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Barriers to knowledge spillovers and regional convergence in an evolutionary model

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Abstract. This paper will present a multi-region/multi-country model in which inter-regional knowledge spillovers determine the growth of regions. Key parameters in the model are the learning capability of a region and the rate of knowledge generation (R&D). The intensity of spillovers depends on geographical distance between regions. The model is investigated by means of simulation techniques. What results is a core-periphery situation, the exact form of which depends on the assumed spatial structure.

The impact of economic integration is investigated by introducing barriers-to-knowledge-spillovers in the model in the form of borders between countries. Contrary to the popular belief and some economic theories, we find that removing such spillover barriers may result in larger disparity of income levels between regions.

Key words: Knowledge spillovers – Regional growth – Evolutionary economic models

JEL classification: O30, O40, R11, R12

1 Introduction

The issue of convergence of gross domestic product (GDP) per capita is the topic of a large and growing literature in economics (e.g., Barro and Sala-i-Martin, 1995; Fagerberg, 1994). The general conclusion from this literature is that convergence, as opposed to divergence, is a special outcome that may prevail between a set of countries that is relatively homogenous in terms of variables such as knowledge generation (R&D), infrastructure, educational systems, etc. This idea is implicit in the notion of ‘conditional convergence’ that arises from new growth models in the neoclassical tradition (e.g., Barro and Sala-i-Martin, 1995), as well as in the so-called technology gap theory (e.g., Fagerberg, 1994).

Economic integration, for example in the form that has been implemented in the European Union, may well help to achieve homogeneity between countries in terms of such structural characteristics, and thus help to achieve convergence (e.g., Ben-David, 1994). However, the empirical evidence seems to point out that convergence is not, or in the best case at very low speed, taking place at the regional level in the Union at large since the start of the 1980s (Fagerberg, Verspagen and Caniëls, 1997).

This paper suggests that the impact of spatial proximity on the diffusion of technological knowledge may be responsible for this paradoxical situation. There is a large literature in economic geography that underlines the importance of proximity for knowledge spillovers. The concept of interest in this literature (for an overview see Baptista, 1998) is the existence of agglomeration economies and its effects on growth. Agglomeration economics are the positive effects of spatial concentration of economic activity on a firm’s or a region’s performance. Agglomeration economies are induced, among other things, by a large opportunity for communication of ideas and experience, which is enhanced by spatial proximity. In this paper we focus on knowledge spillovers as the prime form of agglomeration economies. Several studies (e.g., Acs, Audretsch and Feldman, 1992; Jaffe, Trajtenberg and Henderson, 1993) have confirmed such a positive relation between geographic proximity and knowledge spillovers.

Theoretical reasons for the localized nature of knowledge spillovers are discussed extensively in the literature (e.g., Audretsch and Feldman (1996). Technological knowledge is often informal, tacit and uncodified in its nature (e.g., Pavitt, 1987), implying an easier diffusion over short distances (Jaffe, Trajtenberg and Henderson, 1993). Possibilities for learning-by-doing and learning-by-using, important for the transmission of knowledge, to a large extent come from direct contacts with competitors, customers, suppliers and providers of services (Von Hippel, 1988, 1994) and are therefore also highly dependent on proximity. Interaction between innovators, e.g. in regional networks, helps to reduce the uncertainty in the innovative process. This kind of interaction is highly dependent on geographical proximity (Freeman, 1991). Furthermore, innovation may rely on nearby sources of basic scientific knowledge. Jaffe (1989) and Acs, Audretsch and Feldman (1992) have shown empirically that knowledge spillovers from university research to private firms are facilitated by geographic proximity. Finally, innovative activity is cumulative, meaning that new innovations build upon scientific knowledge generated by previous innovations. Breschi (1995) and Malerba and Orsenigo (1995) point out that the accumulation of innovative activity in a geographic area facilitates the generation of new innovations in this area.

In this paper we incorporate spatial proximity into a technology gap growth model developed earlier by Verspagen (1991). The resulting model, which is discussed in greater detail in Caniëls (2000) is one in which a multitude of geographic units (which will be called regions) interact with each other in terms of knowledge diffusion. These regions may differ with respect to their R&D efforts and their social capability to assimilate knowledge from other regions. Ceteris paribus, knowledge from regions close by diffuses more easily than knowledge from regions far away.

Barriers to trade and barriers to knowledge spillovers can have an important influence on the distribution of growth across regions. First, trade can have an influence on growth, by enhancing specialisation and thus enabling increasing returns to scale. Various trade-growth models explore this relation (Grossman and Helpman, 1990). Second, international specialisation may have an impact on the amount of spillovers that take place within a country relative to the amount between countries (e.g., Coe and Helpman, 1995). Thus, barriers to trade and to knowledge spillovers may well have an influence on the distribution of gaps throughout all regions.

To be able to study these influences, the situation under barriers to trade and knowledge spillovers is compared to a situation in which these barriers are released. In other words, comparing a situation before and after these two forms of economic integration will make it possible to explore the effects of trade barriers on the distribution of growth.

It is difficult to make a clear-cut distinction between barriers to trade and barriers to knowledge spillovers. International barriers to trade come in various formats. Exchange rate volatility, quota's, tariffs and a political unstable situation all form barriers to international trade. Under the (Millian) assumption that trade in goods is accompanied by diffusion of knowledge (every product contains information about for instance its construction that can be deduced by reverse engineering) a barrier to cross country trade can limit the knowledge spillovers in these directions. However, trade is one (indirect) way in which knowledge is diffused.

The aim of this paper is to explore the effects of trade barriers and barriers to knowledge spillovers on regional disparities in growth. The model developed in this paper will take into account increasing returns, through the Verdoorn effect. Specialisation will not be endeepened as a source of disparity across regions, since only one sector will be introduced.

The rest of this paper is organised as follows. In Section 2, the part of the model that describes technological spillovers across regions is presented. Section 3 examines the effect of barriers to knowledge spillovers by means of simulation techniques. Finally, Section 4 summarises the main conclusions from this paper.

2 Description of the spillover system

For simplicity, we disregard any sources of output growth other than the growth of technological knowledge. Specifically, it is assumed that output growth is a linear function of the growth of the knowledge stock:

$$\frac{\dot{Q}_i}{Q_i} = \beta \frac{\dot{K}_i}{K_i}, \tag{1}$$

in which Q_i denotes the level of output of region i and K_i points to the level of the knowledge stock of region i. β is a parameter, indicating the proportion of the knowledge stock growth that results in output growth. Dots above variables denote time derivatives.

