The effect of immigration on convergence dynamics in the US

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Abstract

This paper analyzes the impact of immigration on the dynamics of the cross-sectional distribution of GSP per capita and per worker. To achieve this we combine different approaches: on the one hand, we establish via Instrumental Variable estimation the effect of the inflow of foreign-born workers on output per worker, employment and population; on the other hand, using the Distribution Dynamics approach, we reconstruct the consequences of migration flows on convergence dynamics across US states.

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1 Introduction

The 1990's and the 2000's have witnessed a massive inflow of migrants into the US and this has certainly had a significant redistributive effect within the society. The literature that analyzes this phenomenon has essentially focused on the redistribution across individuals due to variations in wages for workers grouped according to their level of skills. Within a theoretical framework that implies the absence of long-run effects of immigration on productivity, Borjas (2003) and Borjas and Katz (2007) (among many others) assume an infinite elasticity of substitution between immigrant and native workers and find that an inflow of foreign-born population is likely to create a downward pressure on wages of less-educated natives. On the other hand, embracing the same framework but incorporating a positive estimate of the elasticity of substitution between immigrant and native workers with similar characteristics, Card (2009b) and Ottaviano and Peri (2012) find a positive effect on wages for the less-educated as well as for the average natives.

Even if we retain the same theoretical framework, the massive immigration flow experienced in the US is likely to have had redistributive consequences also from a spatial point of view. This could be essentially due to two reasons. Firstly, immigrants tend not to distribute homogeneously across states. According to the American Community Survey data, California is the preferred destination, followed by New York, Texas, Florida, New Jersey and Illinois. Furthermore, the skill distribution for immigrants is characterized by a strong polarization as most of them either acquired a low level of schooling or hold a graduate degree. The heterogeneity in the size and skill composition of the immigration flows across territories is therefore likely to have significant consequences on the magnitude of economic disparities across the territory.

In addition, immigration flows may also have static and dynamic effects on productivity and, through this way, affect economic disparities across space. For example, Ottaviano and Peri (2006) highlight the positive effect of cultural diversity at the urban level on the productivity of native workers, despite differences in the level of education. Hunt and Gauthier-Loiselle (2010) analyze the role of immigration on technological progress as measured by patents and suggest that migrants could positively contribute to the productivity of native researchers at the state level. Finally, Peri (2012) shows that the inflow of foreign-born workers also had a strong positive association with Total Factor Productivity, consistent with the view that more immigrants in a state stimulate its productivity growth.

The general aim of the paper is therefore to identify and quantify the effect of the inflow of foreign-born workers on the evolution of economic disparities among US states.[1] To achieve this, we carry out an analysis of economic convergence in the US from 1970 to 2006 and exploit the information provided by the construction of specific counterfactual scenarios. From a methodological point of view, this task is carried out in two steps. First, we estimate the elasticities of Gross State Product (GSP) per worker, employment and population with respect to employment of foreign-born workers; then, we turn to examine convergence patterns across US states using the Distribution Dynamics approach (Quah, 1993a,b, 1996b,a, 1997). To accomplish this, the coefficients estimated in the previous step are used (in analogy with Cheshire and Magrini, 2000) to derive counterfactual values for per capita GSP levels on hypothetical scenarios that impose *ad hoc* assumptions on the heterogeneity of the growth rate of immigrants across territorial units. Using these counterfactual series, and comparing the results with those derived from the predicted series, makes it possible to evaluate the impact played on the convergence process by immigration flows. In particular, we identify two separate components of immigration flows in the counterfactual scenarios: *i*. international migrations, i.e. flows that have their origin outside of the US territory, and *ii*. secondary migrations, i.e. internal migrations by foreign-born population. In the empirical analysis, we will concentrate on the states: while immigration is regulated at the federal level, chiefly under the rules established in 1952 with the passage of the Immigration and Nationality Act, state governments retain fiscal powers that may affect the direction of the flows.

The main results of the paper indicate that, in line with Peri (2012), im-

[1] The only attempt to analyze the consequences of international migrations on regional convergence we are aware of is the study of Hierro and Maza (2010) on the Spanish experience over the 1996-2005 period. The framework of analysis adopted there is however profoundly different from the one developed in the present paper.

migration spurs employment, population and output per worker growth. In addition, migrations have a very important role in determining the pattern of divergence across states that emerges in the period that ranges from 1970 to 2006; in addition, divergence should not be attributed to the massive inflow of immigrants towards the traditional “gateway” states while a significant, although partial, role might be played by secondary migrations.

The rest of the paper is structured as follows. Section 2 describes the effect that migration flows may have on the distribution of income, Section 3 explains the empirical strategy adopted in the paper, Section 4 presents the empirical analysis and the results, Section 5 concludes.

2 The redistributive effects of immigration

Immigration redistributes income across individuals and, due to location choices, across places. The empirical analysis of the consequences of immigration flows has essentially concentrated on the redistribution due to relative changes in wages for individuals grouped on the basis of personal characteristics either comparing outcomes in different cities or states (Card, 2001, 2009a,b; Card and Lewis, 2007; Ottaviano and Peri, 2005, 2006; Peri, 2012) or studying the evolution of outcomes at the national level (Borjas et al., 1997; Borjas, 2003, 2006; Borjas and Katz, 2007; Ottaviano and Peri, 2012).

All these studies share a simple, common framework that relies on the traditional neoclassical explanation of the growth process (Solow, 1956; Swan, 1956; Ramsey, 1928). Suppose aggregate output Y is realized according to

$$Y = AL^{\alpha}K^{1-\alpha} \tag{1}$$

where A is total factor productivity growing at a constant exogenous rate μ, K is the stock of physical capital, L is the stock of labor that aggregates different types of workers according to a Constant Elasticity of Substitution (CES) function and $\alpha \in (0,1)$ is the share of income that remunerates labor. Assuming that the latter is constant, profit maximization under perfect competition implies that the economy approaches a balanced growth path in the steady state in which output per worker (Y/L) and the average wage rate grow at a constant rate equal to $1/\alpha$ times the growth rate of TFP. This, in turn, means that in the long run the average wage does not depend on the level of labor supply and, hence, on immigration. However, despite the absence of effect on the average wage, this framework predicts that immigration could yield effects at a more disaggregated level depending on workers characteristics. In general, immigrant flows exert a downward pressure on wages of workers of similar characteristics and an upward one on wages of workers with different characteristics. In practice, the differences in the estimated effects on the wage of specific groups of workers largely depend on the assumptions made in the operationalization of the CES aggregator with reference to the degree of substitutability among workers with different characteristics. Thus, assuming an infinite elasticity of substitution between immigrant and native workers, Borjas (2003), Borjas and Katz (2007) and studies on this vein, usually report a negative impact on wages of less-educated natives. On the contrary, Ottaviano and Peri (2012) provide an estimate of the substitution elasticities involved in the CES aggregation of workers and, in line with Card (2009a) and Raphael and Smolensky (2009), report a small but significant degree of substitutability between immigrant and native workers with similar characteristics. Based on the entire set of estimated elasticities, Ottaviano and Peri (2012) confirm earlier results by Card (2009a) finding a small but positive effect of immigrant flows on wages of less-educated natives, a positive effect on the average wage of natives and a strong, negative effect on immigrants that entered the country previously. In addition, they stress the importance of distinguishing between partial and total wage effects. In the case of an in-flow of immigrant workers with a given set of characteristics, the partial wage effect represents the direct impact on the wage of native workers with the same characteristics assuming that the labor supply of all other groups stays constant. In contrast, the total wage effect instead quantifies the impact the wage of native workers with the same characteristics allowing for the indirect impacts of immigration in all other skill groups. Hence, it follows that the total wage effect on groups with given characteristics depend on the relative sizes of these groups, on the relative strengths of the impact of immigrants within and across groups, and on the characteristics profile of migrants.

