THREE ESSAYS ON ILLEGAL IMMIGRATION

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This dissertation consists of three essays studying illegal immigration in the United States. In the first chapter I extend the standard Mortensen-Pissarides labor market model to study the effect of two immigration policies, an amnesty and tighter border enforcement, on the wages and unemployment rates of US natives and Mexican immigrants. A key finding of this paper is that natives might benefit from the presence of illegal workers in the economy. The presence of illegal workers increases firms' incentives to open vacancies, which increases the wages of natives and decreases their unemployment rate. Moreover, this paper also shows that the effect of border enforcement on the number of illegal workers in the US is ambiguous. Tighter border enforcement deters illegal migration of prospective workers, but decreases return migration.

In the second chapter I estimate the effect of legal status on the wages of immigrants using Mexico's Survey of Migration to the Northern Border. I control for possible selection biases and test for selectivity in the population obtaining legal status. The analysis shows that legal workers earn higher wages than illegal workers, especially those working in the production and services sectors. Moreover, within sectors the wage gap varies by occupation, and is larger among individuals working in formal jobs. The results show that once we control for observable characteristics, there is no evidence of selectivity among Mexican workers obtaining legal status.

In the third chapter I study return migration and test Borjas and Bratsberg's (1996) prediction that the return migration process further accentuates the type of selection observed among immigrants moving from Mexico to the US. I use data from the Survey of Migration

to the Northern Border together with a selection model to infer the unobservable skills of Mexican immigrants and the unexpected component of their earnings in the US. The results show that immigrants are negatively selected relative to the Mexican population. Consistent with Borjas and Bratsberg's prediction, return migrants are relatively more skilled than the typical immigrant. Moreover, workers who face more negative unexpected conditions in the US are those who find it optimal to return to Mexico.

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PREFACE

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1.0 INTRODUCTION

This dissertation consists of three essays studying illegal immigration in the United States. In the last four decades, illegal immigration has become one of the most important economic and political issues in the United States. The population of illegal immigrants is estimated to be 11 million and every year an important number of illegal immigrants arrive. Over the last few years, immigration reform has been a controversial issue among policymakers. While there is a broad consensus that comprehensive immigration reform is needed, the terms in which this reform has to be done have been subject of intense debate.

In the first chapter I analyze the effects of two immigration policies intended to decrease the number of illegal workers in the United States: an amnesty and an increase in border enforcement. I use a Mortensen-Pissarides (1994) style labor market model to capture the effect of these policies on two key dimensions in a general equilibrium setting: wages and unemployment rates. I extend the standard Mortensen-Pissarides labor market model to legal and illegal workers, and account for return migration. I calibrate the model and use data on Mexican illegal immigration to quantitatively assess the effect of policies on wages and unemployment rates.

A key finding of this chapter is that natives might benefit from the presence of illegal workers in the economy. The presence of illegal workers might increase firms' incentives to open job vacancies (since illegal workers have low outside options), which would increase the wages of natives and decrease their unemployment rate. Moreover, the results show that the effect of border enforcement on the number of illegal workers in the U.S. is ambiguous. Tighter border enforcement deters illegal migration of prospective workers, but decreases return migration. Moreover, I study the effect of an amnesty in an economy where illegal workers can be paid off the books, or can get formal jobs and have payroll taxes withheld

(e.g. use false social security numbers or social security numbers that belong to someone else). The results show that the larger the proportion of illegal workers paid off the books, the smaller will be the decrease in the wages of workers in the event of an amnesty.

A key assumption of this model is the fact that legal workers earn on average higher wages than illegal workers. An interesting question is whether those wage differences can be explained by differences in migrants' characteristics such as education or occupation, or if those differences are associated with their illegal status. In the second chapter I estimate the effect of legal status on the wages of immigrants using Mexico's Survey of Migration to the Northern Border. I control for possible selection biases and test for selectivity in the population obtaining legal status exploiting the random variation in legal status that comes from a change in the U.S. migration policy.

The analysis shows that legal workers earn higher wages than illegal workers, especially those working in the production and services sectors. Moreover, within sectors the wage gap varies by occupation, and is larger among individuals working in formal jobs. The results also show that once we control for observable characteristics, there is no evidence of selectivity among Mexican workers obtaining legal status.

An important feature of illegal immigration is its high mobility. To better understand the dynamics of the immigrant flow, it is essential to analyze the characteristics of return migrants. Return migration is an important phenomenon that has received little attention in the literature even though it involves a large share of migrants and has large social, economic, and cultural impacts on both, the home and host countries. If long-term settlement is not a random process, return migration will not only affect the composition of the immigrant population and their use of social services in the host country, but also the economic development in the home country through remittances and investment.