New knowledge is assumed to stem from three sources: learning-by-doing (modelled as a Verdoorn effect[1]), spillovers received from surrounding (not necessarily contingent) regions (S_i), and an exogenous rate of growth (ρ_i), which can be thought of as reflecting the impact of exogenous R&D activities in the region. This yields the following equation:

$$\frac{\dot{K}_i}{K_i} = \alpha \left(\lambda \frac{\dot{Q}_i}{Q_i} + S_i + \rho_i \right), \tag{2}$$

in which α and λ are parameters. α points out the extent to which the knowledge stock growth is influenced by the above factors, and λ reflects the intensity of the Verdoorn effect.

For the explanation of the spillover term S, it is convenient to first consider two regions, later on this framework will be extended, and a multi-region model will be constructed. In the two-region setting, it is assumed that there is one technologically advanced region and one backward region. Spillovers depend on the size of the knowledge gap, as well as three different parameters reflecting distinct effects related to the realisation of potential spillovers. We use the following equation to model spillovers:

$$S_j = \frac{\delta_j}{\gamma_{ij}} e^{-\left(\frac{1}{\delta_j} G_{ij} - \mu_j\right)^2}, \quad \text{with} \quad i \neq j, \tag{3}$$

$$G_{ij} = \ln \frac{K_i}{K_j}, \tag{4}$$

in which S_j denotes the spillovers generated by region i and received by region j. G_{ij} denotes the technology gap of region i towards region j, and is defined as the log of the ratio of the knowledge stocks of two regions. The realisation of the potential spillover level depends on the three parameters γ, δ and μ, which we will now discuss in turn.

γ_{ij} is the geographical distance between two regions. If γ_{ij} increases, the spillover is reduced. This assumption stems from the geographical literature. As was discussed in the introduction of this paper, this is based on the assumption that spatial proximity eases spillovers (agglomeration economies), because interaction between the receiver and generator of the spillovers is easier when distance is small. μ_j and δ_j are two parameters that are related to the intrinsic learning capability of region j. These parameters thus reflect the broad concept of 'social capability' to assimilate spillovers (e.g., Abramovitz, 1994). Regions that

[1] The Verdoorn-Kaldor law states that a positive relation exists between the growth of productivity and the growth of output.

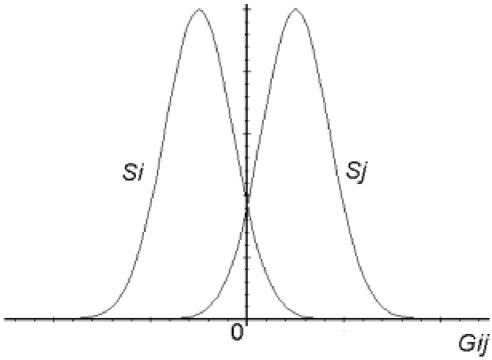

Fig. 1. Spillover curve for two regions

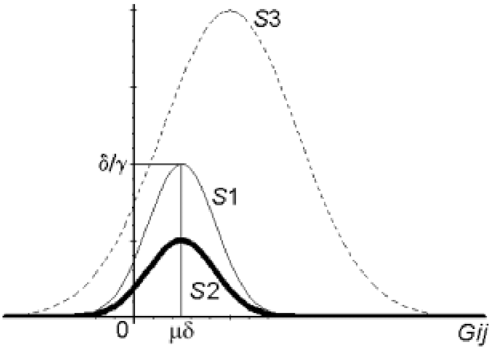

Fig. 2. The influence of geographic distance ($S2$) and the learning capability ($S3$) on the spillover curve of a region

have a high social capability to learn (e.g., a highly educated workforce, good infrastructure, an efficient financial system, etc.), can implement the knowledge from other regions more easily. μ_j and δ_j reflect different parts of the learning capability that will be explained below.

Figure 1 presents the spillover functions for two regions, assuming all parameters to be equal between the regions. The horizontal axis displays the size of the technology gap. Note that a positive value of G_{ij} by definition implies that region j is the backward region. A first characteristic of our model is that, in contrast with most of the catch-up literature, we allow spillovers to occur in two directions, i.e., from the technological leader to backward region(s), and vice versa. Figure 1 shows that, for equal parameter values between the regions, the spillover stream from the advanced to the backward region will be larger than the reverse stream (S_i is always below S_j to the right of the vertical axis). This reflects the notion that the backward region can learn more from the advanced region than the other way around. However, spillovers from a backward region to the leader region also take place because it could well be possible that the backward region has (developed) complementary knowledge, knowledge that was not yet in the hands of the leader. So there always is a small flow of knowledge from laggard to leader, although this quantity quickly goes to zero for large gaps.

The *net* spillover will be equal to zero when the gap between the two regions is zero (i.e., they have equal knowledge stocks). In this situation there are still spillovers, but these are of equal size in both directions. This only holds, however, when the parameters (ρ, λ, μ, δ) are equal between the two regions. In the more general case of unequal parameters between regions, net spillovers may be positive or negative for a gap of value zero.

Figure 2 displays the spillovers received by one region for this two-region model. Note that the top of each spillover curve lies at a technology gap equal to $\mu_j \delta_j$. The maximal spillover corresponding to this is equal to δ_j/γ_{ij}. We take the curve labelled $S1$ as the starting point, and we consider what happens to the spillover function under certain conditions. First, an enlargement of the geographical distance between two regions (higher γ) will lead to lower spillovers received by each region, depicted by the thick line $S2$. Note that an increase in distance shifts the curve down, but leaves the value of the gap for which spillovers are maximal unchanged.

Second, an increase in the learning capability parameter δ of the lagging region will cause the spillover function to shift up, and the maximum of the curve to shift to the right (dotted line $S3$). Thus, with higher δ, the laggard is able to learn more (magnitude of the spillover function) and more easily, or 'earlier' (at a larger technological distance).

As will be explained below, the value of G at which the spillover curve peaks ($\mu\delta$) is important for the result of the model. We therefore wish to allow for the possibility that the maximum of the spillover curve shifts left or right, without affecting the value of the maximum itself. This is the main reason why we have two parameters associated with the learning capability of a region (δ and μ). The parameter μ shifts the maximum of the spillover-curve left or right.

If μ_j is increased, all other things being equal, the level of spillovers in the case of equal knowledge stocks across regions (G=0), is smaller. This indicates that for relatively large μ, the model resembles a regular catch-up model, which is characterised by zero spillovers for zero technological distance. Furthermore, catch-up becomes easier. At a larger technological distance, it is still possible to catch up. How the distinction between catching-up and falling behind works exactly will become clearer after we discuss the net spillover function.

Thus, the difference between the parameters μ and δ is mainly a technical matter. In practice, they can hardly be disentangled in terms of the variables that make up social capability to assimilate spillovers. We mainly use the parameter μ to calibrate the model (i.e., to generate a setup that implies a reasonable borderline between catching-up and falling-behind), while δ is used more actively in the simulation experiments below as an indicator of the learning capability of a region.