From the above discussion, it follows that, even if we adopt the theoretical framework just highlighted and consequently presume that immigration has no long-run effect on the average real wage, immigration flows could still have important redistributive consequences from a spatial point of view. Actually, workers with different characteristics are distributed rather heterogeneously across space. Similarly, immigrant flows tend to head disproportionally towards a limited number of areas of the country and to be concentrated in certain parts of the skill distribution. It is well known that new migrants tend to choose destinations where they have strong migrant networks, and states with large settled immigrant populations are sometimes called "gateway-states". For instance, based on American Community Survey data, in 2010 about two-thirds (65%) of the total foreign-born population lived in just six states (California, New York, Texas, Florida, New Jersey and Illinois)[2] and over one-fourth (25.4%) lived in California. As for the skills, immigrant flows appear to be concentrated in the upper and lower tails of the distribution of schooling attainment. Immigrants are much more likely than natives to have low levels of schooling. For instance, in 2010 about 32% of immigrants had not completed the equivalent of high-school education, compared with only 11% of natives. At the same time, immigrants are as likely as natives to be highly educated, with 27% of immigrants and 28% of natives having completed a bachelor's degree. In contrast, are underrepresented in the middle of the skill distribution, among workers with high-school or some college education (41% for immigrants, 61% for natives). Given this heterogeneous distribution of migrants across states and across skills, the redistributive effects among different groups of workers found in the recent literature are necessarily accompanied by redistributive effects between different areas of the country.

That aside, the theoretical framework adopted in estimating the impact of immigration on wages explicitly omits any effect, static or dynamic, that these flows might have on productivity.[3] In a couple of cross-city studies focusing on the US, Ottaviano and Peri (2005, 2006) find that cultural diversity,

[2] In the 1960s and 1970s, Massachusetts and Pennsylvania were also "gateway" states.

[3] Ozgen et al. (2010), applying several meta-analytical techniques, find that the overall effect of migration on real per capita income growth is positive, although of limited size.

either in terms of variety of workers' mother tongues or in terms of variety of their country of birth, has a net positive effect of on the productivity of natives. They suggest that the effect originates from differences, even at the same level of education, in problem solving, creativity and adaptability between native and foreign-born workers or from the fact that the latter may provide services that are not perfectly substitutable with those of supplied by natives. Similarly, Niebuhr (2010), focusing on a cross-section of German regions, finds evidence favoring the hypothesis that cultural diversity enhances innovation activity. Hunt and Gauthier-Loiselle (2010) study the impact of immigration on technological progress in the US, as measured by patents per capita. In addition to the direct contributions of immigrants to research, they suggest the way in which immigration could favor indirectly innovation is through positive spillovers originating from immigrants to the benefit of fellow researchers, as well as contributing to the exploitation of scale economies or providing skills that are complimentary to those of natives. Gagliardi (2015) finds that skilled immigration has a positive and significant effect on innovation activity within British local labor markets. Peri (2012) finds that the inflow of foreign-born workers has a strong positive association with TFP growth and that efficiency gains tend to be larger for less educated workers. In particular, the author suggests that boost to the efficiency could arise from a process of reorganization of production within firms in which immigrants specialize in manual-intensive tasks and natives take up communication-intensive ones.

Similarly to what seen before, due to differences across locations in their degree of cultural diversity, attitude towards innovation and organization of the production process as well as in the size and skill composition of the immigration flows, strongly different spatial manifestations are likely to arise. Building on the impacts on real wages described above, these further effects of immigration on productivity are likely to affect the relative economic performance of the different areas of the country, interacting with the underlying convergence or divergence dynamics. The goal of our paper is precisely this: to assess the impact of immigration on convergence among US states by isolating the spatial (static and dynamic) impact of the inflow of immigrant workers on the evolution of state disparities in economic performance.

3 The Empirical Strategy

In order to establish the role of international migrations on the dynamics of the cross-sectional distribution of per capita GSP we adopt a two-step strategy:

1. first, drawing extensively on the framework developed by Peri (Peri, 2012; but also Peri and Sparber, 2009), we estimate the impact of international migration on GSP per worker, employment and population;

2. then, we turn to examine convergence patterns across US states using the distribution dynamics approach (Quah, 1993a,b, 1996b,a, 1997). To accomplish this, the coefficients estimated in the previous step are used (in analogy with Cheshire and Magrini, 2000) to derive counterfactual values for GSP per capita and GSP per worker on hypothetical scenarios that impose *ad hoc* assumptions on the distribution of immigrants flows across territorial units. Using these counterfactual series, and comparing the results to those derived from the predicted series, makes it possible to evaluate the impact played on the convergence process by immigration flows.

3.1 Regression analysis

Let us consider the setup of the regression analysis in greater detail. Define the level of output per worker of state s at time t as $\tilde{y}_{st} \equiv Y_{st}/L_{st}$. Taking the log, differentiating with respect to time and rearranging yields

$$\frac{\Delta Y_{st}}{Y_{st}} = \frac{\Delta \tilde{y}_{st}}{\tilde{y}_{st}} + \frac{\Delta L_{st}}{L_{st}} \tag{2}$$

which states that total output in a state increases as a consequence of increased employment and increased output per worker.

Similarly, let P_{st} denote the population of state s at time t and define the corresponding level of output per capita as $y_{st} \equiv Y_{st}/P_{st}$ from which log-differenciation with respect to time yields

$$\frac{\Delta y_{st}}{y_{st}} = \frac{\Delta Y_{st}}{Y_{st}} - \frac{\Delta P_{st}}{P_{st}} \tag{3}$$

Putting equation (2) into (3) we then get:

$$\frac{\Delta y_{st}}{y_{st}} = \frac{\Delta \tilde{y}_{st}}{\tilde{y}_{st}} + \frac{\Delta L_{st}}{L_{st}} - \frac{\Delta P_{st}}{P_{st}} \tag{4}$$

The decomposition in equation (4) is at the basis of the first step of the empirical analysis. In analogy with Peri and Sparber (2009) and Peri (2012), we estimate the impact of immigration by regressing each element of the right-hand side of equation (4) against the percentage change in employment due to immigrants. In particular, we estimate

$$\frac{\Delta b_{st}}{b_{st}} = d_t + d_s + \eta_b \frac{\Delta L^F_{st}}{L_{st}} + \epsilon_{st} \tag{5}$$

where b is alternatively $\tilde{y}$, L or P, L^F is the number of employed immigrants while d_t and d_s are, respectively, decade and state dummies.