In the third chapter I study return migration of Mexican migrants in the United States. I test Borjas and Bratsberg's (1996) prediction that the return migration process accentuates the type of selection that originally characterized the immigrant flow. I use data from the Survey of Migration to the Northern Border together with a selection model to infer the unobservable skills of Mexican immigrants and the unexpected component of their earnings in the U.S. The results show that immigrants are negatively selected relative to the Mexican

population. Consistent with Borjas and Bratsberg's prediction, return migrants are relatively more skilled than the typical immigrant; workers with the lowest unobservable skills are the ones who find optimal to reside in the United States. Moreover, workers who face more negative unexpected conditions in the U.S. are those who find optimal to return to Mexico.

2.0 LABOR MARKET EFFECTS OF IMMIGRATION POLICIES

2.1 INTRODUCTION

In the last four decades, illegal immigration has become one of the most important economic and political issues in the United States (U.S.). The population of illegal immigrants is estimated to be 11 million and every year another 500,000 illegal immigrants arrive.[1] Over the last three years, immigration reform has been a controversial issue among policymakers. While there is a broad consensus that comprehensive immigration reform is needed, the terms in which this reform has to be done have been subject of intense debate. Major policy proposals have centered mainly around two types of changes: (1) increases in border control,[2] and (2) the creation of a pathway toward legal status.[3]

Even though changes to the immigration system have potentially large implications, little research has been devoted to analyze the effects that different policies would have on the U.S. labor market. In this paper I analyze the effects of two immigration policies intended to decrease the number of illegal workers in the U.S.: amnesty and an increase in border enforcement.

I use a Mortensen-Pissarides (1994) style labor market model to capture the effect of these policies on two key dimensions in a general equilibrium setting: wages and unemployment

[1] According to Passel and Cohn (2010), the estimate of the number of unauthorized immigrants arrived from Mexico during the first half of the decade is 500,000.

[2] Border enforcement has been a cornerstone of U.S. immigration policy. Border controls on the flow of illegal Mexican immigrants are of primary importance for several reasons. First, Mexico is the most important source country for U.S. immigration and the leading source of unauthorized immigrants to the U.S. Second, most illegal Mexican entries occur through the southern U.S. border, and third, undocumented Mexican migrants tend to be very mobile, undertaking multiple trips to the U.S. over their life cycle.

[3] A pathway toward legal status is one of the proposals to reform the immigration system that have generated more controversy. The U.S. has not enacted a major amnesty program legalizing undocumented immigrants since 1986 when IRCA granted legal status to 2.7 million illegal workers.

rates. The Mortensen-Pissarides model has become one of the most important frameworks used to study the unemployment and welfare effects of labor market policies. This model is characterized by the existence of search and matching frictions. Each period firms post vacancies in search for workers and a matching function determines the flow of new matches between firms and workers. Wages are determined by Nash bilateral bargaining. After a match is formed and a wage bargained, production starts, output is sold, and the wage is split according to the bargaining rule.

In order to assess the effect of immigration policies in the labor market outcomes of U.S. natives and Mexican immigrants, in this paper I extend the standard Mortensen-Pissarides model to include two types of workers: workers authorized to work (natives and legal immigrants) and illegal workers. Additionally, the model accounts for return migration. Illegal immigrants are characterized by their high mobility. While hundreds of thousands of immigrants enter the U.S. every year, almost half of these migrants return to their home country within twelve months (Reyes and Mameesh (2002), Gitter, Gitter and Southgate (2008)). In this model immigration decisions may not be permanent. Individuals consider the benefits of living in Mexico and the United States and decide whether to migrate or return to Mexico to maximize their expected utility. Finally, I calibrate the model and use data from a rich previously unexplored dataset on illegal migration to quantitatively assess the effect of the two immigration policies.[4]

One of the key findings of this paper is that the presence of illegal immigrants might have a positive effect on the wages of natives. Results show that an amnesty reducing the illegal population by 50 percent would decrease the wages of natives by 0.12 percent and increase their unemployment rate by 0.45 percent. The model predicts that a decrease in the number of illegal workers would decrease firms' incentives to open positions since firms' probability of finding a worker with a low outside option decreases. The decrease in the number of vacancies decreases the probability of finding a job decreasing the wages and increasing the unemployment rate of natives.

[4]I use information from the Survey of Migration to the Northern Border (EMIF), a cross-sectional survey conducted ten times between 1993 and 2005 that samples the flows of migrants between Mexico and the U.S. in the northern border region of Mexico. The survey provides information of the flows of migrants between Mexico and the U.S., and information of the labor market outcomes of illegal workers in the U.S. The survey includes return migrants and workers who settled in the U.S.

With respect to changes in border enforcement, results show that an increase in border enforcement doubling migration cost would increase the number of illegal workers by 0.3 percent, increase the wages of legal workers by 0.03 percent, and decrease the wages of illegal workers by 0.45 percent. The model predicts that the effect of changes in border enforcement on the number of illegal workers in the United States is theoretically ambiguous. While tighter border enforcement deters illegal migration of prospective workers, it also changes incentives for those already in the United States decreasing return migration. Consequently, if tighter border enforcement increases the number of illegal workers in the economy, it will increase the wages of natives and have an ambiguous effect on the wages of illegal workers.

