU countries and the US.

To see what we can learn from this approach we will compare three papers that apply the Ellison and Glaeser (1997) index of concentration to three different countries - Ellison and Glaeser (1997) for the US, Maurel and Sédillot (1999) for France and Devereux et al. (2002) for the UK. The Ellison and Glaeser methodology was discussed briefly when we considered criteria C3 and is outlined in depth by Rosenthal and Strange in this volume, so we do not describe it in detail here. The basic idea is to use micro level firm data to assess whether or not industries are randomly located once we condition on the overall distribution of manufacturing and “lumpiness” due to industrial concentration.

Ellison and Glaeser (1997) consider 459 four-digit industries. Firms can be located in counties, regions or states. Maurel and Sédillot (1999) consider 273 four digit industries. Firms can be located in 22 regions or 95 departments. Finally Devereux et al. (2002) consider 214 industries for 124 postcode areas. Let us start by considering the comparison of the UK and the US. Table 4 presents the most concentrated industries in the UK that can be matched to a reasonable US counterpart, while Table 5 presents the most dispersed industries.²⁷ The first column gives the name of the UK industry. The second gives the rank. For the concentrated industries this ranks from most concentrated, for the dispersed industries from most

²⁶ At the time of writing we are aware that researchers are being given access to these micro-geographic data sets in Belgium, France, Germany, Ireland, Italy, Portugal and the UK.

²⁷ Calculating a more formal correlation is not possible given the problems of matching the classifications. However, a much more systematic attempt to match classifications should be possible.

dispersed. As mentioned above problems with the classifications mean that we cannot always find a match for an industry. Still, the results are fascinating. For the matched top 11 UK industries (i.e. top 5%), all of the US industries are at least in the top 120 industries (i.e. the top 25%). For 10 of them, the US industries are at least in the top 70 industries (i.e. top 15%). For 7 of them the corresponding US industries are (roughly) in the top 20 industries (i.e. top 5%). The most remarkable thing to emerge from this table is the fact that concentrated industries in the UK also tend to be concentrated in the US. The story is more mixed when we turn to the dispersed industries. 6 of the most dispersed industries match with industries that are amongst the 40 most dispersed industries in the US. Ordnance small arms matches exactly for small arms ammunition, but small arms themselves are quite concentrated in the US. The rubber industry appears quite dispersed in the UK, but quite concentrated in the US, and the same is true of tobacco. Again, we would argue that one of the more remarkable things is the similarity between dispersed industries in the UK and the US. The overall picture that emerges is one of very similar concentration patterns. Of course, some differences need explaining, but the similarities are striking.

Table 4: Most concentrated industries in the U.K. and their U.S. counterpart

UK		US
Spinning and weaving	1	13 (Yarn and spinning), 20 (Throwing and winding), 21 (Thread mills)
Jute and Polypropylene	3	17 (Broad woven fabric mills - manmade fibre and silk)
Lace	5	Top 60
Cutlery	6	Top 120
Other carpets	7	6 (carpets and rugs)
Hosiery	9	3 (women's), 5 (men's)
Jewellery	11	8 (costume jewellery), 10 (jewellers material lapidary)
Weaving cotton	13	17 (Broad woven fabric mills - manmade fibre and silk) 28-32? (Broad woven fabric mills cotton)
Caravans	14	36-41 (Motor homes)
Woollen	15	Top 70 (Broad woven fabric mills - woollen)
Spirit distilling	16	2 (Wines, brandy, spirits)

Table 5: Most dispersed industries in the U.K. and their U.S. counterpart

UK		US
Sugar and its by products	1	14 th most dispersed (Cane sugar refining)
Water supply	2	40 most dispersed (Manufactured ice)
Synthetic rubber	3	60 most concentrated (Synthetic rubber)
Rubber tyres	4	Median (Tires and inner tubes)
Tobacco	5	22 nd most concentrated (Tobacco)
Adhesive film	6	40 most dispersed (Adhesives an sealants)
Ordnance small arms	7	6 th most dispersed (Small arms ammunition), 70 most concentrated (small arms)
Telegraph and telephone apparatus	8	30 most dispersed (Telegraph and telephone)
Musical instruments	9	40 most dispersed (Musical instruments)
Wheeled tractors	15	30 most dispersed (Industrial trucks and tractors)

What about France? In Table 6 we compare the results from Maurel and Sédillot (1999) to both the US

and the UK. Again, the match between classifications is not perfect and we have systematically ignored the extraction industries which Maurel and Sédillot (1999) report, but Ellison and Glaeser (1997) do not. The match between rankings here is clearly not quite as tight as for the UK and the US. However, note that for 8 out of the 10 top ranked matched activities, similar industries are above average in both the US and the UK. Only for flat glass and small arms does there seem to be some really different patterns across the three countries.

Table 6: Most concentrated industries in France. and their UK and US counterparts

France		US	UK
Steel pipe and tubes	2	Above median (steel pipe and tubes)	76 (Steel tubes)
Combed wool spinning mills	3	Top 70 (Broad woven fabric mills - woollen)	15 (Woollen)
Wool preparation	5	Top 70 (Broad woven fabric mills - woollen)	15 (Woollen)
Periodicals	6	Top 80 (Periodicals)	14 (Periodicals)
Flat glass	8	Bottom 150 (flat glass)	195 (flat glass)
Carded wool weaving mills; Carded wool spinning mills	11, 15	Top 70 (Broad woven fabric mills - woollen)	15 (Woollen)
Book publishing	13	Top 80 (Book publishing)	26 (Books)
Cutlery	14	Top 120 (Cutlery)	6 (Cutlery)
Small arms	15	6 (small arms ammunition), 60-70 concentrated (small arms)	7 th most dispersed (small arms ordnance)

Rather than going through a similar exercise with dispersed industries, we can use the results in Maurel and Sédillot (1999) to ask what might happen if we could achieve a better ranking between industrial classifications. Table 7, taken from Maurel and Sédillot (1999) reports what happens when we calculate the Ellison and Glaeser (1997) index for 2 digit industries that are broadly comparable across the two countries.

Table 7: Two digit industries rankings in France and the US

	USA	France
Textile mill products	1	2
Leather and leather products	2	1
Furniture and fixtures	3	10
Lumber and wood products	4	8
Primary metal industries	5	9
Instruments and related products	6	5
Transportation equipment	7	17
Apparel and other textile products	8	4
Miscellaneous manufacturing ind	9	6
Chemicals and allied products	10	7
Paper and allied products	11	11
Electronic and other electrical equipment	12	13
Printing and publishing	13	3
Fabricated metal products	14	14
Rubber and misc plastics	15	12
Stone, clay and glass products	16	15
Industrial machinery and equipment	17	16

The Spearman rank correlation between these rankings is 0.6. Maurel and Sédillot (1999) get the same number if they consider the correlation between the levels of the Ellison and Glaeser (1997) index for these 2 digit industries. Again, we are struck by the similarities. Further, if we could explain a small number of differences, for example, publishing and printing, the match between the concentration patterns would really start to look quite strong. Finally, results in Duranton and Overman (2002) suggest that we may need to consider alternatives to Ellison and Glaeser (1997) that are unbiased with respect to spatial scale. This too might help explain some of the differences that we see here.

We believe that our discussion here highlights the possibility for a much more constructive research agenda on the spatial distribution of economic activity in the EU. Using micro-geographical data sets at the national level we should be able to get a much more detailed picture of the similarities and differences between the EU and the US. We should also be able to compare the economic geographies of countries within the EU. Indeed, work in progress by Barrios et al. (2003) provides just such a comparison for Belgium, Ireland and Portugal. Their preliminary results suggest that there are marked similarities between industrial location patterns in Belgium and Portugal while Ireland's pattern of agglomeration differs significantly from the other two countries. However, their results do raise some questions about the applicability of the Ellison and Glaeser index to countries with such different internal geographies (C2 and C5). Our rather casual look at the micro geographic descriptive evidence available for France, the UK and the US, suggests that similar industries are concentrated in all three countries. A much deeper understanding of the similarities would have profound implications for on going research. If concentration patterns are comparable across countries then we should be able understanding those patterns with reference to a large body of existing literature (mostly based on US data). This is *not* what is happening at the moment. The mirror image argument also holds. Where similarities exist, we can

learn about location theory more generally by considering the very good data that is available at the individual country level in the EU.

Of course, such comparisons cannot yet provide us with a direct comparison of the EU and the US. Indeed, similarities at the country level may point to the fact that inertia characterises most location decisions and that EU countries have built their economic spaces before the making of the EU could have a significant impact. Getting at this direct comparison calls for an even more ambitious project structured around the merging of plant level data sets from different EU countries. From our brief discussion however, it should be clear that such an undertaking could have big payoffs in terms of our understandings of the differences between the EU and the US.

2.4. Where we stand

EU area studies presented in this section give us some ideas about broad spatial location patterns both in terms of individual activities and in terms of the core-periphery pattern for aggregate activity. We have some ideas about which types of economic activities are concentrated. We have less idea about whether this makes us different from other economic areas of the world. This is unfortunate, because area-based descriptive work that does not allow comparison with other economic areas cannot really tell us much about location theory more generally. In this section, we have suggested two areas where further descriptive work might deliver interesting insights. First, we would benefit from direct comparisons of EU location patterns with other economic areas, particularly the US. These direct comparisons will need to deal with most of the problems we raised in Section 2.2.1 if they are actually going to be informative about the similarities and differences. Second, given the appalling state of EU wide data, we think that individual level micro-geographic surveys could also be used to facilitate this sort of comparison. Indeed, our limited comparison above suggests that there are many similarities between UK, French and US concentration patterns once we start considering detailed location patterns. This is interesting, because most European area based studies start with the premise that there are fundamental differences between the EU and the US in the nature and strength of agglomeration and dispersion forces. From the evidence we have so far, this argument receives only limited empirical support. Conditional on the location of overall manufacturing, EU industries do seem slightly more dispersed than their US counterparts. However, within country rankings of most to least concentrated industries appear to show a reasonable degree of correlation. We are struck as much by the similarities as the differences. The same will be true when we consider explanations of these patterns, an issue to which we now turn.

3. Explanations

Section 2 has considered what we know about concentration and specialisation in the EU. We now turn to those studies assessing the possible explanations of these patterns. The empirical papers that try to

explain the distribution of economic activities across space share the same global theoretical corpus. This corpus, however, is not unique, homogenous, or unified. Further, and in line with our earlier comments, the existence of an EU area based approach to determinants of location is only truly justified if this body of theory suggests that the EU is somehow different from other economic entities. We consider this issue in Section 4.1. This section also helps when we turn to the interpretation of the empirical studies in the following sections.

3.1. A brief survey of location theory and its application to the EU.

We start by considering the three main families of theory dealing with space and agglomeration - traditional trade theory, economic geography, and urban and spatial economics. We then present a classification of the different forces pushing towards more or less agglomeration. We emphasize that some of these forces are common to different theories. Finally, we study two critical determinants shaping these forces - transaction costs and labour mobility. We argue that justifications for an area based study of EU location patterns requires not only that the EU is different with respect to these determinants, but also that this has significant implications for understanding the economic geography of the EU.