In order to be able to analyse the dynamics of convergence and divergence, we take the time derivative of the technology gap in Equation (4) and substitute equations (1) and (2). For a two-region model this yields:

$$\dot{G}_{ij} = \frac{d}{dt}\ln\frac{K_i}{K_j} = \frac{\dot{K}_i}{K_i} - \frac{\dot{K}_j}{K_j} = \frac{\alpha}{1-\alpha\beta\lambda}((\rho_i - \rho_j) - (S_j - S_i)), \quad with \;\; 0 < \alpha\beta\lambda < 1 \,, \qquad (5)$$

in which α, β and λ are assumed to have the same value in each region. This expression can be analysed using Figure 3.

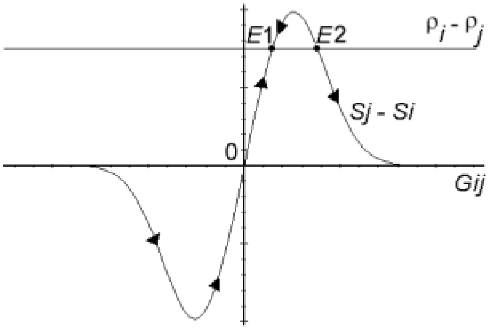

Fig. 3. The dynamics of the model

We will restrict ourselves to describing only one case, namely the one in which region i is the leader and hence the initial gap is positive. We also assume that leadership implies larger R&D efforts, such that $\rho_i > \rho_j$.[2] In Figure 3, $S_j - S_i$ represents the difference in received spillovers between the two regions. The lagging region receives positive net spillovers, as discussed above. Note that we have again assumed $\delta_i = \delta_j$ and $\mu_i = \mu_j$. In the more general case where these assumptions do not hold, the net spillover curve will not intersect with the origin, but this does not change the dynamics in a major way. The horizontal line $\rho_i - \rho_j$ displays the difference in the exogenous rate of growth of the knowledge stock between the two regions.

It is straightforward from equation (5) that when the curve in Figure 3 intersects with the horizontal line $\rho_i - \rho_j$, the time derivative of the technology gap is equal to zero. In other words, the intersection points correspond to equilibrium points. The (leftmost) intersection point at which the S-curve has a positive slope is stable, whereas the other intersection point is unstable. Thus, what happens to the knowledge gap in the long run depends on where the process starts. Starting points to the left of $E2$ will yield convergence to a stable technology gap (corresponding to $E1$). Starting values to the right of $E2$ will yield falling behind, with an ever growing knowledge gap.[3]

Now consider what happens with changing parameter values. We will first consider a variation in the difference in the exogenous rate of growth of the knowledge stock between the two regions, $\rho_i - \rho_j$. If the difference is enlarged

[2] This assumption is not essential as the reader may easily verify by assuming the opposite.

[3] Verspagen (1991) estimates a simpler version of this model for a large sample of countries over the post-war period, and finds that falling behind is a frequent phenomenon.

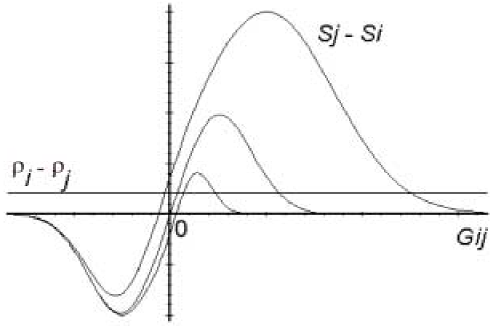

Fig. 4. The impact of the learning capability on the net spillover curve

in favour of the leader, the $\rho_i - \rho_j$ line in Figure 3 moves upward, meaning that the range of technology gaps at which catch-up occurs becomes smaller. Eventually, when the $\rho_i - \rho_j$ line shifts to a position above the net spillover curve, there will be no opportunity at all for catch-up. If, on the other hand, the exogenous rate of growth of the knowledge stock in the backward region is increased (e.g. by expanding research efforts) up to a level comparable with the advanced region, i.e., the $\rho_i - \rho_j$ line ultimately coincides with the horizontal axis, and the (stable) equilibrium gap is zero, implying complete converge in the long run.

Next, we consider the impact of the geographical distance between the two regions. A decrease in the geographical distance has the effect that the spillover curves S_i and S_j increase proportionally to the decrease in geographical distance (explained by Fig. 2) and the maximum of the $S_j - S_i$ curve moves upwards[4].

The effect of an increase in the learning capability of the backward region $j(\delta_j)$ on the $S_j - S_i$ curve is displayed in Figure 4. Note that δ_j is the only parameter that has changed, δ_i is kept constant. It can clearly be seen that on the right hand side of the figure the top of the curve has moved to the upper right of the figure and the curve does not intersect with the origin anymore. What has happened on the left-hand side is a bit more difficult to see. The minimum point has moved upwards so that it is closer to the horizontal axis. Also, there is a small movement of the minimum point away from the y-axis. Figure 5 displays a bifurcation analysis for the parameter δ.

Note that the E_s line for the stable equilibrium can even go below the x-axis if the difference in exogenous growth rates of the knowledge stock is small enough, which illustrates an interesting special case of the model. This situation indicates a take-over in leadership by the (initially) lagging region. In terms of Figure 4, this occurs when the horizontal line $(\rho_i - \rho_j)$ intersects with the $S_j - S_i$ curve left from the y-axis, where the gap is smaller than zero, indicating that region j is the leader region. The combination of a large learning capability in the lagging region together with a small difference in the exogenous rate of growth between

[4] The maximum also moves a little bit away from the y-axis, but this is a very small effect.

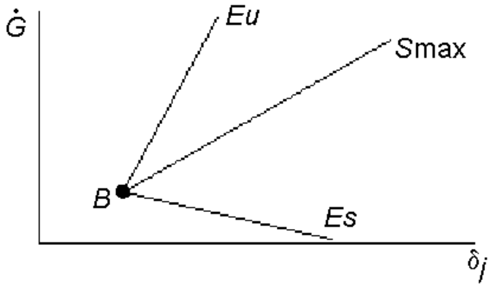

Fig. 5. Bifurcation with respect to the learning capability

laggard and leader gives rise to a take over of the lead position by the backward region. Note that it is primarily learning capability that drives this process of take-over.