These results have important policy implications. First, illegal immigration might have a positive effect on the wages of natives. This is consistent, although due to a different mechanism, to the result of Ottaviano and Peri (2010). They find that the 1990-2006 immigration wave to the U.S. will have a small positive effect on the average wages of natives due to imperfect substitution of immigrants for natives. In my model, the presence of illegal immigrants increases firm's incentives to open vacancies which benefits natives. Second, the model shows that failure to account for return migration might lead us to overestimate the efficacy of border enforcement in decreasing the number of illegal workers in the country. A policy increasing border enforcement might increase the population of illegal workers in the United States, a result in line with the findings of Angelucci (2005).

Finally, I modify the model to study the effect of an amnesty in an economy where illegal workers can be paid off the books, or can get formal jobs and have payroll taxes withheld (e.g. use false social security numbers or social security numbers that belong to someone else). The results show that the larger the proportion of illegal workers paid off the books, the smaller will be the decrease in the wages of workers generated by a decrease in the number of illegal workers in the economy.

2.1.1 Literature Review

The standard Mortensen-Pissarides labor market model has become one of the most important frameworks used to study the unemployment and welfare effects of labor market policies.

Previous studies have analyzed the effect of a variety of policy reforms such as changes in unemployment insurance, taxes and subsidies, and firing costs (Pissarides (1998), Millard and Mortensen (1997), Mortensen and Pissarides (1999)). Moreover, this framework has been frequently used to analyze differences in labor market outcomes of heterogeneous workers (e.g. skilled and unskilled workers (Wong, 2003)), or among individuals working different sectors (e.g. rural and urban sectors (Sato, 2004), or formal and informal sectors (Albrecht, Navarro and Vroman, 2009)). In this paper I extend the standard Mortensen-Pissarides model to include two types of equally productive workers in one labor market: workers with authorization to work (natives and legal immigrants) and illegal workers. Moreover, since undocumented immigrants tend to be very mobile undertaking multiple migration trips over their life cycle, my model accounts for return migration.

A large body of literature has been devoted to analyze the effect of immigration on the wages of natives; however, there has been controversy over the appropriate framework and over the magnitudes involved. Previous studies analyzing cross-city and cross-state evidence in the U.S. have traditionally found small and often insignificant effects of immigration on the wages of native workers (Friedberg and Hunt (1995), Friedberg (2001), and Card (2001, 2005)). A different approach is presented by Borjas (2003) and Borjas and Katz (2007) who emphasize the importance of estimating immigration effects using national level U.S. data. This approach has found a significant negative effect of immigration on the wages of less educated natives. Finally, recent research by Ottaviano and Peri (2010) has found that immigration will have a small positive effect on the average wages of natives. They find that immigrants are imperfect substitutes for native workers of similar education and experience levels and estimate that 1990-2006 immigration wave to the United States will have a very small effect on the wages of native workers with no high school degree (between -0.1 percent and +0.6 percent), a small positive effect on average native wages (+0.6 percent), and a substantial negative effect (-6 percent) on wages of previous immigrants in the long run.

A different line of research has studied the effect of immigration policies on natives and immigrants. Hanson, Robertson, and Spilimbergo (2002) study the impact of border enforcement on wages in the border regions of Mexico and the United States. They find that border enforcement has little impact on wages in U.S. border cities. According to their

findings, border enforcement deters illegal immigrants from crossing, and border regions seem to be adjusting to the influx of illegal immigrants without large changes in wages. Angelucci (2005) studies the effect of border enforcement on the net flow of Mexican undocumented migration. She estimates the impact of enforcement on 1972-1993 migration net flows finding that increases in border controls deter prospective migrants from crossing the border illegally, but lengthen the duration of current illegal migrations. Her estimates of the enforcement overall effect on illegal migration's net flow range across different specifications, from an increase to a decline of about 35 percent of the size of the effect on the inflow. Finally, Kossoudji and Cobb-Clark (2002) estimate the wage benefit received by illegal workers who obtained amnesty under the Immigration Reform and Control Act of 1986 (IRCA). About 2.7 million illegal workers obtained legal status under IRCA. Using a sample of young Latino men who came to the U.S. as unauthorized workers and received amnesty, they find that the benefit of legalization was approximately 6 percent.[5]

2.2 MODEL

2.2.1 Assumptions

This paper introduces a model with two countries: home country (Mexico) and host country (U.S.). In this economy there are two types of equally productive workers: individuals with authorization to work in the U.S. (natives and legal immigrants) and illegal workers.[6] Each period, individuals in Mexico compare their expected earnings in Mexico with their potential earnings in the U.S. net of moving costs and decide to stay or migrate. I assume that all individuals who migrate to the U.S. do it illegally.[7] After spending some time in the U.S.,

[5]The U.S. has not enacted a major amnesty program legalizing undocumented immigrants since the Immigration Reform and Control Act of 1986 (IRCA).

