Latin American Immigration in the United States: Is There Wage Assimilation Across the Wage Distribution?

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Abstract

This paper estimates wage differentials between Latin American immigrant males and U.S. natives along the wage distribution using quantile regression and matching methodologies. The hypothesis of wage assimilation is tested by exploiting the differences by cohort of arrival. The main findings indicate that Latin Americans' wages do not assimilate to those of their native counterparts and that the gaps are wider for the lowest deciles of the distribution. For the cohorts of immigrants who arrived before 1979 the differential is explained almost completely by education, with a negligible effect that cannot be explained by observable characteristics.

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1. Introduction

Immigration has been one of the main contributing factors in shaping today's labor force in the United States. The current wave of immigration, which started in 1965, has different characteristics than previous inflows of immigrants.[1] In particular, the 1965 Immigration Act, by giving preference to family reunification, shifted the region of origin of incoming U.S. immigrants largely to Latin America and Asia, widening the gap between natives and immigrants in terms of language and culture (Borjas, 1995; Card, 2005).

Immigration from Latin America has constituted 40 to 50 percent of total immigration during the current wave. Moreover, according to the American Community Survey (2008), the Hispanic-origin population forms the second largest ethnic group in the United States and represents 15.8 percent of the overall U.S. population.

This paper studies the labor market assimilation process of Latin American immigrant males relative to native-born U.S. males. Despite the numerous studies on the economic assimilation of immigrants, very few have focused on the earnings of Latin American immigrants. Given the growing importance of this group in the U.S. labor market, this paper aims to provide insight into the economic performance of this particular population. Specifically, this paper seeks to address questions such as: Has there been economic assimilation in terms of wage catch-up between Latin American immigrants and natives in the most recent wave of

[1] The first wave of immigration took place from 1840 to 1860 and the primary sending countries were the United Kingdom, Ireland, Germany, and other Northern European countries. During the second wave, from 1880 to 1920, about 20 million immigrants arrived, mostly from Southern and Eastern Europe.

immigration? Does assimilation occur in the case of low, middle, and high-income immigrants, or only at some points of the wage distribution?

Based on the 2000 (1 percent sample) U.S. Census database, this paper uses quantile regression and matching methodologies to estimate wage differentials between Latin American immigrants and U.S. natives at the means and the different deciles of the wage distribution. This provides a quantitative measure of the size of the wage gap between the two groups. Moreover, estimating wage differentials for immigrants' cohorts of arrival provides a test of the wage assimilation of Latin American immigrants over time, according to the concept of economic assimilation first described by Chiswick (1978). In addition, to know the extent in which observable and unobservable factors play a role in explaining the gaps, a wage decomposition based on matching is used. At least two features of this analysis set it apart from previous studies. Through the use of two novel methodologies to test for economic assimilation of Latin American immigrants in the United States we are able to: first, find evidence of assimilation not only in the means but along the wage distribution; and second, assess the observable and unobservable factors that contribute to explain the wage gaps.

The structure of this paper is as follows. The second section presents a general description of Latin American immigrants' characteristics relative to their native and other (non-Latin American immigrant) counterparts. Details of the quantitative methodologies adopted in this analysis are presented in section three. The fourth section discusses the main results of testing assimilation of Latin American immigrants and the factors that explain it. The final section offers a summary and conclusion.

2. Characteristics of Natives and Latin American Immigrants

As mentioned in the introduction, Latin American immigration[2] has accounted for a growing share of total immigration in the U.S. during the post-1965 wave. An important finding of this paper is that, despite their large share in the recent inflow, Latin American immigrants tend to fare poorly in economic terms with respect to natives and immigrants from other countries,[3] mainly because of their low educational attainment and the types of jobs they are able to obtain. Despite differences within the Latin American-born population, it can be argued that these immigrants are similar in aspects such as language, culture, and educational levels that determine to a great extent their economic outcomes in the U.S.

According to the 2000 Census 1 percent Public Use Microdata Samples database, the average hourly wages for U.S. natives, other immigrants, and Latin American immigrants were \$18.37, \$20.72, and \$13.75 in 1999, respectively, for male civilian workers aged 25-64.[4] Those average wages reveal a marked inequality among groups: Latin American immigrants on average earn only 66.4 percent what natives earn per hour, while other immigrants' wages are higher than natives' wages by almost 13 percent.

While the average wages show important differences among the three groups, the distribution of hourly wages (Figure 1) provides a more comprehensive picture. Natives and other immigrants have similar distributions except for the higher kurtosis and greater symmetry of the natives' wage distribution. The Latin Americans' wage distribution reveals important

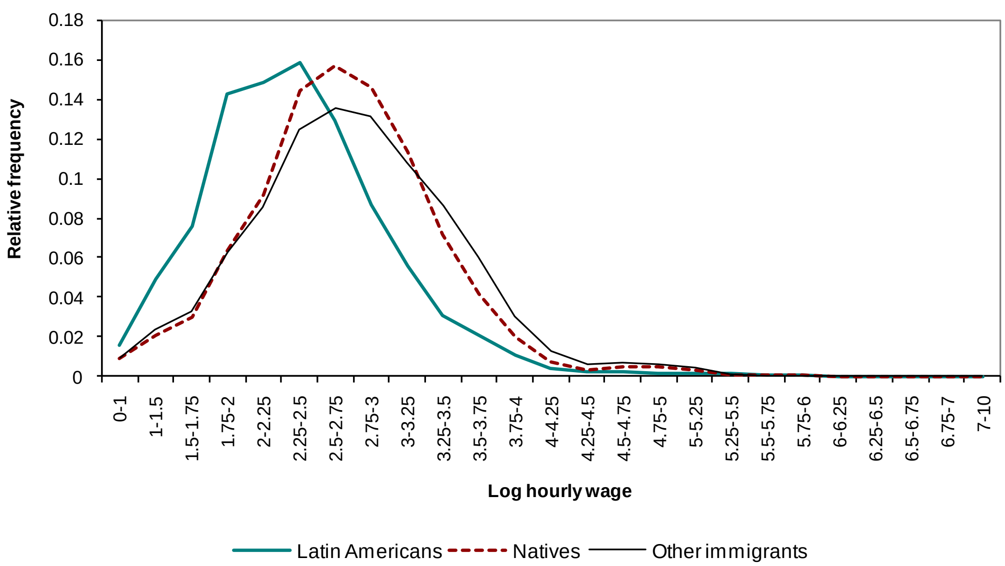
[2] The sending countries in Latin America considered in this paper refer to those territories where the Spanish or Portuguese languages prevail: Mexico; most of Central and South America; and Cuba, the Dominican Republic, and Puerto Rico in the Caribbean. A worker is considered native if born in the U.S.

[3] A native is considered any a person born in the U.S. According to 2000 Census data, in the current wave of immigration, the majority of immigrants from non-Latin-American countries come from the Philippines, China, India, the West Indies, Germany, Canada, and Korea.

[4] When differentiating average hourly wages of natives by race, the results show that average wages are \$16.38 for native black workers and \$18.58 for native non-black workers; Latin American immigrants' wages are significantly lower than native blacks' wages, which tend to be low among natives.

differences vis-à-vis the other groups. While similar in shape to the native distribution, the Latin American immigrants' distribution is shifted significantly to the left of the other two, implying that the bulk of the distribution is concentrated in very low wage levels. The split between Latin American and non-Latin American immigrants distinguishes more accurately the immigrant groups to identify the relevant wage differentials. This does not seem to be achieved by mixing all non-English-speaking immigrants together, as other studies have done in the past.

Figure 1.
Distribution of log hourly wages, male civilian workers (25-64), 1999



Data source: 2000 U.S. Census, Public Use Microdata Sample (1% sample).

In this study, immigrant workers have been divided into cohorts of arrival, given that, according to the theory of economic assimilation, the more recent the arrival, the wider the wage gap with respect to natives because immigrants' skills are not perfectly transferable to the U.S. labor market (Chiswick, 1978). This allows us to eventually find a crossover point where immigrant wages are equal to or higher than those of natives, which is normally expected to happen when the immigrant has spent a considerable amount of time in the U.S. -- after learning the language and making the necessary skill adjustments. In this analysis, cohorts are numbered 1 to 6, where each number groups immigrants arriving in a 5 year period. Cohort 1 is the most recent and cohort 6 the earliest cohort. Table 1 shows, by cohort of arrival, each group of immigrants as a proportion of the total number of immigrants, mean wages, and the percentage of immigrants with at least a high school diploma in each cohort.

Table 1.
Mean wages of immigrant workers (25-64) by cohort of arrival, 1999

`	***Proportion of total immigration (%)***	***Average wage ($)***	***Immigrants with at least high school (%)***	***Proportion of immigrants who came at age 24 or less***
		Latin American		
1995-1999 cohort	46.16	11.49	42.27	23.6
1990-1994 cohort	46.77	12.30	40.32	58.1
1985-1989 cohort	55.06	12.89	40.04	68.9
1980-1984 cohort	47.82	13.85	42.43	75.2
1975-1979 cohort	43.33	15.35	40.10	79.7
Pre - 1975 cohort	39.04	17.91	57.04	89.3
		Non-Latin American		
1995-1999 cohort	53.84	23.90	88.99	13.8
1990-1994 cohort	53.23	22.15	85.63	30.9
1985-1989 cohort	44.94	22.10	85.40	42.2
1980-1984 cohort	52.18	22.11	84.56	54.5
1975-1979 cohort	56.67	23.83	87.28	65.2
Pre - 1975 cohort	60.96	25.76	88.99	85.7

Source: 2000 U.S. Census, Public Use Microdata Sample (1% sample). Sample size: Latin Americans 35,091; non-Latin American immigrants 41,335.

For Latin Americans in general, the earlier the cohort arrived, the higher the mean wage appears to be. While their average wages seem to have stagnated during the first 20 years after arrival, significant increases appear beyond that threshold. Workers who arrived before 1974 earn $17.91 on average, a difference of almost $7 with respect to Latin American immigrants in the most recent cohort, and $2.6 with respect to workers in the cohort arriving from 1975 to 1979. By way of contrast, non-Latin American immigrants tend to have more equal wages across cohorts of arrival; although there is a U-shape pattern with the highest wages observed among the earliest and most recent cohorts.

