



# Neighbour regions as the source of new industries\*

Ron Boschma<sup>1</sup>, Víctor Martín<sup>2</sup>, Asier Minondo<sup>3</sup>

<sup>1</sup> Centre for Innovation, Research and Competence in the Learning Economy (CIRCLE), Lund University and Utrecht University, Heidelberglaan 23584 CS, Utrecht, The Netherlands (e-mail: Ron.Boschma@circle.lu.se)

<sup>2</sup> University Rey Juan Carlos and ICEI, Paseo Artilleros s/n28032 Madrid, Spain (e-mail: victor.martin@urjc.es)

<sup>3</sup> Deusto Business School and ICEI, Camino de Mundaiz 5020012 San Sebastian, Spain (e-mail: aminondo@deusto.es)

Received: 23 March 2015 / Accepted: 28 November 2015

**Abstract.** The development of new industries demands access to local capabilities. Little attention has yet been paid to the role of spillovers from neighbour regions for industrial diversification, nor has the role of network linkages between neighbour regions been investigated. As the spread of capabilities has a strong geographical bias, we expect regions to develop new industries in which their neighbour regions are specialized. To test this hypothesis, we analyse the development of new industries in US states during the period 2000–2012. We show that a US state has a higher probability of developing a comparative advantage in a new industry if a neighbour state is specialized in that industry. We also show that neighbour US states have more similar export structures. This export similarity seems to be explained by higher social connectivity between neighbour states, as embodied in their bilateral migration patterns.

**JEL classification:** R11, N94, O14

**Key words:** New industries, regional branching, diversification, knowledge spillovers, US, regions, exports

## 1 Introduction

The spatial emergence of new industries is high on the scientific and political agenda. Especially in times of economic crisis, regions are searching for opportunities to diversify their industrial structure. An expanding literature claims that the emergence of industries is driven by the degree of relatedness with existing industries in regions, as new industries draw from and recombine local capabilities that are related to theirs (Boschma and Frenken 2011). Recent studies show

---

\* We thank the comments and suggestions by Jacob Holm and other participants at the 2nd Workshop on Industrial Relatedness and Regional Change (Umea University), and participants in Universidad Complutense de Madrid Research Seminar. Asier Minondo acknowledges financial support from the Spanish Ministry of Economy and Competitiveness (MINECO ECO2013-46980-P, co-financed with FEDER), and the Basque Government Department of Education, Language policy and Culture (IT629-13). Victor Martin acknowledges financial support from the Spanish Ministry of Economy and Competitiveness (HAR2013-40760\_R). Ron Boschma acknowledges financial support from the European Union under the FP7 Cooperation Programme: Social Sciences and the Humanities. Grant number 320131.

indeed that new industries emerge systematically from related industries, and that the industrial structure of a regional economy has an impact on the diversification opportunities of regions (Neffke et al. 2011; Boschma et al. 2013; Muneepeerakul et al. 2013; Esslezrbichler 2015).

However, a weakness of the related diversification literature is its almost complete focus on local capabilities, as if regions are self-contained entities. In reality, capabilities may spillover to other regions and trigger the diversification process there. At the same time, the spread of capabilities is heavily constrained by geographical distance: knowledge spillovers are more likely to occur between regions that are geographically close (Jaffe et al. 1993). In the related diversification literature, little attention has been paid to the role of spillovers from neighbour regions for diversification, nor has the role of network linkages between (neighbour) regions been investigated. In a recent paper, Bahar et al. (2014) found that a country had a higher probability to develop a comparative advantage in an industry if a neighbour country had a comparative advantage in that same industry, and that the export baskets of neighbouring countries tend to look more similar. There exists no study that has systematically analysed the effect of neighbours on the probability of regions to develop a comparative advantage in an industry.

The goal of this paper is to fill this gap. The paper has two objectives. The first objective is to assess the effect of neighbouring regions on regional diversification. Following Bahar et al. (2014), we expect regions to develop new industries in which their neighbour regions are specialized. To test this hypothesis, we analyse the development of new industries in US states during the period 2000–2012. As this paper uses trade data to analyse regional diversification, following previous studies (Hidalgo et al. 2009; Boschma et al. 2013), we define new industries as those in which a US state has a low level of trade specialization at the beginning of the period and develops a strong trade specialization at the end of the period. We show that a US state has indeed a higher probability of developing a new industry if a neighbour state is specialized in that industry, and when the US state is well endowed with local capabilities that are related to that industry. The second objective is to assess whether neighbour regions have a higher similarity in their export structures, and whether social connectivity (as proxied by bilateral migration patterns) can explain the differences in the similarity of export structures across regions. Our study finds support for the claim that the export similarity between neighbour states is higher than the export similarity between non-neighbour states, and that social connectivity between US states is correlated positively with export similarity across states.

The structure of the paper is as follows. In Section 2, we describe the theoretical background of the study. Section 3 introduces the data and the methodology, and estimates the impact of specialization in neighbour regions on developing a comparative advantage in that industry in a region. Section 4 investigates whether neighbour regions have a more similar export structure, and if so, to what extent this result (i.e., export similarity) is determined by bilateral migration patterns between neighbouring regions. Section 5 concludes.

## 2 Emerging industries: Local capabilities, neighbour regions and networks

Local capabilities are perceived to be major assets for regions in a globalized world. This has led to a massive research effort to determine which local capabilities matter, and how these can be identified, as some capabilities are intangibles. Maskell and Malmberg (1999) associated local capabilities with a local knowledge base and an institutional setting that are tightly interwoven and the outcome of a long history. Storper (1995) referred to ‘untraded interdependencies’ such as local practices and conventions. These ‘localized capabilities’ have a high degree of tacitness that form a crucial asset for regions because they cannot be easily imitated by other regions (Gertler 2003). As a consequence, regions

develop strong technological and industrial specializations that are hard to challenge, because they are deeply rooted in local capabilities.

Region-specific capabilities provide not only crucial assets on which existing specializations can thrive. There is increasing awareness that local capabilities also operate as a key source of technological and industrial diversification, that is, they provide potentials for regions to diversify into new technologies and industries. At the same time, local capabilities also set limits to this diversification process: if a region does not possess the capabilities required for a new technology or new industry, it will be close to impossible to develop these.

Recently, attention has turned to local capabilities that provide opportunities to recombine pre-existing technologies or industries and that give birth to new activities. Jacobs (1969) was one of the first to claim that variety in regions conditions the scope for recombinant innovations: the more variety, the higher the potential to make new recombinations. Frenken et al. (2007) argued, however, that many technologies and industries cannot be meaningfully combined: variety must be related, that is, cognitively proximate, because this positively affects the scope for knowledge spillovers and learning (Nooteboom 2000). Therefore, recombinations are more likely to come from technologies or industries that share similar knowledge bases: the more variety of related technologies or sectors in a region, the more learning opportunities for local activities, and the higher the potential for local recombinations across technologies or industries.

Hidalgo et al. (2007) claimed that capabilities do not move easily between countries, and therefore are hard to acquire when missing. Therefore, capabilities at the country level determine which new industries are feasible to develop. Capabilities are captured by what they call the 'product space' which specifies the relatedness between products based on the frequency of co-occurrences of export products at the country level. Hausmann and Klinger (2007) demonstrated that countries expand their export activities by moving into products that are related in 'product space' to their current export products. Their studies also showed that countries with a wide range of related products (i.e., related variety) have more opportunities to diversify into new export products, as their capabilities can be redeployed in a larger number of new products.

Capabilities at the regional level (at the sub-national scale) might be as important for related diversification (Martin and Sunley 2006; Fornahl and Guenther 2010). Boschma and Frenken (2011) referred to 'regional branching' as a type of regional diversification in which new industries or technologies emerge from local recombinations of technologically related activities. They claim that related diversification tends to occur through channels of knowledge transfer that are often geographically bounded, such as entrepreneurial spinoffs and labour mobility. There is indeed substantial evidence that firms that originate from local related industries (either as diversifiers or new spinoff companies) are crucial for the development of new industries in a region (Klepper 2007). Labour mobility is regarded as another key mechanism through which knowledge and skills are transferred across (related) industries (Neffke and Henning 2013). As labour mobility occurs mainly within labour market regions (Eriksson 2011), labour flows between local related industries may initiate and contribute to new recombinations and, thus, act as a powerful potential source of regional branching.