We omit the bifurcation analysis for the parameters μ and γ, which are relatively straightforward, and jump to extend the model to a multi-regional case. Suppose we have a world with k regions, so that each region can be characterised by k-1 technology gaps (we omit the trivial case of G_{ii}). Spillovers are received from each of the other regions, so that the S terms in equation (2) now become sums of spillovers over $k-1$ regions. This gives rise to the following equation:

$$\begin{aligned} \dot{G}_{ij} &= \frac{d}{dt}\ln\frac{K_i}{K_j} = \frac{\dot{K}_i}{K_i} - \frac{\dot{K}_j}{K_j} \\ &= \frac{\alpha}{1-\alpha\beta\lambda}((\rho_i - \rho_j) + (\Sigma_n S_{in} - \Sigma_n S_{jn}) - (S_j - S_i)), \\ &\quad \text{with } 0 < \alpha\beta\lambda < 1 \text{ and } n \neq i, j \ , \end{aligned} \tag{5'}$$

in which $\Sigma_n S_{in}$ and $\Sigma_n S_{jn}$ denote the spillovers received by region i and j respectively from all regions n for which $n \neq i, j$ (this term is thus invariant to G_{ij}). Note that equation (5') specifies the growth of the gap between the two regions i and j only. There are k regions in total, thus every region i has k-1 of these equations.

Equation (5'), under the ceteris paribus assumption with respect to the knowledge stocks in regions other than i and j, gives rise to identical figures as Figures 3-5. The only difference is that in the case of equation (5'), $(\rho_i - \rho_j)$ and $(\Sigma_n S_{in} - \Sigma_n S_{jn})$ are lumped together into the horizontal lines that used to be determined by $(\rho_i - \rho_j)$ only. A movement of this horizontal line (and therefore in the horizontal position of $E2$) can now be caused by two factors. First, a variation in the difference between the exogenous rates of growth of the knowledge stocks of two regions (as before), and, second, a difference across regions in the spillovers received from other regions.

The latter term is largely determined by geographic location. The subset of regions to which this term refers does not differ between i and j, but when, for example, region i is closer to the advanced regions than region j is, this gives region i an advantage over region j. Also, the learning capability (δ and μ) has an impact on how ($\Sigma_n S_{in}$ - $\Sigma_n S_{jn}$) differs between i and j.

When we specify a (symmetric) matrix of distances between regions, the model is fully specified, and time paths for the G variables result from any set of initial values. However, for a reasonably large number of regions, these time paths are extremely tedious to work out analytically, which is why we resort to simulations to describe the outcomes of the model. By carrying out many simulations (with randomised initial conditions) it is possible to examine the general behaviour of the model, and we find that certain patterns in the gaps of the knowledge stocks appear repeatedly. All simulations use a Pascal computer program that implements a Runge-Kutta algorithm to numerically solve the differential equations for G.

We use two different geographical spheres (distance matrices). These are a lattice of honeycombs and a globe. Appendix A gives an exact description and a map of these spheres as well as the location of the border which divides each sphere into countries. The regions on these spheres are assumed to be homogeneous areas. In other words, no differences of the relative importance (e.g., political) of the regions are assumed, nor do we assume differences in the degree of connectedness (e.g., the presence of harbours, mountains, roads and railways). Since this is a one-sector model, we also assume that the regions have homogenous economic structures.

The first sphere is a two-dimensional honeycomb pattern, which yields an equal amount of contingent neighbours for each region, with each neighbour having an equally long border. This would not be the case when using a lattice of squares, which would have the additional difficulty of judging the importance of the different kinds of neighbours - queens, bishops or rooks[5] - by assigning weights to them. Because the lattice is flat and has a hexagonal shape in itself, there is always exactly one central region. This region has a favourable location, as will become clear from the experiments.

The second sphere used has the shape of a globe. In the globe, no inherently central location is present. In the case of the globe pentagons had to be added to the hexagons (the regions are constructed as the pattern on a soccer ball, i.e., twelve pentagons and twenty hexagons)[6]. Compared to the lattice of honeycombs,

[5] These terms are borrowed from chess. A queen is allowed to move in all directions indicating that all eight neighbours of a square are equally important. A lattice with these characteristics is called a Moore neighbourhood. A bishop is only allowed to move in a diagonal way, while a rook is only allowed to move horizontally or vertically, meaning that one might want to assign a different (lower) weight to a neighbours, which do not share a border but only one point (the bishops-case) than to neighbours, which do share a border (the rooks-case). When only neighbours of the rook type are considered, the plain is called a von-Neumann neighbourhood.

[6] It is impossible to construct a three-dimensional figure by the single use of hexagons. Hexagons will always produce a flat sphere, since the sum of the angles of three contingent hexagons is equal to 360 degrees. By adding pentagons, the total angle will be less than 360 and thus producing a three-dimensional figure. It would have been possible to construct a three-dimensional sphere by using pentagons only, however, in that case the total number of pentagons (regions) used would be twelve. The globe that is used in the simulations consists of thirty-two planes (regions), which was considered to give more interesting interactions than a sphere containing only twelve planes.

the globe has more geographically central locations, and hence provides a rather different environment for the model of distance-determined spillovers.

Geographic distance in the geographical spheres is measured by assigning a weight of one to neighbouring regions (in the sense that two regions share one border). Regions which do not share a border with a specific region are given a weight by using the concept of nearest neighbours, which means that a different (lower) weight is attributed to a second order neighbour. A second order neighbour does not share a border with a specific region, but does share a border with a neighbour of the specific region. In this way, the distance g_{ij} is determined for every region towards every other region. Now, it is possible to construct a region-by-region matrix of shortest paths. Then, the corresponding weights (γ) are determined using the inverse of the orders (inverse shortest path, Hagett, Cliff and Frey, 1977). Note that this way of measuring the impact of geographical distance is a special case of specifying the impact of distance as $1/(g_{ij}^{x})$, with x equal to 1.

3 Barriers to knowledge spillovers

The existence of national systems of innovation stimulates inter-country regional interaction rather than cross border relationships. The experiments in this section aim to explore the effect of barriers to knowledge spillovers on regional convergence[7]. In this section, a barrier to knowledge spillovers across countries is introduced by reducing the spillovers that cross the border between the countries with one half. The specific effect of introducing knowledge barriers to this model is analysed by comparing the results of this experiment to the results found for the situation of no barriers to knowledge spillovers. The underlying geographical structure is the lattice of honeycombs.

In this experiment, the initial level of the knowledge stock for each region is drawn from a uniform distribution, resulting in several different initial distributions of the knowledge stock across regions. These initial disparities are displayed on the horizontal axis of the figures. The vertical axis shows the coefficient of variation at the end of the simulation period.