The data shown in Table 1 correspond with what Borjas (1995) identified: during the most recent immigration wave, a change in trends has led to a reduction in the quality of immigrants, so that the skill distribution has deteriorated and the wage gap has grown wider. For this reason, as long as immigrants' characteristics differ from those of natives, the wage differentials are expected to be greater (p. 4). Nevertheless, Table 1 makes a distinction between those immigrants with the characteristics mentioned by Borjas. It shows that non-Latin American immigrants, on the contrary, do not exhibit the lower skill distribution or a widened wage gap, so that the two main groups of immigrants are located in both extremes of the skill distribution. From this perspective, low-skilled workers (Latin Americans), who are in short supply in the U.S., as well as high-skilled immigrants (non-Latin American), who are in high demand in the domestic economy, effectively complement the skill endowment of natives.

The overall quality of immigrants does not seem to have decreased, however. If quality is measured by the proportion of immigrants who have attained at least a high school education, the quality of immigrants does not seem to change significantly between cohorts. In the case of non-Latin American immigrants, this proportion tends to remain constant across cohorts at around 87 percent. Also, immigrants who arrived in the most recent cohort (1995-1999) are slightly more educated than those who arrived in the earliest cohort (1974 and before). On the other hand, the fraction of Latin Americans with a high school education or more has also been stable at about

40 percent, except for the earliest cohort, which has a considerably larger proportion of educated workers at 57 percent. The fact that immigrant quality as measured by educational attainment has not decreased over time indicates that the most recent cohorts are even more educated than previous ones.[5]

As discussed in the earnings and immigration literature, the foregoing difference in wages can be attributed to diverse factors, with acquired skills and educational attainment ranking high among the most important factors required for success as an immigrant. Table A-1 in the annex shows the proportion of natives and immigrants arrayed according to demographic and work characteristics (every column totals 100 percent). The most salient feature shown in the table is that Latin American immigrants are concentrated in the lowest education categories. Of all Latin Americans, 48.9 percent have less than a high school education, 6.7 percent have no schooling, 18.9 percent are high school graduates and 25 percent have tertiary education.

The picture for natives and other immigrants is significantly different. About 90 percent of natives have at least a high school diploma, whereas for other immigrants the corresponding figure is 87 percent. Native workers are nearly evenly distributed among the three highest levels of education, while 46.3 percent of other immigrants are heavily concentrated in the group with a college degree or more.

So far, a preliminary conclusion of this analysis is that Latin Americans tend to have the lowest wages apparently because they have low educational attainment levels. Although the Census does not ask where education was obtained, it is possible that education acquired in the

[5] Borjas (1985) states that, when analyzing a cross-section of immigrants, recent cohorts contain a more representative selection of the immigrant pool because immigrants in earlier cohorts have been self-selected to include only the most successful among them (pp. 466-467). Therefore, if education is not significantly different across cohorts, immigrants who have arrived recently tend to be more educated than earlier immigrants. Only in the case of Latin American immigrant cohorts 1 to 5 with respect to cohort 6 is there some evidence of deterioration in the skills of immigrants in terms of education.

U.S. is regarded by employers as more valuable because it typically develops skills specific to the U.S. labor market, such as preparation for certain occupations, and English proficiency. According to the wage assimilation theory, skills acquired in the receiving country are more transferable than the schooling attained in the home country. If this were true, workers who obtain most of their education in the U.S. would receive higher wages after a considerable amount of time in the U.S., because their skills would be more comparable to those of natives. On the other hand, workers who do not receive their education in the U.S. would tend to have lower wages when compared with similar natives (Chiswick, 1978).

The potential of obtaining education in the U.S. could be examined by looking at the age in which both groups of immigrants arrived in the U.S. It is expected that the younger the immigrants come, the more possibilities they have of acquire U.S.-specific skills. Table 1 shows the proportion of immigrants in every cohort who arrived in the U.S. at age 24 or less. It is clear that the proportion of Latin Americans coming at young ages, and therefore having the greatest potential of getting educated in the U.S., is higher than that for non-Latin Americans in all cohorts. However, despite the fact that Latin Americans come at earlier ages, they do not achieve the levels of education that non-Latin American immigrants exhibit, suggesting that their low wages may not be a product of the lack of transferability of the skills they previously acquired in their native countries.

Besides education, it is also worth analyzing other characteristics that may play a role in the differences of wages between natives and immigrants. Table A-1 shows that the age structure of Latin American immigrants is more concentrated in people between the ages of 25 to 34 years than the other two population groups, while the age structures of natives and other immigrants are very similar to each other. Younger workers not only lack experience in the labor market but are also likely to have arrived in a recent cohort, increasing the probability of receiving a low wage. For this reason, the fact that the age structure of Latin American immigrants is concentrated in the younger ages may also be correlated with their low wages. With respect to the area of residence, both groups of immigrants tend to be concentrated in metropolitan areas with more than 80 percent of the individuals living in big cities, while the figure for natives is 52 percent.

The variables related to employment show that the most common jobs for natives and non-Latin American immigrants are managerial and professional occupations. In contrast, Latin American immigrants are overrepresented in occupations such as production, transportation and material moving, and service-related occupations. In terms of industry, 38 percent or more of individuals in all three groups work in the service sector. However, 4.8 percent of Latin Americans work in agriculture, while only 1.7 percent of natives and 0.5 percent of other immigrants belong to this sector. A similar situation occurs in the construction industry, which employs 11.3 percent of Latin American immigrants, compared to only 7.1 percent of natives and 4.3 percent of other immigrants.

3. Methodology for Estimating Wage Differentials between Immigrants and Natives

Estimating wage differentials between immigrants and U.S. natives not only provides a quantitative measure of how wide the average wage gap is; it also provides a test for the economic assimilation hypothesis.

The literature on economic assimilation of immigrants in the United States has mainly explored the differentials between natives and all immigrants, or between natives, immigrants from English-speaking countries, and immigrants from non-English-speaking countries.[6] This paper focuses on quantifying the differentials between natives and Latin American immigrants because that group has accounted for a large proportion of total immigration since 1965, and because combining all immigrants together may be hiding differences in the skills immigrants possess.[7]

According to the theory of economic assimilation, "because knowledge and skills are not perfectly mobile across countries, other things the same, immigrants initially would have earnings significantly lower than native-born persons, but the gap would narrow the longer they are in the United States" (Chiswick, 1978, p. 899). In other words, recently arrived immigrants tend to have fewer of the characteristics that natives do, such as knowledge of the customs and language needed to find a job, and have less job-specific training. With more time in the U.S., immigrants can acquire the skills necessary for the labor market, which tends to equalize their characteristics vis-à-vis those of natives.

This section describes the methodologies used for calculating the wage differentials and testing wage assimilation.

3.1 Quantile Regression

The first approach involves estimating an earnings equation along the lines proposed by Chiswick (1978). The dependent variable of the model (log hourly wage) would depend on years of schooling, labor market experience, and labor market experience squared. Other controls that can be included are socio-demographic determinants (race, marital status), geographical location,

[6] See, for example, Chiswick (1978,1986), Borjas (1985,1995), LaLonde and Topel (1990), Funkhouser and Trejo (1995), and Chiswick *et al* (2008).

[7] As mentioned before, Canadians, Europeans, and Asians, the most represented immigrant groups in the U.S. after Latin Americans, tend to be highly qualified, while Latin Americans tend to be the least skilled immigrants.

and weeks worked during the last year. In the case of immigrants, this function also includes a variable reflecting the time the immigrant has spent in the U.S. Equation (1) shows the specification used in this paper:[8]

$$\log(hrwage) = \beta_0 + X_i\beta_i + W_j\beta_j + \alpha_3 Lamerican + \alpha_4 Other + \sum_{m=2}^{6}\alpha_m cohort_m + \sum_{n=2}^{6}\alpha_n (cohort_n * other) + \varepsilon_i \qquad (1)$$

Where the natural logarithm of the hourly wage depends on a set of demographic characteristics X_i, including education in the form of dummies for level of education attained (excluding college or more); a set of work variables, W_j, such as type of employment, occupation, and industry; and time since immigration expressed in the form of dummies for cohort (excluding the most recent cohort), as well as the interaction between each cohort and the dummy for other immigrant. From the immigrant status dummies, the cohort dummies, and the interactions, it is possible to estimate the wage differentials for immigrants who arrived in different cohorts; that is, this exercise provides a means for testing whether wage assimilation occurs, and when it occurs. In other words, if the differential estimated for some cohort is not statistically different from zero and remains equal to zero or positive for older cohorts, it can be concluded that immigrants' wages have assimilated to those of natives. In order to identify this, it is necessary to calculate the partial effect of being an immigrant on hourly wage through the following derivative:

$$\frac{\partial(\log(hrwage_i))}{\partial(Lamerican)} = \alpha_3 + \alpha_m \qquad (2)$$

[8] A full description of the 2000 U.S. Census variables used in this paper can be found in table A-2 in the annex.

This is, given that the dummy for cohort 1 is excluded, the coefficient α_3 is the estimated wage differential for those Latin Americans who arrived in the most recent cohort of immigrants. For other cohorts, the partial effect is calculated according to equation (2), with *m* depending on the cohort defined in the econometric specification. According to the wage assimilation literature, it is expected that the older the cohort, the more similar the wage is compared to natives with the same characteristics. This implies that if the sign of α_3 is large and negative, the values for the α_m must be positive and eventually larger than α_3, so that the differential with respect to natives is estimated to be lower for older cohorts.

Besides OLS, equation (1) can be estimated using a methodology that allows us to find the differentials at different points of the wage distribution. This is crucial, because the conditional mean analysis may be hiding some effects that can only be considered when analyzing the entire wage distribution. It also allows for a calculation of the partial effect for cohorts -- equation (2) -- at different deciles, as explained previously. This analysis is potentially interesting because the differential between Latin Americans and natives may be lower at the bottom of the distribution for reasons associated with the floor effect of the minimum wage. Also, as mentioned by Chiswick *et al.* (2008), “in the study of immigrant earnings, the concentration of immigrants in the U.S. among the least skilled, and amongst the most skilled, suggests that the quantile regression approach may have merit” (p. 356).

