

European regional convergence revisited: the role of space and intangible assets*

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Abstract

The contributions evaluating convergence across European regions are now numerous and take a wide variety of approaches. However, evidence for the most recent period (2003–2009) is still scant, and studies considering the role of intangible assets in the enlarged European Union are virtually nonexistent. This article focuses on the convergence patterns of income per capita in 216 European regions during the period 1995–2009. Following the distribution dynamics approach, several conditioning schemes are considered, including geography and a set of intangible assets. In contrast to studies analyzing earlier periods, the results suggest a process of convergence, especially in the most recent years. In addition, convergence processes might be affected by the conditioning factors introduced in the analysis.

Keywords: conditioning schemes, income convergence, intangible assets, stochastic kernel

JEL classification: C14; D30; O47; R11

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1. Introduction

Regional socioeconomic cohesion is one of the issues to which the European Union (EU) has historically devoted a great deal of attention. This question was especially reinforced in the Treaty of the European Union (1992), which called for a balanced development, as well as economic and social cohesion. The need for policies to promote both regional development and a reduction of the economic disparities across regions has increased remarkably after the latest enlargements of 2004 and 2007. Accordingly, the agenda of the so-called Cohesion Policy is articulated around three main objectives, namely, regional convergence, regional competitiveness and European territorial cooperation. However, the economic resources devoted to these policies are not equally distributed. In particular, the objective of regional convergence—aimed at reducing regional disparities by helping those regions whose income per capita is below the 75% of the EU average—is especially important, given that it receives 81.5% of the budget.

At the same time, the issue of convergence has been a subject of intense debate in the economic literature. Different theories, concepts and measures of convergence, as well as a wide variety of statistical techniques have been proposed (for a excellent review, see Islam, 2003; Magrini, 2004). In the European regional context, many studies have considered the distribution dynamics approach, initially introduced by Danny Quah (see Quah, 1993a,b, 1996a,b,c, 1997). This approach allows scholars to evaluate how the entire cross-section distribution of income per capita evolves over time, analyzing changes in its external shape, intra-distribution dynamics and long-run tendencies. A list of the main contributions using this approach includes but is not restricted to Quah (1996b), López-Bazo et al. (1999), Cuadrado-Roura et al. (2002), Le Gallo and Ertur (2003), Le Gallo (2004) and Fischer and Stumpner (2008), among others.

A common conclusion might be drawn from these studies, namely the bimodality of the cross-section of income distribution, which means that there are two differentiated groups of regions, or convergence clubs. There is, on the one hand is the group of relatively poor regions and, on the other hand, another group comprising regions around the mean income. These two groups are particularly persistent over time. This result would be compatible with the pioneering findings by Quah (1996b), who first suggested the existence of these two groups, which he termed “twin peaks”, and that show the tendency of the economies to diverge rather than to converge.

Most of these studies, however, focus on periods ending at the beginning of the last

decade, before the EU witnessed its biggest enlargement with twelve new accessions in years 2004 and 2007. These new members are all former members of the Soviet bloc, and are now economies in transition with levels of income per capita far below the EU average. Therefore, an analysis of the most recent years might be of interest from the convergence point of view. This paper aims to contribute to the literature by focusing on the distribution dynamics of income per capita for a sample of 216 European regions (NUTS 2)¹ during the period 1995–2009, which has been possible following the update of the Eurostat database.² Additionally, although the study of the convergence patterns in this period is, *per se*, innovative, a further key innovation is the attention devoted to the conditioning factors that might have affected the convergence process. In a first step, the article focuses on the spatial spillovers, which have been proved to be relevant for convergence in the European context (see Le Gallo, 2004; Ertur et al., 2006; Fischer and Stumpner, 2008). However, evidence for the most recent years is still yet to come.

In a further stage, some intangible assets are considered as conditioning factors including technological, human and social capital. The endogenous growth theory claims that innovation and learning processes accompanied by high levels of human capital are essential for development. The model proposed by Azariadis and Drazen (1990) suggests that low levels of human capital might be responsible for a poverty trap. Other contributions, such as Acemoglu (1996) and Redding (1996), indicate that the complementarities between R&D and education are the likely determinants. In addition, these activities are reinforced by social interaction and face-to-face contact, which facilitate assimilation and knowledge transmission. This is actually the role of the other piece of the puzzle, social capital. Some recent contributions such as Akçomak and Ter Weel (2009) and Barrutia and Echebarria (2010) suggest that social capital is linked to innovation and others such as Dearmon and Grier (2011) and Bjørnskov (2009) conclude that it is also positive for the creation of human capital.

The remarkable importance of these intangible assets in promoting regional efficiency is one of the reasons they are considered as strategic factors in the “Europe 2020 Strategy”, which sets the bases for economic development on knowledge, innovation, efficiency and competitiveness. Recently, Dettori et al. (2012) found positive links between intangi-

¹NUTS stands for Nomenclature of Territorial Units for Statistics. In particular, NUTS 2 is the level of disaggregation to which the Cohesion Policy objectives are addressed.

²Unfortunately, the same process means that data for the Italian, Austrian and Hungarian regions are only available from 2000 onwards. Accordingly, these three countries are excluded from the analysis.

ble assets and efficiency, which translate into productivity improvements. Consequently, the different endowments of intangible assets might explain the differences in regional performance, as well as possibly affecting the regional income convergence process and conditioning the success of the Cohesion Policy. Although these conditioning schemes are not completely innovative—contributions such as Ezcurra et al. (2005) and Mora (2008) considered similar proposals—the existing evidence confines the analysis to the late nineties and the samples do not include the new European members.

Therefore, the contribution of this study to the literature is twofold. First, it expands previous studies by considering the period 1995–2009 and a wider sample including the regions from countries that recently joined the EU. Second, as well as spatial conditioning, it examines the role of three types of intangible assets, for which it provides an in-depth separate analysis. In this regard, the inclusion of social capital as a conditioning factor is especially innovative. The beneficial effects of social capital are not exclusively confined to promoting innovation and human capital, but it also positively influences economic development at both regional and country level (see, for instance Putnam, 1993; Knack and Keefer, 1997; Beugelsdijk and Van Schaik, 2005; Peiró-Palomino and Tortosa-Ausina, 2013b). Yet, as indicated, its role in the European convergence process remains entirely unexplored.

The study first focuses on the dynamics of the cross-section of income distribution without conditioning. This will allow us to evaluate whether there is evidence of convergence, or whether the twin peaks in the distribution of income persist for the most recent period. In a second step, it examines the implications of the different conditioning factors by computing nonparametric conditional stochastic densities following Quah's (1997) suggestions, and implemented using techniques developed by Hyndman et al. (1996). The latter, despite providing particularly clear insights on the conditioning effects, these techniques have been used in very few studies (see Fischer and Stumpner, 2008; Poletti Laurini and Valls Pereira, 2009).

The remainder of the paper is structured as follows. Section 2 provides both a general review of the convergence approaches and technical notes on distribution dynamics, the approach followed in this paper. Section 3 presents the sample and the data and Section 4 displays the results for both the unconditioned scenario and the different conditioning schemes. Finally, Section 5 provides some concluding remarks.

2. The empirical framework

2.1. Competing methods for studying convergence

The study of convergence has been addressed from different perspectives. One of these is *regression analysis*, as in the work of Barro and Sala-i-Martin (1992) and Mankiw et al. (1992). This approach mainly focuses on evaluating the existence of the so-called β -convergence and its findings are consistent with the neoclassical growth model (Durlauf, 1996). There is evidence of β -convergence when a negative coefficient is found for β in the following equation:

$$\Delta(\ln y_{i,t}) = a + \beta \ln(y_{i,t-1}) + \mu_{i,t} \quad (1)$$

where $\Delta(\ln y_{i,t})$ is the growth of income between periods t and $t - 1$, a is a constant term capturing technology, $\beta \ln(y_{i,t-1})$ is the lagged income and $\mu_{i,t}$ is the error term.

