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Dissecting convergence: occupation rates, structural changes, and sectoral factor reallocations behind regional growth

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Abstract

Most studies on convergence analyze the dynamics of per capita income, instead of the theoretically more appropriate product per worker (PPW). This study deals with the latter, providing information on the dynamics of regional product, net of the regional dynamics of occupation rates. It also assesses the contribution of different sectors to regional growth dynamics, stressing the role of sectoral structure changes in the regional dynamics of PPW, bringing some ideas from economic development literature into the convergence debate. Third, this study analyzes the possible influence of factor reallocation among sectors to regional growth. Empirical evidence on the case of Brazilian states in the period 1981-1997 is offered.

Key-Words: Regional convergence, regional growth, sectoral composition and regional growth, factor reallocation and regional growth

JEL Classification: O180; R110; R150

Dissecting convergence: occupation rates, structural changes, and sectoral factor reallocations behind regional growth

1. Introduction

Most studies on convergence analyze the dynamics of per capita income (PI), instead of the theoretically more appropriate product per worker (PPW). In order to achieve results compatible with growth models, it is implicitly assumed that unemployment rates are relatively stable over time and that occupation rates (occupied population / total population) do not vary across spatial units (countries or regions). Moreover, the use of PI does not allow for the analysis of the intra and inter sectoral contributions to the behavior of aggregate productivity.

This study deals with PPW, providing information on the dynamics of regional product, net of the dynamics of occupation rates. It also assesses the contribution of different sectors to the dynamics of aggregate PPW. With the methodology applied in this study, it is possible to obtain evidence on the role of regional sectoral structure changes in the dynamics of PPW, bringing some ideas from economic development literature to the convergence debate .

The paper is organized into five sections plus this introduction. Section 2 shows that the dynamics of PI reflects the behavior of both occupation rates and PPW. In Section 3, traditional convergence tests are applied to both PI and PPW for the case of Brazilian states, and illustrating the importance of the behavior of occupation rates to the results. Section 4 presents evidence on the contribution of different sectors to aggregate PPW growth. Section 5 explores the possible influence of the reallocation of labor among sectors on the dynamics of aggregate PPW. The conclusions of the study are presented in Section 6.

2. Using PI instead of PPW: what do we lose?

As mentioned above, most studies use PI as a proxy for PPW in empirical convergence studies, be it within the Neoclassical Growth Model framework or under the convergence relations derived from the Endogenous Growth Model. This could be inadequate if the occupation rate presents a large variance among spatial units, or if its dispersion varies significantly over time.

Let Y be the real product, N the population, and L the occupied population of a spatial unit. It is easy to verify that

$$\frac{Y}{N} = \frac{L}{N}\frac{Y}{L} \Rightarrow \ln(Y / N) = \ln(L / N) + \ln(Y / L) \qquad (1)$$

With *L/N* being the per capita employment. The dispersions of these aggregates in a given moment *t* are related as

$$\sigma_{ly}^2 = \sigma_l^2 + \sigma_y^2 + 2.Cov\,(l, y) \Rightarrow \sigma_{ly} = \sqrt{\sigma_l^2 + \sigma_y^2 + 2.r.\sigma_l.\sigma_y} \qquad (2)$$

Where ly = ln(*Y/N*), l = ln(*L/N*), y = ln(*Y/L*), r is the correlation coefficient among the log of per capita employment and PPW, and σ is the standard deviation of the variables. From this expression, it is clear that changes in PPW can be amplified (narrowed) if this variable is positively (negatively) correlated with the log of per capita employment.

Notice that even without changes in the dispersion of per capita employment, consistence with growth models requires the equality of per capita employment among spatial units. Under the neoclassical approach, for example, if rich spatial units present lower (higher) per capita employment, as compared to poor spatial units, the speed of convergence can be underestimated (overestimated). Concentrating on PPW thus provides evidence on convergence net of the possible effects of differentials in per capita employment across spatial units.

However, this is not the sole or main analytical advantage of using PPW. Consider a spatial unit composed of *n* sectors, with a constant returns to scale production function presenting Hicks-neutral technical progress (*F*), differentiable over capital (*K*) and labor (*L*). These factors are assumed to be homogeneous across sectors. We can write

$$Y_i = F^i\left(K_i, L_i, t\right) = A_i(t).F^i\left(K_i, L_i\right), \text{ or} \tag{3}$$

$$y_i = A_i(t) f^i\left(k_i\right) \tag{4}$$

Where $i = 1, \ldots, n$; $A_i(t)$ is a sectoral technology index; $y = Y / L$, and $k = K / L$. The aggregate product and the PPW are

$$Y = \sum_i Y_i \quad \text{and} \quad y = \sum_i \frac{L_i}{L}\frac{Y_i}{L_i} = \sum_i \gamma_i y_i \tag{5}$$

Where $\gamma_i = L_i / L$. From equation (5), it is possible to obtain the aggregate PPW growth as a sum of two terms

$$g_y = \sum_i \rho_i g_{yi} + \sum_i \rho_i g_{\gamma i} \tag{6}$$

Where *g* indicates the rate of change of the variable and $\rho_i = \left(Y_i / Y\right)$. The first term is the weighted average of the sectoral PPW change; the second term measures the impact of labor reallocation among sectors with different PPW, an aspect that has a long tradition in development literature and that has only recently been introduced into the convergence debate[1]. This effect can constitute an independent source of PPW growth. For reasons to be explained further ahead in this paper, we note this as *gre*, for “gross reallocation effect”.

[1]Syrquin (1984) provides a good review of studies on growth emphasizing the impact of this effect. Dollar and Wolff (1988) and Cuadrado-Roura, Garcia-Greciano and Raymond (1999) explore this effect in convergence studies of PPW of countries and regions.

Another way of presenting this effect stresses its dependence on the sectoral PPW differentials

$$gre = \sum_i \rho_i g_{yi} = \sum_i g_{Li}(\rho_i - \gamma_i) = \frac{1}{Y}\sum_i \dot{L}_i(y_i - y) \qquad (7)$$

Where "•" indicates variation over time[2]. Thus, an increase in the occupation rate in sectors with higher (lower) PPW has a positive (negative) effect on growth. Substituting the sources of sectoral PPW growth from equation (4) into equation (6), provides an initial decomposition of the sources of PPW growth.

$$g_y = \sum_i \rho_i \alpha_i g_{ki} + \sum_i \rho_i \hat{A}_i + \sum_i \rho_i g_{\gamma i} \qquad (8)$$

Where $\alpha_i = F_{Ki}.K_i / Y_i$. That is, PPW growth is the result of the accumulation of capital per worker and of sectoral technical progress, $\hat{A}_i$, plus an effect resulting from the reallocation of labor among sectors with different average products. Out of equilibrium, this effect, if positive, provides a contribution to growth through a better allocation of resources (labor, in this case) in the economy.