3.1.1. Theories of space and location

Trade theory under constant returns to scale and perfect competition

Theories of comparative advantage make clear predictions about location. Trade allows specialization with each location specialising in the goods in which it has a comparative advantage. In Ricardian models comparative advantage is a result of exogenous technology differences, in Heckscher-Ohlin a result of exogenous differences in endowments. We refer to this strand of literature as “traditional trade theory”.

Economic geography

This set of models adopts assumptions polar to traditional trade theory. Technology is increasing returns to scale and identical across locations. Competition is imperfect. Endowments are identical, but factors may be mobile across locations so that incomes and factor prices can be endogenously driven by location choices. Increasing returns encourage firms to concentrate output in a limited number of plants. The location of these plants will depend on agglomeration and dispersion forces. Core locations give good access to suppliers and customers (cost and demand linkages). Peripheral locations avoid product and factor market competition. If agglomeration forces dominate dispersion forces, firms concentrate in a few places and export to other locations. We refer to this strand of literature as “economic geography”. See Ottaviano and Thisse in this volume for a detailed review.

Urban and spatial economics

Economic geography models emphasise cost and demand linkages as the key agglomeration force. Urban and spatial economics considers additional agglomeration externalities arising from localised

knowledge spillovers, labour market considerations and the provision of public goods. We refer to this strand of literature as “urban economics”. See Duranton and Puga in this volume for a detailed review.

3.1.2. Agglomeration and dispersion forces

Each of these theories contains features that explain the forces driving location and thus allow us to assess how these might differ for the EU. Our strategy is not to consider all of these in details, but instead to consider the main forces that shape the distribution of economic activities and consider how these forces might differ between the EU and other areas.

Local endowments

In many models local endowments have a direct impact on location. Considered in their broadest sense local endowments can capture the effects of factors, technology, physical geography (including natural resources), local public goods (including transport networks), cultural goods and local institutions or legislation. Although most theories take these endowments as given, physical geography is the only one which is clearly exogenous. Factor endowments are endogenous if factors are mobile while technology may depend on the composition and size of local industry. Local public goods are only exogenous if provision is independent of local economy composition and finance is not local (as for some public services in Europe). This suggests key ways in which the EU may differ from other areas. Either with respect to its physical geography or with respect to other endowments and their responsiveness to local economic conditions.

Within industry interactions

In most theoretical models a key factor shaping the distribution of spatial activity are interactions between local agents. Here we consider within industry (or localisation) economies that arise because of interactions between agents in the same industry. Urban economics and economic geography consider within industry demand and cost linkages as one source of localisation economies. These effects can also occur in traditional trade models. There is a key difference however - demand and cost linkages are magnified in economic geography models due to the presence of increasing returns to scale. Technological spillovers and labour market externalities can also work within industry while localisation diseconomies are also possible when good and factor market competition depends on the number and size of local competitors in the same industry.

Do within industry interactions provide a second source of differences between the EU and other areas? The answer is not clear and would involve EU industries “working” in different ways from the same industries in other areas. Different contractual settings might influence the degree of outsourcing and thus the nature of inter-firm input-output linkages. Different labour market institutions could change the way in which labour market externalities operate in the EU, while different intellectual property rights could change the nature of technological spillovers. Finally, different anti-trust regimes might change the

nature of local competition. All of these are possibilities, but we know little about whether or not they are realities.

Between industry interactions

Between industry interactions (or urbanization economies) depend on overall activity in an area. The impact may vary across activities. For example, access to final demand will depend on the overall population but will matter more for industries that sell a high proportion of their output to final consumers. Local public goods provision can also depend on overall size, as can cost linkages and technological spillovers. In some theories, where CES preferences (or technology) mean that variety increases utility (or efficiency), diversity matters rather than overall size. Jacobs (1969) also claims that many technology spillovers depend on diversity. Urbanisation diseconomies, including congestion effects, occur if firms compete for the same factors (e.g. land) or customers.

Do between industry interactions provide a third source of differences between the EU and other areas? As before, contractual arrangements, labour market institutions, anti-trust laws and intellectual property rights could all play a role. Another more realistic possibility is that institutional differences concerning land use and local taxation may change the nature of urbanisation diseconomies. Again, we have little idea if these possibilities are realities.

3.1.3. The determinants of agglomeration and dispersion forces

It is clear from the discussion above that we do not have a clear idea how individual agglomeration and dispersion forces may differ between the EU and other areas. Here, we briefly consider the factors that can explain why the strength of these forces may be different in the EU.

Transaction costs

Transaction costs play a key role in determining the location of activity. For high transaction costs, economic activities are dispersed. The agglomeration gains that could emerge from concentration are more than offset by dispersion forces. As long as economic activities remain dispersed, lowering transaction costs increases the level of trade between locations. For a range of intermediate transaction costs firms have incentives to agglomerate despite competition and congestion. If transaction costs fall far enough, the process of concentration may be reversed due to congestion costs induced by spatial concentration. Whether this happens depends on the assumptions made on the nature of competition and the degree of product differentiation, increasing returns to scale, and factor mobility. As we know of no compelling evidence to suggest that these three factors should be modelled differently in the EU we do not consider this issue further. However, differences in factor mobility may matter and it is to this issue we now turn.

Factor mobility

To see the importance of labour mobility note simply that if higher real wages in core regions encourage migration this both increases demand linkages and mitigates product and factor market competition. Although this migration may increase congestion and land prices these effects may be secondary and thus, in models where factors are mobile, activity should be at least as concentrated for any given level of transaction costs.

Location in the EU: two key differences?

Casual observation suggests that the EU has higher transaction costs and lower labour mobility than the US. More formal analysis confirms this.²⁸ It is these two key differences which have been used to justify an area based approach to explaining location in the EU. For the moment, we put aside whether this is a valid justification and turn to consider the explanatory literature in depth and assess what it tells us about the role of these differences.

3.2. Industrial localisation in the EU

In this section we consider explanations of the location patterns of particular industries. In the next section we consider labour productivity and wages. In the final section we turn to consider the dynamics of localisation.

3.2.1. Trade based approaches

Traditional trade theories emphasise supply considerations as the key determinant of the location of different industries. Two additional factors, the distribution of demand and the ease of trade, should also play a role. As we saw above, these two factors have a stronger impact in economic geography models with imperfect competition and increasing returns to scale. Both sets of models predict that the impact of explanatory factors will differ across industries.

Traditional trade models that explain location in terms of differences in technology or factors can be used to derive simple estimating equations by imposing few additional assumptions. For example, Harrigan (1997) assumes a translog functional form for the revenue function and technological differences that are Hicks neutral and industry specific to derive the following specification straight from theory:

$$s_i^k = \sum_{h=1}^K a_{kh} \ln \theta_i^h + \sum_{f=1}^F r_{kf} \ln v_i^f + \varepsilon_i^k .$$

²⁸ A large number of studies in the run up to the single market showed that EU markets were significantly segmented for a wide range of goods. On labour mobility to give just one example, Eichengreen (1993) shows that the elasticity of inter-regional migrations with respect to local wages is twenty-five times higher in the US than in Great-Britain.

where k indexes goods ($k = 1, \dots, K$), f indexes factors ($f = 1, \dots, F$), s_i^k is the share of good k value added in location i 's GDP, θ_i^h is a scalar productivity parameter measuring the productivity in industry h of location i relative to productivity in a base country and v_i^f is location i 's endowment of factor f . The a 's and r 's are parameters to be estimated. Harrigan (1997) estimates this specification industry by industry using a panel of OECD countries. Note that the a 's and the r 's are industry specific, so the way technology and factor supplies affect output is only constrained to be the same across locations not industries. In contrast, as we will see, economic geography models that need to incorporate both supply and demand effects impose more structure on the differences across industries. These differences will usually be parameterised using observable industry characteristics so that the specification involves the interaction between industry *and* country characteristics. That is, both elements determine location, a point that is not taken into account in the papers we presented in Section 2.2.5.

Ellison and Glaeser (1999) develop one such estimating equation using the simple location model that they used to justify their dartboard approach in Ellison and Glaeser (1997). In their model, an industry consists of a number of plants that choose locations sequentially to maximize profits. Expected profits depend on both location specific costs and spillovers from other firms. Location specific costs, or natural advantages, are divided into observable and unobservable components. Choosing a particular probability distribution for the unobserved component allows the authors to solve for the expected share of employment in each industry and thus specify an index of geographic concentration beyond that accounted for by observed natural advantage. For their empirical work, they need to specify how observed natural advantage affects expected profit. When doing this they “economize the number of parameters by assuming that the effect on industry profitability of the difference in the cost of a particular input [across locations] is proportional to the intensity with which the industry uses the input, rather than estimating a separate coefficient for each industry” (Ellison and Glaeser (1999, p. 313)). These

assumptions make expected shares, $E(s_i^k)$, a nonlinear function of $\sum_{f=1}^F \beta_f y_{kf} p_i^f$ where p_i^f is the price of natural endowment f in location i , y_{kf} the intensity with which industry k uses factor f and β_f are coefficients to be estimated. Comparing this to the expression derived by Harrigan (1997), we see that these intensities are common across industries. Thus parameterising the coefficients in this way reduces the number of coefficients on endowments from $K \times F$ to F . The resulting expression gives location shares as a function of the interaction between industry characteristics *and* location characteristics. Estimation involves pooling across industries and locations.

Although Ellison and Glaeser (1999) propose a simple firm location model to justify their estimating equation, the assumption that intensities can be used to parameterise responsiveness of profits to natural endowments is essentially *ad hoc*. Midelfart-Knarvik et al. (2000) develop a trade model which gives theoretical underpinnings to the estimation strategy proposed by Ellison and Glaeser (1999). The model

allows for endowments, final demand effects, and demand and cost linkages on intermediate inputs. The model is based on a constant returns to scale production function with production using both primary factors and intermediate goods. Factors are immobile across countries but goods can be shipped by incurring a trade costs that is origin, destination and industry specific. Preferences are CES with an Armington assumption so that goods are also differentiated according to source. However, the model assumes perfect competition. Implicitly, each variety is produced by a large number of producers implying marginal cost pricing. Since the number of varieties is indeterminate in equilibrium due to constant returns to scale, the authors have to make the black box assumption that the number of varieties is proportional to industry and country size. Using the same notation as above, linearizing the model gives relative shares, s_i^k as a function of $\sum_{f=1}^F \beta_f y_{kf} p_i^f + \sum_{h=1}^K \beta_h y_{kh} mp_i^h$ where mp_i^h is the elasticity of market potential in country i with respect to industry characteristic h .²⁹ That is, shares are predicted by the interaction between location characteristics and intensities, as in Ellison and Glaeser (1999). The two types of interactions reflect the fact that both input price variation and demand variation matter for output shares.