β -convergence can be either conditional or unconditional, depending on whether or not the above equation includes control variables capturing particular conditions of the geographical areas analyzed.³ Conditional β -convergence means that economies are catching up with their own steady state, conditioned by the particularities of each area. However, unconditional β -convergence is a much broader concept implying that the poorer economies catch up with the richer ones. The regression approach, both for conditional and unconditional convergence has been examined using cross-section approaches (Barro and Sala-i-Martin, 1992; Mankiw et al., 1992), time series (Lee et al., 1997; Evans and Karras, 1996), and panel data (Islam, 1995; Evans, 1998). Unfortunately, none of these approaches is free from criticism.

Cross-section approaches can be affected by omitted variable bias, since the constant a in Equation (1) might be reflecting other features apart from technology, such as climate or institutions (Durlauf and Johnson, 1995). Time series analyses are limited to reduced form equations, with no attempt to link the estimation results with parameters of the growth model, and therefore limiting policy implications (Islam, 2003). Finally, panel data specifications, despite addressing some of the drawbacks of both cross-section and time series approaches, are also susceptible to some problems, namely, the likely existence of

³Equation (1) describes the basic framework of β -convergence without control variables. Common controls are population growth and both physical and human capital investment (see Barro and Sala-i-Martin (1992) and Mankiw et al. (1992)).

endogeneity bias (Caselli et al., 1996), as well as both small sample bias and the issue of short frequency (see Islam, 2003). In general terms, as suggested by Evans (1997) and Durlauf and Quah (1999), the problems associated with the regression approach are all linked to the accomplishment of the restrictive parametric assumptions of the regression models to produce consistent estimators.

In order to overcome the limitations of regression analysis, other techniques are focused on the cross-section distribution of income. Within this approach scholars have based their analyses on the study of either σ -convergence (see Lichtenberg, 1994; Lee et al., 1997), or the *distribution dynamics* developed by Danny Quah (see Quah, 1993b, 1996c, 1997), whose findings are consistent with the endogenous growth theories (Durlauf, 1996). While both perspectives focus on the income distribution, they are not closely related.⁴ Whereas the former refers to a reduction in the dispersion of levels of income across economies—i.e., it only focuses on one feature of the distribution, namely the variance, the latter evaluates how the entire shape of the distribution evolves over time, as well as allowing identification of the position of each economy within the distribution, i.e., whether intra-distribution mobility exists. However, it could be argued that the absence of a model prevents the analysts from studying the determinants of convergence.

This disadvantage can be overcome with the introduction of the so-called conditioning schemes (Quah, 1997), which permits the distribution of income to be conditioned by a set of factors potentially affecting convergence. Therefore, the distribution dynamics approach might become a more attractive technique in order to study the convergence patterns, which has led to a considerable increase in the number of applications to increase remarkably, including those contributions mentioned in the Introduction.

2.2. Technical notes on distribution dynamics

Distribution dynamics' methods focus on the study of the cross-section distribution of the variable of interest, usually income per capita. This approach is framed within the set of nonparametric techniques, which are particularly powerful for studying the data structure. Nonparametric methods have the advantage of not requiring any preliminary assumptions on the distribution and are especially useful for explanatory aims. They rely completely on the data and let them to "speak for themselves", thus providing a better understanding

⁴In fact, σ -convergence is actually more related to β -convergence. Islam (2003) provides a detailed explanation on their relationship.

of how they behave. Following this approach, we find evidence of convergence when the probability mass in the distribution of income accumulates around a certain value. If the data are standardized, then we have convergence “to the mean” when the probability mass concentrates around the unity.

Yet this nonparametric approach, which mainly relies on visual tools, has been criticised (see Scott, 1992), since if the technique allows for any particular feature of the data to be unveiled, then the final graphical result might be difficult to interpret if the number of observations is high. Nevertheless, this problem can be solved by smoothing the data. While various alternatives are available for this purpose, kernel smoothing is the most popular for its particularly good properties. The approach consists of estimating the following density function for income per capita at different periods t :

$$\hat{f}_t(y) = \frac{1}{nh} \sum_{i=1}^n K\left(\frac{1}{h}\|y - Y_i\|\right) \quad (2)$$

where n is the number of regions, Y_i is the income per capita (standardized), K is a kernel function and h is the bandwidth parameter. Finally, $\|\cdot\|$ is a measure of distance, for instance the Euclidean distance.

The kernel selected is the Gaussian kernel, although differences between competing alternatives are slight,⁵ whereas of much greater importance is the selection of the bandwidth (h), which determines the amplitude of the bumps (Silverman, 1986). When h is too small it produces an excessive number of bumps (undersmoothing), which severely hinders understanding of the data structure. In contrast, when h is too large, some of the features of the data might remain hidden (oversmoothing). Therefore, the selection of the appropriate bandwidth parameter is an essential decision in kernel smoothing. The bandwidth was selected by using the method proposed by Sheather and Jones (1991), based on the solve-the-equation plug-in approach, whose good performance has been demonstrated in several studies (see Jones et al., 1996).

While the above analysis is a good strategy to study the cross-section of income in a given period (t), it does not permit the study of the internal dynamics of the distribution, which actually shows if the economies remain stable in their relative positions or, on the contrary, they transit to a different stage of development. This issue can be approached by

⁵Other alternatives are the triangular, the rectangular or the Epanechnikov kernel. In particular, the Gaussian kernel obeys to the expression $K(x) = (\sqrt{2\pi})^{-1} \exp\left(-\frac{1}{2}x^2\right)$.

means of stochastic kernels, which allow the examination of the law of motion describing how the income distribution at time t , denoted by F_t , converts into F_{t+s} at period $t + s$. The distribution F_{t+s} evolves according to the following n -th order Markov process:

$$\forall s \geq 1 : F_{t+s} = M^s F_t \quad (3)$$

where M maps F 's transition from period t to period $t + s$.

The construction of M can be either discrete or continuous. In the discrete case, M is a transition probability matrix showing the probability of one economy moving between a finite number of states, measured as intervals of income. Each element (i, j) in M is the probability that an economy in state i will move to state j in the next period. However, some authors such as Quah (1997) or Bulli (2001), among others, point out that the long-run behavior of F 's distribution is conditioned by the number of states, defined *a priori* by the analyst. Income level is a continuous variable, and therefore a more appropriate strategy is a continuous approach that considers an infinite number of states (Fischer and Stumpner, 2008). In the continuous approach, M becomes a representation of a stochastic kernel describing the evolution of the cross-section distribution of income over time.

Let us denote as Y_i and M_i the income of region i in periods t and $t + s$ ($s \geq 1$), respectively. Then, the associate cross-section distributions for all the regions in the sample can be denoted as $f_t(y)$ and $f_{t+s}(m)$ and its time evolution is expressed as:

$$f_{t+s}(m) = \int_0^\infty v_s(m|y) f_t(y) dy \quad (4)$$

where $v_s(m|y)$ is the conditional density which shows the probability of a region transiting between two specific states, given its relative income at period t . This conditional density can be estimated following Rosenblatt's (1969) proposal (see Hyndman et al., 1996), which consists of computing the conditional density by dividing the bivariate density function by the implied marginal:

$$\hat{v}_s(m|y) = \frac{\hat{f}_{t,t+s}(y, m)}{\hat{f}_t(y)} \quad (5)$$

where

$$\hat{f}_{t,t+s}(y, m) = \frac{1}{nh_y h_m} \sum_{i=1}^n K\left(\frac{1}{h_y} \|y - Y_i\|_y\right) K\left(\frac{1}{h_m} \|m - M_i\|_m\right) \quad (6)$$

is the combined density of (M, Y) and

$$\hat{f}_t(y) = \frac{1}{nh_y} \sum_{i=1}^n K\left(\frac{1}{h_y} \|y - Y_i\|_y\right) \quad (7)$$

is the marginal density of Y , and h_y and h_m are the bandwidth parameters.

The conditional densities are computed using Hyndman et al.'s (1996) methods, which provide different alternatives for displaying the densities. On the one hand, three-dimensional plots show the stacked conditional densities for a grid of values of the conditioning variable, which are particularly useful for interpreting the results of conditioning. On the other hand, high density region plots (HDR) delimit high density areas by means of shaded regions of varying intensity. In particular, the colored areas represent—from the darkest to the lightest shade—50%, 90% and 99% of the probability mass, respectively.