Although the above decomposition is exact, it is not possible to associate the reallocation effect (third term) to a factor affecting the growth of aggregate PPW that is independent from the others. As Syrquin (1988) shows, it does not take into account the effect of labor reallocation on the sectoral K/L ratios. Therefore, it does not measure the impact of productivity at the margin, being only a gross measure. It is also a partial measure of factor reallocation, for it does not take into account the effects of the reallocation of other factors. Moreover, a positive reallocation effect can occur in a dynamic context even if resources are optimally allocated before and after the change. Syrquin (1984, 1988), for example, deals with the case considered by the Rybczinski Theorem, of a small country producing two goods. In this case, under the Theorem conditions, an increase in capital stock in equilibrium leads to a reallocation of labor to the capital-intensive sector, which is also the one with the highest PPW.

Since (*Ki/Li*) is constant, PPW remains constant in each sector, but the aggregate PPW is increased by the amount of the reallocation effect. In this case, the increase in PPW is not produced by labor reallocation as such, since the resources were optimally allocated, but must be attributed to capital accumulation.

If the reallocation effect is produced by disequilibria and lagged adjustments in the factor markets, it adds a new source to PPW growth, which is not associated to the accumulation of capital per worker or to the sectoral technical progress. This independent source corresponds to the share of technical progress or growth of total factor productivity that is not attributed to the sectors. In addition, if this effect is produced by responses of factors to return differentials between sectors, the marginal product differentials explain its presence and determine its magnitude.

The contribution of factor reallocation to growth, or the "total reallocation effect" (*TRE*), can be obtained from equation (3) and the aggregate growth rate as

$$TRE = \hat{A} - \sum_i \rho_i \hat{A}_i = \sum_i \rho_i \alpha_i g_{\mu i} + \sum_i \rho_i \beta_i g_{\gamma i} \tag{9}$$

Where $\mu_i = K_i / K$, $\gamma_i = L_i / L$ and $g_{\mu i}$ and $g_{\gamma i}$ are growth rates. This expression indicates that the economy's rate of technical progress is given by the weighted average of sectoral technical progress rates (technical progress or intra-sectoral component) plus the effect of factor reallocation among sectors (technical progress or inter-sectoral component)[3].

The existence of inter-sectoral components depends on non-instantaneous factor adjustments to different returns, given by the marginal products, that is, on lagged reaction of factors. Thus

[2] Using $g_L = \sum_i \frac{\dot{L}_i}{L_i}\frac{L_i}{L}$ and $\frac{\rho i - \gamma i}{L_i} = \frac{1}{Y}\left(\frac{Y_i}{L_i} - \frac{Y}{L}\right)$.

[3] These expressions are attributed to Massel (1961), probably the pioneer in demonstrating these different effects.

$$
\begin{aligned}
TRE &= \sum_i \rho_i \alpha_i g_{\mu i} + \sum_i \rho_i \beta_i g_{\gamma i} \\
&= \frac{1}{Y}\sum_i \dot{K}_i F_{Ki} - \frac{1}{Y} g_K \sum_i K_i F_{Ki} + \frac{1}{Y}\sum_i \dot{L}_i F_{Li} - \frac{1}{Y} g_L \sum_i L_i F_{Li} \qquad (10) \\
&= \frac{1}{Y}\sum_i \dot{K}_i \left(F_{Ki} - F_K\right) + \frac{1}{Y}\sum_i \dot{L}_i \left(F_{Li} - F_L\right)
\end{aligned}
$$

Where F_z *(z=K,L)* is the marginal product of factors, and *i* is the sector taken as reference. Therefore, the two terms indicate that the presence of the reallocation effect, as an independent contributor to the growth of the aggregate product and of PPW, has its origin in the disequilibrium in the factor markets. That is, in the marginal productivity differentials among sectors, which are not corrected by instantaneous factor adjustments. Considering these arguments, it is then possible to reconsider the meaning of the components of equation (8). Under instantaneous adjustment and perfect equilibrium in factor markets, the first and third terms on the right-hand side represent the contribution of the accumulation of capital per worker. The second represents the contribution of technical progress, reflecting exclusively sectoral technical progress.

Thus, assuming instantaneous adjustment in factor markets, only intra-sectoral sources of change in PPW are present.

If we allow for lags in factor adjustments to return differentials, that is, disequilibrium in some factor markets, the total reallocation effect (*TRE*) appears as an additional source for PPW growth. In this case, part of this effect, corresponding to the gross reallocation effect (*gre*), is represented by the third term in the right-hand side of the equation. The other two terms reflect simultaneously: capital accumulation, sectoral technical progress, and the remaining components of *TRE*. In this situation, both intra-sectoral (accumulation of capital per worker and sectoral technical progress) and inter-sectoral sources of PPT change would be present.

For a comprehensive study of convergence, these sources must be taken into account. In a context of perfect factor adjustment to return differentials, convergence of aggregated PPW of different spatial units must be associated to intra-sectoral sources. That means that sectoral PPW grows faster in poorer spatial economies, be it due to a greater relative capital per worker accumulation, or to a relatively faster sectoral technical progress in these economies, or both. On the other hand, if the differences in the returns of at least some factors show some persistence, due to lagged adjustments, and if these disequilibrium situations are predominant in the poor economies, convergence movements of aggregate PPW might be associated to the operation of either intra-sectoral or inter-sectoral sources.

3. Convergence with PI and PPW: an empirical comparison

As an illustration, we analyze 19 Brazilian states over the period 1981-1997, using the same database as in Azzoni et al (2000). Data for PI are from estimations of regional accounts from the official Brazilian statistics agency, IBGE[4]. PPW data are from yearly household surveys developed by IBGE, aggregated using the sampling weights to replicate states' aggregates[5]. States in the sparsely populated Amazon region were omitted for lack of information.

We compute Sigma and Beta convergence indicators for both PI and PPW and compare the results. For the former, we calculate the traditional indicators of regional income dispersion, such as the standard deviation of the log of the variables, the coefficient of variation (CV), Williamson's weighted coefficient of variation (Iw) and Theil's coefficient (Theil). For the latter, we estimate convergence regressions with both cross-section and panel data.

