THE EARNING LOSSES AFTER MIGRATION IN BRAZIL

1. Introduction

The effects of migration on wages in the host region depend mostly on the way the abilities distribution of migrants can be compared to the abilities distribution of non-migrant population. A stylized fact of this literature is that migrants are not a random sample from the source region. In this sense, using panel data of the RAIS-Migra from 1995 and 2002, the aim of this paper is to estimate the impacts of migration and assimilation on wage differentials.

Specifically, the data allow tracking workers in the labor market among different Brazilian states along the time, with information about wages before and after migration. As a result, we can use the fixed effects method in order to control the self-selection bias. First, we analyses the effects of migration on wages. Second, we examine the economic adjustment of migrants, estimating the effect of assimilation on wages. Then, the main contribution of this study is to evaluate the wage differentials of migrants in the host region after the control of non-observable characteristics.

In case of migration in Brazil, São Paulo is the state that absorbs the most part of migrants. Additionally, the flow of workers and the wage differentials among São Paulo and the other Brazilian states as well are important. In this sense, the analysis will focus on the labor market of this state.

The most important results attest the presence of omitted bias in OLS regressions as a consequence of migrants' self-selection. Seemingly, migrants have wage gains relative to non-migrants in the OLS regressions. However, this wage advantage expires when we include the control of non-observable abilities. The negative coefficient obtained from fixed effects wage regressions shows the wage losses to the worker after migration to São Paulo. Most part of these losses are a result of the higher cost of living in such state. In the assimilation analysis, the evidences show that the period of residence in São Paulo is an important variable to determine the migrant earnings after the inclusion of individual fixed effects. There is a wage convergence after 1.4 years, but the returns growth occurs at decreasing rates in 3 years at most. At least, the gains from out-migration are positive, even after the inclusion of fixed effects. This can be understood since the cost of living in São Paulo is an important factor in the out-migration event.

This paper is organized as follows. The next section presents the database used and the summary statistics. The econometric model of the migration impact on wages is presented in section 3. Following, the results of return estimated considering observable and non-observable characteristics, and the assimilation process are presented in section 4. Finally, we present the concluding remarks in section 5.

2. Data and summary statistics

The database used in this paper is the RAIS-Migra, a panel data from the Labor Ministry of Brazil. Its main characteristic is to track the same worker in the formal labor market with information about their wages before and after the migration. As we have a large number of individuals – about 24 million workers in the formal sector a year –, we built a one percent random sample from the total. The dataset was drawn to follow the professional route of workers who were in the São Paulo state at least in one of the years between 1995 and 2002. First, we used a balanced panel, which have 172.536 observations and the same number of 21,567 individuals by year (see table 1). The migrants are almost 2% from the total of personnel. Second, we considered the unbalanced panel, with 262,751 observations. The number of individuals is not the same over years, because of workers were not always employed in the formal labor market in the period. As a result, the migrant percentage in the unbalanced panel is almost 3%, larger than in the balanced panel.

<TABLE 1 ABOUT HERE>

The empirical analysis is conducted to workers from 14 to 65 years old and with non-zero earnings.[1] The *migration* variable turns to 1 when the worker moves to São Paulo and continues computing this value while he stays in this state. It turns to 0 when there is not migration or when the worker leaves São Paulo. Another important variable is the *years since migration,* which computes the number of years the worker stays in São Paulo after migration and turns to zero when the person is a settler. The other variables used in the analysis are: age, tenure, gender, education, industry, occupation, and the year dummies.

Another important group to be analyzed are the workers that egress from São Paulo. The *out-migration* variable is similarly defined to the in-migration, assuming a value equal to 1 when the individual exit from São Paulo and while staying in another state. A particular group of out-migrants are the returning migrants, i.e., workers who moved to São Paulo in a specific year and came back to their source state after some years. The variable of *return migration* is equal to 1 when this kind of worker mobility occurs, and equal to 0 otherwise.

Table 2 shows the average profile of migrants. They are 35 years old, male (80%), with tenure of about 3 years, high school (23%), from the service sector (48%), and from blue-collar occupations (35%). The number of migrants in this panel is 7,453, approximately 3% of the workers as a whole. In general, out-migrants are 35 years old, male (79%), with tenure of 2.8 years and high school (27%). They also work at service sector and in blue-collar occupations, with an average wage of R$1,853. The subset of return migrants has more tenure, and has a higher share of high school (32%), but with a lower average wage than out-migrants and also in-migrants (R$1.614).[2]

<TABLE 2 ABOUT HERE>

3. Empirical literature

In this section, the estimation procedure of wages considers the selection and the assimilation under the individual fixed effects approach. The standard procedure in the majority of econometric studies in the migration literature (Borjas, 1987, 1989, 1999; Chiswick, 1978; Chiswick *et al.*, 2005) has the Mincerian equation (Mincer, 1974) as the starting point:

$$Y_{it}=X_{it}\beta_t + \delta_t M_{it} + \varepsilon_{it} \qquad (1)$$

Y_{it} is the log of worker wage i in the cross-section t ($t=1995, ..., 2002$);
X_{it}: vector of social and economical characteristics;
M_{it}: migration dummy (1 if migrant; 0 otherwise);
δ_t , β_t: estimated coefficients;
ε_{it}: random error.

However, an important stylized fact in the economic literature is the self-selection of migrants. As the migrants have personal characteristics, which make them different from other individuals, the formers will have more wage gains than the others will. The methodological procedure that involves the estimation of wage equations should consider this question, whose main point is related to the causality attribution. According to the classical paper of Angrist and Krueger (1999), the ideal experiment could be obtained with the observation of the same person in two different situations at the same time, and controlling by other variables, which have effects on the wages. As stressed by Menezes-Filho (2001; 2002), the researcher would like to have the access to data with information about migrant wages before and after the migration. This is the contra factual experiment that considers the wage differentials in a causal way: the gains and/or losses after migration could be measured by a common test of means.

[1] The earnings are obtained from RAIS-Migra in nominal minimum wages. They were converted to Reais, deflated by the IPCA – a Brazilian price index for consume –, and after by the ICV – a cost of living index – computed by Azzoni *et al.* (2003).
[2] These additional tables - out-migrants and return-migrants - can be obtained with authors by request.

The point is that migrants are a self-selected group in comparison to the rest of the population. Migrants have more probability to be successful even if they have not moved. The estimated wage differentials probably will be biased, even using controls as age, tenure, gender, education, sector and occupation. This kind of situation may occur because the observed controls used will not capture the characteristics which may change the differences in wages between migrants and non-migrants.

The use of panel data allows a more effective solution to this problem than the use of aggregated data. Using fixed individual effects in the panel dataset, we can estimate the mean effect of migration on wages and compare the results for migrants and non-migrants (Booker *et al.*, 2007). This is possible by the establishment of an appropriated comparison set of non-migrants based on the random selection of migrants (Peterson e Howell, 2003). Using this approach, it is not necessary to model the process by which the migrants are self-selected, as in the pioneer study of Heckman (1979). Some studies considered this selection problem using several controls, but they did not use panel data. The problem in these cases is that they were not able to build a random selection. It is important to highlight that the fixed effects method do not consider the situation of workers who can change some characteristics contemporaneously with the migration (Hanushek *et al.*, 2005). However, these changes will be a possible source of bias to estimate just in case of a systematic pattern of episodes contemporaneous with the migration.