Midelfart-Knarvik et al. (2002) estimate the model using data from OECD STAN for 14 European countries and 33 manufacturing industries for four periods (1970-73, 1980-83, 1990-93, 1994-97). They allow for six interaction effects. Three capture Heckscher-Ohlin effects (agricultural, low/medium skill and high skill endowments) and three capture geography effects (cost linkages on intermediate inputs, final demand / transport costs interaction, and intermediate demand linkages). Taking the empirical specification to the data is not straightforward due to data availability. Factor prices have to be proxied using information on endowments. Capturing the geography effects involves estimating market potentials with all the problems we alluded to in Section 2.1.2. In addition some explanatory variables are endogenous according to theory. Given the lack of suitable instruments, the results may be biased to the extent that these variables are in fact endogenous in practice.

The preferred specification, allowing coefficients on the interactions to vary over time, explains 14 to 18% of the country-industry variation. When country and industry fixed effects are introduced, the R^2 increases to between 17 and 24%. Introducing fixed effects controls for omitted variables, such as physical geography, and does not change the basic results. In contrast to the studies using concentration indices discussed in Section 2.2.5, Heckscher-Ohlin effects are present in all periods although there is some variation over time. The skilled labour endowment variable is always strongly significant and has the highest impact. Intermediate cost linkages, have a positive impact on the relative industry share but

²⁹The actual expression involves centering each interaction with respect to a reference industry and a reference country. These references reflect the general equilibrium nature of the model. They are not predetermined and must be estimated. This has the added attraction that the reference points make the explanatory variables comparable across both industries and countries and remove the need for fixed effects. Finally, the theoretical derivation suggests that some variables enter as levels and some as elasticities.

are only significant in the final period. Intermediate demand linkages are significant in all time periods.³⁰ Changes across time suggest that the effect of cost linkages is increasing relative to demand linkages although these changes are not significant. Overall, results on the economic geography variables suggest that intermediate cost and demand linkages matter for location, while final demand does not. This approach has the appealing property that it gives a fairly simple functional form while allowing for a variety of agglomeration and dispersion forces. Differences in factor endowments and intensities induce specialization, while trade costs mean that the location of intermediate and final demand matters. However, the model does not include any imperfect competition and increasing returns to scale effects. As underlined in Section 3.1 both of these may have an important impact on agglomeration since they magnify both demand and competition effects. Unfortunately experience from theoretical modelling suggests that including these additional effects can lead to complex functional forms that are not analytically tractable. Taking these models to data is difficult and the complexity could lead to empirical exercises that are not easily interpretable.

3.2.2. Dixit-Stiglitz based approaches

Work by Gaigné et al. (2002) highlights the possible problems. They develop an *R*-region, *S*-industry location model based on increasing returns to scale production functions that use both intermediate inputs (a CES combination of output from all *S* industries) and *I* different types of skilled labour. Firms compete on a monopolistically competitive goods market (à la Dixit and Stiglitz, 1977). Solving the model involves assuming that workers are sectorally mobile, but spatially immobile. More problematically, the empirical exercise only considers the firm labour demand equation, but no other equilibrium relationships. This ignores many critical endogenous effects, in particular the endogeneity of demand and firm location choices. Linearizing the model gives the number of plants in a region-industry as a complex non linear function of demand and supply conditions.³¹ Interestingly many of the variables enter in the form of interactions suggesting that it may be possible to extend the approaches outlined above while maintaining the basic idea of the importance of interactions between industry and location characteristics.

Even with good data from France the authors are not able to measure many of these variables precisely and instead are forced to approximate them or even ignore them. In the end, they estimate a reduced form model to explain the region-industry location coefficient as a linear function of local labour costs, local final demand, local vertical linkages, a labour productivity effect and a competition effect. Estimation is performed on a spatial panel of 67 sectors and 341 French labour market areas allowing for sector and region fixed effects. At this spatial scale, the authors find that vertical linkages induce firms to

³⁰ The final demand transport cost interaction has a negative sign, which contradicts theory, but results are only significant when pooling across all four time periods.

³¹ Specifically: vertical linkages between all industries, the intensity with which each industry uses each type of labour, the wage of each type of labour in each location, the employment in each sector in each location, substitution elasticities, local demand for each final and intermediate good, final and intermediate goods prices, the share of household expenditures on the good, the fixed cost of each sector, the variable cost of each sector and the transport cost in each sector.

agglomerate but final demand has no effect. Industry by industry estimation suggests that local labour costs tend to encourage dispersion in roughly 50% of industries, but play no role in the location of the remaining 50%.

At a first pass, the paper by Gaigné et al. (2002) looks like it might justify the approach based on Kim (1995) that we discussed above. On closer inspection however, it becomes clear that the theory is only being used to help give the functional form for the explanatory variables and does not help determine how these variables should really affect the location coefficient. We feel this serves to strengthen the point that we made above. A fully specified economic geography model does not deliver predictions on the relationship between industry characteristics and industrial concentration so simple as those assumed by many authors (see Section 2.2.5) as soon as the number of regions exceeds two. On the other hand, estimating the fully structural model is not possible with the data that is available.

3.2.3. Cournot competition based approaches

Work by Combes and Lafourcade (2001) shows that a more tractable structural model can be developed in a Cournot competition framework. They consider an R -region, S -industry model where single plant firms produce for their local market and export to all other regions. Labour and all S goods are used as inputs. Technology is increasing returns to scale Cobb-Douglas and independent of region. Wages are assumed to be the same in all regions³². However, non-labour input prices are endogenous and determined by Cournot competition and thus depend on the number of plants located in each region and on inter-region transaction costs. The main agglomeration force in the model comes from intermediate and final demand linkages. Demand is larger in regions where more plants are located. In addition, imperfect competition and strategic interaction mean that input prices are lower in more central regions and this cost-linkage gives these regions an endogenous comparative advantage. Offsetting this is the fact that lower prices reduce mark-ups in large regions. Despite the similarities in terms of agglomeration and dispersion forces, these price and competition mechanisms are very different from those in monopolistic competition settings *à la* Dixit and Stiglitz (1977) where mark-ups are constant and independent of plant locations.

Combes and Lafourcade (2001) estimate the model using French data for 341 employment areas and 64 industries. Teixeira (2002) applies the same model to Portuguese data for 18 districts and 21 industries. In both cases, the only parameter in the model for which real data is not available is the

³² This is the only assumption that does not make this model a full general equilibrium one. Labour is also assumed to be immobile across regions and unemployment is supposed to emerge in all regions.

industry k specific inter-regional transaction cost t_{ij}^k between region i and j . Given data on generalized road transport costs t_{ij} ,³³ both papers assume that industry specific transaction costs are given by:

$$t_{ij}^k = v^k t_{ij},$$

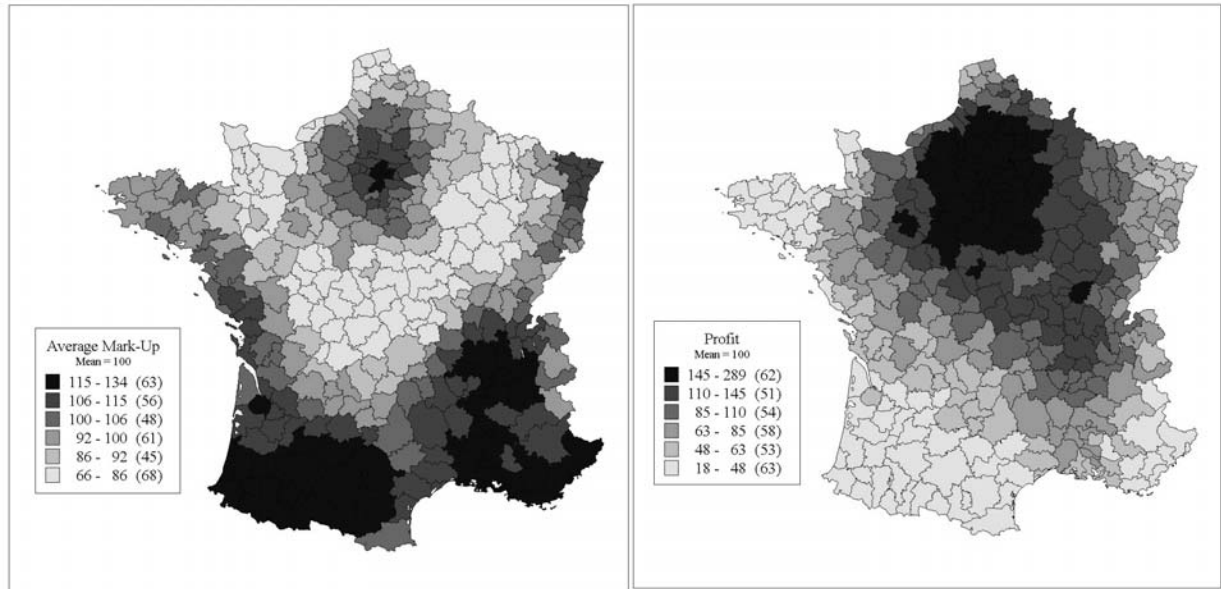
where v^k is an industry specific parameter to be estimated. The v^k parameters encompass all of the effects in the model and have no straightforward interpretation. However, they do serve two purposes. First, a test of the model can be based on the fact that negative v 's are not consistent with the model. Second, given that the underlying model is structural, the estimated parameter values can be used to simulate the change in economic geography in response to changes in the economic environment.

In both France and Portugal, the model is clearly not rejected by the data. In France, only one out of 70 industries has a significantly negative coefficient. At a more aggregate level (10 industries), all 10 coefficients are positive, 9 significantly. For Portugal, the 21 coefficients estimated are all significantly positive, most of them at the 1% level. Region and industry fixed effects significantly improve the fit. These fixed effects may capture forces that are not present in the model, for instance endowment effects, physical geography features, or good access to the rest of the world. Last, controlling for endogeneity by instrumenting leads to comparable results.

In addition to a test of the Cournot competition model, the results can be used to examine other spatial features of the two economies. As a first example, the model can be used to compute variables that are not directly observable. Figure 4 reproduces estimates of the average mark-up per unit sold and the variable profit per plant, on the left and right hand maps, respectively. The average mark-up presents an interesting spatial pattern simultaneously high around Ile-de-France and in peripheral regions, while low in between. In central regions, marginal and transport costs are low, but competition is high with the costs effects dominating. In peripheral regions, marginal and transport costs are high, but competition is low and the competition effect dominates. Firms in intermediate regions benefit neither from low cost nor low competition. Despite these findings on mark-ups, production per plant and profit per plant show a marked core periphery pattern decreasing from the centre to the periphery.

³³ See Combes and Lafourcade (2003) for a detailed description of the methodology used to calculate these costs.

Figure 4: Average mark-up (left), Variable profit per plant (right)



As a second example, the model can be used to calculate the degree of trade integration. France appears to be much more integrated than Portugal with transaction costs ten times higher in the latter than the former. Many other predictions of the model can be re-examined once the model is estimated. We cannot detail them here, but the above examples underline how fully structural estimations on detailed subnational data allow us to reach conclusions on general theoretical mechanisms and to provide precise comparisons across EU countries.