The results on Sigma convergence are presented in Table 1 and in Figures 1 and 2. It can be observed that the regional dispersion in the period is limited, for both variables. A slight upward trend is present in the 1980's and a declining trend in the 90's, but considering the end years of 1981 and 1997, the change is very small. It is also clear that the behavior is similar for both variables, PI and PPW. This result is the consequence of the relative stability of the dispersion of occupation rates, presented in Figure 3. These results are quite different from the ones observed in the Spanish case

[4] http://www.ibge.gov.br/ibge/estatistica/economia/contasregionais/.
[5] PNAD – *Pesquisa Nacional por Amostra de Domicílios* provided by the Brazilian Statistics Institute (*Instituto Brasileiro de Geografia e Estatística – IBGE*) (www.ibge.gov.br/ibge/estatistica/populacao/trabalhoerendimento/pnad99/).

by Cuadrado-Roura et al (1999). In that case, dispersion of PPW diminished but the increasing dispersion in occupation rates prevented a decrease in the dispersion of PI.

<< Figures 1, 2 and 3. Table 1 >>

As for Beta convergence, we regress the rates of growth of PI and PPW against their initial levels, using both cross-section and panel data. The cross-sections are estimated using the form

$$\Delta \ln y_{it} = \alpha + \beta \ln y_0 + \varepsilon_{it}$$
$$\Delta \ln y_{it} = \alpha + \beta \ln y_0 + \gamma \ln S_i + \varepsilon_{it}$$

Where y indicates income (either PI or PPW) and S_i is the average number of years of schooling[6]. Both versions can be derived either from the Neoclassical or the Endogenous Growth models, with different causes for an eventual presence of a negative relationship between growth and initial income level: in the former, a faster accumulation of capital per worker in poor states; in the latter, higher rates of technical progress in those states. The first form relates to absolute convergence (identical steady state income levels); the second relates to conditional convergence (differing steady state income levels).

For the panel data estimations, ~~the 16-year period was split into 4 equal-length~~we use 4-year rolling sub-periods, and estimate ~~. We use~~ the form

$$\Delta \ln y_{it} = \alpha + \beta \ln y_{it-1} + \mu_i + \eta_t + \varepsilon_{it}$$

With η_t representing a period-specific dummy and μ_i a state-specific effect, generally associated to the initial technological conditions. The regressions are estimated with Least Squares Dummy Variables (LSDV)[7]. The results are presented in Table 2. It must be noted that the panel data estimated coefficients are not strictly comparable to

[6] As a proxy for human capital. We have also experimented with other proxies, such as enrollment rates, with similar results.
[7] This estimator has asymptotic properties similar to the Minimum Distance Estimator, and generates exactly the same estimates as the Fixed Effects Estimator (Islam, 1995). We have also tried GMM, but could not find good instruments.

the ones estimated with cross-sections, for they depend on the time interval considered; however, the estimated speeds of convergence are comparable.

The cross-section results indicate no sign of absolute convergence for both PI and PPW, replicating the results of Azzoni et al (2000) for the same time period. They are also compatible with the results on Sigma-convergence already shown. As for conditional convergence, the scenario is different: we find evidence of it for PI but not for PPW[8]. The estimated speed of convergence, around 2% per year, is similar to the ones obtained by Mankiw, Romer and Weil (1992) and Barro and Sala-i-Martin (1995). The results indicate that the use of PI overestimates the speed of convergence, due probably to the fact that rich states present higher occupation rates.

The panel data results indicate clearly the bias present in cross-section estimates, produced by the correlation between the initial technological conditions (omitted) and the initial level of income, which tends to underestimate the convergence coefficient (Islam, 1995). The evidence now points to the existence of conditional convergence for both variables, at a much higher speed[9]. This result indicates that the present regional inequality is closer to the steady state equilibrium inequality, since the estimated period of time to attain half-convergence is very short. Another interesting result is the change in the importance of education when other regional characteristics (state dummy variables) are included[10]. Again, the speed of convergence is higher for PI than for PPW.

<< Table 2>>

Table 3 presents the state dummy variable coefficients estimated in equations represented in columns (4) and (7) of Table 2 (conditional convergence with panel data). The states are shown in decreasing order of 1997 PPW, with the intermediary income state of Pernambuco taken as a reference. Thus, the coefficients indicate variations around that state's PI or PPW. When significant, the coefficients present the expected sign, indicating that rich states present characteristics other than human capital that are more favorable to growth. The distribution between positive and negative coefficients is almost symmetrical for PI and not so much for PPW. The values are higher for PI than for PPW and so is the range of values: the distance

[8] This result is robust for other forms of measuring education.
[9] Again, replicating the results of Azzoni et al (2000).

between São Paulo, the richest state, and the poorest, Maranhão, is 1.962 for PI and 1.345 for PPW. This evidence suggests that the regional characteristics embedded in the regional dummies are less important for the analysis of the productive system of the states, that is, when PPW is considered, than for the explanation of differences in the dynamics of income in general (PI). This indicates that regional factors such as cultural and institutional differences, that are part of the local conditionants, are more important in the determination of the behavior of PI and less directly related to employment and production decisions (PPW).

The results clearly show that using PI leads to results that are not exactly the ones that would have been obtained with the more correct use of PPW, although the differences in the case at hand are not impressive. As a matter of fact, for the Brazilian case in the period analyzed, the dynamics of PI reflects reasonably well the dynamics of PPW, a result similar to the one obtained by Barro (1991) for American states; it is very different, though, from the ones obtained by Cuadrado-Roura et al (1999) for the case of Spanish regions.

<< Table 3 >>

4. Sectoral convergence sources

The previous section has illustrated that the use of PI as a proxy for PPW can lead to biases when occupation rates are different across spatial units. This is not, however, the sole analytical advantage, for the use PPW allows for the consideration of the intra and inter sectoral sources of aggregate growth. In this section we split the aggregate production of each state into four sectors: agriculture, manufacturing, construction and services. Figure 4 and Table 4 present the dispersion of the log of PPW as an indicator of Sigma-convergence for each sector. Note that dispersion is increasing for agriculture and services and decreasing for manufacturing; for construction the situation is not clear.

<< Table 4 and Figure 4>>

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[10] Azzoni et all (2000) shows that other variables are important for the determination of the dynamics of PI for the same states.

Moving on to Beta convergence, the same previous regressions were estimated with sectoral data, with results presented in Table 5. In general, they confirm the results on Sigma convergence presented before, for absolute convergence is present only for manufacturing and construction. For services, the coefficient is positive and significant, indicating a divergence trend; this sector and agriculture do not show even conditional convergence (for cross-section regressions). The panel data results show once again the underestimation of the convergence coefficient in cross-section estimates; it also shows that non-education specificities in the regions are more important than education for convergence. In fact, when state dummies are included, conditional convergence occurs and education becomes non-significant.