While still little is known about these underlying mechanisms, there is substantial evidence of related diversification at the regional scale. Qualitative case studies show that new industries in regions are often deeply rooted in local related activities (Chapman 1992; Glaeser 2005). Quantitative studies have provided evidence that regions diversify into industries that are closely related to their existing activities. Neffke et al. (2011) was the first study at the regional level to show that the entry probability of a new industry in a region is positively related with relatedness with existing industries in the region. Follow-up studies have confirmed that relatedness is indeed a driving force behind diversification of regions in new industries (Essletzbichler 2015), new technologies (Van der Wouden 2012; Kogler et al. 2013; Rigby 2013; Boschma et al. 2015; Feldman et al. 2015) and new eco-technologies (Tanner 2014, 2015; Van den Berge

and Weterings 2014). Boschma et al. (2013) demonstrated that local capabilities are a more important driver of regional diversification than national capabilities.

Despite all this evidence, one could argue that the weakness of the related diversification literature is its almost complete reliance on local and national capabilities. Although there are good reasons to state that capabilities are locally sticky and hard to copy by other regions (Markusen 1996), it might not be excluded either. In reality, regions are not self-contained entities: they interact with other regions. Capabilities may spillover to other regions and trigger diversification through inter-regional trade (Boschma and Iammarino 2009) and labour mobility of star scientists, key engineers and top managers who embody scientific, technical and managerial competences (Ottaviani and Peri 2006; Saxenian 2006; Trippel 2013). There is increasing evidence that non-regional linkages are indeed key to avoid lock-in in regions (Asheim and Isaksen 2002; Moodysson 2008; Dahl Fitjar and Rodríguez-Pose 2011).

Having said that, we also expect the spread of capabilities to be heavily constrained by geographical distance. As shown first by Jaffe et al. (1993), and later confirmed by other studies (e.g. Anselin et al. 1997; Varga 2000), geography imposes severe barriers to the diffusion of knowledge. Therefore, knowledge spillovers occur more likely within regions, and between regions that are geographically close, than between regions that are geographically far. Bahar et al. (2014) have explored how this rapid geographical decay of (tacit) knowledge diffusion is reflected in patterns of comparative advantage of countries. Contrary to traditional accounts in trade theory that claim that a higher intensity of trade at shorter distances would lead neighbouring countries to specialize in different rather than similar industries, Bahar et al. (2014) expect that neighbouring countries develop similar specializations instead, because of significant obstacles to knowledge diffusion across large distances. Their study found that export portfolio's of neighbouring countries look indeed more similar, even after controlling for similarity in other dimensions than geographical proximity, like factor endowments, cultural factors and demand structures. Moreover, their study showed that a country had a higher probability to develop a comparative advantage in an industry if a neighbour country had a comparative advantage in that same industry before.

The regional diversification literature has not yet paid attention to the possible effect of spillovers from neighbour regions on diversification. There exists no paper that has systematically analysed the effect of neighbours on the probability of regions to develop a comparative advantage in an industry. Such a study on regional diversification at the sub-national level would also allow us to control for country specific effects, such as language, currency or law. Moreover, Bahar et al. (2014) could not exclude the possibility that their findings were driven by factors other than knowledge diffusion, such as social interaction. Head et al. (2015) show that professional ties facilitate the diffusion of knowledge and highlight that these professional ties are geographically biased. In the context of trade, Millimet and Osang (2007) show that the level of bilateral migration is correlated with the amount of trade between US states. Combes et al. (2005) and Garmendia et al. (2012) found that both social and business connectivity facilitated trade between French and Spanish regions respectively. In this paper, we test whether social connectivity, as proxied by bilateral migration, is correlated with export similarity between regions.<sup>1</sup>

In sum, this paper focuses on two research questions. The first concerns the question whether a region has a higher probability of developing a new industry when a neighbour region is specialized in that industry, and when the region is well endowed with local capabilities that are related to that industry. We analyse the development of new industries in US states during

<sup>1</sup> As explained by Rauch (2001), migrants facilitate bilateral trade and investment because they reduce the information barriers between the host and the home country.

the period 2000–2012. New industries are defined as those in which the US state had a low trade specialization at the beginning of the period of analysis and develops a strong trade specialization at the end of the period of analysis. The second question addresses whether export structures between neighbour regions in the US show a higher degree of similarity, and whether the degree of social connectivity between regions is correlated with export similarity between regions.

### 3 Neighbour states and the development of new industries in US regions

To determine whether the specialization of a US state in an industry facilitates that a neighbour region also specializes in the same industry, following Bahar et al. (2014), we estimate the following regression equation:

$$N_{s,i,t+5} = \alpha + \beta_1 \ln(RCA_{ns,i,t}) + \beta_2 RCA_{s,i,t} + \beta_3 d_{s,i,t} + \mu_{i,t} + \mu_{s,ns,t} + \varepsilon_{s,i,t}, \quad (1)$$

where  $N_{s,i,t+5}$  takes the value of 1 if US state  $s$  develops a new industry  $i$  between year  $t$  and year  $t+5$  and zero otherwise. We consider that a new industry  $i$  is developed if US state  $s$  had a revealed comparative advantage (RCA) below 0.5 at the beginning of the period ( $t$ ), and a RCA higher than 1 after 5 years ( $t+5$ ).<sup>2</sup> Following Balassa (1965), RCA is determined dividing the share of an industry in a US state exports by the share of that industry in world exports. A RCA higher than 1 denotes that the US state is specialized in that industry. The industries in which state  $s$  had a RCA equal or above 1 at  $t$  are excluded from the sample.

Our variable of interest is  $\ln(RCA_{ns,i,t})$ , the natural logarithm of the RCA of the neighbour state with the highest RCA in industry  $i$ .<sup>3</sup> The RCA of the neighbour state with the highest RCA enters in logarithms to attenuate the bias that might be generated by some extremely large RCA indexes.<sup>4</sup> We expect the coefficient  $\beta_1$  to be positive. It is important to point out that the RCA of the neighbour captures the net effect that the neighbour has on the probability of developing a new industry. The main argument of our paper is that neighbouring regions contribute to the development of new industries in which they are specialized through spillover effects. However, regions might also hinder the development of industries in which they are specialized in neighbour regions due to competition effects.  $RCA_{s,i,t}$  is the comparative advantage of state  $s$  in industry  $i$  at the beginning of the period. As this variable is constrained between zero and 0.5, it does not need to be transformed into natural logarithms; besides, using the absolute RCA value allows to include the industries with a RCA equal to zero at  $t$  in the sample.

The variable  $d_{s,i,t}$  denotes the density around industry  $i$  at the beginning of the period. Density measures to what extent a US state has the capabilities to develop the new industry  $i$ . A state will have a larger probability to possess those capabilities if the new industry is close to the industries in which the state is specialized; this closeness is measured by the proximity index developed by Hidalgo et al. (2007). Boschma et al. (2013) show that regions will have a larger probability to develop a new industry if their productive structure is close to this new industry. Algebraically, density is obtained through the following expression:

<sup>2</sup> We performed the empirical analyses for three alternative thresholds for the beginning of the period RCA index: below 1, equal or below 0.2, and equal and below 0.1. As explained in the robustness section, the estimations are robust to the alternative thresholds.

<sup>3</sup> Neighbour states are defined as states sharing both a section of the border or a point of the border.

<sup>4</sup> We also transform the RCA variable into a revealed symmetric comparative advantage (RSCA) variable (Laursen 2015). The RSCA is defined as  $(RCA-1)/(RCA+1)$  and has a  $[-1,1]$  range. Our results are robust to this transformation.

$$d_{S,i,t} = \frac{\sum_j \phi_{i,j,t} x_{s,j,t}}{\sum_j \phi_{i,j,t}}, \quad (2)$$

where  $x_{s,j,t}$  takes the value of 1 if state  $s$  has a comparative advantage in product  $j$  at time  $t$  and zero otherwise, and  $\phi_{i,j,t}$  is the proximity index between products  $i$  and  $j$  at time  $t$  calculated as:

$$\phi_{i,j,t} = \min\{P(RCAx_{i,t}|RCAx_{j,t}), P(RCAx_{j,t}|RCAx_{i,t})\}, \quad (3)$$

where  $P(RCAx_{i,t}|RCAx_{j,t})$  is the conditional probability of having a comparative advantage in product  $i$ , given that the US state has a comparative advantage in product  $j$ , and  $P(RCAx_{j,t}|RCAx_{i,t})$  is the conditional probability of having a comparative advantage in product  $j$ , given that the US state has a comparative advantage in product  $i$ . If a US state has a comparative advantage in all goods related to product  $i$ , density will take the value of one. However if US state  $s$  does not have a comparative advantage in any of the products related to product  $i$ , density will take the value of zero. Finally, we control for year-specific industry fixed effects ( $\mu_{i,t}$ ) and year-specific US state + neighbour US state fixed effects ( $\mu_{s,ns,t}$ );  $\alpha$  is a constant and  $\varepsilon_{s,i,t}$  is the random error term.

