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Technological dynamics and social capability: US states and European nations

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Abstract

This article analyzes factors shaping technological capabilities in USA and European countries, and shows that the differences between the two continents in this respect are much smaller than commonly assumed. The analysis demonstrates a tendency toward convergence in technological capabilities for the sample as a whole between 1998 and 2008. The results indicate that social capabilities, such as well-developed public knowledge infrastructure, an egalitarian distribution of income, a participatory democracy and prevalence of public safety condition the growth of technological capabilities. Possible effects of other factors, such as agglomeration, urbanization, industrial specialization, migration and knowledge spillovers are also considered.

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1. Introduction

In trying to explain, and possibly influence, long-run economic growth, scholarly attention has increasingly turned to the role of social factors and institutions. Policy, however, continues to be influenced by theoretical perspectives that attribute cross-country differences in income and productivity to a single factor—the resources devoted to research and development (R&D) (Romer, 1990; Aghion and Howitt, 1992). In response, governments have crafted policies that focus on increasing R&D expenditures. For example, in Europe, the so-called Lisbon Strategy (Lisbon European Council, 2000) stated that R&D investment should increase to 3% of GDP within a decade, with the purpose of making Europe 'the most competitive and dynamic knowledge-based economy in the world'. The adoption of this goal was influenced by the observation that the US share of R&D to GDP is almost double the European level. In the USA, conversely, fears of falling behind have created calls for increased government R&D spending and for policies to subsidize private sector investments in R&D, especially at the sub-national state level (National Governor's Association, 2007).

Arguably, an important shortcoming of the analysis underlying the Lisbon Strategy, and similar policy discussions, is the narrow focus on R&D expenditures. Although R&D is certainly important, supporting social, institutional and economic factors need to be in place to absorb R&D investments and ultimately lead to economic growth (Fagerberg et al., 2007). Myriad factors highlighted in Porter (1990)'s four-factor diamond model; the literature on national and regional systems of innovation (Lundvall, 1992; Nelson, 1993; Braczyk et al., 1998) and constructs such as social capability (Abramovitz, 1986), social capital (Coleman, 1988; Putnam, 1993) or the social filter (Rodríguez-Pose, 1999; Crescenzi et al., 2007) are demonstrated to affect technological capabilities. The analysis of technological growth, especially as it guides policy and investment decisions, would benefit from a wider perspective.

Moreover, much of the prevailing analysis is based on the comparison of heterogeneous geographical entities. Comparisons between Europe and the USA often overlook the variation within the latter, comparing variable means for the entire USA against individual European countries. There is much to be gained potentially by comparing US states against European countries. For example, Sweden invests nearly 4% of its GDP in R&D, which is about the same as California or Massachusetts. However, this investment is about eight times that of several European countries, such as Romania, Slovakia or Greece or US states, such as Wyoming or Louisiana. King (2004) finds that parts of Europe compare well with the most advanced US States for other social and economic indicators. Consideration of spatial heterogeneity when analyzing technological and social dynamics provides a more nuanced understanding of the conditions for policy interventions.

Crescenzi et al. (2007) provides the only prior attempt to examine differences in technological capabilities by comparing US cities to European regions. This article offers two extensions. Crescenzi et al. (2007) find differences in the technological and territorial dynamics between the two continents. However, their conclusions are based on continent-specific regressions that employ different independent variables. This article argues that robust conclusions about differences in technological dynamics require a common framework for the comparison. Therefore, we analyze technological dynamics in the two continents using the same model and a set of identical indicators for European countries and US states. To measure innovation, Crescenzi et al. (2007) use patent counts as their dependent variable in an innovation production function for the period of 1990–2002. However, patents primarily reflect invention, not innovation, and are much more widely used in some technological fields (e.g. chemicals, biotechnology, etc.) than in others (Smith, 2004). Bias may result for regions with different patterns of specialization when patents are used as the sole measure of innovation. In contrast, this article considers a broader set of indicators related to technological dynamics.

The next section outlines a synthetic framework for analyzing technological dynamics that takes into account innovation theory (Kline and Rosenberg, 1986; Fagerberg et al., 2004), development studies (Adelman and Morris, 1965; Kim, 1980, 1997; Lall, 1992), economic history (Abramowitz, 1986), sociology (Coleman, 1988) and economic geography (Feldman and Kogler, 2010). The framework suggests that firm-level *technological capabilities* are conditioned by *social capabilities*, such as the development of the public knowledge infrastructure, the supply of skilled labor and social and political characteristics that influence firms' activities. The analysis also considers the possible effects of other factors, such as agglomeration, urbanization, industrial specialization, migration and knowledge spillovers. Section 3 presents the 75 geographical entities (48 states in the continental USA and 27 countries in Europe) that form the empirical basis of the article and considers how capabilities may be measured empirically. Section 4 presents the results of our econometric estimation and compares the conclusions reached in this article with previous research. Finally, Section 5 concludes with what can be learned about what shapes technological dynamics in the USA and Europe and considers the policy implications.

2. Technological dynamics: a synthetic framework

The ultimate source of long-run economic growth is widely acknowledged to be technology, defined as knowledge about how to produce goods and services.[1] However, the tendency to reduce knowledge to artifacts and technology to machinery has been widespread. Even a highly heterodox economist such as Veblen (1915, 191)—who was the first to analyze the process of technological catch-up—argued, '... machine technology can be held and transmitted ... and the acquisition of it by such transfer is no laborious or uncertain matter'. In short, building technological capabilities should seemingly be straightforward and was expected to lead to widespread economic growth.

Neoclassical economists in the early post-war period shared this optimistic mood about economic growth. According to Robert Solow (1956), technology—or knowledge—should be regarded as a public good freely available to anybody, independent of background or location. It follows that technology should be expected to benefit everybody to the same extent—an assumption widely adopted in subsequent applied research. For example, the leading researcher of cross-country economic growth differences in the early post-war period, Edward Denison (1967, 282), stated: 'Because knowledge is an international commodity, I should expect the contribution of advances of knowledge (...) to be of about the same size in all the countries ...'. The expectation was rapid convergence in productivity and income worldwide. However, historical evidence did not validate these optimistic predictions. In fact, global disparities in development are far greater today than before the industrial revolution (Landes, 1998).

A more realistic understanding of the factors that condition technological dynamics and economic growth is emerging. It is increasingly recognized that a worldwide stock of homogenous knowledge, capable of flowing across the globe at the speed of light and being exploited by anyone as much as they like, does not exist. In fact, already the Nobel laureate Friedrich von Hayek (1945) pointed out that it is impossible for any actor, being a person a firm or a government, to have the 'perfect knowledge' relevant for the solution of an economic problem. Just to identify what the relevant areas of knowledge are, may in fact be quite challenging. Moreover, as Hayek repeatedly stressed, not all knowledge is scientific. Much knowledge is practical, personal and context-specific (Polanyi, 1958, 1966). As a consequence, to successfully access and gainfully use knowledge, familiarity with context may be required. This is one important reason why geographic proximity may be important for realizing the benefits of knowledge investments (Jaffe et al., 1993; Audretsch and Feldman, 1996).

