

No. 2255

**UNEMPLOYMENT CLUSTERS ACROSS
EUROPEAN REGIONS AND COUNTRIES**

Diego Puga and Henry G. Overman

INTERNATIONAL TRADE



Centre for Economic Policy Research

UNEMPLOYMENT CLUSTERS ACROSS EUROPEAN REGIONS AND COUNTRIES

Henry G Overman, London School of Economics
Diego Puga, University of Toronto and CEPR

Discussion Paper No. 2255
October 1999

Centre for Economic Policy Research
90–98 Goswell Rd, London EC1V 7RR
Tel: (44 20) 7878 2900, Fax: (44 20) 7878 2999
Email: cepr@cepr.org, Website: <http://www.cepr.org>

This Discussion Paper is issued under the auspices of the Centre's research programme in **International Trade**. Any opinions expressed here are those of the author(s) and not those of the Centre for Economic Policy Research. Research disseminated by CEPR may include views on policy, but the Centre itself takes no institutional policy positions.

The Centre for Economic Policy Research was established in 1983 as a private educational charity, to promote independent analysis and public discussion of open economies and the relations among them. It is pluralist and non-partisan, bringing economic research to bear on the analysis of medium- and long-run policy questions. Institutional (core) finance for the Centre has been provided through major grants from the Economic and Social Research Council, under which an ESRC Resource Centre operates within CEPR; the Esmée Fairbairn Charitable Trust; and the Bank of England. These organizations do not give prior review to the Centre's publications, nor do they necessarily endorse the views expressed therein.

These Discussion Papers often represent preliminary or incomplete work, circulated to encourage discussion and comment. Citation and use of such a paper should take account of its provisional character.

Copyright: Henry G Overman and Diego Puga

ABSTRACT

Unemployment Clusters Across European Regions and Countries*

European regions have experienced a polarisation of their unemployment rates between 1986 and 1996, as regions with intermediate rates have moved towards either extreme. This process has been driven by changes in regional employment, only partly offset by labour force changes. Regions' outcomes have closely followed those of neighbouring regions. This is only weakly explained by regions being part of the same Member State, having a similar skill composition, or broad sectoral specialisation. Even more surprisingly, foreign neighbours matter as much as domestic neighbours. All of this suggests a reorganisation of economic activities with increasing disregard for national borders.

JEL Classification: E24, F15, R12

Keywords: unemployment, European regions, distribution dynamics

Henry G Overman
Department of Geography and
Environment
London School of Economics
Houghton Street
London WC2A 2AE
UK
Tel: (44 171) 955 6581
Fax: (44 171) 955 7412
Email: h.g.overman@lse.ac.uk

Diego Puga
Department of Economics
University of Toronto
150 St. George Street
Toronto, Ontario M5S 3G7
CANADA
Tel: (1 416) 978 4375
Fax: (1 416) 946 5312
Email: dpuga@chass.utoronto.ca

* Overman is also affiliated with the Centre for Economic Performance at the London School of Economics; he gratefully acknowledges funding from the United Kingdom Economic and Social Research Council. Puga is also affiliated with the Canadian Institute for Advanced Research, the Centre for Economic Performance at the London School of Economics and the Norges Handelshøyskole; he gratefully acknowledges funding from the Social Sciences and Humanities Research Council of Canada and from the Connaught Fund and the Joint Research Initiative of the University of Toronto. Both authors would like to thank Gilles Duranton, Maia Güell, Hubert Jayet,

Angelo Melino, Andrew Oswald, Nadia Soboleva, Dan Trefler and participants at various seminars for helpful discussions. This Paper was started while Puga was visiting the Centre for Economic Performance, continued while Overman was visiting the University of Toronto and concluded while both authors were visiting the Norges Handelshøyskole. The hospitality of these institutions is greatly appreciated.

Submitted 27 July 1999

NON-TECHNICAL SUMMARY

When we think about differences in unemployment rates across Europe, we normally think of differences across countries. However, such differences in the national average unemployment rates hide large differences in unemployment rates across regions within countries. The case of Italy is best known, with Campania having a 1996 unemployment rate 4.4 times as high as Valle d'Aosta. But large regional differences exist in all European countries. In the United Kingdom, Merseyside has an unemployment rate 3.2 times that of the Surrey-Sussex region; in Belgium, the unemployment rate of Hainut is 2.2 times that of Vlaams Brabant; in Spain, Andalucía has an unemployment rate 1.8 times that of La Rioja; in France, Languedoc-Roussillon has a rate twice that of Alsace; and so on.

In the decade up to the mid-1980s, the average European unemployment rate was rising. However, differences in unemployment rates across European regions were very stable, with regional labour forces adjusting just enough to offset ongoing changes in regional employment. In this Paper we start by showing that the evolution of the regional distribution of unemployment rates over the last decade has been quite different. The average European unemployment rate was the same, 10.7%, in 1996 as in 1986 and the decade separating them could be thought of as covering a full cycle in unemployment rates. Yet during this decade there has been a polarisation of unemployment rates across the regions of the EU. To go beyond the limited conclusions that can be drawn from comparing summary statistics over time, we look at the evolution of the shape of the whole distribution of European unemployment rates. We also track the outcomes of individual regions. Regions that in 1986 had a low unemployment rate relative to the EU average still tended to have a relatively low unemployment rate in 1996. Similarly, regions that in 1986 had a relatively high unemployment rate still tended to have a relatively high unemployment rate in 1996. However, regions with intermediate initial unemployment rates had mixed fortunes. Some saw a marked fall in their relative unemployment rate, while others saw it rise and still others saw it roughly unchanged.

We show that this process has been driven by changes in regional employment rather than by changes in demographic structure or labour market participation. There has been some labour force adjustment to regional employment changes. Regions with relatively low unemployment rates have typically experienced above average labour force growth, while regions with relatively high unemployment rates have generally experienced a below average increase, or a fall, in their labour force. However, this adjustment has been insufficient to prevent the polarisation of European unemployment rates.

What factors might be driving this polarisation? The simplest explanation would be that some countries have managed to sort out their unemployment problems, while others have not. However, other characteristics of regions may also matter. Regions differ in the sectoral composition of their employment; in the age, sex and skill structure of their populations; and in their geographical location within the EU. Regions initially specialised in agriculture or manufacturing may have seen their unemployment rates rise as the EU production structure moves away from those sectors. Similarly, regions with a high proportion of low-skilled workers may have seen their unemployment rates rise as production shifts from low-skilled to high-skilled employment. Other changes to the EU production structure may be equally as important, but have received much less attention. Over the last decade, the Member States of the EU have pushed ahead with ever-closer economic integration. Recent theoretical developments suggest that such a process can be associated with the emergence of spatial concentrations of employment and that with falling barriers to trade these may extend across national borders. If regional labour forces do not fully adjust to such employment changes, then geographical location may be important in explaining the increased polarisation of unemployment rates.

We use two complementary techniques, one parametric, one non-parametric, to examine these alternative explanations. The non-parametric technique involves grouping regions by some common characteristic (like State Membership, or similar skill composition) and then examining the similarity of unemployment outcomes within groups. This technique has the distinct advantage that it allows for different regional characteristics to matter to different degrees for different parts of the distribution. Its main disadvantage is that it only allows one to consider a single factor at a time. To ensure that our results are robust in this respect, we finish with a more standard parametric analysis. This also allows us to consider the importance of cross border effects.

Both the parametric and non-parametric techniques show that regions' unemployment outcomes have closely followed those of neighbouring regions. This is only weakly explained by regions being part of the same Member State, having a similar skill composition, or broad sectoral specialisation. Remarkably, we find that neighbouring regions across national borders are as important as domestic neighbours in determining unemployment outcomes. The clusters of high and low unemployment that have emerged over the last decade show little respect for national borders.

The EU has experienced a period of rapid and deep integration over the last decade. Portugal and Spain became Member States in 1986. Over this same period, there has been a revival of interest by economists in location issues. Recent models of trade and location formalise cumulative causation

mechanisms, to show that regions that are similar, or even identical, in underlying structure, can end up having very different development paths. Many of those models focus on how the propensity of firms and workers to agglomerate in space changes as regions become more integrated. With little worker mobility and institutional constraints on regional wage disparities, the conclusion is that closer economic integration will result in increasing concentration of economic activities across space.

Where would we expect to see agglomeration reflected? Looking at Mexico and the United States, other papers have pointed to wages. However, the weak responsiveness of European regional wages to local economic conditions suggests that in Europe agglomeration will be reflected instead in employment. The aforementioned models of location do not incorporate unemployment explicitly. However, with limited labour force adjustment to regional employment changes, we can expect changes in employment to be largely translated into changes in unemployment. The distinguishing feature of this story is that regions with similar characteristics may have very different outcomes. At the same time, if clusters of activity are of a size larger than the regions considered, neighbouring regions will tend to experience similar outcomes, even if they are in different Member States.

The fact that unemployment outcomes are so much more homogenous across neighbours, foreign and domestic, than across regions in the same Member State also tells us something about the spatial dimensions of the emerging clusters of high and low unemployment in Europe. The average Member State has 13.6 regions, while the average neighbourhood has 5.6 regions. Hence these are clusters of typically less than one half of the size of the average Member State of the European Union, but often extend across national borders and include regions from more than one Member State.

That also has important implications for policy. European regional policy has traditionally targeted mainly regional differences in income per capita, but is increasingly shifting its focus towards tackling regional differences in unemployment rates. There is a clear empirical reality underlying this change in emphasis: in contrast to the divergence of unemployment rates across European regions, differences in regional incomes per capita are narrowing. But there is one important additional difference. While inequalities in incomes per capita exhibited a core-periphery gradient, unemployment clusters are more localised and emerging in both the core and the periphery of the EU. There is strong political opposition to tackling these growing unemployment rate differences through increased labour mobility. Recent location theories suggest that the self-reinforcing nature of agglomerations will make these hard to break once they become established. However, given that the unemployment clusters we find are not very large and are scattered across Europe, it may be politically viable as well as more efficient to implement

policies that accept some clustering and larger mobility within a neighbourhood.

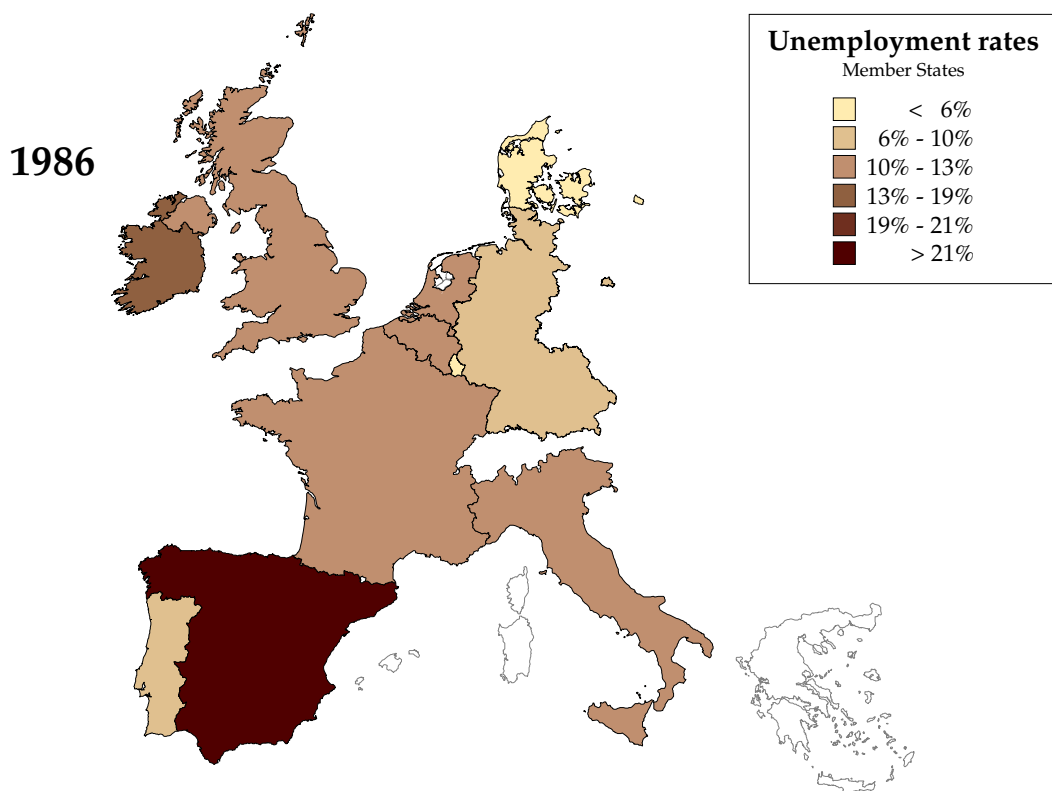


Figure 1. National unemployment rates in Europe

1. Introduction

When we think about differences in unemployment rates across Europe, we normally think of differences across countries as represented in Figure 1. This is a useful starting point that leads naturally to trying to understand, for instance, why the average unemployment rate of Spain is so much higher than that of Portugal¹. However, the national averages represented in Figure 1 hide large differences in unemployment rates across regions *within* countries. The case of Italy is best known, with Campania having a 1996 unemployment rate 4.4 times as high as Valle d’Aosta. But large regional differences exist in all European countries. In the United Kingdom, Merseyside has an unemployment rate 3.2 times that of the Surrey-Sussex region; in Belgium, the unemployment rate of Hainut is 2.2 times that of Vlaams Brabant; in Spain, Andalucía has an unemployment rate 1.8 times that of La Rioja; in France, Languedoc-Roussillon has a rate twice that of Alsace; and so on.

The map at the top of Figure 2 plots regional unemployment rates for the contiguous European Community of 1986 (more details on the regional coverage are given below). While the map is drawn for 1986, the regional distribution would look very similar for earlier years². In the decade up to the mid 1980s, the average European unemployment rate was rising. However, differences

¹On this respect, see Blanchard and Jimeno (1995); Bover, García-Perea, and Portugal (1998); Castillo, Dolado, and Jimeno (1998a,b).

²Unfortunately, only a more limited regional coverage is available before 1986.