3.2.4. Where do we go from here?

Two features separate the approaches presented in this section from those we outlined in Section 2.2.5. First they use all available information instead of working on summary statistics. The results suggest that this presents a much richer picture of the determinants of location in the EU. Moreover, the use of underlying models is crucial in both the specification and interpretation of results. Clearly considerable work is still needed on these models. In particular, we do not yet have a fully specified general equilibrium economic geography model which can be taken to the available data.

In addition, it is not yet explicit what these models tell us about the difference between the EU and the US. Precise comparisons between the Ellison and Glaeser (1999) results for the US and those from Midelfart-Knarvik et al. (2002) for the EU are not possible because of the range of variables included in the US study that do not fit in to the theoretical specification used for the EU. However, it does appear that in both cases natural endowments have a greater role to play in explaining industrial location than economic geography forces. This may be because of the assumption intensive way that economic geography forces enter in to the theoretical specification. It may also reflect the fact that the theoretical specification does not yet capture increasing returns to scale effects. Taking the comparison at face value however might help us understand some of the similarities that we uncovered in Sections 2.2 and 2.3. If

natural endowments are important in explaining location patterns and trade acts as a substitute for factor mobility then we may find similar location patterns in the EU and the US despite the fact that factors are less mobile in the EU.

The structural models suggest another route for making comparisons both across the EU and between the EU and the US. Here is not the place for an in-depth discussion of the pros and cons of structural estimation³⁴ but we do note that replications of this kind of methodology provide one way of comparing agglomeration mechanisms in different economies. Indeed, the comparison of the extent of integration in France and Portugal is a first step along these lines. Clearly, estimating the same model for the US would also lead to comparisons between EU economies and the US. However, as in our discussion of the use of micro-level data, we note that considerable work may need to be done before this sort of approach can allow us to make comparisons between the EU as a whole and the US. This suggests that these comparisons may tell us more about the role of differences in labour mobility (which is relatively low even within EU countries) than they do about the role of transaction costs (where presumably the largest EU-US differences occur because of high inter-country transaction costs).

As these papers stand, they tell us more about economic geography in general than they do about the specifics of the EU. That is, they are an example of the kind of work on EU data that may end up being ignored as part of the area-based approach, but are really about fundamental aspects of economic geography. In particular, this work has provided theoretical foundations for some existing studies on US data and has highlighted a number of methodological problems with existing studies.

3.3. Labour productivity and wages inequalities

The previous section considers the role of agglomeration forces in determining employment shares of particular locations. However, these agglomeration effects may actually impact directly on productivity and only indirectly on employment concentration via the differences in local productivity this generates. In some cases, in particular when thinking about employment dynamics, this may be problematic if productivity advantage translates in to employment savings rather than higher employment. Indeed, as argued in Combes et al. (2002), higher productivity implies larger employment only if the demand elasticity is sufficiently large and if the substitution of other inputs for labour is not too important. If we are primarily interested in these differences in productivity, then it makes sense to study the impact of agglomeration externalities directly, instead of considering indirect evidence via employment shares.

These regional differences in labour productivity may be large. For instance, Ciccone (2002) reports that the five most productive NUTS 3 regions in Germany are 140% more productive than the five least productive. The gap for France, Italy and Spain is 66% and 33% for the UK. We note in passing, that

³⁴ The interested reader is referred to Combes and Lafourcade (2001) for the arguments in favour. To Sutton (2000) for a more critical perspective.

these figures are close to those obtained for the US by Ciccone and Hall (1996) who find that output per worker in the most productive state is two thirds higher than in the least productive.

Given these large differences we now turn to consider the evidence on local productivity differences in the EU. Before we start, note that lack of data means these studies only work with differences in labour productivity, not total factor productivity. We begin by considering direct evidence on labour productivity, before turning to the literature that uses wages as an index of labour productivity. Once we do this, we have to deal with an extra complication – labour is not homogenous and so we need to account for local differences in skills. In contrast to the literature on localisation, these two types of studies have tended to focus on what kind of local economic structure most enhances productivity, without worrying too much about the underlying causes. However, these studies sometimes do try to distinguish between within and between interactions. While the objectives of the literature differ somewhat, the issue of the role of theory in structuring empirical work is a common thread that connects the two literatures. We finish the section by considering a fully structural approach pioneered by Hanson (2002) on US data that has been replicated for data from a few European countries. For all of the approaches we consider here, comparable studies exist for the US, allowing an interesting comparison with the European results.

3.3.1. Labour productivity

Based on a methodology close to Ciccone and Hall (1996), Ciccone (2002) studies the impact of employment density on labour productivity at the NUTS 3 regional level for a subset of the EU including France, Germany, Italy, Spain, and the UK. Even though the impact of only one factor is studied, the methodology that considers both fixed effects and instrumentation allows a rigorous comparison with the results obtained for the US.

Estimations are based on the specification of a local production function that includes three inputs, (labour, human and physical capital) and an externality arising only, by assumption, from local production density. Labour productivity is derived directly from this specification. Data on physical capital is not available. However, using the optimality condition for physical capital use, Ciccone argues that the total production level and the capital rental price can be substituted for this unobservable endowment. Assuming that capital markets clear at a geographical level higher than NUTS 3, these prices can be treated as supra-regional fixed effects. This leaves regional labour productivity as a function of supra-regional fixed effects, the share of different education levels in regional employment (proxies for human capital), and of the regional employment density. An extension allows externalities to arise from contiguous regions. In this case, labour productivity also depends on the contiguous regions employment densities.

Before presenting the results, we offer a few comments on this framework. First, only the net impact of density is estimated allowing for possible congestion effects and decreasing labour marginal productivity. Indeed, the framework can only be used to estimate these net effects as congestion and

agglomeration effects cannot be identified separately. Second, fixed effects not only capture the role of physical capital, but also control for exogenous differences in labour productivity across regions due to differences in endowments or technology. As no time series data is available, the supra-regional fixed effects assume that these exogenous differences are identical for all sub-regions. Last, and most importantly, note that it is crucial to instrument the main explanatory variable, density. Since the specification only relies on a production function, both traditional trade theory and economic geography tell us that labour productivity and employment density are simultaneously determined. Ciccone (2002) argues that regional total land areas is a proper instrument for density since NUTS 3 region borders have, in most cases, been established more than a century ago and thus have no reason to be correlated with current productivity shocks. Total land area is very well correlated with current employment density, however, making it a good instrument.

The data used to implement this methodology offer an excellent example of the problems one may encounter with EU wide data, as detailed in Section 1. First, data are available only for five countries, consisting of 628 NUTS 3 regions. No capital endowments are available at this geographical level so only labour, and not total factor, productivity can be computed. This data restriction explains the choice of the dependent variable as well as the fixed effect trick used to deal with the local capital endowment. Because employment density may have different effects on agricultural productivity, the data needs to separate out manufacturing and services. Unfortunately, only total value added is available at the NUTS 3 level in Italy and the UK so the share of agriculture at the NUTS 2 level has to be used to estimate this share. For the human capital variables, the problem is that the number of education levels reported differs across countries. Finally, data are not available at exactly the same dates for the different countries, so data is used from the period 1986 to 1988. All of this clearly demonstrates that EU wide studies can be performed only at the cost of this kind of imprecision with the data.

Turning to the results, a first regression with no instrumentation and only country fixed effects gives a precise estimate of elasticity of labour productivity with respect to employment density equal to 5.1%.³⁵ At the other extreme, when regressions are instrumented and include NUTS 2 fixed effects and neighbouring regions density effects, the lowest estimate of the impact of local density on productivity is equal to 4.4%, with a 1% standard error. The impact of neighbouring region density is 3.3%, which adds to the local effect. A somewhat lower estimate, 3.4%, is obtained when the share of agriculture in value added is included in the regressions to account for within region differences in terms of agriculture occupancy. This extra variable may be endogenous, however, and no instruments are found to tackle this problem. Employment density is shown to be moderately endogenous and thus require instrumentation. Differences across European countries appear to be rather small. Estimates for Germany, France, and

³⁵ White robust standard error is 0.42%.

Spain are close to 5%, are 3.2 percentage points higher for the UK and 2.5 percentage points lower for Italy. None of these differences are significant, however.

Interestingly, the impact of employment density on labour productivity is extremely close to the US figure leading Ciccone (2002, in abstract) to conclude that his “empirical results suggest that agglomeration effects in [France, Germany, Italy, Spain and the UK] are only slightly smaller than agglomeration effects in the US: the estimated elasticity of (average) labour productivity with respect to employment density is 4.5% compared to 5% in the US.” Therefore, the robust methodology proposed in this study not only evaluates the elasticity of labour productivity with respect to density at the NUTS 3 level in Europe but also allows us to conclude that Europe and the US share a very similar effect of global agglomeration on local labour productivity.

3.3.2. Wages

Ciccone (2002) represents the only EU wide evidence we have on regional productivity differences. Slightly more evidence is available if we turn from EU wide studies to national studies. Unfortunately, even for given countries, a time series of value added often is not available at the regional level. However, if one is willing to assume that local labour markets are perfect, labour productivity should be equal to wage and wage data are more generally available. With this assumption in mind, we now turn to additional evidence on labour productivity differences that come from studies on wages inequalities in the EU. Once again, evidence from the US, presented in Glaeser and Maré (2001) acts as an interesting reference point even if the methodologies are not as closely comparable as in the previous section.

As a general point failure to control for heterogeneous skill composition across regions may considerably limit the interpretations that can be given to regional differences in labour productivity or wages. Higher productivity or wages might not reflect local agglomeration externalities at all, but only differences in local labour composition. For this reason, Ciccone (2002) included education controls in his regressions. If one thinks that the composition of regional labour markets is relatively constant across time, regional fixed effects might also partly control for such problems.

Duranton and Monastiriotis (2002) highlight the main issues in their investigation of the role that such labour characteristics may have on the evolution of earnings across UK regions. Their work is based on a panel of the 12 UK NUTS 1 regions spanning from 1982 to 1997. Data is available on both earnings and local labour market characteristics including gender composition, education and experience levels. Without any controls, average earnings in the two richest regions, London and the South East were 121% and 103% higher than the national average in 1982. The gap increased to 137% and 109% by 1997. The coefficient of variation across regions has increased almost threefold. All of this shows an important increase in inequalities across the UK regions during the period. Three phenomena explain this trend. First, educational attainment, already higher in London and in the South East, increased more rapidly there than anywhere else. As educated people are paid more, this magnified differences in regional

earnings. Second, the national gap in earnings between skilled and unskilled worker simultaneously increased, which favoured more skilled regions. Third, London initially had lower returns to education, but the difference decreased during the period. Importantly, none of these explanations of the divergence of regional earnings in the UK refers to agglomeration externalities, even though more dense areas such as London appear to be favoured. The spatial sorting of skilled workers, not agglomeration effects appear to be the main explanation. These results highlight the importance of controlling for skills and labour sorting when explaining wages inequalities in the EU. This is true, despite the fact that inter-regional mobility is supposed to be low and falling in the UK.