1 For a more extensive treatment of the relationship between innovation and economic development and the role of capabilities in this context, see Fagerberg et al., (2010).

Even in cases where relevant knowledge is identifiable, codified and easily accessible, there is no guarantee that it can be successfully transferred. Knowledge may, for example, be difficult to understand and absorb. Higher education at the doctorate level may be required to gain the capabilities needed to understand, absorb and exploit detailed scientific knowledge (Cohen and Levinthal, 1990). Building such capabilities may be demanding, costly and time-consuming, for an individual, firm or society. In addition, innovative firms cannot rely on only one type of knowledge. They need to be able to combine many different types, related to, for example, finance, logistics, products, markets and production.

Technological capability, a term coined by the Korean development economist Linsu Kim (1980), captures 'the ability to make effective use of technological knowledge in efforts to assimilate, use, adapt and change existing technologies, . . . to create new technologies and to develop new products and processes . . .' (Kim, 1997, 4). Kim further distinguished between different technological capabilities depending on the complexity of the challenge. He identified production capability, which is required to operate production efficiently; investment capability, required to enter into new lines of business and finally, innovation capability, which is needed if the firm wishes to develop entirely new products or processes. According to Kim, as the distance to the technology frontier decreases, the requirements with respect to capabilities become more stringent.

A central insight from the literature on innovation is that a firm's technological capabilities do not depend solely on its own internal activities, but also depends on the capabilities of its customers, suppliers and other firms and external organizations with which the firm interacts. The term innovation system is often used to characterize the web of institutions, networks and organizations that support and facilitate firm-level innovation [see Edquist (2004) for a survey]. Such systems can be found at different levels, such as the national[2] (Lundvall, 1992; Nelson, 1993), regional (Braczyk et al., 1998) or sectoral (Malerba, 2004). Organizations, such as universities, R&D institutes, etc., which furnish firms with knowledge, expertise and highly skilled labor are a central feature of systems (Nelson, 1993). Institutions, for example legal mechanisms for the protection of intellectual property rights, are also considered to be important elements of innovation systems (Granstrand, 2004). The net may be cast even wider. Edquist (1997), for example, includes 'all important economic, social, political, organizational, institutional and other factors that influence the development, diffusion and use of innovations' (1997, 14) in the definition of an innovation system.

Hence, the ability of a firm to generate and benefit from technological capabilities also depends on the social, institutional and political characteristics of the environment in which it is embedded. In fact, Adelman and Morris (1965, 578), in an in-depth study of a number of development indicators, pointed out that 'the purely economic performance of a community is strongly conditioned by the social and political setting in which economic activity takes place'. The economic historian Moses Abramowitz (1986, 25) described these characteristics as social capability, which he defined as 'countries' levels of general education and technical competence, the commercial, industrial and financial institutions that bear on the abilities to finance and operate

2 Lall (1992) similarly suggested the term 'national technological capability' for (nation-level) factors that condition firm-level technological capability. He particularly emphasized finance, the provision of skills and 'technological effort' (associated with measures such as R&D, patents, etc.).

modern, large-scale business, and the political and social characteristics that influence the risks, the incentives and the personal rewards of economic activity'. Writers on social capital, such as Coleman (1988) and Putnam (1993) also emphasized the importance of social structure, such as norms and networks, for the efficiency of society and its economic performance.[3]

Developing and sustaining technological capabilities may also depend on location. More densely populated regions may be advantaged as larger markets allow for a richer set of capabilities to develop (Jacobs, 1969; Bairoch, 1988; Feldman, 1994). Moreover, capability development may be enhanced by the activity of proximate actors (Feldman and Kogler, 2010). Regional industrial specialization allows for greater exploitation of economies of scale and a deepening of technological capabilities (Iammarino and McCain, 2006). However, a highly specialized economy may also reduce the firm's ability to absorb knowledge by limiting the scope of discovery and the diversity of external capabilities (Feldman and Audretsch, 1999). This can be mitigated through the migration of skilled personnel who help diffuse knowledge (Henderson, 2010).

In sum, a technologically lagging country or region may benefit from exploiting knowledge developed elsewhere (Gerschenkron, 1962; Abramovitz, 1986; Landes, 1998). But as Abramovitz (1986, 388) pointed out: the potential for rapid growth of a country or region 'is strong not when it is backward without clarification, but rather when it is technologically backward but socially advanced'. Thus, technological dynamics—including the ability to learn from others—are conditioned by wider social, institutional and economic factors, which need to be taken into account. The problem is how to exploit these insights in actual empirical research. This is the topic explored in the next section.

3. Measuring capabilities in Europe and the USA

This article analyzes US states and European countries as units of observation.[4] The data set consists of observations for 48 US states and 27 European countries between 1998, before the Lisbon Strategy was adopted, and 2008, the beginning of the economic downturn. Table 1, which provides some main statistics on the 75 units, shows that US states and European countries are relatively similar in geographical size. However, the latter tend to be more densely populated, hence larger in terms of population. As pointed out above, since population size and density are factors that may affect technological dynamics in their own right, it is important to control for this when assessing for the impact of other factors.

We use factor analysis to concisely capture the dimensions of technological and social capabilities. Factor analysis is used widely in the social sciences and more recently in research on innovation (Adelman and Morris, 1965; Temple and Johnson, 1998; Fagerberg et al., 2007; Crescenzi et al., 2007; Fagerberg and Srholec, 2008). This method constructs a composite variable based on the insight that different indicators reflecting

3 For an overview and discussion of different usages of the term social capital, see Portes (1998).

4 Countries/regions not connected to the rest of continent were excluded (Hawaii and Alaska in the USA, Iceland, Malta and Cyprus in Europe). In addition, in the USA, the District of Columbia (home to the capital of the country) was excluded, because it is a district, not a state.

Table 1. US states and European countries: population and land area, 1998

	USA				Europe			
	Mean	CoV	Min	Max	Mean	CoV	Min	Max
Population (milllion people)	5.6	1.07	0.5	32.7	18.2	1.22	0.4	82.0
Land area (thousand km^2)	159.7	0.76	2.7	678.1	171.9	0.97	2.6	632.8
Population density (people per km^2)	68.8	1.37	1.9	421.4	124.9	0.81	14.5	463.6
Number of observations		48				27		

CoV, coefficient of variation.
Source: Table A1.