Equation (3) provides the econometric specification for the quantile regression model:[9]

$$\mathrm{y_i} = \mathrm{x_i}\beta_\theta + \varepsilon_\theta, \quad \mathrm{Quant}_\theta(\mathrm{y_i} \mid \mathrm{x_i}) = \mathrm{x_i}\beta_\theta \qquad (3)$$

[9] For a complete explanation of the quantile regression specification applied to the topic of this paper, see Chiswick *et al.* (2008).

Where $\mathrm{Quant}_\theta(y_i \mid x_i) = x_i\beta_\theta$ refers to the conditional quantile of y_i, conditional on the vector of characteristics of workers specified in equation (1), and $\theta \in (0,1)$. This model requires that the error is independent from regressors for all θ, that is, $\mathrm{Quant}_\theta(u_{\theta i} \mid x_i) = 0$.

3.2 Non-parametric wage decomposition

The estimation of equation (1) allows the calculation of a wage differential controlling for workers' characteristics, but it gives no information about the portion of the wage gap explained by non-observable factors. To address this, we use the wage-decomposition developed by Ñopo (2008).

The approach followed is a non-parametric extension of the Oaxaca (1973) and Blinder (1973) decomposition which, through the use of matching, finds the differences in wages attributable to workers' characteristics and to an unexplained component. While the Oaxaca-Blinder decomposition is the most widely-used methodology in the literature, matching presents important advantages over the traditional approach: i) it compares wages only in the common supports of the empirical distributions of workers' characteristics, thus eliminating the problem of mis-specification arising from comparing non-comparable individuals; ii) it gives information about the distribution of unexplained differences in wages (not just the average); and iii) since it is non-parametric, it does not require the estimation of earnings equations and, therefore, there is no need to presume linear relationships among variables nor to validate model assumptions (Ñopo, 2008). On the side of the disadvantages, it is worth mentioning the "curse of dimensionality" that occurs when there are many explanatory variables in non-parametric models in general.

Since the procedure is based on matching, two groups of individuals (males and females, or natives and immigrants, as in this application) are matched according to their individual characteristics, which are expected to be related to earnings (age, education, type of employment, *et cetera*). While the interpretation of the gap follows the usual Oaxaca-Blinder framework, its construction is made of four additive elements:

$$\Delta = (\Delta_X + \Delta_M + \Delta_F) + \Delta_0 \tag{4}$$

The component Δ_X is, as in Oaxaca-Blinder, the portion of the gap attributed to differences in the distribution of observable characteristics of males and females over the common support. However, matching goes beyond Oaxaca-Blinder as it controls not only for differences in average characteristics of the two groups, but also for the distributions of those characteristics that individuals in different groups share.

The elements Δ_M and Δ_F are the fractions of the gap that can be explained by the existence of males with combinations of characteristics that no female can match, and vice versa. In the case of Δ_M, the most common example is a young, highly educated male who works in a high-paying position, and for whom it is difficult to find a woman who matches this profile. Hence, these two components are related to the observations that lie beyond the common support of the distribution of observable characteristics.

So far, the three first components of the wage gap represent the difference in observable characteristics that play a role in determining the gap between the two groups. The last component,Δ_0, is attributed to the existence of differences in characteristics rewarded by the labor market that are unobservable to the researcher, e.g. discrimination. Therefore, Δ_0 can be interpreted as the remaining portion of the wage gap, given a hypothetical situation in which individuals belonging to different groups have the same distribution of observable characteristics.[10]

4. Estimation of Wage Differentials between Latin American Immigrants and U.S. Natives

The two methodologies presented in the previous section allow us to quantify the wage differential both in the mean and across the wage distribution. In this section, the hypothesis of wage assimilation is tested by estimating the wage differential between immigrants in every cohort of arrival and U.S. natives through quantile regression and a non-parametric decomposition using 2000 U.S. Census data. If we find that the wage differential is not significant for a specific cohort, it is possible to conclude that wage assimilation has occurred, and that it has taken place after the specific length of residency in the United States (given by the cohort). Section 4.1 presents the results for the quantile regression analysis, and section 4.2 shows the results obtained through the matching decomposition.

4.1 Quantile regression

Table A-3 in the annex presents OLS and quantile regression estimates, including control variables for civilian working males aged 25-64. The first column lists the results obtained using OLS and subsequent columns show the results for deciles 1 through 9 of the wage distribution. The estimations are done for the entire sample, including U.S. natives, as well as all cohorts of Latin American and non-Latin American immigrants. As mentioned in the previous section, the differential between natives and immigrants is estimated by introducing dummies for immigrant

[10] For details about the matching algorithm and asymptotic consistency proofs of the estimators derived from this methodology, see Ñopo (2008).

and interactions between immigrant dummies, and dummies for cohort of arrival. It is important to note that it is possible that these coefficients present some kind of bias, because: i) return migration is not a random process in the immigrant population; and ii) the cross-section coefficients implicitly assume that the average quality of cohorts does not change over time (Borjas, 1985). While the first reason cannot be controlled for in any cross-section analysis, the second does not seem to be critical in this application, as mentioned in Section 2.

Given the sample size (553,990 individuals), all demographic and work characteristics are significant and show the expected sign. In terms of the rewards to education, the educational dummies presented in column 1 of Table A-3 show that -- everything else being equal -- workers with no schooling earn, on average, 52.3 percent less per hour with respect to workers with a college degree or more; with 1 to 8 years of education completed, they earn 51.4 percent less; with 9 to 11 years of education completed, 45.4 percent less, with high school diploma, 34.1 percent less, and with some college, 24.8 percent less.

It is worth noting, however, that moving up the decile distribution, the difference in pay increases monotonically for all education levels compared to individuals with college or more. So, for example, a person with some college earns 9.4 percent less per hour than a person with college or more in the first decile of the distribution, but in the last decile this difference reaches 36.3 percent. The greatest increase in the difference from the 1st to the 9th decile is observed for individuals with a high school education, a group for which the difference in hourly wages with respect to individuals with college or more increases 30.1 percentage points from the first to the last decile. As mentioned in Chiswick *et al.* (2008), education has a smaller impact on wages at the lower deciles, which can be probably attributed to differences in school quality, the higher impact of over-education in the lower deciles, and the stronger effect of omitting ability in better-educated individuals (p. 13).

The age at which individuals maximize their wage also differs across deciles. For the average of the population it is 49.1 years, but it drops to 28.5 years in the first decile, 42.5 in the second, and thereafter it exceeds the average in all deciles except the last. The fact that the age of maximization of wages is lower in the first decile with respect to the rest could imply that persons located in the bottom of the distribution earn consistently lower wages throughout their lives, so the maximization of earnings occurs at an early age when individuals' strength and vitality, needed to accomplish physical tasks, are high.

The rewards for living in a metropolitan area tend to increase when moving up the distribution. All else being equal, a person in the first decile who lives in a metropolitan area garners an hourly wage only 10 percent higher than a non-metropolitan-dweller, but the differential increases up to 18 percent in the higher deciles of the distribution. On the contrary, being a household head decreases in importance when moving up the decile distribution, probably because most household members in the highest deciles hold high-paying jobs, and there is less pressure for the household head to be the primary source of income.

Another interesting feature shown in Table A-3 is that the regression constants tend to increase with the decile. This could imply that omitted variables may play a more important role in explaining hourly wages in the highest deciles; that is, variables such as ability may explain an important part of the differences in wages but it is not possible to include them as regressors.

The results of the differentials' estimations between Latin American immigrants and natives controlling for worker characteristics and cohorts of arrival show that the differentials become smaller as the cohort is older (in terms of how long ago they arrived).[11] According to the wage assimilation theory, because there is no perfect transferability of knowledge and skills, "other things the same, immigrants would have earnings significantly lower than native born persons, but the gap would narrow the longer they are in the United States" (Chiswick, 1978, p. 899). Table A-3 and Figure 2 show this is exactly what happens in the case of Latin American immigrants. OLS estimates an average differential for cohort 1 (the most recent cohort) of -25.6 percent; for cohort 2 it is -18.4 percent, for cohort 3 it is -17.8 percent, for cohort 4 it is -16.4 percent, for cohort 5 it is -10.1 percent, and for cohort 6 it is -8.3 percent. As predicted by the wage assimilation theory, the more recent the arrival, the wider the gap. For Latin Americans it seems that there is no crossover point, since wage differentials, even for the cohort of earliest arrival, remain negative and significant.

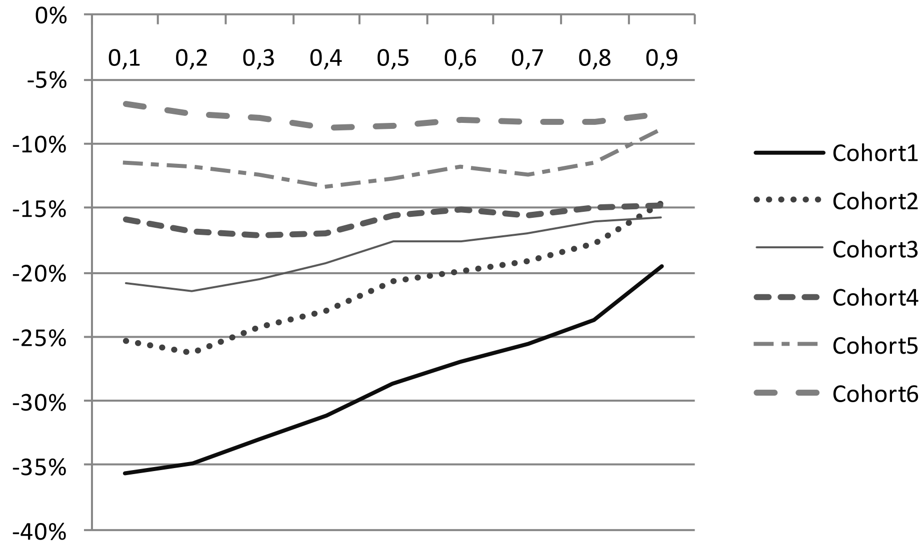
Figure 2 provides a richer picture of the differential per cohort calculated across the wage distribution. Latin Americans in cohort 1 (1995-1999) present by far the widest gaps with respect to natives, particularly in the first deciles of the distribution where the differentials reach levels above 30 percent. Individuals arriving in the most recent cohort located near the top of the distribution fare better relative to natives but the differential remains high at about -20 percent.