<< Table 5 >>

The analysis of the estimated sectoral dummy coefficients, presented in Table 3, is interesting (again, the middle income state of Pernambuco is taken as reference). For agriculture, in comparison to the aggregate product, there is a less symmetrical distribution, since the dummies for the poor states appeared as non-significant, indicating a more homogeneous situation in comparison to Pernambuco (only the two poorest states, Maranhão and Piauí, present negative significant coefficients). This may be related to similar conditions, such as weather, technological development, land tenure structure, etc. For manufacturing, only one state presents a non-significant dummy coefficient, indicating that this sector is highly differentiated across space; in comparison to agriculture, there is a change of signs for four states: Mato Grosso and Mato Grosso do Sul, in the Brazilian agricultural frontier, become negative, and the two petroleum-related states belonging to the poor Northeast region, Bahia and Sergipe, become positive. Construction is the sector less region-differentiated and the service sector is the one with the closest behavior to the aggregate PPW, as indicated by the distribution of the dummy coefficient values.

In summary, agriculture and services favor divergence and manufacturing favors convergence[11]. As for agriculture, given this sector's dependence on natural conditions, the result is not surprising. In fact, the states traditionally important in this sector are the ones with better performance. The converging role of manufacturing is

[11] The Brazilian experience is not much different either from the American case, as indicated in Amos (1990), Barro and Sala-i-Martin (1992) and Magura (1999), or the Mexican case, as observed by Mallick and Carayannis (1994).

also expected, being this the most mobile of sectors. The service sector seems to be dependent on the scale or the size of the state's economy, for 5 out of 7 of the richest states are above the average in this case. All in all, it is clear that the use of PPW allows for a step forward in the analysis of convergence, that is, identifying the sectors behind the dynamics of aggregate PPW

5. Factor reallocation and convergence

Section 3 showed that using PI as a proxy for PPW can be misleading. Section 4 showed another advantage of using PPW, that is, the possibility of identifying the sectoral sources behind convergence. In this section we analyze a third aspect, that is, the influence of factor reallocations among sectors within spatial units. We concentrate on reallocation of labor, for no data on capital for states is available for the Brazilian case. As shown in Section 2, if the instantaneous equalization of factor returns does not occur, there may be another source for the growth of aggregate total factor productivity, represented by factor reallocations among sectors.

The first step to investigate the existence of such a factor in the case at hand is to analyze the changes in the sectoral structure of employment across sectors and states. Table 6 shows the change in employment by sector for the Brazilian states in the period 1981-1997. It can be seen that agriculture presents negative, and service positive, variations in all states; manufacturing and construction present varied movements, depending on the state. The individual variations are higher for poor states.

<< Table 6 >>

In order to identify the most important sectors in this process, we compute the dispersion measure proposed by Cuadrado-Roura et al (1999)

$$I_c = \sum_{e}^{N}\left[\sum_{i}^{n}\left(P_{ei} - P_{ti}\right)^2\right] / N \qquad (11)$$

where P_{si} is the share of employment in sector i in state s; P_{ti} is the share of employment in sector i in the country; N is the number of states and n is the number of sectors. This index is in fact the sum of the sectoral indexes

$$I_i = \sum_{e}^{N} \left(P_{ei} - P_{ti}\right)^2 / N \qquad (12)$$

The results are presented in figures 5 and 6, for the aggregate and for each of the four sectors, respectively. It is clear that there is a decreasing trend in dispersion of the sectoral mix of Brazilian states, a trend that is most pronounced in the 80's; Figure 6 shows that this trend is common for all sectors, but agriculture has the highest change, reflecting the loss in the participation of this sector in the poor states. Thus, there is a clear trend towards the homogenization of the productive structures of Brazilian states, with a decrease in the share of agriculture and an increase in the share of services. This trend is stronger in poor states, which show the strongest decrease in the share of construction. For manufacturing, the changes are less evident.

<< Figures 5 and 6>>

The operation of a labor reallocation effect in increasing PPW requires migration over time of labor from less productive to more productive sectors, leading differentials in returns to vanish, or at least diminish~~, over time~~. The results indicate that sectors expected, in a non-equilibrium situation, to supply workers to other sectors are really the ones that would tend to pay lower wages. Table 7 presents a comparison of per capita income of workers in different sectors with agriculture and construction. It is clear ~~the~~ that manufacturing and services pay higher income to workers than agriculture and construction and these differences are stronger for the poorest states.

<< Table 7 >>

These differences, however, could be due to differences in the quality of labor in different sectors. In order to test for that, we have regressed the average level of income against education, sectoral, time and state dummies. The following equation is estimated

$$\log y_{it} = a + bEd_{it} + \sum_j c_j S_{ji} + \sum_e d_e E_{ei} + I_{et} + D_t + \varepsilon_{it} \qquad (15)$$

Where a is a constant; y_{it} is the state i average income level in time t; Ed_{it} is the number of years of schooling; S_{jt} is a sectoral dummy (agriculture is the base sector); E_{ei} is a state dummy (Pernambuco is the base state); I_{et} is the participation of manufacturing in the state's total product; and D are time dummies. The regression was estimated with OLS for all states and for different groups of states (the official Brazilian macro regions).

Table 8 presents the estimated sectoral dummy coefficients, with and without the variable indicating education, allowing for the assessment of the importance of homogenizing the labor force, in terms of this variable, for labor income differentials across sectors. The results without education (first column in each region) clearly show that all three sectors present higher income than agriculture in all cases, except the Center-West region. When education is included, things change completely. For the country as a whole, and for all four macro regions, manufacturing shows no difference from agriculture. That is, the differential between agriculture and manufacturing is fully explained by the higher educational level of workers in the latter. As for the service sector, there is no indication that its income is different ~~than~~ from agriculture for all macro regions, although for the country as a whole it is significantly different, and with a negative sign. Thus, higher education explains higher payments also for the services sector. Construction maintains higher remuneration than agriculture for all regions but the Center-West.

The results for the sectoral share changes presented in Table 6 are highly important. They indicate that, for the Brazilian case, there is no sign of a factor reallocation effect as an independent source of PPW growth across states. In other words, the changes in employment structure, favoring services against agriculture, do not seem to be related to differentials in labor income across sectors. These movements might be related to differentials in capital accumulation in the states, in a context of sectors characterized by different factor intensities. This result is quite different from the ones obtained by Cuadrado-Roura (1998) and Cuadrado-Roura et all (1999) for the Spanish case, where the inter-sectoral labor reallocations in poor regions explained convergence in aggregate PPW, in a context of absence of PPW convergence in all sectors. However, our results are similar to the ones obtained by Bernard and Jones (1996), for 14 OECD countries, and by Dollar and Wolf (1988), for manufacturing across 13 industrialized countries.