As a comparison, consider results for the US reported in Glaeser and Maré (2001), that try to evaluate the impact of skill composition on the wage premium, i.e. the fact that wages are higher in cities. Results from two sources of individual data, the Panel Study of Income Dynamics (PSID) and the National Longitudinal Survey of Youth (NLSY) are comparable. The wage premium in dense metropolitan areas is estimated to be 28.2% and 24.9%, in each panel respectively, falling to 25.9% and 24.5% once they allow for labour market, occupational, and education controls. One could therefore conclude that the skill bias is not so strong as for the UK. However, once individual fixed effects, controlling for any possible individual abilities, are included simultaneously with a tenure variable, the wage premium in dense metropolitan areas falls to 4.5% and 10.9%, respectively.³⁶ Individual abilities and tenure would divide the wage premium by between 2.3 and 6.3. Comparable magnitudes are obtained for the wage premium in non-dense metropolitan areas. Once again, controlling for skills and for individual fixed effects drastically changes the verdict on the impact of agglomeration economies.

A more direct comparison to Glaeser and Maré (2001) is provided by Combes et al. (2003) who extend these ideas and methodology to France and to determinants of local wages other than density. Their aim is to explain the impact on city-industry wage inequalities of skills and individual abilities, natural endowments (geography features, but also possibly technology or public good endowment), within industry and between industry interactions. The data are an example of the excellent data that may exist at the country level in Europe. The panel they use follows individuals providing earnings information across time, locations and occupation. The data is annual covering 1976-1998 and may be disaggregated across 341 regions and 114 industries (including both manufacturing and services). Their sampling framework selects 1/20th of the data leaving them with 2,664,474 person-year observations.

Estimation results show that a very large proportion of regional wage inequalities are explained by individual abilities. Estimation using individual fixed effects alone gives an R^2 of 69%. This rises to 80% with all explanatory variables but falls to only 31% without individual fixed effects. As for the US, comparisons with aggregate regressions, suggest that observed individual characteristics, such as

³⁶ The wage premium disappears altogether once they control for urban costs (housing plus commuting). That is, there is no evidence of a *real* wage premium in Metropolitan Areas once we allow for individual effects.

occupation, only capture individual abilities very imperfectly. Localization and urbanization economies remain significant but their magnitude is at the lower bound of those found in the literature (see Rosenthal and Strange in this volume). For instance, the elasticity of wages with respect to density is around 6% on aggregate data, which is close to the estimates found on labour productivity both for the EU and the US by Ciccone (2002) and Ciccone and Hall (1995). But this elasticity falls to around 3.5% when individual abilities are controlled for. Furthermore, density is endogenous and when instrumented by population density, its effects fall to 2.5%. Similarly, the impact of specialisation on wages, falls from 4.3% when estimated on aggregate data to 2.1% once individual abilities are taken into account. These results underline that workers sort across space, which significantly biases upward both localization and urbanization economies. This sorting is occurring in France and the UK much as it is in the US. Once again, we are struck by the similarity of the results. Despite measured differences in short run labour mobility, the impact of sorting is broadly similar across these three economies.

3.3.3. Monopolistic competition based approaches

Studies in the two previous sections provide interesting, and robust, descriptive results on local determinants of labour productivity and wage inequalities. As for much of the localisation literature, links with theory remain rather fuzzy and distant. Estimations are based on the specification of a production function only. Hanson (2002) pioneered a fully structural approach to consider wages inequalities based on an economic geography model. While he implemented his methodology on US data, his approach has been replicated on several European countries. Mion (2002) considers 103 provinces in Italy, Roos (2001) considers 327 districts for West Germany (327 districts), Brackman et al. (2002) consider 151 districts for East and West Germany and de Bruyne (2003) considers 43 districts for Belgium.

These structural estimations allow for clear US/EU comparisons but there are two important drawbacks to this approach to wages inequalities. First, estimations cannot be performed at the industry level due to the lack of data. Second, use of one model restricts the agglomeration forces at play to those based on monopolistic competition and love of diversity in final consumption. However, as this framework is one of the most frequently used in theoretical economic geography, we consider these estimations as an important contribution to understanding the empirical economic geography of the EU.

These structural estimations are based on the Helpman (1998) economic geography model. Though very close in spirit to Krugman (1991b), a few key assumptions make it different in terms of economic implications. Instead of assuming that a constant returns to scale / perfectly competitive sector produces a homogenous good that can be freely exported (“agriculture”), this good is assumed to be non tradable and its local endowment exogenously fixed (“housing”). As a result, its price differs across locations, and increases with the size of the local population. This creates an additional dispersion force absent from Krugman (1991b). An agglomeration force is also suppressed: The homogenous good income, higher in larger areas, is redistributed at the national level and not locally. While functional equilibrium

relationships may look very similar in both models, they lead to opposing comparative statics in terms of one crucial parameter, the interregional transaction cost. While reducing transaction costs increases agglomeration in Krugman (1991b), it makes regions more similar in Helpman (1998). These results are not contradictory however. Each model emphasizes one side on the well-known bell shaped curve that links transaction costs and regional inequalities (see Puga (1999)). It is important to keep in mind this difference when interpreting the estimation results. Finally, note that equilibria in the Helpman (1998) model are interior, while one region may end up with no manufacturing employment in Krugman (1991b), a problematic property when one deals with real data. Indeed, this is the main reason why Hanson (2002) chose to estimate the Helpman (1998) model. See Head and Mayer in this volume for more discussion of this issue

The estimated specification is directly derived from the theoretical model. It links the wage in a given region to a market potential function of income, wage, and housing stock in all other regions, discounted by distance. More precisely, estimations are based on the following equation:

$$\log(w_i) = \alpha_0 + \frac{1}{\sigma} \log \left(\sum_k Y_k^{\frac{1-\sigma(1-\mu)}{\mu}} w_k^{\frac{\sigma-1}{\mu}} H_k^{\frac{(\sigma-1)(1-\mu)}{\mu}} e^{-\tau(\sigma-1)d_{ik}} \right),$$

where w_k , Y_k , and H_k are the wage, total income, and housing stock in region k , respectively. d_{ik} is the distance between regions i and k . σ is the elasticity of substitution between varieties, μ is the share of non-housing goods in total final consumption, and τ reflects the impact of distance on inter-regional transaction costs³⁷. The model is consistent only under the following constraints:

$$\sigma > 1, 0 \leq \mu \leq 1, \text{ and } \tau \geq 0.$$

Two critical econometric issues characterize the estimation of this equation. One is the need to use non-linear estimation taking in to account the constraints due to the links between the parameters. All the studies use non linear constrained estimation procedures although Mion (2002) also proposes an appealing alternative approach based on linearization. Second, endogeneity may clearly bias the parameter estimates. First, the dependent variable directly enters as an explanatory variable. Second, local income, which enters as an explanatory variable, is simultaneously determined with wages in the long run equilibrium. Third, even if housing stocks are exogenous in the model, they are probably dependent on local incomes in the data. Notice also that including local fixed effects makes sense in this setting to control for all forces not considered in the theoretical model and constant across time. However, if important for the spatial distribution of economic activities, these fixed effects should again be correlated with the residuals. Hanson (2002) tackles this last endogeneity issue by first-differentiating the series. In

³⁷ α_0 is function of σ , μ , and of the fixed cost, but this cannot be identified in the first differences estimations performed.

addition, he computes explanatory variables at a geographical level higher than the one of the dependent variable. County wages are regressed on the explanatory variables computed for sixteen ring areas surrounding the county. Following Hanson (2002), Roos (2001), de Bruyne (2003), and Mion (2002), also use a higher administrative level. While simplifying computations, it is doubtful, however, that such an estimation procedure controls for endogeneity: If explanatory variables are correlated with residuals at the lowest level, their sum should share the same property. Furthermore, as argued by Mion (2002), this is close in its spirit to an instrumental variable method, where instruments would be the aggregated explanatory variables, but it is much less efficient since a lot of information is lost. Hanson (2002) also presents regressions excluding the observations related to the largest counties, which does not change his results markedly, and finally proposes a non-linear instrument variable method, based on the county population levels lagged by more than 10 years, which seems to be the most reasonable approach.

The US and EU results are easy to compare since the same model is estimated with the same non-linear estimation procedure. However, only Roos (2001) and Mion (2002) present results for first-differences and only the latter presents instrumented results for Europe.

Results for the elasticity of substitution, σ , are fairly consistent across studies. US estimates vary between 4.9 and 7.6, equal 6.2 in West Germany, 5.5 in Belgium and are between 5.9 and 6.7 in Italy. In all studies, σ is often not precisely estimated, and is not significantly different from 0 in West Germany and Belgium, possibly due to the aggregation procedure used for explanatory variables. When this aggregation procedure is not performed, σ is much more precisely estimated: equal to 3.9 in Germany and only 1.9 for Italy. These results suggest that EU consumers more strongly differentiate varieties implying higher mark-ups in Europe than in the US. Turning to the share of housing in consumption, it is estimated to be negative, although insignificant, in Germany and Belgium. In the other studies, it is significantly positive, taking the same value of around 0.1 in the US, in West Germany and Italy. This estimate is pretty low. Hanson (2002) argues that a reasonable value should be at least 0.2. The value of $\sigma(1-\mu)$ determines whether wages reflect only exogenous housing endowments, or are also determined by the model's endogenous agglomeration and dispersion forces. A value greater than 1 signifies the former.³⁸ For all countries, the value is less than one (although not always significantly) suggesting that endogenous economic geography forces matter in shaping the spatial wage distribution. Finally, distance is found to significantly increase transaction costs for all countries but West Germany where the effect is not significant. Unfortunately, the impact of distance is not comparable across countries since it depends on the way (e.g. geodesic *vs* real) and the units in which distance is measured (time *vs* distance for instance).