Table 2. Indicators of technological capability: descriptive statistics

	USA				Europe			
	1998		2008		1998		2008	
	Mean	CoV	Mean	CoV	Mean	CoV	Mean	CoV
PCT patents (per milllion people)	143	0.84	176	0.75	92	1.21	147	1.03
Business R&D (percent of GDP)	1.54	0.94	1.57	0.75	0.85	0.80	1.02	0.77
Venture capital (percent of GDP)	0.15	1.18	0.11	1.47	0.06	0.95	0.04	1.08
Number of observations		48				27		

CoV, coefficient of variation.
Source: Table A1.

the same social phenomenon are likely to be strongly correlated. All variables are entered with a log transformation in the factor analysis to limit the influence of outliers.[5]

Table 2 contains descriptive statistics for the chosen indicators of firm-level technological capabilities, which focus on business R&D, patenting [under the Patent Cooperation Treaty (PCT)] and financing of innovation.[6] These indicators primarily reflect what Kim (1997) called 'innovation capability' and 'finance capability'. As the table shows, on average, USA is solidly ahead of Europe on all three indicators. A third aspect of technological capability according to Kim is 'production capability', which—although more elementary than the ones mentioned above—is often considered to be of great importance, particularly in developing countries (Fagerberg and Srholec, 2008). Unfortunately, no relevant indicators of production capability were available for the present sample. However, this may not be of consequence for the analysis as the countries and states included here are relatively advanced economies.

5 Missing data have been estimated by linear interpolation. R&D data from New Mexico has been adjusted due to a break in time series during the period 1998–2002; details are available from the authors upon request.
6 Sources and definitions are provided in Table A1.

Table 3. Technological capability: factor analysis results

	Factor loading
PCT patents (per milllion people)	0.91
Business R&D (percent of GDP)	0.92
Venture capital (percent of GDP)	0.67
Number of observations	825

Note: The extraction method is principal-component factors; based on pooled annual data for 75 observations during 1998–2008.
Source: Table A1.

Table 4. Technological capability, top and bottom 15 observations, 2008

Top 15		Bottom 15	
Massachusetts	77.1	Estonia	41.3
California	74.3	Portugal	40.0
New Hampshire	66.3	Hungary	39.3
Washington	66.2	South Dakota	38.5
New Jersey	63.4	Arkansas	37.1
Minnesota	62.9	Wyoming	36.9
Connecticut	62.6	Louisiana	35.2
Sweden	62.3	Mississippi	34.9
Delaware	61.7	Greece	29.4
Switzerland	61.5	Lithuania	29.3
Finland	60.7	Latvia	29.1
Colorado	60.3	Slovakia	27.9
Michigan	58.9	Poland	27.4
Oregon	58.4	Bulgaria	25.2
Denmark	58.3	Romania	22.3

Source: Table A1.

Table 3 presents the factor analysis of the three technology indicators on annual observations during 1998–2008 for the 75 US states and European countries covered by the investigation. As the table shows, the three indicators are strongly correlated. The principal factor, called *Technological Capability* (TECH), explains 70.7 % of the total variance. The resulting factor score was normalized to a 0–100 range, with zero for the least advanced and 100 for the most advanced region:

$$100 \times \left(\frac{\mathrm{TECH}_i - \min(\mathrm{TECH})}{\max(\mathrm{TECH}) - \min(\mathrm{TECH})} \right) \qquad (1)$$

Table 4 reports the constructed levels of technological capability for the top and bottom quintiles of the distribution for the final year of the analysis. Comparing the two continents reveals that most of the top performers are US states. However, this group also includes four European countries: Sweden, Switzerland, Finland and

Table 5. Technological capability: descriptive statistics

	USA		Europe		Total sample	
	1998	2008	1998	2008	1998	2008
Mean	50.2	52.0	39.8	44.7	46.5	49.4
CoV	0.24	0.18	0.39	0.27	0.31	0.22
Number of observations	48		27		75	

CoV, coefficient of variation.
Source: Table A1.

Denmark.[7] In contrast, European countries, mostly former socialist economies from Eastern Europe, dominate the bottom quintile. Omitting the former socialist countries from the calculation of the mean level of technological capability in Europe would give a number almost identical to that of the USA. Hence, the much discussed difference in technological capabilities between the USA and Europe vanishes if we limit the comparison to Western Europe.

Table 5 contains descriptive statistics of technological capability for the initial and final year. The table confirms that on average, technological capability is higher in USA than in Europe. However, the difference between the two continents has been much reduced during the period under consideration here. Moreover, there has been a significant drop in the coefficient of variation. To get a better impression of this process, Figure 1 plots the initial level of technological capability on the vertical axis against the growth rate of this variable on the horizontal axis, forming four quadrants. The top-left quadrant consists of initially advanced regions that have grown slowly, while the bottom-right quadrant contains of initially lagging regions that are catching up technologically. The great majority of the observations fall into these two quadrants, indicating that a process of technological convergence has taken place during the period covered by the investigation.

Next, we searched for data on what can be called social capabilities—social, institutional and political characteristics that may condition economic and technological dynamics. Several aspects may be distinguished: the knowledge infrastructure (including the availability of highly skilled labor); the prevalence of norms, values and institutions that support the functioning of society (and the economy) and the working of the labor market.[8] We measure the latter through the log of the percentage of (working age) population that take part in it (LABOR). For the two former factors, there are several sources of information that may be relevant, so in these cases we will, as before, construct composite variables with the help of factor analysis.

For the knowledge infrastructure (Table 6) we use variables reflecting the development of the science system (scientific publishing), university R&D expenditures, government R&D expenditures and tertiary education. Initially, USA was ahead of Europe on all

7 Note that there are three times as many US states as European countries, so the share of European countries in the top quintile is not far from their share of the total sample.

8 See Rodríguez-Pose (1999) for a discussion of how the working of the labor market may condition technological change and its economic effects.