Clearly, as emphasized by Peri and Sparber (2009) and Peri (2012), it is difficult to establish a causal link between immigration and economic outcomes due to simultaneity and omitted variable biases. For this reason, we carry out Instrumental Variable (IV) estimates in which, following the just mentioned authors, we employ several variables as instruments. The first variable, originally devised by Card (2001) and then used in several other studies (Card, 2009b; Peri, 2012; Peri and Sparber, 2009), is the imputed number of immigrants constructed as the weighted average of decade-by-decade nationwide immigrant workers inflow by 10 different origin areas, with weights reflecting their location-specific share in 1960. In addition, we pay some consideration to spatial effects. In actual facts, the location of immigrants is not random as destination depends, among other things, on distance from the entry point. Consequently, we include among the instruments a couple of variables reflecting (the inverse of)[4] distance of a states' center of gravity from entry points for Mexican migrants (interacted with decade dummies) to predict the inflow of workers in decades with larger Mexican immigration.

[4] Peri (2012) also includes distance related variables among the instruments; in that case, however, the variables report the logarithm of distance rather than its inverse as in the present case.

3.2 Counterfactual Scenarios

From the estimated elasticities $\hat{\eta}_P$, $\hat{\eta}_L$ and $\hat{\eta}_{\tilde{y}}$, using the observed values for the explanatory variables in equation (5) we then calculate the predicted levels of GSP per worker and GSP per capita. More precisely, to obtain the predicted values we use the values of the percentage change in employment due to immigrants estimated in the first stage of the 2SLS procedure and the observed values for all other variables.

In addition, in analogy with Cheshire and Magrini (2000), we construct some counterfactual scenarios based on different assumptions with respect to the distribution of immigrant workers across states. The first counterfactual scenario emphasizes the effect from traditional "gateway-states" such as California, Florida, Illinois, New Jersey, New York and Texas which continue to be home to large percentages of immigrants. In order to set up such a scenario (hereafter, the "gateways" scenario), in each decade we impose that the shock represented by the inflow of immigrant workers is homogeneously distributed across all states but the 6 "gateways". In operative terms, to achieve this, for all states but the 6 "gateways", the (estimated) percentage change in employment due to immigrant workers is set equal to the decade-specific cross-sectional average (net of the shock occurring to the "gateways").

The second counterfactual scenario attempts to highlight the role of secondary migration. In fact, growth in a state's foreign-born population occurs through movements from abroad or through foreign-born migrants' secondary migration from elsewhere in the United States after their initial arrival. Once arrived in a "gateway" state, many movers from abroad then relocate to different areas of the country in response to economic incentives much like other groups (Cadena, 2013; Card and Lewis, 2007). This phenomenon has gained particular importance in recent decades also because, as reported by Perry and Schachter (2003), recent arrivals to the United States had higher mobility rates than foreign-born people who entered before 1980. So, although the six gateway states were still receiving large numbers of immigrants during the 1990s, three of them (California, New York, Illinois) experienced substantial net outmigration that included a sizable foreign-born component during the 1990s and two (California and New York) started to play an important role in the redistribution of the foreign-born population across the United States as the net domestic outmigration rates for the foreign-born exceeded the rates for natives. On the same vein, Bean et al. (2007) report that during this decade there was a substantial out-migration of Mexicans from most traditional Mexican-receiving US states and these flows were heading towards those states experiencing faster economic growth. As a result of these flows, the relative importance of traditional “gateway-states” has visibly declined: while almost three-quarters of immigrants lived in one of the traditional “gateway-states” in 1990, this proportion dropped to 65% by 2010. At the same time, other states have witnessed a rapid increase in their foreign-born population. Focusing on internal migration of the foreign-born, Perry and Schachter (2003) report that the states with the higher rates of net migration during the first half of the 1990s where Nevada (276.0), North Carolina (187.0) and Georgia (178.1). Frey (2002), using Census data on foreign-born residents who arrived in the United States to live prior to 1990, finds that the states that obtained the largest inflows from secondary migration of the foreign-born during the 1990-2000 period where Nevada (72,471), Arizona (60,597), Georgia (59,384) and North Carolina (46,566). Based on these figures, therefore, four states (Nevada, Arizona, Georgia and North Carolina) are identified as the main recipients of secondary migration flows from the 1990s. Consequently, the second countefactual scenario (hereafter, the “secondary migration” scenario) is constructed by imposing, from 1990 onwards, that for all states but the 4 “gainers” from secondary migration flows, the (estimated) percentage change in employment due to immigrants is set equal to the decade-specific cross-sectional average (net of the change faced by the “gainers”).

Finally, in the third counterfactual scenario the differential effect of immigration is instead completely neutralized by imposing a homogenous shock across all states by enforcing that the (estimated) percentage change in employment due to immigrants is, for each state, equal to the overall, decade-specific cross-sectional average. Hereafter, this scenario will be referred to as the “all” scenario.

These predicted and counterfactual series represent the inputs for the Distribution Dynamics analysis that will allow to analyze the impact of immigration flows on the dynamics of the cross-sectional distribution of GSP per capita and GSP per worker.

3.3 Distribution Dynamics Analysis

The most frequently adopted notion of convergence is β-convergence, whose theoretical foundations lie in the traditional neoclassical growth model originally set out by Solow (1956) and Swan (1956). Technically, as is well known, the key parameter to be empirically estimated is the rate β at which the representative economy approaches its steady-state growth path (Barro and Sala-i Martin, 1991, 1992, 2004). This approach, however, has stimulated the critical attention of many scholars who have emphasized its limitations and proposed alternatives (for an account of this literature see, among others Durlauf and Quah, 1999; Temple, 1999; Islam, 2003; Magrini, 2004, 2009; Durlauf et al., 2005). In our view, its most important drawback relates to the lack of informative content: concentrating on the behavior of a representative economy, the best this approach can do is to describe how this economy converges to its own steady-state; it is however completely silent on what happens to the entire cross-sectional distribution of economies. For this reason, here we opt for the continuous state-space distribution dynamics approach first introduced by Quah (1996a, 1997), in which the evolution of the cross-sectional distribution of per capita income is examined directly, using stochastic kernels to describe both the change in the distribution's external shape and the intra-distribution dynamics.