Using the longitudinal data of RAIS-Migra from 1995 to 2002, we can estimate the wage equations to migrants and non-migrants in São Paulo state. The functional form of these regressions is as following. The log wage is the dependent variable and the control variables are age, age squared, tenure, tenure squared, and dummies of education, sector, occupation, year and gender. These independent variables are subsumed in the X vector. The wage differentials associated to the migrants are δ, while θ and λ are the wage differentials related to *years since migration* (YSM_i *e* YSM_i^2). The time dummies are T_t, and ε_i is the disturbance term, with variance σ_ε^2. In order to deal with the endogeneity problem, we can include a fixed effect, c_i, in the regression. The identification hypothesis of the model asks for $E(\varepsilon_i|c_i, M_i, YSM_i) = 0$, i.e., the correlation between M_i, YSM_i and ε_i is caught by a covariate which do not vary over the years.[3] Following, the traditional model that considers a quadratic assimilation curve:

$$Y_{it} = \alpha + \beta X_{it} + \delta M_{it} + \theta YSM_{it} - \lambda YSM_{it}^2 + c_i + T_t + \varepsilon_{it} \qquad (2)$$

It is important to notice that the abilities growth in the host region depends on duration, i.e., on the years since migration. Therefore, c_i and YSM_i will be correlated if the non-observed ability of workers shifts over the years. In this case, the OLS estimates of equation (2) will be biased. As we have a dataset for eight years, we assumed that θ and λ do not change over years and by migrant cohorts as well. Then, the fixed effect estimator is obtained by differencing the individual values of each variable and their mean values. This procedure eliminates the c_i term, avoiding possible effects of an individual ability bias. The new estimates are consistent and efficient.

The main idea of this approach is to verify whether the longitudinal changes in wages can be explained by *M* and *YSM*. In general, *YSM* and YSM^2 have coefficients with undetermined signals. If $\theta>0$ and $\lambda>0$, the relation between the wage distribution and *YSM* has an inverted *U* shaped form. It is important to notice, however, that the hypothesis $E(\varepsilon_i|c_i, M_i, YSM_i) = 0$ may not be sufficient to eliminate the endogeneity. It can appear in case of a random shock that causes a wage increase to workers anyway, i.e., independently of them migrating or not.

4. Results

As the migrants are self-selected in comparison to the rest of the population, it is important to consider the approach that includes the non-observable characteristics in the estimation process. In this sense, the relative wages of migrants are estimated from a Mincerian equation, expanded by the gradual inclusion of controls. This expansion starts with the inclusion of the observable characteristics until the

[3] As a significant part of workers move to São Paulo over the years, the coefficients of wage differentials between migrants and non-migrants can be identified after the inclusion of fixed effects.

final inclusion of the fixed effects.

Furthermore, we evaluate the migrant assimilation in São Paulo. This is possible through the inclusion of the variable *years since migration*. Using the fixed effects method, we can capture the real migrant adjustment and avoid the self-selection bias. We also consider some robustness tests, analyzing the effects of migration on wages in several subsamples. Finally, we estimate the relative wages of people who exit from São Paulo.

4.1. Evidences about the migrant self-selection

The following analysis uses different specifications to the X vector to estimate the wage differentials of migrants in São Paulo. Tables 3 and 4 show us the results of the estimates by using the balanced and the unbalanced panels, respectively. In general, we can confirm the existence of positive selection of migrants in both panels. Therefore, it is necessary to consider the problems of self-selection bias in order to obtain a correct estimate of migrant wages.

First considering the balanced panel (table 3), the three first columns show the OLS estimates, while the two last ones show the random and the fixed effects estimates. In general, the wage returns are higher when fewer controls are taken into account. These returns begin to decrease since more controls are included in the regressions. For example, the log of migrant wages is 32% higher than the log of non-migrant wages in model (1), whose unique covariates are the constant term and the year dummies.[4] Following the sequence of models, the estimated coefficient falls to 24% in model (2), and to 18% in model (3). These results, however, can be biased through the migrant self-selection. Therefore, we add two other models to table 3 in order to solve this kind of problem. Using either the random effects or the fixed effects model, the estimates converge to the same result: the coefficient turns to a negative signal, which is significant at a 1% level. This can be interpreted as a migration in which the workers are not absolutely aware about the costs related to the movement, especially to the cost of living in the host state. As a result, the cost of living in São Paulo is an important cause of the estimated wage losses. In fact, the cost of living in São Paulo is the highest, in average, among the metropolitan regions in Brazil from 1996 to 2002.

<TABLE 3 AND 4 ABOUT HERE>

It is important to observe that the individuals are present in the sample along the years as a whole in the balanced panel. As several workers can stay in the host state for some years and then exit from the formal labor market, the wage returns can be overestimated whether the balanced panel is considered. Then, we use the unbalanced panel in order to estimate the relative wages. As we can see in table 4, whereas the relative wage of migrants in the regression (1) is 14% higher than the wages of other workers, in regression (2) it is 16%, and in regression (3), which contains the education dummies, it is just 11%. Following the same sequence of analysis of table 3, the random effects coefficient is not significant at conventional statistic levels, and the inclusion of the fixed effects generates a negative wage return. These results are different from those obtained using the balanced panel. A possible explanation is that the balanced panel contains just the most skilled workers. In contrast, the unbalanced panel contains all the movers and that who exit from a formal job. The results of the fixed effects model attest, in fact, that the migrants from the unbalanced panel have less non-observable abilities than the migrants from the balanced panel. Therefore, the forthcoming analysis will be based on the unbalanced panel.

An additional argument in favor to the use of the unbalanced panel is the Hausman test result. At the bottom of table 4, we can observe the Hausman test using the unbalanced panel. The result rejects the random effects model in favor to the fixed effects model.[5] However, regarding to the balanced panel,

---

[4] This wage percentage is calculated by $[100(e^{(coef.)} - 1)]$, that is equivalent to 38% in this case. However, we adopt the same simplification of Borjas (1999), who uses the variation percentages in terms of logarithm differences.

[5] Based on these results, the next estimates will report just the fixed effects model in this paper.

table 3 does not reports the Hausman test results because the model fitted on balanced sample fails to meet the asymptotic assumptions of this test.

Overall, it is important to highlight that the relative wages after the control by the fixed effects have a negative signal and are significant at the conventional statistic levels irrespective to the adopted panel. The main result of this section answers to one of our previous questions. It shows that migrants have relative wage losses of 1.6% after migration when their self-selection is taken into account by the fixed effects model. This result contrasts strongly to that obtained by OLS, whose estimated coefficients are positive, with wage gains of 11,5%. These returns are related to the positive selection of migrants, since the OLS estimates do not capture the non-observable abilities of workers.