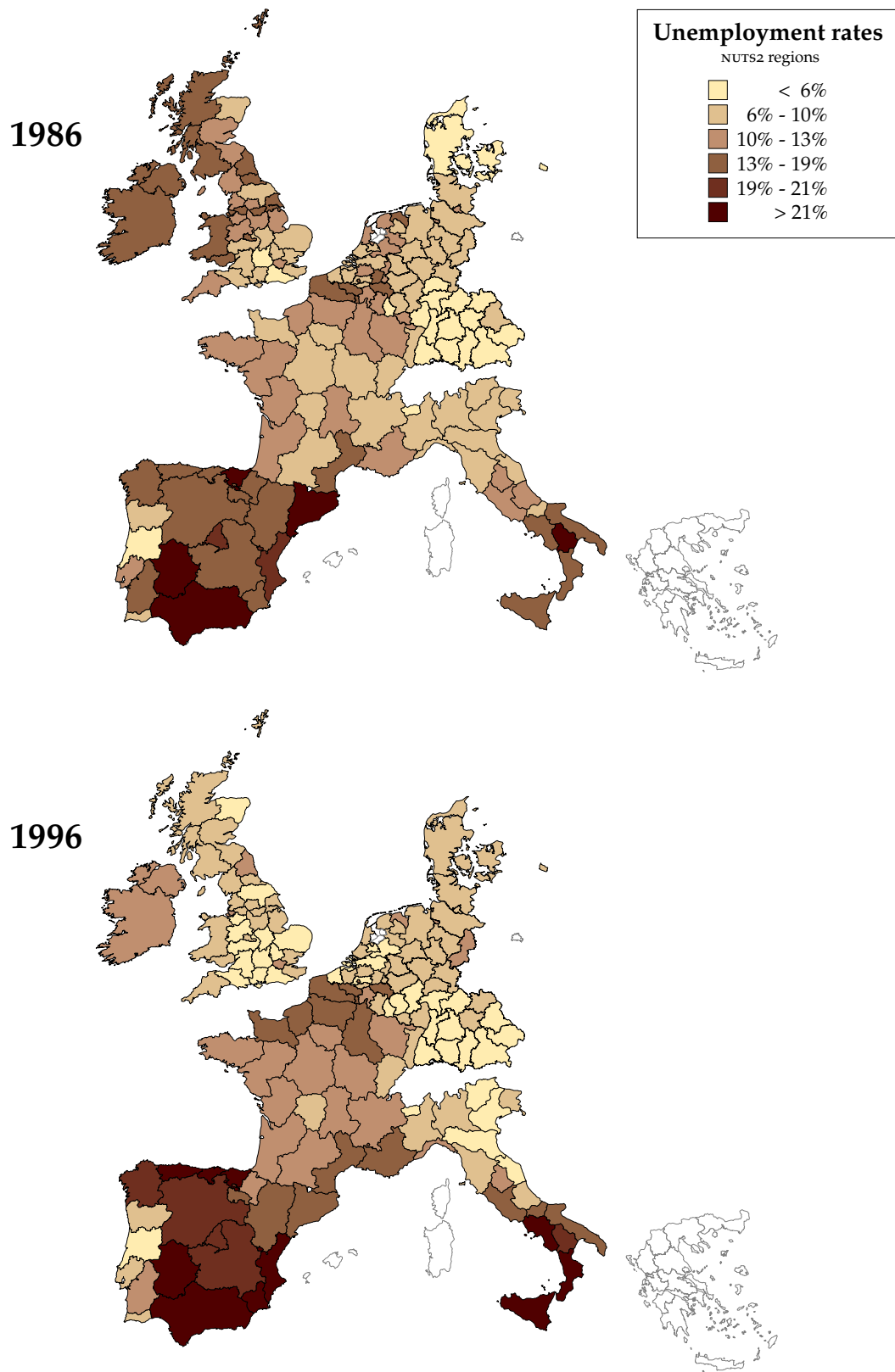


Figure 2. Regional unemployment rates in Europe

in unemployment rates across European regions were very stable, with regional labour forces adjusting just enough to offset ongoing changes in regional employment (see chapter 6 in Layard, Nickell, and Jackman, 1991). The map at the bottom of Figure 2 suggests that something has changed over the last decade, and that the stability described by Layard *et al.* (1991) up to the mid 1980s no longer holds. The average unemployment rate for regions in these maps was the same, 10.7%, in 1996 as in 1986, and the decade separating them could be thought of as covering a full cycle in unemployment rates³. Yet the map for 1996 looks different enough from that for 1986, that one starts to wonder what has happened to the distribution of European regional unemployment rates over this period. The answer to that question is the starting point of this paper.

We begin by showing that, during the decade from 1986 to 1996, there has been a polarisation of unemployment rates across the regions of the European Union (EU). To go beyond the limited conclusions that can be drawn from comparing summary statistics over time, Section 2 looks at the evolution of the shape of the whole distribution of European unemployment rates. We also track the outcomes of individual regions. Regions that in 1986 had a low unemployment rate relative to the EU average still tended to have a relatively low unemployment rate in 1996. Similarly, regions that in 1986 had a relatively high unemployment rate still tended to have a relatively high unemployment rate in 1996. However, regions with intermediate initial unemployment rates had mixed fortunes. Some saw a marked fall in their relative unemployment rate, while others saw it rise, and still others saw it roughly unchanged.

We show that this process has been driven by changes in regional employment rather than by changes in demographic structure or labour market participation. There has been some labour force adjustment to regional employment changes. Regions with relatively low unemployment rates have typically experienced above average labour force growth, while regions with relatively high unemployment rates have generally experienced a below average increase, or a fall, in their labour force. However, this adjustment has been insufficient to prevent the polarisation of European unemployment rates.

What factors might be driving this polarisation? The simplest explanation would be that some countries have managed to sort out their unemployment problems, while others have not. However, other characteristics of regions may also matter. Regions differ in the sectoral composition of their employment; in the age, sex and skill structure of their populations; and in their geographical location within the EU. Regions initially specialised in agriculture or manufacturing may have seen their unemployment rates rise as the EU production structure moves away from those sectors. Similarly, regions with a high proportion of low skilled workers may have seen their unemployment rates rise as production shifts from low skilled to high skilled employment. Other changes to the EU production structure may be equally as important, but have received much less attention. Over the last decade, the Member States of the EU have pushed ahead with ever closer economic integration. Recent theoretical developments suggest that such a process can be associated with the emergence of spatial concentrations of employment, and that

³The average European unemployment rate in 1986 (for regions belonging to what was then the European Economic Community) was 10.7%, starting to come down from a peak of 10.8% one year before that. It kept coming steadily down to 8.1% in 1990, and then steadily up to a new peak of 11% in 1994, after which it fell back to its 1986 rate of 10.7% in 1996.

with falling barriers to trade these may extend across national borders. If regional labour forces do not fully adjust to such employment changes, then geographical location may be important in explaining the increased polarisation of unemployment rates.

We use two complementary techniques, one parametric, one nonparametric, to examine these alternative explanations. The nonparametric technique involves grouping regions by some common characteristic (like State Membership, or similar skill composition) and then examining the similarity of unemployment outcomes within groups. This technique has the distinct advantage that it allows for different regional characteristics to matter to different degrees for different parts of the distribution. Its main disadvantage is that it only allows one to consider a single factor at a time. To ensure that our results are robust in this respect, we finish with a more standard parametric analysis. This also allows us to consider the importance of cross border effects.

Both the parametric and nonparametric techniques show that regions' unemployment outcomes have closely followed those of neighbouring regions. This is only weakly explained by regions being part of the same Member State, having a similar skill composition, or broad sectoral specialisation. Remarkably, we find that neighbouring regions across national borders are as important as domestic neighbours in determining unemployment outcomes. The clusters of high and low unemployment that have emerged over the last decade show little respect for national borders.

2. The evolution of the distribution of unemployment rates

As the data to be studied we take *Europe relative* unemployment rates from 1986 to 1996. The Europe relative unemployment rate is defined as the ratio of the regional unemployment rate to the European wide average unemployment rate. Working with relative, as opposed to absolute unemployment rates, helps remove co-movements due to the European wide business cycle and trends in the average unemployment rate. As mentioned in the Introduction, the average European unemployment rate was the same in 1996 as in 1986, 10.7%, and the decade in between can be regarded as covering a full cycle.

The unemployment rate series are computed from the harmonised unemployment rates and labour force data contained in the Regio database produced by Eurostat (Eurostat, 1998). These data are based on the results of the Community Labour Force Survey, carried out in Spring each year.

The analysis focus on the contiguous European Community of 1986. That is, those regions of the EU that satisfy the following three criteria:

1. Have been part of the EU (European Economic Community before 1 November 1993) from 1986 to 1996.
2. Are in a Member State which has a land border with at least one other Member State containing at least one region satisfying (1).
3. Have a land border with at least one other region satisfying (1) and (2).

The definition of regions corresponds to level two of the Nomenclature of Territorial Units for Statistics (NUTS2), a hierarchical classification with three regional levels established by Eurostat to provide comparable regional breakdowns of EU Member States. There are 150 NUTS2 regions satisfying criteria (1) to (3) above. The average NUTS2 region in our data set had a land area of 13,800 square kilometres and a population of 2.1 million in 1996 (that is slightly larger than the US State of Connecticut and with two thirds of its population).

The Data Appendix gives full details of the regional coverage and data sources.

The shape of the distribution

What has happened to the distribution of regional unemployment rates over the decade beginning in 1986? One way to answer this question would be to compare summary statistics of the distribution of regional unemployment rates across time. For instance, the Theil index for the distribution of regional unemployment rates increased from 0.10 in 1986, to 0.13 in 1996. However, such an exercise gives at best limited conclusions (as a recent radio broadcast on behalf of Ontario's teachers put it 'averages, like promises, don't mean much'). Instead, we consider the evolution of the entire distribution. Figure 3 plots a sequence of kernel estimates of the density of Europe relative unemployment rates for four years: 1986, 1989, 1993, and 1996⁴. The density plots can be interpreted as the continuous equivalent of a histogram, in which the number of intervals has been let tend to infinity and then to the continuum. By definition of the data, 1 on the horizontal axis indicates the European average unemployment rate, 2 indicates twice the average, and so on.

Two features are particularly noticeable in Figure 3. First, as we move through the decade, the distribution of unemployment rates for a majority of regions becomes more concentrated below the European average: the peak of the distribution, close to the average in 1986, moves slightly leftwards and the mass becomes more narrowly concentrated around that peak. Second, there is a growing group of regions with unemployment rates above twice the European average: these regions produce the 'bulge' in the upper tail of the distribution — to see this most clearly, contrast the mass above twice the European average unemployment rate in 1986 and 1996. Looking through the four snapshots we see that these two features have slowly evolved over the decade. Therefore, over time more regions have unemployment rates below the European average, or above twice that average, and less regions have unemployment rates between the average and twice the average.

Mobility and persistence

The density plots are suggestive of a gradual polarisation of European regional unemployment rates. However, this interpretation cannot be supported by the density plots alone. The collection of densities tell us nothing about the identity of regions in the distribution of regional unemployment rates. Is it true that a group of low unemployment regions and a group of high unemployment regions has slowly emerged, while regions with intermediate unemployment rates have moved

⁴All densities are calculated nonparametrically using a Gaussian Kernel with bandwidth set as per section 3.4.2 of Silverman (1986). The range is restricted to the positive interval using the reflection method proposed in Silverman (1986). Calculations were performed with Danny Quah's *tsrf* econometric shell (available from <http://econ.lse.ac.uk/~dquah/>).

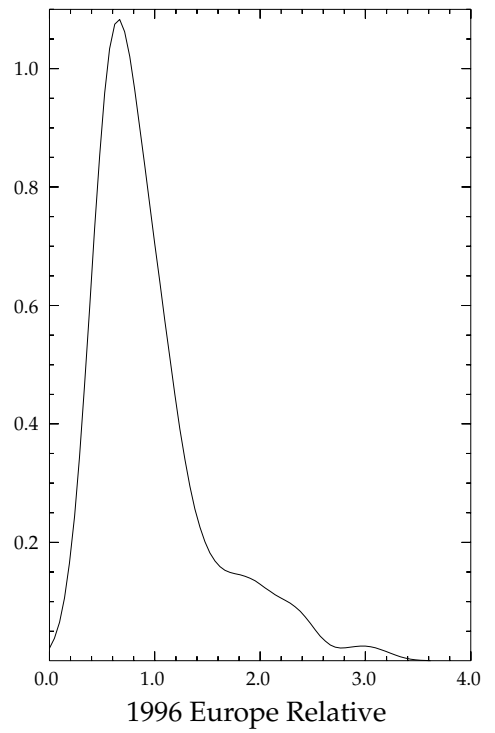
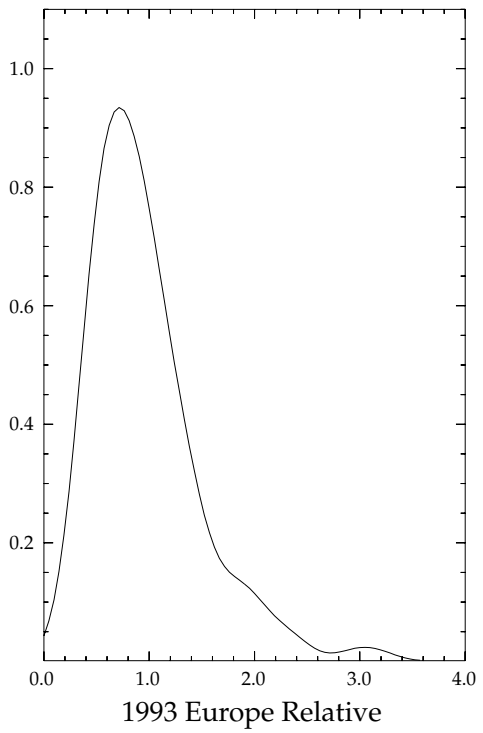
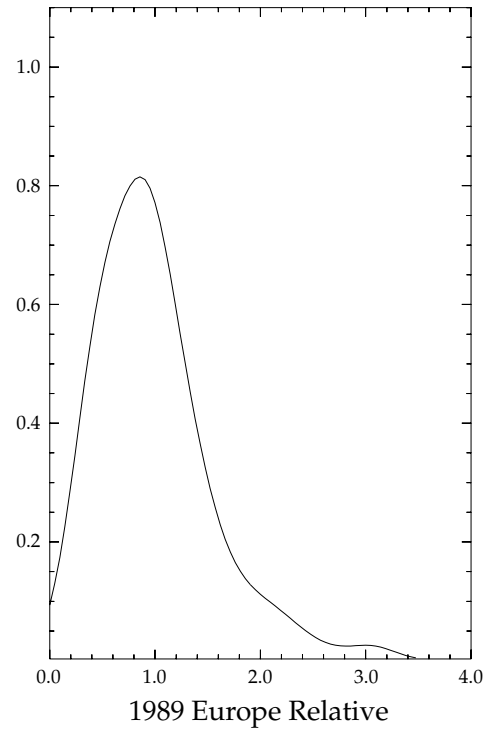
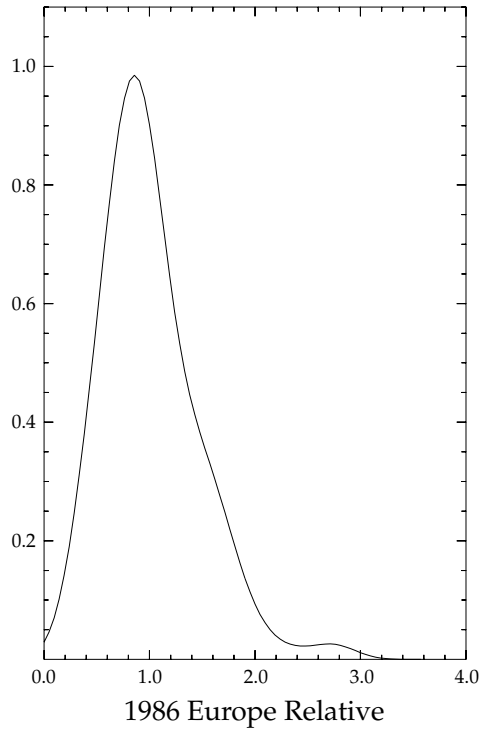


Figure 3. Densities of Europe relative unemployment rates

1986 Europe Relative		n	1996 Europe Relative				
			[0-0.6)	[0.6-0.75)	[0.75-1)	[1-1.3)	[1.3-∞)
32	[1.3-∞)		0.00	0.00	0.16	0.22	0.62
32	[1-1.3)		0.06	0.22	0.34	0.19	0.19
42	[0.75-1)		0.24	0.29	0.26	0.21	0.00
23	[0.6-0.75)		0.52	0.26	0.09	0.09	0.04
21	[0-0.6)		0.81	0.19	0.00	0.00	0.00

Table 1. 1986 to 1996 Europe relative transition probability matrix

closer to the tails of the distribution? Certainly, more regions had low or high unemployment rates in 1996 than in 1986, but what was their relative position in previous years? Does this collection of snapshots actually just show churning of the unemployment rate distribution, the random ups and downs of regional fortunes, or are they the result of a more structured process?