In simple terms, indicate with $\bar{y}_{i,t}$ the level of income (per capita or per worker) of state s at time t relative to the cross-sectional average. Next, denote with $F(\bar{y}_t)$ the distribution of $\bar{y}_t$ and, assuming it admits a density, indicate this density with $f(\bar{y}_t)$. Finally, assume that the dynamics of $F(\bar{y}_t)$, or equivalently of $f(Y\bar{y}_t)$, can be modeled as a first order process. As a result, the density prevailing at time $t+s$ is given by

$$f\left(\bar{y}_{t+s}\right) = \int_{-\infty}^{\infty} f\left(\bar{y}_{t+s}|\bar{y}_t\right)\, f\left(\bar{y}_t\right)\, d\bar{y}_t \tag{6}$$

where the stochastic kernel $f(\bar{y}_{t+s}|\bar{y}_t)$ maps the density at time t into the density at time $t+s$. This element is the corner-stone of the approach as its (nonparametric) estimate provides information both on the change in the external shape of the distribution and, more importantly, on the movement of the economies from one part of the distribution to another between time t and time $t+s$. Convergence can hence be analyzed directly from the shape of a plot of the stochastic kernel estimate or, assuming that the process behind (6) follows a time homogenous markov process, by comparing the shape of the initial distribution to the stationary (or ergodic) distribution which is the limit of $f(\bar{y})$ as $s \to \infty$.

Effectively, the stochastic kernel in equation (6) is a conditional density function, an estimate of which can be obtained through a kernel density estimator. However, Hyndman et al. (1996) suggest that this popular estimator might have poor bias properties.[5] To clarify this, let $M(\bar{y}_t)$ indicate the mean of the conditional density $f(\bar{y}_{t+s}|\bar{y}_t)$. As emphasized by Hyndman et al. (1996), the bias of estimate of the conditional density function depends on the bias of estimate of the mean function. Unfortunately, the mean function estimator implicit in the traditional kernel estimator of the conditional density is the local constant estimator which is known to have poor bias properties. Hence, these poor bias properties are carried over onto the conditional density estimate. To overcome this problem, these authors then develop a mean-bias adjustment procedure that entails estimating $M(\bar{y}_t)$ using a smoother characterized by better bias properties and then substitute this estimate in place of the original one. One such smoother is, for instance, the local linear estimator (Loader, 1999).

Important implications for the analysis could also arise from its spatial dimension. Gerolimetto and Magrini (2016) note that the estimate of $M(\bar{y}_t)$ is in fact an autoregression and emphasize that the asymptotic properties of the adopted smoother are usually based on the assumption that the error terms are zero mean and uncorrelated. However, in the analysis of economic convergence across spatial units, the involved variables are usually characterized by spatial dependence. Within the distribution dynamics approach the issue is typically tackled by adopting a spatial filtering technique before proceeding with the estimates. For example, Basile (2010) fits a spatial autoregressive model and employs residuals for subsequent analysis while Fischer and Stumpner (2008) and Maza et al. (2010) employ a filtering approach based on the local spatial autocorrelation statistic *Gi* developed by Getis and Ord (1992). A strict assumption however underlies this approach: spatial dependence is seen as a nuisance element that should be eliminated

[5] The local constant estimator is known to be biased on the boundaries and also in the interior, especially when the mean function is characterized by an evident curvature or simply the scatter plot of the design points is irregular.

in order to avoid the risk of losing the statistical properties of the estimates (Anselin, 1988, 2002). Differently from this view, Gerolimetto and Magrini (2016) think that spatial dependence is often likely to be a substantive element of the process under study and this, in particular, should be the case when studying economic convergence across regional units. Just to give an example, not only it is well known that the level of per capita income in a US state is correlated to the level observed in neighboring states but, as shown by Rey (2001), also the mobility of the states within the cross-sectional distribution of per capita income is significantly affected by the relative position of geographical neighbors within the same distribution. In such instances, spatial dependence appears to embody valuable information on convergence dynamics and adopting a spatial filtering technique represents a controversial strategy (Magrini, 2004) as it may yield misleading results. To address the issue, therefore, Gerolimetto and Magrini (2016) first develop a two-step nonparametric regression estimator for spatially dependent data that moves from the standard local linear estimator and does not require *a priori* parametric assumptions on spatial dependence as information on its structure is in fact drawn from a nonparametric estimate of the errors spatial covariance matrix. Then, they employ this spatial nonparametric (local linear) estimator in the mean-bias adjustment procedure put forward by Hyndman et al. (1996). In the present paper, we adopt the strategy developed by Gerolimetto and Magrini (2016) and therefore enrich the estimate of the conditional density through an estimate of the mean function that, in addition to Hyndman et al.s' original suggestion, allows also for spatial dependence.

4 Empirical Analysis

We adopt states as the territorial unit of analysis. This is done for two reasons. First, while immigration is regulated at the federal level, chiefly under the rules established in 1952 with the passage of the Immigration and Nationality Act, state Governments retain fiscal powers that may affect the direction of the flows. Secondly, as emphasized by Peri and Sparber (2009), the immigrant share of employment varies greatly across US states.[6]

[6] Borjas (2003) and Borjas and Katz (2007) criticize this choice on the basis that states are open economies and the effects of immigration in one state could spill into others through

As recalled at the outset, the definition of most variables employed in the regression analysis coincide exactly with those in Peri (2012) as we exploit the dataset included in the downlodable supplementary material of the paper. In line with the analysis conducted there, the period of analysis stretches between 1970 and 2006.[7]

4.1 Regression Analysis

The estimated impacts of immigration on employment and labor productivity reported in Table 1 are obviously in line with those reported by Peri (Peri, 2012, Table 2, column 1). In particular, we find that the elasticity of employment is just above 1 while the elasticity of income per worker is marginally smaller (0.92).[8] Both effects of immigration appear to be highly statistically significant thus confirming that more immigrants in a state stimulate the growth of both its productivity and employment.

In addition, the last column of Table 1 also reports that the impact of immigration on population exceeds 1; as with the other elasticities, also this impact arising from the inflow of migrants appears to be strongly statistically significant.

Finally, Table 2 reports the results of a test for spatial autocorrelation in the regression residuals. In particular, the table reports, for each regression and each decade, the p-values of a Moran's I test on the residuals obtained using a 5-nearest neighbor spatial weights matrix. In at least two of the three residual sets, the test does not seem to suggest the presence of particularly severe problems.

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the migration of natives. Peri and Sparber (2009) however note that there is little evidence in the literature that natives respond to immigration through interstate migration.

[7] Although required data are certainly available for more recent years, we have decided to maintain the original time-horizon essentially because it allows to avoid to contaminate the results with the effects of the Great Recession during which migration flows both from outside and within the US territory declined quite markedly.

[8] The minor differences with the elasticities reported by Peri are essentially due to the fact that, among the instruments, we employ the inverse of distance from the border rather than its logarithm. In addition, we corrected a few data entries relative to Delaware's employment in 1990.