The wage losses that occur after the control of non-observable heterogeneity attest that the workers move without the complete knowledge of the costs related to the migration. As an important component of these costs is the cost of living in São Paulo, the expectation that workers have of enlarging wages when living and working in São Paulo is not achieved. That is because the monetary illusion derived from an imperfect set of information during their migration decision. As a result, some immediate questions appear. How is the adjustment of these migrants in the labor market of the host state? Are the initial losses persistent or are they overcome over the years? The answers to these questions sum to the debate on the attendance necessity of the migration flows in the country and on the best composition of individual qualifications to the migrants. Both topics are intrinsically related to the absorption capacity of workers in São Paulo's labor market.

4.2. Migrant assimilation

The main question of this section is to know how many years the migrant spend to amplify his/her earnings in the host region. Although the worker has wage losses in moving to São Paulo, one may acquire additional information about the host region throughout the years. For instance, he/she may know what and where the jobs which pay more are.

Table 5 presents some results on the migration adjustment of movers in São Paulo state. Specifically, this adjustment is related to the coefficient of the *years since migration* variable. It shows the wage distribution of workers according to the permanence in the host region. As the return resulting from duration is also a question related the migrant self-selection, the control of non-observable abilities is also necessary.

< TABLE 5 ABOUT HERE >

Firstly, we include the controls of the observable characteristics in the OLS regression. The expected result of the assimilation effect on migrant wages is a consequence of the years in the host country. However, the self-selection of migrants may bias the estimates. The non-observable characteristics, such as ability, motivation, enterprising, etc., change among migrants and may explain a large part of the gains associated to the duration. In this sense, the use of the fixed effects method helps to the correct wage estimation of the migrants' duration in São Paulo because we can control their non-observable characteristics.

As we can see, models 1 to 4 in table 5 show the wage estimates to non-migrants, migrants, and to the workers as a whole. On one hand, the results attest the wage losses after migration, since the partial effect of migration on wages is –2.9% in the fixed effects model. On the other hand, there is a wage return of +7.7% in the OLS model. However, the time since migration is an important variable on the determination of migrants' relative wages. In the OLS model, the coefficients of *YSM* and YSM^2 are significant at 1% level and coherent with the migration theory. The estimated values are +4.7% and –0.7%, respectively, evidencing an inverted U-shaped curve. In contrast, the fixed effects model shows a lower *YSM* coefficient of 2.8%. The quadratic component keeps the same negative signal, but reduces to –0.5%. Therefore, the assimilation is overestimated in the OLS model. Considering the partial effect,

$\left(\frac{\partial Y}{\partial M}\right) = -0.029 + 0.028(YSM) - 0.005(YSM)^2$, the migrants' adjustment happens under lower effects on wages than the OLS estimation. Figure 1 clarifies this situation.

<FIGURE 1 ABOUT HERE>

In short, these results show that the earning convergence occurs 1.4 years after migration. However, the wage growth happens with decreasing rates, within 3 years at most. As we have the control of non-observable workers' abilities, this fact can be a consequence of wage gains opportunities in São Paulo. Therefore, the initial costs of migration, including the cost of living, causes a 2.9% fall on wages. Additionally, there is a significance loss of the migration effect throughout time. We can conclude that the information set of migrants is incomplete. On their migration decision, workers have a monetary illusion because they see just the nominal wage, but not the real wage.

4.3. Migration effects in different samples

When a worker moves to São Paulo, there are wage losses in comparison to the non-migrants. Several reasons can explain the wage losses after migration. Our hypothesis is that the decrease in wages has the cost of living as an important cause. Then, what are the characteristics of workers with large wage losses? Some groups can be more affected by these losses than others can.

Table 6 compares relative wages of migrants in four different subsamples. The aim of this table is to test the significance of wage differences among the selected groups: gender, tenure before migration, age, and education). In the first column, we can see that there are wage differences of 3.4% for the migrant men in comparison to the non-migrants. This difference is also significant in comparison to the migrant women, but just at the level of 10%.

<TABLE 6 ABOUT HERE>

The second column shows the estimates of migrant wage differentials according to the job tenure before migration. The migrants with more tenure are that with job tenure higher than 18.5 months. The wage differences between the both groups are significant at 5% level, as we can see in the F-test in the last column of the table. While the losses to the less experienced workers are at 4.1%, those with more tenure have losses of just 1.6%.

In the subsample that characterizes the wage differentials by age (third column), the wage return of the young migrants is higher than that of the old ones. The old migrants have wages 8.3% less than that of non-migrants, and this difference is statistically significant, as we can see in the last column. These higher losses to the old migrants can be related to the short period they have to obtain the return of the migration investment.

In column (4), we compared the wage differentials between migrants and non-migrants by educational levels. According to the human capital model, the more educated workers can be more efficient in finding and evaluating job opportunities. As a result, they can reduce the migration costs. The results show that there is a large contrast between high educated and low educated workers. On one hand, the group of migrants less educated has losses of 5% in comparison to the non-migrants. On the other hand, the migrants with high education earn 7% more than non-migrants. We can conclude that there are vacancies to more qualified workers in the labor market.

Another important issue to be analyzed is the geographical distribution of the relative wage of migrants according to their source region, sector and occupation. This is the main idea of table 7, which compares the estimated wages in three different subsamples. First considering the source region, the results can be observed in the first column. The wage losses after migration can be observed to movers who come from other states of Southeast region (-5%), followed by those movers from the South region (-4%). On the other hand, migrants from the Northeast region have positive wage returns of 5.2%. These effects are related to the real wage correction. When the Northeast workers move to São Paulo, they have real wage gains. Considering the F test, in the last column, only the differences between the Southeast and the Northeast are significant at conventional statistic levels. Then, the high cost of living between these two regions is an important factor to the high earning inequality of the country.

<TABLE 7 ABOUT HERE>

Other relevant point to be analyzed are the wage differences by sectors. As we can see in the second column, the highest losses to migrants are concentrated in industry (-7%) and in service sector (-5%) as well. In contrast, migrants from agriculture and trade have the highest wage gains (+11% and +6%, respectively).

Finally, regarding to the occupations, the relative wages can be observed in the third column. The highest losses are in occupations of the less qualified workers (occupation 6 and 5).[6] The wage gains, however, are not only concentrated in the occupations of high skilled workers (occupation 1), but also in farming, forestry activities and fishing (occupation 5). The F-test to the significance of the differences, the coefficients of occupation (5), (1) and (3) are significant.

4.4. Self-selection of out-migrants

A supplementary topic in the analysis of migration flows in São Paulo is the out-migration event. The panel has 7,467 out-migrants, and 7,453 migrants. As we can see in figure 2, the number of out-migrants is larger than the number of in-migrants since 2000, and this difference is increasing until 2002, achieving 10%. Due to this preliminary evidence, our initial hypothesis is that the cost of living may be one of the causes of this large exit flow. However, in order to verify this hypothesis, it is necessary to consider the unobserved abilities of workers who exit from São Paulo.

Table 8 is analogous to table 4, showing the relative wages between out-migrants and the other individuals. The control variables were included gradually, until the final inclusion of non-observed effects. The results show that, even after the fixed effects addition, the return wages are positive. Then, there are more out-migrants than in-migrants, and the formers have a wage 4.2% higher than non-migrants. In contrast, in-migrants have a lower wage (-1.6%) than the other workers. This evidences show that the cost of living is an important factor in the out-migration event.