The model is estimated with a linear probability model. An advantage of this model is that it can handle the large number of fixed effects of our regression equation.<sup>5</sup> In particular, we use the `reg2hdfc` Stata command developed by Guimarães and Portugal (2010). However, the limitation of the linear probability model is that the effect of independent variables on the dependent variable is constant. In addition to that, the linear probability model can yield predicted probabilities below zero and above one. Moreover, the linear probability model is inherently heteroscedastic. In order to control for heteroscedasticity, we estimate the model with clustered standard errors at the state + neighbour state level. An alternative to the linear probability model is the system-GMM model, which addresses the endogeneity problems that might exist in our sample. However, as we only had two time periods, we cannot estimate this model.

To calculate US states RCA and density, we combine data on US state-level exports from the US Census Bureau Database and world exports from the Comtrade database. Our data uses the Harmonized System 4-digit disaggregation, which distinguishes 1,268 products (industries). We exclude from the sample the US states that do not have neighbour US states: Alaska and Hawaii. Figure 1 presents the histogram of the average number of new industries that emerge in a US state in a 5 year window. The histogram follows a normal distribution. Figure 2 shows the average number of new industries developed every 5 years in US states. A darker shade implies a higher number of new industries. On average, a US state develops 36 new industries every 5 years, with a standard deviation of 11. The unconditional probability to develop a new industry is 3.8 per cent. The states that add more industries per period are Colorado and Virginia, and the states that add a fewer number of industries are Louisiana and West Virginia. While there is not a clear pattern of spatial concentration, the regional divisions that develop a higher number of new industries are New England (40) and South Atlantic (39), while the regional divisions which develop a lower number of new industries are the Pacific (25) and West South Central (29). Regarding new industries, most of them belong to chemicals (section VI of the Harmonized Classification), machinery and electrical (section XVI), and metals (section XV). In particular, within chemicals, the industries that appear as new a higher number of times are inorganic chemicals (code 28), organic chemicals (code 29) and miscellaneous chemicals products (code 38); within machinery and electrical, nuclear reactors, boiler, machinery and

<sup>5</sup> Probit and logit models, due to the incidental parameters problem, can lead to biased and inconsistent estimates in the presence of a large number of fixed effects (Greene 2008).

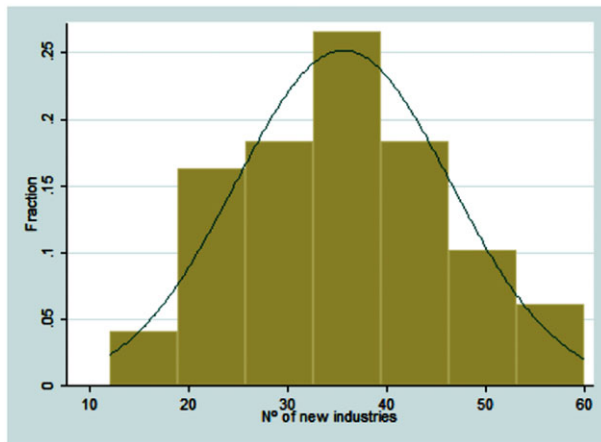


Fig. 1. Number of new industries that emerge in a US state during a 5 year window

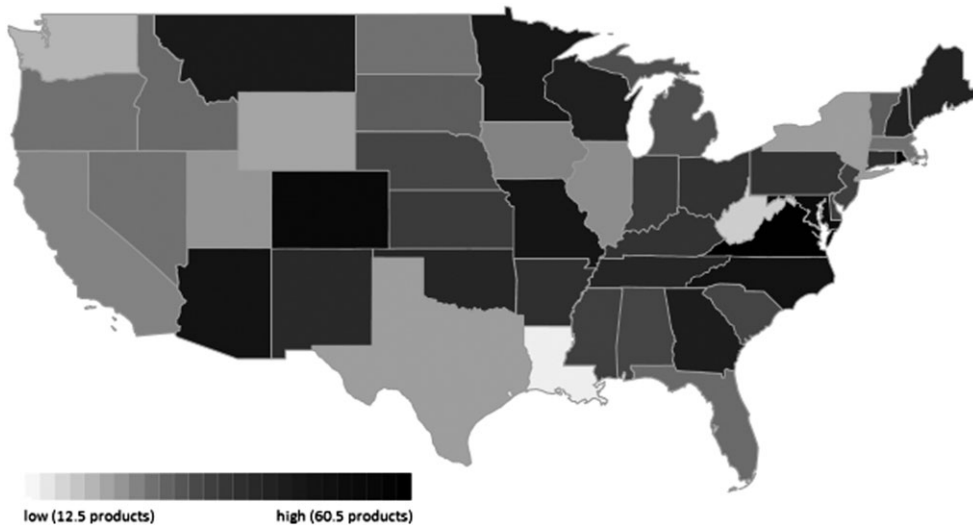


Fig. 2. Average number of jumps in a 5-year interval, 2002–2012

chemical appliances (code 84), and electrical machinery and equipment (code 85); within metals, iron and steel (codes 72 and 73) and aluminum (code 76).

Table 1 presents the results of our baseline regressions. In columns 1 and 2 the dependent variable is whether US state *s* develops a new industry *i* between year *t* and year *t* + 5. As expected, we find that the RCA index of the neighbour state with the highest RCA coefficient is positive and statistically significant. This result shows that the probability of developing a new industry in a US state is positively correlated with the specialization of a neighbour state in that industry. To measure the economic significance of this latter figure, we have to compare it with the unconditional probability of developing a new industry: 3.8 per cent. A standard deviation increase in the (log) RCA of the neighbour leads to a 21 per cent increase in the probability of developing a new industry ( $[2 \times 0.004]/0.038$ ). The initial RCA of a state in industry *i* is also positively correlated with the development of a new industry. The density coefficient is also positive and statistically significant, confirming that having a trade specialization in industries that are close to the new industry facilitates the development of this new industry. In fact, a

**Table 1.** Development of new industries. Baseline regressions

Dependent variable	Jump	Jump	RCA growth	RCA growth
Initial RCA	<.5 (1)	<.5 (2)	<1 (3)	<1 (4)
RCA index neighbour(log)	0.004*** (0.000)	See Figure 3	0.006*** (0.001)	See Figure 4
RCA	0.252*** (0.010)	0.251*** (0.010)	-0.210*** (0.005)	-0.211*** (0.005)
Density	0.373*** (0.131)	0.358*** (0.133)	1.153*** (0.086)	1.132*** (0.088)
N	83,598	83,598	93,867	93,867
r <sup>2</sup>	0.091	0.091	0.130	0.130

*Notes:* All independent variables are measured at the beginning of the period. The sample pools 5-year interval observations for the period 2002–2012. All regressions include year-specific state + neighbour state fixed effects and year-specific industry fixed effects. Standard errors clustered at the state + neighbour level in parentheses. \*\*\* statistically significant at 1%.

standard deviation increase in density leads to a 59 per cent increase in the probability of developing a new industry ( $[0.06 \times 0.373]/0.038$ ). Hence, the effect of density on the probability of developing a new industry is almost three times larger than the effect of the neighbour with the highest RCA index.