4.2 Convergence Analysis

Having estimated the elasticities η_P, η_L and $\eta_{\tilde{y}}$, we can now evaluate the impact of immigrant workers on the distribution of GSP per worker and GSP per capita across states.

The output of the empirical analysis of distribution dynamics is essentially a set of pictures: a three-dimensional plot of the estimated stochastic kernel, the corresponding Highest Density Region plot (Hyndman, 1996) in which the vertical strips represent conditional densities for a specific value in the initial year dimension and, for each strip, darker to lighter areas display the 10%, 50% and 90% highest density regions, and a plot comparing the initial distribution with the ergodic one. Each of the figures reported in this paper (Figures 1 to 4) will then show three such sets: one will report the outcome of the analysis carried out on data predicted through the IV regressions and the other two will depicts the estimates for alternative counterfactual scenarios. The information provided by each set of pictures is then complemented by some statistics on dispersion of the initial and ergodic distributions; these statistics are collected in Tables 3 and 4.

Before proceeding to the analysis of the figures, a note on the estimate of the stochastic kernel. As anticipated in Section 3.3, this estimate is carried out using the procedure developed by Gerolimetto and Magrini (2016) in which the mean function of the conditional density is obtained using a spatial nonparametric estimator. The results of the Moran's I test on the residuals of the estimate of $M(\bar{y}_t)$ that substantiate this choice are reported in Table 7. It is clear from this table than with just one exception, all residuals obtained using the traditional nonparametric smoother in the estimate of $M(\bar{y}_t)$ display spatial dependence to a significative extent. In contrast, essentially no signs of spatial dependence are found in the residuals from the estimates produced using the spatial nonparametric estimator.

Figure 1 shows three sets of such figures with respect to the evolution of the distribution of income per capita over the 1970-2006 period. To interpret these results, let us start from rightmost set of pictures corresponding to the "all" scenario. As explained in Section 3.2, in this scenario we completely neutralize the differential effect of immigration by imposing that, for each state, the (estimated) percentage change in employment due to immigrant workers is equal to the overall, decade-specific cross-sectional average. The comparison between initial and ergodic distributions estimated under this scenario indicates a clear tendency towards persistence: in other words, if we neutralize the differential effect of migrations, the external shape of the cross-sectional distribution remains essentially unaffected. Next, moving to the “gateway” scenario, we can see what happens once the differential effect of immigrant flows directed towards the traditional gateways states is introduced. The comparison between initial and ergodic distributions in the central column of Figure 1 suggests that, despite their importance in absolute terms, the flows of immigrant workers directed towards the traditional gateway states modify only marginally the previous results by introducing a modest tendency towards divergence in the cross-sectional distribution. A much stronger tendency towards divergence is instead portrayed in the leftmost set of pictures that correspond to the predicted data. This implies that, once the differential effect of the flows of immigrant workers is entirely considered, cross-sectional disparities in per capita income manifest a marked tendency to increase over the 1970-2006 period. This is confirmed by the statistics on dispersion in Table 3: both the variation coefficient and the interquartile range of the ergodic distribution denote a substantial increase with respect to the corresponding values for 1970 distribution on predicted data while no appreciable differences are evident in the two counterfactual scenarios. The results of the two-sample Cramér-von Mises tests[9] shown in Table 4 reinforce this conclusion: the null hypothesis that the initial and ergodic samples are drawn from the same distribution is safely accepted in both counterfactual scenarios; in constrast the null is strongly reject when the predicted data are used. All in all, therefore, the underlying message is that the flows of immigrant workers greatly contribute to the increase of per capita income disparities across states over the 1970-2006 period; further, this result is not due to the role played by the traditional “gateway” states but rather by the flows directed (or re-directed) to all other states.

We can now move to the analysis of the series on income per worker.

[9] The Kolmogorov-Smirnov test is the most commonly adopted test that measures the probability that a chosen univariate dataset is drawn from the same parent population as a second dataset. In particular, the Kolmogorov-Smirnov test is a nonparametric test based on the Kolmogorov-Smirnov statistics that measures the supremum distance between the empirical distribution functions (EDF). However, whenever the EDFs have the same mean values as in the present case, then the EDFs cross each other and the maximum deviation between the distributions is reduced. In such instances, the Cramér-von Mises test that measures the sum of square deviations between the EDFs is a more appropriate choice.

As shown in the set of pictures corresponding to the “all” scenario of Figure 2, also in the case of income per worker no tendencies to change the cross-sectional distribution are found during the 1970-2006 period once the differential effect of immigration is neutralized. Differently from the case of income per capita, however, once the effects of the flows of immigrant workers are reintroduced in the analysis, either partially (the “gateway” scenario) or fully (using predicted data), no radical changes to the cross-sectional distribution can be noted. In fact, the pictures comparing initial and ergodic distributions, the statistics reported in Table 3, as well as the Cramér-von Mises tests reported in Table 4, suggest only a quite marginal tendency towards convergence.

As explained in Section 3.2, since the 1990s, not only the relative importance of traditional “gateway-states” has visibly declined, but the phenomenon of secondary migration has gained strong momentum. The final part of this analysis is then aimed at ascertaining the contribution of secondary migration of foreign-born workers to the evolution of income disparities across states. Given than this is a recent phenomenon, the analysis will concentrate on the 1990-2006 period.

The rightmost set of pictures in Figure 3 confirm also for this shorter period that, once the differential effect of the flows of immigrant workers is neutralized, the dynamics of the cross-sectional distribution of per capita income are characterized essentially by persistence. Once the attention is concentrated on those states that have been the main recipients of re-location flows by foreign-born workers (the central set of pictures corresponding to the secondary scenario), a tendency towards an increase of the cross-sectional disparities is detected. This is confirmed by the statistics in Table 5 according to which, for instance, the interquartile range of the ergodic distribution increases by 0.0076 with respect to its initial value, an increase of about 33%; further confirmation of this increase in disparities also comes from the Cramér-von Mises test (Table 6) according to which we can safely reject the null that the 1990 and ergodic samples come from the same reference distribution. An even more radical increase in disparities is then found when the impact of all flows of immigrant workers is considered using the predicted data. In this case, the shape of the ergodic distribution describes a sharp raise in spatial disparities with an increase of 0.0214 of the interquartile range from its 1990 value (Table 5), a value that corresponds to an almost

93% increase, while the Cramér-von Mises statistic increases to 11.8 (Table 6). In addition, the comparison between the distributions also suggests the emergence of a pattern of club convergence given the evident bimodality present in the shape of the ergodic.