<< Table 8 >>

6. Conclusions

The main results of this paper can be summarized as follows. For the 19 Brazilian states analyzed, in the period 1981-1997, the dynamics of PI inequality reflected, mainly, the dynamic of PPW, although using PI overestimated the speed of convergence. The dispersion of occupation rates presented few oscillations. Therefore, the inequality dynamics of both PI and PPW is explained by the behavior of sectoral labor productivity. As ~~far~~ for~~as~~ the sectoral sources, the results show that only manufacturing favors convergence, with agriculture and services acting otherwise. For construction, the results are less conclusive.

Finally, in spite of the important changes in the sectoral structure of employment, especially in poorer states, the evidence does not reveal the existence of a gross reallocation effect, as an independent source of aggregate PPW growth. Since it was not possible to associate the changes in employment across sectors to differentials in wages, the structural changes have no explanatory power for the dynamics of PPW across states. Only intra-sectoral sources were at work in the case analyzed.

Although our results do not show any sign of the latter factor, it does not mean that it is not important in every case. As found in the Spanish scenario, this factor could have an important role in convergence studies.

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Figure 1 - Standard deviation of ln PI

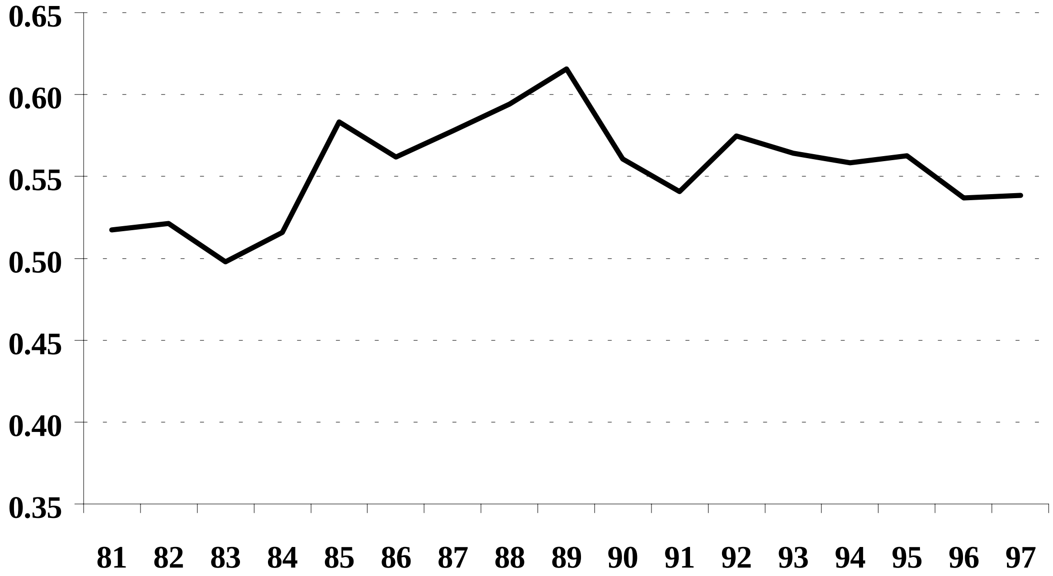

Figure 2 - Standard deviation of ln PPW

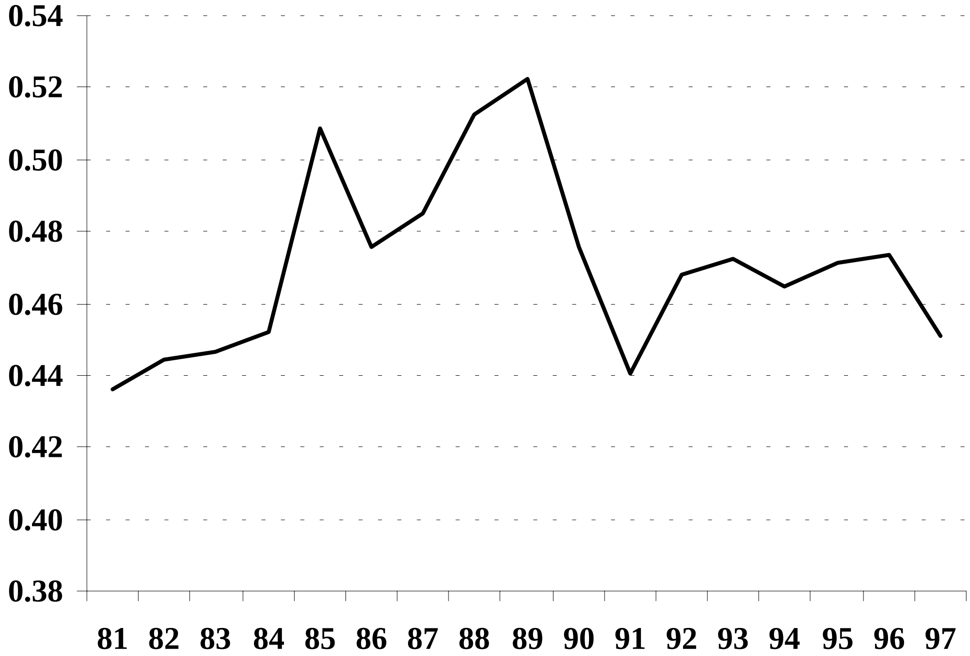

Figure 3 - Dispersion of ln (Occupied/Total Population)