It appears from Figure 6 that there exist several levels of disparity that are 'natural'. Most prominent are simulations in which the final coefficient of variation has a value around 0.6, simulations in which the final coefficient of variation is about 2.8 and simulations in which the final coefficient of variation is about 3.9. These 'natural' levels of dispersion originate from the amount of regions that has fallen behind at the end of the simulation period. Note that a higher coefficient of variation indicates a larger dispersion between the gaps towards the leader. A coefficient of variation around 3.9 at the end of the simulation indicates that one region has fallen behind, i.e., displays a very large gap towards the leader. A final coefficient of variation around 2.8 indicates that two regions

[7] Appendix B shows the values of all parameters and variables as they are used for each (set of) simulations.

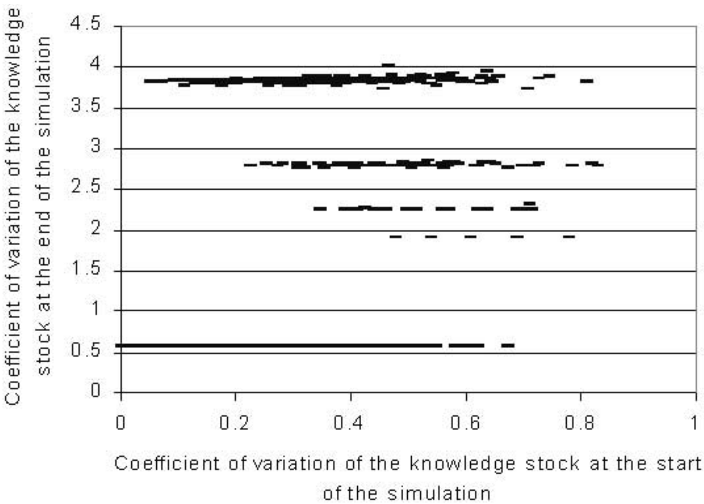

Fig. 6. No barriers to knowledge spillovers (lattice)

have fallen behind. All levels of dispersion in Figure 6 can be explained in this way.

In brief, the case in which there are no barriers to knowledge spillovers shows a prominent presence of falling behind. In fact, only the case in which the final coefficient of variation is about 0.6 indicates a situation in which no regions fall behind. The accompanying distribution of the gaps across regions is displayed in Figure 8. Note that a certain polarisation occurs, meaning that the regions that are geographically close to the central region display the lowest gaps.

Turning to Figure 7 for the introduction of barriers to knowledge spillovers in the experiment, we find many observations with a coefficient of variation ranging from nearly 0.95 up to almost 0.98 at the right-hand side of the figure. The broadness of the range indicates that many runs have a similar, however slightly different, coefficient of variation. The differences in disparity within this small range are due to the 'normal' variation between runs within one interval.

The figure displays a few observations with a coefficient of variation of about 0.875. This is the effect of falling behind of regions within the second country (the leader). Falling behind in this experiment is much less likely compared to the strong presence in the case of no barriers to knowledge spillovers. Also, falling behind in Figure 7 leads to less final disparity, contrary to the case of no barriers to knowledge spillovers in which falling behind induced a higher disparity at the end of the simulation (Fig. 6).

Note that the comparison between Figures 6 and 7 yields a quite paradoxical result: introducing (removing) barriers to knowledge spillovers leads to less (more) disparity of income levels between regions. This is certainly against the intuition of European policy makers, who have been trying to increase 'cohesion' between European regions by removing trade- and other barriers between countries in the European Union. Also, some of the literature on endogenous growth

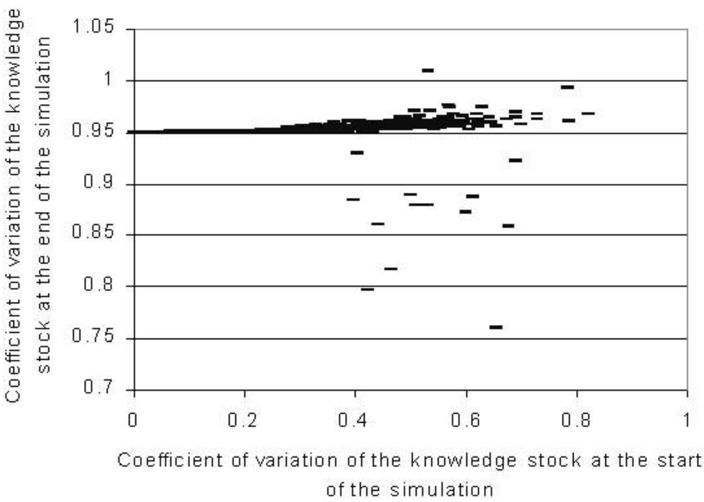

Fig. 7. Barriers to knowledge spillovers (lattice)

(e.g., Grossman and Helpman, 1991) tends to argue that enabling spillovers between countries tends to generate convergence.

The explanation for this paradoxical result lies in the importance of distance for spillovers, which is clearly a force that generates a tendency for concentration. With barriers to spillovers, this force is obviously weaker, and hence a number of local centres will result from the spillover dynamics. The existence of more than one centre implies that a backward region will, on average, be closer to a (local) centre, and hence overall disparity in the amount of spillovers received is lower as compared to a situation with only one centre (no barriers to spillovers).

Another point originates from Figure 7. At the right-hand side, the coefficient of variation is slightly higher than to the left, while this effect is absent from Figure 6. Because one of the two countries (the left one in Appendix A, Fig. 14) receives little spillovers due to the barriers to cross border spillovers, the equilibrium gap (towards every individual region from this country converges) continues to grow during the transitory dynamics. At a high initial coefficient of variation (right-hand side of the figure), large initial differences between regions are present. Apparently, this causes a relatively high variety in equilibrium gaps across regions (of the left-hand side country) within a run. Therefore, the overall disparity is higher than in the case where initial differences across regions are smaller (left-hand side Fig. 7).

The two panels in Figure 9 show the effect of barriers to knowledge spillovers as there are initial variations in the learning capability and the exogenous rate of growth of the knowledge stock, respectively. Both parameters are drawn from a uniform distribution of decreasing size, where the upper boundary is fixed at 2, and the lower boundary is varied. The horizontal axis in each panel in Figure 9 shows the lower boundary. The vertical axis shows the frequency of the coefficient of variation of the gaps. The shades in the figures correspond to

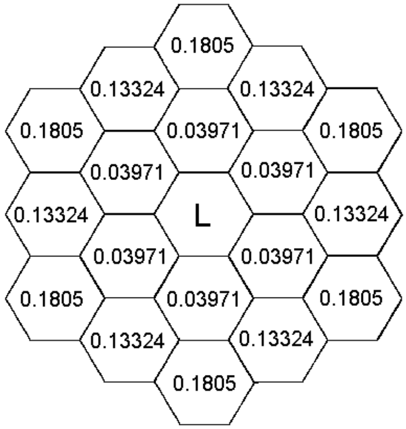

Fig. 8. Regional gaps in a lattice of honeycombs (L denotes the leader region)

frequencies over fifty runs, with complete black corresponding to a frequency of fifty (i.e., all runs). White shades indicate very low (sometimes zero) frequencies.