In column (1), we assume that there is a log-linear relationship between the neighbour state RCA index and the probability of developing a new industry. However, it might be the case that a state should have a minimum RCA level to exert an influence on neighbour states. It might be also the case that once a state reaches an RCA level, further increases in the RCA level do not increase knowledge spillovers. To capture these effects, we define five intervals for the neighbour state RCA index: 0–0.5; 0.5–1; 1–2; 2–4; and more than 4. Except for the last, differences between intervals are constant in relative terms. To visualize the relationship between neighbour RCA index and the probability to develop a new industry, we draw a step function with the estimated coefficients for every interval.<sup>6</sup> If there was a linear relationship between the probability of developing a new industry and the neighbour state RCA index, the height of the steps should be the same. As shown in Figure 3, this is not the case. There is a similar increase in the probability of developing a new industry when the RCA of the neighbour increases from the 0–0.5 range to the 0.5–1 range, and when it increases from the 0.5–1 range to the 1–2 range. However, the probability of developing a new industry increases more than proportionally when the RCA index of the neighbour rises to the 2–4 range, and even more when the RCA index is larger than 4. This result points out that the probability to develop a new industry increases when the neighbour has achieved a high degree of specialization (more than four times the average trade specialization) in the industry. For example, moving from a neighbour in the 0–0.5 RCA index interval to a neighbour in the = 4 > RCA index interval would increase the probability of developing a new industry, over the unconditional probability, by 58 per cent (0.022/0.038). Estimates for additional intervals, not reported in the figure, suggest that the influence of the neighbour does not increase further when RCA indexes are higher than 4.

In columns 3 and 4, we substitute the dependent variable in Equation 1 with the annual average growth rate in industry  $i$  RCA index. The sample for this analysis is composed by all industries whose initial RCA index was below 1 at the beginning of

<sup>6</sup> Intervals enter the regression equation as dummies. The omitted category is the 0–0.5 interval.



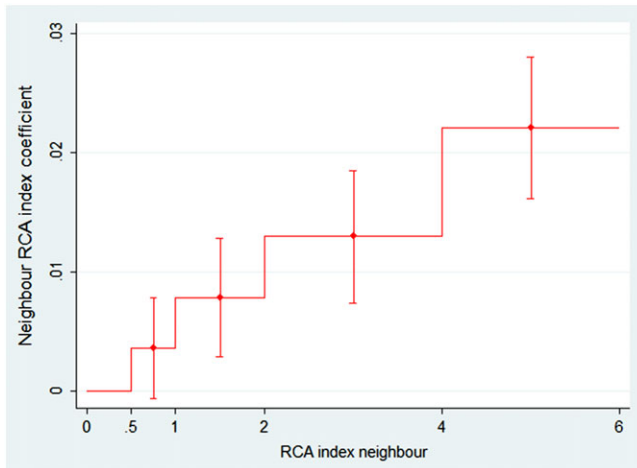


Fig. 3. Step function for neighbour RCA index and the probability of developing a new industry

the period. Our expectation is that the larger the neighbour state industry  $i$  RCA index the larger the growth in industry  $i$  RCA index. The neighbour RCA index coefficient in column 3 is positive and statistically significant, confirming the expectation. According to this coefficient, a standard deviation increase in the neighbour (ln) RCA index would lead to a 1.2 percentage point increase in the average annual RCA index growth. Note that now the (initial) RCA index is negative; this result is sensible, as percentage increases are easier to achieve if the initial RCA level is lower. The density coefficient remains positive and statistically significant, and its value increases substantially. In column (4), we perform estimations for different levels of neighbour state RCA indexes. As shown in Figure 4, the height between steps is similar. This points out that there is an almost log-linear relationship between increases in the neighbour state RCA index and the average annual growth rate in the RCA index.

It is interesting to compare our results with the country-level estimations in Bahar et al. (2014). They use a sample of 123 countries for the year 2000. Their neighbour RCA

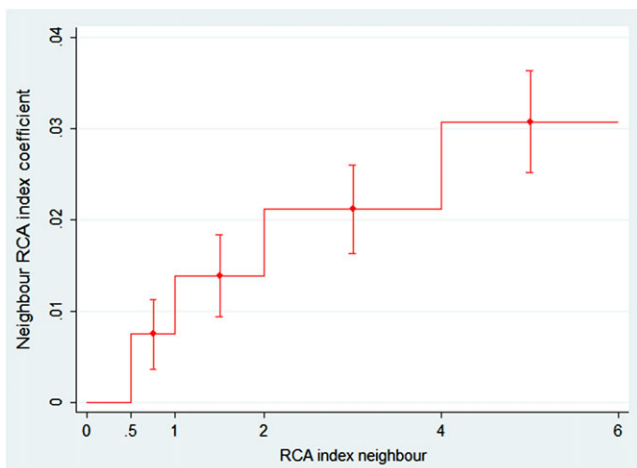


Fig. 4. Step function for neighbour RCA index and the average annual growth rate in the RCA index

**Table 2.** Development of new industries. Robustness analyses

Analysis	Persistence	Alternative definition new industry	Random neighbours	Random neighbours	10-year interval	10-year interval
Dependent variable	Jump (1)	Jump (2)	Jump (3)	RCA growth (4)	Jump (5)	RCA growth (6)
RCA index neighbour (log)	0.003*** (0.000)	0.003*** (0.000)	-0.007*** (0.003)	-0.015*** (0.003)	0.005*** (0.001)	0.005*** (0.001)
RCA	0.203*** (0.009)	0.260*** (0.021)	0.253*** (0.010)	-0.212*** (0.004)	0.268*** (0.011)	-0.283*** (0.007)
Density	0.296*** (0.106)	0.225* (0.127)	0.287*** (0.106)	1.094*** (0.075)	1.025*** (0.158)	2.265*** (0.183)
N	81,028	69,294	90,373	100,776	42,015	47,190
r <sup>2</sup>	0.083	0.079	0.133	0.160	0.107	0.150

*Notes:* All independent variables are measured at the beginning of the period. Except for columns (5) and (6), the sample pools 5-year interval observations for the period 2002–2012. All regressions include year-specific state + neighbour state fixed effects and year-specific industry fixed effects. Standard errors clustered at the state + neighbour level in parentheses. \*\*\* and \* statistically significant at 1% and 10%.

coefficient is equal to ours: 0.004. This result is surprising, because we expected a higher neighbour RCA coefficient in the regional sample than in the country sample, as barriers to knowledge flows ought to be lower between regions than between countries. We also find that the density coefficient in our estimation (0.373) is three times higher than in their estimation (0.130; Table 8 – Panel A, Specification 1). These differences are in line with Boschma et al. (2013), that concludes that the productive structure has a much larger influence on the development of new industries at the regional level than at the national level.

In order to test the robustness of our results, we perform some additional estimations. First, we only consider as jumps those industries that keep, at least, a comparative advantage one year after the jump.<sup>7</sup> As shown in Table 2 (column 1), the neighbour state RCA index coefficient drops to 0.003, but remains statistically significant. Second, we use an alternative definition for new industry. Now, a US state develops a new industry if at the beginning of the period the RCA index was equal or below 0.2 and at the end of the period it was higher than 1. The coefficient drops from 0.004 (Table 1, column 1) to 0.003 (Table 2, column 2), but remains statistically significant.<sup>8</sup> Third, we test whether the positive correlation between the neighbour RCA index and the development of new industries occurs by chance. To test this hypothesis, following Bahar et al. (2014), we pick each state's neighbours randomly. The sole condition is that the number of neighbours picked at random should be the same as the actual number of neighbours a US state has. We generate random neighbours 500 times, and each time we select the RCA index of the random neighbour with the highest RCA index. Then, we average the RCA indexes selected in each of the 500 iterations and introduce that value into the regression.<sup>9</sup> As shown in Table 2, columns (3) and (4), the neighbour RCA coefficients are negative and statistically significant. These results confirm that the positive

<sup>7</sup> We use the year 2008 for the first interval and 2013 for the second interval.

<sup>8</sup> We also estimate the model with ten-fold jumps. The main conclusions are not altered.

<sup>9</sup> In these estimations the year-specific state + neighbour state fixed effects are also chosen at random.