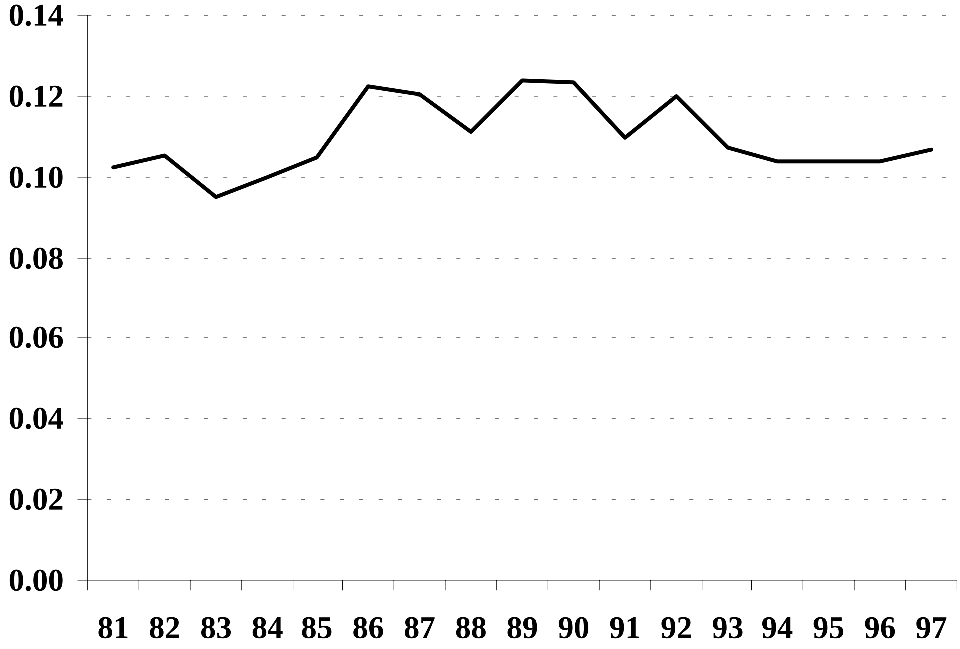

Figure 4 - Standard deviation of log sectoral PPW

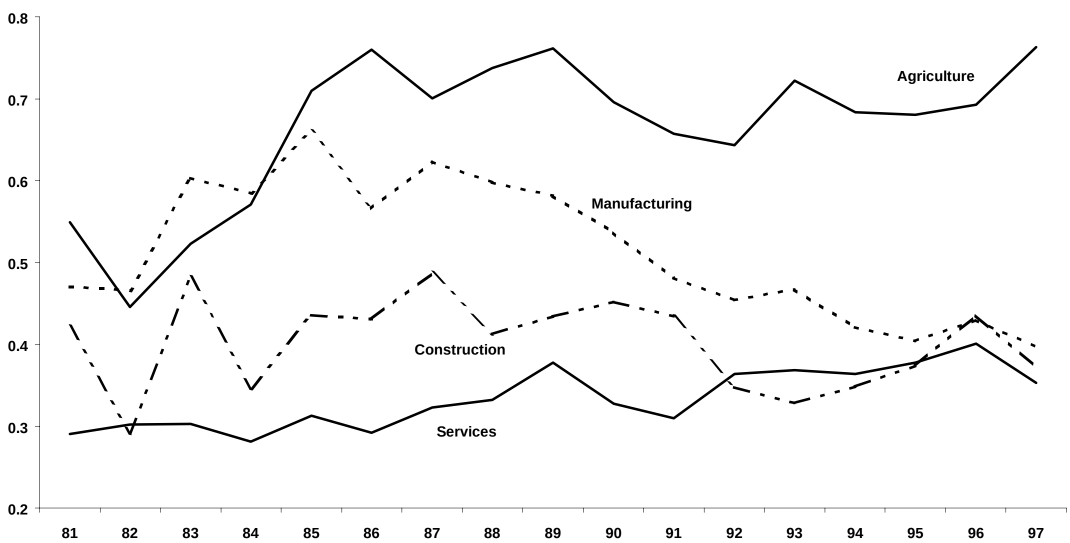

Figure 5 - Dispersion of employment sectoral structure across states

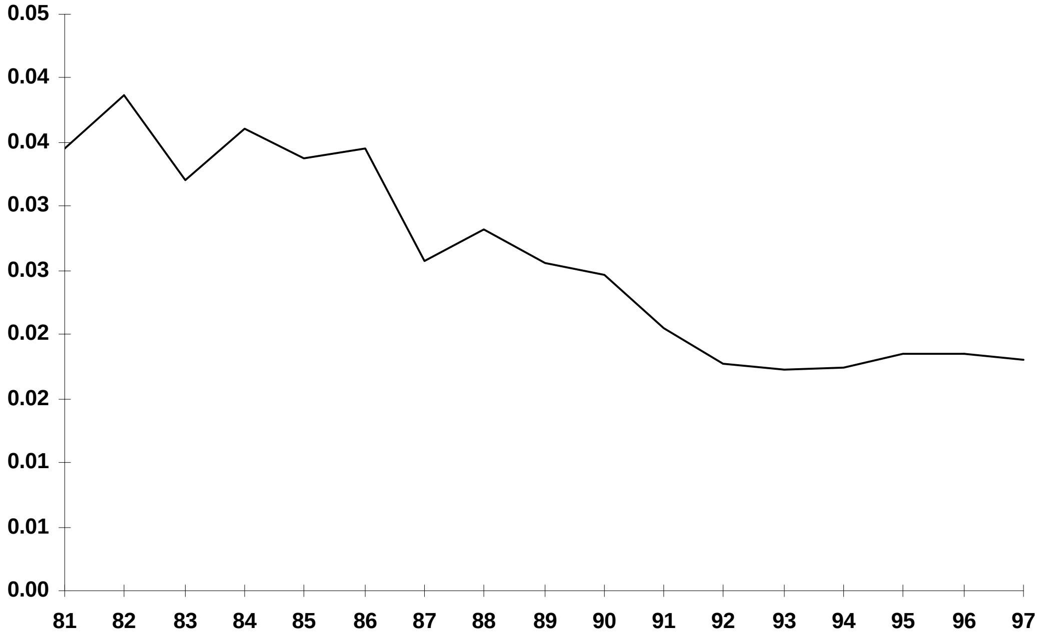

Figure 6 - Dispersion of employment structure across states

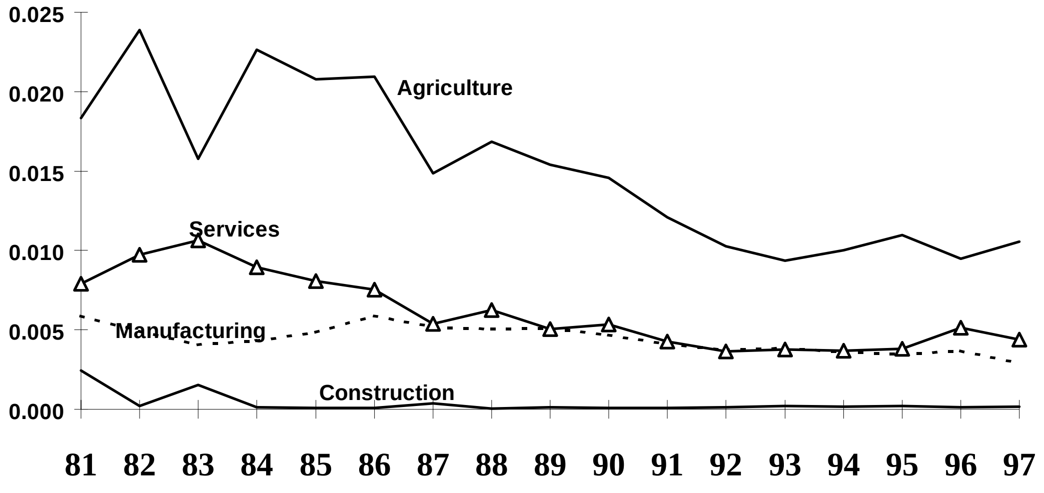

Table 1 - Sigma Convergence Indicators

	PI				PPW				Occupied/Total Population (OP/TP)			
Year	Theil	Coefficient of Variation	Williamson Iw	St. Deviation ln PI	Theil	Coefficient of Variation	Williamson Iw	St. Deviation ln PPW	Theil	Coefficient of Variation	Williamson Iw	St. Deviation ln (OP/TP)
1981	0.1226	0.5104	0.4929	0.5172	0.0851	0.4161	0.3781	0.4363	0.0051	0.1056	0.1165	0.1024
1982	0.1256	0.5184	0.4931	0.5214	0.0905	0.4234	0.3880	0.4442	0.0053	0.1069	0.1146	0.1051
1983	0.1133	0.4843	0.4507	0.4978	0.0843	0.4147	0.3710	0.4464	0.0044	0.0977	0.1072	0.0950
1984	0.1199	0.4909	0.4534	0.5159	0.0838	0.4203	0.3679	0.4521	0.0048	0.1026	0.1130	0.1001
1985	0.1477	0.5321	0.4693	0.5832	0.0930	0.4455	0.3728	0.5089	0.0053	0.1076	0.1156	0.1046
1986	0.1376	0.5122	0.4565	0.5617	0.0810	0.4178	0.3528	0.4756	0.0071	0.1244	0.1249	0.1222
1987	0.1486	0.5491	0.4917	0.5778	0.0972	0.4418	0.3920	0.4851	0.0069	0.1215	0.1209	0.1203
1988	0.1584	0.5688	0.4999	0.5943	0.1050	0.4720	0.4097	0.5127	0.0060	0.1142	0.1154	0.1114
1989	0.1721	0.5940	0.5014	0.6156	0.1055	0.4989	0.4107	0.5221	0.0074	0.1268	0.1244	0.1240
1990	0.1447	0.5511	0.4840	0.5608	0.0936	0.4539	0.3890	0.4758	0.0073	0.1270	0.1238	0.1234
1991	0.1323	0.5202	0.4581	0.5406	0.0813	0.4216	0.3647	0.4404	0.0057	0.1108	0.1111	0.1094
1992	0.1485	0.5469	0.4672	0.5745	0.0897	0.4613	0.3841	0.4678	0.0067	0.1163	0.1080	0.1200
1993	0.1437	0.5385	0.4615	0.5643	0.0928	0.4492	0.3837	0.4723	0.0054	0.1059	0.1004	0.1070
1994	0.1401	0.5255	0.4435	0.5583	0.0858	0.4396	0.3677	0.4647	0.0051	0.1027	0.0956	0.1036
1995	0.1436	0.5373	0.4555	0.5625	0.0931	0.4550	0.3874	0.4713	0.0051	0.1027	0.0927	0.1039
1996	0.1320	0.5175	0.4372	0.5371	0.0951	0.4613	0.3966	0.4734	0.0051	0.1044	0.1029	0.1040
1997	0.1324	0.5184	0.4434	0.5386	0.0894	0.4415	0.3842	0.4510	0.0054	0.1057	0.0926	0.1066

Table 2 – Convergence Equation Results

	PPW				PI		
	Cross-Section		Panel		Cross-Section		Panel
	1	2	3	4	5	6	7
Constant	0.256	1.907	**8.264**	**7.976**	**0.205**	**1.508**	**9.769**
	-0.551	-1.14	**-0.96**	**-0.937**	**-0.423**	**-0.588**	**-4.065**