Cohort 2 (1990-1994) exhibits a pattern similar to cohort 1 but the differential is narrower, ranging from -26.3 percent in the 2nd decile to -14.6 percent in the 9th decile. It can be inferred, therefore, that the hourly wages earned by Latin American immigrants who have arrived in the United States during the 1990 decade differ substantially from those of natives who share the same demographic and work characteristics. It is important to note, however, that

[11] The estimated differential including all cohorts of immigrants together, that is, without including cohort dummies, is -15.7 percent.

individuals in the bottom deciles fare much worse than those at the top deciles, although this does not mean that the latter fare well in general, when compared to U.S. natives.

Figure 2.
Wage differentials calculated across the wage distribution by cohort of arrival
Latin American immigrants vs. U.S. natives
Civilian male workers (25-64)



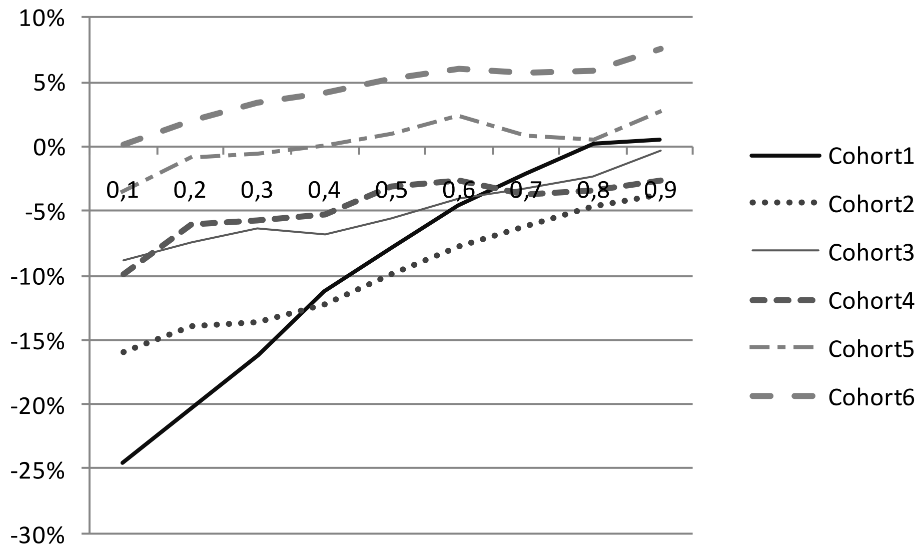
Source: Estimates in table A-3. 2000 U.S. Census data (1% sample).

Latin American immigrants arriving in cohorts 3 (1985-1989), 4 (1980-1984) and 5 (1975-1979) also show a tendency to have lower differentials at the upper-end of the distribution but the reduction is not as sharp as that observed for immigrants in cohorts 1 and 2. Across deciles, the differential oscillates between -21.5 percent and -15.6 percent for cohort 3; -17.9 percent and -14.9 percent for cohort 4; and -12.7 percent and -8.9 percent for cohort 5. The differentials for cohort 6 (1974 and before), on the other hand, remain constant around -8 percent across the wage distribution. It is worth mentioning that for all deciles in all cohorts the wage gap between Latin Americans and natives is always negative and statistically significant.

The results by cohort and decile can be interpreted along the findings of Duleep and Regets (1992, 1994, 1996) and Borjas (1995, 1999), who find an inverse relationship between entry earnings and earnings growth over time. Keeping in mind the problems associated with the dynamic interpretation of coefficients in a cross-section analysis, wage growth among Latin Americans (if it occurs at all) would be higher in the first deciles of the distribution. This is because immigrants at the bottom of the distribution start with the highest differentials in cohort 1, but by the time individuals in the same deciles reach cohort 6, they have a differential similar to those observed in the top deciles of the same cohort. That is, the earnings of immigrants in the first deciles may grow faster than those in the higher deciles.

By way of comparison, OLS and quantile regression estimates allow a calculation of the differential between non-Latin American immigrants and natives. Figure 3 shows that despite the differentials of approximately -25 percent for the earliest cohort in the first decile, there is wage assimilation for the 8^{th} and 9^{th} deciles for the same cohort. This means that a non-Latin American immigrant who has arrived in the U.S. in 1995-1999 and is located in the highest deciles of the wage distribution has an average wage that is not statistically different from the wage of a U.S. native with similar characteristics who is also in the top of the distribution. The same is true for cohorts 2, 3 and 4 with the difference that the gaps are narrower than those observed in cohort 1 for the first deciles of the distribution. Cohorts 5 and 6 of non-Latin American immigrants are completely assimilated, and in many deciles their wages are even statistically higher than those of U.S. natives.

Figure 3.
Wage differentials calculated across the wage distribution by cohort of arrival
Other immigrants vs. U.S. natives
Civilian male workers (25-64)



Source: Estimates in table A-3. 2000 U.S. Census data (1% sample).

Comparing the coefficients obtained for the dummy for Latin American immigrant across the different quantiles permits an assessment of the advantages of estimating the wage differentials across the deciles of the wage distribution. This implies testing if the difference in the value of the coefficients is statistically significant for every pair of coefficients (not shown). For the deciles that are close in the distribution, there is no evidence that the estimated coefficients are different. For example, estimates for decile 3 are statistically equal to estimates for deciles 4, 5, 6, and 7 at the 5 percent level. In general, estimates for deciles 1, 2, 8, and 9 are different from the estimates obtained for the central deciles of the distribution. For this reason, the quantile regression approach provides a greater insight than OLS, as it successfully uncovers the differences between immigrants and natives across the wage distribution.

4.2 Matching decomposition

Besides estimating the differential between U.S. natives and immigrants, it is worth exploring the observable and unobservable factors that contribute to this differential across the wage distribution. Although the methodology developed in the previous section is useful to consider distributional effects by decomposing wage gaps at the different quantiles of the error distribution, decomposing the gap using the Oaxaca-Blinder approach presents the problem of differences in the supports mentioned in section 3. The decomposition based on matching individuals with similar characteristics permits the identification of the fractions of the wage gap attributed to observable and unobservable characteristics, not only in the average, but also across the wage distribution.

The annex reports the results of applying matching to natives and all cohorts of Latin American immigrants in Table A-4, and Latin Americans in each cohort compared to the whole group of natives in Tables A-5 to A-10. The rows in each table report the calculated wage gap (Δ), its four components ($\Delta_X, \Delta_N, \Delta_I, \Delta_0$), the percentage of natives and Latin American immigrants in the common support, and an estimate of the standard error of the unexplained component. The columns, on the other hand, show the variables that are included in every step of the calculation, which are the same used in the quantile regression estimation. The results obtained from including variables belonging to the demographic set of characteristics appear at the top of the tables. These are included sequentially one by one, so that the last column reports the results of including all variables of the demographic set together. This column is transcribed in the first column of the bottom part of the table. To this set, a different variable related to work characteristics is added in every subsequent column. The last column reports the calculations for the whole set of demographic and work variables included together.

The differential, including all cohorts of immigrants together, is calculated to be -13.9 percent. The age, marital status, and racial characteristics explain only a small part of the differential; that is, Δ_0 remains high when only these characteristics are included, given that only 1.5 percentage points of the 13.9 percent differential is explained by this set of observable variables. When education is included, 8.4 percentage points of the gap is explained by observable characteristics. This means that, if natives and Latin American immigrants had the same distribution of age, marital status, race, and education, the differential between the two groups would be reduced to -5.5 percent, a remnant that is attributed to the existence of characteristics that the researcher cannot observe. Including the remaining demographic variables does not further reduce the unexplained component. On the contrary, it increases to -6.1 percent and -5.8 percent after controlling for residence in a metropolitan area and being a household head, respectively. Therefore, it seems clear that education is the most important variable explaining the gap when the complete demographic set is included, because it contributes the most to reducing the unexplained component of the wage gap.

The percentage of individuals in the common support of the distribution remains high when including the demographic set. This means that natives and Latin American immigrants are fairly similar in terms of demographic characteristics, so the differential must be explained by other characteristics (probably related to work), or to unobservables. This is also confirmed by the negligible magnitude of Δ_N and Δ_I -- the fractions of the gap explained by characteristics of natives that immigrants cannot match, in the first case; and characteristics of immigrants that natives do not share, in the second. In addition, from the first part of Table A-4 it is evident that the standard error associated to Δ_0 drops from 0.11 percent if only age is included, to 0.06 percent when all variables in the demographic set are taken into account.

The results obtained from matching job-related variables are presented in the second part of table A-4. Since it is not possible to know *a priori* which variables are less endogenous than others, the four of them are added separately to the demographic set. Including the work variables in this fashion allows us to maintain a high percentage of individuals in the common support. Different to what was observed in the demographic set results, where 100 percent of natives were in the common support, the proportion of natives in the common support is reduced but it is never less than 99 percent. Latin American immigrants in the common support, however, drop to a minimum of 93.8 percent when the variable industry is included.

The only variable able to provide a further reduction of Δ_0 -- besides that obtained when controlling for education -- is occupation. In this case, the unexplained component represents 4.8 percentage points of the total gap, while the part of the gap explained by individuals in the common support increases to 9.4 percentage points. When the full set of variables is included, the fraction of the gap explained by characteristics of Latin Americans that are not shared by natives, Δ_I, is 3.2 percent, which is the highest value for this component in any combination of variables included. In addition, the percentage of Latin American immigrants in the common support of the distribution for the full set is 77.7 percent. Both factors, Δ_I and the common support, suggest that the major difference between the two groups is related to work characteristics that Latin American immigrants do not share with natives, specifically occupation and industry.