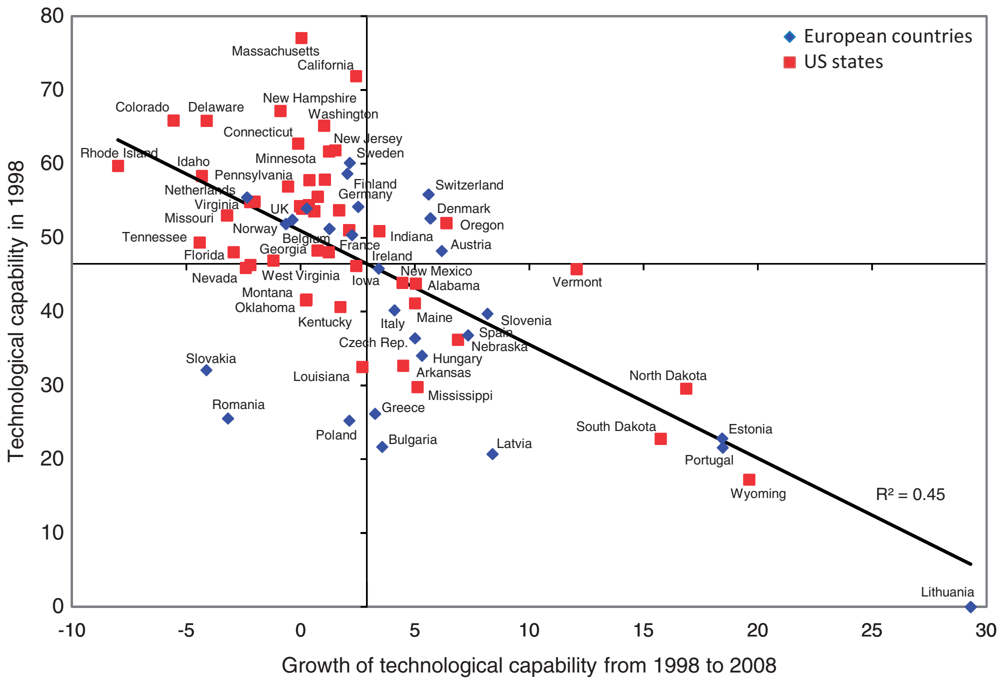

Figure 1. Convergence in technological capability 1998-2008.

four counts, but USA subsequently lost its lead in University R&D. Government R&D appears to be a special case: not only is the US level much higher than that of Europe, but the coefficients of variation are also notably higher.[9] Table 7 presents the factor analysis of the four knowledge infrastructure indicators on annual observations during 1998–2008 for the 75 US states and European countries. With the sole exception of Government R&D, all indicators are strongly correlated. The first principle factor, called *Knowledge Infrastructure* (INFRA), accounts for 57.0% of the variation.

Although relatively good statistics exist on knowledge infrastructure and the labor market, the remaining, more qualitative aspects may be more difficult to measure with precision, particularly for a sample containing both US states and European countries. Nevertheless, four variables which reflect the working of society in various ways: income inequality, voter turnout,[10] incarceration rate (the share of population in prison) and the frequency of homicides were identified. The two former reflect how

9 This reflects the importance of defense R&D in the USA, which tends to be located in remote places away from other research environments, possibly to minimize spillovers, which may be seen as a possible security risk or alternatively as a means to boost lagging states.

10 Voter turnout may be influenced by different regulations across the units included in our sample. In some European countries voting is in principle obligatory, but as this is not enforced, we consider it unlikely that this influences voting much. Most US states (but not all) require voters to register in advance which may act as an impediment to voting (and hence reduce voter turnout). To improve comparability we have, following previous research on the subject (Rosenstone and Wolfinger, 1978; Fenster, 1994; Brians and Grofman, 2001; Knack, 2001), estimated the likely effect on voter turnout of such regulations and adjusted the data accordingly. See Appendix A.1 for details on the method used for US voter turnout adjustment.

Table 6. Indicators of knowledge infrastructure: descriptive statistics

	USA				Europe			
	1998		2008		1998		2008	
	Mean	CoV	Mean	CoV	Mean	CoV	Mean	CoV
Scientific articles (per million people)	1044	0.55	1085	0.54	643	0.78	775	0.63
University R&D (percent of GDP)	0.35	0.49	0.41	0.43	0.31	0.61	0.43	0.52
Government R&D (percent of GDP)	0.30	3.02	0.36	2.70	0.22	0.51	0.20	0.43
Tertiary attainment (percent of population)	23.8	0.19	28.5	0.19	17.6	0.36	24.2	0.30
Number of observations	48				27			

CoV, coefficient of variation.
Source: Table A1.

Table 7. Knowledge infrastructure: factor analysis results

	Factor loading
Scientific articles (per million people)	0.93
University R&D (percent of GDP)	0.87
Government R&D (percent of GDP)	0.06
Tertiary attainment (percent of population)	0.81
Number of observations	825

Note: The extraction method is principal-component factors; based on pooled annual data for 75 units during 1998–2008.
Source: Table A1.

inclusive society is with respect to participation in the political process and distribution of the value it produces. Incarceration is a mix of the incidence of crime and how society handles it, which reflects inclusiveness, whereas the homicide rates primarily reflect public safety and hence the quality of governance in this particular respect.[11]

Table 8 contains descriptive statistics on the social cohesion indicators. Income inequality, incarceration and homicides are clearly higher and election turnout lower, when we compare USA with Europe. Table 9 reports the results of a factor analysis of the four indicators. One principal factor with eigenvalue >1, explaining 74 % of the total variance was found. The factor, labeled *Social Cohesion* (SOCIAL), loads positively on election turnout and negatively on income inequality, incarceration and homicides and the reported correlation with the indicators is very high.

11 As we show in Table A2 at the country level, incarceration and homicides are strongly correlated with a number of other commonly used indicators for social capital and/or the quality of governance, such as willingness to take part in civic activities, satisfaction with how society is governed and indicators of law and order at the country level. These indicators do not exist for US states, so we cannot include them here.

Table 8. Indicators of social cohesion: descriptive statistics

	USA				Europe			
	1998		2008		1998		2008	
	Mean	CoV	Mean	CoV	Mean	CoV	Mean	CoV
Income inequality (quintile ratio)	6.2	0.10	7.4	0.13	4.4	0.26	4.7	0.25
Election turnout (percent of population)	54.6	0.11	61.6	0.09	71.0	0.17	67.9	0.20
Incarceration (per 100,000 people)	732	0.39	864	0.36	165	0.77	153	0.49
Homicides (per million people)	70.6	0.54	59.9	0.49	34.2	1.18	23.2	0.97
Number of observations	48				27			

CoV, coefficient of variation.
Source: Table A1.

Table 9. Social cohesion: factor analysis results

	Factor loading
Income inequality (quintile ratio)	−0.87
Election turnout (percent of population)	0.76
Incarceration (per 100,000 people)	−0.92
Homicides (per million people)	−0.88
Number of observations	825

Note: The extraction method is principal-component factors; based on pooled annual data for 75 units during 1998–2008.
Source: Table A1.

Table 10 provides some descriptive statistics on the three aspects of social capability. The table confirms that there are big differences in social characteristics between the two continents. Social cohesion, in particular, is much more developed in Europe than in USA and this hardly changes during the period under consideration here. This contrasts with knowledge infrastructure and labor participation, for which the USA is in a clear lead throughout the period.[12] However, this lead becomes smaller over time.