The natural way to answer these questions is to track the evolution of each region's relative unemployment rate over time. An easy way to do this is to construct transition probability matrices. For a discrete stochastic process with an integral number of possible outcomes or states, each row of this matrix takes a given state and shows the probability of transiting to any other state. Constructing a transition probability matrix for a continuous variable requires a discretisation of the space of possible outcomes.

Table 1 does this with the space of relative unemployment rates, to construct the transition probability matrix between the 1986 and 1996 distributions of Europe relative unemployment rates⁵. Reading along the bottom row of the matrix, we observe strong persistence for regions starting with an unemployment rate below 0.6 times the European average: by 1996, 81% remained below 0.6 times the European average, 19% had an unemployment rate between 0.6 and 0.75 times the average, and none had a relative unemployment rate higher than that. The next row up tells us that of those regions with an initial unemployment rate between 0.6 and 0.75 times the European average, 26% remained in that range, while 52% saw their unemployment rate fall below 0.6 times the average. Jumping to the top row we also see strong persistence amongst the regions with highest unemployment rates: of the regions with an initial unemployment rate above 1.3 times the European average, 61% remained above 1.3 times the average in 1996, while 23% moved to between the average and 1.3 times the average. However, regions with unemployment rates between 0.75 and 1.3 times the European average (third and fourth rows from the bottom) had experienced much greater mobility — regions with initial unemployment rates between 0.75 times the average and the average ended up almost equally distributed across the four intervals between 0 and 1.3 times the average.

Europe relative unemployment rates are, by nature, a continuous variable. There is a degree of

⁵The table gives two additional pieces of information. The first column gives n , the number of regions that begin their transitions in a give state. The second column gives the classes that divide up the state space.

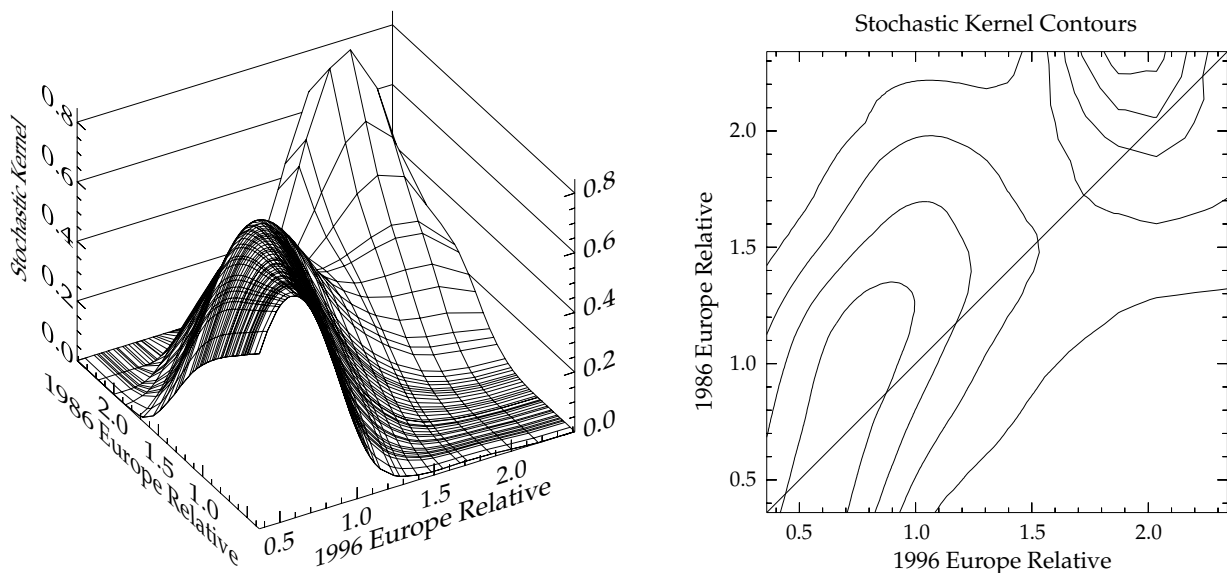


Figure 4. 1986 to 1996 Europe relative Stochastic Kernel

arbitrariness involved in choosing a specific discretisation, and changing from one discretisation to another can easily distort the ‘true’ picture of transitions. In addition, many interesting details are lost as a result of the discretisation.

Figure 4 resolves these problems by avoiding any discretisation, and plotting the transition kernel from the 1986 distribution of Europe relative unemployment rates to the 1996 distribution of Europe relative unemployment rates. One can think of this kernel as the result of taking the transition probability matrix of Table 1 and letting the number of possible states tend to infinity and then to the continuum (see the Technical Appendix for a formal definition)⁶. The plot on the right hand side of the figure is a contour plot of the three dimensional kernel on the left. The contour plot works in exactly the same way as the more familiar contours on a standard geographical map. Lines on the contour plot connect points at the same height on the three dimensional kernel. An additional straight line is drawn in the contour plot to mark the diagonal, where all mass would be concentrated if there was complete persistence in the distribution.

Figure 4 confirms that there has been a polarisation of regional unemployment rates between 1986 and 1996, as suggested by the transition probability matrix⁷. Regions that in 1986 had a low unemployment rate relative to the European average tended to maintain or reduce their low relative unemployment rate over the next decade. Similarly, regions that in 1986 had a high unemployment rate relative to the European average in 1996 still tended to have a relatively high unemployment rate. However, regions with intermediate unemployment rates had mixed fortunes: some saw their relative unemployment rate fall, while others saw it rise. Still others saw it roughly unchanged.

⁶The three dimensional stochastic kernel plots are drawn so that the density of lines reflects the underlying number of observations on which that part of the kernel is estimated. This procedure makes the pictures easier to read and more informative, but does not change the shape of the kernel.

⁷In fact, discrete intervals for the matrix were chosen to reflect accurately the ‘true’ continuous kernel equivalent.

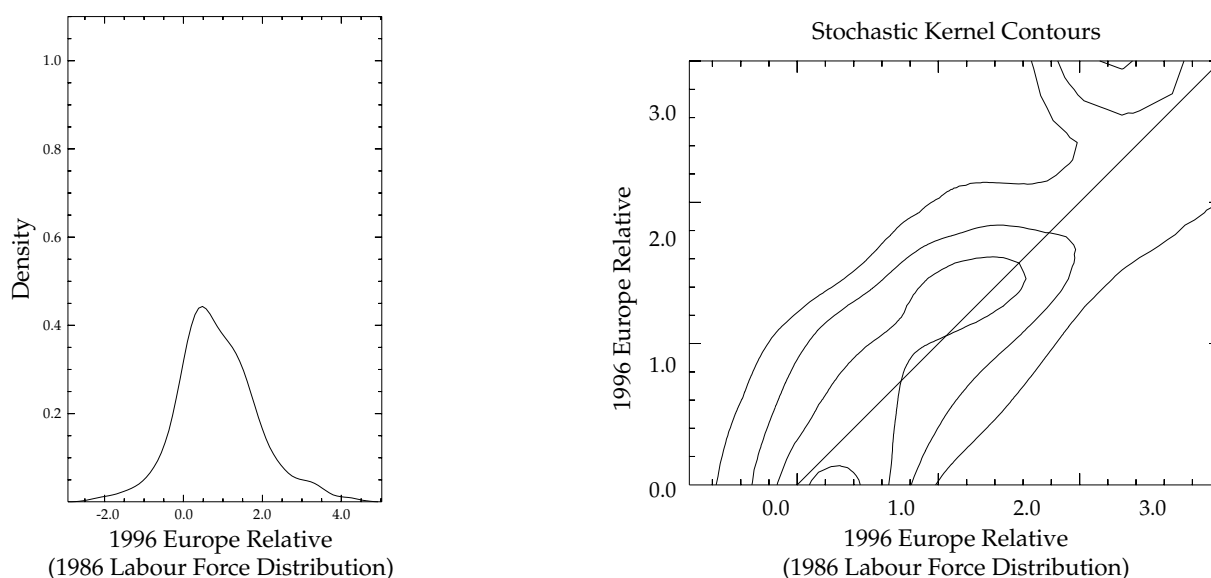


Figure 5. Counterfactual 1996 Europe relative (with 1986 labour force distribution)

Employment and labour force changes

By definition, unemployment rates equal one minus the ratio of employment to labour force. Thus the evolution of the distribution of regional unemployment rates can in principle reflect changes in regional demographic structure or labour market participation, as well as changes in regional employment. Has the recent polarisation of European regional unemployment rates been driven mainly by changes in regional employment? What role have changes in the regional distribution of labour force played? Or to put these questions in another way, how different would the distribution of regional unemployment rates have been in 1996, had the distribution of the European labour force across individual regions remained unchanged with respect to 1986⁸? Figure 5 provides the answer.

The plot on the left hand side of Figure 5 graphs the density of a ‘counterfactual’ distribution of ‘unemployment rates’. These ‘unemployment rates’ are computed from actual values of regional employment in 1996, and hypothetical values of regional labour force constructed by disaggregating total European labour force in 1996 according to its 1986 distribution. This represents what the distribution of Europe relative unemployment rates would have looked like had there been no differences across regions in terms of labour force changes, but with employment still changing as it did in each region. The hypothetical nature of these rates is emphasised by the fact that, unlike actual unemployment rates, they are not bounded below by zero. This is because there are regions whose employment grew by more than the sum of their unemployed population in 1986 and the amount by which their labour force would have grown if it had grown at the same rate as total European labour force (6.3%). Comparing this density plot with the ‘true’ one (1996

⁸Our choice of unemployment rates rather than employment rates as the variable of interest is partly motivated by this analysis of labour force changes. Computation of both rates involves normalising the employment of regions of different sizes. However, normalising by labour force rather than working age population provides interesting additional insights. At the same time, it should be noted that our finding of a polarisation of the distribution of unemployment rates carries over to the distribution of employment rates.

plot in Figure 3), we see essentially the same features. However, there is a wider dispersion around the average (which, by construction, is the same in both cases) when the distribution of labour force is held constant. Changes in the regional distribution of the European labour force between 1986 and 1996 therefore made regional unemployment rates in 1996 less unequal than they would otherwise have been.

But have changes in the regional distribution of the European labour force significantly altered the relative position regions would otherwise have had in the distribution of Europe relative unemployment rates? The plot on the right hand side of Figure 5 shows that, in general, they have not. In Figure 4 we produced a stochastic kernel tracking regional positions in the distribution of Europe relative unemployment rates in 1996, given positions in the 1986 distribution. Similarly, in Figure 5 we produce the contour plot of a stochastic kernel tracking regional positions in the distribution of counterfactual 1996 Europe relative unemployment rates, given their positions in the distribution of actual 1996 Europe relative regional unemployment rates. Unlike the other kernels in the paper, this one is not square, reflecting the fact that actual unemployment rates are bounded below by zero while the counterfactual ones are not.

The diagonal on the contour plot marks the position of regions with average labour force growth between 1986 and 1996. The concentration of mass close to the diagonal shows that the unemployment rates of individual regions would have been similar even without any differences in the evolution of their labour force. However, for all of the distribution there is some mass on both sides of the diagonal, showing that for all ranges of the unemployment rate distribution there have been regions with above average and below average labour force growth between 1986 and 1996.

The key is to identify whether, for a given interval on the vertical axis, there is more mass to the left of the diagonal (reflecting most regions in that range having above average labour force growth) or to its right (below average labour force growth). Starting from the top of the picture, regions with 1996 unemployment rates above 2.4 times the European average generally had above average labour force growth. However, from the 1996 plot in Figure 3 we see this part of the kernel is computed from very few regions (in fact only three). It is also almost entirely driven by the Spanish region Andalucía⁹. The rest of the distribution behaved pretty much as one would expect. Most of the regions with 1996 unemployment rates between 1.6 and 2.4 times the European average had either below average increases or decreases in their labour force (the exceptions were again a few Spanish regions with large increases in participation rates). Those with 1996 unemployment rates between the average and 1.6 times the average generally had above average increases in their labour force. These increases were even larger for most regions with below average unemployment rates.

⁹This region accounts for more than 50% of the labour force in this range of 1996 Europe relative unemployment rates (but for less than 2% of the total European labour force). Despite a 21.5% employment growth between 1986 and 1996, a 25.3% labour force growth over this decade kept Andalucía's unemployment rate as Europe's highest in 1996, at 32.4%. Andalucía's labour force growth resulted from a combination of demographic trends and changes in labour market participation. Natural population growth — helped by changes in age structure, but almost unaffected by tiny net immigration flows — resulted in a 9% increase in the population of working age between 1986 and 1996. At the same time, the increased participation of women in the labour force (42.5% of those between 15 and 64 years of age in 1996, up from 25.2% in 1986) more than offset the fall in male participation rates (from 75.9% in 1986 to 72.9% in 1996) and raised the total participation rate from 49.9% to 57.4%.

Thus, the distribution of labour force across European regions over this period tended to adjust to compensate, in part, for changes in the regional distribution of employment. Layard *et al.* (1991) explain that, between the 1960s and the late 1980s, regional labour force adjustment in Europe just offset changes in regional employment, leaving differences in unemployment rates and relative wages very stable¹⁰.

In this Section we have shown that, since 1986, labour force adjustment has no longer been able to keep up with employment changes, and has been clearly insufficient to prevent a polarisation of European regional unemployment rates. We now turn to trying to understand the factors behind the markedly different unemployment outcomes of regions during this process.

3. Conditioning

How do we set about understanding the factors behind the features highlighted in Section 2? In this section, we consider a nonparametric approach which allows us to study the importance of these different factors in a simple way. In the next section we look at a parametric approach that provides complementary insights.

The nonparametric approach we develop here builds on a collection of tools proposed by Quah (1996, 1997a) for studying the dynamics of evolving distributions. These techniques are a first step in allowing us to understand the evolution of the entire cross section rather than the behaviour of a representative region. As will become clear, moving away from the standard representative region assumption gives us a number of interesting additional insights. Multiple equilibria and path dependency characterise a number of theories of regional development. Thus, regions with similar characteristics may have different development paths. Interactions between regions may further distort the link between individual regional characteristics and development paths. A proper understanding of the evolution of the distribution of unemployment rates may therefore involve more than understanding the evolution of a single representative region as in standard regression analysis.