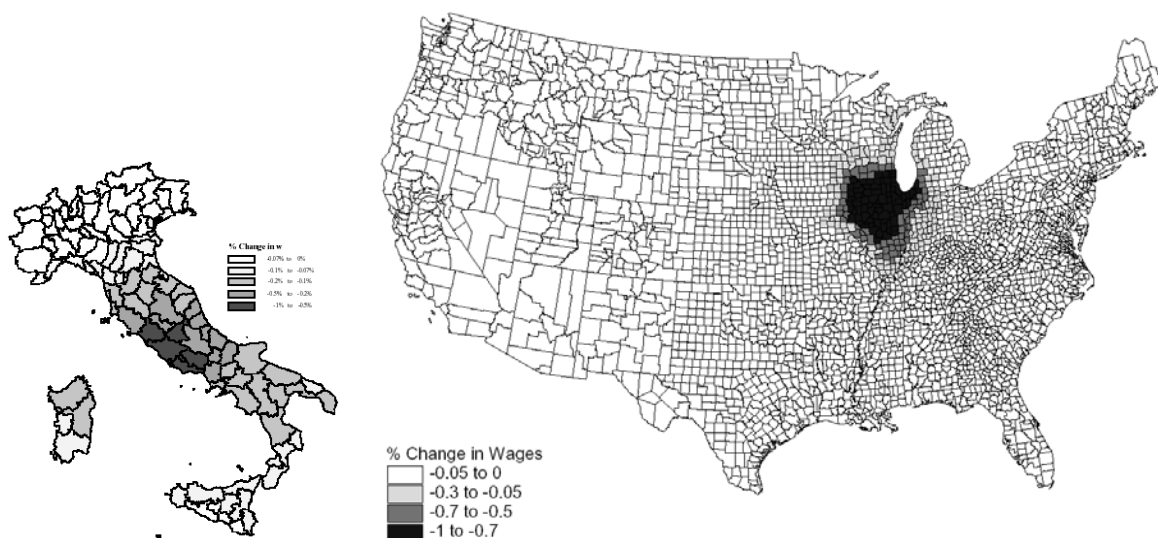
³⁸ This is the no-black hole condition. The interpretation of the condition is different in Krugman (1991b) and Helpman (1998) since it implies full agglomeration in the former and full dispersion in the latter.

From a technical view point, the non-linear estimation results may be sensitive to the choice of starting point. Given this, one can question the validity of first differencing and instrumenting such estimations. Mion (2002) proposes an alternative approach, linearizing the equilibrium equations of the Helpman (1998) model, as Combes and Lafourcade (2001) do for the structural estimation of their Cournot competition model (see Section 3.2.3). This is quite simple once a different specification for the impact of distance on transaction cost is assumed. Mion (2002) adopts a power function that is standard in empirical trade, θd_{ik}^{-1} , where θ is estimated. Mion (2002) also proposes using the Arellano and Bond (1991) procedure for dynamic panels to properly instrument the estimation and take endogeneity into account.³⁹ The reader is referred to Mion (2002) for further details. This procedure leads to very precisely estimated parameters. The elasticity of substitution is 3.4, which is reasonable when one considers that the manufacturing sector may cover a large spectrum of goods. The share of housing is 0.2. The two together give a value of $\sigma(1-\mu)$ significantly lower than 1. Hence, as estimated by Mion (2002), the Helpman (1998) model seems to explain spatial wage inequalities in Italy quite well. The explanatory power is actually higher than for the US, although the estimated values of underlying parameters are not so different.

As an example of the predictions that can be made on the basis of this structural estimation, Figure 5 presents the simulated wage changes induced by a 10% negative income shock in the five Latinium regions in Italy (Figure 5-left, reproduced from Mion, 2002) and in Illinois in the US (Figure 5-right, reproduced from Hanson, 2002). The role of distance appears to be quite important, the effect of the 10% shock being lower than 1% even in the closest areas, and lower than 0.1% for the farthest. The distance and magnitude of the shock impact are comparable, but, due to the different sizes of both countries, this implies that a much smaller share of the country is affected in the US. This may be due also to the fact that both estimations do not use the same specification of distance, Hanson's exponential choice converging faster towards zero.

³⁹ This methodology is closeto the one adopted by Henderson (1997) and Combes et al. (2002) to study local employment short-run dynamics: See Section 3.4.2 below.

Figure 5: Simulated wages changes in Italy (left) and the US (right)



3.3.4. Where do we go from here?

The structural estimations we have just presented allow for precise comparisons intra-EU and between EU countries and the US. Again, data availability means we are somewhat from being able to use these approaches for a comparison of the EU as a whole with the US.

The studies also provide interesting extensions, in terms of econometric methodology. If one believes in the role of skills and spatial labour sorting as underlined by the earlier wage inequalities studies, the Helpman-Hanson structural estimation should be extended along a number of lines. First, skills and ability should be controlled for. Hanson (2002) is the only study to do so using local education levels. One might think that the consideration of local fixed effects is enough to address this issue, due to the inertia of the local skill composition but this remains to be proved and our discussion of results on spatial sorting urge caution in drawing that conclusion. Second, this methodology has not been implemented for different industries. Again, one may think that differences across industries should be important. A multi-industry extension of the monopolistic competition economic geography model is surely worth considering. This would certainly also need to include a differentiated input setting, as found in Krugman and Venables (1995).

More generally, the two structural approaches, we have considered, dealing with employment and wage inequalities, are complementary in the sense that they are based on different theoretical models and therefore on different agglomeration and dispersion mechanisms. In both cases, the main agglomeration force relies on final demand linkages playing on increasing returns to scale while dispersion is fostered by some kind of increased competition in central places. However the underlying mechanisms are quite different. The second approach, based on monopolistic competition *à la* Dixit and Stiglitz (1977), makes the role of love of diversity central, whereas imperfect competition mechanisms are rather soft. In

the first approach, Cournot competition on homogenous goods ensures competition is stronger and that real strategic interactions take place. Results from both sets of estimations can thus be viewed as a first comparison of two competing settings. This remains rough, however, and should be made more precise. Indeed, European area-based studies have for the moment mainly tried to assess whether a given model explains the observed spatial patterns. There is obviously another use of structural estimations, which consists in testing given models against one another. This is often more difficult, since the same specification has to be consistent with both models, the value of the estimated parameters allowing us to select one of them. In trade theory, Davis and Weinstein (1999) take this approach for testing traditional trade theory against trade theory under increasing returns to scale (see Head and Mayer in this volume). However, these kinds of tests have not yet been implemented in economic geography.

What should be clear from our brief survey is that this sort of approach may present yet another way to make general comparisons between the economic geographies of different areas. Again, we think that the results available so far point more towards similarities across the EU and the US than differences. These similarities occur despite underlying differences in mobility and the extent of integration.

3.4. The dynamics of localisation in the EU

The studies presented in sections 3.2 and 3.3 explain employment, labour productivity and wages as functions of local characteristics *at the same date*. We now turn to the analysis of local *growth* as a function of *past* determinants. This literature talks to an old debate on whether local externalities are mainly static or dynamic. The literature in this section assumes that local externalities affect local growth while effects were assumed to be instantaneous in the studies in the previous section.

The earlier literature sought to determine the impact on local growth of localization economies (within industry interactions) and urbanization economies (between industry interactions). This body of work also considered the role of other factors such as local competition or plant size. As a general point, notice that even if authors mainly interpret these variables as capturing technological spillovers, many other market based interpretations can be given as is clear from our theory survey in Section 3.1.

We begin by considering determinants of long-run growth before turning to the study of short-run dynamics, which allows us both to refine our conclusions and to tackle important endogeneity problems. In both cases, we argue that EU results are again not so dissimilar from results for the US.

3.4.1. Long-run growth

The methodology

Glaeser et al. (1992), followed by Henderson et al. (1995), first proposed regressing local employment growth over a longish period of time on initial economic characteristics. These papers regress city-industry employment growth on a specialization index and on an industrial diversity index, both

computed at the city level. The former should capture all within industry interactions and the latter all between industry ones. The specialization index is the share of the industry in the city. To measure diversity, Glaeser et al. (1992) use the share of the five largest industries in the city excluding own industry, while Henderson et al. (1995) use a Herfindhal index computed on all industry shares in the city employment. Glaeser et al. (1992) also include the number of plants per employee (the inverse of plant average size as used by Kim, 1995) as a competition index, while Henderson et al. (1995) ignore this variable, but do include city employment in all other industries as an extra urbanization variable. Both papers include a number of additional controls.

Results for the US are not consistent across the two studies. Glaeser et al. (1992) find that local growth is positively influenced by diversity and negatively by plant size and specialisation. In contrast, localization economies are at work in all five industries studied in Henderson et al. (1995), while urbanization ones are observed in the high-technology sectors only. These discrepancies might be explained by appealing to data (the fact that the period considered is not the same - 1956-1987 *versus* 1970-1987 and that Glaeser et al. (1992) includes services, while Henderson et al. (1995) do not), estimation (Glaeser et al. (1992) regressions are pooled whereas Henderson et al. (1995) are run industry by industry) or problems with the overall methodology.

Combes (2000) identifies a number of problems with these two papers and the papers that replicate them for other city systems, especially in Europe. The first relates to the inclusion of city-industry employment level in addition to specialization and total employment. In Henderson et al. (1995) both specialization and total employment have positive impacts on employment growth, while industry employment has a negative effect. The positive coefficient on specialization is interpreted as evidence of localisation economies. But, to increase specialisation either industry employment must rise or total city employment must fall and both of these other explanatory variables induce offsetting negative effects. Thus, if we include more than one city employment variable we break the link between the specialisation index and localisation economies. A similar argument can be made for the link between total employment and urbanisation economies. A second source of problems relates to the need to include industry fixed effects when running pooled estimations. Glaeser et al. (1992) centre some but not all variables using national values of the variables. Clearly, centring all variables or including fixed effects would be preferable. Other pitfalls relate to the problems of interpreting plant size variables (as discussed in Section 2.2.5), the endogeneity of variables, potential selection problems if industries are not present in a city in the first period and the need to account for the fact that employment data might be censored.

Replications on EU countries

If we ignore these methodological points and take results from the EU at face value, the evidence appears to support the Glaeser et al. (1992) findings rather than those of Henderson et al. (1995). Paci and Usai (2002) consider Italian data for 1991-1996 at a very low geographical scale (784 local labour systems). They find evidence of a positive effect of local industrial diversity and a negative impact

of specialization. Contrary to Glaeser et al. (1992), they also find a positive impact of firm size. Further evidence from Italy, this time for 92 Provincias, is provided by Cainelli and Leoncini (1999). They also find a negative impact of specialization, but effects are reversed for firm size and diversity. Now both impact negatively on local growth. When Italy is sub-divided in to four large regions, the impact of diversity becomes positive for both North industrialized regions. Still in Italy, and again at the local labour system level, but for 1971-1991, Forni and Paba (2001) estimate a specification in which specialization in all 88 industries is separately introduced in the explanatory variables. They find that both own specialization and specialization in related industries favour local growth. In the Netherlands in the 1990s and for two different geographical scales (57 cities at the country level (1991-1997) and 416 zip codes in South-Holland (1988-1997)), van Soest et al. (2002) find a similar role for diversity and specialization, and a negative role of plant size, as in Glaeser et al. (1992). Almeida (2001), using 1985-1994 data for the 275 Portuguese “concelhos”, finds that the impact of local characteristics varies across activities. Services and most manufacturing sectors show a negative effect of specialisation and plant size, and a positive impact of diversity. There are a few industries, however, for which the opposite holds. These results are broadly consistent with those of Combes (2000) for the 341 French employment areas for 1984-1993. His estimations, taking account of the points that we raise above, find that diversity has a positive effect on service sectors and a negative effect on manufacturing. Specialisation has a negative effect in both cases. Again, for some industrial sectors specialisation has a positive impact. In addition, he distinguishes the effect of competition from that of plant size. Both appear to have a negative impact in most sectors.