The matching decomposition for natives and Latin American immigrants by cohort shows the same pattern for education, occupation, and industry found in Table A-4. The differential calculated for Latin American immigrants in cohort 1 (1995-1999) is -19.9 percent, and the unexplained portion of the gap is never below -10 percent for any combination of variables (see table A-5). When education is included, Δ_0 is -12.1 percent; it increases when the rest of the demographic variables, part-time status, and type of employment are included. It reaches its lowest level (-10.6 percent) when occupation is included. In the case of cohort 1, the theory of wage assimilation appears to be confirmed since individuals arriving in the most recent cohort are less likely to have the skills necessary for participating in the U.S. labor market. Therefore, not only do we find a wage gap higher than the average of -13.9 percent for the whole group of Latin American immigrants, but the unexplained component of the gap accounts for more than half of it. It is worth noting that the common support is dramatically reduced to 44.8 percent in the case of Latin Americans when the full set of variables is included. This represents further evidence for the wage assimilation hypothesis because it means that a great proportion of Latin American immigrants in cohort 1 do not have many of the characteristics of natives.

The gap for cohort 2 (1990-1994) is estimated at -17.8 percent (Table A-6). While it is smaller than the gap for cohort 1, it remains high and the unexplained component represents half or more of Δ. Again, education and occupation are the variables that most reduce the unexplained component. This component is -10.9 percent when age, marital status, race and education are included, and -8.7 percent when the demographic set and occupation are included. As the results for cohort 1 showed, the percentage of Latin American immigrants in the common support is low at 43.2 percent when the full set of variables is included, implying again that natives have characteristics that immigrants do not share even after up to ten years of living in the U.S.

Table A-7 shows a differential of -16.1 percent between natives and Latin American immigrants who arrived between 1985 and 1989 (cohort 3). Education and industry are the variables that achieve the highest reduction in Δ_0. Including the full set of characteristics further reduces the unexplained fraction of the gap to -9.4. Note that even when this level of Δ_0 is observed, the proportion of the total gap that it represents is 58 percent; that is, despite the fact that the value of the total gap is lower for cohort 3 than for the two most recent cohorts, the fraction of the gap that remains unexplained is higher. Nevertheless, when the full set is included the percentage of Latin Americans in the common support is 48.4 percent, about 5 percentage points higher than the percentages for cohorts 1 and 2. Given the relatively higher portion of the gap that is unexplained and the increase in similarities between natives and Latin Americans in cohort 3, it might be possible that discrimination or other unobservables plays a more important role for immigrants in this cohort. This could be due to the fact that between 1985 and 1989 the proportion of immigrants from Latin America in the whole immigrant pool was over 55 percent (see table 1), and they are also the group with less education of all cohorts. Also, many of these workers were able to stay in the U.S., therefore affecting the natural process back migration, since the U.S. enacted in 1986 an amnesty for illegal immigrants (Immigration Reform and Control Act – IRCA).

Results for cohort 4 (1980-1984) indicate that the gap is about -13.5 percent, an estimate close to the average gap when all cohorts are taken into account (Table A-8). As in cohorts 1 and 2, education and occupation are the variables that most reduce the unexplained part of the gap. However, this component remains high -- around 50 percent in all combinations of characteristics. The implication in terms of the role of discrimination is analogous to that discussed in the results for cohort 3.

The results for cohort 5, the cohort of immigrants who arrived between 1975 and 1979, show that the wage differential is -10.8 percent (Table A-9). The part of the gap attributed to characteristics in the common support increases to 8 percentage points when education is included in addition to age, marital status, and race.

According to Table A-10, the estimated gap between natives and Latin American immigrants in cohort 6 (pre-1975) is -5.8 percent. Note that the reduction in the gap from cohort 5 to cohort 6 is higher (5 percentage points) than in previous cohorts. While a differential close to -6 percent could be said to be small, it is still significant, so it is possible to conclude that there is no catch up between Latin American immigrants and U.S. natives even after 25 years in the U.S., although the upward pattern in wages for older cohorts is evident.

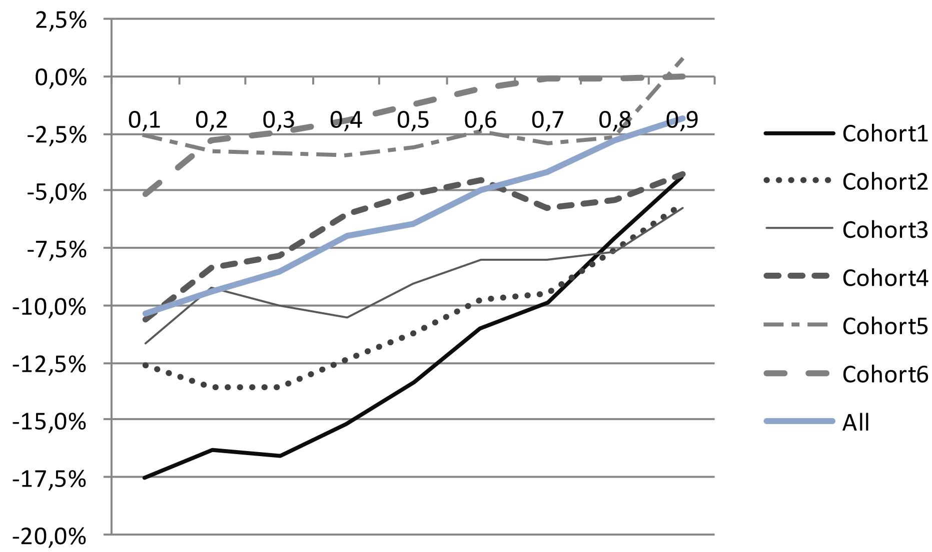
The most important result for cohorts 5 and 6, however, is that the unexplained portion of the differential becomes close to zero when controlling for the full set of variables, in the case of cohort 5, and for education, in the case of cohort 6. A 95 percent confidence interval for Δ_0 for the full set in cohort 5 is between -0.58 percent and -0.33 percent, and for the demographic set excluding metropolitan and household head status in cohort 6 it is between 0.17 percent and 0.49 percent. This means that if Latin American immigrants had the same distribution of the variables included in these two sets, the differential could be explained totally by differences in education in cohort 6 and the full set of characteristics in cohort 5. There would be no discrimination or other unobservable factors affecting wages of Latin Americans if they had the same distribution of characteristics than natives; that is, a wage gap exists between these two groups fundamentally because Latin Americans are less educated than natives.

Another feature of the matching decomposition that is interesting to exploit is the possibility of generating an empirical distribution of unexplained differences in pay. Figure 4 shows the calculated value for Δ_0 across the 1st and 9th deciles of the wage distribution for the average as well as for cohorts 1 to 6. The unexplained component is calculated taking into consideration the full set of demographic and work variables. The graph shows that the unexplained component follows a similar pattern to figures 2 and 3; that is, it increases monotonically with deciles when all Latin American immigrants are included. It is -10 percent in the first decile but becomes less than -2.5 percent in the last. Therefore, for all cohorts of immigrants, discrimination and other unobservables are significantly higher in the lowest deciles of the distribution. In other words, up to 10 percentage points of the wage gap between U.S. natives and Latin American immigrants in the lowest deciles of the wage distribution is explained by unknown factors. On the other hand, the gap that exists between the two groups in the top deciles is barely related to unobservables; it is likely that the gap in these deciles is explained mostly by differences is characteristics such as education, as mentioned before.

The unexplained component by cohort behaves similarly to the gaps obtained through quantile regression. All cohorts tend to have a greater portion of the unexplained wage gap in the first deciles and less in the top deciles, although this happens to a less extent in cohorts 5 and 6. Cohort 1 is again the most disperse; while the unexplained component is about -17.5 percent in the first decile, it is less than -5 percent in the last. Also, in the last two deciles of the wage distribution, Δ_0 for cohort 1 is equal or less than what is observed for this component in cohorts 2, 3, and 4. A possible explanation for this observation is that newly-arrived Latin American immigrants are more similar to U.S. natives than previous cohorts of arrival. For example, the efforts that have been made in Latin American countries to achieve universal enrollment in education might mean that recently-arrived immigrants have education levels more comparable to those of natives. Also, many of the immigrants in the top deciles may have acquired most of their education in the U.S., so that they are familiarized with the language and the labor market.

Cohorts 5 and 6 present an interesting pattern in the unexplained component of the gap. It tends to be constant and less than -5 percent across all deciles with a slight decrease at the upper-end of the distribution. In cohort 6, Δ_0 becomes virtually zero for all deciles after the 6^{th}. That is, if a wage gap exists between natives and Latin Americans who arrived in cohort 6, it is essentially because immigrants do not have observable characteristics comparable to those of natives. There is no discrimination towards Latin Americans who arrived in 1974 and before for the highest deciles of the wage distribution.

Figure 4.
Unexplained component of the wage differentials calculated across the wage distribution by cohort of arrival
Latin American immigrants vs. U.S. natives
Civilian male workers (25-64)



Source: Results from tables A-4 to A-10. 2000 U.S. Census data (1% sample).

5. Conclusions

This paper developed a quantile regression strategy and a non-parametric decomposition to estimate the wage differentials existing between Latin American immigrants and U.S. natives. Besides having a quantitative estimate of the wage gaps between Latin American immigrants and U.S. natives, the differentials allowed to test the hypothesis of wage assimilation through the use of cohorts of arrival in the means and along the wage distribution.

Controlling for demographic and work characteristics, both methodologies estimate a negative and significant differential of -15.7 percent in the case of OLS, and -13.9 percent with matching. Across the wage distribution, both methodologies predict a negative differential for all deciles, in particular for those at the bottom of the distribution. However, these differentials tend to attenuate the longer the immigrant is in the United States. In line with the results of Duleep and Regets (1994, 1995, 1996) and Borjas (1995, 1999), cohort of arrival analysis shows evidence towards an inverse relationship between immigrants' entry earnings and earnings growth, particularly in the first deciles of the distribution. This means that the earnings of immigrants who start with a low hourly wage grow more rapidly than earnings of immigrants located at the top of the distribution. The reason for this is that wage differentials between natives and Latin American immigrants in cohorts 5 and 6 are constant across the distribution, while differentials for the first cohorts decrease monotonically the higher the decile.