Both the stacked densities and the HDR plots actually map the transition between two distributions. In the basic scenario (unconditioned), it is equivalent to studying the regional intra-distribution mobility over time, i.e., the transition from period t to $t + s$, conditioned on the relative income of each region at period t . When other conditioning factors are considered, a conditioned distribution is constructed according to the relative level of the conditioning factor in each region, and the transition from the original distribution to the conditioned one allows the influence of the conditioning factor to be evaluated. If the probability mass in the graphs concentrates along the main diagonal it means that the conditioning factor has no influence, since the relative position of the economies remains unaltered. However, if the probability mass accumulates toward the conditioned series, then the conditioning factor has some explanatory power.

3. Sample and data

The sample consists of 216 European regions at NUTS 2 level. Regional income per capita in Purchasing Parity Standards (PPS) for the entire period 1995–2009 was provided by Eurostat.⁶ Regional data on the intangible assets were taken from different sources. Unfortunately, these data are not available for the entire period, but only for a few non consecutive years. In order to capture the initial conditions of the economies, the data were taken as close as possible to the beginning of the period (1995).

The first intangible asset considered is technological capital (TC), measured as the num-

⁶<http://epp.eurostat.ec.europa.eu>.

ber of patent applications adhering to the Patent Cooperation Treaty (PTC). This ensures the economic value of the patents, since registering a patent under this system is expensive. The data come from the OECD REGPAT database,⁷ and the indicator is constructed by taking the stock of patents over the total population in 1998 (first year available). The data is regionalized according to the residence of the inventor. Where there is more than one inventor, each region receives a proportional quota.

The human capital (HC) indicator is constructed by considering the percentage of the population aged between 24 and 65 with tertiary education (ISCED 5 and 6) in 2000, the first year for which Eurostat provides regional data on human capital.

Finally, social capital (SC) is perhaps the most difficult asset to measure, since this concept encompasses a mixture of different components (Bjørnskov, 2006). In this paper, social capital is proxied by an indicator of interpersonal trust, which is by far the most commonly used in the social capital literature (see, for instance, Zak and Knack, 2001; Dearmon and Grier, 2009; Bjørnskov, 2012; Peiró-Palomino and Tortosa-Ausina, 2013a). The indicator is constructed using data from the European Values Study (EVS)⁸, which provides regional data on social values and beliefs. Interpersonal trust is measured by the question *“Generally speaking, would you say that most people can be trusted, or that you cannot be too careful in dealing with people?”*. Two possible answers are provided, namely: (i) *“most people can be trusted”*; and (ii) *“can’t be too careful”*. The trust index is constructed by considering the percentage of respondents who answered *“most people can be trusted”* in the wave of 1999.⁹

Table 1 provides the sample of regions and Table 2 contains some descriptive statistics for the three intangible assets. Although there are noticeable differences among all three assets, technological capital has the most disparities.

4. Results

In this section the techniques described above are applied. The 14 year period (1995–2009) is subdivided in two seven-year subperiods, taking 1995, 2002 and 2009 as references. For each of these three years a kernel density of income without conditioning on any other

⁷<http://www.oecd.org/sti/inno/oecdpatentdatabases.htm>

⁸<http://www.europeanvaluesstudy.eu>.

⁹In contrast with all the other variables in the analysis, aggregated at NUTS 2 level, the indicator of social capital is constructed at NUTS 1 level because this is the smallest level of disaggregation for some countries. Accordingly, all the regions belonging to the same NUTS 1 area are assumed to have identical level of social capital. This assumption is plausible, since in many countries cross regional differences in social capital are slight and only noticeable at the country level.

variable (univariate analysis) is computed in a first stage. This simple analysis (results are provided in Section 4.1), is a powerful tool to analyze how the distribution of income across Europe's regions has evolved over the period considered. Multiple conditioning schemes are considered in a further stage, and are explained in detail in Section 4.2. This more comprehensive analysis will allow us to evaluate with some precision the role played by the different conditioning factors in the convergence process.

4.1. Unconditioned analysis

The results for the dynamics of the cross-section of relative income are provided in both Figures 1 a) and b). Figure 1 a) displays box plots. They show a remarkable reduction in disparities, especially during the subperiod 2002–2009. The size of the box, containing 50% of the probability mass shrank substantially, and the two adjacent values—i.e. the horizontal lines at the bottom and the top of the box plots—are closer in 2009. In addition, the position of the median inside the box changed over the period. In 1995 the distribution was quite asymmetric, unlike in 2009, the year in which the median is in the middle of the box. These two changes summarize a process of convergence between 1995 and 2009 that accelerated in the subperiod 2002–2009. However, the outlying observations corresponding to overperformers increased from three in 1995 to nine in 2009. In general terms, however, the box plots highlight a reduction in the income disparities across the European regions.

Perhaps more information can be gained from Figure 1 b), which shows kernel densities for the cross-section of income corresponding to the years 1995, 2002 and 2009. The density for 1995 reveals a marked bimodality. On the one hand, the largest group of regions is located around 1.2 times the average income. On the other hand, there is a large amount of probability mass below 0.5 times the average income. This bimodality in 1995 is a well-known result, in line with previous contributions using the distribution dynamics approach (see, for instance Le Gallo, 2004; Fischer and Stumpner, 2008; Ezcurra, 2010). The density for 2002 shows that the bimodality persists, although it fell substantially. However, as noted in the preceding paragraph, the main process of convergence takes place in the 2002–2009 period. The density for 2009 shows that the second mode, corresponding to the regions below 0.5 times the average, has almost disappeared. In addition, the largest mode has moved to the left and the greatest probability density is now around the mean.

Although differences between distributions can be noticed visually, their equality was formally tested using the Li (1996) test, based on the generally accepted idea of measur-

ing the global distance (closeness) between two densities.¹⁰ Table 3 provides the results for these tests. In particular, the null hypothesis of equality of distributions is rejected at the 1% level when comparing the distributions for the years 1995 and 2009, 2002 and 2009. However, the distributions for 1995 and 2002 are not statistically different. Therefore, the general conclusion of this first analysis is that the disparities across European regions shrank dramatically between 1995 and 2009, but the major process of convergence took place in the subperiod 2002–2009, when the distribution of income evolved towards unimodality.

The above analysis helps to understand the evolution of the cross-section of income over time. However, because the economies' relative positions in income distribution might have changed, in the next stage of the analysis the intra-distribution mobility will be evaluated. In order to do so, stochastic kernels are computed by estimating the distribution of income at period $t + s$ (2009), conditioned on the regional relative income at period t (1995). The conditional probabilities are obtained by estimating the joint density at periods t and $t + s$ and then dividing by the marginal distribution (see Section 2.2).

Figures 2 a) and b) show the stacked densities and the associated HDR plot, respectively. Both plots are complementary tools in order to study the intra-distribution mobility. As previously noted in Section 2.2, a large amount of probability mass around the main diagonal indicates persistence, which would be linked to the idea that the economies have remained in the same position over the studied period. The reader might notice from Figures 2 a) and b) that this is not actually the case. Only a small group of rich economies and some regions around 0.7 times the average income remained stable. However, the relative position of the economies above the average in 1995 worsened by 2009 and it improved for those below the average (this can be seen especially clearly from Figure 2 b). This pattern of intra-distribution mobility, in which the poorer economies improve slightly and the richer ones worsen substantially supports the change in the shape of the kernel densities analyzed above. These results differ from previous findings for European regions following the distribution dynamics approach: however these disparities might be explained by the period analyzed.¹¹

¹⁰See Kumar and Russell (2002) for technical details and Murillo-Melchor et al. (2010) or Thieme et al. (2012) for recent applications.

¹¹Figures 2 a) and b) were also computed for the subperiods 1995–2002 and 2002–2009. The results for the first subperiod are aligned to the findings by Fischer and Stumpner (2008). These results are not included in order to save space but can be provided upon request.

4.2. Factors conditioning the convergence process

So far, the analysis has focused on the study of income distribution and its intra-distribution mobility. This section goes further and evaluates the contribution of different factors to the convergence process. Geographical factors are included in the analysis: insomuch as they have an effect on economic activity, one would expect neighboring regions to be more likely to converge than distant ones. The importance of spatial effects has been assessed in many different geographical contexts by authors such as Le Gallo and Ertur (2003), Tortosa-Ausina et al. (2005) or, more recently, by Fischer and Stumpner (2008).