< FIGURE 2 AND TABLE 8 ABOUT HERE>

An important subgroup are the workers of return migration, as we can see in Figure 3. The return migration represents about 27% of the out-migration event (1,985 observations), in the average of the years 1997 to 2002. Table 9 shows that the coefficients are not significant at 10% level, i.e., the migrants that return to their state do not have significant wage gains. Than, we can conclude that this type of migration is not well-succeed.

<FIGURE 3 AND TABLE 9 ABOUT HERE>

4.5. An additional robustness test

In order to obtain a precise estimation of wages, it is important to consider a correct control group to the migration dummy. For instance, when estimating the in-migrants wage differentials, the results attest the wage losses after migration, about –2.9% in the fixed effects model. However, workers who exit from Sao Paulo are also in the control group. As these out-migrants may obtain a different wage in another state, the relative wage losses estimates can be biased. According to our findings in section 4.4,

---

[6] (1) Scientifical, technical and artistical, (2) Legislative, executive, judiciary, public sector and directors, (3) Managerial, (4) Trade and services of tourism and embellishment, (5) Farming, forestry activities and fishing, (6) Blue-collars.

the out-migrants have higher relative wages (+4.2%) out of São Paulo state. Therefore, the estimated wage losses to in-migrants may be overstated.[7]

<TABLE 10 ABOUT HERE>

To obtain more accuracy on our analysis, we estimated the migrant earnings including dummy variables to cover every class of mobility in the same regression: in-migrant, out-migrant, and return migration dummies. These control variables addition was made gradually, as we can see in table 10. Columns 1 to 4 show us fixed effects regressions on the earnings relative to non-migrants. The first column shows us the estimated coefficients, which includes the migration dummy, and the out-migration dummy as well. The estimates attest that the relative wage is not significant at conventional statistic levels. The out-migration dummy, on the other hand, is statistically significant at 1% level, and has a positive coefficient of 0.043. In the second column, instead of adding a unique out-migration dummy, we separated it into migrants that leave Sao Paulo (out of SP) and migrants that are coming back to their home state (return-migrant). The estimated coefficients are the following. The migration dummy presents a negative signal, although it still is not significant at conventional levels. On the other hand, those migrants that leave Sao Paulo have a wage 6.5% higher than that from non-migrants. The return-migrants group do not have significant statistically coefficients. As these results do not consider the years since migration and its quadratic form as well, we added these variables in the models of column 3 and 4. Both models present evidences that YSM is important to be considered as explanatory variables. However, it is in column 4, where all the variables are added, that the results are more interesting. The migration dummy has a coefficient of -0.019, which is statistically significant. Workers that leave Sao Paulo (out of SP) exhibit the same coefficient (0.065) from model 2. The return migration still has a coefficient that is not significant at conventional levels. Regarding the YSM and YSM^2, both coefficients are significant and have very similar values in comparison to that from table 5.

The general idea is that the estimated relative wages were overestimated. However, after considering the correct control variables in this sort of analysis, the main results are kept. Although the magnitude of relative wages is reduced, the migration losses persist.

5. Concluding remarks

The aim of this paper is the analysis of the effects of migration on wages in Brazil. Using panel data of the RAIS-Migra (Labor Ministry of Brazil) from 1995 to 2002, the relative wage of migrants was estimated by the fixed effects method. The main idea is to catch the bias from the self-selection of migrants. The most important results attest the presence of omitted variable bias from the positive selection of migrants. While the relative wages have a positive signal in the OLS estimation, they turn to a negative signal in the fixed effects estimation. This fact show that migrants have a wage decrease caused by the costs of moving, particularly the cost of living. Therefore, the worker who moves to São Paulo has a monetary illusion.

Afterwards, we estimated the assimilation effects of workers on wages, also controlling the individual fixed effects. The results suggest that the time since migration is an important variable on the migrants' wages, even with the individual fixed effects control. The estimated assimilation curve has an inverted U-shaped form, whose estimated coefficients are 0,028 and –0.005. In general, these results show that the wage convergence happens 1.4 years after migration, but this wage increases at decreasing rates, within 3 years at most.

Overall, the costs of adjustment in the host place, including the cost of living as well, are larger than the instant gains. Therefore, the information set of migrants is incomplete because they do not observe the real wage.

[7] We also found in last section that return migrants have no wage differences in comparison to the other workers. Besides that, they are less representative than the workers that leave São Paulo. Then, the initial idea of a possible overestimation can be maintained.

It is important to highlight that some specific groups of workers do not face losses after migration. For instance, there is a huge contrast between workers who have the undergraduate level and those with just incomplete elementary school. While the former have positive returns of 7% after migration, the last have a wage loss of 5% in comparison to the non-migrants. Then, there are vacancies to more qualified professionals in São Paulo's labor market. Other positive wage returns are verified, as in the agriculture and trade sectors, in the Northeast region, and at agriculture, forest and fishing and at scientific occupations.

Finally, the wage returns were also estimated to the out-migrants. Even after the fixed effects inclusion, there are positive gains. The return migration, a subset of out-migrants, does not have significant gains at 1% level. Therefore, our results are consistent with the fact that the high cost of living in São Paulo can bring back migrants to their source place, and also generate an out-migration from São Paulo to other Brazilian states.

6. References

ANGRIST, J. and KRUEGER, A. (1999) Empirical strategies in labor economics. *In*: ASHENFELTER, O. and CARD, D. **Handbook of labor economics**. Elsevier, v. 3A.

AZZONI, C. et al. (2003) Comparações da Paridade do Poder de Compra entre cidades: aspectos metodológicos e aplicação ao caso brasileiro. Pesquisa e Planejamento Econômico, v. 33, n. 1.

BOOKER, K. et al. (2007). The impact of charter school attendance on student performance. Journal of Public Economics, v. 91, p. 849–876.

BORJAS, G. Self-Selection and the Earnings of Immigrants. (1987) American Economic Review, v. 77(4), p. 531-553.

_________. Immigrant and emigrant earnings: a longitudinal study. (1989) Economic Inquiry, 27:21-37, 1989.

_________. The Economic Analysis of Immigration. (1999) Handbook of Labor Economics, vol. 3.

CHISWICK, B. R. The Effect of Americanization on the Earnings of Foreign-Born Men. (1978), Journal of Political Economy, v. 86, p. 897- 921.

CHISWICK, B. R.; LEE, Y. L.; MILLER P.W. (2005) Longitudinal analysis of immigrant occupational mobility: A test of the immigrant assimilation hypothesis, International Migration Review, v. 39, n.2.

HECKMAN, J. Sample selection bias as a specification error. (1979) Econometrica, v. 47, n. 1, p. 153-161.

MENEZES-FILHO, N. (2002) Equações de rendimentos: questões metodológicas. In: CORSEUIL, C. H. et al (Orgs). Estrutura salarial: aspectos conceituais e novos resultados para o Brasil. Rio de Janeiro: IPEA.

MENEZES-FILHO, N. Microeconometria. (2001) In: LISBOA, M. E MENEZES-FILHO, N. Microeconomia e sociedade no Brasil. Rio de Janeiro: Editora Contra-capa.