The underlying idea is to look at how closely the evolution of each region's unemployment rate has followed that of some group of regions which we would expect to behave similarly. To do this we establish a mapping from a region's unemployment rate relative to the European average to the same region's unemployment rate relative to the group average. We group regions by a number of different criteria. Specifically, these groups of regions will be regions in the same Member State, regions that are geographical neighbours, regions with similar sectoral composition, and regions with similar proportions of low skilled.

These mappings are an extension of the transition kernels used in Section 2. Those kernels characterise the transitions across a decade. They are a mapping from the 1986 distribution of unemployment rates to the 1996 distribution. The Technical Appendix shows that this

¹⁰Layard *et al.* (1991) focus on ongoing changes in employment sustaining persistent differences in unemployment rates. In contrast, Decressin and Fatàs (1995) study adjustment to one-off region-specific shocks, and show that the relative regional unemployment rate tends to come back to its trend within four years — a comparable time to the US, even though adjustment in Europe occurs mainly through changes in participation rates, while in the US adjustment takes place mainly through migration (see Blanchard and Katz, 1992).

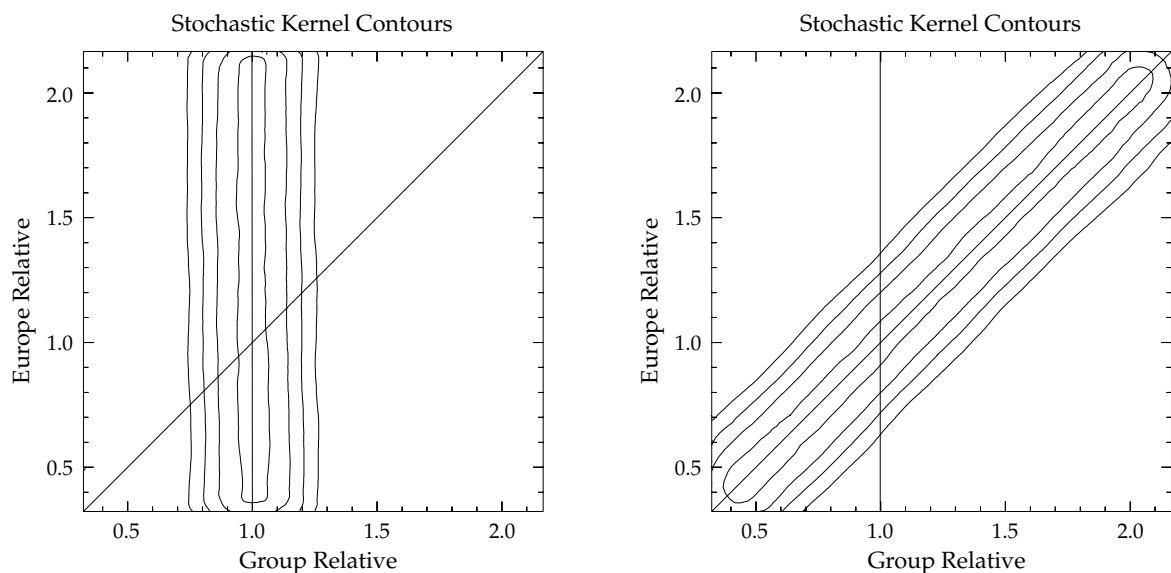


Figure 6. Benchmark stochastic kernels

interpretation can be formalised using basic definitions and results from measure theory. That Appendix also shows that a similar construction can be used to explain the mapping between any two distributions, not just distributions of the same variable at different points in time.

We study the evolution of the distribution of unemployment rates in levels, not the pattern of changes in these unemployment rates. To see why this is more informative, imagine two situations, one where unemployment rates are converging, the other where unemployment rates are diverging. The distribution of changes in unemployment rates across regions could be identical for both cases — some regions with positive changes, some with negative changes. However, studying the evolution in levels allows the two situations to be clearly distinguished: convergence shows up as a collapsing of the distribution, divergence as a spreading out. For similar reasons, conditioning in terms of levels is more informative than conditioning in terms of changes. However, the main reason for working with levels rather than changes is to exploit one of the most useful features of our approach: the ability to identify the same factor as having a different degree of relevance for different ranges of the original distribution. This is only possible if the distribution is specified in terms of a variable where similar values correspond to similar experiences. In our case, that implies working with unemployment rates rather than with changes in unemployment rates.

Conditioning on Member State

Possibly the simplest explanation for the polarisation of unemployment rates is that over this decade some EU Member States have managed to sort out their unemployment problems, while others have not.

An extreme version of this argument would have all regions within each State with almost identical unemployment rates throughout the decade. In that case, any differences in regional unemployment rates would be due to regions being in States with different national unemploy-

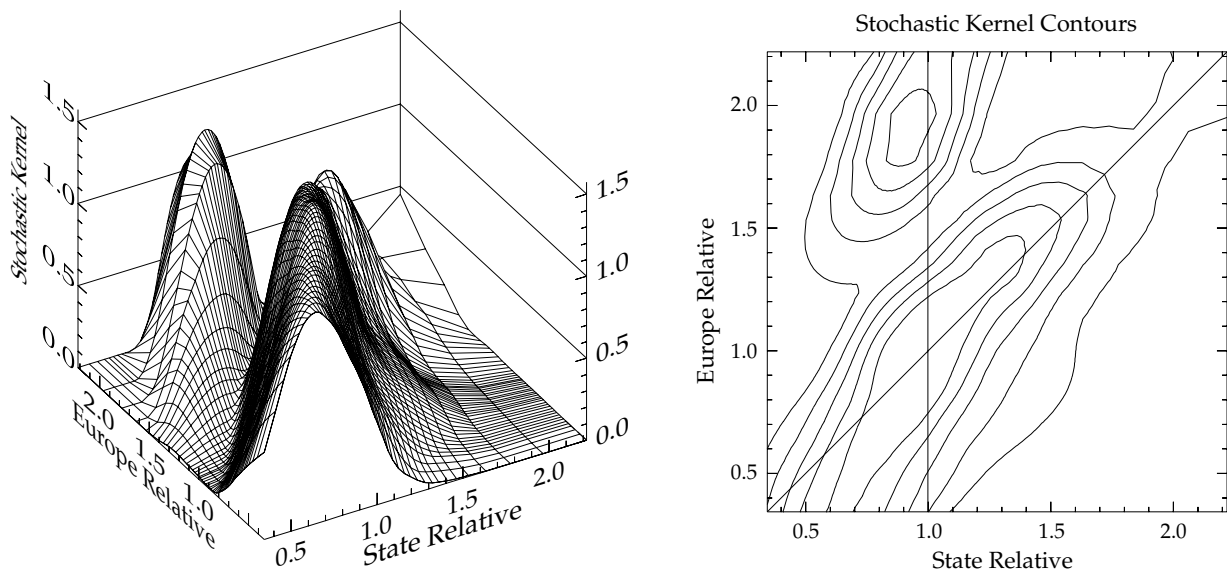


Figure 7. Europe relative to State relative stochastic kernel

ment rates, and the polarisation of unemployment rates would have arisen as countries with intermediate rates drifted apart. In this extreme benchmark case, regardless of a region's *Europe relative* unemployment rate, its unemployment relative to the average for other regions in the same Member State (*State relative*) will be close to one. The stochastic kernel mapping Europe relative to State relative unemployment rates would then have almost all mass on the vertical line centered at one. The contour plot on the left of Figure 6 illustrates this benchmark.

The opposite extreme would have a similar regional distribution within each State, and almost identical State averages throughout the decade. In that case, the polarisation of unemployment rates could have arisen from mean preserving spreads of the regional distribution within Member States. In the corresponding benchmark, each region's State relative unemployment rate would be very close to its Europe relative unemployment rate. The stochastic kernel mapping Europe relative to State relative unemployment rates would then have almost all mass concentrated on the diagonal. The contour plot on the right of Figure 6 illustrates this benchmark.

As we move through the kernels in the remainder of the paper, it will be useful to keep these two benchmarks in mind. When looking for criteria by which to group regions, our objective will be to find one that produces a kernel as close as possible to the benchmark on the left of 6, and as different as possible from the benchmark on the right.

In reality we see neither of these extremes. Figure 7 shows the actual Europe relative to State relative stochastic kernel. The kernel is calculated using data for all eleven years. For unemployment rates below 1.5 times the European average, the kernel is concentrated close to the diagonal, showing that each region's position with respect to the European average is not dissimilar from its position with respect to its State average.

Further, regions do not even tend to move strongly with their State over time. If a region followed changes in its State average, there would be a wide vertical spread of mass, which is not present in Figure 7. This is because the Europe relative unemployment would change over

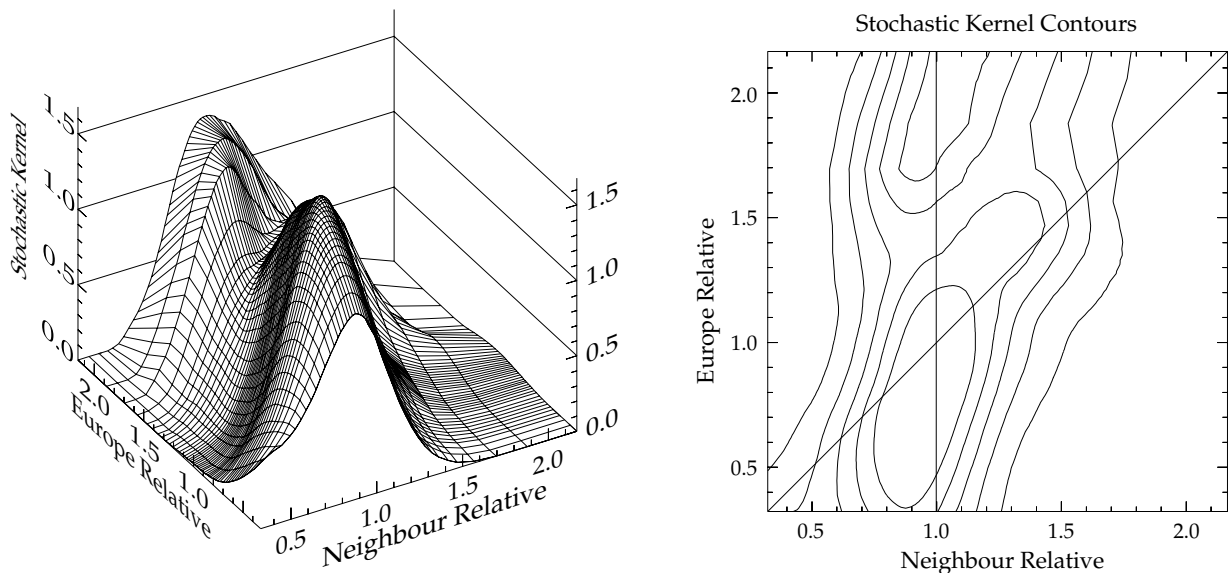


Figure 8. Europe relative to neighbour relative stochastic kernel

time with changes in the State average, but the State relative unemployment rate would remain constant. This is consistent with other evidence about the diminishing economic significance of national borders in Europe¹¹.

The range above 1.5 times the European average stands out from the rest. Some high Europe relative unemployment outcomes correspond to high State outcomes. The spike at around the European average in this range corresponds to approximately the one half of Spanish regions with unemployment rates close to the Spanish average, plus Ireland (which is classified as a single NUTS2 region, so by construction its unemployment rate is the State average) prior to 1994. However, there are also regions in this range whose outcome differs as much from their State average as from the European average, leading to a wide spread of mass above one and close to the diagonal. This was a small group of regions in 1986, formed by Basilicata and Campania in Southern Italy, Northern Ireland, and five regions in the North of England and the South of Scotland. Over the next decade the British regions dropped from this group as their unemployment rates came closer to those of their Southern neighbours. At the same time, this group expanded to include regions on both sides of the French-Belgian border, all of Southern Italy, and the regions on France's Mediterranean Coast.

Conditioning on geographical neighbours

We have suggested in the previous subsection that ongoing European integration may mean that national borders are becoming less important in determining regional outcomes. Geographical location may still matter however, though perhaps at levels below the nation state. Could the

¹¹For instance, Fatàs (1997, p.759) finds that during the period '1966–1992, the correlation [of employment growth rates] of regions across national borders has been increasing over time while, at the same time, the cross-regional correlation within countries has decreased. [...] For example, in the post-EMS [European Monetary System] period, northern Italian regions display higher correlations with German regions than with southern Italian regions.'

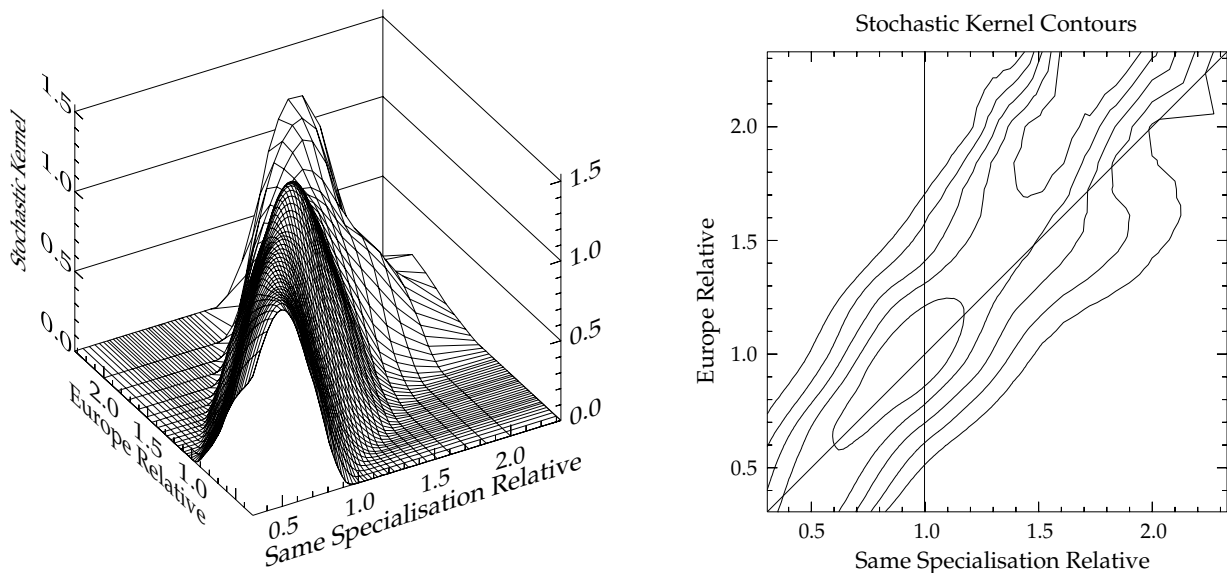


Figure 9. Europe relative to same specialisation relative stochastic kernel

evolution of European unemployment disparities be understood in terms of the evolution of groups of neighbouring regions with similar outcomes that transcend national boundaries?

To answer this question we construct a kernel mapping Europe relative to *neighbour relative* unemployment rates, defined as each region's unemployment rate divided by the labour force weighted average of the unemployment rates of contiguous regions (not including the region itself).