Moving to the series on income per worker, the picture that emerges from the analysis in the "all" scenario reported in Figure 4 is, once more, one of absolute persistence: neutralizing the differential effect of immigrant workers' flows leads to an ergodic distribution that is almost completely coincident to the one that refers to 1990. Once the effect of secondary migration is allowed in again (the central set of pictures), a modest increase in disparities can be noted with an ergodic distribution characterized by an almost 30% increase of the interquartile range with respect to the initial (Table 5); according to the Cramér-von Mises test (Table 6), the null hypothesis can be rejected at the 10% significance level only. As in the case of income per capita, also for income per worker disparities increase much more radically if the impact of all flows of immigrant workers is included: the ergodic distribution is far less peaked than the initial, the interquartile range increases by 60% and the Cramér-von Mises statistic raises significantly.

The overall picture that emerges from the analysis conducted in this paper can be summarized as follows. All in all, disparities across states manifest a clear tendency to increase over the 1970-2006 period. This is true both using income per capita (Figure 1, "predicted" case) and income per worker (Figure 3, "predicted" case) data; this tendency is more marked for income per capita, and becomes stronger in the latter part of the considered period (Figures 2 and 4). In addition, the analysis suggests that this tendency towards divergence cannot be attributed to the role played by the traditional "gateway" states ("gateway" scenarios of Figures 1 and 3). Finally, secondary migration instead appears to provide a modest contribution to the divergence pattern ("secondary migration" scenarios of Figures 2 and 4).

5 Conclusions

It is a well known fact that immigrant flows have important redistributive effects across individuals. However, strongly different spatial manifestations are also likely to arise due to differences across locations in the composition of the labor supply, attitude towards innovation, cultural diversity and organization of the production process as well as in the size and skill composition of the immigration flows. This paper has therefore analyzed the consequences of the recent massive inflow of foreign-born population into the US on the evolution of income disparities across states.

First of all, we find evidence in favor of immigration spurring employment, population and output per worker growth, as the estimated elasticities are close to 1. This is in line with previous results by Peri (2012).

For what concerns the analysis of convergence dynamics, in general terms we find a tendency for state levels of both income per capita and income per worker to diverge over the analyzed period. In particular, this tendency appears to be stronger for the former variable and for the 1990-2006 period.

The analysis of counterfactual scenarios clearly shows that the inflow of migrant workers played a fundamental role in these dynamics: neutralizing the differential effect of immigrant workers' flows almost completely eliminates the tendency towards divergence. In addition, the other findings from the counterfactual scenarios indicate that the increase in spatial economic disparities cannot be attributed to the inflow of migrants into the traditional "gateways", while a contribution, although partial, is provided by secondary migration of foreign-born migrants after their initial arrival in the United States, a phenomenon that has gained particular importance in last few decades also because recent arrivals to the United States have higher mobility than earlier ones.

The possible implications of the latter results are of interest. The fact that secondary migrations contribute (although partially) to the divergence process and that, as noted by Cadena (2013) and Card and Lewis (2007), immigrants relocate to different areas of the country in response to economic incentives much like other groups seems to suggests that in recent decades inter-state migrations have not played a mitigating role in the evolution of spatial economic disparities.

Tables

Table 1: 2SLS Estimates of the Impact of Immigration

	GSP per worker	**Employment**	**Population**
coefficient	0.9244	1.0387	1.1136
s.e.	0.1641	0.2722	0.1399
p-value	0.00	0.00	0.00

Table 2: Moran's *I* p-values on Regression Residuals

	GSP per worker	**Employment**	**Population**
1960-1970	0.00	0.32	0.00
1970-1980	0.03	0.00	0.00
1980-1990	0.00	0.00	0.01
1990-2000	0.95	0.05	0.00
2000-2006	0.22	0.08	0.00

Note: Moran's *I* test is carried out using a 5-nearest neighbor spatial weight matrix.

Table 3: Distribution Dynamics 1970-2006 – summary of statistics

	predicted		**counterfactual gateways**		**counterfactual all**	
GSP per capita	CV	IR	CV	IR	CV	IR
ergodic	0.0315	0.0492	0.0204	0.0303	0.0189	0.0266
Δ from 1970	0.0092	0.0223	0.0002	0.0043	-0.0013	0.0006
GSP per worker	CV	IR	CV	IR	CV	IR
ergodic	0.018	0.0265	0.0177	0.0249	0.0161	0.0219
Δ from 1970	0.0018	0.0043	0.0014	0.0027	-0.0002	-0.0003

Note: IC stands for Interquartile Range, CV stands for Coefficient of Variation.

Table 4: Distribution Dynamics 1970-2006 – Cramér-von Mises test

	predicted		**counterfactual gateways**		**counterfactual all**	
	statistic	p-value	statistic	p-value	statistic	p-value
GSP per capita	2.3173	0.0000	0.0929	0.6684	0.0054	1.0000
GSP per worker	0.2339	0.2187	0.2738	0.1656	0.1348	0.4682

Table 5: Distribution Dynamics 1990-2006 – summary of statistics

	predicted		**counterfactual secondary migration**		**counterfactual all**	
GSP per capita	CV	IR	CV	IR	CV	IR
ergodic	0.0249	0.0445	0.0201	0.0307	0.0192	0.0272
Δ from 1990	0.0077	0.0214	0.0030	0.0076	0.0000	0.0032
GSP per worker	CV	IR	CV	IR	CV	IR
ergodic	0.0169	0.0291	0.0147	0.0233	0.0135	0.0201
Δ from 1990	0.0038	0.0109	0.0019	0.0053	0.0006	0.0021

Note: IC stands for Interquartile Range, CV stands for Coefficient of Variation.

Table 6: Distribution Dynamics 1990-2006 – Cramér-von Mises test

	predicted		**counterfactual secondary migration**		**counterfactual all**	
	statistic	p-value	statistic	p-value	statistic	p-value
GSP per capita	11.8003	0.0000	1.1054	0.0020	0.0528	0.9168
GSP per worker	4.0541	0.0000	0.3395	0.1072	0.0644	0.8461