[6]I do not differentiate between legal immigrants and natives. I assume that the differences in job market outcomes of natives and illegal immigrants in the U.S. are mainly due to their "illegal status" and not to the fact of being foreign-born. The terms legal workers and natives are used indistinctively throughout the paper.

[7]Since the number of Mexican workers who enter legally to the U.S. and overstay, or who enter with a tourist visa and decide to work illegally in the U.S. is relatively small, I assume that all workers enter the U.S. illegally. Estimates of Warren (2003) suggest that the share of Mexican legal visitors who overstay is

when an illegal worker loses his job he faces a new decision: he can either return to Mexico or stay in the U.S. Once again, he makes his decision by comparing his expected earnings in Mexico and the U.S.

The U.S. labor market is formed by firms and workers. Each period firms post a certain number of vacancies in search for workers and a matching function determines the flow of new matches between firms and workers. When firms post vacancies, they only know the conditional probability that the match will be formed with a legal or an illegal worker. Once the match is formed, firms realize the worker's type. Wages are determined by Nash bilateral bargaining with an exogenous surplus sharing rule. After a match is formed and a wage bargained, production starts, output is sold, and the wage is split according to the bargaining rule. Firms enter the economy until all rents from new vacancy creation are exhausted.

2.2.2 Workers in Mexico

In period t workers in Mexico draw an ε from a density $f(\varepsilon)$ that determines their income in Mexico.[8] Once they observe their ε they decide whether to stay or migrate. In period $t+1$ a worker who has migrated will receive $U_I - k$ where U_I is the worker's utility of being unemployed in the U.S., and k is a measure of his migration costs. A worker who decided to stay in Mexico will receive $B_M(\varepsilon)$ in period $t+1$. Therefore, the expected worker' utility can be written as

$$B_M(\varepsilon) = \varepsilon + \beta \int \max\left\{U_I - k, B_M(\varepsilon')\right\} f(\varepsilon') d\varepsilon'.$$

I define $\overline{\varepsilon}_M$ as the reservation income in Mexico that makes workers indifferent between stay and migrate, so

$$B_M(\overline{\varepsilon}_M) = U_I - k.$$

Therefore, workers with $\varepsilon < \overline{\varepsilon}_M$ will migrate to the U.S. while workers with $\varepsilon > \overline{\varepsilon}_M$ will stay in Mexico.

lower than that of other nationalities because it is easier for Mexicans to make illegal entries than to get visitor visas.

[8] Epsilon (ε) can be interpreted as a measure of workers' income in Mexico and is uniformly distributed between ε_1 and ε_2.

2.2.3 Workers in the U.S.

When an illegal worker in the U.S. loses his job he faces a new decision: he can either stay in the U.S. or return to Mexico. In period t an unemployed worker in the U.S. draws an ε from the density $f(\varepsilon)$ and compares the utility of being unemployed in the U.S. (U_I) with the expected value of returning to Mexico ($B_M(\varepsilon)$). I define $\overline{\varepsilon}_{US}$ as the reservation income to be received in Mexico that will make a worker indifferent between stay and return, so

$$B_M(\overline{\varepsilon}_{US}) = U_I.$$

Therefore, workers with $\varepsilon < \overline{\varepsilon}_{US}$ will stay in the U.S., and workers with an $\varepsilon > \overline{\varepsilon}_{US}$ will return to Mexico.

2.2.4 Workers' Value Functions

Each period, workers can be either employed or unemployed. Legal and illegal employed workers produce output y and receive wages w_L and w_I respectively. If a worker loses his job he joins the unemployment pool. The value function of an unemployed worker is given by

$$U_n = b_n + \beta \left(q(\theta) W_n + (1 - q(\theta)) U_n \right)$$

where $n = L, I$ represents legal and illegal workers, b_n is the unemployment income (e.g. unemployment benefits, leisure), and β is the discount factor. If an unemployed worker finds a job, which occurs with probability $q(\theta)$, his utility in the next period is given by W_n. If he remains unemployed, which occurs with probability $1 - q(\theta)$, his utility is U_n.

For legal workers, the utility of being employed is given by

$$W_L = w_L + \beta \left(\delta_L W_L + (1 - \delta_L) U_L \right)$$

where δ_L is the probability that the match will continue next period, and $(1 - \delta_L)$ is the probability that the match will end (job destruction rate). The utility of being employed depends on the worker's wage and the discounted value of his expected utility next period: he will receive W_L if he is still employed, and U_L if he becomes unemployed.