4. Exploring technological dynamics

To analyze the growth in technological capability over time in the two continents we employ an application of the standard *epidemic* model of technology diffusion (Metcalfe, 1988; Fagerberg et al., 2007). This model has been widely used in econometric studies of economic growth and technological change [see Fagerberg (1994) for an overview] or technological change across countries (Fagerberg and

12 The result for labor participation is consistent with the well-known US–Europe employment gap (Gregory et al., 2007).

Table 10. Social capabilities: descriptive statistics

	USA		Europe		Total sample		Total sample	
	Mean		Mean		CoV		Share of variation	
							Between	Within
	1998	2008	1998	2008	1998	2008	1998–2008	
Knowledge infrastructure	67.1	72.2	51.9	64.2	0.27	0.18	0.95	0.05
Social cohesion	23.5	23.5	69.6	67.8	0.71	0.68	0.98	0.02
Labor participation	75.4	66.2	41.2	50.2	0.38	0.30	0.93	0.07
Number of observations	48		27		75		825	

CoV, coefficient of variation.
Source: Table A1.

Verspagen, 1996; Fagerberg et al., 1997; Sala-i-Martin, 1996). This model is sometimes characterized as a *conditional convergence* model, which, however, may be consistent with the expectation of convergence (Solow, 1956) as well as divergence across countries or regions (Barro and Sala-i-Martin, 1995).

The basic model is:

$$\begin{aligned}\Delta\mathrm{TECH} = \mathrm{TECH}_t - \mathrm{TECH}_{t-1} &= \beta_0 + \beta_1\mathrm{TECH}_{t-1} + \beta_2\mathrm{INFRA}_{t-1} \\ &+ \beta_3\mathrm{SOCIAL}_{t-1} + \beta_4\mathrm{LABOR}_{t-1} + \beta_5\mathrm{X}_{t-1} + e_t\end{aligned} \tag{2}$$

in which t denotes the period, TECH is technological capability, INFRA is knowledge infrastructure, SOCIAL is social cohesion and LABOR represents the working of the labor market (as reflected in the labor market participation rate). X is a set of other conditioning factors and e is the standard residual.

Knowledge flows may be, as pointed out earlier, conditioned by distance. The research shows that spatially conditioned knowledge or technology spillovers are locally limited and that their effects tend to wane beyond a radius of a few 100 km (Moreno et al., 2005; Rodríguez-Pose and Crescenzi, 2008; Feldman and Kogler, 2010; Rodríguez-Pose, 2011). Hence, their effects would generally fall within the borders of our relatively large geographical units. But there could nevertheless be spatial spillovers along shared borders. The variable *TECHspill* tests for the possibility of interaction effects between the technological capabilities of regions with common borders. This variable represents the technological capabilities of neighboring regions weighted by, for each neighboring region, the common border as a share of the total border of the receiving region and the population density[13] around that common border:[14]

$$TECHspill_i = \sum_j (\mathrm{TECH}_j - \mathrm{TECH}_i) \times \frac{b_{ij}}{\sum b_i} \times w_{ij} \tag{3}$$

13 We want to thank one of the referees for the suggestion that the possibility for spillovers may depend on the population density of the border area.

14 The total border of a region includes in addition to borders to neighboring regions in the sample, also coastline, shoreline and borders with countries or regions not included in the present sample. Data on the

where i is the receiving region, j is the neighboring region, TECH is technological capability, b_{ij} is the length of the common border, b_i denotes the total length of the border and w_{ij}[15] refers to the estimate of population density in 100 km zone on both sides of the border. As, by assumption, there is little to learn from those who are less knowledgeable than yourself, we impose the restriction that $(\text{TECH}_j - \text{TECH}_i) = 0$, if $(\text{TECH}_j - \text{TECH}_i) < 0$.

Knowledge or technology spillovers may also depend on the migration of skilled personnel. However, for the present sample, information on the skill level of migrants was not available. Therefore, following Crescenzi et al. (2007), we used net migration as a share of the total population of the region to measure this dimension (MIGRATE).[16] As previously mentioned, the analysis also controls for territorial characteristics, such as log of population density (POPDEN), log of population size (SIZE) and how specialized the country or region is (K-INDEX). The latter was, following Midelfart-Knarvik et al. (2002) and Crescenzi et al. (2007), measured as the deviation from an average pattern of specialization of the geographical entities included in the investigation.[17]

Table 11 presents the main results. The first column shows results of the basic model in which the growth in technological capability is regressed against initial values of the technological and social capabilities, using ordinary least squares (OLS). The initial level of TECH displays a large and significantly negative coefficient, indicating a strong tendency for technological catching up. INFRA and SOCIAL are also positive and significant: a well-developed knowledge infrastructure and favorable social conditions are clearly important for the development of technological capability. However, the estimated coefficient of the labor market variable LABOR, although positive, fails to be significant at a 10% level. To check the robustness of the above result, column 2 repeats the analysis on annual data. The basic results however remain the same.[18]

In regressions on pooled cross-sectional and time series data, it is customary to test for the possible effect on the estimates of allowing for unidentified cross-sectional factors that do not change over time, reflecting, say, culture or other time-invariant factors. A so-called fixed-effect regression, reported in column 3 of Table 11, does this by excluding all cross-sectional variance from the test. This, naturally, will reduce the impact of variables that do not change much over time, as—in the present case—the

length of the land borders between the US states was obtained from The State Border Data Set (http://www.econ.umn.edu/~holmes/data/BorderData.html). There are 109 borders between contiguous US states. Data on the USA–Canada or USA–Mexico border length, the length of the coastline and the length of the shoreline of the Great Lakes was obtained from the US statistical Abstract, 2010. Data on the length of the land borders between the European countries and their total border length, including coastline, was derived from the on-line edition of the CIA World Factbook.

15 For the definition of w_{ij}, see Appendix A.2 for the method used to adjust the spillover variable by population on the border.

16 The MIGRATE variable stands for the total net (im)migration over the period as percent of population in the initial period.

17 The K-INDEX is based on GDP data by 25 sectors according to NACE, rev. 1.1 in Europe and the 2002 NAICS classification in the USA. It is computed on the basis of the overall sample, that is, not for Europe and the USA separately, because after some adjustments the industry definition at the chosen level of aggregation was very similar. More details on the computation are available from the authors upon request.

18 Note that while the cross-sectional regression reports coefficients over a 10-year period, the coefficients of the pooled regression reflect changes from one year to the next, so the magnitude of the estimated coefficients is smaller in the latter case.