The first panel of Figure 9 shows the results for an initial variation in the learning capability. A comet-shape appears, in which 'the comet' (the dark spot at the right of the figure) leaves two clear trails: a long one coming from the lower left and a shorter trail originating from the upper left. This indicates that an increase in initial disparity across regions induces two effects. The upper trail suggests higher disparity, however, a stronger effect originates from the lower trail, which suggests smaller disparity across regions. The more unequal regions are in terms of their learning capability, the more differences in disparity exist across runs.

A similar comet-shape appears when we observe the results for a variation in the exogenous rate of growth of the knowledge stock (Fig. 9, Panel 2). Again, there appear two trails of which the lower one is longer. Based on this observation, a variation in the exogenous rate of growth of the knowledge stock seems to have a similar influence on the behaviour of the model than a variation in the learning capability (although the absolute influence differs).

Figure 10 observes the distribution of the gaps (after 1000 simulation periods) across regions for the case that all regions are (initially) equal ($\delta_i = \delta$, $\mu_i = \mu$, and initially all values for G are equal to zero), except for their geographic location. The number within each honeycomb in Figure 10 indicates the size of the gap of the region toward the leader region (average over the last 100 periods in a run). The regions that have a large gap towards the leader region are white whereas the leader region and regions with a very small gap towards the leader are coloured grey. The thick line demarcates the border between the two countries.

The pattern shows strong inter-country variation, rather than inter-regional variation. All regions within a country have identical colours. The second (right-hand side) country includes the region that on a world level has the most favourable geographic location, i.e., the central region. This simple fact brings

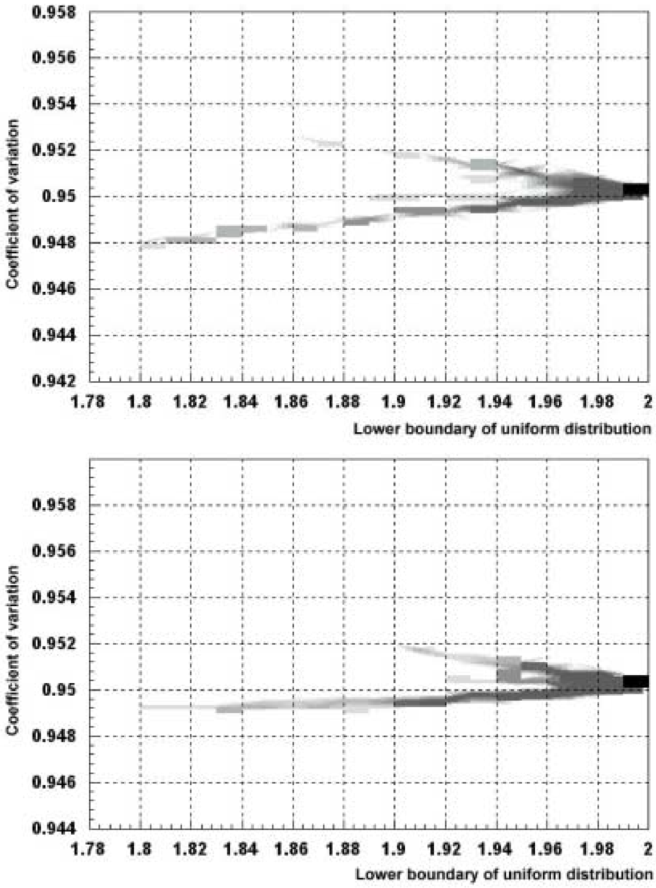

Fig. 9. Panel 1: Frequency diagram of the coefficient of variation at the end of the run. Initial variation in the learning capability simulated on the lattice. Panel 2: Frequency diagram of the coefficient of variation at the end of the run. Initial variation in the exogenous rate of knowledge generation simulated on the lattice

country 2 technological and economic leadership. The regions of country 1 neighbouring to the overall central region, undergo a large disadvantage of the border. Their spillovers from the advanced country 2 are reduced by one half. Still, because these regions are close to the border, they will become local centres, thus indicating the paradoxical result of the model (removing barriers to spillovers leads to divergence) that was explained above.

A further observation that is related to this phenomenon is that in the second country, the leader region is located in the most favourable geographic position (the central location) within the country, rather than the most favourable position in the world. The world-leader region is therefore not the overall central region in world. The other regions within country 2 show gaps that are (line-) symmetrically distributed around the leader region. Thus, within country 2 the ‘usual’

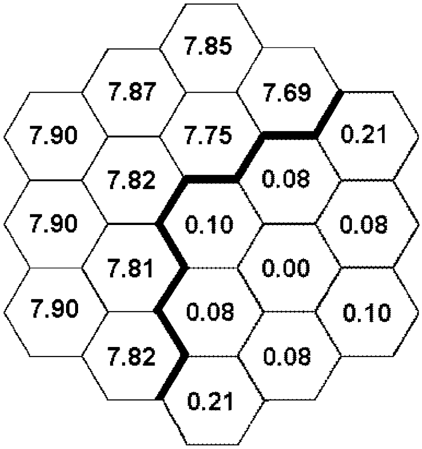

Fig. 10. Final gaps when all regions are initially equal

polarisation (as documented in Figure 8) takes place, in the sense that the regions that are geographically close to the central region display the lowest gaps.

Summarising, a variation in one of the parameters (learning capability or exogenous rate of growth of the knowledge stock) suggests that two states appear as ‘attractors’ of the dynamics of the model. In one of these states, the disparity is larger than in the distribution shown by Figure 10, in the other state the disparity in the gaps across regions is smaller. The latter state seems to occur most often, thus suggesting that initial differences in learning capability or exogenous rate of knowledge generation lead to a lower disparity across regions.

This result is similarly paradoxical as the one that was obtained before on the impact of barriers to spillovers. It says that if regions become more similar, income levels will diverge. As noted in the introduction, this is clearly against the main conclusion from the literature on conditional convergence. This literature argues that when regions become similar in terms of structural characteristics, they will tend to converge to the same steady state growth path. The explanation for this paradoxical result in our model is that the structural differences between regions tend to counteract the centralizing tendency of distance-dependent spillovers. Thus, the mechanism generating the paradox is essentially the same as with the previous paradox: by ‘endowing’ some of the non-central regions with high value for ρ or δ, ‘local centres’ are created and overall disparity goes down.