For an illegal worker, the utility of being employed is given by

$$W_I = w_I + \beta \left(\delta_I W_I + (1 - \delta_I) \widetilde{U_I} \right)$$

where δ_I is the probability that the match will continue next period and $(1 - \delta_I)$ is their job destruction rate. His utility depends on his wage and the discounted value of his expected utility next period. If the match continues he receives W_I. Since an unemployed illegal worker can stay in the U.S. or return to Mexico if he becomes unemployed, his utility $\widetilde{U_I}$ can be written as

$$\widetilde{U_I} = F(\overline{\varepsilon}_{US}) U_I + (1 - F(\overline{\varepsilon}_{US})) \int_{\overline{\varepsilon}_{US}}^{\infty} B_M(\varepsilon') f(\varepsilon' | \varepsilon' > \overline{\varepsilon}_{US}) d\varepsilon'.$$

If the worker stays in the U.S. his utility is U_I and if he returns to Mexico his utility is $B_M(\varepsilon)$. $F(\overline{\varepsilon}_{US})$ is the probability of having ε lower than $\overline{\varepsilon}_{US}$ (the worker finds optimal to stay in the U.S.), and $(1 - F(\overline{\varepsilon}_{US}))$ is the probability of having ε higher than $\overline{\varepsilon}_{US}$ (the worker finds optimal to return).

It is important to note that the job destruction rate is different between legal and illegal workers and tends to be higher among undocumented workers due to law enforcement (workers can be apprehended and deported) and to the presence of temporary workers (e.g. target earners) in the U.S.

2.2.5 Firms' Value Functions

Each period firms post a certain number of vacancies (i.e. job openings) in search for workers at a cost c per unit of time. The flow of new matches between firms and workers is determined by a matching function. If a firm is matched with a legal or an illegal worker where $n = L, I$, its value function is given by

$$J_n = y - w_n + \beta \left(\delta_n J_n + (1 - \delta_n) V \right)$$

where y denotes the output produced, w_n is the wage paid to each type of worker and V is the value of a firm with an open vacancy. The value of a firm will be given by the output produced net of wages plus the discounted value of the utility of the firm next period. If the

match continues, which occurs with probability δ_n, the value of the firm next period is J_n. If the match ends, which occurs with probability $(1-\delta_n)$, the firm will have an open vacancy and its utility will be V.

The value of a firm with an open vacancy V can be written as

$$V = -c + \beta \left[p(\theta) \left(aJ_L + (1-a) J_I \right) + (1 - p(\theta)) V \right]$$

where $p(\theta)$ is the probability of filling a vacancy, a is the conditional probability that the match will be formed with a legal worker, and $(1-a)$ is the conditional probability that the match will be formed with an illegal worker. Therefore, the value of a firm with an open vacancy will depend on the cost of posting the vacancy and the discounted value of the firm next period. If the firm fills the vacancy, which occurs with probability $p(\theta)$, its value is J_L if the match is with a legal worker and J_I if the match is with an illegal worker. If the vacancy remains open next period, which occurs with probability $(1 - p(\theta))$, the value of the firm is V.

With respect to creation of new jobs, I assume free entry into the economy. In equilibrium $V = 0$, which implies that firms create job vacancies until any incremental profit is exhausted. Finally, the conditional probability that the match is formed with a legal worker is given by

$$a = \frac{u_L}{u_L + u_I}$$

where u_L and u_I are the number of unemployed legal and illegal workers respectively.

2.2.6 Match Formation

When firms post vacancies they know the conditional probability that the match will be formed with a legal worker (a) and the conditional probability that the match will be formed with an illegal worker $(1-a)$. If v and u are the number of vacancies and unemployed workers respectively, then in a given period of time there will be $m(u,v)$ matches between firms and workers. The total number of matches, is given by the matching technology

$$m(u,v) = \frac{uv}{\left(u^\iota + v^\iota\right)^{\frac{1}{\iota}}}$$

where $u = u_L + u_I$. The matching technology is homogeneous of degree one, increasing and concave in its two arguments, and exhibits constant returns to scale. This matching function was chosen following the specification presented by Den Haan, Ramey and Watson (2000). One of the advantages of using this function over the traditional Cobb-Douglas specification is that this function guarantees matching probabilities between zero and one for all u and v.

Let $\theta = \frac{v}{u}$ be the vacancy-unemployment ratio (or labor market tightness). Then the probability of filling a vacancy $p(\theta)$ is given by

$$p(\theta) = \frac{m(u,v)}{v} \ ,$$

and the probability of finding a job $q(\theta)$ is given by

$$q(\theta) = \frac{m(u,v)}{u} = \theta p(\theta) \ .$$

Note that $p'(\theta) < 0$ and $q'(\theta) > 0$. Therefore, the probability of filling a vacancy is higher when the labor market is not tight and the probability of finding a job is higher when the labor market is tight.

2.2.7 Wage Determination

Once a match has been formed, and the firm observes the worker's type, wages are determined by Nash bargaining. Firms and workers have to negotiate, and outside options are worse than an agreement because both parties would need to search again. The Nash solution is to set w_L and w_I to maximize the product surpluses

$$\max_{w_L} (W_L - U_L)^{1-\eta} (J_L - V)^{\eta}$$

and

$$\max_{w_I} (W_I - \widetilde{U}_I)^{1-\eta} (J_I - V)^{\eta},$$

where η is a bargaining parameter.