Comparison of Figure 8 with Figure 7 shows that regional outcomes are much closer to outcomes of neighbours than to those of regions in the same Member State, except for the highest range of unemployment rates. Although the neighbour relative kernel still twists towards the diagonal for the middle unemployment regions, it is far more concentrated around the vertical line on one for regions with low and middle rates. This shows that while regions have followed very different evolutions relative to the European average, they have had very similar outcomes to those of their neighbours. This is particularly clear when one contrasts Figures 7 and 8, in the 'twist' of the bottom peak and the 'depth' of the valley between the two peaks in the three dimensional plot. Alternatively, one can count up the number of lines from the 'bottom' of the contour plot in Figures 7 and 8 (they are plotted at the same heights). Both the lower peak and the valley between the peaks in the neighbour relative kernel incorporate far more mass than the corresponding areas in the State relative kernel. The fact that the valley in the neighbour relative kernel is not as deep is particularly relevant, because it is in this intermediate range of unemployment rates that regions with similar starting positions have had very different evolutions. Also, note that a regions' domestic neighbours are part of the groups used to construct either kernel. In Figure 8, however, other regions in the same State are included. In Figure 7 they are not, but foreign neighbours are. Foreign neighbours are therefore much more closely related to a region in terms of unemployment outcomes than regions in the same State that are not contiguous. In Section 4 we show that, in fact, foreign neighbours are as important as domestic neighbours.

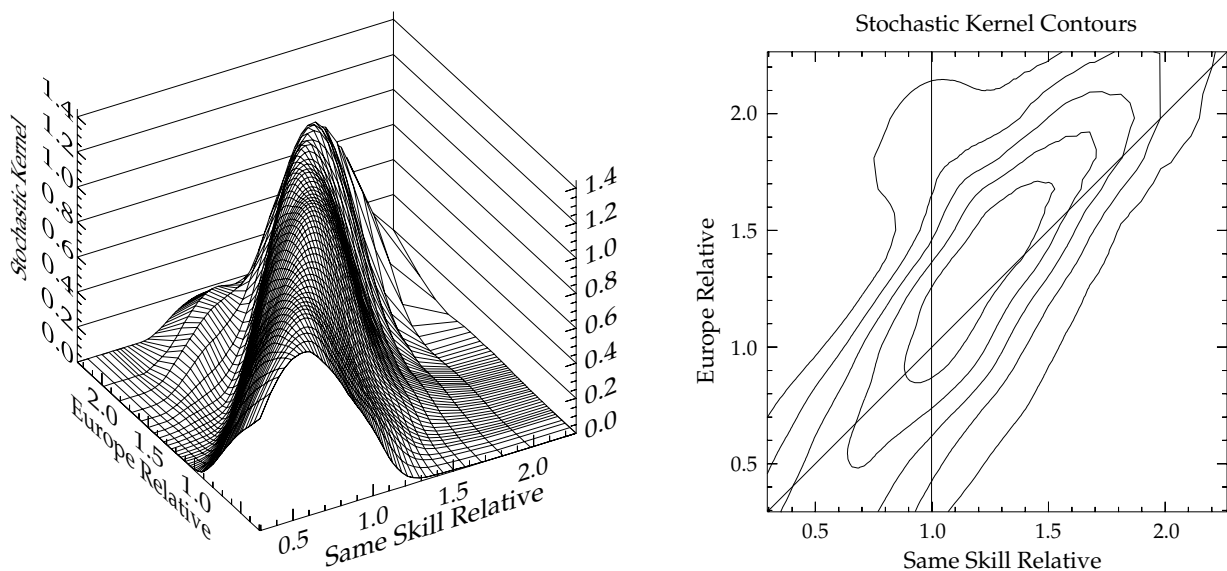


Figure 10. Europe relative to same skill relative stochastic kernel

The similarity of outcomes across neighbours could simply be driven by neighbouring regions having similar characteristics that are important determinants of unemployment rates. We now turn to two such determinants which have received particular attention.

Conditioning on same broad sectoral specialisation

The period 1986 to 1996 saw the continuation of an ongoing shift of European employment from agriculture, mining, and industry into services. If, as we have seen, labour force adjustment is slow, then regions with high initial specialisation in declining sectors may have seen their unemployment rates rise and not recover. Could this be driving the polarisation of unemployment rates across Europe? And can the importance of neighbours be justified by those regions with heavy industrial or primary employment being contiguous? Figure 9 suggests that the answer to both questions is no. This figure provides the stochastic kernel mapping Europe relative unemployment rates to *same specialisation relative* unemployment rates. This conditioning groups regions by the sector (agriculture and other primary sectors, manufacturing, or services) in which the initial share of regional employment was highest, relative to the average European share.

The concentration of mass on the diagonal of Figure 9 suggests that regions with similar initial specialisation have seen very different outcomes. This is probably due to the fact that the largest drop in agricultural and manufacturing employment had already taken place before the beginning of the period we consider. In the 15 years between 1971 and 1986 the share of manufacturing in European employment fell from 41% to 33%, while the share of services rose from 45% to 59%. In the next ten years to 1996, the share of manufacturing only fell by another three percentage points to 30%, while that of services rose to 65%. Spatial concentrations of declining sectors are not the key component driving the neighbours effect.

		State Relative					
<i>n</i>							
Europe Relative	240	[1.45-∞)	0.00	0.06	0.43	0.13	0.38
	201	[1.15-1.45)	0.00	0.13	0.16	0.52	0.18
	577	[0.75-1.15)	0.00	0.05	0.68	0.18	0.09
	330	[0.55-0.75)	0.06	0.30	0.50	0.12	0.02
	302	[0-.55)	0.30	0.36	0.32	0.01	0.00
		[0-0.55)	[0.55-0.75)	[0.75-1.15)	[1.15-1.45)	[1.45-∞)	

		Neighbour Relative					
<i>n</i>							
Europe Relative	240	[1.45-∞)	0.00	0.04	0.45	0.30	0.21
	201	[1.15-1.45)	0.00	0.06	0.40	0.37	0.16
	577	[0.75-1.15)	0.01	0.07	0.63	0.21	0.07
	330	[0.55-0.75)	0.04	0.16	0.72	0.07	0.01
	302	[0-.55)	0.22	0.17	0.55	0.06	0.00
		[0-0.55)	[0.55-0.75)	[0.75-1.15)	[1.15-1.45)	[1.45-∞)	

		Same Specialisation Relative					
<i>n</i>							
Europe Relative	240	[1.45-∞)	0.00	0.00	0.01	0.25	0.74
	201	[1.15-1.45)	0.00	0.00	0.35	0.36	0.29
	577	[0.75-1.15)	0.00	0.15	0.68	0.16	0.01
	330	[0.55-0.75)	0.23	0.45	0.32	0.00	0.00
	302	[0-.55)	0.68	0.32	0.00	0.00	0.00
		[0-0.55)	[0.55-0.75)	[0.75-1.15)	[1.15-1.45)	[1.45-∞)	

		Same Skill Relative					
<i>n</i>							
Europe Relative	240	[1.45-∞)	0.00	0.00	0.15	0.24	0.61
	201	[1.15-1.45)	0.00	0.01	0.28	0.56	0.14
	577	[0.75-1.15)	0.00	0.11	0.64	0.18	0.07
	330	[0.55-0.75)	0.17	0.33	0.41	0.07	0.02
	302	[0-.55)	0.48	0.25	0.26	0.00	0.00
		[0-0.55)	[0.55-0.75)	[0.75-1.15)	[1.15-1.45)	[1.45-∞)	

Table 2. Europe relative to group relative transition probability matrices

Conditioning on similar skill composition

There has been some discussion as to whether changes in the patterns of relative labour demand and supply in Europe have resulted in a rise in unemployment rates for the low skilled relative to unemployment rates for the high skilled (see, for instance, Krugman, 1994; Manacorda and Petrongolo, 1998; Nickell and Bell, 1995). One possible implication of this is that the evolution of regional unemployment rates may reflect the underlying skill composition of regional labour forces. Have regions with a large proportion of workers with low skills seen their unemployment rate rise, while regions with a small proportion of workers with low skills have seen their unemployment fall?

Figure 10 plots the stochastic kernel mapping Europe relative to *same skill relative* unemployment rates. We construct the kernel using nine groups of regions that have a similar percentage of adult population with less than upper secondary education (divided into equally spaced intervals between 0% and 90%). The concentration of mass on the diagonal reflects that the distribution of unemployment rates across each of our nine groups of regions with similar labour force skill composition is not dissimilar from the distribution of unemployment rates across all European regions. A region's skill composition tells us very little about the evolution of its unemployment rate since 1986. This is clearly not the key component driving the neighbours effect either.

Discretisation

In order to check the visual ranking of the kernels, we discretise the state space of relative unemployment rates and calculate the transition matrices that are the discrete versions of the continuous stochastic kernels. These discretisations, presented in Table 2, allow us estimate the relative mass in different areas of the kernels without having to integrate explicitly.

To interpret these matrices it is useful to compare them with the same benchmarks we used to interpret the corresponding stochastic kernel: large numbers on the column for the interval containing one, versus large numbers on the diagonal. We see that the Europe relative to neighbour relative matrix has all diagonal elements smaller than those of the other three kernels. At the same time, all other elements in the central column are larger in the Europe relative to neighbour relative matrix.

This confirms our earlier conclusion, that the unemployment outcomes of individual regions have closely followed those of their neighbours, much more so than the average outcomes of other regions within the same Member State, or other European regions with the same sectoral specialisation, or skill composition. That suggests that there is a truly spatial component to the neighbours effect. To be reasonably sure, however, we have to check that the neighbours effect remains strong, even after controlling for similarities in regional characteristics. With that purpose, we now move to parametric techniques that will also complement the kernel results in other respects.

4. Regression results

The stochastic kernels of the previous section are attractive for a number of reasons. Grouping regions by common characteristics can be a useful way of thinking about which interactions between them help the most in understanding individual outcomes. The kernels also have a distinct advantage over parametric specifications, in that they make it easy to identify different behaviour at different parts of the distribution. For example, we have seen that many of the regions with very high unemployment rates have similar, large, fractions of their population with low education; at the same time, skill composition does not appear to be important for discriminating between unemployment outcomes for any other than these very high unemployment regions. Their main disadvantage over parametric approaches is that the kernels only allow us to consider one factor at a time.

In this section, we complement the stochastic kernel results with a number of parametric specifications. These regression results confirm the robustness of the kernel results. Even after controlling for a variety of other important factors, geographical neighbours remain key in explaining the evolution of regional unemployment. The parametric specification also allows us to separate out neighbours in the same Member State from neighbours in different States.

To keep the parametric specification simple, we examine the crosssection of changes in regional unemployment rates as a function of State, regional and neighbour characteristics¹².

Heuristically, we can divide changes in a region's unemployment rate into two components. They can be seen as being partly the result of a regions' initial structure — initial sectoral specialisation, skill composition, age and sex structure of population, and national differences in labour market structure and institutions, have all been identified as important explanatory factors for unemployment outcomes. This suggests that variables describing those initial characteristics should be an important element of our regressions. At the same time, there is a more endogenous component to the evolution of unemployment rates, related to the movement of firms and workers in to, and out of, regions. Further, this correlation in movements is interesting in its own right — especially if those flows seem to be correlated across national borders. Information on such flows is not readily available, and finding suitable instruments to incorporate them into empirical work is not easy. Even for sectoral structure of employment, there is no time series for the regions covered. However, we can capture some of this endogenous effect if, as suggested by the location argument outlined above, firm and worker movements are correlated across neighbouring regions. We do this by using the unemployment rate of surrounding regions¹³.

Table 3, column 1, shows ordinary least squares results for our first empirical specification. The dependent variable is the (logarithm of the) change in the unemployment rate of region i between 1986 and 1996. We consider a number of different explanatory variables. Two variables capture the

¹²The closest counterpart to the stochastic kernel analysis would probably be a suitably defined panel specification. Unfortunately, the lack of reasonable exogenous time varying instruments makes it unfeasible to estimate such a panel, while allowing for the endogeneity of right hand side variables and the (auto)correlation structure of the regional residuals.

¹³Of course, there are other reasons why a region's unemployment rate may be related to that of its neighbours. In particular, functional labour markets might extend across the administrative boundaries that define our regions. We return to this issue below.

Dependent variable	1	2	3	4	5	6	7	8	9	10
Δ unemployment 1986–1996	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
% low skill	0.241** (0.094)	0.239** (0.932)	0.231** (0.101)	0.233** (0.099)	0.225** (0.103)	0.230** (0.098)	0.235** (0.091)	0.222** (0.080)	0.222** (0.096)	0.228* (0.083)
% medium skill	-0.109 (0.152)	-0.058 (0.189)	-0.115 (0.157)	-0.081 (0.195)	-0.063 (0.166)	-0.005 (0.191)	-0.104 (0.152)	0.013 (0.192)	-0.050 (0.165)	0.049 (0.192)
initial % agriculture	-0.024 (0.021)	-0.029 (0.020)	-0.024 (0.021)	-0.028 (0.020)	-0.032* (0.019)	-0.038* (0.020)	-0.025 (0.020)	-0.038* (0.021)	-0.034* (0.019)	-0.045** (0.020)
initial % manufacturing	-0.220** (0.086)	-0.204** (0.085)	-0.219** (0.089)	-0.207** (0.092)	-0.258** (0.090)	-0.231** (0.095)	-0.216** (0.088)	-0.176** (0.086)	-0.252** (0.091)	-0.207** (0.092)
initial female participation			0.002 (0.133)	-0.016 (0.149)	-0.208 (0.157)	-0.222 (0.165)			-0.221 (0.158)	0.253 (0.171)
% young			0.090 (0.205)	0.066 (0.213)	0.331 (0.204)	0.266 (0.217)			0.290 (0.210)	0.157 (0.234)
initial unemployment					-0.182** (0.070)	-0.165** (0.071)			-0.187** (0.072)	-0.165** (0.077)
Δ neighbours' unemployment	0.589** (0.106)	0.735** (0.272)	0.584** (0.109)	0.674** (0.256)	0.524** (0.114)	0.693** (0.259)				
Δ domestic neighbours							0.606** (0.115)	0.935** (0.252)	0.551** (0.120)	0.828** (0.240)
Δ foreign neighbours							0.514** (0.174)	0.670** (0.325)	0.415** (0.169)	0.581* (0.342)
Adjusted R ²	0.72	0.72	0.72	0.72	0.73	0.73	0.72	0.72	0.72	0.72
No. observations	147	147	147	147	147	147	147	147	147	147

Country dummies included, but not reported, in all specifications
Heteroscedastic robust standard errors in parenthesis
** denotes coefficient significantly different from zero with 5% confidence level, * with 10% level

Table 3. Regression results

initial structure of employment in the region — percentage of regional employment in agriculture, mining, forestry, and fishing, and percentage of regional employment in manufacturing. Two variables capture the skill composition of the the region — the percentage of adult population with low skills (less than upper secondary education), and the percentage with medium skills (completed upper secondary education). The change in neighbours' unemployment rate is constructed from the average unemployment rate of each regions' geographical neighbours, as in Section 3. All explanatory variables are expressed in logarithms. Country dummies are included, but not reported, in this and all other specifications. We exclude from the regressions Member States classified as a single NUTS2 region (Denmark, Ireland, and Luxembourg). Further details on data definitions and sources are given in the Data Appendix. Heteroscedastic robust standard errors are reported in parenthesis under each estimate.