The analysis also includes the intangible assets introduced in Section 3. Dettori et al. (2012) concluded that intangible assets positively affect regional efficiency in the European regional context, and that translates into improvements in total factor productivity (TFP). According to Fischer et al. (2009), technological capital—measured as the stock of patents—is related to TFP and it is subject to spillover effects. In the same line, Rodríguez-Pose and Crescenzi (2008) conclude that R&D efforts (in general the higher the R&D effort, the higher the number of patents) are partly responsible for economic growth in European regions. In addition, these effects are reinforced by other socioeconomic conditions that facilitate the assimilation of innovation and its transformation into economic growth (Rodríguez-Pose and Crescenzi 2008, p.63).

One of these factors is human capital, whose importance for growth processes was highlighted at the beginning of the nineties by Mankiw et al. (1992). When considering relatively advanced economies, which is actually the case of most of the European regions, measuring human capital as the percentage of highly educated workers (tertiary studies) has become common practice (see, for instance Crespo-Cuaresma et al., 2011; Dettori et al., 2012). This strategy might be particularly appropriate mainly for two main reasons: i) most regions might show similar levels in primary and secondary school schooling rates; and ii) it is reasonable to think that tertiary education is more closely related to high value added economic activities, which are those leading regional productivity increases and economic performance. Therefore, in relatively advanced economies the positive outcomes of human capital might come mainly from tertiary education, which provides high-skilled workers. The results found by Crespo-Cuaresma et al. (2012) support this hypothesis.

Finally, there is wide academic consensus that the effects of social capital are seen in reduced transaction costs in economic operations. Social capital facilitates coordination and cooperation, helps solve problems of collective action, reduces the incentives for oppor-

tunism and egoism, and mitigates information asymmetries between negotiating parties. In addition, it is also beneficial for other activities that promote economic development, such as innovation and knowledge diffusion (Akçomak and Ter Weel, 2009), the creation of human capital (Bjørnskov, 2009; Dearmon and Grier, 2011), investment (Zak and Knack, 2001; Peiró-Palomino and Tortosa-Ausina, 2013b), financial development (Guiso et al., 2004), and better government (Bjørnskov and Méon, 2013), among other related activities.¹²

Therefore, in as far as these assets might promote regional development, one might expect that regions with similar endowments of these assets to also be similar in terms of income per capita. In order to evaluate the extent to which the above-mentioned factors have contributed to the convergence process, four new income series are constructed (one spatially conditioned and three intangible assets conditioned). In the new series, income in each region is not relativized according to the sample mean, as in the unconditioned analysis, but according to the neighboring regions, excluding the region itself. In the case of the spatial factors, neighbors are considered as those regions within a delimited distance.¹³ In the case of the intangible assets conditioning, neighbors are those regions sharing levels of these assets in a given period t , which corresponds to the closest year to the beginning of the period for which data on each of the intangible assets are available.

4.2.1. Spatial conditioning

This section considers the effect of the physical neighbors on the convergence process. In order to transform the original income series into a spatially conditioned series, a spatial-weights matrix W is constructed. In doing so, the distance between the region's capital cities is calculated.¹⁴ Then, following Le Gallo (2004), a threshold corresponding to the first quartile of the distance is established. Consequently, the spatial effects are supposed to take place only below this threshold and those regions beyond that distance are replaced by zero in the matrix. Following common practice in the spatial econometric literature (see, for instance Anselin et al., 2004), the square of the inverse of the distance is calculated for those regions below the threshold. After that, the rows in the matrix are normalized such

¹²For a comprehensive discussion on social capital theory and its links to economic development, see, for instance, Westlund (2006).

¹³Additional details are provided in Section 4.2.1.

¹⁴Another possibility would be to consider the centroid of each region. Nevertheless, for some regions the centroid may correspond to an inhabited area. Capital cities, however, are normally centers of intense economic activity from where spatial effects would be spread across space. For those regions with no official capital city, the most economically influential city was selected.

that each row sums to one, and therefore the influence of each neighbor is relative to the distance from its location. Finally, the income in each region is relativized according to the average income of its neighbors, excluding the region itself, and taking into account the varying influence of each neighbor given by the spatial-weights matrix.

The kernel density for the spatially conditioned income is displayed by the dotted red line in Figure 3 for the years 1995, 2002 and 2009. The result is revealing, especially for 1995. Compared to the original distribution, shown by the solid black line, the mode below 0.5 times the average income has disappeared. Another mode around 1.4 times the average has emerged but, in general terms, the distribution is tighter than the original one, indicating evidence of convergence if each region is compared to its physical neighbors. In years 2002 and 2009 the distribution becomes even sharper, reinforcing the hypothesis of spatial convergence, although the small second mode around 1.4 times the average still persists. The corresponding Li (1996) tests in Table 3 corroborate that that visual differences are actually statistically significant for the three years of reference (1995, 2002 and 2009).

A more precise picture of how neighboring effects have affected the distribution of income is provided by Figure 4 a) and b), which consider data for the entire period (1995–2009). They clearly show a counter-clockwise shift of the probability mass toward the X axis, i.e., the spatially conditioned income series. When income data is relativized to the neighbors' income, the poorer regions improve and the richer ones worsen, with the exception of a small group of the richest regions, for which there is evidence of strong persistence in their relative position. This result evidences the importance of spatial effects in the European context, and shows that the convergence process is stronger when each economy is compared to its geographical neighbors. In other words, as suggested by Fischer and Stumpner (2008), such a result would imply that the probability of the regions transiting across income levels might be limited by the existence of spatial effects.

4.2.2. Intangible assets conditioning

Now the possible influence of the intangible assets is assessed. As in the previous analysis, the original data series, relative to the global average, was transformed into series relative to the neighbors' average. In this section, however, neighbors are considered those regions in the same quartile of the distribution of the corresponding intangible asset in a year as close as possible to the beginning of the period (1995). Each region's income is therefore relativized according to the average of its neighbors, excluding the region itself.

We first turn to the influence of **technological capital (TC)**, the dotted green line in Figure 3 shows the kernel density for the income relative to the average of the neighbors' technological capital for 1995, 2002 and 2009. When the data are conditioned, there is evidence of convergence in the three years. The marked mode of the original distribution at around 0.5 times the average income in 1995 has completely disappeared in the technological capital relativized data. In addition, the main mode is slightly below the average and another small mode around 1.5 times the average emerges, although it is admittedly smaller than the main one. This secondary mode smoothes in 2002 and appears again in 2009, but the main feature that can be seen from the distribution is that it becomes progressively sharper, which is a sign of convergence.

Figure 5 a) shows the transition from the original income distribution to the TC conditioned. The stacked kernel densities are far from the main diagonal and the probability mass tends to concentrate towards the X axis, i.e. the conditioned series. The high density region (HDR) plot displayed in Figure 5 b) clearly reflects this process. The regions below the average improve substantially and performance in the regions far above the average is moderated when their income is relativized to their neighbors' technological capital. However, there is evidence of persistence for the small group of the richest regions. Li (1996) tests in Table 3 corroborate the difference between the original and the conditioned distributions. This holds for averaged data (1995–2009), as well as for the distributions in the three years analyzed, namely 1995, 2002 and 2009. Therefore, the regional endowments of technological capital might have actually driven the convergence patterns in Europe. The effect of technological capital on the convergence process is comparable to that of geography, analyzed in the previous section.

Regarding **human capital (HC)**, the dashed-dotted dark blue line in Figure 3 shows the kernel density for the income relative to the average of the neighbors' human capital for 1995, 2002 and 2009. Compared to the original series, the second mode around 0.5 times the average in 1995 disappears in the conditioned series. However, the distribution of the conditioned series is more dispersed, especially if it is compared to both the spatial and the technological conditioned distributions. Nevertheless, for years 2002 and 2009 the distribution becomes tighter, indicating convergence. In line with the unconditioned distribution, a small mode appears around 1.8 times average income in 2009.