Productivity growth

If our primary interest is productivity then, as before, working on employment growth might be problematic because positive productivity shocks could impact employment growth negatively if production is not expanded sufficiently. In addition, some agglomeration effects may directly impact on labour supply without affecting productivity. Both these effects make the employment growth interpretations difficult and suggest that determinants may be different for productivity growth. If data is available, it is clearly preferable to work on this variable directly.

de Lucio et. al. (2002) assess the links between labour productivity and localization and urbanization economies in Spain. They find no effects of competition or diversity on labour productivity growth, and a U-shaped effect for specialization. Low levels of specialization reduce productivity growth, while high levels foster it. Studying 784 local labour systems in Italy, Cingano and Schivardi (2002) make two contributions. First, they use total factor productivity growth as the dependent variable. They show that both specialization and city size have a positive impact. This positive impact is also observed on wage growth. In contrast, diversity, competition, and plant size variables are not significant. Second, using the same sample, they study the differences that are observed when working on local employment growth as dependent variable. They show that the effects of specialization and city size are reversed, becoming

negative, while the other local characteristics now have a significant impact on local employment growth. This appears to confirm that the local growth of employment and productivity may be fostered by different determinants.

3.4.2. Short-run dynamics and endogeneity controls

City employment is sometimes available for many consecutive years. In this case, it is possible to use the three dimensions of the panel (city, industry, and time) to improve the methodology. First, industry and city fixed effects may be included. Importantly, this controls for local effects that do not change across time. As a consequence, the identification of local externalities is only based on changes across time. The panel dimension also allows for a real test of whether externalities are static or dynamic. Indeed, including many lags and testing their significance qualifies the duration of the effects. Thus, fixed, static, and dynamic effects are properly distinguished in time series approaches.

Endogeneity is a very important issue in this literature. Both fixed effects and other explanatory variables are likely to be correlated with unobserved shocks to city industry growth (the dependent variable). One can deal with the fixed effects endogeneity by simply first differencing the series. The remaining endogeneity, present in any theory dealing with agglomeration (see Section 3.1), must be controlled for using instrumental variable methods. This is rarely done in long-run estimations. de Lucio, et al. (2002) is the exception on European data.

Henderson (1997) is the first implementation of this time series methodology, using data on 742 urban U.S. counties between 1977 and 1990. He finds strong localization economies that die out after six years. Note, however, that the simultaneous introduction of specialisation and lagged values of the dependent variable leads to the same interpretation problems as we discussed with respect to the long-run methodology. Urbanization economies are smaller but also persist longer, at least till the end of the time horizon (eight or nine years back).

Combes et al. (2002) implement this methodology for 341 French metropolitan employment areas levels and for 36 manufacturing and services industries between 1984 and 1993. The Henderson (1997) methodology is extended by noticing that city-industry employment is the product of the average city-industry plant size times the city-industry number of plants. Therefore, local employment growth can be decomposed in to internal growth (the growth of the size of existing plants), and external growth (the creation of new plants).⁴⁰ The determinants of the dynamics of both variables are simultaneously studied

⁴⁰ This local growth decomposition leads to further policy issues. One can compare the impact of a given policy on each growth component or determine what is the optimal policy for each target. Indeed, Duranton and Puga (2001) show that the impact of urbanization economies may differ from localization ones depending on the product life cycle. Industrial diversity favours innovations and therefore fosters plant creation. Less urbanized but more specialized areas favour mass production. Actually, in France, 72% of plant relocations take place from an area with above median diversity to an area with above median specialization in the corresponding sector. Moreover, the pattern is stronger for plants in more innovating and technology intensive sectors.

in a VAR setting and therefore linked to each others dynamics. Model selection techniques are used to determine the duration of local effects. Combes et al. (2002) prefer not to use the specification including the own industry employment both in logarithm and level. Localization economies are captured only through the inclusion of the lagged dependent variable. They consider two alternative measures of diversity in addition to total employment as well as two indices of local competition. For France the selected model, an ARMA (1,1), has an order that is low compared to the between six and nine order processes found by Henderson (1997). Hence, in France, static externalities appear to be prevalent while in the US, dynamic effects are more important. The approach proposed by Combes et al. (2002) allows for additional results. In France, on average, larger areas have both more plants and larger average plant size in all industries while a pool of industries of comparable size favours both internal and external growth, even if the total number of these industries does not need to be large. Hence, technological spillovers could work across selected industries but need not extend to all of them, as long-run regressions seem to imply. The impact of local competition is shown to be non linear. Plants appear to be larger in areas where they are more numerous, but of uneven size. This suggests that large leaders may encourage growth in smaller plants surrounding them. On the other hand, the number of plants grows faster in places where plants are less numerous and of even size. Replicating the methodology on other European countries could lead to potentially interesting pan-European comparisons.

3.4.3. What we learn and a comparison with the US

Regressions in this local growth literature share some poor properties with the reduced form estimations of section 2.2.5. First, precise theoretical foundations are lacking and no structural approach has been developed to formalise this work. Local productivity, or productivity growth, is assumed to depend on local economic characteristics in a black-box fashion. Most of the underlying models do not go further than the specification of a production function and the use of first-order conditions with respect to input choices. This also prevents us from testing one given theory against others and only determines the local economic structure that has the strongest impact on growth without identifying the channels through which this works. Second, the city-industry dependent variable is a function of own city characteristics only, and not on other cities. In static contexts, more structural approaches assuming trade between regions imply inter-city effects, which is almost never taken into account here. Some authors, such as Cingano and Schivardi (2002) include market potential variables as controls, but this remains crude.

Overall, the evidence suggests that localization economies seem to be absent in the EU, as Glaeser et al. (1992) found for the U.S. One possible exception may be for high specialization levels in Spanish provinces. More often, diversity has a positive impact on local labour growth, which is again consistent with the US findings. Another common feature is that results vary considerably across industries. For instance, a common finding is that urbanization economies appear to be stronger in high-tech and service industries than in manufacturing. Finally, local effects dissipate quicker in France than in the US. As well as these similarities in terms of findings, we again note that some of these EU studies have broader

methodological implications for future empirical work.

4. Conclusions

This chapter set out to describe the economic geography of the EU and to consider what we know about the forces determining that geography. At times, our review has been fairly critical. European data is a mess and European researchers have often not used this data as efficiently as possible. But some positive lessons also emerge, and it is these that we want to focus on in this conclusion.

First, we do know much more about the economic geography of the EU as a whole than we did a decade ago. Many gaps remain to be filled, but we do now have some idea of the spatial structure of both aggregate activity and particular industries. One key gap in our knowledge remains. That is, how does the economic geography of the EU compare to that of other large integrated economic areas? In practice, answering this question will involve identifying how the economic geography of the EU differs from that of the US. This question is of fundamental importance for a very simple reason. Empirical work suggests two key ways in which the EU is different from the US. Our product markets are less integrated and our labour is less mobile. Theory tells us that these two factors *could* be enough to leave the EU with a very different economic geography to the US. Current empirical evidence does not allow us to assess whether these two factors *do* mean that the economic geography of the EU and the US are different. Resolving this issue is important, because it will be fundamental in deciding whether a separate European area based literature is really needed, or whether empirical research on the EU is just about studying the same economic geography mechanisms with different data.

The evidence that we do have so far points to some marked similarities. Micro level data suggests that the same kind of industries may be localised in both the EU and the US. Other work, suggests that there are similarities between the EU and the US in the workings of the agglomeration and dispersion forces that determine economic geography. We have seen that similarities between the two areas exist in the relationship between wages and density, the determinants of wage differences and the spatial nature of these differences, and the dynamics of city growth in both the short and long run. Given the excellent data that is becoming available across the EU, making further significant progress on resolving these issues should be the main task for the coming decade.

References

- Aiginger, K. and L. Wolfgang (2002), "Regional concentration in the United States and Europe: Who follows whom?", *Weltwirtschaftliches Archiv* 138:1-28.
- Almeida, R. (2001): "Local characteristics and growth in Portuguese regions", processed Universitat Pompeu Frabra.
- Amiti, M. (1999), "Specialization patterns in Europe", *Weltwirtschaftliches Archiv* 135:1-21.

- Arellano, M. and S. R. Bond (1991), "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations", *Review of Economic Studies* 58:277-297.
- Barrios, S., L. Bertinelli, E. Strobl, A.-C. Teixeira (2003), "Agglomeration economies and the location of industries: Evidence for three small European countries", processed CORE, Louvain La Neuve.
- Brakman, S., H. Garretsen, and M. Schramm (2002), "The spatial distribution of wages and employment: Estimating the Helpman-Hanson model", processed University of Nijmegen.
- Brülhart, M. (1998a), "Economic geography, industry location, and trade: The evidence", *The World Economy*, 21:775-801.
- Brülhart, M. (1998b), "Trading places: Industrial specialization in the European Union", *Journal of Common Market Studies* 36:319-346.
- Brülhart, M. (2001a), "Evolving geographic concentration of European manufacturing industries", *Weltwirtschaftliches Archiv* 137:215-243.
- Brülhart, M. (2001b), "Growing alike or growing apart? Industrial specialisation of EU countries" in: C. Wyplosz, ed. *The Impact of EMU on Europe and the Developing Countries* (Oxford University Press).
- Brülhart, M. and J. Torstensson (1996), "Regional integration, scale economies and industry location in the European Union", CEPR discussion paper, no. 1435.
- Brülhart, M. and R. Traeger (2002), "An account of geographic concentration patterns in Europe", processed University of Lausanne.
- Cainelli, G., and R. Leoncini (1999), "Externalities and long-term industrial development. Some empirical evidence from Italy", *Revue d'Economie Industrielle* 90:25-39.
- Cawley, R. and M. Davenport (1988), "Partial equilibrium calculations of the impact of internal market barriers in the European Community", in Commission of the European Communities Research on the cost of non-Europe, Vol 2: Studies on the economics of integration (European Commission Luxembourg).
- CEPII (1997), "Trade patterns inside the single market" in *The single market review, subseries IV: Impact on trade and investment* (Commission of the European Communities, Brussels).
- Chatelus G. and A. Ulied (1995), *Final Report on Union Territorial Strategies linked to the Transeuropean Transportation Networks*, Paris/Barcelona.
- Christaller, W. (1933), *Die zentralen Orte in Süddeutschland; eine ökonomisch-geographische Untersuchung über die Gesetzmässigkeit der Verbreitung und Entwicklung der Siedlungen mit städtischen Funktionen*, Jena: Verlag Gustav Fischer: published in English (1966) as *The Central Places in Southern Germany* (Prentice Hall, Englewood Cliffs, NJ).
- Ciccone, A. (2002), "Agglomeration effects in Europe", *European Economic Review* 46:213-227.
- Ciccone, A., and R. Hall (1996), "Productivity, and the density of economic activity", *American Economic Review* 86:54-70.
- Cingano, F. and F. Schivardi (2002), "Identifying the sources of local productivity growth", processed Bank of Italy.
- Combes, P.-P. (2000), "Economic structure and local growth: France, 1984-1993", *Journal of Urban Economics* 47:329-355.
- Combes, P.-P., G. Duranton, and L. Gobillon (2003), "Wage differentials across French local labour markets: Endowments, skills, and interactions", processed LSE, London.
- Combes, P.-P., and M. Lafourcade (2001), "Transportation costs decline and regional inequalities: Evidence from France", CEPR discussion paper, no. 2894.
- Combes, P.-P., and M. Lafourcade (2003), "Core-periphery patterns of generalized transport costs: France, 1978-1998", CEPR discussion paper, no. 3958.
- Combes, P.-P., T. Magnac, and J.-M. Robin (2002), "The dynamics of local employment in France", CEPR discussion paper, no. 3912.
- Copus A. (1997), *A New Peripherality Index for European NUTS II Regions, Report for the Highlands and Islands European Partnership*.
- Davis, D., and D. Weinstein (1999), "Economic geography and regional production structure: An empirical investigation", *European Economic Review* 43:379-407.