Table 11. Exploring technological dynamics, 1998–2008

	(1) Cross-sectional OLS	(2) Pooled OLS	(3) Fixed-effects model	(4) Between model
Constant	9.105***	3.872***	14.237**	0.783**
	(2.679)	(0.693)	(6.103)	(0.302)
$TECH_{t\text{-}1}$	−0.440***	−0.095***	−0.576***	−0.041***
	(0.071)	(0.019)	(0.060)	(0.007)
$INFRA_{t\text{-}1}$	0.176***	0.047***	0.172**	0.016**
	(0.058)	(0.012)	(0.072)	(0.007)
$SOCIAL_{t\text{-}1}$	0.042**	0.006*	−0.014	0.004*
	(0.017)	(0.004)	(0.040)	(0.002)
$LABOUR_{t\text{-}1}$	0.027	0.010	0.091***	0.006
	(0.022)	(0.007)	(0.030)	(0.004)
Period dummies	No	Yes	Yes	No
ρ			0.81	
R^2 within			0.51	
R^2 between				0.36
R^2 overall	0.60	0.33		
F	11.60***	15.04***	30.21***	9.66***
Number of units	75	75	75	75
Number of observations	75	750	750	750

Note: Robust standard errors in brackets; *, **, *** denote significance at the 10, 5 and 1% levels, respectively.

Social Cohesion variable (Table 10), and this is also what the test shows.[19] The corresponding test when the time series part of the variance has been removed—a so-called Between Regression—is reported in column 4. The results are, as should be expected, close to those obtained in the cross-sectional regression (column 1).

Table 12 includes the other possible conditioning factors discussed above one by one,[20] using regression robust to outliers,[21] but in no case was the estimated impact found to be significantly different from zero at the 10% level of significance. Thus, the main results are found to be robust to the inclusion of these additional variables. We also tested for the possibility that the variables have different effects in the USA and Europe, respectively, by interacting the independent variables one-by-one with a dummy variable for Europe (EUROPE). The results, which are reported in Table 13, indicate that none of these interaction affects are supported at conventional levels of significance.

These results run counter those reported by Crescenzi et al. (2007) for an earlier time period. They found that spatially conditioned technology spillovers mattered in Europe

19 An alternative to the fixed-effect estimator is a so-called random-effect estimator in which only a part of the cross-sectional variable is removed (and treated as random). However, random-effect estimators are built on stronger assumptions than fixed-effects (Wooldridge, 2002, 286–291). A Hausman specification test reveals that the assumptions on which the random-effect model is based do not hold in the present case, and that the estimator therefore cannot be used (Hausman, 1978).

20 As four of the five additional variables depend on population in various ways, this was considered to be the most appropriate procedure.

21 Using the procedure suggested by Li (1985).

Table 12. Testing for possible impact of other variables, robust OLS, 1998–2008

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	8.540***	8.691***	8.887***	8.213**	17.065**	8.047***
	(2.237)	(2.393)	(2.241)	(3.839)	(7.461)	(2.886)
$TECH_{t-1}$	−0.435***	−0.437***	−0.416***	−0.434***	−0.419***	−0.441***
	(0.044)	(0.046)	(0.047)	(0.047)	(0.045)	(0.050)
$INFRA_{t-1}$	0.176***	0.176***	0.159 ***	0.178 ***	0.178 ***	0.178***
	(0.043)	(0.043)	(0.045)	(0.045)	(0.042)	(0.043)
$SOCIAL_{t-1}$	0.045**	0.045**	0.040**	0.045**	0.045**	0.045**
	(0.018)	(0.018)	(0.019)	(0.018)	(0.018)	(0.018)
$LABOR_{t-1}$	0.029	0.029	0.035	0.029	0.014	0.033
	(0.025)	(0.026)	(0.026)	(0.026)	(0.028)	(0.029)
$TECHspill_{t-1}$		−0.014				
		(0.089)				
$MIGRATE_{t-1}$			−0.167			
			(0.156)			
$K\text{-}INDEX_{t-1}$				0.007		
				(0.055)		
$SIZE_{t-1}$					−0.547	
					(0.453)	
$POPDEN_{t-1}$						0.123
						(0.469)
R^2	0.49	0.49	0.52	0.50	0.49	0.48
AIC	92.87	93.86	77.47	88.06	97.65	101.08
BIC	104.16	107.52	93.19	102.45	111.03	114.08
Deviance	1073.44	1073.88	1065.24	1078.17	1050.06	1067.77
F	26.07***	20.50***	21.26***	20.56***	21.25***	20.55***
Number of observations	75	75	75	75	75	75

Note: Outliers are excluded based on pooled OLS estimate; standard errors in brackets; *, **, *** denote significance at the 10, 5 and 1% levels, respectively. $MIGRATE_{t-1}$ refers to the lagged net migration rate during 1993–1997.

but not in the USA, whereas this relationship was opposite for migration. It should be noted, though, that there are a number of differences between this study and that of Crescenzi et al. First, their dependent variable is patent growth, not broader technological capability.[22] Second, Crescenzi et al. (2007) compare US cities with European regions (at the NUTS 1–2 level, i.e. countries or parts thereof). Hence, their units are smaller, and it is possible that this might explain some of the differences in results, for example, with respect to the impact of technological spillovers, which as several studies show tend to be of rather limited geographical reach (Moreno et al., 2005; Rodriguez-Pose and Crescenzi, 2008). Third, the present study considers a more recent time period and includes the countries in Eastern Europe, which may particularly explain differences with respect to migration. During the 1990s the EU initiated internal

22 Indeed, using patents as the dependent variable reproduces the results of Crescenzi et al. (2007) as the additional coefficient of $MIGRATE_{t-1}$* EUROPE becomes negative and significant at 5% level. The results are available from the authors on request.

Table 13. Testing for differences in variable impact between USA and Europe, robust OLS, 1998–2008

	Coefficient	Standard error	Probability
$TECH_{t-1}$* EUROPE	−0.029	0.051	0.567
$INFRA_{t-1}$ * EUROPE	0.001	0.033	0.971
$SOCIAL_{t-1}$* EUROPE	−0.040	0.039	0.313
$LABOUR_{t-1}$* EUROPE	0.002	0.028	0.951
$TECHspill_{t-1}$* EUROPE	0.153	0.201	0.448
$MIGRATE_{t-1}$* EUROPE	−0.556	0.513	0.282
$K\text{-}INDEX_{t-1}$* EUROPE	0.026	0.054	0.629
$SIZE_{t-1}$* EUROPE	0.129	0.167	0.444
$POPDEN_{t-1}$* EUROPE	0.170	0.577	0.769