**Table 3.** Development of new industries. Total RCA and number of neighbours

Dependent variable	Jump (1)	Jump (2)	Jump (3)	Jump (4)	Growth (5)	Growth (6)	Growth (7)	Growth (8)
RCA sum neighbour (log)	0.004*** (0.000)	0.004*** (0.000)			0.007*** (0.001)	0.006*** (0.001)		
N° of neighbours		0.000 (0.001)				-0.001 (0.001)		
RCA >1 sum neighbour (log)			0.006*** (0.002)	0.002 (0.002)			0.008*** (0.002)	0.003* (0.002)
N° of neighbors with RCA>1				0.011*** (0.003)				0.011*** (0.002)
RCA	0.252*** (0.013)	0.242*** (0.015)	0.312*** (0.021)	0.308*** (0.021)	-0.210*** (0.006)	-0.201*** (0.007)	-0.186*** (0.007)	-0.189*** (0.007)
Density	0.351** (0.154)	0.008 (0.026)	0.033 (0.220)	-0.007 (0.222)	1.150*** (0.114)	0.256*** (0.030)	0.850*** (0.158)	0.815*** (0.159)
N	83,598	83,598	23,154	23,154	93,867	93,867	28,592	28,592
r2	0.087	0.081	0.143	0.143	0.126	0.117	0.167	0.168

*Notes:* All independent variables are measured at the beginning of the period. The sample pools 5-year interval observations for the period 2002–2012. Regressions (1), (3), (4), (5), (7) and (8) include year specific state and product fixed effects. Regressions (2) and (7) include year-specific product fixed effects. Standard errors clustered at the state level in parentheses. \*\*\*, \*\*, \* statistically significant at 1%, 5% and 10% respectively.

correlation between neighbours RCA and the development of new industries is not the result of a random event.<sup>10</sup> Fourth, we analyse whether results are robust to using a 10-year interval instead of a 5-year interval. As shown in columns (5) and (6), the neighbour RCA index coefficient remains positive and statistically significant.

In the baseline and robustness analyses, we only assess the contribution of the neighbour with the highest RCA to the development of new industries. We also explored whether the differences in the number of neighbours and their combined RCA also influences the probability of developing a new industry. First, we analyse whether the total RCA of the neighbours influences the probability of developing a new industry. To estimate this equation, we remove the year-specific US state + neighbour US fixed effects and substitute them by year-specific US state fixed effects. Table 3 (column 1) shows that the coefficient for total neighbour RCA is positive and statistically significant, and its value is the same as in the baseline regression (Table 1, column 1). In column 2, we introduce the number of neighbours. To estimate this regression, we remove the year-specific state fixed effects because they are perfectly collinear with the number of neighbours. We find that the number of neighbours has no effect on the combined RCA coefficient, suggesting that it is the total RCA of neighbour regions, and not the number of neighbours, which determines the probability of developing a new industry. Note that when we remove the year-specific state level fixed effects, the density coefficient becomes not significant. This result suggests that it is the differences in density within the state, rather than the absolute levels of density, which drives the development of new industries. In Column (3), we introduce the total RCA of the neighbours that have, at least, an RCA equal or higher than one. Note that this condition reduces severely the number of observations in the sample. We find that the combined RCA coefficient, 0.006, is higher than in column (1), confirming, as we saw in Figure 3, that the influence of neighbours will be higher if they have a comparative advantage in the product. Note that the density coefficient, although positive, is statistically not significant. This result

<sup>10</sup> Alternatively, we also ran a different regression for each of the 500 random draw of neighbours. In none of these regressions the coefficient for the neighbour with the highest RCA was positive and statistically significant.

might suggest that if the RCA of the neighbours in a product is high enough, it might overcome the limitations of the local industrial structure. However, we should be careful with this interpretation because the truncation of the database might lead to biased results, as we only keep those industries in which neighbour regions are specialized. In column (4), we introduce the number of neighbours with a RCA equal or higher than 1. Note that in this estimation, we can keep the year-specific state fixed-effects, because the number of neighbours with RCA equal or higher than one varies across products. Remarkably, the combined RCA coefficient becomes statistically not significant and the number of neighbours is positive and statistically significant. According to this result, it is the number of neighbours with comparative advantage in the product, rather than the total RCA of the neighbours with a comparative advantage, which determines the probability of developing a new industry. This result might be explained by the fact that effect of the RCA seems to reach a plateau once the RCA is higher than four (see Figure 3); as 99 per cent of US states have four or less neighbours with a comparative advantage in an industry, the probability of developing an industry might be more correlated with the number of neighbours with RCA equal or higher than 1 than the combined RCA of the neighbours with a comparative advantage.

Columns (4) to (8) re-estimate the regression equations using the growth rate of the RCA of the industries with an RCA below 1 as dependent variable. Similar to the jump analyses (columns 1 to 4), the combined total RCA is positive and statistically significant in columns (5), (6) and (7). The coefficient for the number of neighbours with a comparative advantage is also positive and statistically significant in Column (8). However, in the growth estimation, the total combined RCA is also positive and statistically significant, although by a small margin. It is interesting to see that in the growth estimations, density is always positive and statistically significant. This result points out that US states increase their specialization in industries that use their current capabilities.

The dynamic analyses conclude that there is a positive correlation between developing a new industry and the trade specialization of neighbour regions in the same industry. In the next section, we adopt a static view and analyse whether neighbour regions have also more similar export patterns.

#### 4 Similarities in export structures between neighbour US states

If knowledge diffuses at short distances, adjacent regions should share more knowledge. Hence, we would expect adjacent regions to have a more similar export pattern than non-adjacent regions. To test this hypothesis, following Bahar et al. (2014), we calculate the following export similarity index:

$$S_{S,S'} = \frac{\sum_i (r_{S,i} - \bar{r}_S) (r_{S',i} - \bar{r}_{S'})}{\sqrt{\sum_i (r_{S,i} - \bar{r})^2 \sum_i (r_{S',i} - \bar{r}_{S'})^2}}. \quad (4)$$

This export similarity index is based on the Pearson correlation coefficient, where  $r_{S,i}$  is the log of the RCA of state  $s$  in industry  $i$  and  $\bar{r}_S$  is the average of  $r_{S,i}$  over all industries in state  $s$ .<sup>11</sup> This index will take positive values if US state  $s$  and US state  $s'$  are specialized in similar industries, and negative values if they are specialized in different industries.

<sup>11</sup> More specifically,  $r_{S,i}$  is the log of the RCA + 0.1. The RCA enters in logs because very large RCA indexes might bias the covariance index. The 0.1 fraction is added to include in the analysis the industries whose RCA index is zero.

**Table 4.** Summary statistics for variables used in the similarity analysis (average years 2002 and 2007)

Variable	Mean	Standard deviation
Similarity index	0.198	0.098
Distance (km.)	1,966.8	1,137.5
Neighbor	0.093	0.290
Total bilateral trade (Ln)	6.590	3.151
Dif. GDP per capita (Ln)	0.233	0.286
Dif. Physical capital per worker (Ln)	1.409	1.241
Dif. Human capital per worker (Ln)	1.633	0.038
Dif. Land per worker (Ln)	0.052	1.339
Total bilateral migration	506,907	98,223

Source: See text.

To test whether US states that are geographically closer have more similar export structures, we estimate the following regression equation:

$$S_{s,s',t} = \alpha + \beta \ln dist_{s,s'} + \gamma n_{s,s'} + \delta'X + \mu_{s,t} + \mu_{s',t} + \varepsilon_{s,s',t}, \quad (5)$$

where  $S_{s,s',t}$  is the export similarity between US state  $s$  and US state  $s'$  at time  $t$ ,  $\alpha$  is a constant,  $dist_{s,s'}$  is the distance between state  $s$  and state  $s'$ ,  $n_{s,s'}$  is a dummy variable that takes the value of 1 if state  $s$  is adjacent to state  $s'$  and zero otherwise,  $X$  is a vector of controls,  $\mu_{s,t}$  is a year-specific  $s$  state fixed effect,  $\mu_{s',t}$  is a year-specific  $s'$  state fixed effect, and  $\varepsilon_{s,s',t}$  is the random error. Controls vector  $X$  includes differences between US states in GDP *per capita*, physical capital per worker, human capital per worker and land per worker; it also includes the bilateral trade between US states and the accumulated 5-year bilateral migration between US states. As mentioned before, previous studies have shown that the diffusion of knowledge is deterred by geographical distance (Jaffe et al. 1993). Hence, we expect the similarity between export structures to be negatively correlated with distance. Boschma and Frenken (2011), and Neffke et al. (2011) also point out that diversification drivers, such as spin-offs, workers mobility or entrepreneurship, are geographically biased. According to the classical international trade theories, countries or regions specialize in products in which they are relatively productive, or in products that use its abundant factors intensively. Therefore, we expect differences in factors endowments and productivity, proxied by GDP *per capita*, to have a negative impact on the similarity of export structures across states. Finally, the literature has highlighted that networks also facilitate the diffusion of knowledge (Rauch 2001). Hence, we expect more socially linked regions to have higher export similarity. Following previous studies, we proxy the degree of social connectivity with the level of bilateral migration between regions (Combes et al. 2005; Millimet and Osang 2007).