The analysis provided by matching is informative in terms of examining which factors exert more influence in explaining the wage gap. For all cohorts together and for every cohort individually, education is the variable that contributes to explain the major part of the gap. In other words, including education as an explanatory variable reduces significantly the component of the gap attributed to unobservables. Occupation and industry have also an important explanatory role, but there is no other variable besides education that can explain the major part of the wage gap in all cohorts. This is particularly relevant in the analysis of cohorts 5 and 6, for which including education reduces the unexplained portion of the gap virtually to zero, so that differences in wages between natives and Latin American immigrants who arrived in the United States 25 years ago or more are almost completely explained by differences in education and not by unobservables such as discrimination.

The main result found in this paper is that immigrants coming from Latin American countries tend to be unsuccessful in terms of catching up with natives' wages, even when they are compared only to natives with the same characteristics and when they spend a significant amount of time in the U.S. It is evident; however, that Latin-American immigrants' earnings tend to grow over time although not as much as it is needed to close the wage gaps. As mentioned in the previous paragraph, this finding can be explained by the fact that Latin Americans do not have education levels similar to those of natives.

Finally, the distinction proposed in this paper – to consider Latin American immigrants separately from other immigrants -- seems to be more accurate than the standard grouping of immigrants in English-speaking vs. non-English-speaking migrants. This is due to the fact that the most important source of wage inequality is in differences in education, and separating Latin Americans from other immigrants successfully makes this distinction.

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Annex.

Table A-1. Descriptive Statistics

	Native (%)	Latin American(%)	Non-Latin American (%)
Age			
25 to 34	25.91	38.23	27.29
35 to 44	32.43	33.41	33.12
45 to 54	28.16	20.12	26.57
55 to 65	13.50	8.23	13.02
Marital Status			
Married, spouse present	65.49	59.46	67.36
Other	34.51	40.54	32.64
Race			
Black	9.26	1.56	10.77
Other	90.74	98.44	89.23
Education			
No schooling	0.24	6.66	1.31
1 to 8 years of education completed	1.50	27.71	3.46
9 to 11 years of education completed	8.15	21.23	8.11
High school diploma	29.78	18.92	17.44
Some college	30.86	15.48	23.37
College or more	29.46	10.00	46.31
Household in metropolitan area			
No	48.07	18.66	16.52
Yes	51.93	81.34	83.48
Household head			
No	41.04	47.73	44.67
Yes	58.96	52.27	55.33
Type of employment			
Wage-employee	89.15	91.14	87.78
Self-employed	10.85	8.86	12.22
Part-time			
No	81.15	83.62	81.07
Yes	18.85	16.38	18.93
Occupation			
Management, professional and related occupations	37.13	15.38	43.28
Service	11.97	22.92	14.68
Sales and office	25.28	16.01	21.72
Farming, fishing and forestry	0.59	4.51	0.30
Construction, extraction and maintenance	10.12	15.17	6.36
Production, transportation and material moving	14.90	26.01	13.66
Industry			
Agriculture, forestry, fishing and hunting	1.71	4.82	0.52
Mining	0.53	0.27	0.16
Construction	7.08	11.31	4.32
Manufacturing	15.29	19.47	16.08
Trade	13.64	13.04	13.53
Transportation, warehousing, information and communications	7.71	5.70	7.57
Utilities	1.17	0.40	0.51
Finance, insurance, real estate, and rental and leasing	6.90	4.05	7.06
Service	39.79	38.73	46.55
Public administration	6.19	2.20	3.70
Sample size	477,564	35,091	41,335

Source: 2000 U.S. Census, Public Use Microdata Sample (1% sample).

Table A-2. Variables Description

Variable	Description
Dependent	
log(hrwage)	Natural logarithm of the individual's hourly wage for 1999, computed by dividing the annual income for 1999 by the product of weeks worked in 1999 and hours worked per week in 1999. The wage variable reports each respondent's total pre-tax wage and salary income -- that is, money received as an employee-- for the previous year.
Independent	
Age	Reports the person's age in years as of last birthday
Agesq	Age squared
Married	Dummy variable, 1= the individual is married, spouse present
Black	Dummy variable, 1= the individual is black
Education	Set of dummy variables identifying the highest educational level attained by the individual (college or more is excluded)
No schooling	1=individual has no education
1 to 8 years completed	1=individual has 1 to 8 years of education completed
9 to 11 years completed	1=individual has 9 to 11 years of education completed
High school	1=individual has high school diploma
Some college	1=individual has 1 to 3 years of college education
College or more	1=individual has college degree or more
Metropolitan	Dummy variable, 1=indvidual reports living in a metropolitan area
Household head	Dummy variable, 1=indvidual is the household head
Latin American	Dummy variable, 1= immigrant comes from one of the Latin American countries as defined in the text
Other immigrant	Dummy variable, 1= immigrant comes from a country not located in Latin America
Cohort	Set of dummy variables that distinguish immigrants according to their year of arrival in the U.S. (Cohort 1 excluded)
Cohort 1	0 to 5 years since arrival, workers who arrived between 1995 and 2000
Cohort 2	6 to 10 years since arrival, workers who arrived between 1990 and 1994
Cohort 3	11 to 15 years since arrival, workers who arrived between 1985 and 1989
Cohort 4	16 to 20 years since arrival, workers who arrived between 1980 and 1984
Cohort 5	21 to 25 years since arrival, workers who arrived between 1975 and 1979
Cohort 6	26 or more years since arrival, workers who arrived before 1974
Self-employed	Dummy variable, 1=indvidual reports living in a metropolitan area
Part-time	Dummy variable, 1=individual works 40 hours a week or less
Occupation	Set of dummy variables identifying occupation (management and professional occupations excluded)
Service	
Sales	
Farm	
Construction	
Production	
Industry	Set of dummy variables identifying industry in which the individual works (service is excluded)
Agriculture	
Mining	
Construction	
Manufacturing	
Trade	
Tranportation and Communications	
Utilities	
Finance	
Government	

Table A-3. OLS and quantile regression estimates

	Variable	OLS	Quantile 10th	20th	30th	40th	50th	60th	70th	80th	90th
Demographic variables	Constant	1.77	1.26	1.46	1.59	1.68	1.77	1.80	1.94	2.10	2.35
		(-0.018)	(-0.021)	(-0.016)	(-0.014)	(-0.013)	(-0.013)	(-0.015)	(-0.016)	(-0.018)	(-0.027)
	Age	0.05	0.04	0.04	0.04	0.04	0.04	0.05	0.05	0.05	0.05
		(-0.00089)	(-0.00097)	(-0.00077)	(-0.00065)	(-0.00062)	(-0.00066)	(-0.00075)	(-0.00077)	(-0.00087)	(-0.0013)
	Age squared	-0.0005	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0005	-0.0004	-0.0004	-0.0004
		(-0.000011)	(-0.000011)	(-0.000009)	(-0.000007)	(-0.000007)	(-0.000008)	(-0.000009)	(-0.000009)	(-0.00001)	(-0.000015)
	Married	0.16	0.13	0.13	0.13	0.13	0.13	0.14	0.14	0.13	0.14
		(-0.002)	(-0.002)	(-0.002)	(-0.002)	(-0.002)	(-0.002)	(-0.002)	(-0.002)	(-0.002)	(-0.003)
	Black	-0.11	-0.12	-0.12	-0.11	-0.11	-0.11	-0.11	-0.11	-0.10	-0.09
		(-0.004)	(-0.004)	(-0.004)	(-0.003)	(-0.003)	(-0.003)	(-0.003)	(-0.003)	(-0.004)	(-0.005)
	Metropolitan area	0.18	0.10	0.12	0.14	0.15	0.16	0.17	0.17	0.18	0.18
		(-0.002)	(-0.002)	(-0.002)	(-0.002)	(-0.002)	(-0.002)	(-0.002)	(-0.002)	(-0.002)	(-0.003)
	Household head	0.11	0.13	0.12	0.12	0.11	0.10	0.10	0.10	0.09	0.08
		(-0.003)	(-0.003)	(-0.003)	(-0.002)	(-0.002)	(-0.002)	(-0.002)	(-0.002)	(-0.003)	(-0.004)
	No schooling	-0.52	-0.47	-0.46	-0.47	-0.49	-0.52	-0.57	-0.57	-0.58	-0.59
		(-0.013)	(-0.022)	(-0.013)	(-0.012)	(-0.011)	(-0.011)	(-0.012)	(-0.014)	(-0.013)	(-0.019)
	1 to 8 years	-0.51	-0.36	-0.39	-0.43	-0.45	-0.51	-0.57	-0.58	-0.59	-0.62
		(-0.007)	(-0.008)	(-0.006)	(-0.006)	(-0.005)	(-0.005)	(-0.007)	(-0.007)	(-0.007)	(-0.011)
	9 to 11 years	-0.45	-0.31	-0.33	-0.36	-0.40	-0.44	-0.49	-0.49	-0.51	-0.54
		(-0.005)	(-0.005)	(-0.005)	(-0.004)	(-0.004)	(-0.004)	(-0.004)	(-0.004)	(-0.005)	(-0.007)
	High school	-0.34	-0.16	-0.20	-0.25	-0.29	-0.33	-0.36	-0.38	-0.40	-0.46
		(-0.004)	(-0.003)	(-0.003)	(-0.003)	(-0.003)	(-0.003)	(-0.003)	(-0.003)	(-0.003)	(-0.005)
	Some college	-0.25	-0.09	-0.15	-0.18	-0.22	-0.24	-0.26	-0.28	-0.30	-0.36
		(-0.003)	(-0.003)	(-0.003)	(-0.003)	(-0.003)	(-0.003)	(-0.003)	(-0.003)	(-0.003)	(-0.005)
Immigration dummies	Latin American	-0.26	-0.36	-0.35	-0.33	-0.31	-0.29	-0.27	-0.26	-0.24	-0.20
		(-0.009)	(-0.013)	(-0.011)	(-0.01)	(-0.009)	(-0.008)	(-0.01)	(-0.011)	(-0.013)	(-0.015)
	Cohort2	0.07	0.10	0.09	0.09	0.08	0.08	0.07	0.06	0.06	0.05
		(-0.013)	(-0.017)	(-0.014)	(-0.013)	(-0.012)	(-0.011)	(-0.013)	(-0.015)	(-0.016)	(-0.024)
	Cohort3	0.08	0.15	0.13	0.12	0.12	0.11	0.09	0.09	0.08	0.04
		(-0.012)	(-0.016)	(-0.013)	(-0.012)	(-0.011)	(-0.011)	(-0.012)	(-0.013)	(-0.015)	(-0.02)
	Cohort4	0.10	0.20	0.18	0.16	0.14	0.13	0.12	0.10	0.09	0.05
		(-0.013)	(-0.018)	(-0.014)	(-0.012)	(-0.011)	(-0.012)	(-0.012)	(-0.014)	(-0.015)	(-0.019)
	Cohort5	0.16	0.24	0.23	0.21	0.18	0.16	0.15	0.13	0.12	0.11
		(-0.015)	(-0.019)	(-0.015)	(-0.013)	(-0.012)	(-0.013)	(-0.013)	(-0.015)	(-0.017)	(-0.022)
	Cohort6	0.17	0.29	0.27	0.25	0.22	0.20	0.19	0.17	0.15	0.12
		(-0.013)	(-0.017)	(-0.013)	(-0.013)	(-0.011)	(-0.01)	(-0.012)	(-0.014)	(-0.015)	(-0.022)
	Non-Latin Americar	-0.12	-0.25	-0.20	-0.16	-0.11	-0.08	-0.05	-0.02	0.00	0.00
		(-0.01)	(-0.016)	(-0.011)	(-0.011)	(-0.01)	(-0.009)	(-0.009)	(-0.01)	(-0.01)	(-0.012)
	Cohort2	-0.06	-0.02	-0.02	-0.06	-0.09	-0.10	-0.10	-0.11	-0.11	-0.09
		(-0.019)	(-0.026)	(-0.021)	(-0.019)	(-0.02)	(-0.018)	(-0.018)	(-0.021)	(-0.024)	(-0.034)
	Cohort3	-0.02	0.01	0.00	-0.03	-0.07	-0.09	-0.09	-0.10	-0.10	-0.05
		(-0.019)	(-0.026)	(-0.021)	(-0.019)	(-0.017)	(-0.018)	(-0.019)	(-0.019)	(-0.022)	(-0.031)
	Cohort4	-0.04	-0.05	-0.04	-0.05	-0.08	-0.08	-0.10	-0.12	-0.12	-0.08
		(-0.02)	(-0.026)	(-0.02)	(-0.019)	(-0.017)	(-0.017)	(-0.018)	(-0.019)	(-0.02)	(-0.028)
	Cohort5	-0.03	-0.03	-0.03	-0.05	-0.07	-0.07	-0.08	-0.10	-0.12	-0.08
		(-0.022)	(-0.028)	(-0.02)	(-0.019)	(-0.018)	(-0.019)	(-0.019)	(-0.022)	(-0.025)	(-0.03)
	Cohort6	0.00	-0.04	-0.05	-0.05	-0.07	-0.07	-0.08	-0.09	-0.10	-0.05
		(-0.018)	(-0.024)	(-0.018)	(-0.018)	(-0.016)	(-0.016)	(-0.016)	(-0.018)	(-0.02)	(-0.028)