We now investigate whether these results also hold in simulations where the globe is used as the geographical structure. A variation in the initial stock of knowledge across regions leads to a disparity in gaps across regions as displayed in Figure 11. The first panel in Figure 11 shows the results without barriers to knowledge spillovers. The interpretation of this figure is comparable to the interpretation of Figure 6. The highest disparity at the end of the simulation occurs when one or more regions have fallen behind. Only the case in which the

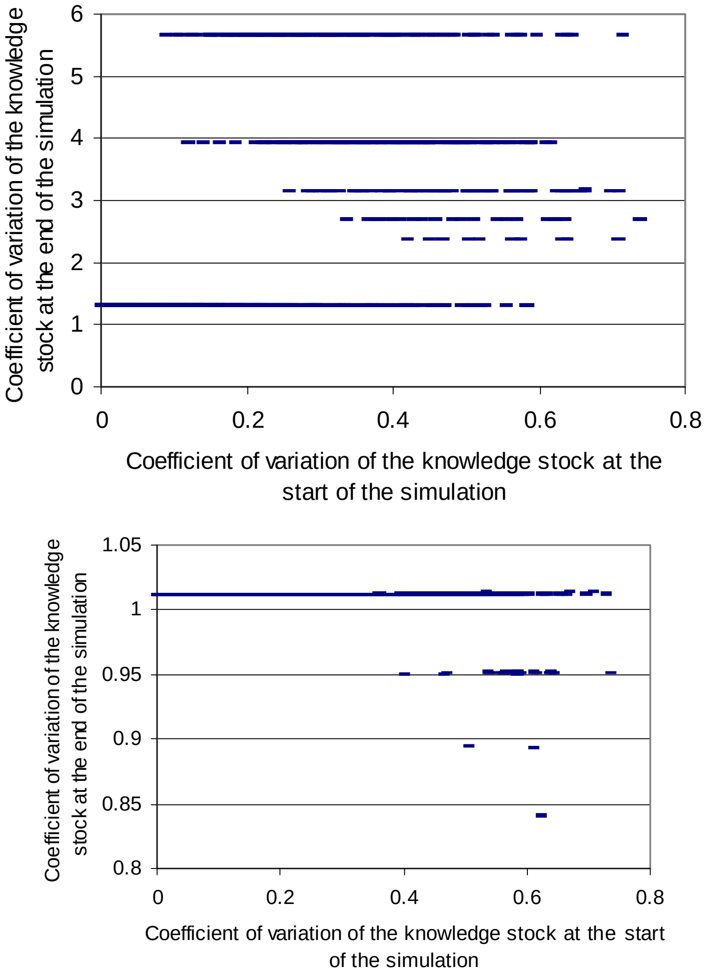

Fig. 11. Panel 1: Initial versus final disparity, no barriers to knowledge spillovers, the globe. Panel 2: Initial versus final disparity under barriers to knowledge spillovers, the globe

final coefficient of variation is about 1.3 indicates a situation in which no regions fall behind.

The second panel in Figure 11 shows the effect of an introduction of barriers to knowledge spillovers. Whereas the final disparity of 1.0117 results independent of the initial disparity across regions, a few times a lower final coefficient of variation comes about, but only for large initial coefficients of variation. Similar to the experiment for the lattice of honeycombs this is due to falling behind *within* the leader country.

Comparing the two panels, we find, just as was the case with the lattice, that introducing barriers to knowledge spillovers will reduce the average level of disparity. However, in this case, the low level of disparity that is found for the experiments with barriers to knowledge spillovers is also quite often found when

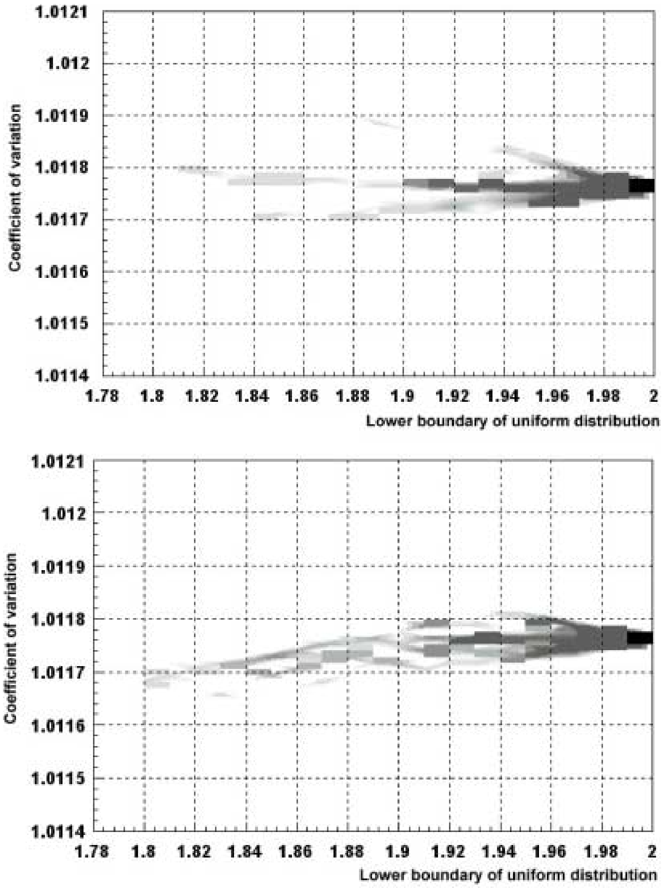

Fig. 12. Panel 1: Frequency diagram of the coefficient of variation at the end of the run under barriers to knowledge spillovers. Initial variation in the learning capability, simulated on the globe. Panel 2: Frequency diagram of the coefficient of variation at the end of the run under barriers to knowlegde spillovers. Initial variation in the exogenous rate of knowledge generation, simulated on the globe

knowledge spillovers are free. In other words, the paradoxical effect of spillovers-barriers seems to be somewhat less serious in this particular case. Obviously, this is due to the fact that the globe already has many 'local centres', the occurrence of which is the main phenomenon explaining the paradox.

Panel 1 of Figure 12 shows the disparity in each run for a variation in the learning capability. A comet-shape occurs, indicating that an increase in initial disparity across regions induces not only less disparity across regions at the end of the simulation but could also cause more disparity. The more unequal regions are in terms of their learning capability, the more differences in disparity exist across runs. However, there seem to be (three) different paths along which the coefficient of variation groups (three trails). One trail is moving upward from the black cell towards the upper left. A second path stretches out in a slightly

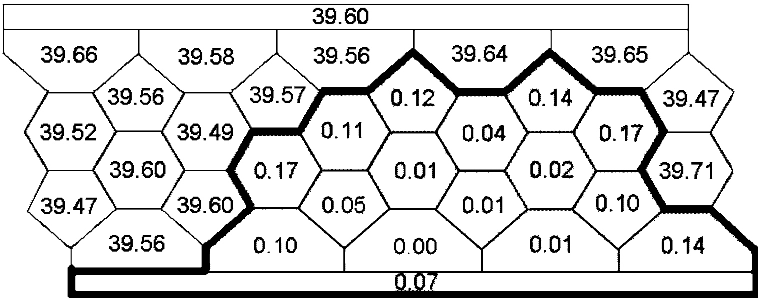

Fig. 13. Final gaps when all regions are initially equal

downward direction (from right to left). The third trail is horizontal. Panel 2 shows the results for a variation in the exogenous rate of knowledge generation. Again, a comet-shape appears, however, no separate trails are distinguished.