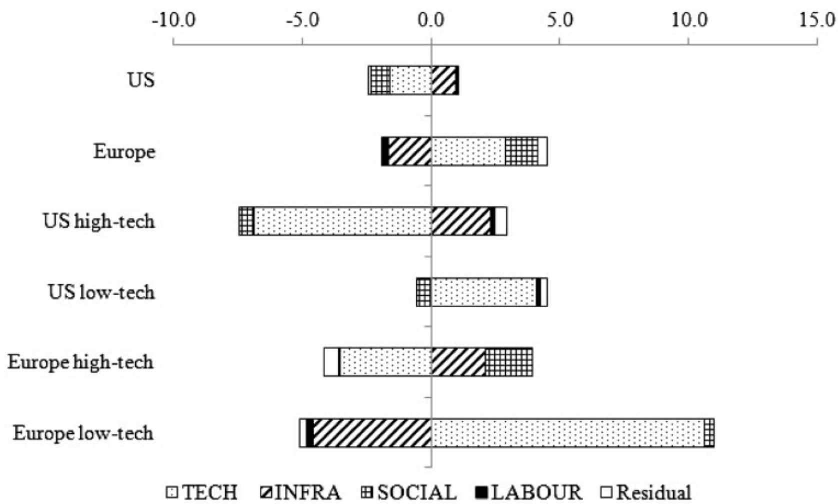

Figure 2. Estimated contributions to change in technological capability 1998-2008, relative to sample average.

labor market reforms to make cross-border migration easier, while simultaneously the new democracies in Eastern Europe gradually became more integrated into the European economy. Increased migration followed in the wake of these changes, reducing the difference between the two continents in this particular respect.[23]

Figure 2 illustrates the estimated contributions to the observed changes in technological capability (relative to the sample average) for the USA and Europe and two subgroups within each continent (high-tech and low-tech regions, defined as the upper and lower third of the distribution, when ranked by initial technological

23 While in the early 1990s migration was about twice as high in the USA than in Europe, the difference between the two continents were gradually reduced in the years that followed so that, towards the end of our period, it had almost ceased to exist.

capability).[24] As for the US–Europe comparison, the US states were, on average, more advanced technologically to begin with than their European counterparts, indicating a smaller potential for learning from others and this contributed to somewhat slower growth in the USA than in Europe. This effect was accentuated by relatively low social cohesion in the USA, which reduced growth there while boosting it in Europe. In contrast, the knowledge infrastructure, which on average is more developed in USA than in Europe, had the opposite effect. This mainly benefitted the high-tech regions in the USA, and therefore led to less convergence there than might otherwise have been expected.

The division of Europe into high-tech and low-tech regions reveals that the technological laggards, mostly former socialist countries, have only partially managed to exploit the scope for catch-up in technology made possible by the availability of more developed technological capabilities elsewhere. The model highlights two reasons for this. First, the knowledge infrastructure is much better developed in the high-tech part of Europe. This contributes to boosting growth there, while at the same time slowing down the catch-up of the laggards. Second, social cohesion is much higher in the high-tech part of Europe than elsewhere, and this also improves the performance of this part of Europe compared with other regional groupings. Thus, the relatively favorable development of high-tech Europe during this period is due in no small part to their ability to match technological capability with well-developed social capabilities.

5. Conclusions

In designing policy, politicians draw on underlying models of thought to guide their actions. Particularly in Europe but arguably throughout the developed world, increasing R&D investment has been seen as the appropriate strategy to realize economic growth and respond to a perceived loss of international competitiveness. Although R&D is certainly important, both the theory and empirical evidence discussed in this article suggest that R&D investments need to be complemented by social capabilities. Although most previous empirical work, and much of the policy discussion, compares individual European countries with the USA as whole, this article changes the unit of observation from the entire US economy to individual states, which arguably are more comparable with European countries. Our results indicate that well-developed social capabilities impact the degree to which European countries and US states succeed in developing technological capabilities. Policy makers who do not take these lessons into account may fail to reach the desired results of the policies they pursue.

As for technological capability, the results suggest that most European countries are just as capable as US states. Hence, the worry expressed by many European policy makers over Europe lagging behind the US appears misguided. In fact, the major difference between the two continents is not so much related to their top performers as to the fact that Europe includes a number of formerly socialist countries in Eastern Europe, which understandably have not yet managed to generate technological capabilities comparable to those of Western Europe. As for social capabilities, the

24 The calculation is based on the estimates from column 1, Table 11 (the basic model). Luxembourg, an extreme outlier in INFRA in Europe, was excluded from the illustration.

biggest difference between US states and European countries is to be found in what has been termed social cohesion, which reflects norms, values and institutions that facilitate economic activities and for which US states tend to lag considerably behind Europe. US states continue to excel is the development of the (public) knowledge infrastructure, their lead vis-à-vis European countries has been steadily shrinking, however, and in some areas, such as university R&D, Europe is now ahead of the USA.

It has been common among policy makers, media and scholars to assume that the difference in performance across the USA and Europe reflects fundamental differences in how the two economies work. The research presented here does not support this perspective, but rather suggests—at least as far as technological dynamics is concerned—that the underlying factors that influence dynamics among European countries as well as US states tend to be the same in most cases. However, as both Europe and the USA are quite heterogeneous entities, the observed dynamics may well differ, as will the future growth challenges ahead. Due to its recent history, Europe has much larger internal differences in technological capability and this has, at least for the period under consideration here, contributed to more vibrant internal dynamics, with several previously socialist countries in the East catching up technologically at rapid speed. The challenge for European policy makers, in a time of crisis, will be to sustain this fortuitous trend by continuing to invest in the public knowledge infrastructure, such as higher education, and preventing social conditions from deteriorating. In contrast to the European example, technological dynamics in the USA are hampered by adverse social conditions. To change this trend, what is needed are comprehensive policies supporting the development of the public knowledge infrastructure and improving the broader social conditions that influence technological and territorial dynamics.

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Appendix

A. Data sources and definitions

A.1 *US voter turnout adjustment*

The US voter turnout may be biased downwards, because most US states require voters to register for election in advance. However, several US states have adopted the so-called election day registration (EDR) that minimized this impediment: Maine, Minnesota and Wisconsin in the 1970s, Oregon in 1980s; Idaho, New Hampshire and Wyoming in the 1990s and Iowa, Montana and North Carolina in the 2000s (North Dakota is excluded from this analysis, because there are no registration provisions since 1951). To improve comparability with Europe, we have estimated the impact of the EDR on voter turnout in presidential elections during the period 1960–2008 with the help of fixed-effects panel data model and adjusted the data. The model includes the outcome lagged by one period, a dummy for the state–year when the EDR was adopted for the first time and period dummies to control for common shocks as covariates. The results confirm that the impact of the EDR is highly statistically significant increasing voter turnout by 2.66% points. Hence, the voter turnout data of states in years in which the EDR was not in place have been adjusted upward accordingly. Brians and Grofman (2001) used extensive individual-level data to estimate the EDR impact from 1972 to 1996 and their results indicate that under EDR, voter turnout was about 4% points higher than under a 15-day closing date and 5% points higher than under a typical 30-day closing date before election, respectively; based on values for employed, married, white, median-age, middle-class males. Fenster (1994) using state-level data estimated that the first wave of EDR in the 1970s resulted in 4.73% point difference in election turnout. Knack (2001) on the base of state-level data found that in presidential elections the new wave of EDR programs adopted in the early 1990s was associated with a turnout increase of 2.92% points. Hence, the impact tends to decline over time, which is also supported by more detailed analysis of trends in our data. But this is not surprising, as the National Voter Registration Act of 1993 included registration provisions, such as the active motor voter program, that significantly removed barriers to voting. Given the fact that our analysis includes the most recent