- De Bruyne, K. (2003), "The location of economic activity. Is there a spatial employment structure in Belgium?", processed CES-KU, Leuven.
- De Lucio, J., J. Herce, and A. Goicolea (2002), "The effects of externalities on productivity growth in Spanish industry", *Regional Science and Urban Economics* 32:241-258.
- Devereux, M., R. Griffith, and H. Simpson (2002), "The geographic distribution of productive activity in the UK", forthcoming *Regional Science and Urban Economics*.
- Dixit, A. and J. Stiglitz (1977), "Monopolistic competition and optimum product diversity", *American Economic Review* 67:297-308.
- Duranton, G., and H. G. Overman (2001), "Testing for localisation using micro-geographic data", CEPR discussion paper, no. 3379.
- Duranton, G., and V. Monastiriotis (2002), "Mind the gaps: The evolution of regional inequalities in the UK 1982-1997", *Journal of Regional Science* 42:219-256
- Duranton, G. and D. Puga (2001), "Nursery cities", *American Economic Review* 91:1454-1477.
- Ellison, G., and E. Glaeser (1997), "Geographic concentration in US manufacturing industries: A dartboard approach", *Journal of Political Economy*, 105:889-927.
- Ellison, G., and E. Glaeser (1999), "The geographic concentration of industry: Does natural advantage explain agglomeration?", *American Economic Review* 89:311-316.
- Eichengreen, B. (1993), "Labour markets and European monetary unification", in P. Masson and M. Taylor (eds.), *Policy Issues in the Operation of Currency Unions* (Cambridge University Press, Cambridge) 130-162.
- Engels, F. (1845), *Die Lage der arbeitenden Klasse in England* (Liepzig): published in English (1958) as *The Condition of the Working Class in England*, (Stanford University Press, Stanford, CA).
- Forni, M., and S. Paba (2001), "Knowledge spillovers and the growth of local industries", CEPR discussion paper, no. 2934.
- Gagné, K., J.-P. Huiban, and B. Schmitt (2002), "Do labour costs and home market size matter for local industrial specialisation? Evidence for France", processed ENSEAD Dijon.
- Glaeser, E., H. Kallal, J. Sheinkman, and A. Schleifer (1992), "Growth in cities", *Journal of Political Economy* 100:1126-1152.
- Glaeser, E. and D. Maré (2001), "Cities and skills", *Journal of Labor Economics* 19:316-342.
- Greenway, D. and R.C. Hine (1991), "Intra-industry specialization, trade expansion and adjustment in the European economic space", *Journal of Common Market Studies* 29: 603-622.
- Gutiérrez, J., and P. Urbano (1996), "Accessibility in the European Union: Impact of the trans-European Road Network", *Journal of Transport Geography* 4:15-25.
- Haaland, J.I., Kind, H.J., K.-H. Midelfart-Knarvik, and J. Torstensson (1999), "What determines the economic geography of Europe?", CEPR discussion paper no. 2072.
- Hallet, M. (2000), "Regional specialisation and concentration in the EU" The European Commission, Directorate General for Economic and Financial Affairs Economic Papers no. 141.
- Hanson, G. (2002), "Market potential, increasing returns, and geographic concentration", processed University of Michigan, November. Revised version of NBER working paper, no. 6249, February 1998.
- Harrigan, J. (1997), "Technology, factor supplies and international specialisation: Estimating the neo-classical model", *American Economic Review* 87: 475-494.
- Harris (1954), "The market as a factor in the localisation of industry in the United States" *Annals of the Association of American Geographers* 64: 315-348.
- Head, K., and T. Mayer (2002), "Illusory border effects: How far is an economy from itself?", CEPR discussion paper, no. 2002-01.
- Helg, R., P. Manasse, P. Monacelli and R. Rovelli (1995) "How much (a)symmetry in Europe? Evidence from industrial sectors", *European Economic Review* 39:1017-41.
- Helpman, E. (1998), "The size of regions", in D. Pines, E. Sadka, and I. Zilcha, eds., *Topics in Public Economics* (Cambridge University Press, Cambridge) 33-54.
- Henderson, V. (1997), "Externalities and industrial development", *Journal of Urban Economics* 42:449-

- Henderson, V., A. Kuncoro, and M. Turner (1995), "Industrial development in cities", *Journal of Political Economy* 103:1067-1152.
- Henner, H.F. (1976), "La specialisation internationale de l'economie francaise", *Revue Economique* 27: 31-53.
- Hine, R.C. (1989), "Customs union enlargement and adjustment: Spain's accession to the European Community", *Journal of Common Market Studies* 28:1-27.
- Jacobs, J. (1969), *The Economy of Cities* (Random House, New-York).
- Kaplow, L. (2002), "Why measure inequality?" NBER, working paper no. 9342.
- Keeble, D., P.L. Owens and C. Thompson (1982), "Regional accessibility and economic potential in the European Community", *Regional Studies* 16:419-432.
- Keeble, D., J. Offord and S. Walker (1988), *Peripheral Regions in a Community of Twelve Member States*, Report for the European Commission, Brussels.
- Kim, S. (1995), "Expansion of markets and the geographic distribution of economic activities: the trends in US regional manufacturing structure, 1860-1987", *Quarterly Journal of Economics* 110:881-908.
- Krugman, P. (1991a), *Geography and Trade* (MIT press, Cambridge, Massachusetts).
- Krugman, P. (1991b), "Increasing returns and economic geography", *Journal of Political Economy* 99: 483-499.
- Krugman, P. and A. J. Venables (1995), "Globalization and the inequality of nations", *Quarterly Journal of Economics* 110: 857-880.
- Lutter, H. (1993), "Accessibility and regional development of European regions and the role of transport systems" *European Regional Planning*, Report no 55, Council of Europe Press, Luxembourg.
- Marshall, A. (1890), *Principles of Economics* (Macmillan Press Ltd, London).
- Maurel, F., and B. Sédillot (1999), "A measure of the geographic concentration in French manufacturing industries", *Regional Science and Urban Economics* 29:575-604.
- Midelfart-Knarvik, K.H. and H.G. Overman (2002), "Delocation and European integration: Is structural spending justified", *Economic Policy* 35: 323-359.
- Midelfart-Knarvik, K.H., H.G. Overman, S.J. Redding and A.J. Venables (2002), "Integration and industrial specialisation in the European Union", *Revue Economique* 53: 469-481.
- Midelfart-Knarvik, K.H., H.G. Overman, S.J. Redding and A.J. Venables (2003), "The location of European Industry", *Forthcoming European Economy*.
- Midelfart-Knarvik, K.H., H.G. Overman, and A.J. Venables (2000), "Comparative advantage and economic geography: Estimating the location of production in the EU", *CEPR discussion paper no. 2618*.
- Mion, G. (2002), "Spatial externalities and empirical analysis: The case of Italy", *CORE discussion paper no. 2003/15*.
- Molle, W. (1997), "The regional economic structure of the European Union: an analysis of long term developments" in: K. Peschel, ed., *Regional Growth and Regional Policy Within the Framework of European Integration* (Physica-Verlag, Heidelberg) 66-86.
- OECD (1987), *Structural Adjustments and Economic Performance*, OECD, Paris.
- OECD (1994), *Manufacturing Performance: A Scoreboard of Indicators*, OECD, Paris.
- OECD (1999), *EMU: Facts, challenges and policies*, OECD, Paris.
- OECD (2001) *STAN database*, OECD, Paris.
- Overman, H. G., and D. Puga (2002), "Unemployment clusters across European countries and regions", *Economic Policy* 34: 117-147.
- Paci, R and S. Usai (2002), "Externalities and local economic growth in manufacturing industries" *CRENOS working paper no 01/13*.
- Paluzie, E., Ons, J. and Tirado, D.A. (2001), "Regional integration and specialization patterns in Spain", *Regional Studies* 35: 286-96.
- Pratten, C. (1988), "A survey of the economies of scale", in *Research on the "Cost of Non-Europe"*

- (Commission of the European Communities ed.), vol. 2, Studies on the Economies of Integration, Luxembourg.
- Puga, D. (1999), "The rise and fall of regional inequalities", *European Economic Review* 43:303-34.
- Redding S.J. and A.J. Venables (2002), "Economic geography and international inequality", forthcoming *Journal of International Economics*.
- Roos, M. (2001), "Wages and market potential in Germany", *Jahrbuch für Regionalwissenschaft* 21:171-195.
- Schürmann, C. and A. Talaat (2000), Towards a European Peripherality Index, Final Report. Institut fuer Raumanpanung, Dortmund. Report for DG Regio.
- Schürmann, C., Spiekermann, K., Wegener, M. (2001), Regional economic impacts of trans-European transport networks. In: WCTR Society (ed.): 2001 WCTR Proceedings.(WCTR Society, Seoul).
- Smith, B. (1975), "Regional specialisation and trade in the United Kingdom", *Scottish Journal of Political Economy* 22: 39-56.
- Spiekermann K. and M. Wegener (1994), "The shrinking continent: New time-space maps of Europe" *Environment and Planning B* 21: 653-673.
- Spiekermann K. and M. Wegener (1996), "Trans European Networks and unequal accessibility in Europe" *European Journal of Regional Development* 4: 35-42.
- Storper, M., Y. Chen and F. De Paolis (2002), "Trade and the location of industries in the OECD and European Union", *Journal of Economic Geography* 2: 73-107.
- Sutton, J. (2000), *Marshall's Tendencies: What Can Economists Know?* (MIT press, Cambridge, Massachusetts).
- Teixeira, A. (2002), "Transport policies in light of the New Economic Geography", processed CORE, Louvain La Neuve.
- Vickerman, R., K. Spiekermann, and M. Wegener (1999), "Accessibility and economic development in Europe", *Regional Studies* 33:1-15.
- Van Soest, D., S. Gerking, and F. van Oort (2002), "Knowledge externalities, agglomeration economies, and employment growth in Dutch cities", CentER discussion paper no 2002-41.
- WIFO (1999), "Specialisation and (geographic) concentration of European manufacturing", background paper for The competitiveness of European Industry; the 1999 report, EC Enterprise Directorate-General, working paper no 1, Brussels.