We can see that the coefficient on the percentage of adult population with low skills is positive, large, and significant, as would be expected. After conditioning on the other variables, a high proportion of population with low skills is associated with an increase or less of a decrease in regional unemployment. The coefficient on medium skills, however, is not significantly different from zero. This suggests that it is the lower end of the skill distribution that most markedly affects regional labour market outcomes.

Regarding the initial sectoral composition of employment, the coefficient on the percentage of employment in agriculture and other primary sectors is not significantly different from zero. However, the percentage of employment in industry at the beginning of the period has a negative effect on unemployment rate changes. This somewhat surprising result can be explained by noting that, for most of the Northern and Central European regions traditionally specialised in heavy industry, the worst part of the adjustment was over by the mid 1980s. Since then many of these regions have in fact seen their unemployment rate fall. Something that distinguishes these regions from heavy industrial regions in Southern Europe, where adjustment has taken place later, is the different proportions of population with low skills. It is therefore not unreasonable that, after controlling for skills, the effect of manufacturing specialisation on unemployment changes comes out to be negative.

The most remarkable aspect of these results, however, is that the evolution of the unemployment rate in neighbours has a very strong and significant effect, even after controlling for regional industrial structure and skill composition. To understand the evolution of a region's unemployment we therefore need to consider its geographical position in addition to regional specific characteristics. We return to the interpretation of this result below. Before that, let us discuss a number of econometric issues.

We have chosen to capture the linkages between neighbouring regions through the incorporation of a labour force weighted unemployment rate variable, rather than through covariance assumptions on the error structure. We think that in the present context this specification is preferable. We would expect that predictable increases in neighbouring unemployment should feed through to regional unemployment through a number of mechanisms. Such expected increases are, by definition, orthogonal to the error, and thus best captured through the inclusion

of a 'spatially lagged' dependent variable¹⁴. Introduction of a spatially lagged dependent variable is problematic, however, as the variable is correlated with the error (a region's unemployment effects its neighbour's unemployment, which in turn effects the region's unemployment, and so on). To solve this problem, we instrument for the spatially lagged dependent variable.

Our earlier discussion suggests that neighbour's initial sectoral employment shares, and the skill, age and sex composition of their workforces are all possible instruments for the spatially lagged unemployment rates. These variables should pick up the exogenous impact that we outlined above. We would also like to instrument for the endogenous effect of the movement of firms and workers across regions. Recent location theories suggest that such movements will be related to some measure of 'market potential'¹⁵. To do this, we construct a market potential variable, defined as the inverse of distance weighted sum of European regional Gross Domestic Products¹⁶. Instrumental variables (IV) results using this set of instruments are presented in Table 3, column 2. The table shows that instrumenting does not change our initial results. The proportions of low educated and initial industrial employment remain significant. The effect of neighbours' unemployment remains strong and significant¹⁷.

Our second specification introduces two additional variables. As youth unemployment rates are high and rising, and regions differ in the age structure of their population, we control for the percentage of population that reached working age during the period (those aged between 15 and 25 in 1996). Additionally, in the mid-1980s regions female participation rates differed widely across European regions. Some regions, in Spain, had participation rates as low as 18%, while others, in the UK, had rates above 50%. Over the decade, female participation rates have significantly converged across European regions. This has resulted in huge increases in labour force, not always matched by comparable increases in employment¹⁸. We therefore control for the initial female participation rate in each region. OLS results are in column 3. Both coefficients have the expected sign, but are insignificant. Further investigation reveals that the percentage young becomes significant if we drop percentage low skilled and female participation. Female participation remains (just) insignificant when we drop out percentage young and low skilled. This occurs because all three variables are highly correlated — although percentage low skilled appears to matter most. Column 4 shows that instrumenting does not change the results.

Column 5 shows the OLS results when we introduce the initial unemployment rate. The only change here is that the agriculture variable becomes significant, but only at the 10% level. Column 6 shows that, once again, instrumenting doesn't change these results.

We have seen that neighbours are important. In Section 3 we argued that foreign neighbours mattered more than regions in the same State that are not contiguous. We now take this one step further and ask how important foreign neighbours are relative to domestic neighbours. The

¹⁴See Anselin (1988) for further discussion.

¹⁵See Fujita and Krugman (1995) for theoretical foundations, and Hanson (1998) for an empirical implementation.

¹⁶Thus, for region i , market potential is defined as $mp_i = \sum_{j \neq i} GDP_j / d_{i,j}$, where $d_{i,j}$ is the great circle distance between region i and region j , and GDP_j is the GDP of region j , and the sum is over all regions in the European Union excluding region i itself.

¹⁷In this, and all subsequent specifications we cannot reject the validity of our instrument set at the 5% confidence level using the test proposed by Davidson and MacKinnon (1993).

¹⁸See Wasmer (1998) for an exposition of this argument.

surprising answer is that they are equally as important. This is shown in Columns 7–10, where we split the neighbours variable for border regions into two components, that due to domestic neighbours and that due to foreign neighbours¹⁹. There are 51 such border regions (around a third of the sample)²⁰. Column 7 provides OLS results for the basic specification. We see that foreign neighbours have a significant effect on border regions. Further, we are unable to reject the hypothesis that the coefficients on both domestic and foreign neighbours are identical (the test has a value of 0.9 and is distributed $\chi^2(1)$).

Again, both neighbours effects are possibly endogenous. To correct for this we instrument for both domestic and foreign neighbours. The results are reported in column 8. We see that foreign neighbours continue to have a significant effect on border regions. Again, we are unable to reject the hypothesis that the coefficients on both domestic and foreign neighbours are identical. Next we introduce the additional variables considered before. This specification is presented in columns 9 (OLS) and 10 (IV). We see that the results are consistent with previous ones, although the significance of foreign neighbours drops slightly. However, we still cannot reject the hypothesis that the coefficients on both domestic and foreign neighbours are identical.

We have also tried a number of alternative specifications, not reported in the table. For instance, we have tried including the average change for unemployment for regions with a similar initial sectoral specialisation, a similar skill composition of adult population, and so on. The results are still remarkably robust.

There are a number of possible interpretations for the importance of geographical neighbours. First, the results could be driven by neighbouring regions having in common important determinants of unemployment rates. However, we have already taken this into account by controlling for the State to which regions belong, as well as for important regional characteristics²¹.

A second, rather mechanical, explanation is that functional labour markets extend across our geographical units. That is, neighbouring NUTS2 regions may actually form one labour market with substantial commuting flows between regions. Although relevant for smaller regions, this is not so important for NUTS2 regions, with the known exceptions of the Netherlands and areas surrounding London, Paris, Brussels, Bremen and Hamburg (see Cheshire and Carbonaro, 1996, for further discussion). Further, neighbourhood effects remain equally strong across national borders, and we know that cross border commuting flows are tiny. Cross border flows represented only 0.2% of the total European labour force in 1990 (de Falleur and Vandeville, 1996). Of these 316,000 cross-border workers, roughly 50% are workers commuting to Switzerland (not included in our sample). A further 40,000 represent flows into Luxembourg (which is excluded from our regressions). Thus, there are only approximately 100,000 cross-border commuting flows for the border regions in our sample. Even on the German-French border, where commuting flows are strongest, the total flows are 43,970, which is less than 0.8% of the combined border region labour force of 5,300,000.

¹⁹For the domestic and foreign neighbours variables, the labour force weights are those used when constructing our original neighbourhood variable. This ensures, that the sum of the two variables is the original neighbourhood variable, and that the coefficients are directly comparable.

²⁰If we drop out the UK's 35 regions, which include only one border region, then border regions make up nearly half the sample. The results do not change for this restricted sample.

²¹The fact that we are estimating in changes rather than levels should largely take care of fixed effects as well.

A third explanation is that the location and relocation decisions of workers and firms, in combination with weak labour force adjustment, have resulted in clusters of high and low unemployment larger than our geographical units and crossing national boundaries. However, we know that net migration flows across European regions are tiny, and not very responsive to differences in wages or unemployment rates (see, for instance, Eichengreen, 1993). This is particularly marked for cross-country migration flows, to the extent that only 1.5% of EU workers have a job in a Member State different from that in which they were born (<http://citizens.eu.int/en/en/newsitem-2.htm>)

All of this suggests that the spatial spillover results could reflect firm relocations that are occurring on the basis of geographical areas somewhat larger than NUTS2, but somewhat smaller than Member States. Looking with hindsight at the maps in Figure 2, we can in fact see the emerging clusters of high and low unemployment. These clusters do not conform to a standard core-periphery gradient. Instead high and low unemployment clusters have appeared in both the core and the periphery of the EU, often extending across national borders.

5. An example of two border regions in Belgium

In 1986 the Belgian region of Limburg had an unemployment rate 1.2 times the Belgian average and 1.3 times the European Union average. By 1996 its unemployment rate had fallen below both the Belgian and EU averages. Just across the border from Limburg (Belgium), two Dutch regions had similar experiences. The unemployment rates of Limburg (Netherlands) and Noord-Brabant fell relative to both the Dutch and EU averages.

Back in Belgium, 90 kilometres South-West of Limburg, the region of Hainaut started with a similar unemployment rate in 1986. However, instead of falling as it did in Limburg, this rate rose both in absolute terms and relative to both the Belgian and EU averages. Just across the border from Hainaut, the French region of Nord-Pas de Calais also saw its unemployment rate increase in both absolute and relative terms.

The different fortunes of these two Belgian regions were not driven by changes in demographic structure or labour market participation. Both regions had growing labour forces, but Limburg's actually grew more than twice as fast. The reason for Limburg's success is that its employment grew even faster than its labour force, and over four times faster than Hainaut's. A similar process occurred in the two Dutch neighbours of the Belgian Limburg. These regions that did relatively well had large and growing labour forces. But they also had a rate of employment growth that more than matched their labour force growth, and that brought their unemployment rates down. By contrast Nord-Pas de Calais, the French neighbour of Hainaut that did relatively badly, lost employment while its labour force was rising.

The drop in Limburg's unemployment rate versus Hainaut's rise cannot be put down to differences in the skill composition of their labour force. Both these Belgian regions had a similar percentage of their population with less than upper secondary education. And the French region of Nord-Pas de Calais, despite having a smaller fraction of people with less than upper secondary education than either of the Belgian regions, had a worse unemployment outcome.

Further, the evolution of these regions was not due to their different initial sectoral composition.

Admittedly in 1986 Nord-Pas de Calais was a predominantly industrial region. But Hainaut also saw its unemployment rate rise and in 1986 was concentrated in services. In contrast, the Belgian success story Limburg was concentrated in industry and of its two neighbours, one was mainly industrial (Noord-Brabant), the other service based (Limburg). No simple story of sectoral changes explains the relative performance of these regions²².

Given the small flows of workers across these borders, both in terms of commuting and permanent moves, one can hardly argue that there are functional labour markets extending across these regions. However, firms do seem to find it attractive to exploit other advantages of location close to these borders, such as the ability to use suppliers from different countries. The areas on the borders between Belgium and France and Belgium and the Netherlands have provided traditional locations for industry. However, in recent years these two borders have experienced very different evolutions. The most publicised case came in 1997 as Renault announced the closure of its Vilvoorde plant on the Belgian border with France. This raised protests at the loss of 3,100 jobs, at a time when Renault was planning to expand operations in other parts of Europe. At about the same time in Limburg (Netherlands), Volvo introduced a three-shift working schedule in its Nedcar joint plant with Mitsubishi, to double production over the following three years, drawing on suppliers from both sides of the Belgian-Dutch border. And on the Belgian side of this border, General Motors was also expanding production at its Antwerp plant.

Starting from similar conditions, the Belgian regions Limburg and Hainaut saw very different evolutions in their unemployment rates, but in each case these were very similar to those of their foreign neighbours. In this paper we have shown that this story is not unique, but representative of a broader pattern that has developed across Europe.

6. Concluding comments

This paper has shown that European regions have experienced a polarisation in their unemployment rates between 1986 and 1996. Regions with low rates in 1986 had low rates in 1996, regions with high rates in 1986 had high rates in 1996, while regions with intermediate rates in 1986 have tended to move towards the extremes of the distribution. This process has been driven by changes in regional employment rather than by changes in demographic structure or labour market participation. While there has been some labour force adjustment to regional employment changes, this has been insufficient to prevent the polarisation of European unemployment rates. Further, the outcomes of individual regions have closely followed those of their geographical neighbours.

This neighbours result could be driven by neighbouring regions having similar characteristics. For example, neighbouring regions often have similar employment structures, or similarly skilled labour forces. However, we have shown that the importance of neighbours' outcomes is only weakly driven by skill composition and broad sectoral specialisation. The same is true with respect to other regional characteristics, such as the sex and age structure of population.

²²Possible differences between the Flemish and French speaking regions of Belgium cannot explain these changes either. Contiguous to both the Flemish speaking Belgian Limburg and to the Dutch Limburg is the French speaking Belgian region of Liège, which also experienced a reduction in its unemployment rate.

Alternatively, the neighbours result could be driven by the fact that different European Union Member States have had different unemployment experiences, and regions within the same Member State tend to move together. However, we have also shown that regional outcomes only follow average Member State outcomes to a small extent. Further, the outcome of both own state and foreign neighbours matters equally for regional outcomes.

So, what is driving this emerging pattern of cross border unemployment clusters? We think it may be the result of firm location and relocation decisions, reflected in agglomerations of activity over geographical areas somewhat larger than NUTS2, but somewhat smaller than nation states. Worker relocations could also matter, but we know net flows of workers between European regions are small.

The EU has experienced a period of rapid and deep integration over the last decade. Portugal and Spain became Member States in 1986. Customs formalities for shipments of goods across the internal borders of the EU disappeared 1 January 1993. Border controls for movements of people across the Member States signing the Schengen agreement (Belgium, France, Germany, Luxembourg, Netherlands, Portugal, and Spain) disappeared 26 March 1995. Transport infrastructure has also been greatly improved — for instance, the number of kilometres of motorways in the European Economic Community of 1986 increased by a third between 1986 and 1994, and in Portugal and Spain it more than tripled.

Over this same period, there has been a revival of interest by economists in location issues. Recent models of trade and location formalise cumulative causation mechanisms, to show that regions which are similar, or even identical, in underlying structure can end up having very different development paths. Many of those models focus on how the propensity of firms and workers to agglomerate in space changes as regions become more integrated (see Ottaviano and Puga, 1998, for a survey). With little worker mobility, and institutional constraints on regional wage disparities, the conclusion is that closer economic integration will result in increasing concentration of economic activities across space (Puga, 1999).

Where would we expect to see agglomeration reflected? Looking at Mexico and the United States, Hanson (1997*a,b*, 1998) and Ciccone (1997) point to wages. However, the weak responsiveness of European regional wages to local economic conditions suggests that in Europe agglomeration will be reflected instead in employment. The aforementioned models of location do not incorporate unemployment explicitly. However, with limited labour force adjustment to regional employment changes (as found in Section 2), we can expect changes in employment to be largely translated into changes in unemployment. The distinguishing feature of this story is that regions with similar characteristics may have very different outcomes. At the same time, if clusters of activity are of a size larger than the regions considered, neighbouring regions will tend to experience similar outcomes, even if they are in different Member States.