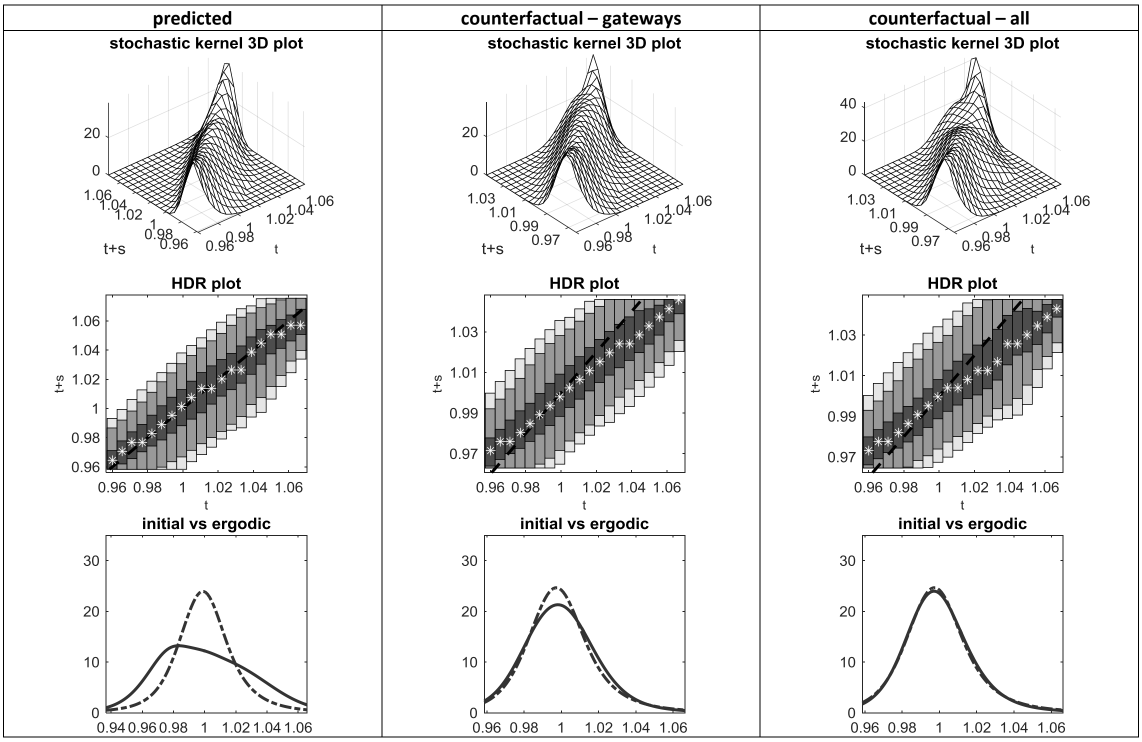
Table 7: Moran's *I* p-values on Data and Nonparametric Regression Residuals

	GSP per capita	**GSP per worker**
Data		
1970 (predicted)	0.00	0.00
1990 (predicted)	0.00	0.00
2006 (predicted)	0.01	0.03
2006 (counterfactual - gateways)	0.01	0.16
2006 (counterfactual - all)	0.00	0.06
Mean function estimate - nonparametric regression residuals		
1970 (predicted) - 2006 (predicted)	0.00	0.00
1970 (predicted) - 2006 (counterfactual - gateways)	0.00	0.00
1970 (predicted) - 2006 (counterfactual - all)	0.00	0.00
1990 (predicted) - 2006 (predicted)	0.00	0.00
1990 (predicted) - 2006 (counterfactual - second migration)	0.30	0.18
1990 (predicted) - 2006 (counterfactual - all)	0.00	0.01
Mean function estimate - spatial nonparametric regression residuals		
1970 (predicted) - 2006 (predicted)	0.47	0.97
1970 (predicted) - 2006 (counterfactual - gateways)	0.28	0.34
1970 (predicted) - 2006 (counterfactual - all)	0.10	0.26
1990 (predicted) - 2006 (predicted)	0.19	0.52
1990 (predicted) - 2006 (counterfactual - second migration)	0.25	0.83
1990 (predicted) - 2006 (counterfactual - all)	0.01	0.21

Note: Moran's *I* test is carried out using a 5-nearest neighbor spatial weight matrix.