The effects of human capital conditioning are more visible in Figures 6 a) and b). Human capital has the greatest effects in the poorest regions (below 0.6 times the average),

which dramatically improve when their income is compared to the regions with similar levels of human capital. In addition, the relative position of regions between 1.5 and 3 times the average income (especially the range between 2 and 3) worsens in the HC conditioned series. Nevertheless, for the group of the richest economies, the plots show high persistency in their relative positions after human capital is taken into account. The general conclusion of this conditioning scheme, however, is that human capital has played a relevant role in the convergence process, comparable to those of geography (spatial effects) and technological capital. Li (1996) tests in Table 3 indicate that, considering average data for the entire period, the original distribution differs from the human capital conditioned distribution, which lends strong support to this hypothesis. However, its influence was more decisive at the beginning of the period, since the HC conditioned distributions for 2002 and 2009 do not statistically differ from the original.

Finally, the influence of **social capital (SC)** is considered. The dashed light blue line in Figure 3 displays the kernel distribution for the income relative to neighbors in social capital for the years 1995, 2002 and 2009. The density in 1995 presents remarkable differences compared to the unconditioned distribution. As in the previous conditioned series, the mode below 0.5 times the average income has completely disappeared. Nevertheless, the mode around 1.5 times the average income emerges, which also appeared in both the original and the human capital conditioned series. In 2002 this second mode is exacerbated but it is substantially smoothed in 2009. In the latter year, the distribution of the social capital conditioned series is very similar to that for the unconditioned data and human capital conditioned.

To better analyze the role of social capital in the convergence process, Figure 7 a) and b) show the stacked densities and the HDR plots, respectively. The role of social capital seems to be more limited for the regions between 0.7 and 1.2 times the average as well as for the richest regions, which show persistence in their relative positions. However, for the group of the poorest economies (those below 0.5 times the average income), the conditioning process reveals a substantial improvement, and the relative position of those regions between 1.5 and 3 times the average in the unconditioned distribution worsens in the SC conditioned series. The effect of social capital is quite similar to that of human capital. On average, Li (1996) tests in Table 3 corroborate that the SC conditioned distributions differ statistically from the original. These differences are also significant for the years 1995 and 2002, but not for 2009, indicating that, similar to human capital, the effect of social capital

was more notable at the beginning of the period.

The individual analysis of the conditioning factors leads us to the general conclusion is that, on average, all these factors have a substantial influence in the convergence process. The factors with the greatest impact are spatial effects and technological capital, while both human and social capital have a more limited effect, especially in the second subperiod (2002–2009).

5. Concluding remarks

The issue of convergence among European regions has generated an intense academic debate in relatively recent times. This paper has assessed the dynamics of income per capita for a sample of 216 European regions, attempting to contribute to the literature in two different aspects. First, it extends the time span of previous studies by focusing on the period 1995–2009, and second, it considers a set of conditioning factors of the convergence process, including the spatial effects and a set of intangible assets. Conditioned nonparametric stochastic kernels were computed and implemented using Hyndman et al.'s (1996) techniques, which allowed us to analyze the effects of conditioning with greater precision.

The unconditioned analysis showed a process of convergence, especially in the period 2002–2009. This finding contrast with previous contributions, which find strong evidence of polarization for earlier periods. Therefore, the results for the most recent period might suggest a change in that polarization tendency, implying that the twin peaks suggested by Quah (1996a) have diminished and European regions in 2009 are much more similar in terms of income than they were in 1995. The results for the conditioning schemes reveal that all the conditioning factors considered have had a remarkable effect in the period analyzed. This effect, while substantial throughout the entire period, is especially noticeable in 1995, when income distribution becomes unimodal when it is conditioned, regardless of the factor considered. This process is more clearly highlighted by the stochastic kernels, which show important intra-distribution movements from the original series to the conditioned ones.

Given that convergence is a key objective for the EU, the results might have policy implications. Insofar as regions with similar levels of intangible assets are more likely to converge in income per capita, the degree of success of the European regional policies can be seriously conditioned on the regional disparities in terms of these assets and, consequently, the efforts should aim to achieve similar stocks of intangible assets. They are

actually considered as strategic factors for the “Europe 2020 Strategy”, and the results from this analysis highlight its importance. This is also true for the case of social capital, the inclusion of which is completely innovative in a convergence analysis. The results suggest that social features, in particular interpersonal trust, help in explaining regional disparities in Europe, which suggests that efforts should also be addressed at homogenizing sociological aspects. In addition, the role played by the spatial effects throughout the entire period highlights the importance of spillover effects. Thus, if the intangible assets in a given region are improved, neighboring regions might also benefit from that improvement.

However, it is worth noting that the influence of the conditioning factors was, in general, stronger at the beginning of the period than in the latter years, whereas the process of income convergence is stronger precisely at the end of the period. This finding might suggest that elements other than the ones considered in this paper might have affected regional convergence. An alternative explanation holds that the high growth among most of the new members of the EU in recent years is explained merely by joining the EU and receiving cohesion funds as a result, since these regions were below the 75% of the average income. Finally, a third likely explanation should not be disregarded. Some peripheral countries such as Spain, Greece and Portugal experienced intense economic growth in the second subperiod. However, this growth is no longer explained by the intangible assets, but it is a consequence of the bubble preceding the economic recession. Therefore, although the results found are encouraging, they should be considered with caution. This study opens the door for further research initiatives in the immediate future, especially when even more recent regional data becomes available. This will be essential to assess whether converging tendencies remain unaltered during the current years of economic crisis.

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Table 1: The sample

Country	ID	Region	NUTS code
Belgium	1	Région de Bruxelles-Capitale	B10
	2	Antwerpen	B21
	3	Limburg (BE)	B22
	4	Oost-Vlaanderen	B23
	5	Vlaams-Brabant	B24
	6	West-Vlaanderen	B25
	7	Brabant Wallon	B31
	8	Hainaut	B32
	9	Liège	B33
	10	Luxembourg (BE)	B34
	11	Namur	B35
Bulgaria	12	Severozapaden	BG31
	13	Severen tsentralen	BG32
	14	Severoiztochen	BG33
	15	Yugoiztochen	BG34
	16	Yugozapaden	BG41
	17	Yuzhen tsentralen	BG42
Czech Republic	18	Praha	CZ01
	19	Strední Cechy	CZ02
	20	Jihozápad	CZ03
	21	Severozápad	CZ04
	22	Severovýchod	CZ05
	23	Jihovýchod	CZ06
	24	Strední Morava	CZ07
	25	Moravskoslezsko	CZ08
Denmark	26	Hovedstaden	DK01
	27	Sjælland	DK02
	28	Syddanmark	DK03
	29	Midtjylland	DK04
	30	Nordjylland	DK05
Germany	31	Stuttgart	DE11
	32	Karlsruhe	DE12
	33	Freiburg	DE13
	34	Tübingen	DE14
	35	Oberbayern	DE21
	36	Niederbayern	DE22
	37	Oberpfalz	DE23
	38	Oberfranken	DE24
	39	Mittelfranken	DE25
	40	Unterfranken	DE26
	41	Schwaben	DE27
	42	Berlin	DE30
	43	Brandenburg - Nordost	DE41
	44	Brandenburg - Südwest	DE42
	45	Bremen	DE50
	46	Hamburg	DE60
	47	Darmstadt	DE71
	48	Gießen	DE72
	49	Kassel	DE73
	50	Mecklenburg-Vorpommern	DE80
	51	Braunschweig	DE91
	52	Hannover	DE92
	53	Lüneburg	DE93
	54	Weser-Ems	DE94
	55	Düsseldorf	DEA1
	56	Köln	DEA2
	57	Münster	DEA3
	58	Detmold	DEA4
	59	Arnsberg	DEA5
	60	Koblenz	DEB1
	61	Trier	DEB2