Solving for w_L and w_I I find that

$$w_L = (1-\eta)y + \eta(1-\beta)U_L$$

and

$$w_I = (1-\eta)y + \eta(1-\beta)\widetilde{U_I}.$$

Notice that the wage depends on productivity as well as on workers' outside options. The difference in the wages of legal and illegal workers

$$w_L - w_I = \eta(1-\beta)(U_L - \widetilde{U_I}),$$

is proportional to the difference in the expected utility of unemployment of legal and illegal workers. Therefore, we can identify two mechanisms that affect the wage gap between legal and illegal workers:

1. If unemployed legal workers have higher utility flow than unemployed illegal workers the wage gap will be higher. This is due to the fact that when bargaining with the firm, legal workers have better outside options than illegal workers, so they get higher wages.
2. If the probability of being terminated is higher for illegal workers, then undocumented workers have a lower utility from being unemployed because their employment relationships are short-lived.

2.2.8 Equilibrium Steady State

In steady state, the flows into and out of unemployment are equal. The steady state condition for unemployment of legal workers is given by

$$u_L = u_L\left(1 - q(\theta)\right) + (1-\delta_L)(\mu_L - u_L)$$

where μ_L is the number of legal workers and u_L is the number of unemployed legal workers. Each period the number of unemployed workers equals the number of workers who were unemployed last period and did not find a job, and the workers who were employed last period $(\mu_L - u_L)$ and lost their job.

The steady state condition for unemployment of illegal workers is given by

$$u_I = u_I\left(1 - q(\theta)\right) + (1-\delta_I)e_I F(\overline{\varepsilon}_{US}) + (\mu_I - u_I - e_I)F(\overline{\varepsilon}_M)$$

where μ_I is the total number of Mexican workers (in Mexico or the U.S.), and u_I and e_I are the number of unemployed and employed Mexican illegal workers in the U.S.

Each period the number of unemployed illegal workers in the U.S. equals the number of workers who were unemployed last period and did not find a job, the workers who were employed last period, lost their job, and decided to stay in the U.S., and the workers from Mexico who decided to migrate this period.

In steady state the flow of workers entering the U.S. must equal the flow of workers leaving the country. Therefore, the steady state condition is given by

$$(1-\delta_I)(1-F(\overline{\varepsilon}_{US}))e_I = (\mu_I - u_I - e_I)F(\overline{\varepsilon}_M)$$

where the number of workers who lost their job and return to Mexico is equal to the number of workers who decided to migrate to the U.S.

2.3 DISCUSSION OF THE EFFECTS OF POLICIES

2.3.1 Effects of an Amnesty

In this section I discuss quantitatively the effect of an amnesty granting legal status to a proportion of the illegal population in the economy. Since the model cannot be solved analytically, I provide intuition on the implications of this policy on the labor market outcomes of natives and immigrants.

An amnesty decreases the number of illegal workers and increases the number of legal workers in the economy. According to the model, a decrease in the number of illegal workers would decrease firms' incentives to post vacancies since firms' probability of finding a worker with a low outside option decreases. The decrease in the number of vacancies decreases labor market tightness (θ), the probability of finding a job $(q(\theta))$, and therefore, increases the unemployment rate of both legal and illegal workers (u_L and u_I).

With respect to wages the model predicts that the decrease in the probability of finding a job $(q(\theta))$ will worsen workers' outside options decreasing the wages received by both types of workers (w_L and w_I).

In this model the presence of illegal workers in the economy has a positive effect on the wages of natives in the long run. This is consistent, although due to a different mechanism, to the result of Ottaviano and Peri (2010). They find that the 1990-2006 immigration wave to the U.S. will have a small positive effect on the average wages of natives due to imperfect substitution of immigrants for natives.

2.3.2 Effects of an Increase in Border Enforcement

I capture the effect of an increase in border enforcement by changing migration costs. The model predicts that higher migration costs (measured in months of earnings in Mexico) would decrease $\overline{\varepsilon}_M$ which implies that less individuals would find optimal to migrate. With respect to the workers in the U.S., the model predicts that $\overline{\varepsilon}_{US}$ increases and more workers find optimal to stay in the U.S. Therefore, the overall effect of an increase in migration costs in the number of illegal workers in the U.S. is ambiguous.

If the overall effect is an increase in the illegal population, the model predicts that firms will have incentives to increase the number of vacancies since firms' probability of finding workers with a low outside option increases. The increase in the number of vacancies increases labor market tightness (θ), the probability of finding a job $(q(\theta))$, and therefore, decreases the unemployment rate of both legal and illegal workers (u_L and u_I).

With respect to wages of legal workers (w_L) the model predicts that the increase in the probability of finding a job $(q(\theta))$ will improve workers' outside options increasing their wages.