Mincer, J. Schooling, experience and earnings. (1974) New York: National Bureau for Economic Research.

MINISTÉRIO DO TRABALHO E EMPREGO. (2003) Raismigra: modelos painel e vínculo – orientações para uso. (Manuscript).

MINISTÉRIO DO TRABALHO E EMPREGO. Raismigra. (1995-2002). Brasília: MTE.

PETERSON, Paul E.; Howell, William G. (2003) Latest results from the New York City voucher experiment. Harvard University Working Paper.

FIGURES AND TABLES

Figure 1: The effects of assimilation on wages

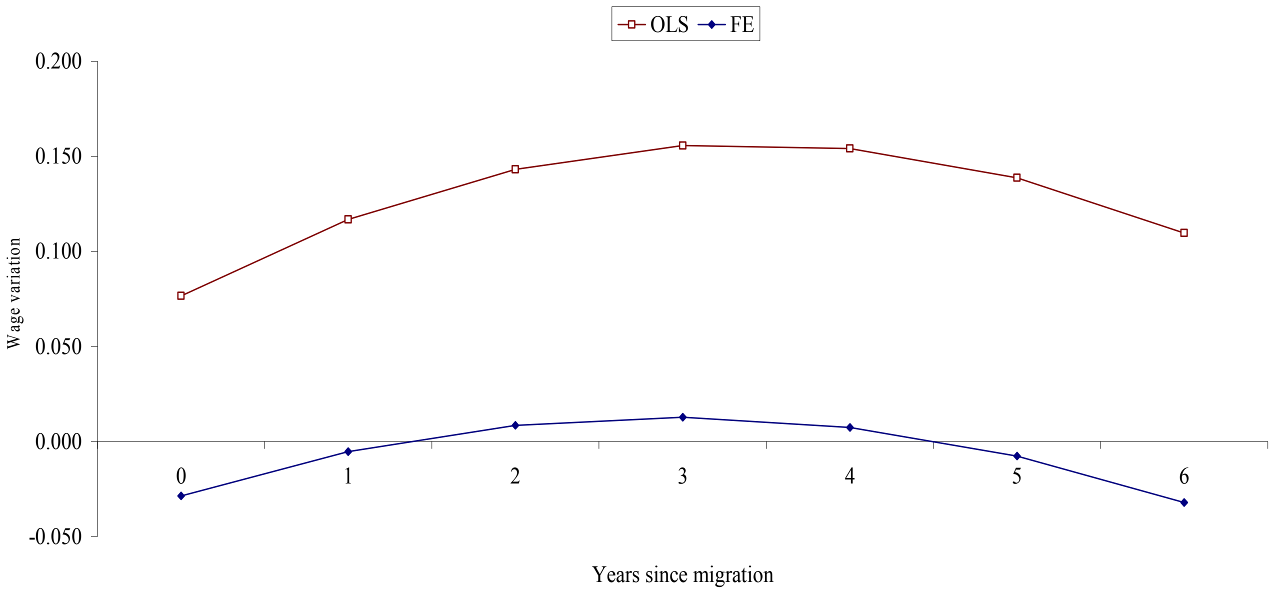

Figure 2: Out-migrants vs. In-migrants

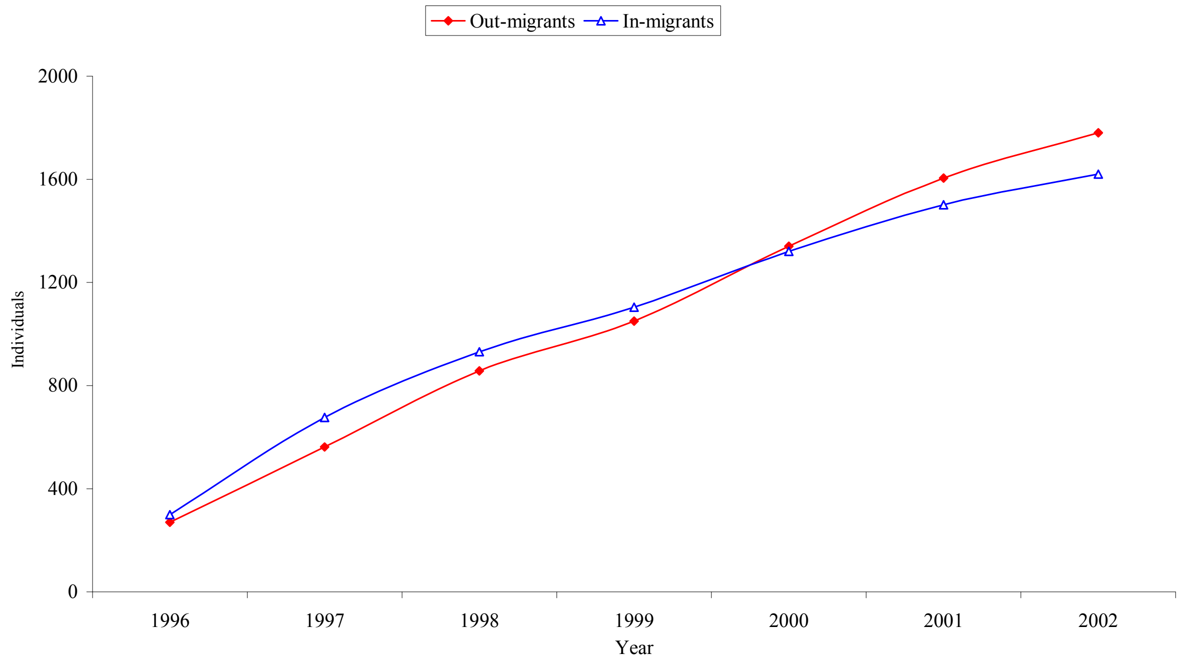

Figure 3: Out-migrants and returning migrants

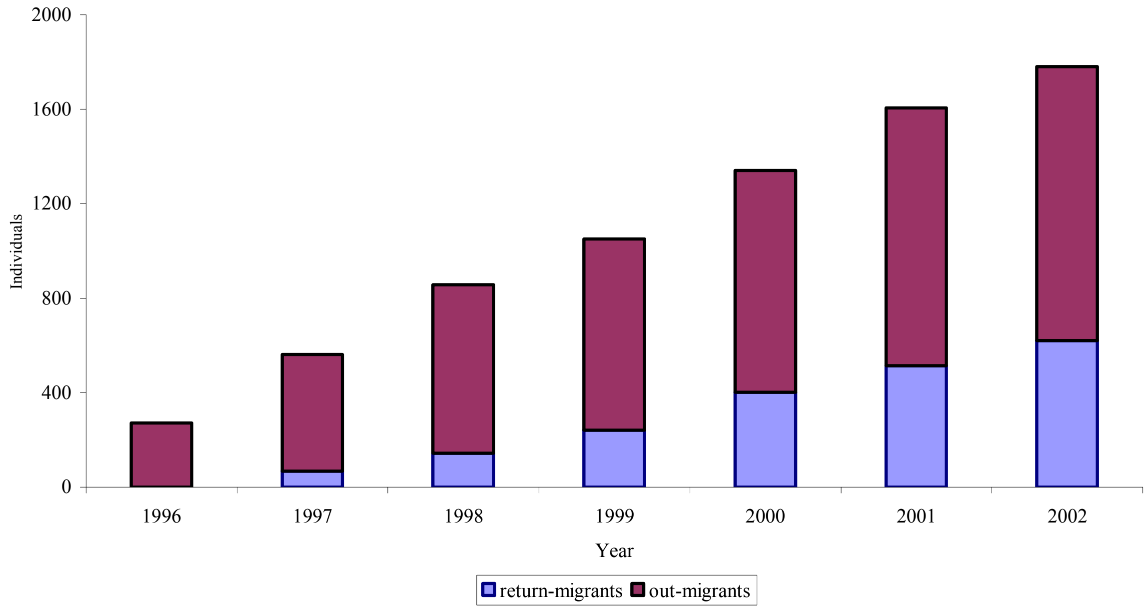

Table 1: Frequency of migrants and non-migrants in the balanced and unbalanced panels