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Country	ID	Region	NUTS code
	62	Rheinessen-Pfalz	DEB3
	63	Saarland	DEC1
	64	Chemnitz	DED1
	65	Dresden	DED2
	66	Leipzig	DED3
	67	Sachsen-Anhalt	DEE0
	68	Schleswig-Holstein	DEF0
	69	Thüringen	DEG0
Eesti	70	Eesti	EE00
	71	Anatoliki Makedonia	GR11
	72	Kentriki Makedonia	GR12
	73	Dytiki Makedonia	GR13
	74	Thessalia	GR14
	75	Ipeiros	GR21
	76	Ionia Nisia	GR22
	77	Dytiki Ellada	GR23
	78	Stereia Ellada	GR24
	79	Peloponnisos	GR25
	80	Attiki	GR31
	81	Voreio Aigaio	GR32
	82	Notio Aigaio	GR33
	83	Kriti	GR34
	84	Galicia	ES11
	85	Principado de Asturias	ES12
	86	Cantabria	ES13
	87	País Vasco	ES21
	88	Comunidad Foral de Navarra	ES22
	89	La Rioja	ES23
	90	Aragón	ES24
	91	Comunidad de Madrid	ES30
	92	Castilla y León	ES41
	93	Castilla-la Mancha	ES42
	94	Extremadura	ES43
	95	Cataluña	ES51
	96	Comunidad Valenciana	ES52
	97	Islas Baleares	ES53
	98	Andalucía	ES61
	99	Región de Murcia	ES62
	100	Île de France	FR10
	101	Champagne-Ardenne	FR21
	102	Picardie	FR22
	103	Haute-Normandie	FR23
	104	Centre	FR24
	105	Basse-Normandie	FR25
	106	Bourgogne	FR26
	107	Nord - Pas-de-Calais	FR30
	108	Lorraine	FR41
	109	Alsace	FR42
	110	Franche-Comté	FR43
	111	Pays de la Loire	FR51
	112	Bretagne	FR52
	113	Poitou-Charentes	FR53
	114	Aquitaine	FR61
	115	Midi-Pyrénées	FR62
	116	Limousin	FR63
	117	Rhône-Alpes	FR71
	118	Auvergne	FR72
	119	Languedoc-Roussillon	FR81
	120	Provence-Alpes-Côte d'Azur	FR82
	121	Corse	FR83
Latvia	122	Latvija	LV00

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Country	ID	Region	NUTS code
Lithuania	123	Lietuva	LT00
Netherlands	124	Groningen	NL11
	125	Friesland	NL12
	126	Drenthe	NL13
	127	Overijssel	NL21
	128	Gelderland	NL22
	129	Flevoland	NL23
	130	Utrecht	NL31
	131	Noord-Holland	NL32
	132	Zuid-Holland	NL33
	133	Zeeland	NL34
	134	Noord-Brabant	NL41
	135	Limburg (NL)	NL42
Poland	136	Lódzkie	PL11
	137	Mazowieckie	PL12
	138	Malopolskie	PL21
	139	Slaskie	PL22
	140	Lubelskie	PL31
	141	Podkarpackie	PL32
	142	Swietokrzyskie	PL33
	143	Podlaskie	PL34
	144	Wielkopolskie	PL41
	145	Zachodniopomorskie	PL42
	146	Lubuskie	PL43
	147	Dolnoslaskie	PL51
	148	Opolskie	PL52
	149	Kujawsko-Pomorskie	PL61
	150	Warminsko-Mazurskie	PL62
151	Pomorskie	PL63	
Portugal	152	Norte	PT11
	153	Algarve	PT15
	154	Centro (PT)	PT16
	155	Lisboa	PT17
	156	Alentejo	PT18
Romania	157	Nord-Vest	RO11
	158	Centru	RO12
	159	Nord-Est	RO21
	160	Sud-Est	RO22
	161	Sud - Muntenia	RO31
	162	Bucuresti - Ilfov	RO32
	163	Sud-Vest Oltenia	RO41
164	Vest	RO42	
Slovenia	165	Vzhodna Slovenija	SI01
	166	Zahodna Slovenija	SI02
Slovakia	167	Bratislavský kraj	SK01
	168	Západné Slovensko	SK02
	169	Bratislavský kraj	SK03
	170	Západné Slovensko	SK04
Finland	171	Itä-Suomi	FI13
	172	Etelä-Suomi	FI18
	173	Länsi-Suomi	FI19
	174	Pohjois-Suomi	FIA
Sweden	175	Stockholm	SE11
	176	Östra Mellansverige	SE12
	177	Småland med öarna	SE21
	178	Sydsverige	SE22
	179	Västsverige	SE23
	180	Norra Mellansverige	SE31
	181	Mellersta Norrland	SE32
182	Övre Norrland	SE33	
	183	Tees Valley and Durham	UKC11

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Table 1 – Continued from previous page

Country	ID	Region	NUTS code
	184	Northumberland and Tyne and Wear	UKC2
	185	Cumbria	UKD1
	186	Cheshire	UKD2
	187	Greater Manchester	UKD3
	188	Lancashire	UKD4
	189	Merseyside	UKD5
	190	East Yorkshire and Northern Lincolnshire	UKE1
	191	North Yorkshire	UKE2
	192	South Yorkshire	UKE3
	193	West Yorkshire	UKE4
	194	Derbyshire and Nottinghamshire	UKF1
	195	Leicestershire	UKF2
	196	Lincolnshire	UKF3
	197	Herefordshire	UKG1
	198	Shropshire and Staffordshire	UKG2
	199	West Midlands	UKG3
	200	East Anglia	UKH1
	201	Bedfordshire and Hertfordshire	UKH2
	202	Essex	UKH3
	203	Inner London	UKI1
	204	Outer London	UKI2
	205	Berkshire	UKJ1
	206	Surrey	UKJ2
	207	Hampshire and Isle of Wight	UKJ3
	208	Kent	UKJ4
	209	Gloucestershire	UKK1
	210	Dorset and Somerset	UKK2
	211	Cornwall and Isles of Scilly	UKK3
	212	Devon	UKK4
	213	West Wales and The Valleys	UKL1
	214	East Wales	UKL2
	215	Eastern Scotland	UKM1
	216	South Western Scotland	UKM2

Table 2: Descriptive statistics for the intangible assets

Variable	Year	Mean	s.e.	Min.	1 st quartile	Median	3 rd quartile	Max.
Technological capital (TC)	1998	54.351	117.728	0.000	2.590	18.480	56.575	1,135.770
Human capital (HC)	2000	0.207	0.078	0.060	0.154	0.205	0.259	0.489
Social capital (SC)	1999	0.302	0.144	0.076	0.208	0.268	0.373	0.700

Notes: Technological capital is measured in levels (Stock of patents over total population), and both human and social capital are measured in percentages.

Table 3: Distribution hypothesis tests (Li, 1996)

Null hypothesis (H_0)	T-test statistic	p-value
$f_{1995} = f_{2002}$	0.503	0.308
$f_{1995} = f_{2009}$	3.505	0.000
$f_{1995} = f_{1995}^{SP}$	16.131	0.000
$f_{1995} = f_{1995}^{TC}$	6.591	0.000
$f_{1995} = f_{1995}^{HC}$	2.572	0.005
$f_{1995} = f_{1995}^{SC}$	3.407	0.000
$f_{2002} = f_{2009}$	2.291	0.011
$f_{2002} = f_{2002}^{SP}$	15.122	0.000
$f_{2002} = f_{2002}^{TC}$	5.783	0.000
$f_{2002} = f_{2002}^{HC}$	0.609	0.271
$f_{2002} = f_{2002}^{SC}$	2.649	0.004
$f_{2009} = f_{2009}^{SP}$	6.970	0.000
$f_{2009} = f_{2009}^{TC}$	2.775	0.003
$f_{2009} = f_{2009}^{HC}$	0.379	0.353
$f_{2009} = f_{2009}^{SC}$	0.829	0.205
$f_{AV} = f_{AV}^{SP}$	13.724	0.000
$f_{AV} = f_{AV}^{TC}$	9.092	0.000
$f_{AV} = f_{AV}^{HC}$	4.078	0.000
$f_{AV} = f_{AV}^{SC}$	4.620	0.000

Notes: In all cases, the alternative hypothesis (H_1) is $f_x \neq f_y$, where f_x and f_y are the two distributions under comparison. The superscripts SP, TC, HC and SC refer to the spatial, technological capital, human capital and social capital conditioned distributions, respectively. The subscript AV refers to averaged data (1995-2009), corresponding to Figures 4, 5, 6 and 7.