The fact that unemployment outcomes are so much more homogenous across neighbours, foreign and domestic, than across regions in the same Member State also tells us something about the spatial dimensions of the emerging clusters of high and low unemployment in Europe. The average Member State has 13.6 regions, while the average neighbourhood has 5.6 regions. Hence these are clusters of typically less than one half of the size of the average Member State of the

European Union, but often extend across national borders and include regions from more than one Member State. This is similar to the geographical dimensions of agglomerations that Hanson (1998) finds looking at regional wages in the United States (US).

That also has important implications for policy. European regional policy has traditionally targeted mainly regional differences in income per capita, but is increasingly shifting its focus towards tackling regional differences in unemployment rates. Contrasting our results with those of Quah (1997b) shows the empirical reality underlying this change in emphasis — in contrast to the divergence of unemployment rates across European regions, Quah shows that differences in regional incomes per capita are narrowing. But there is one important additional difference. While inequalities in incomes per capita exhibited a core-periphery gradient (Keeble, Offord, and Walker, 1988), unemployment clusters are more localised and emerging in both the core and the periphery of the EU. There is strong political opposition to tackling these growing unemployment rate differences through increased labour mobility. Recent location theories suggest that the self-reinforcing nature of agglomerations will make these hard to break once they become established. However, given that the unemployment clusters we find are of not very large size and scattered across Europe, it may be politically viable as well as more efficient to implement policies that accept some clustering and larger mobility within a neighbourhood.

References

- Anselin, Luc. 1988. *Spatial Econometrics: Methods and Models*. Dordrecht: Kluwer Academic Publishers.
- Blanchard, Olivier Jean and Juan Francisco Jimeno. 1995. Structural unemployment: Spain versus Portugal. *American Economic Review* 85(2):212–218.
- Blanchard, Olivier Jean and Lawrence F. Katz. 1992. Regional evolutions. *Brooking Papers on Economic Activity* (1):1–61.
- Bover, Olimpia, Pilar García-Perea, and Pedro Portugal. 1998. A comparative study of the Portuguese and Spanish labour markets. Working Paper 9807, Banco de España.
- Castillo, Sonsoles, Juan José Dolado, and Juan Francisco Jimeno. 1998a. The fall in consumption from being unemployed in Spain and Portugal. Discussion Paper 1953, Centre for Economic Policy Research.
- Castillo, Sonsoles, Juan José Dolado, and Juan Francisco Jimeno. 1998b. A tale of two neighbour economies: Labour market dynamics in Spain and Portugal. Discussion Paper 1954, Centre for Economic Policy Research.
- Centraal Bureau Voor de Statistiek. 1987. *Regionaal Statistisch Zakboek 1986*. The Hague: Centraal Bureau Voor de Statistiek.
- Cheshire, Paul and Gianni Carbonaro. 1996. Urban economic growth in Europe: Testing theory and policy prescriptions. *Urban Studies* 33(7):1111–1128.
- Ciccone, Antonio. 1997. Dynamic externalities and the spatial distribution of wages in the US. Processed, University of Berkely.

- Davidson, Russell and James G. MacKinnon. 1993. *Estimation and Inference in Econometrics*. New York: Oxford University Press.
- de Falleur, M. and V. Vandeville. 1996. Cross-border flows of workers in Europe: Facts and determinants. In Harvey Armstrong and R. W. Vickerman (eds.), *Convergence and Divergence Among European Regions*. London: Pion.
- Decressin, Jörg and Antonio Fatàs. 1995. Regional labor market dynamics in Europe. *European Economic Review* 39(9):1627–1655.
- Eichengreen, Barry. 1993. Labor markets and European monetary unification. In Paul R. Masson and Mark P. Taylor (eds.), *Policy Issues in the Operation of Currency Unions*. Cambridge: Cambridge University Press, 130–162.
- Eurostat. 1989. *Regions: Statistical Yearbook 1988*. Luxembourg: Office for Official Publications of the European Communities.
- Eurostat. 1990. *Regions: Statistical Yearbook 1989*. Luxembourg: Office for Official Publications of the European Communities.
- Eurostat. 1995. *Regions: Nomenclature of Territorial Units for Statistics (NUTS)*. Luxembourg: Office for Official Publications of the European Communities.
- Eurostat. 1997. *Education Across the European Union: Statistics and Indicators 1996*. Luxembourg: Office for Official Publications of the European Communities.
- Eurostat. 1998. *Regio Database*. Luxembourg: Eurostat. May 1998 CD-ROM version.
- Fatàs, Antonio. 1997. EMU: Countries or regions? Lessons from the EMS experience. *European Economic Review* 41(3–5):743–751.
- Fujita, Masahisa and Paul R. Krugman. 1995. When is the economy monocentric? Von Thünen and Chamberlin unified. *Regional Science and Urban Economics* 25(4):508–528.
- Hanson, Gordon H. 1997a. Increasing returns, trade, and the regional structure of wages. *Economic Journal* 107(440):113–133.
- Hanson, Gordon H. 1997b. Localization economies, vertical organisation, and trade. *American Economic Review* 86(5):1266–1278.
- Hanson, Gordon H. 1998. Market potential, increasing returns, and geographic concentration. Working Paper 6429, National Bureau of Economic Research. URL <http://www.nber.org/>.
- Keeble, David, John Offord, and Sheila Walker. 1988. *Peripheral Regions in a Community of 12 Member States*. Luxembourg: Office for Official Publications of the European Communities.
- Krugman, Paul R. 1994. Past and prospective causes of high unemployment. *Federal Reserve Bank of Kansas City Economic Review* 79(4):23–43.
- Layard, Richard, Stephen Nickell, and Richard Jackman. 1991. *Unemployment: Macroeconomic Performance and the Labour Market*. Oxford: Oxford University Press.
- Manacorda, Marco and Barbara Petrongolo. 1998. Skill mismatch and unemployment in OECD countries. Discussion Paper 307, Centre for Economic Performance, London School of Economics.

- Nickell, Stephen and Brian Bell. 1995. The collapse in demand for the unskilled and unemployment across the OECD. *Oxford Review of Economic Policy* 11(1):40–62.
- Ottaviano, Gianmarco I. P. and Diego Puga. 1998. Agglomeration in the global economy: A survey of the ‘new economic geography’. *The World Economy* 21(6):707–731.
- Puga, Diego. 1999. The rise and fall of regional inequalities. *European Economic Review* 43(2):303–334.
- Quah, Danny T. 1996. Regional convergence clusters across Europe. *European Economic Review* 40(3–5):951–958.
- Quah, Danny T. 1997a. Empirics for growth and distribution: Stratification, polarisation, and convergence clubs. Discussion Paper 324, Centre for Economic Performance, London School of Economics. URL <http://econ.lse.ac.uk/~dquah/>.
- Quah, Danny T. 1997b. Regional cohesion from local isolated actions: I. historical outcomes. Discussion Paper 378, Centre for Economic Performance, London School of Economics. URL <http://econ.lse.ac.uk/~dquah/>.
- Silverman, B. W. 1986. *Density Estimation for Statistics and Data Analysis*. New York: Chapman and Hall.
- UNESCO. 1976. *International Standard Classification of Education (ISCED)*. Paris: United Nations Educational, Scientific and Cultural Organization.
- Wasmer, Etienne. 1998. Can labour supply explain the rise of unemployment and inequality in OECD countries? Discussion Paper 410, Centre for Economic Performance, London School of Economics. URL <http://www.ecare.ulb.ac.be/ecare/etienne/home.htm>.

Data Appendix

Our definition of regions corresponds to level two of the Nomenclature of Territorial Units for Statistics (NUTS), 1995 version (Eurostat, 1995). The NUTS was established by Eurostat to provide comparable regional breakdowns of the Member States of the European Union. It is a hierarchical classification with three regional levels: each Member State is partitioned into an integral number of NUTS1 regions, each of which is in turn partitioned into an integral number of NUTS2 regions, each of which is in turn partitioned into an integral number of NUTS3 regions. (There are two additional sub-regional or local levels, NUTS4 and NUTS5, of which only the latter, consisting of Communes or their equivalent, is defined for all Member States). In 1996 the EU had 77 NUTS1 regions, 206 NUTS2 regions, and 1,031 NUTS3 regions. Eurostat (1995) also calls NUTS2 regions ‘Basic Regions’, and describes these as the appropriate level for analysing regional-national problems; it is also the level at which both national and Community regional policies are generally implemented.

NUTS2 regions correspond to national administrative units in Austria (Bundesländer), Belgium (Provinces), Finland (Suuralueet), Germany (Regierungsbezirke), Greece (Development Regions), Italy (Regioni), Netherlands (Provincies), Portugal (Comissaoes de Coordenação Regional), and Sweden (Riksområden). NUTS2 regions also correspond to national administrative units, but with exceptions, in France (Régions, plus the four Départements d’Outre Mer), and Spain (Comunidades

Autónomas, plus Ceuta y Melilla). Three Member States are classified as a single NUTS2 region: Denmark, Ireland, and Luxembourg. In the United Kingdom, Groups of Counties have been introduced as an intermediate (NUTS2) level between NUTS1 (Standard Regions) and NUTS3 (a combination of Counties and Local Authority Regions) units.

The data set includes (with a single exception, documented below) all the NUTS2 regions of the EU that satisfy the following three criteria:

1. Have been part of the EU (European Economic Community before 1 November 1993) from 1986 to 1996.
2. Are in a Member State which has a land border with at least one other Member State containing at least one region satisfying (1).
3. Have a land border with at least one other NUTS2 region satisfying (1) and (2).

We include as land borders water borders less than five kilometres wide. This leads us to consider as geographical neighbours regions separated by a river (such as Zeeland and Zuid-Holland in Netherlands). It also leads to the inclusion of Sicilia (Italy), which, although an island, is only separated from Calabria (Italy) by the 3,300 metres-wide Strait of Messina — soon to be joined by a single span suspension bridge (see <http://www.strettodimessina.it/>).

From the 206 NUTS2 regions that formed the EU in 1996, 30 are excluded from the analysis because they were not part of the European Economic Community in 1986: the nine NUTS2 regions of Austria, the six NUTS2 regions of Finland, and the eight NUTS2 regions of Sweden, all of which became part of the EU with the accession of these three Member States in 1995; and the seven NUTS2 regions of Germany that were part of the former Democratic Republic of Germany (Brandenburg, Mecklenburg-Vorpommern, Sachsen, Dessau, Halle, Magdeburg, and Thüringen), which only became part of the EU with German reunification in 1990.

Greece has no land border with any other Member State, so its 13 NUTS2 regions are also excluded.

Finally, another 12 NUTS2 regions are excluded because they have no land border with any other NUTS2 region satisfying criteria (1) and (2): Baleares, Ceuta y Melilla, and Canarias (Spain), Corse, Guadeloupe, Martinique, Guyane, and Réunion (France), Sardegna (Italy), Açores, and Madeira (Portugal), are all entirely surrounded by water and/or by territories which are not part of the EU; Berlin (Germany) is entirely surrounded by NUTS2 regions which were part of the former Democratic Republic of Germany.

Flevoland (Netherlands) is the only region that satisfies criteria (1)-(3) above but has been excluded due to lack of data: there is no labour force or unemployment data for Flevoland for 1986, even from national sources (see *Centraal Bureau Voor de Statistiek*, 1987). Flevoland was created as a separate administrative unit (Provincie) in 1986 from the union of the Noordoost, Oostelijk Flevoland, and Zuidelijk Flevoland polders, reclaimed from the IJssel lake (a lake that used to be part of Zuiderzee, a former inlet of the North Sea), and in 1996 accounted for 1.8% of the population and 5.8% of the land area of Netherlands.

The 150 NUTS2 regions used are:

Belgium (11)	Brussels, Antwerpen, Limburg (Belgium), Oost-Vlaanderen, Vlaams Brabant, West-Vlaanderen, Brabant Wallon, Hainaut, Liège, Luxembourg (Belgium), Namur.
Denmark (1)	
France (21)	Ile-de-France, Champagne-Ardenne, Picardie, Haute-Normandie, Centre, Basse-Normandie, Bourgogne, Nord-Pas-de-Calais, Lorraine, Alsace, Franche-Comté, Pays de la Loire, Bretagne, Poitou-Charentes, Aquitaine, Midi-Pyrénées, Limousin, Rhône-Alpes, Auvergne, Languedoc-Roussillon, Provence-Alpes-Côte d'Azur.
Germany (30)	Stuttgart, Karlsruhe, Freiburg, Tübingen, Oberbayern, Niederbayern, Oberpfalz, Oberfranken, Mittelfranken, Unterfranken, Schwaben, Bremen, Hamburg, Darmstadt, Giessen, Kassel, Braunschweig, Hannover, Lüneburg, Weser-Ems, Düsseldorf, Köln, Münster, Detmold, Arnsberg, Koblenz, Trier, Rheinhessen-Pfalz, Saarland, Schleswig-Holstein.
Ireland (1)	
Italy (19)	Piemonte, Valle d'Aosta, Liguria, Lombardia, Trentino-Alto Adige, Veneto, Friuli-Venezia Giulia, Emilia-Romagna, Toscana, Umbria, Marche, Lazio, Abruzzo, Molise, Campania, Puglia, Basilicata, Calabria, Sicilia.
Luxembourg (1)	
Netherlands (11)	Groningen, Friesland, Drenthe, Overijssel, Gelderland, Utrecht, Noord-Holland, Zuid-Holland, Zeeland, Noord-Brabant, Limburg (Netherlands).
Portugal (5)	Norte, Centro (Portugal), Lisboa e Vale do Tejo, Alentejo, Algarve.
Spain (15)	Galicia, Asturias, Cantabria, País Vasco, Navarra, Rioja, Aragón, Madrid, Castilla-León, Castilla-La Mancha, Extremadura, Cataluña, Comunidad Valenciana, Andalucía, Región de Murcia.
United Kingdom (35)	Cleveland-Durham, Cumbria, Northumberland-Tyne and Wear, Humber-side, North Yorkshire, South Yorkshire, West Yorkshire, Derbyshire-Nottinghamshire, Leicestershire-Northamptonshire, Lincolnshire, East Anglia, Bedfordshire-Hertfordshire, Berkshire-Buckinghamshire-Oxfordshire, Surrey-East-West Sussex, Essex, Greater London, Hampshire-Isle of Wight, Kent, Avon-Gloucestershire-Wiltshire, Cornwall-Devon, Dorset-Somerset, Hereford-Worcestershire-Warwickshire, Shropshire-Staffordshire, West Midlands (County), Cheshire, Greater Manchester, Lancashire, Merseyside, Clwyd-Dyfed-Gwynedd-Powys, Gwent-Mid-South-West Glamorgan, Borders-Central-Fife-Lothians-Tayside, Dumfries-Galloway-Strathclyde, Highlands-Islands, Grampian, Northern Ireland.