Source: 2000 U.S. Census, Public Use Microdata Sample (1% sample). Bootstrapped standard errors in paretheses (500 replications). Sample size is 553,990.

	Variable	OLS	Quantile								
			10th	20th	30th	40th	50th	60th	70th	80th	90th
Occupation	Service	-0.34	-0.26	-0.28	-0.29	-0.29	-0.30	-0.30	-0.30	-0.30	-0.31
		(-0.004)	(-0.005)	(-0.004)	(-0.004)	(-0.003)	(-0.003)	(-0.004)	(-0.004)	(-0.004)	(-0.006)
	Sales	-0.22	-0.16	-0.19	-0.21	-0.21	-0.21	-0.20	-0.19	-0.19	-0.18
		(-0.004)	(-0.004)	(-0.003)	(-0.003)	(-0.003)	(-0.003)	(-0.003)	(-0.003)	(-0.004)	(-0.006)
	Farming	-0.11	-0.50	-0.42	-0.36	-0.30	-0.23	-0.09	-0.10	-0.13	-0.14
		(-0.013)	(-0.018)	(-0.01)	(-0.009)	(-0.01)	(-0.009)	(-0.02)	(-0.017)	(-0.017)	(-0.024)
	Construction	-0.25	-0.10	-0.13	-0.14	-0.16	-0.17	-0.17	-0.17	-0.19	-0.23
		(-0.004)	(-0.004)	(-0.003)	(-0.003)	(-0.003)	(-0.003)	(-0.003)	(-0.003)	(-0.004)	(-0.005)
	Production	-0.32	-0.26	-0.27	-0.28	-0.28	-0.27	-0.26	-0.25	-0.26	-0.28
		(-0.004)	(-0.004)	(-0.003)	(-0.003)	(-0.003)	(-0.003)	(-0.003)	(-0.003)	(-0.003)	(-0.005)
Type of empl.	Self-employed	-1.55	-2.34	-2.46	-2.51	-2.51	-2.44	-1.38	-0.63	-0.33	-0.10
		(-0.006)	(-0.003)	(-0.003)	(-0.003)	(-0.003)	(-0.006)	(-0.036)	(-0.009)	(-0.007)	(-0.008)
	Part-time	-0.06	-0.19	-0.17	-0.13	-0.10	-0.08	-0.05	0.02	0.13	0.32
		(-0.005)	(-0.005)	(-0.004)	(-0.004)	(-0.004)	(-0.004)	(-0.005)	(-0.006)	(-0.006)	(-0.01)
Industry	Agriculture	-0.43	0.02	-0.03	-0.08	-0.15	-0.21	-0.42	-0.37	-0.33	-0.31
		(-0.011)	(-0.006)	(-0.005)	(-0.005)	(-0.005)	(-0.007)	(-0.019)	(-0.015)	(-0.013)	(-0.017)
	Mining	0.25	0.18	0.21	0.22	0.23	0.24	0.24	0.23	0.22	0.20
		(-0.011)	(-0.019)	(-0.01)	(-0.01)	(-0.009)	(-0.011)	(-0.009)	(-0.009)	(-0.009)	(-0.011)
	Construction	0.11	0.13	0.12	0.11	0.10	0.11	0.12	0.12	0.12	0.12
		(-0.005)	(-0.004)	(-0.004)	(-0.003)	(-0.003)	(-0.004)	(-0.004)	(-0.004)	(-0.004)	(-0.006)
	Manufacturing	0.21	0.28	0.25	0.23	0.21	0.20	0.18	0.16	0.14	0.11
		(-0.003)	(-0.004)	(-0.003)	(-0.003)	(-0.002)	(-0.003)	(-0.003)	(-0.003)	(-0.003)	(-0.004)
	Trade	0.08	0.09	0.07	0.06	0.05	0.06	0.06	0.05	0.05	0.05
		(-0.004)	(-0.005)	(-0.004)	(-0.003)	(-0.003)	(-0.003)	(-0.003)	(-0.003)	(-0.004)	(-0.006)
	Transp. & Comm.	0.17	0.21	0.21	0.20	0.19	0.18	0.17	0.15	0.14	0.12
		(-0.004)	(-0.005)	(-0.004)	(-0.004)	(-0.003)	(-0.003)	(-0.003)	(-0.003)	(-0.004)	(-0.006)
	Utilities	0.32	0.38	0.37	0.37	0.36	0.34	0.31	0.29	0.27	0.24
		(-0.006)	(-0.012)	(-0.009)	(-0.006)	(-0.006)	(-0.006)	(-0.005)	(-0.006)	(-0.006)	(-0.009)
	Finance	0.19	0.13	0.12	0.12	0.13	0.16	0.18	0.20	0.23	0.34
		(-0.006)	(-0.005)	(-0.005)	(-0.005)	(-0.004)	(-0.004)	(-0.006)	(-0.006)	(-0.007)	(-0.013)
	Government	0.14	0.22	0.21	0.19	0.17	0.16	0.15	0.13	0.11	0.07
		(-0.004)	(-0.006)	(-0.004)	(-0.004)	(-0.004)	(-0.004)	(-0.004)	(-0.004)	(-0.004)	(-0.006)

Source: 2000 U.S. Census, Public Use Microdata Sample (1% sample). Bootstrapped standard errors in paretheses (500 replications). Sample size is 553,990.

Table A-4. Matching decomposition – All cohorts of arrival

	Age	+ Marital Status	+ Race	+ Education	+ Metropolitan	+ Household head
Δ	-13.88%	-13.88%	-13.88%	-13.88%	-13.88%	-13.88%
$\Delta 0$	-13.28%	-12.97%	-12.40%	-5.52%	-6.09%	-5.81%
ΔN	0.00%	0.00%	0.00%	0.00%	0.00%	-4.94E-06
ΔI	0.00%	0.00%	0.00%	0.00%	0.03%	0.10%
ΔX	-0.59%	-0.90%	-1.48%	-8.36%	-7.82%	-8.16%
% Native in CS	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
% LA Immigrant in CS	100.00%	100.00%	100.00%	99.98%	99.55%	98.82%
Std. Error $\Delta 0$	0.108%	0.090%	0.086%	0.066%	0.061%	0.060%

	Demographic set	& Part-time	&Type of empl.	& Occupation	& Industry	Full set
Δ	-13.88%	-13.88%	-13.88%	-13.88%	-13.88%	-13.88%
$\Delta 0$	-5.81%	-6.06%	-7.04%	-4.81%	-5.27%	-5.47%
ΔN	-4.94E-06	-3.20E-05	-0.08%	-0.07%	-0.07%	-0.80%
ΔI	0.10%	0.17%	0.42%	0.40%	0.38%	3.17%
ΔX	-8.16%	-7.98%	-7.18%	-9.40%	-8.93%	-10.77%
% Native in CS	100.00%	99.98%	99.90%	99.31%	99.24%	93.86%
% LA Immigrant in CS	98.82%	98.23%	98.28%	95.75%	93.76%	77.68%
Std. Error $\Delta 0$	0.060%	0.059%	0.057%	0.058%	0.058%	0.059%