Figure 1: Income distribution, unconditioned

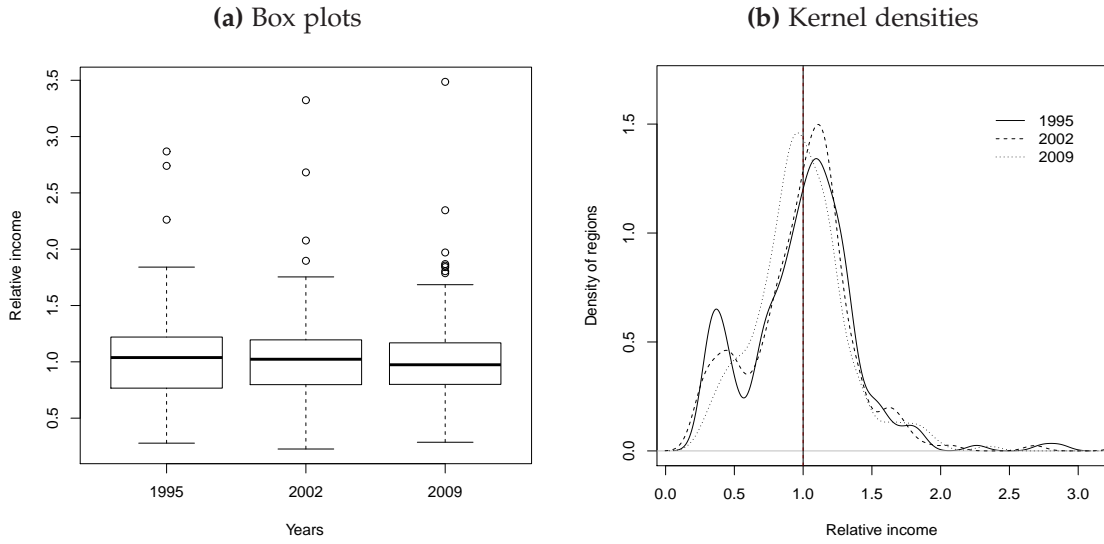
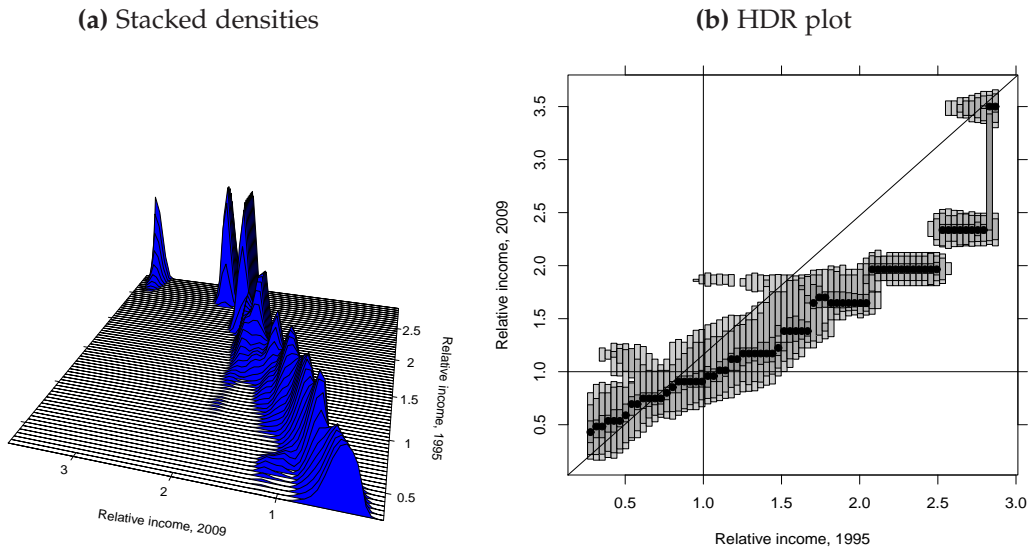
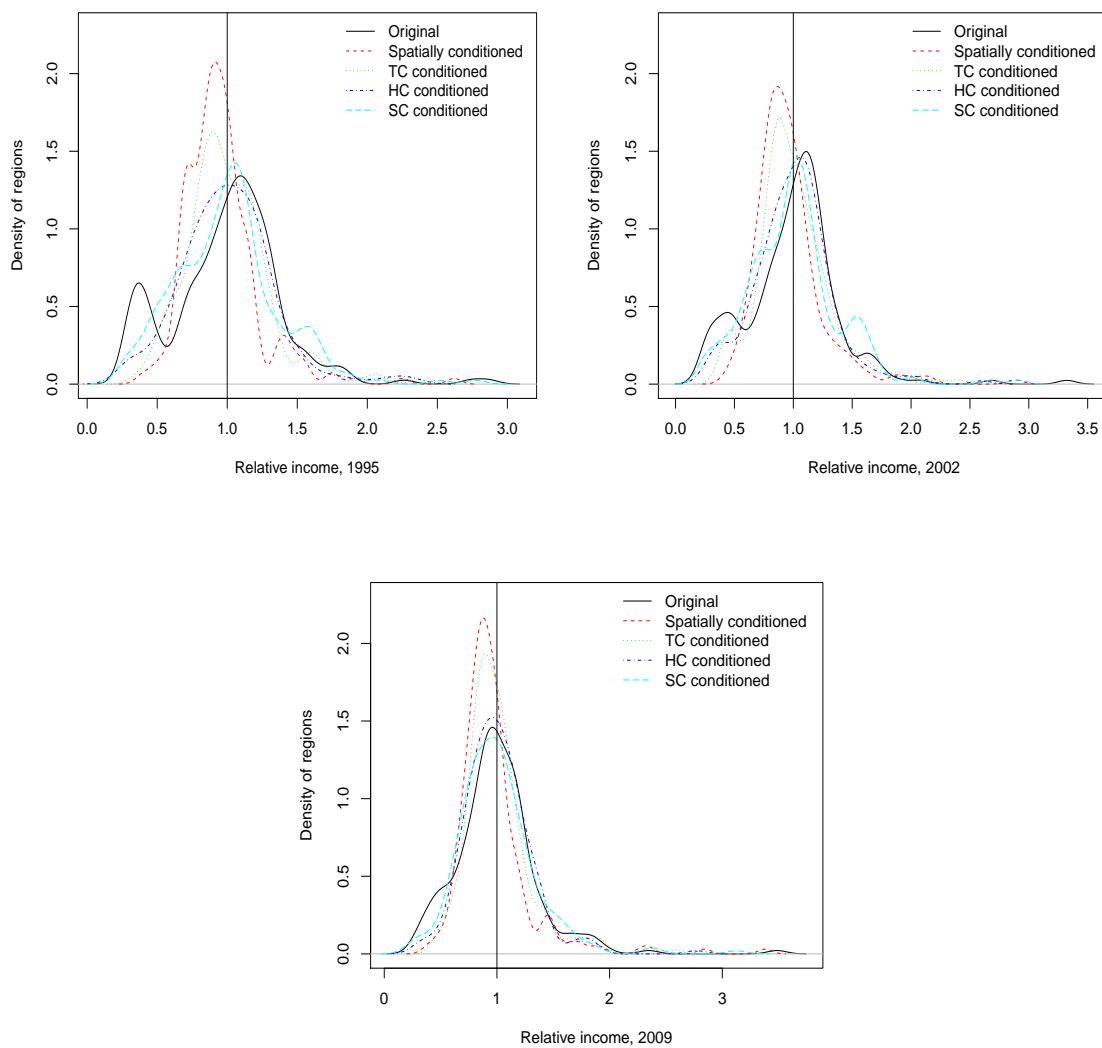


Figure 2: Intra-distribution mobility, unconditioned



Notes: Subfigure a) shows stacked stochastic kernels while subfigure b) displays the equivalent HDR plot. In the latter, 50%, 95% and 99% of the probability mass is represented by the gray bars, from the darkest to the lightest shade, respectively.