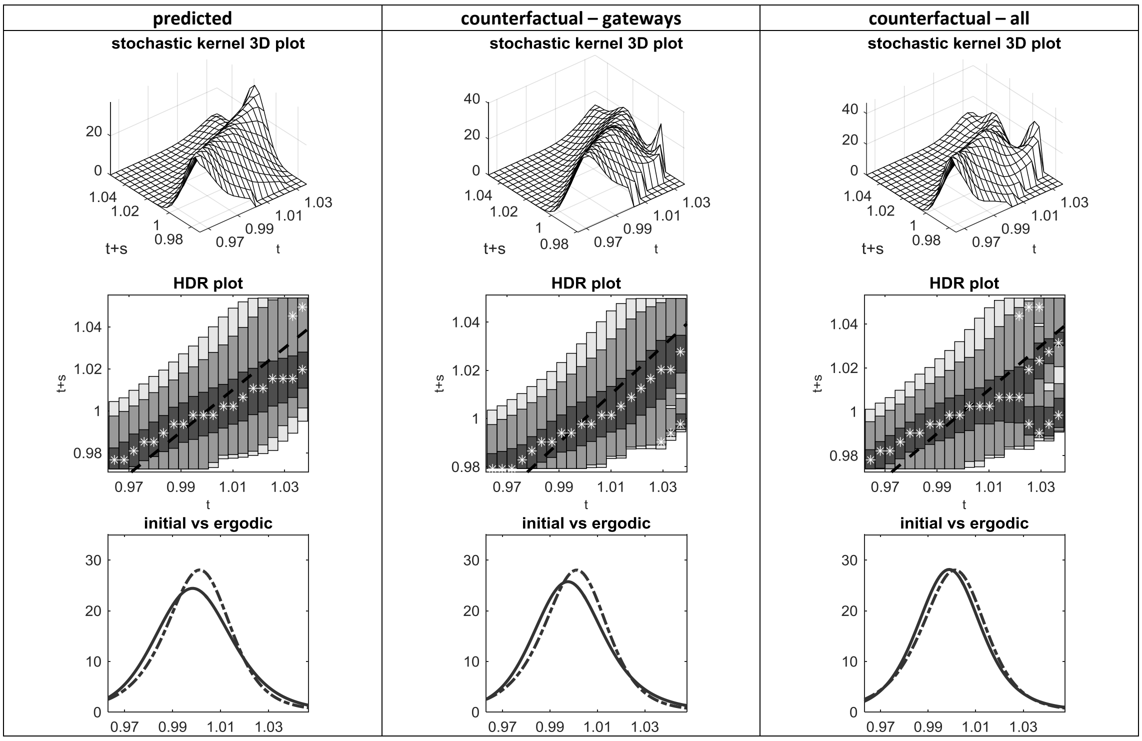
Figures

Figure 1: Distribution Dynamics of GSP per capita – 1970-2006



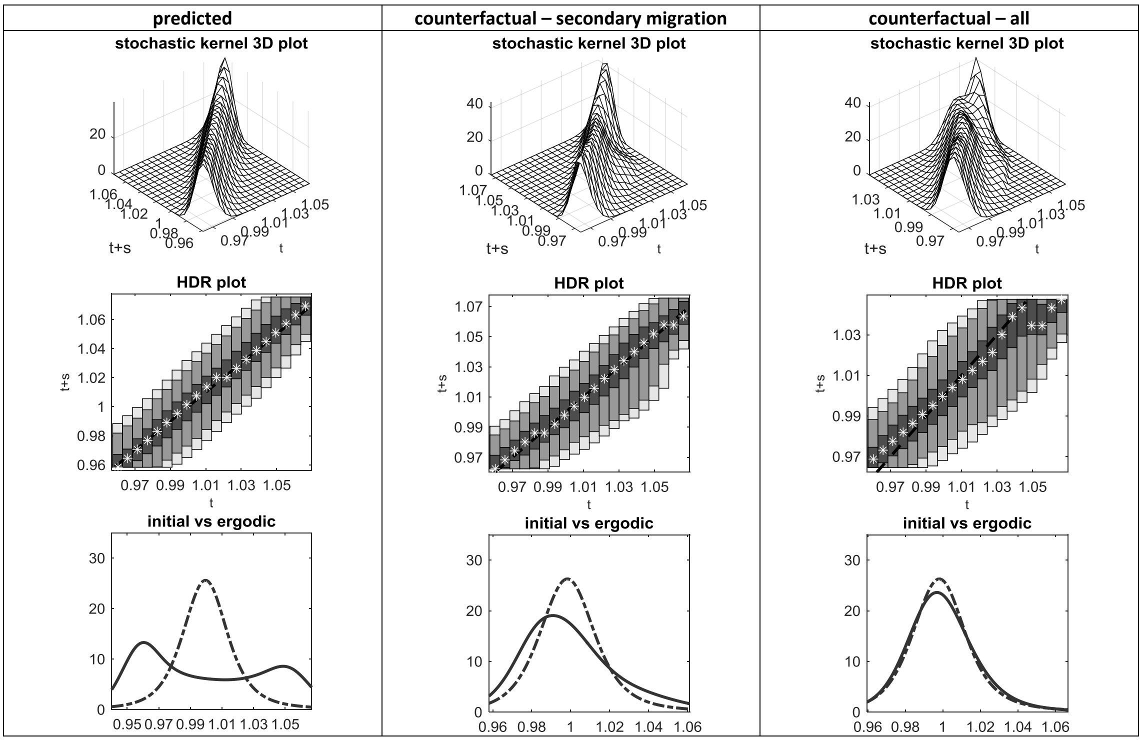
Notes: Estimates use an adaptive bandwidth (span = 0.7) based on a cross-validation minimization in the initial year dimension, a cross-validation minimization bandwidth in the final year dimension and a Gaussian kernel. Mean bias adjustment is obtained via the SNP (local linear) estimator with a cross-validation minimization bandwidth. In contour and highest density region (HDR) plots, the dashed line represents the main diagonal, the asterisk the modes. In the comparison between distributions, the dashed line represents the initial year and the continuous line represents the ergodic.

Figure 2: Distribution dynamics of GSP per worker – 1970-2006



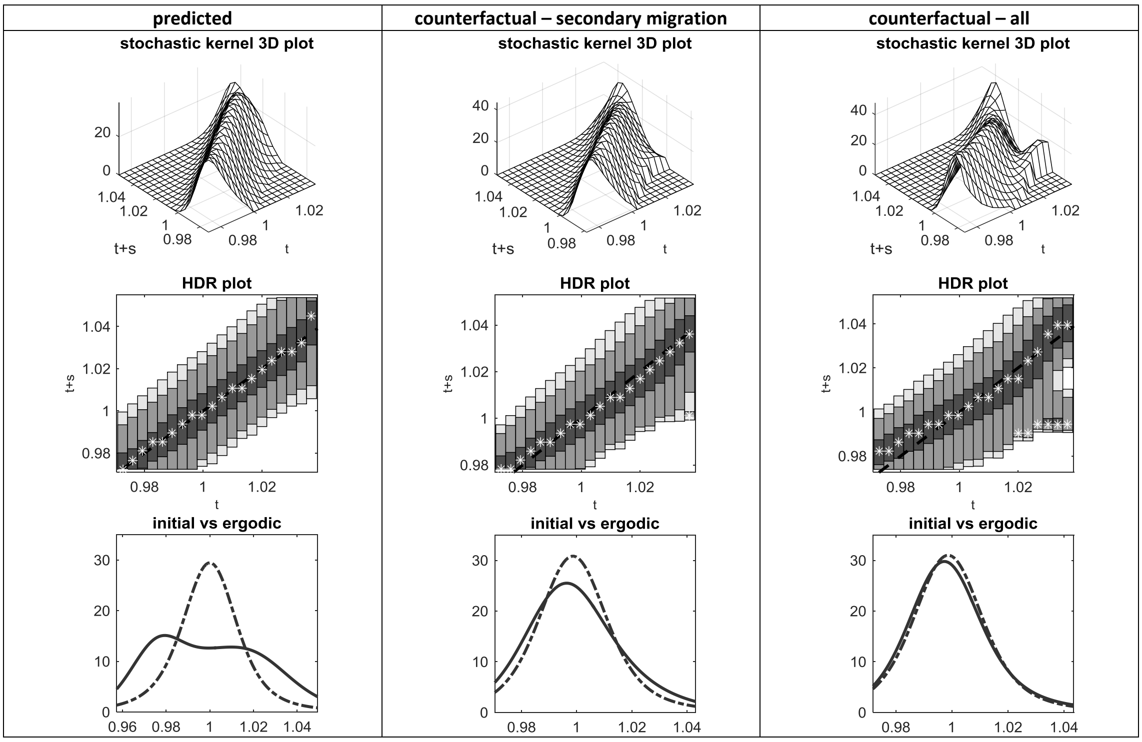
Notes: Estimates use an adaptive bandwidth (span = 0.7) based on a cross-validation minimization in the initial year dimension, a cross-validation minimization bandwidth in the final year dimension and a Gaussian kernel. Mean bias adjustment is obtained via the SNP (local linear) estimator with a cross-validation minimization bandwidth. In contour and highest density region (HDR) plots, the dashed line represents the main diagonal, the asterisk the modes. In the comparison between distributions, the dashed line represents the initial year and the continuous line represents the ergodic.

Figure 3: Distribution dynamics of GSP per capita – 1990-2006



Notes: Estimates use an adaptive bandwidth (span = 0.7) based on a cross-validation minimization in the initial year dimension, a cross-validation minimization bandwidth in the final year dimension and a Gaussian kernel. Mean bias adjustment is obtained via the SNP (local linear) estimator with a cross-validation minimization bandwidth. In contour and highest density region (HDR) plots, the dashed line represents the main diagonal, the asterisk the modes. In the comparison between distributions, the dashed line represents the initial year and the continuous line represents the ergodic.

Figure 4: Distribution dynamics of GSP per worker – 1990-2006



Notes: Estimates use an adaptive bandwidth (span = 0.7) based on a cross-validation minimization in the initial year dimension, a cross-validation minimization bandwidth in the final year dimension and a Gaussian kernel. Mean bias adjustment is obtained via the SNP (local linear) estimator with a cross-validation minimization bandwidth. In contour and highest density region (HDR) plots, the dashed line represents the main diagonal, the asterisk the modes. In the comparison between distributions, the dashed line represents the initial year and the continuous line represents the ergodic.

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