Distance between US states is calculated as the driving distance between the two main cities of each US state. We calculate these distances using the Microsoft Mapoint 2012 (Microsoft, Redmond, WA) and CDXZipStream (CDX Technologies, Randolph, NJ) software. Data for GDP *per capita*, relative factor endowments and bilateral trade come from the US Census Bureau. Data on bilateral migration is obtained from the US Internal Revenue Service (<http://www.irs.gov>). Table 4 presents summary statistics of these variables.

Figure 5 compares the density function of export similarities between non-neighbour US states with the density function of export similarities between neighbour states. Clearly, the density function for neighbour states is to the right of the density function of non-neighbour states, pointing out that neighbour states have, on average, a higher similarity in the export structure than non-neighbour states. To confirm this hypothesis, we estimate Equation 3 pooling data for the years 2002 and 2007. Table 5 presents the results of the estimations.

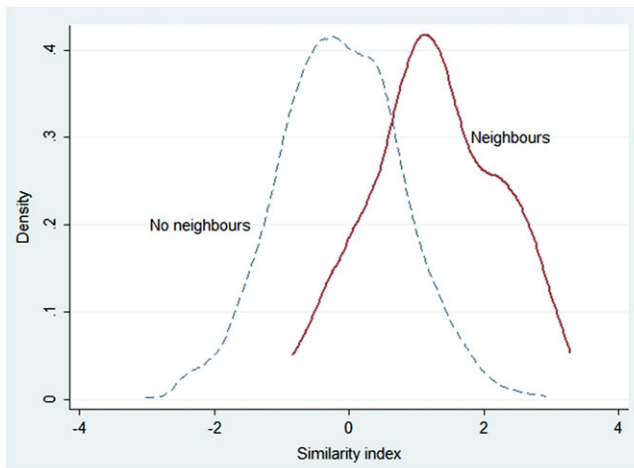


Fig. 5. Similarities density functions: non-neighbours vs. neighbours

To facilitate the reading of the results, we normalize the export similarity index, with mean zero and unit standard deviation. In column (1), we estimate the regression only with distance and the fixed effects as independent variables. As expected, the distance coefficient is negative and statistically significant, confirming a negative correlation between distance and similarity in export structures. In particular, a standard deviation increase in the (log) of distance leads to 0.84 standard deviations reduction in the export similarity index ( $1.1 \times 0.763$ ).

In column (1), we assume that there is a log-linear relationship between the export similarity index and distance. To test the validity of this hypothesis, we divide the distance into intervals. We define six intervals, starting from 0–100 km., 100–200 200–400, 400–800, 800–1600, and more than 1600.<sup>12</sup> The distance doubles between an interval and the next, so the increase in distance is constant in relative terms. Figure 6 presents a step figure showing the change of the distance coefficient for each distance interval (0–100 is the omitted interval). We can see that the coefficients for the 100–200 interval and for the 200–400 interval have the zero value within their  $\pm 5\%$  confidence interval. From the 400–800 interval onwards, the negative value of the distance coefficient increases at a relatively constant proportion. The figure points out that up to 400 km., distance seems to exert a mild negative effect on export similarity. After that interval, the negative effect rises proportionally with distance. Due to this non-linear relationship between distance and similarity, in the rest of estimations, distance is introduced in intervals in the regression.

In column (3), we introduce the neighbour state dummy variable in the regression. The coefficient is very large and statistically significant: the export similarity between neighbour states is around 0.4 standard deviations higher than the export similarity between non-neighbour states. This large coefficient is striking providing that the regression already controls for the lower distance between neighbour states. In column (4), we introduce the number of commuting zones that are shared between neighbour states.<sup>13</sup> Our expectation is that the number of shared commuting zones is positively correlated with the similarity in the export structure between states. Shared commuting zones allow a higher interaction between professionals of neighbour

<sup>12</sup> The maximum distance in our database is 4,924 kilometres.

<sup>13</sup> These data were obtained from United States Department of Agriculture Economic Research Service, <http://www.ers.usda.gov/data-products/commuting-zones-and-labor-market-areas.aspx>. In the year 2000 there were 3,141 commuting zones in the US, of which only 3.6 per cent were shared between states.

**Table 5.** Export similarity

Similarity indicator	Pearson (1)	Pearson (2)	Pearson (3)	Pearson (4)	Pearson (5)	Pearson (6)	Finger-Kreinin (7)
Distance (log)	-0.763*** (0.036)	See Figure 6	Interval	Interval	Interval	Interval	Interval
Neighbor			0.434*** (0.099)	0.304*** (0.109)	0.194** (0.097)	-0.093 (0.101)	0.064 (0.089)
N° of shared commuting zones				0.139** (0.058)	0.199*** (0.059)	0.085 (0.061)	0.038 (0.042)
GDPpc (diff)					-0.367** (0.164)	-0.356** (0.158)	-0.278* (0.151)
Physical capital per worker (diff)					-0.391*** (0.055)	-0.402*** (0.052)	-0.189*** (0.051)
Human capital per worker (diff)					-3.154*** (0.613)	-2.438*** (0.588)	0.157 (0.463)
Land per worker (diff)					-0.175*** (0.025)	-0.085*** (0.025)	-0.073*** (0.023)
COM					0.016** (0.007)	-0.010 (0.007)	-0.016** (0.008)
Bilateral migration (log)						0.456*** (0.045)	0.191*** (0.040)
N	2,352	2,352	2,352	2,352	2,352	2,352	2,352
r2	0.612	0.626	0.634	0.636	0.681	0.709	0.736

Notes: The sample pools year 2002 and year 2007 observations. All regressions include year-specific state fixed effects. Standard errors clustered at the state-pair level in parentheses. \*\*\*, \*\*, \* statistically significant at 1%, 5% and 10% respectively.

states, which raises the probability that neighbour regions will have access to similar capabilities and, hence, be able to specialize in similar goods. As expected, the coefficient for the number of commuting zones is positive and statistically significant, confirming that the higher the number of shared commuting zones, the higher the similarity in export structures. We can see, as well, that there is a drop in the value of the neighbour coefficient, pointing out that this coefficient was capturing the effect of the number of shared commuting zones.

In column (5), we introduce additional controls that might explain why neighbour regions have a higher export similarity. These include controls on relative factor endowments: human capital, capital per worker and land per worker, differences in income *per capita* levels, and the amount of bilateral trade between US states. The coefficients reported in Table 5 (column 5) are in line with the theoretical expectations: differences in income *per capita* and in factor endowments are negatively correlated with export similarity. Classical theories of trade also predict that regions should trade more with more dissimilar regions in terms of export structure. In contrast to this expectation, we get a positive coefficient for the amount of bilateral trade. This result might point out that other factors, such as the existence of economies of scale and love for variety might characterize the pattern of trade between US states (Helpman and Krugman 1985), or that production processes within an industry are fragmented across US states (Hillberry and Hummels 2008). The introduction of the new control variables reduces substantially the value of the neighbour state coefficient, declining from 0.304 (column 4) to 0.194 (column 5) (36% reduction). In contrast, the coefficient for shared commuting zones rises from 0.139 to 0.199 (43% increase): once we control for differences in productivity and factor endowments, sharing a commuting zones has a larger positive effect on export similarity.