Regional unemployment rates and labour force from 1986 to 1996 are taken from the harmonised unemployment rates (table `regio/unemp/un3rt`) and labour force (table `regio/unemp/un3wpop`) in the May 1998 version of the Regio database published by Eurostat (Eurostat, 1998).

These data are based on the results of the Community Labour Force Survey (LFS). The Community LFS is carried out in Spring each year and for each Member State provides the number of the unemployed (in accordance with the definition of the International Labour Office), and

the labour force (labelled 'working population') for April. The national unemployment data are subsequently regionalised to NUTS2 level on the basis of the number of persons registered at unemployment offices in April of the reference year (with the exceptions of Greece, Spain, Italy, Portugal, Finland, and Sweden, where the regional unemployment structures are taken from the Community LFS). The national labour force data are regionalised to NUTS2 level according to the results of the Community LFS. The regional unemployment rates are then obtained by dividing the number of the unemployed by the labour force.

The Regio database has no data on unemployment rates or labour force for two years, 1986 and 1987, for 13 of the targeted regions: all the NUTS2 regions of Netherlands, and Algarve (Portugal). For all of them (except the Dutch region of Flevoland, as documented above) comparable data has been obtained as follows. For the NUTS2 regions of the Netherlands in 1986 and 1987, the total number of the unemployed in the Netherlands in table /regio/unemp/un3pers of the Regio database has been regionally disaggregated to NUTS2 level, on the basis of the number of the unemployed in each region from table II.4 of Eurostat (1989), which are also derived from the Community LFS. Similarly, the total labour force of the Netherlands in table /regio/unemp/un3wpop of the Regio database has been regionally disaggregated to NUTS2 level, on the basis of regional labour force figures from table II.2 of Eurostat (1990) (for 1986), and of regional labour force figures computed by dividing the number of the unemployed by the corresponding unemployment rates in table II.4 of Eurostat (1989) (for 1987). Regional unemployment rates have then been calculated by dividing the number of the unemployed by the labour force. For Algarve (Portugal) in 1986 and 1987, employment and unemployment figures have been privately obtained from national sources (Portugal's Instituto Nacional de Estatística for employment, and Direcção de Serviços de Estudos de Mercado de Emprego for unemployment), and corrected for the factor by which each of these sources underestimates the corresponding Community LFS data for all the other NUTS2 regions that, together with Algarve, constitute the NUTS1 region Continente (Norte, Centro, Lisboa e Vale do Tejo, and Alentejo). Labour force has been calculated as the sum of the employed and the unemployed, and the unemployment rate by dividing the number of the unemployed by the labour force.

Regional unemployment rates and labour force are used to construct five series of relative unemployment rates: unemployment rates relative to the European average (*Europe relative* for brevity), unemployment rates relative to the average for other regions in the same Member State (*State relative*), unemployment rates relative to the average for contiguous regions (*neighbour relative*), unemployment rates relative to the average for other regions with the same broad sectoral specialisation (*same specialisation relative*), and unemployment rates relative to the average for other regions with a similar split of low/high educational attainment (*same skill relative*). In all cases averages used to construct the relative series refer only to regions included in the analysis. The information on State membership and contiguity is taken off the paper maps in Eurostat (1995).

To obtain groupings by broad sectoral specialisation, regions are classified according to the sector in the NACE-CLIO R3 classification (agricultural, forestry and fishery products; manufactured products; and market services) in which their share of total employment was highest relative to the EU average in 1988. The basis for these calculations are the total employment data by NACE-CLIO R3

sector (table /regio/lfs-r/lf2emp) in Eurostat (1998). These data are available for the 150 regions we are interested in only for 1988, but this is close enough to the beginning of the time frame considered to describe early specialisation.

To obtain groupings by low/high educational attainment, regions are classified according to the percentage of their population aged 25 to 59 in 1995 with less than upper secondary education — less than level 3 of the International Standard Classification of Education (ISCED) classification (UNESCO, 1976). These data are from table E14 in Eurostat (1997). These data are not ideal in that they refer to the adult population and not to the labour force, and they are only available for the 150 regions we are interested in for a single year, 1995. However, they are the best available at this level of regional disaggregation. We use them to construct nine groups of regions: regions where less than 10% of 25 to 59 year olds have less than upper secondary education, regions with more than 10% but less than 20%, and so on in ten percentage points intervals until regions where more than 80% but less than 90% of 25 to 59 year olds have less than upper secondary education.

The regression analysis of Section 4 uses the same data sources as the non parametric section. For the purpose of splitting population by skill there, low skill is taken to be an educational attainment of less than upper secondary education (below level 3 of the ISCED classification). Medium skill is an educational attainment of upper secondary education (level 3 of the ISCED classification). High skill is an educational attainment of higher education (levels 5, 6, and 7 of the ISCED classification). To calculate the percentage of young population, the young are taken to be those that reached working age during the sample period (those aged between 15 and 25 in 1996). These data are obtained from table /regio/lfs-r/lf2emp) in Eurostat (1998). Initial female participation rates are those for 1986 from table /regio/lfs-r/lf2actrt) in Eurostat (1998), completed with Eurostat (1989). For the calculation of the measure of initial market potential, used as one of the instruments in the instrumental variable estimations of Section 4, 1986 regional GDP levels are from table /regioecon-r/egdp/e2gdp) in Eurostat (1998). The distance between each pair of NUTS 2 regions is the great circle distance between their geographical centres, the coordinates of which have been obtained from http://shiva.pub.getty.edu/tgn_browser/.

Technical Appendix

More familiar applications of stochastic kernels use observations on random draws from a Markov process to estimate the underlying transition characteristics of that process. In contrast, in this paper we are interested in mappings from one distribution to another distribution. For example, this may be a mapping from the distribution of Europe relative unemployment rates at one point in time to the distribution of Europe relative unemployment rates at another point in time, or it may be the mapping from the distribution of Europe relative unemployment rates to the distribution of neighbour relative unemployment rates. In this Technical Appendix, we show that standard stochastic kernels can still be used to characterise the mappings between any two distributions, providing that we are careful about the space on which we define those stochastic kernels.

Let the two distributions of interest be γ and λ . Then we seek a mapping \mathcal{T}^* such that $\lambda = \mathcal{T}^*(\gamma)$. Our underlying state space is the pair (I, \mathfrak{X}_I) , where I is the unit interval and \mathfrak{X}_I

is the collection of Borel sets of the real line that are subsets of the unit interval. However, we define stochastic kernels on the more general state space $(\mathbb{R}, \mathfrak{X})$, where \mathbb{R} is the real line and \mathfrak{X} the collection of its Borel sets. We do so with the understanding that these definitions are valid for restrictions of the general state space to the specific unit interval state space.

Consider the most familiar case first, where we are interested in transitions over time and the distributions of interest are λ_t and λ_{t-1} . Recall the standard definition of a transition function.

Transition function definition. Let (Z, \mathfrak{Z}) be a measurable space. A transition function is a function $Q : (Z, \mathfrak{Z}) \rightarrow [0, 1]$ that satisfies two conditions:

- (i) For each $z \in Z$, $Q(z, \cdot)$ is a probability measure on (Z, \mathfrak{Z}) .
- (ii) For each $A \in \mathfrak{Z}$, $Q(\cdot, A)$ is a \mathfrak{Z} -measurable function.

The standard interpretation is that $Q(a, A)$ is the probability that next periods realisation lies in the set A , given that this period's realisation is a . There are two useful functions associated with the standard transition function.

Two useful functions.

1. For any \mathfrak{Z} -measurable function f , define $\mathcal{C}f$ by $(\mathcal{C}f)(z) = \int f(z')Q(z, dz')$, for all $z \in Z$.
2. For any probability measure λ on (Z, \mathfrak{Z}) define $\mathcal{C}^*\lambda$ by $(\mathcal{C}^*\lambda)(A) = \int Q(z, A)\lambda(dz)$, for all $A \in \mathfrak{Z}$.

The interpretation is as follows. $(\mathcal{C}f)(z)$ is the expected value of the function next period, given that the current state is z . \mathcal{C} maps the space of bounded functions to the space of bounded functions and is known as the Markov operator associated with Q . $(\mathcal{C}^*\lambda)(A)$ is the probability that the state next period lies in the set A if the current state is drawn according to the probability measure λ . \mathcal{C}^* maps the space of probability measures to the space of probability measures and is known as the adjoint of \mathcal{C} . Thus $\lambda_t = \mathcal{C}^*(\lambda_{t-1})$.

This \mathcal{C}^* is closely related to the mapping \mathcal{T}^* that we are interested in estimating. However two extensions are necessary. First, we want to allow for mappings between any two distributions, not just sequential distributions. Second, for empirical applications, we want to allow for generalised disturbances that may affect the mapping between distributions.²³ The extension to any two distributions is achieved through the use of the standard stochastic kernel definition.

Stochastic kernel definition. Let (X, \mathfrak{X}) and (Y, \mathfrak{Y}) be measurable spaces. Let ϕ be a probability measure on (X, \mathfrak{X}) and ψ be a probability measure on (Y, \mathfrak{Y}) . A stochastic kernel relating ϕ to ψ is a mapping $M_{\phi, \psi} : (X, \mathfrak{X}) \rightarrow [0, 1]$ that satisfies three conditions:

- (i) For all $y \in Y$ the restriction $M_{(\phi, \psi)}(y, \cdot)$ is a probability measure.
- (ii) For all $A \in \mathfrak{Y}$ the restriction $M_{(\phi, \psi)}$ is \mathfrak{X} -measurable.
- (iii) For all $A \in \mathfrak{Y}$ we have $\phi(A) = \int M_{(\phi, \psi)}(y, A)d\psi(y)$.

²³We have implicitly absorbed this generalised error in to our definition of \mathcal{T}^* .

Consider (iii). In the initial distribution, for given y , there is some fraction $d\psi(y)$ of regions with unemployment rates close to y . Count up all regions in that group whose unemployment rate subsequently fall in a given \mathcal{Y} -measurable subset $A \subseteq \mathbb{R}$ of the second (later/conditional) distribution. When normalised by the fraction of the total number of regions this count is precisely $M_{(\phi,\psi)}(y, A)$. Thus $M_{(\phi,\psi)}(y, A)$ is the probability that a region's realisation in the later/conditional distribution lies in the set A , given that the initial realisation is y . Evaluate the integral $\int M_{(\phi,\psi)}(y, A)d\phi(y)$. This gives the fraction of regions that end up in state A regardless of their initial position. If this equals $\phi(A)$ for all measurable sets A , then ϕ must be the measure associated with the subsequent distribution of unemployment rates. Conditions (i) and (ii) just ensure that this interpretation is valid. In particular, (ii) ensures that the right hand side of (iii) is a well defined Lebesgue integral, while (i) ensures that the right hand side of (iii) is a weighted average of probability measures and thus is itself a probability measure. It is easy to see that a transition kernel is a stochastic kernel for which the two spaces (X, \mathfrak{X}) and (Y, \mathfrak{Y}) are the same.

To allow for generalised disturbances we need to be able to model random elements drawn from a collection of probability measures. Following Quah (1997a) we proceed as follows. First we define a Banach space that contains all possible probability measures. We then use this Banach space and suitably defined open sets on that space to define a measurable space which we can, in turn, use to model random elements drawn from collections of probability measures.

Let $\mathcal{B}(\mathbb{R}, \mathfrak{X})$ be the Banach space of bounded finitely additive set functions on the measurable space $(\mathbb{R}, \mathfrak{X})$ with total variation norm

$$\text{for all } \phi \text{ in } \mathcal{B}(\mathbb{R}, \mathfrak{X}) : \|\phi\| = \sup \sum_j |\phi(A_j)|,$$

where the supremum is taken over all $\{A_j : j = 1, 2, \dots, n\}$ finite measurable partitions of \mathbb{R} .

Empirical distributions on \mathbb{R} are identified with probability measures on $(\mathbb{R}, \mathfrak{X})$. Probability measures are elements of $\mathcal{B}(\mathbb{R}, \mathfrak{X})$ that are countably additive and assign value one to the entire space \mathbb{R} . We use the set of bounded finitely additive set functions, because a collection of probability measures can never form a linear space. The set of boundedly-additive set functions includes probability measures and does form a linear space. We can then use the total variation norm to make this space Banach. Once probability measures are embedded in a Banach space, it makes sense to talk about two probability measures (and the associated distributions) getting closer to one another. Further, if we define a measure of distance, we can define open sets of probability measures (relative to this distance measure) and use these open sets to generate (Borel) σ -algebras on the Banach space. Given such a σ -algebra, we can model random elements drawn from collections of probability measures. This is the data of interest when we are modelling the dynamics of distributions.

Let \mathfrak{B} denote the σ -algebra generated by the open sub-sets (relative to the total variation norm topology) of $\mathcal{B}(\mathbb{R}, \mathfrak{X})$. Then $(\mathcal{B}, \mathfrak{B})$ is another measurable space. By construction, each ϕ_i associated with an observed (or derived) empirical cross sectional distribution F_i is a member of $(\mathcal{B}, \mathfrak{B})$. If $(\Omega, \mathfrak{F}, \text{Pr})$ is the underlying probability space, then ϕ_i is the value of an $\mathfrak{F}/\mathfrak{B}$ -measurable map $\Phi(\Omega, \mathfrak{F}) \rightarrow (\mathcal{B}, \mathfrak{B})$. We can define probability measures on $(\mathcal{B}, \mathfrak{B})$ that will allow us to deal with the generalised disturbances that affect the mapping between distributions.

Now, let $\mathbf{b}(\mathbb{R}, \mathfrak{X})$ be the Banach space under sup norm of bounded measurable function on $(\mathbb{R}, \mathfrak{X})$. Fix a stochastic kernel M and construct an operator \mathcal{T} (similar to \mathcal{C}) that maps the space of bounded measurable functions on to itself:

$$\text{for any } f \in \mathbf{b}(\mathbb{R}, \mathfrak{X}) \text{ define } \mathcal{T}f \text{ by } (\mathcal{T}f)(z) = \int f(z')M(z, dz'), \text{ for all } z \in \mathbb{R}.$$

This mapping has the same interpretation as \mathcal{C} in the (useful) function 1 above. Now we can denote the adjoint of \mathcal{T} by \mathcal{T}^* . Thus:

$$\text{for any probability measure } \lambda \text{ on } (\mathbb{R}, \mathfrak{X}) \text{ define } \mathcal{T}^*\lambda \text{ by } (\mathcal{T}^*\lambda)(A) = \int M(z, A)\lambda(dz), \text{ for all } A \in \mathfrak{X}.$$

From the Riesz Representation Theorem, the dual space of $\mathbf{b}(\mathbb{R}, \mathfrak{X})$ is $\mathbf{B}(\mathbb{R}, \mathfrak{X})$, the collection of bounded finitely additive set functions. Thus \mathcal{T}^* maps the collection of bounded finitely additive set functions on to itself. It is also precisely the mapping (iii) in the stochastic kernel definition. In our empirical analysis, we estimate $M(\phi, \psi)(y, \cdot)$ (the probability distribution of a region's realisation in the later/conditional distribution given that the initial realisation is y) for a whole range of y values. Here, we have shown that this does indeed allow us to trace out \mathcal{T}^* , the generalised mapping between any two distributions.