Finally, for illegal workers the model predicts that the effect of tighter border enforcement has an ambiguous effect on their wages. On the one hand, the increase in the probability of finding a job $(q(\theta))$ improves workers' outside options increasing their wages. However, the increase in migration costs also worsens workers' outside options (workers are less likely to undertake multiple trips to the U.S.) decreasing their wages.

Table 1: Parameters and Calibrated Targets

Parameter	Value	Source
Output	$y = 1$	Normalization
Discount Factor	$\beta = 0.996$	Pissarides (09)
Bargaining parameter	$\eta = 0.5$	Pissarides (09)
Unemp Income/Leisure Legal	$b_L = 0.71$	Hal & Milgrom (08)
Destruction rate Legal	$1 - \delta_L = 0.034$	Shimer (04)
Destruction rate Illegal	$1 - \delta_I = 0.063$	EMIF 93-05
Migration costs	$K = 4$	EMIF 93-05
Legal Population US	$\mu_L = 0.9$	CPS 00-10
Mexican Population	$\mu_I = 0.1$	ENNVIH 2002, DHS(05&06)
Parameter	Value	Calibration Target
Vacancy cost	$c = 0.377$	Wage gap $\frac{w_L}{w_I} - 1 = 0.09$
Distribution parameter	$\varepsilon_2 = 1.51$	Wage gap $\frac{w_{Mex}}{w_{US}} - 1 = -0.84$
Leisure Illegal	$b_I = 0.235$	Unemployment rate $u = 0.10$
Parameter Matching Function	$\iota = 0.691$	Market tightness $\theta = 0.72$

2.4 QUANTITATIVE ANALYSIS

Next, I use the model to quantitatively assess the effect of an amnesty and tighter border enforcement. I fix some parameters apriori using values typically used in Mortensen-Pissarides style models, a second group of parameters are set using different data sources on illegal immigration, and finally a third group of parameters are calibrated to match some targets in the data. The parameters and calibration targets are summarized in Table 1.

Since legal and illegal workers are assumed to be equally productive, I set the output produced by both types of workers to $y = 1$. The time unit is a month, therefore, the discount factor $\beta = 0.996$ reflects an annual discount rate of 4.8 percent (Pissarides (2009)). I give the worker and firm equal bargaining power by setting $\eta = 0.5$ (Pissarides (2009)). The income equivalent that unemployed legal workers give up to take a job is set at $b_L = 0.71$. It includes both unemployment insurance and the value of time (Hall and Milgrom (2008)). Finally, the job separation rate for legal workers $(1 - \delta_L)$ is set to 0.034 which implies that among legal workers jobs last for about 2.5 years on average (Shimer (2005)).

In order to estimate the job separation rate for illegal workers I use information from the Survey of Migration to the Northern Border (EMIF). The EMIF is a cross-sectional survey conducted ten times between 1993 and 2005 that samples the flows of immigrants between Mexico and the U.S. in the northern border region of Mexico.[9] Using a subsample of 5,752 Mexican male illegal workers interviewed between 1993 and 2005 who were employed at the time of the survey in the U.S. and report information on the duration of their longest job held in the U.S., I estimate an average job duration of 15.8 months and set the job separation rate for legal workers $(1-\delta_I)$ to 0.063.[10]

Migration costs in months of earnings in Mexico (K) are estimated using transportation cost, smuggler fees and other expenses incurred during the trip. Data on smuggler fees, other expenses, average distance from the city of origin to the city of destination, and average monthly earnings in Mexico prior migration are obtained from the EMIF. Estimates on the transportation cost per mile from Mexico to the U.S. are estimated using information from different transportation companies in Mexico and the U.S. The estimates show that on average, migration costs for workers who entered between 1998 and 2005 were 4 months of their income prior migration.[11]

The proportion of legal and illegal workers in the economy μ_L and μ_I are set at 0.9 and 0.1 respectively. While μ_L represents the number of legal workers in the U.S., μ_I represents the number of Mexican workers in the U.S. and in Mexico (potential migrants). Using information from the 2000 Mexican and U.S. Censuses I find estimates of their labor force. In order to find an estimate of the number of workers in Mexico who can potentially migrate, I use information from the Mexican Family Life Survey (MxFLS). This representative Mexican survey devotes a section to analyze migration behavior and specifically asks individuals if they would like to migrate. According to the survey, 15 percent of the individuals surveyed reported intention to migrate.[12] Finally, estimates from the Department of Homeland

[9] The survey is conducted in eight Mexican border cities. Within each city, individuals are sampled at different locations including bus stations, airports, train stations, international bridges, ports of entry and Mexican customs inspection stations. The EMIF identifies illegal, temporary workers and return migrants.

[10] Using information from the EMIF I also estimate the job separation rate for legal immigrants $(1-\delta_L) = 0.0312$. This result is in line with the one obtained by Shimer (2005) for U.S. workers of $(1-\delta_L) = 0.034$.