Initial Income (Ln y_0)	-0.01	-0.275	**-0.946**	**-0.943**	0.01	**-0.272**	**-0.998**
	-0.06	-0.161	**-0.108**	**-0.109**	-0.053	**-0.103**	**-0.068**
Education (S_h)		**0.165**		0.07		**0.209**	0.045
		-0.078		-0.062		**-0.064**	-0.043
Speed of Convergence (λ)			0.731	0.718		0.0198	1.553
State Dummies			Yes	Yes			Yes
Time Dummies			Yes	Yes			Yes
Number of Observations	19	19	247	247	19	19	247
R^2	0.0012	0.1885	0.5689	0.5738	0.0015	0.2975	0.7294

Obs: Standard deviations within parenthesis. All regressions are heteroskedasticty-robust. Shadowed cells indicate significance at a 5% level.

The the speed of convergence was calculated from the neoclassical model: $\beta = -(1-e^{-\lambda t})$.

Table 3 – Estimated state dummy coefficients

State	PI	PPT				
		All Sectors	Agriculture	Manufacturing	Construction	Services
SP	1,094	0,596	1,205	0,686	0,206	0,564
	(0,115)	(0,157)	(0,188)	(0,075)	(0,061)	(0,085)
RJ	0,813	0,386	0,386	0,501	0,095	0,420
	(0,099)	(0,139)	(0,144)	(0,076)	(0,066)	(0,085)
RS	0,827	0,375	1,155	0,560	-0,029	0,393
	(0,112)	(0,164)	(0,192)	(0,068)	(0,085)	(0,076)
SC	0,717	0,327	0,942	0,422	-0,131	0,348
	(0,108)	(0,162)	(0,198)	(0,067)	(0,082)	(0,079)
ES	0,514	0,227	0,720	0,623	0,350	0,270
	(0,083)	(0,133)	(0,114)	(0,081)	(0,075)	(0,089)
PR	0,573	0,235	1,014	0,574	0,293	0,252
	(0,088)	(0,129)	(0,132)	(0,075)	(0,071)	(0,059)
MG	0,439	0,155	0,612	0,406	0,085	0,189
	(0,069)	(0,101)	(0,111)	(0,054)	(0,057)	(0,048)
MS	0,363	0,049	1,357	-0,142	0,027	0,040
	(0,068)	(0,096)	(0,135)	(0,049)	(0,053)	(0,031)
MT	0,160	0,005	0,983	-0,414	-0,243	0,203
	(0,059)	(0,082)	(0,111)	(0,049)	(0,055)	(0,057)
BA	-0,009	-0,041	0,003	0,377	-0,406	0,008
	(0,037)	(0,049)	(0,036)	(0,064)	(0,187)	(0,031)
SE	0,131	0,092	0,003	0,620	-0,032	-0,143
	(0,081)	(0,129)	(0,037)	(0,135)	(0,106)	(0,075)
RN	-0,179	-0,138	-0,069	-0,100	-0,063	-0,249
	(0,032)	(0,050)	(0,074)	(0,060)	(0,066)	(0,041)
CE	-0,312	-0,263	-0,507	-0,426	-0,119	-0,175
	(0,035)	(0,054)	(0,056)	(0,083)	(0,088)	(0,039)
GO	-0,031	-0,194	0,801	-0,236	-0,226	-0,037
	(0,056)	(0,085)	(0,120)	(0,049)	(0,052)	(0,041)
AL	-0,264	-0,120	-0,192	-0,149	-0,035	-0,107
	(0,069)	(0,085)	(0,113)	(0,068)	(0,093)	(0,061)
PB	-0,457	-0,297	0,035	-0,403	-0,226	-0,315
	(0,055)	(0,075)	(0,062)	(0,062)	(0,067)	(0,037)
PI	-0,824	-0,639	-0,412	-0,871	-0,857	-0,377
	(0,082)	(0,104)	(0,082)	(0,104)	(0,113)	(0,063)
MA	-0,868	-0,749	-0,792	-0,932	-0,896	-0,379
	(0,059)	(0,092)	(0,088)	(0,091)	(0,091)	(0,061)