Table A-5. Matching decomposition – Cohort 1

	Age	+ Marital Status	+ Race	+ Education	+ Metropolitan	+ Household head
Δ	-19.88%	-19.88%	-19.88%	-19.88%	-19.88%	-19.88%
$\Delta 0$	-18.71%	-16.65%	-15.12%	-12.13%	-13.04%	-13.06%
ΔN	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
ΔI	0.00%	0.00%	0.02%	0.00%	0.22%	0.38%
ΔX	1.18%	-3.23%	-4.79%	-7.76%	-7.06%	-7.20%
% Native in CS	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
% LA Immigrant in CS	100.00%	100.00%	99.69%	97.42%	95.15%	93.27%
Std. Error $\Delta 0$	0.220%	0.177%	0.165%	0.104%	0.085%	0.080%

	Demographic set	& Part-time	&Type of empl.	& Occupation	& Industry	Full set
Δ	-19.88%	-19.88%	-19.88%	-19.88%	-19.88%	-19.88%
$\Delta 0$	-13.06%	-13.37%	-16.19%	-10.58%	-12.37%	-11.67%
ΔN	0.00%	-6.06E-05	-0.13%	-0.07%	-0.07%	-0.51%
ΔI	0.38%	0.75%	3.54%	1.56%	1.01%	6.25%
ΔX	-7.20%	-7.26%	-7.10%	-10.79%	-8.45%	-13.96%
% Native in CS	100.00%	99.98%	99.82%	99.26%	99.07%	94.11%
% LA Immigrant in CS	93.27%	91.09%	88.10%	81.03%	74.71%	44.76%
Std. Error $\Delta 0$	0.080%	0.077%	0.067%	0.070%	0.068%	0.070%

Table A-6. Matching decomposition – Cohort 2

	Age	+ Marital Status	+ Race	+ Education	+ Metropolitan	+ Household head
Δ	-17.78%	-17.78%	-17.78%	-17.78%	-17.78%	-17.78%
$\Delta 0$	-17.03%	-16.59%	-16.22%	-10.91%	-10.97%	-10.60%
ΔN	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
ΔI	0.00%	0.00%	0.02%	0.02%	0.18%	0.36%
ΔX	-0.75%	-1.19%	-1.58%	-6.88%	-6.99%	-7.53%
% Native in CS	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
% LA Immigrant in CS	100.00%	100.00%	99.10%	98.90%	94.94%	92.72%
Std. Error $\Delta 0$	0.228%	0.185%	0.174%	0.107%	0.087%	0.084%

	Demographic set	& Part-time	&Type of empl.	& Occupation	& Industry	Full set
Δ	-17.78%	-17.78%	-17.78%	-17.78%	-17.78%	-17.78%
$\Delta 0$	-10.60%	-11.42%	-12.25%	-8.73%	-11.38%	-9.50%
ΔN	0.00%	0.00%	-0.11%	-0.07%	0.02%	-0.49%
ΔI	0.36%	0.83%	2.58%	1.55%	1.14%	5.14%
ΔX	-7.53%	-7.19%	-8.00%	-10.53%	-7.55%	-12.92%
% Native in CS	100.00%	100.00%	99.86%	99.06%	98.89%	93.60%
% LA Immigrant in CS	92.72%	88.89%	88.90%	79.86%	72.52%	43.15%
Std. Error $\Delta 0$	0.084%	0.081%	0.068%	0.074%	0.070%	0.076%

Table A-7. Matching decomposition – Cohort 3

	Age	+ Marital Status	+ Race	+ Education	+ Metropolitan	+ Household head
Δ	-16.09%	-16.09%	-16.09%	-16.09%	-16.09%	-16.09%
$\Delta 0$	-16.98%	-16.78%	-15.97%	-11.88%	-15.83%	-15.78%
ΔN	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
ΔI	0.00%	0.00%	0.02%	0.00%	0.13%	0.37%
ΔX	0.89%	0.69%	-0.14%	-4.22%	-0.40%	-0.68%
% Native in CS	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
% LA Immigrant in CS	100.00%	100.00%	99.10%	97.13%	95.74%	91.46%
Std. Error $\Delta 0$	0.208%	0.165%	0.155%	0.104%	0.082%	0.080%

	Demographic set	& Part-time	&Type of empl.	& Occupation	& Industry	Full set
Δ	-16.09%	-16.09%	-16.09%	-16.09%	-16.09%	-16.09%
$\Delta 0$	-15.78%	-14.96%	-13.69%	-13.29%	-11.84%	-9.37%
ΔN	0.00%	0.00%	-0.12%	-0.03%	-0.05%	-0.91%
ΔI	0.37%	0.68%	1.40%	1.23%	0.61%	4.70%
ΔX	-0.68%	-1.81%	-3.68%	-4.00%	-4.81%	-10.51%
% Native in CS	100.00%	100.00%	99.84%	99.39%	99.41%	93.41%
% LA Immigrant in CS	91.46%	89.25%	89.82%	81.39%	73.71%	48.36%
Std. Error $\Delta 0$	0.080%	0.078%	0.064%	0.072%	0.070%	0.071%

Table A-8. Matching decomposition – Cohort 4

	Age	+ Marital Status	+ Race	+ Education	+ Metropolitan	+ Household head
Δ	-13.54%	-13.54%	-13.54%	-13.54%	-13.54%	-13.54%
$\Delta 0$	-15.35%	-15.27%	-14.53%	-7.47%	-8.18%	-7.22%
ΔN	0.00%	0.00%	0.00%	0.00%	0.00%	-3.18E-05
ΔI	0.00%	0.00%	0.00%	-0.03%	0.21%	0.41%
ΔX	1.81%	1.73%	0.98%	-6.05%	-5.58%	-6.73%
% Native in CS	100.00%	100.00%	100.00%	100.00%	100.00%	99.98%
% LA Immigrant in CS	100.00%	100.00%	100.00%	98.50%	95.34%	93.09%
Std. Error $\Delta 0$	0.232%	0.183%	0.171%	0.106%	0.084%	0.080%

	Demographic set	& Part-time	&Type of empl.	& Occupation	& Industry	Full set
Δ	-13.54%	-13.54%	-13.54%	-13.54%	-13.54%	-13.54%
$\Delta 0$	-7.22%	-7.73%	-8.30%	-6.55%	-6.88%	-6.63%
ΔN	-3.18E-05	-3.18E-05	-0.03%	-0.10%	-0.09%	-0.83%
ΔI	0.41%	0.75%	2.03%	1.44%	1.15%	5.39%
ΔX	-6.73%	-6.56%	-7.24%	-8.33%	-7.72%	-11.47%
% Native in CS	99.98%	99.98%	99.95%	99.22%	99.27%	93.86%
% LA Immigrant in CS	93.09%	90.71%	90.31%	82.09%	75.68%	48.77%
Std. Error $\Delta 0$	0.080%	0.077%	0.065%	0.072%	0.069%	0.070%

Table A-9. Matching decomposition – Cohort 5

	Age	+ Marital Status	+ Race	+ Education	+ Metropolitan	+ Household head
Δ	-10.82%	-10.82%	-10.82%	-10.82%	-10.82%	-10.82%
$\Delta 0$	-11.55%	-11.54%	-11.00%	-2.87%	-3.78%	-3.98%
ΔN	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
ΔI	0.00%	0.00%	0.00%	0.08%	0.44%	0.61%
ΔX	0.73%	0.72%	0.18%	-8.02%	-7.49%	-7.45%
% Native in CS	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
% LA Immigrant in CS	100.00%	100.00%	100.00%	98.06%	94.29%	92.04%
Std. Error $\Delta 0$	0.283%	0.222%	0.207%	0.127%	0.101%	0.097%

	Demographic set	& Part-time	&Type of empl.	& Occupation	& Industry	Full set
Δ	-10.82%	-10.82%	-10.82%	-10.82%	-10.82%	-10.82%
$\Delta 0$	-3.98%	-3.81%	-4.63%	-1.27%	-2.30%	-0.45%
ΔN	0.00%	-1.23E-04	-4.50E-04	-0.04%	-0.10%	-0.89%
ΔI	0.61%	1.07%	2.42%	1.79%	1.30%	5.89%
ΔX	-7.45%	-8.07%	-8.57%	-11.31%	-9.72%	-15.38%
% Native in CS	100.00%	99.97%	99.95%	99.10%	99.13%	92.94%
% LA Immigrant in CS	92.04%	88.90%	89.14%	80.70%	74.30%	44.74%
Std. Error $\Delta 0$	0.097%	0.093%	0.075%	0.079%	0.074%	0.075%

Table A-10. Matching decomposition – Cohort 6

	Age	+ Marital Status	+ Race	+ Education	+ Metropolitan	+ Household head
Δ	-5.76%	-5.76%	-5.76%	-5.76%	-5.76%	-5.76%
$\Delta 0$	-5.46%	-5.55%	-5.15%	0.33%	-1.26%	-1.22%
ΔN	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
ΔI	0.00%	0.00%	0.00%	0.06%	0.23%	0.29%
ΔX	-0.29%	-0.21%	-0.61%	-6.15%	-4.73%	-4.82%
% Native in CS	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
% LA Immigrant in CS	100.00%	100.00%	100.00%	99.65%	97.77%	96.90%
Std. Error $\Delta 0$	0.222%	0.172%	0.161%	0.099%	0.081%	0.077%

	Demographic set	& Part-time	&Type of empl.	& Occupation	& Industry	Full set
Δ	-5.76%	-5.76%	-5.76%	-5.76%	-5.76%	-5.76%
$\Delta 0$	-1.22%	-1.64%	-1.78%	-1.22%	-0.68%	-1.70%
ΔN	0.00%	-3.79E-05	0.00%	-0.09%	-0.08%	-1.03%
ΔI	0.29%	0.53%	1.17%	1.03%	1.11%	5.60%
ΔX	-4.82%	-4.63%	-5.15%	-5.48%	-6.10%	-8.63%
% Native in CS	100.00%	99.97%	99.98%	99.47%	99.52%	94.79%
% LA Immigrant in CS	96.90%	95.19%	95.18%	88.94%	85.41%	61.71%
Std. Error $\Delta 0$	0.077%	0.074%	0.063%	0.069%	0.065%	0.066%