Table A1. Variable sources and definitions

Indicator	Unit	Source of data	
		US states	European countries
Scientific articles: the number of articles published in journals classified and covered by Science Citation Index (SCI) and Social Sciences Citation Index (SSCI); fractional assignments.	Per million working-age population	The Patent Board	NSF, Science and Engineering Indicators 2010
PCT patents: the number of PCT patent applications; fractional counts; by inventor(s)' country(ies) of residence and by the priority date	Per million working-age population	OECD REGPAT Database	OECD Patent Database
Business R&D: expenditures on R&D performed by the business sector	Percent of GDP	OECD.Stat Regional Statistics	Eurostat on-line
University R&D: expenditures on R&D performed by the higher education and private and nonprofit sectors	Percent of GDP	OECD.Stat Regional Statistics	Eurostat on-line
Government R&D: expenditures on R&D performed by the government sector	Percent of GDP	OECD.Stat Regional Statistics	Eurostat on-line
Venture capital: early stage, expansion and replacement venture capital investments	Percent of GDP	SSTI and the PWC Moneytree Report	Eurostat on-line
Tertiary attainment: persons with tertiary education attainment (levels 5–6 of ISCED 1997)	Percent of population aged 25 years and older	US Census Bureau	Eurostat on-line
Income inequality: the ratio of total income received by 20% of the population with the highest income (top quintile) to that received by 20% of the population with the lowest income (lowest quintile).	Top per lowest quintile	Bernstein et al. (2008) and McNichol et al. (2012)	Eurostat on-line
Election turnout: voter turnout in presidential elections in the USA and parliamentary elections in Europe	Percent of voting-age population	US Census Bureau	Eurostat on-line
Incarceration: prisoners in state correctional authorities and local jails in the USA and prison population in Europe	Per 100,000 adults	US Bureau of Justice Statistics	Eurostat on-line
Homicide: the number of homicides, i.e. murder and non-negligent manslaughter	Per million adults	Uniform Crime Reporting Statistics	Eurostat on-line
Labor force participation: the ratio of the labor force to the working-age population, where the labor force is the sum of the numbers of persons employed and unemployed.	Percent of labor force in working-age population	OECD.Stat Regional Statistics	Eurostat on-line

(continued)

Table A1. Continued

Indicator	Unit	Source of data	
		US states	European countries
Migration: the net migration rate given by the change of population plus deaths minus births as the proportion of the initial population.	Percent of population	US Census Bureau	Eurostat on-line
Population: the number of inhabitants	People	OECD.Stat Regional Statistics	Eurostat on-line
Land area: surface area; excluding area under inland water	Squared kilometer	OECD.Stat Regional Statistics	Eurostat on-line
Population density: the number of inhabitants per surface area	People per squared kilometer	OECD.Stat Regional Statistics	Eurostat on-line
K-index: the deviation from an average pattern of specialization of the geographical entities included in the sample based on GDP data in 25 sectors.	Index	US Bureau of Economic Analysis	Eurostat on-line

Table A2. Correlation with cross-country indicators from other sources

Indicator	Source	Correlation coefficient: Incarceration (per 100,000 people)	Correlation coefficient: Homicides (per million people)
Governance	Fagerberg and Srholec (2008)	−0.58	−0.52
Political system		−0.66	−0.60
Voice and accountability	Kaufmann, et al. (2009)	−0.64	−0.61
Political stability and absence of violence/terrorism		−0.65	−0.63
Government effectiveness		−0.61	−0.61
Regulatory quality		−0.45	−0.42
Rule of law		−0.69	−0.70
Control of corruption		−0.65	−0.64
Agreement with the statement that generally speaking, most people can be trusted	World Value Survey 1998 or the nearest	−0.58	−0.38
Affirmative answer on belonging to a voluntary organization		−0.68	−0.51
Affirmative answer on doing unpaid work for voluntary organizations		−0.55	−0.39
Affirmative answer on ever signing a petition		−0.61	−0.55
Satisfaction with the way democracy is developing in the country on a 4-point scale from not at all to very much		−0.57	−0.65
Confidence in the parliament on a 4-point scale from none at all to a great deal		−0.60	−0.62
Confidence in the justice system on a 4-point scale from none at all to a great deal		−0.60	−0.64
A view on how well things are going with the system for governing the country on a 10-point scale from bad to good		−0.57	−0.58
Preparation to actually do something to improve the conditions of people in the same neighborhood/community on a 5-point scale from absolutely no to absolutely yes		−0.66	−0.72

Note: All indicators, except of the indexes derived from Fagerberg and Srholec (2008) and Kaufmann, et al. (2009), are used in logs. Number of countries differs depending on data availability.

period, therefore, the impact estimated in this article is consistent with the existing literature on this topic.

A.2 *Adjustment of the spillover variable by population on the border*

Sparsely populated borders are likely to induce less knowledge spillovers than densely populated ones. As comparable hard data on border population between the US states on the one hand and European countries on the other hand do not exist, the density of population on the border needs to be estimated. Hence, we create a Likert scale weighting factor w_{ij} with a 4-point scale ranging from low to high border population density with the help of which the spillover potential of unpopulated borders is scaled down and that of highly populated borders are scaled up.

More specifically, w_{ij} refers to population density in a 100 km buffer zone on both sides of the border, as most spillovers have been shown to concentrate within a 200 km radius. Spillover intensity is assumed to exponentially decrease with distance from the border approaching 0 about 100 km from the border, thus a large city 10 km from the border is understood as far more relevant than the same city 90 km inland. By taking into account the geographic, demographic and natural conditions, we evaluated each border on a 4-point scale as follows:

0—very sparsely populated, that is, desert, tundra, marsh, deep forest, high mountains, arctic or other wilderness, as if there was no common border (e.g. California–Nevada and Norway–Finland).

1—low population density, that is, small towns, villages, rural areas (e.g. Iowa–Minnesota, France–Spain).

2—medium population density, that is, urban areas close to the border, but not right at the border; the border represents a barrier of some sort, as population density is lower at the border than deeper inland (e.g. Ohio–Pennsylvania, Austria–Czech Republic).

3—high population density, that is, major population centers on both sides, dense settlements regardless of the border, for example, metropolitan areas spanning across US states and cross-border regions in Europe (e.g. New York–New Jersey, Belgium–Netherlands).