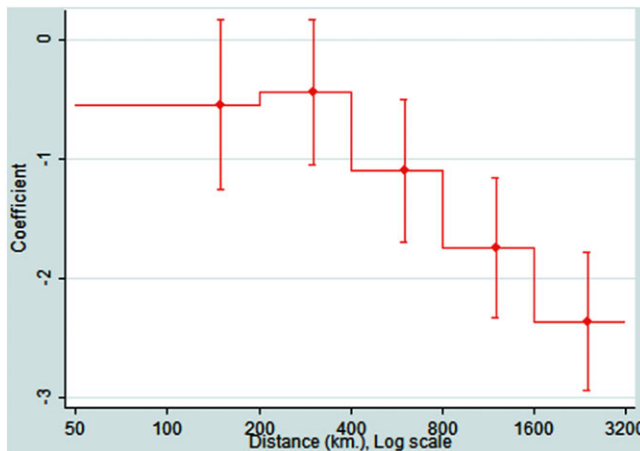


Fig. 6. Step function for the distance coefficient in export similarity

We also compared our results on the similarities between US states exports with those obtained by Bahar et al. (2014) on the similarities between country exports. When they introduce all the control variables, the distance coefficient is  $-0.316$  and the adjacent-country coefficient is  $0.650$  (Table 3, specification 3). Our equivalent (log) distance coefficient is  $-0.475$ , and our adjacent-state coefficient is  $0.414$ . These coefficients are obtained running our specification (3), and using distances (in logs) instead of distance intervals. The differences in the distance coefficient might be explained by the fact that we use driving distances whereas Bahar et al. (2014) use great circle distances. In fact, if we use great circle distances between US states centroids, our distance coefficient drops to  $-0.199$  and our neighbour coefficient rises to  $0.662$ , a result very similar to that found by Bahar et al. (2014). This result points out that additional forces that might explain the geographical bias of knowledge transfer seem to have similar effects within countries and across countries.

As discussed in Section 2, this may be due to social connectivity (Millimet and Osang 2007; Garmendia et al. 2012). To test whether social connectivity is correlated with export similarity between regions, we introduce the level of bilateral migration between US states in the regression. As explained before, this data is obtained from the US Internal Revenue Service (IRS). The IRS determines whether a tax payer has migrated to another state comparing her address in tax-year  $t$  and tax-year  $t + 1$ . The level of bilateral migration is calculated as the accumulated migration flows in the five years previous to the analysis. So, for the year 2002, we use the accumulated figure for the period 1997–2001, and for the year 2007 analysis, we use the accumulated figure for the period 2002–2006. As shown in Table 4 (column 6), the coefficient for bilateral migration is positive and statistically significant, as expected. This result confirms that social connectivity is correlated positively with export similarity. The remarkable result is that when we control for bilateral migration, the neighbour coefficient and the number of shared commuting zones coefficient become statistically not significant. As bilateral migrations are larger between bordering US states, if we do not control for this variable, the border dummy and the number of shared commuting zones capture the positive effect that migration has on knowledge spillovers and on export similarity. Although it is not reported in the paper, all the distance interval coefficients become statistically not significant as well. This latter result points out that the negative effect of distance on export similarity is explained by the influence this variable has on bilateral migration.



To test the robustness of our result, in column (7), we use an alternative index to measure similarity between export structures, the Finger and Kreinin index (Finger and Kreinin 1979). This index is defined as follows:

$$FKS_{s,s'} = \sum_i \min \left( \left[ \frac{x_{s,i}}{\sum_i x_{s,i}} \right], \left[ \frac{x_{s',i}}{\sum_i x_{s',i}} \right] \right). \quad (6)$$

The Finger and Kreinin similarity index (FKS) is the sum of the minimums of each industry  $i$  export share for a pair of US states ( $s, s'$ ). The index takes the maximum value of 1 when the distribution of exports across industries is the same in state  $s$  and  $s'$ , and takes the minimum value of zero if there is no overlap in the distribution of exports. As shown in column 7, the use of the Finger-Kreinin index does not alter the main results of previous estimations.

## 5 Conclusions

If knowledge spillovers decay with distance, we expect regions to develop new industries in activities in which their neighbour regions are specialized. We confirm this hypothesis using data for US states during the period 2002–2012. In particular, a US state with a neighbour highly specialized in an industry has a 58 per cent higher probability to develop that industry than another US state with a neighbour poorly specialized in that industry. From a static perspective, we also show that sharing a border with another US states raises the similarity between export structures by 0.43 standard deviations. Our analyses suggest that the similarity in export structures between neighbour regions is positively correlated with higher social connectivity. These findings complement the regional diversification literature that has focused almost entirely on the importance of local capabilities in related industries. Our analyses also replicate this finding: density had a strong and positive effect on developing a new industry in a US state, and this density effect is stronger than the effect of neighbour regions that are specialized in that industry.

As in any study, our study also generates new research challenges. First, we have referred to knowledge spillovers more in general to claim that regions are more likely to develop new industries when their neighbour regions are specialized. This finding is interesting, as well-known studies on the geography of knowledge spillovers in the US (e.g. Jaffe et al. 1993; Anselin et al. 1997; Varga 2000; Crescenzi et al. 2007) have shown that knowledge spillovers tend to occur mainly within US states, and hardly cross US state boundaries. These studies have focused largely on academic knowledge spillovers, based on patent and research collaboration data. As our study works with trade data, we could focus on all industries in the whole economy. In that sense, it would be interesting to analyse more in detail whether the effect of neighbouring regions differs between industries, and between low and high-tech industries in particular.

Our study has not measured knowledge spillovers *per se*, and through which channels (such as observational learning, entrepreneurship, labour mobility, trade patterns, research collaborations, etc.) this spatial diffusion process across neighbouring regions actually takes place. In this study, we looked at the role of social connectivity between regions as a potential channel. The next step is to explore which channels on which geography imposes barriers on knowledge diffusion, can be held responsible for this neighbouring effect, and how they drive regional branching. This would shed light on how network relations more in general shape the diffusion of capabilities across regions, and how these affect diversification opportunities of regions, a topic which has not yet been studied in a systematic way (Crespo et al. 2014). Although neighbouring regions are likely to be more connected, it is a fact that regions are also connected over large geographical distances, especially large urban centres (see e.g., Ponds et al. 2007).

While this role of non-regional linkages is covered in our analytical framework through fixed effects, more explicit attention on their role in the regional branching process is an interesting future research avenue.

Another research challenge is to include the role of institutions which has shown to have an impact on diversification at the national scale (Boschma and Capone 2015). Institutions could be included in our analytical framework both as a local capability variable (next to density, which captures local related capabilities) and as a similarity indicator, capturing the effect of institutional or cultural proximity between regions.

## References

- Anselin L, Varga B, Acs Z (1997) Local geographic spillovers between university research and high technology innovations. *Journal of Urban Economics* 42: 422–448
- Asheim BT, Isaksen A (2002) Regional innovation systems. The integration of local ‘sticky’ and global ‘ubiquitous’ knowledge. *Journal of Technology Transfer* 27: 77–86
- Bahar D, Hausmann R, Hidalgo CA (2014) Neighbours and the evolution of the comparative advantage of nations: Evidence of International Knowledge Diffusion? *Journal of International Economics* 92: 111–123
- Balassa B (1965) Trade liberalization and revealed comparative advantage. *Manchester School of Economics and Social Studies* 33: 99–123
- Boschma R, Balland PA, Kogler DF (2015) Relatedness and technological change in cities: The rise and fall of technological knowledge in US metropolitan areas from 1981 to 2010. *Industrial and Corporate Change* 24: 223–250
- Boschma R, Capone G (2015) Institutions and diversification: Related versus unrelated diversification in a varieties of capitalism framework. *Research Policy* 44: 1902–1914
- Boschma R, Frenken K (2011) Technological relatedness and regional branching. In: Bathelt H, Feldman MP, Kogler DF (eds) *Beyond Territory. Dynamic Geographies of Knowledge Creation, Diffusion and Innovation*, Routledge, London
- Boschma RA, Iammarino S (2009) Related variety, trade linkages and regional growth. *Economic Geography* 85: 289–311
- Boschma R, Minondo A, Navarro M (2013) The emergence of new industries at the regional level in Spain: A proximity approach based on product-relatedness. *Economic Geography* 89: 29–51
- Chapman K (1992) Continuity and contingency in the spatial evolution of industries. *The case of petro-chemicals. Transactions of the Institute of British Geographers* 17: 47–64
- Combes PP, Lafourcade M, Mayer T (2005) The trade-creating effects of business and social networks: Evidence from France. *Journal of International Economics* 66: 1–29
- Crescenzi R, Rodríguez-Pose A, Storper M (2007) The territorial dynamics of innovation: A Europe–United States comparative analysis. *Journal of Economic Geography* 7: 673–709
- Crespo J, Suire R, Vicente J (2014) Lock-in or lock-out? How structural properties of knowledge networks affect regional resilience. *Journal of Economic Geography* 14: 199–219
- Dahl Fitjar R, Rodríguez-Pose A (2011) When local interaction does not suffice: Sources of firm innovation in urban Norway. *Environment and Planning A* 43: 1248–67
- Eriksson R (2011) Localized spillovers and knowledge flows: How does proximity influence the performance of plants? *Economic Geography* 87: 127–152
- Esslezbichler J (2015) Relatedness, industrial branching and technological cohesion in US metropolitan areas. *Regional Studies* 49: 752–766
- Feldman MP, Kogler DF, Rigby DL (2015) rKnowledge: The spatial diffusion and adoption of rDNA Methods. *Regional Studies* 49: 798–817
- Finger JM, Kreinin ME (1979) A measure of ‘export similarity’ and its possible uses. *Economic Journal* 89: 905–912
- Fornahl D, Guenther C (2010) Persistence and change of regional industrial activities. The impact of diversification in the German machine tool industry. *European Planning Studies* 18: 1911–1936
- Frenken K, Van Oort FG, Verburg T (2007) Related variety, unrelated variety and regional economic growth. *Regional Studies* 41: 685–697
- Garmendia A, Llano C, Minondo A, Requena F (2012) Networks and the disappearance of the intranational home bias. *Economic Letters* 116: 178–182
- Gertler MS (2003) Tacit knowledge and the economic geography of context, or the undefinable tacitness of being (there). *Journal of Economic Geography* 3: 75–99
- Glaeser EL (2005) Reinventing Boston: 1630–2003. *Journal of Economic Geography* 5: 119–153
- Greene WH (2008) *Econometric analysis* (6th edn). Pearson, Upper Saddle River, NJ