	Balanced panel			Unbalanced panel		
Year	Migrants	Non-migrants	Total	Migrants	Non-migrants	Total
1995	-	-	-	-	-	-
1996	154	21,413	21,567	299	33,488	33,787
1997	254	21,313	21,567	676	36,820	37,496
1998	333	21,234	21,567	932	37,226	38,158
1999	439	21,128	21,567	1,105	36,983	38,088
2000	522	21,045	21,567	1,320	36,923	38,243
2001	574	20,993	21,567	1,501	36,921	38,422
2002	618	20,949	21,567	1,620	36,937	38,557
Total	**2,894**	**148,075**	**150,969**	**7,453**	**255,298**	**262,751**

Source: Data from Labor Ministry of Brazil - RAISMIGRA-1995-2002.

Table 2: Variable definitions and basic statistics - unbalanced panel

	Migrants			Non-migrants		
	N	**Mean**	**SD**	**N**	**Mean**	**SD**
Dependent variable						
Log wages	7,453	7.00	0.99	255,298	6.84	0.83
Independent variables						
Age	7,453	34.56	8.50	255,298	36.01	9.54
Tenure	7,453	39.12	56.71	255,298	76.92	72.81
Gender						
Female	1,491	20.01	-	90,874	35.60	-
Male	5,962	79.99	-	164,424	64.40	-
Total	7,453	100.00	-	255,298	100.00	-
Education level						
Illiterate	81	1.09	-	3,050	1.19	-
Incomplete 1st. elementary level	540	7.25	-	17,405	6.82	-
1st. Elementary level	824	11.06	-	33,517	13.13	-
Incomplete 2nd. elementary level	913	12.25	-	34,843	13.65	-
2nd. Elementary level	1,122	15.05	-	42,908	16.81	-
Incomplete medium school	452	6.06	-	18,373	7.20	-
Medium school	1,718	23.05	-	54,902	21.51	-
Incomplete higher degree	500	6.71	-	12,343	4.83	-
Higher degree	1,303	17.48	-	37,957	14.87	-
Total	7,453	100.00	-	255,298	100.00	-
Sector						
Public Administration	197	2.64	-	51,392	20.13	-
Farming	279	3.74	-	10,507	4.12	-
Trade	858	11.51	-	31,247	12.24	-
Construction	887	11.90	-	8,129	3.18	-
Mining	14	0.19	-	535	0.21	-
Manufacturing	1,589	21.32	-	66,728	26.14	-
Public Utilities	55	0.74	-	3,471	1.36	-
Services	3,574	47.95	-	83,289	32.62	-
Total	7,453	100.00	-	255,298	100.00	-
Occupation						
Occupation 1	1,012	13.58	-	39,860	15.61	-
Occupation 2	488	6.55	-	7,470	2.93	-
Occupation 3	1,343	18.02	-	60,522	23.71	-
Occupation 4	1,703	22.85	-	56,463	22.12	-
Occupation 5	277	3.72	-	9,857	3.86	-
Occupation 6	2,630	35.29	-	81,126	31.78	-
Total	7,453	100.00	-	255,298	100.00	-

Table 3: Wage differentials between migrants and non-migrants (balanced panel)

	Dependent variable: Log of real wages				
Independent variables	(1) OLS	(2) OLS	(3) OLS	(4) RE	(5) FE
Migrant	0.317***	0.241***	0.178***	-0.019**	-0.041***
	(0.018)	(0.015)	(0.013)	(0.009)	(0.009)
Gender	…	0.316***	0.352***	0.216***	…
		(0.004)	(0.004)	(0.007)	
Tenure	…	0.001***	0.002***	0.001***	0.001***
		(0.000)	(0.000)	(0.000)	(0.000)
Tenure^2	…	0.000***	0.000***	0.000	-0.000***
		(0.000)	(0.000)	(0.000)	(0.000)
Age	…	0.099***	0.083***	0.064***	…
		(0.001)	(0.001)	(0.001)	
Age^2	…	-0.001***	-0.001***	-0.001***	…
		(0.000)	(0.000)	(0.000)	
Illiterate	…	…	-0.140***	-0.042***	…
			(0.017)	(0.014)	
Incomplete 1st. elementary level	…	…	-0.250***	-0.113***	…
			(0.007)	(0.008)	
1st. Elementary level	…	…	-0.208***	-0.085***	…
			(0.006)	(0.007)	
Incomplete 2nd. elementary level	…	…	-0.129***	-0.039***	…
			(0.006)	(0.006)	
Incomplete medium school	…	…	0.135***	0.073***	…
			(0.007)	(0.007)	
Medium school	…	…	0.337***	0.143***	…
			(0.005)	(0.006)	
Incomplete higher degree	…	…	0.642***	0.328***	…
			(0.009)	(0.008)	
Higher degree	…	…	0.824***	0.474***	…
			(0.007)	(0.008)	
Constant	7.023***	4.647***	4.820***	5.415***	7.016***
	(0.006)	(0.026)	(0.024)	(0.031)	(0.007)
Sector dummies	No	Yes	Yes	Yes	Yes
Occupation dummies	No	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
R^2	0.0071	0.3512	0.4596	0.4436	0.0976
(within)	-	-	-	0.0466	0.0517
(between)	-	-	-	0.5093	0.1483
F test	135.69	3521.58	4117.44	-	336.11
No. observations	150,969	150,969	150,969	150,969	150,969
No. individuals	-	-	-	21,567	21,567

Source: Data from Labor Ministry of Brazil - RAISMIGRA-1995-2002.

*** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

Table 4: Wage differentials between migrants and non-migrants (unbalanced panel)

	Dependent variable: Log of real wages				
Independent variables	(1) OLS	(2) OLS	(3) OLS	(4) RE	(5) FE
Migrant	0.143***	0.164***	0.114***	0.005	-0.016**
	(0.012)	(0.009)	(0.008)	(0.006)	(0.006)
Gender	…	0.298***	0.341***	0.215***	…
		(0.003)	(0.003)	(0.005)	
Tenure	…	0.003***	0.003***	0.002***	0.002***
		(0.000)	(0.000)	(0.000)	(0.000)
$Tenure^2$	…	-0.000	-0.000***	-0.000***	-0.000***
		(0.000)	(0.000)	(0.000)	(0.000)
Age	…	0.092***	0.077***	0.068***	…
		(0.001)	(0.001)	(0.001)	
Age^2	…	-0.001***	-0.001***	-0.001***	…
		(0.000)	(0.000)	(0.000)	
Illiterate	…	…	-0.115***	-0.028***	…
			(0.012)	(0.010)	
Incomplete 1st. elementary level	…	…	-0.236***	-0.107***	…
			(0.005)	(0.006)	
1st. Elementary level	…	…	-0.180***	-0.081***	…
			(0.004)	(0.005)	
Incomplete 2nd. elementary level	…	…	-0.106***	-0.036***	…
			(0.004)	(0.004)	
Incomplete medium school	…	…	0.123***	0.063***	…
			(0.005)	(0.005)	
Medium school	…	…	0.331***	0.147***	…
			(0.004)	(0.004)	
Incomplete higher degree	…	…	0.657***	0.353***	…
			(0.007)	(0.006)	
Higher degree	…	…	0.856***	0.527***	…
			(0.006)	(0.006)	
Constant	6.869***	4.623***	4.754***	5.099***	6.852***
	(0.004)	(0.018)	(0.017)	(0.023)	(0.005)
Sector dummies	No	Yes	Yes	Yes	Yes
Occupation dummies	No	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
R^2	0.0027	0.3554	0.4570	0.4383	0.1706
(within)	-	-	-	0.0422	0.0431
(between)	-	-	-	0.5142	0.2396
F test	90.06	5817.76	6514.88	-	473.09
Breusch Pagan	-	-	-	$\chi 2$ (1) = 410.000	
Hausman	-	-	-	$\chi 2$ (20) = 12.603,92	
No. observations	262,751	262,751	262,751	262,751	262,751
No. individuals	-	-	-	42,140	42,140

Source: Data from Labor Ministry of Brazil - RAISMIGRA-1995-2002.

*** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

Table 5: Wage differentials between migrants and non-migrants - years since migration

Dependent variable: Log of real wages				
	Non-migrants	Migrants	Migrants and non-migrants	
Independent variables	(1) OLS	(2) OLS	(3) OLS	(4) FE
Migrant	…	…	0.077***	-0.029***
			(0.012)	(0.007)
Years since migration	…	0.028*	0.047***	0.028***
		(0.015)	(0.014)	(0.007)
Years since migration^2	…	-0.005*	-0.007**	-0.005***
		(0.003)	(0.003)	(0.001)
Gender	0.339***	0.392***	0.341***	…
	(0.003)	(0.022)	(0.003)	
Tenure	0.003***	0.005***	0.003***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Tenure^2	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Age	0.077***	0.094***	0.077***	…
	(0.001)	(0.007)	(0.001)	
Age^2	-0.001***	-0.001***	-0.001***	…
	(0.000)	(0.000)	(0.000)	
Illiterate	-0.122***	0.159*	-0.115***	…
	(0.012)	(0.086)	(0.012)	
Incomplete 1st. elementary level	-0.236***	-0.210***	-0.236***	…
	(0.005)	(0.035)	(0.005)	
1st. Elementary level	-0.181***	-0.149***	-0.180***	…
	(0.004)	(0.028)	(0.004)	
Incomplete 2nd. elementary level	-0.107***	-0.054**	-0.106***	…
	(0.004)	(0.027)	(0.004)	
Incomplete medium school	0.120***	0.212***	0.123***	…
	(0.005)	(0.036)	(0.005)	
Medium school	0.330***	0.367***	0.331***	…
	(0.004)	(0.025)	(0.004)	
Incomplete higher degree	0.648***	0.915***	0.657***	…
	(0.007)	(0.037)	(0.007)	
Higher degree	0.845***	1.209***	0.856***	…
	(0.006)	(0.035)	(0.006)	
Constant	4.774***	4.183***	4.754***	6.852***
	(0.017)	(0.127)	(0.017)	(0.005)
Sector dummies	Yes	Yes	Yes	Yes
Occupation dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
R^2	0.4536	0.5648	0.4570	0.1713
(within)	-	-	-	0.0432
(between)	-	-	-	0.2408
F test	6,433.45	303.97	6,132.71	432.71
No. observations	255,298	7,453	262,751	262,751
No. individuals	-	-	-	42,090

Source: Data from Labor Ministry of Brazil - RAISMIGRA-1995-2002.

*** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

Table 6: Wage differentials in selected subsamples: gender, tenure, age and education

Dependent variable: Log of real wages					
Independent variables	**(1)**	**(2)**	**(3)**	**(4)**	F-test
Migrant*Female	-0.005	…	…	…	3.46*
	(0.015)				
Migrant*Male	-0.034***	…	…	…	…
	(0.008)				
Migrant*Low tenure	…	-0.041***	…	…	4.00**
(tenure <18,5 months)		(0.009)			
Migrant*High tenure	…	-0.016*	…	…	…
(tenure >=18,5 months)		(0.009)			
Migrant*Young	…	…	0.012	…	69.03***
(age <34 years)			(0.009)		
Migrant*Old	…	…	-0.083***	…	…
(age >=34 years)			(0.010)		
Migrant*Education < 2nd. Ellementary level	…	…	…	-0.047***	…
				(0.011)	
Migrante*2nd. Ellementary level	…	…	…	-0.042***	0.11
				(0.012)	
Migrant*High school	…	…		-0.048***	0.01
			…	(0.011)	
Migrant*Undergraduate	…	…		0.070***	41.81***
			…	(0.015)	
R^2	0.1712	0.1715	0.1683	0.1751	
(within)	0.0432	0.0432	0.0435	0.0434	
(between)	0.2406	0.2409	0.2364	0.2460	
No. observations	262,751	262,751	262,751	262,751	
No. individuals	42,090	42,090	42,090	42,090	

Source: Data from Labor Ministry of Brazil - RAISMIGRA-1995-2002.

*** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

Table 7: Wage differentials in selected subsamples: source region, sector, and occupation

Dependent variable: Log of real wages				
Independent variables	**(1)**	**(2)**	**(3)**	F-Test
Migrant*CO	-0.024	…	…	1.54
	(0.019)			
Migrant*N	-0.047	…	…	0.01
	(0.035)			
Migrant*NE	0.052***	…	…	30.70***
	(0.016)			
Migrant*SE	-0.050***	…	…	…
	(0.010)			
Migrant*S	-0.041***	…	…	0.31
	(0.012)			
Migrant*Public administration	…	-0.000	…	3.59*
		(0.036)		
Migrant*Farming	…	0.107***	…	26.86***
		(0.032)		
Migrant*Trade	…	0.063***	…	42.61***
		(0.017)		
Migrant*Construction	…	-0.002	…	12.22***
		(0.016)		
Migrant*Mining	…	-0.091	…	0.03
		(0.126)		
Migrant*Manufacturing	…	-0.071***	…	…
		(0.013)		
Migrant*Public utilities	…	-0.085	…	0.04
		(0.066)		
Migrant*Services	…	-0.049***	…	2.27
		(0.009)		
Migrant*Occupation 1	…	…	0.064***	51.65***
			(0.016)	
Migrant*Occupation 2	…	…	-0.037	1.59
			(0.023)	
Migrant*Occupation 3	…	…	-0.013	11.11***
			(0.014)	
Migrant*Occupation 4	…	…	-0.046***	1.78
			(0.013)	
Migrant*Occupation 5	…	…	0.083***	21.80***
			(0.031)	
Migrant*Occupation 6	…	…	-0.067***	…
			(0.010)	
R^2	0.1703	0.1716	0.1702	
(within)	0.0433	0.0435	0.0435	
(between)	0.2393	0.2403	0.2389	
No. observations	262,751	262,751	262,751	
No. individuals	42,090	42,090	42,090	

Source: Data from Labor Ministry of Brazil - RAISMIGRA-1995-2002.

*** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

Table 8: Wage differentials of out-migrants

Independent variables	(1) OLS	(2) OLS	(3) OLS	(4) RE	(5) FE
Out-migrant	0.065***	0.113***	0.076***	0.044***	0.042***
	(0.012)	(0.009)	(0.008)	(0.006)	(0.006)
Gender	…	0.299***	0.341***	0.215***	
		(0.003)	(0.003)	(0.005)	
Tenure	…	0.003***	0.003***	0.002***	0.002***
		(0.000)	(0.000)	(0.000)	(0.000)
Tenure^2	…	-0.000	-0.000***	-0.000***	-0.000***
		(0.000)	(0.000)	(0.000)	(0.000)
Age	…	0.092***	0.077***	0.067***	
		(0.001)	(0.001)	(0.001)	
Age^2	…	-0.001***	-0.001***	-0.001***	
		(0.000)	(0.000)	(0.000)	
Illiterate	…		-0.116***	-0.028***	…
			(0.012)	(0.010)	
Incomplete 1st. elementary level	…	…	-0.236***	-0.107***	…
			(0.005)	(0.006)	
1st. Elementary level	…	…	-0.180***	-0.080***	…
			(0.004)	(0.005)	
Incomplete 2nd. elementary level	…	…	-0.106***	-0.036***	…
			(0.004)	(0.004)	
Incomplete medium school	…	…	0.123***	0.062***	…
			(0.005)	(0.005)	
Medium school	…	…	0.331***	0.147***	…
			(0.004)	(0.004)	
Incomplete higher degree	…	…	0.659***	0.352***	…
			(0.007)	(0.006)	
Higher degree	…	…	0.857***	0.527***	…
			(0.006)	(0.006)	
Constant	6.872***	4.624***	4.756***	5.101***	6.848***
	(0.004)	(0.018)	(0.017)	(0.023)	(0.005)
Sector dummies	No	Yes	Yes	Yes	Yes
Occupation dummies	No	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
R^2	0.0020	0.3548	0.4567	0.4385	0.1737
(within)	-	-	-	0.0424	0.0432
(between)	-	-	-	0.5144	0.2440
F test	73.48	5799.15	6500.05		474.95
Breusch Pagan	-	-	-	$\chi2$ (1) =	410,000
Hausman	-	-	-	$\chi2$ (20) =	11.818,45
No. observations	262,751	262,751	262,751	262,751	262,751
No. individuals	-	-	-	42,090	42,090

Source: Data from Labor Ministry of Brazil - RAISMIGRA-1995-2002.

*** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

Table 9: Wage differentials of returning migrants

Independent variables	(1) MQO	(2) MQO	(3) MQO	(4) EA	(5) EF
Return-migrant	-0.026	0.020	-0.015	-0.017	-0.013
	(0.021)	(0.017)	(0.015)	(0.011)	(0.011)
Gender	…	0.300***	0.342***	0.215***	…
		(0.003)	(0.003)	(0.005)	
Tenure	…	0.003***	0.003***	0.002***	0.002***
		(0.000)	(0.000)	(0.000)	(0.000)
$Tenure^2$	…	0.000	-0.000***	-0.000***	-0.000***
		(0.000)	(0.000)	(0.000)	(0.000)
Age	…	0.092***	0.077***	0.068***	…
		(0.001)	(0.001)	(0.001)	
Age^2	…	-0.001***	-0.001***	-0.001***	…
		(0.000)	(0.000)	(0.000)	
Illiterate	…	…	-0.115***	-0.028***	…
			(0.012)	(0.010)	
Incomplete 1st. elementary level	…	…	-0.236***	-0.107***	…
			(0.005)	(0.006)	
1st. Elementary level	…	…	-0.180***	-0.080***	…
			(0.004)	(0.005)	
Incomplete 2nd. elementary level	…	…	-0.106***	-0.036***	…
			(0.004)	(0.004)	
Incomplete medium school	…	…	0.123***	0.063***	…
			(0.005)	(0.005)	
Medium school	…	…	0.332***	0.147***	…
			(0.004)	(0.004)	
Incomplete higher degree	…	…	0.659***	0.352***	…
			(0.007)	(0.006)	
Higher degree	…	…	0.858***	0.527***	…
			(0.006)	(0.006)	
Constant	6.876***	4.624***	4.755***	5.099***	6.852***
	(0.004)	(0.018)	(0.017)	(0.023)	(0.005)
Sector dummies	No	Yes	Yes	Yes	Yes
Occupation dummies	No	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
R^2	0.0019	0.3543	0.4565	0.4382	0.1715
(within)	-	-	-	0.0422	0.0431
(between)	-	-	-	0.5140	0.2409
F test	70.36	5784.14	6491.46		472.85
Breusch Pagan	-	-	-	$\chi2$ (1) = 410.000	
Hausman	-	-	-	$\chi2$ (21) = 11.950,38	
No. observations	262,751	262,751	262,751	262,751	262,751
No. individuals	-	-	-	42,090	42,090

Source: Data from Labor Ministry of Brazil - RAISMIGRA-1995-2002.

*** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

Table 10: Wage differentials between migrants and non-migrants - Fixed effects regressions

Dependent variable: Log of real wages				
Independent variables	(1)	(2)	(3)	(4)
Migrant	0.002	-0.004	-0.011	-0.019**
	(0.007)	(0.007)	(0.008)	(0.008)
Out-migrant	0.043***	…	0.042***	…
	(0.007)		(0.007)	
Return-migrant	…	-0.011	…	-0.015
		(0.012)		(0.012)
Out of SP	…	0.065***	…	0.065***
		(0.008)		(0.008)
Years since migration	…	…	0.027***	0.030***
			(0.007)	(0.007)
Years since migration^2	…	…	-0.005***	-0.005***
			(0.001)	(0.001)
Tenure	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Tenure^2	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	6.765***	6.766***	6.766***	6.766***
	(0.005)	(0.005)	(0.005)	(0.005)
Sector dummies	Yes	Yes	Yes	Yes
Occupation dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
R^2	0.1739	0.1731	0.1744	0.1737
(within)	0.0432	0.0434	0.0433	0.0435
(between)	0.2442	0.2428	0.2452	0.2438
F test	432.71	303.97	6132.71	6433.45
No. observations	262,751	262,752	262,753	262,754
No. individuals	42,090	42,091	42,092	42,093

Source: Data from Labor Ministry of Brazil - RAISMIGRA-1995-2002.

*** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.