Table 4 - Ln PPW coefficient of variation

Year	Agriculture	Manufacturing	Construction	Services
1981	0.4414	0.4018	0.3523	0.2883
1982	0.4171	0.4105	0.2593	0.2933
1983	0.4601	0.5069	0.4284	0.2936
1984	0.5622	0.5456	0.2709	0.2798
1985	0.6639	0.5937	0.3293	0.3044
1986	0.7513	0.5040	0.3510	0.2860
1987	0.7011	0.5354	0.4013	0.3248
1988	0.7060	0.5091	0.3608	0.3308
1989	0.7448	0.4933	0.3769	0.3837
1990	0.7102	0.4376	0.3655	0.3299
1991	0.7156	0.4162	0.3354	0.3123
1992	0.7287	0.4214	0.3071	0.3691
1993	0.7408	0.3853	0.2956	0.3766
1994	0.6736	0.3730	0.3011	0.3615
1995	0.7027	0.3946	0.3360	0.3846
1996	0.7013	0.3723	0.3832	0.4051
1997	0.7608	0.3723	0.3443	0.3623

Table 5 - Sectoral convergence regressions

	Agriculture			Manufacturing			Construction			Services		
	Cross-section		Panel	Cross-section		Panel	Cross-section		Panel	Cross-section		Panel
Constant	-1.593	3.951	**7.097**	**4.016**	**5.742**	**9.912**	**7.867**	9.087	**-7.573**	**-1.533**	-0.202	**679**
	-2.36	-3.048	**-0.638**	**-1.236**	**-2.162**	**-0.785**	**-1.904**	-5.271	**-0.742**	**-0.524**	-0.988	**-83**
Initial Income (ln y_o)	0.196	-0.601	**-0.905**	**-0.162**	**-0.645**	**-1.089**	**-0.811**	-0.973	**-0.833**	**0.168**	-0.071	**-66**
	-0.28	-0.41	**-0.093**	**-0.027**	**-0.288**	**-0.085**	**-0.213**	-0.67	**-0.085**	**-0.06**	-0.14	**-91**
Education (S_h)		**0.64**	0.024		0.137	0.031		0.07	-0.015		**0.119**	-0.037
		-0.26	-0.108		-0.126	-0.03		-0.243	-0.055		**-0.049**	-0.047
Time Dummies			Yes			Yes			Yes			Yes
State Dummies			Yes			Yes			Yes			Yes
Number of Observations	19	19	247	19	19	247	19	19	247	19	19	247
R^2	0.044	0.049	0.8024	0.31	0.359	0.666	0.4692	0.4718	0.6674	0.199	0.404	0.624

Obs: Standard deviation in parenthesis. Shadowed cells indicate significance at 5%. All regressions are heteroskedasticity-robust

Table 6 - Changes in sectoral shares, by state

States*	Agriculture	Manufacturing	Construction	Services
SP	-3,51%	-9,04%	-0,31%	12,86%
RJ	-1,80%	-6,51%	-1,59%	9,90%
RS	-8,19%	0,38%	-0,94%	8,75%
SC	-10,00%	-1,12%	2,32%	8,80%
ES	-10,92%	0,35%	-1,44%	12,01%
PR	-18,14%	3,20%	0,74%	14,20%
MG	-12,15%	1,25%	0,29%	10,61%
MS	-4,27%	0,10%	-3,11%	7,29%
MT	-9,92%	1,33%	-0,46%	9,06%
PE	-11,34%	-3,77%	-1,41%	16,52%
BA	-13,07%	-1,36%	0,21%	14,21%
SE	-11,36%	-6,62%	-4,39%	22,37%
RN	-11,32%	-0,65%	-4,47%	16,44%
CE	-1,97%	-3,99%	-12,38%	18,34%
GO	-11,20%	2,44%	-0,84%	9,60%
AL	-19,72%	-0,43%	-3,34%	23,49%
PB	-4,92%	-1,69%	-2,79%	9,31%
PI	-14,09%	0,91%	-3,77%	17,76%
MA	-12,28%	1,68%	-1,25%	11,85%

* States are in decreasing order of aggregate PPW (1997)

Table 8 - Labor income differentials (Dependent variable: log *y*)

	All States		Southeast		South		Center-West		Northeast	
Education	-	**0.183**	-	**0.128**	-	**0.117**	-	**0.194**	-	**0.127**
		-0.021		**-0.037**		-0.038		-0.093		-0.02
Manufacturing Dummy	**0.437**	-.143	**0.614**	0.122	**0.383**	0.061	-0.042	-0.358	**0.537**	.087
	-0.025	(.078)	**-0.034**	-0.147	**-0.03**	-0.108	-0.085	-0.208	**-0.032**	(.077)
Services Dummy	**0.465**	**-0.517**	**0.513**	-.178	**0.371**	-.190	**0.163**	-0.741	**0.576**	-.157
	-0.019	**-0.115**	**-0.028**	(.209)	**-0.032**	(.186)	**-0.035**	-0.437	**-0.026**	(.121)
Construction Dummy	**0.419**	**0.12**	**0.413**	**0.212**	**0.311**	**0.171**	**0.099**	-0.155	**0.565**	**0.322**
	-0.022	**-0.039**	**-0.035**	**-0.074**	**-0.032**	**-0.054**	**-0.05**	-0.129	**-0.029**	**-0.05**
Number of Observations	1292	1292	272	272	204	204	204	204	612	612
R^2	0.736	0.765	0.837	0.843	0.851	0.856	0.472	0.492	0.763	0.778

Obs: All regressions include State and Time dummies