Thus, in general, the figures for the globe show similar trends as for the lattice, although the amount, direction and clarity of the trails (for an initial random variation in δ or ρ) differs somewhat.

The distribution connected to the situation in which regions have the same initial values is shown by Figure 13[8] . As before we find a strong inter-country difference. Within the leader country a polarisation occurs (less clear from Figure 13) around the leader region.

This set of experiments sheds light on the effect of barriers to knowledge spillovers on the model. A striking result is that a clear difference in the average gap between two countries occurs. In one country, all regions will tend to an equilibrium in which their gap toward the leader region (located in the other country) is very large. The country containing the leader region shows polarisation. This result indicates that the 'adverse' effect of variety in learning capability and exogenous rate of growth of the knowledge stock, i.e. more initial variety causing less final disparity across regions, only holds within a country.

4 Summary and conclusions

This paper has presented a model for knowledge spillovers based on geographical distance as well as technological distance. The regions in our model receive knowledge spillovers from other regions, and this enables them to grow rapidly. Our model is similar to some of the models found in the 'technology gap' tradition of analysing convergence of GDP per capita. Compared to these models, we add

[8] Note that the geographic structure of country 2 is a-symmetrical. Therefore, it is less easy to see that the leader region is centrally located within country 2. The same experiment has been executed for a different, symmetric geographic structure for both countries. The results with respect to disparity (for all ranges) are similar. The only advantage of a symmetric geographic structure is that it enables us to immediately see the polarisation around the central region of the leader country.

the spatial distance effect on spillovers. The further away other regions are, the less strong spillovers from these regions are.

The analysis pays special attention to the impact of barriers to knowledge spillovers, which are modelled by assuming that cross border knowledge flows are lower than inter-country flows. The analysis shows that reduced cross border flows (existence of spillovers-barriers) leads to convergence between regions. This is a paradoxical result that goes against the common wisdom in some models of spillovers and endogenous growth, and against the main tenets of policies aimed at further European integration. We find a similar effect due to structural differences between regions (rate of knowledge generation, capability to assimilate spillovers). Increasing such differences between regions leads to lower levels of income disparity.

The explanation for these paradoxical results lies in the existence of ‘local centres’ in the case of barriers to spillovers, or (large) structural differences between regions. Borders between countries (acting as barriers to spillovers) and (random) differences in terms of structural characteristics may benefit relatively peripheral regions, which may then become local centres. Other (more) peripheral regions that are nearby will benefit from this, and lower disparity may thus result. The policy implications of this conclusion are that in a process of further European integration, regional policies are gaining importance. Such policies should be aimed at creating local growth poles, which may then also generate ‘belts’ of prosperity around them.

Appendix A

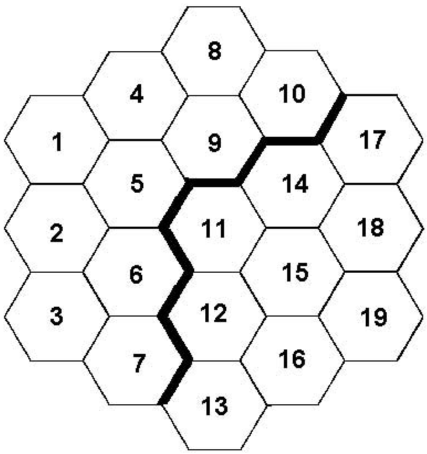

Fig. 14. Two countries on a lattice of honeycombs

Figure 14 displays the topography of the regions on a lattice of honeycombs. The number within each hexagon was used to establish the geographical distances

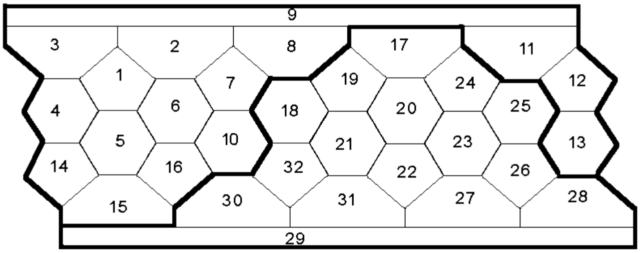

Fig. 15. Two countries on a globe

between all hexagons. Figure 15 represents a globe with twelve pentagons and twenty hexagons. For the graphical representation, we used the same principle that was applied in making a map of the world. Hence, the regions close to the poles look larger as they actually are, while the regions around the equator show their true proportions. At the bottom and at the top are regions 29 and 9. These are pentagons, for example region 9 borders to five regions, namely 3, 2, 8, 10 and 11. Regions 29 and 9 are in reality as large as region 1. The graphic representation of a globe has also as a consequence that for example region 3 seems to differ in size from region 6. Again, this is not the case in reality, region 3 is an ordinary hexagon. The same goes for all the other regions bordering 9 or 29. It should also be noted that region 11 borders not only to regions 9, 10, 24, 25 and 12, but also to region 3. In this way, region 12 also borders to regions 3 and 4, region 13 has regions 4 and 14 as direct neighbours as well, whereas region 28 also shares a border with regions 14 and 15.

Appendix B

Default levels of the variables and values of the parameters:
1 (Catch-up parameter, μ)
0.005 (β)
0.005 (α)
1 (Verdoorn parameter, λ)
γ (geographical distance) is constructed with the help of two different types of distance tables, one for each sphere.

Appendix C

Level of the knowledge stock and values of the parameters in each figure:

Fig.	$\rho = 1$	$\delta = 1$	Knowledge stock = 10	$\rho \in$ [1.8, 2.0]	$\delta \in$ [1.8, 2.0]	Knowledge stock $\in$ [0, 2]	Time simulated = 10000	Time simulated = 1000
6	x	x				x	x	
7	x	x				x		x
8	x	x	x				x	
9(1)	x		x		x			x
9(2)		x	x	x				x
10	x	x	x					x
11(1)	x	x				x		x
11(2)	x	x				x		x
12(1)	x		x		x			x
12(2)		x	x	x				x
13	x	x	x					x

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