- Guimarães P, Portugal P (2010) A simple feasible procedure to fit models with high-dimensional fixed effects. *Stata Journal* 10: 628–649
- Head K, Li YA, Minondo A (2015) *Geography, ties and knowledge flows: Evidence from citations in mathematics*. Unpublished paper
- Helpman E, Krugman P (1985) *Market structure and foreign trade. Increasing returns, foreign competition and the international economy*. The MIT Press, Cambridge, MA
- Hausmann R, Klinger B (2007) *The structure of the product space and the evolution of comparative advantage*. CID Working Paper 146, Harvard
- Hidalgo CA, Klinger B, Barabási AL, Hausmann R (2007) The product space conditions the development of nations. *Science* 317: 482–487
- Hillberry R, Hummels D (2008) Trade responses to geographic frictions: A decomposition using micro-data. *European Economic Review* 52: 527–550
- Jacobs J (1969) *The economy of cities*. Vintage Books, New York
- Jaffe AB, Trajtenberg M, Henderson R (1993) Geographic localization of knowledge spillovers as evidenced by patent citations. *The Quarterly Journal of Economics* 108: 577–598
- Klepper S (2007) Disagreements, spinoffs, and the evolution of Detroit as the capital of the US automobile industry. *Management Science* 53: 616–631
- Kogler DF, Rigby DL, Tucker I (2013) Mapping knowledge space and technological relatedness in US Cities. *European Planning Studies* 21: 1374–1391
- Laursen K (2015) Revealed comparative advantage and the alternatives as measures of international specialization. *Eurasian Business Review* 5: 99–115
- Markusen A (1996) Sticky places in slippery space. A typology of industrial districts. *Economic Geography* 72: 293–313
- Martin R, Sunley P (2006) Path dependence and regional economic evolution. *Journal of Economic Geography* 6: 395–437
- Maskell P, Malmberg A (1999) The competitiveness of firms and regions. Ubiquitification and the importance of localized learning. *European Urban and Regional Studies* 6: 9–25
- Millimet DL, Osang T (2007) Do state borders matter for US intranational trade? The role of history and internal migration. *Canadian Journal of Economics* 40: 93–126
- Moodysson J (2008) Principles and practices of knowledge creation: On the organization of ‘buzz’ and ‘pipelines’ in life science communities. *Economic Geography* 84: 449–469
- Muneepeerakul R, Lobo J, Shuttters ST, Gomez-Lievano A, Qubbaj MR (2013) Urban economies and occupation space: Can they get ‘there’ from ‘here’? *PLoS ONE* 8(9): e73676. doi: 10.1371/journal.pone.0073676
- Neffke F, Henning M (2013) Skill-relatedness and firm diversification. *Strategic Management Journal* 34: 297–316
- Neffke F, Henning M, Boschma R (2011) How do regions diversify over time? Industry relatedness and the development of new growth paths in regions. *Economic Geography* 87: 237–265
- Nooteboom B (2000) *Learning and innovation in organizations and economies*. Oxford University Press, Oxford
- Ottaviani G, Peri G (2006) The economic value of cultural diversity: Evidence from US cities. *Journal of Economic Geography* 6: 9–44
- Ponds R, Van Oort RG, Frenken K (2007) The geographical and institutional proximity of research collaboration. *Papers in Regional Science* 86: 423–443
- Rauch JE (2001) Business and social networks in international trade. *Journal of Economic Literature* 39: 1177–1203
- Rigby D (2013) Technological relatedness and knowledge space: Entry and exit of US cities from patent data. *Regional Studies* 49: 1–16
- Saxenian AL (2006) *The new argonauts. Regional advantage in a global economy*. Harvard University Press, Cambridge, MA
- Storper M (1995) The resurgence of regional economies, ten years later: The region as a nexus of untraded interdependencies. *European Urban and Regional Studies* 2: 191–221
- Tanner AN (2014) Regional branching reconsidered: Emergence of the fuel cell industry in European regions. *Economic Geography* 90: 403–427
- Tanner AN (2015) The emergence of new technology-based industries: The case of fuel cells and its technological relatedness to regional knowledge bases. *Journal of Economic Geography*, forthcoming. doi: 10.1093/jeg/lbv011
- Trippi M (2013) Scientific mobility and knowledge transfer at the interregional and intraregional level. *Regional Studies* 47: 1653–1667
- Van den Berge M, Weterings A (2014) *Relatedness in eco-technological development in European regions*. Paper in Evolutionary Economic Geography 14.13, Utrecht University, Utrecht
- Van der Wouden F (2012) *The role of relatedness in economic variety on knowledge production of US cities between 1975 and 2005*. MA thesis, Department of Economic Geography, Utrecht University
- Varga A (2000) Local academic knowledge spillovers and the concentration of economic activity. *Journal of Regional Science* 40: 289–309



**Resumen.** El desarrollo de nuevas industrias requiere el acceso a las capacidades locales. Hasta ahora se ha prestado poca atención al papel de los *spillovers* de las regiones vecinas en la diversificación industrial, y tampoco se ha investigado el papel de los vínculos de red entre regiones vecinas. Dado que la difusión de las capacidades tiene un fuerte sesgo geográfico, se espera que las regiones desarrollen nuevas industrias en las que las regiones vecinas ya están especializadas. Para probar esta hipótesis, se analizó el desarrollo de nuevas industrias en estados de los EE.UU. durante el período 2000–2012. Se demuestra que un estado de los EEUU tiene una probabilidad más alta de desarrollar una ventaja comparativa en una industria nueva si un estado vecino ya está especializado en esa industria. También se muestra que en los EE.UU. los estados vecinos tienen estructuras de exportación más similares. La explicación de esta similitud en la exportación parece ser una mayor conectividad social entre estados vecinos, tal como se refleja en sus patrones de migración bilateral.

**要約:**新しい産業の発展には、地域の受容能力に合わせる必要がある。これまで、近接地域からのスピルオーバー効果が産業の多様化において果たす役割についてはほとんど注目されておらず、近接地域間におけるネットワークによる結びつきについてもほとんど研究されていない。受容能力の拡がり方には地理的に大きな偏りがあるため、新しい産業が発達した地域の近接地域でもその産業が発展すると仮定した。この仮説を検証するため、2000年から2012年までの米国の各州における新しい産業の発展を分析した。ある新しい産業が発達している州に隣接する州は、その産業での比較優位性を得る可能性が高いことを示す。また、近接する州と州では、エクスポートの構造が相互によく類似することも示す。この類似性は、近接州間における社会的な連携を構築する可能性の高さにより説明されるようであり、その連携は住民の州間の双方向の移動パターンに表れている。