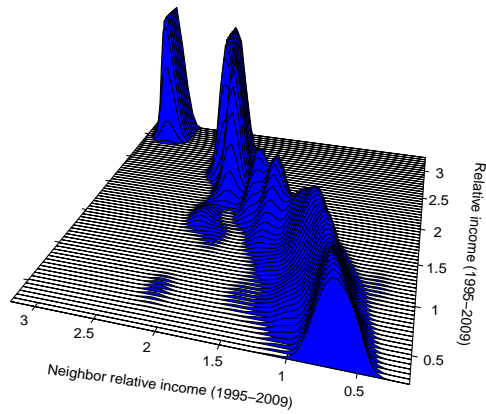
Figure 3: Conditioned densities: 1995, 2002 and 2009



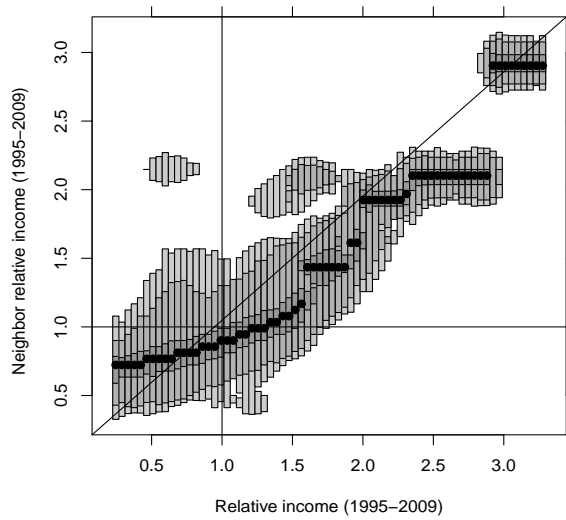
Notes: In the figures, the original distribution corresponds to the unconditioned series of income and the spatially conditioned represents the effect of the neighbors. TC, HC and SC represent the technological, human and social capital conditioned series, respectively.

Figure 4: Spatial conditioning

(a) Stacked densities: Original vs spatially conditioned



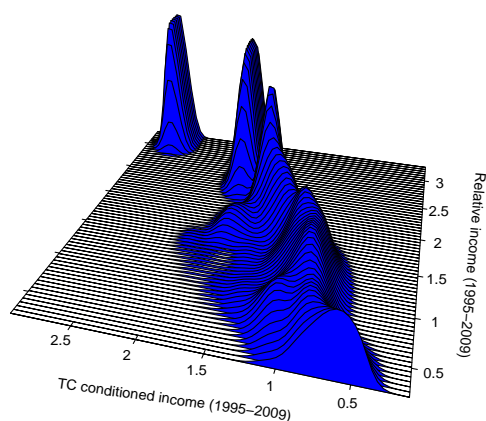
(b) HDR plot: Original vs spatially conditioned



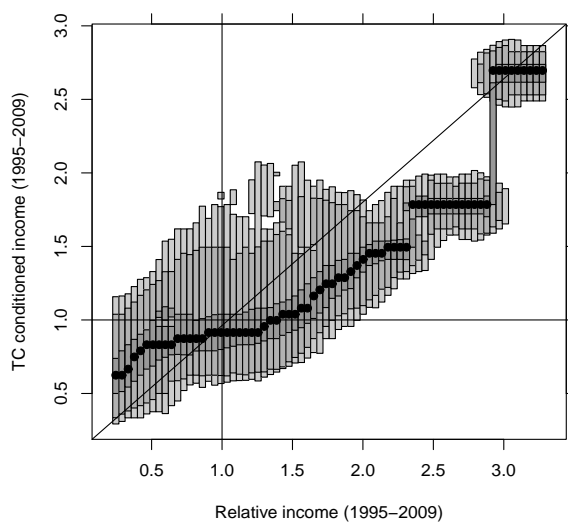
Notes: Subfigure a) shows stacked stochastic kernels while subfigure b) displays the equivalent HDR plot. In the latter, 50%, 95% and 99% of the probability mass is represented by the gray bars, from the darkest to the lightest shade, respectively.

Figure 5: Technological capital (TC) conditioning

(a) Stacked densities: Original vs TC conditioned



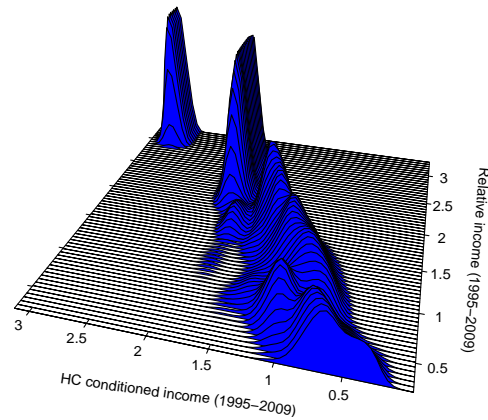
(b) HDR plot: Original vs TC conditioned



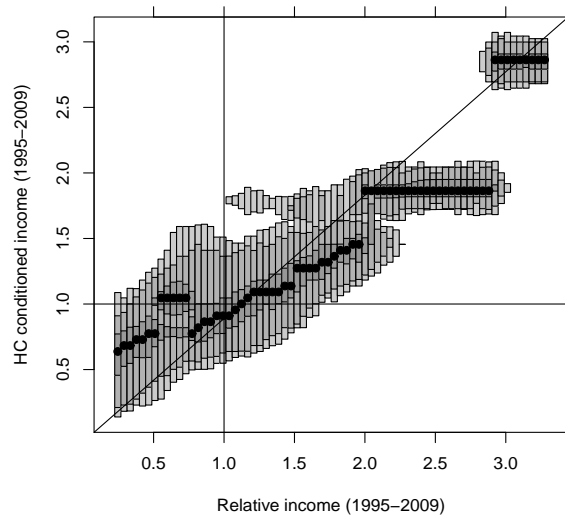
Notes: Subfigure **a**) shows stacked stochastic kernels while subfigure **b**) displays the equivalent HDR plot. In the latter, 50%, 95% and 99% of the probability mass is represented by the gray bars, from the darkest to the lightest shade, respectively.

Figure 6: Human capital (HC) conditioning

(a) Stacked densities: Original vs HC conditioned



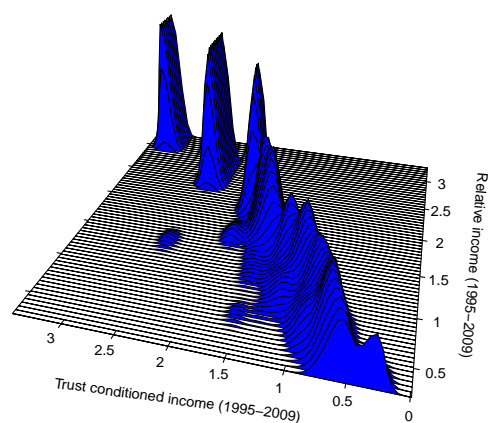
(b) HDR plot: Original vs HC conditioned



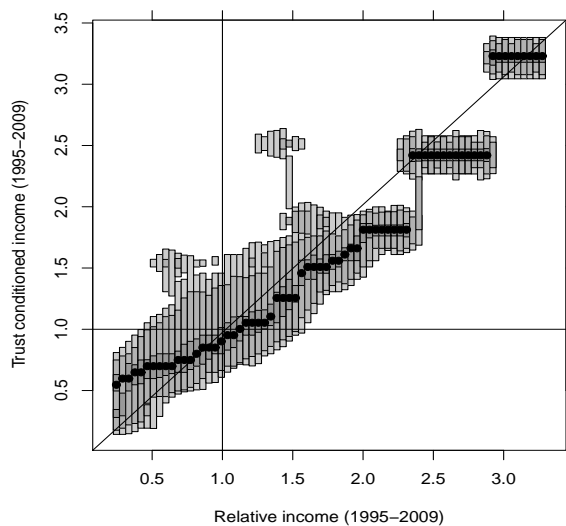
Notes: Subfigure **a)** shows stacked stochastic kernels while subfigure **b)** displays the equivalent HDR plot. In the latter, 50%, 95% and 99% of the probability mass is represented by the gray bars, from the darkest to the lightest shade, respectively.

Figure 7: Social capital (SC) conditioning

(a) Stacked densities: Original vs SC conditioned



(b) HDR plot: Original vs SC conditioned



Notes: Subfigure **a**) shows stacked stochastic kernels while subfigure **b**) displays the equivalent HDR plot. In the latter, 50%, 95% and 99% of the probability mass is represented by the gray bars, from the darkest to the lightest shade, respectively.