[11] Migrants paid on average \$960 (in 2001 US dollars) in smuggler fees, \$170 (in 2001 U.S. dollars) in transportation and other expenses, while their average monthly income prior migration was \$270 (in 2001 US dollars).

[12] There are other two surveys that inquire about the individuals desire to migrate. According to the

Security show that in 2000 the number of illegal workers in the U.S. was 4.7 million.

The last group of parameters c, ε_2, b_I and ι are chosen calibrating them to match the wage gap between legal and illegal workers, the wage gap between Mexico and the U.S., the U.S. unemployment rate, and labor market tightness. Using information from the EMIF, I estimate a wage gap between legal and illegal Mexican migrants of 9 percent for the period between 1993 and 2005. The second target to match is the wage gap between workers in Mexico and in the U.S. Using census data for Mexico and the U.S. in 2000 I find that average wages in Mexico are 84 percent lower than those obtained by recent immigrants in the U.S. With respect to the unemployment rate, several authors have argued that the targeted steady state rate of unemployment should include more than the rate of workers counted as unemployed as the model does not account for non-participation. For example, Krause and Lubik (2007) chose an unemployment rate of 12 percent, Den Haan, Ramey and Watson (2000) 11 percent, Petrosky-Nadeau (2009) 10 percent, and Gertler and Trigari (2009) 7 percent. Using a midpoint between the later authors I set the unemployment rate of 10 percent. Finally, I set $(\theta) = 0.72$, the sample mean for the market tightness between 1960 and 2002 estimated by Pissarides (2009).[13]

The calibrated parameters are the following. The vacancy posting cost per period is $c = 0.377$ (close to the 0.356 found by Pissarides (2009)), the upper bound of the distribution of epsilon is set to $\varepsilon_2 = 1.51$,[14] the unemployment income for unemployed illegal workers (leisure) obtained in the calibration is $b_I = 0.235$, and the parameter matching function $\iota = 0.691$.

2007 Gallup World Poll "Mexicans and Migration", 9.5% of the individuals surveyed would like to move permanently to the US if they had the opportunity. A second survey is the Latinobarómetro public opinion survey. This survey reports that 10.5% of the individuals surveyed in Mexico in 2002 responded that they and their families have seriously considered migrating to the U.S. These surveys report estimates lower than those from the MxFLS. While the Gallup Survey refers exclusively to permanent migrations, Latinobarómetro refers to migration decision of complete families.

[13] This value is estimated by using Job Openings and Labor Turnover Survey (JOLTS) data since December 2000 and the Help-Wanted Index (HWI) adjusted to the JOLTS units of measurement before then (Pissarides (2009)).

[14] Epsilon (ε) follows a uniform distribution between ε_1 and ε_2.

Table 2: Model's Predictions - Amnesty Decreasing the Illegal Population by 50 percent

	μ_I=0.1	μ_I=0.05	Difference
Vacancy/unemployment ratio	0.720	0.660	-0.060
Probability of filling vacancy	0.428	0.445	0.017
Probability of finding a job	0.308	0.294	-0.015
Unemployment rate legal	9.93%	10.38%	0.45%
Unemployment rate illegal	17.0%	17.7%	0.70%
Wage legal	0.971	0.970	-0.12%
Wage illegal	0.891	0.889	-0.27%
Wage initially illegal	0.891	0.929	4.32%
Wage gap	9.01%	9.17%	-0.16%
Average wage	0.965	0.967	0.24%
Welfare employed legal	236.4	235.9	-0.23%
Welfare employed illegal	197.2	196.0	-0.59%
Welfare unemployed legal	235.7	235.1	-0.24%
Welfare unemployed illegal	195.4	194.1	-0.63%

2.4.1 Results: Effect of an Amnesty

Table 2 shows the effect of an amnesty granting legal status to 50 percent of the illegal population. The results show that this policy would decrease market tightness, increase the probability of filling a vacancy $p(\theta)$ from 42.8 percent to 44.5 percent, and decrease the probability of finding a job $q(\theta)$ from 30.8 percent to 29.4 percent. The decrease in the probability of finding a job increases the unemployment rate of legal workers by 0.45 percent and the unemployment rate of illegal workers by 0.70 percent. The results also show that the presence of illegal workers have a positive effect on the wages of natives. The amnesty would decrease the wages of natives by 0.12 percent and decrease the wages of illegal workers by 0.27 percent. Figure 1 shows the effect of an amnesty granting legal status to different proportions of the illegal population in the U.S.[15]

[15] The horizontal axis of Figure 1 indicates the proportion of the illegal workers remaining after the amnesty. The graph on top shows the unemployment rates of legal (natives) and illegal workers. The graph in the bottom shows the wages of legal (natives) and illegal workers. In the baseline scenario the population illegal workers is set at 10 percent.

Figure 1: Effect of an Amnesty on the Wages and Unemployment Rates of Legal and Illegal Workers.

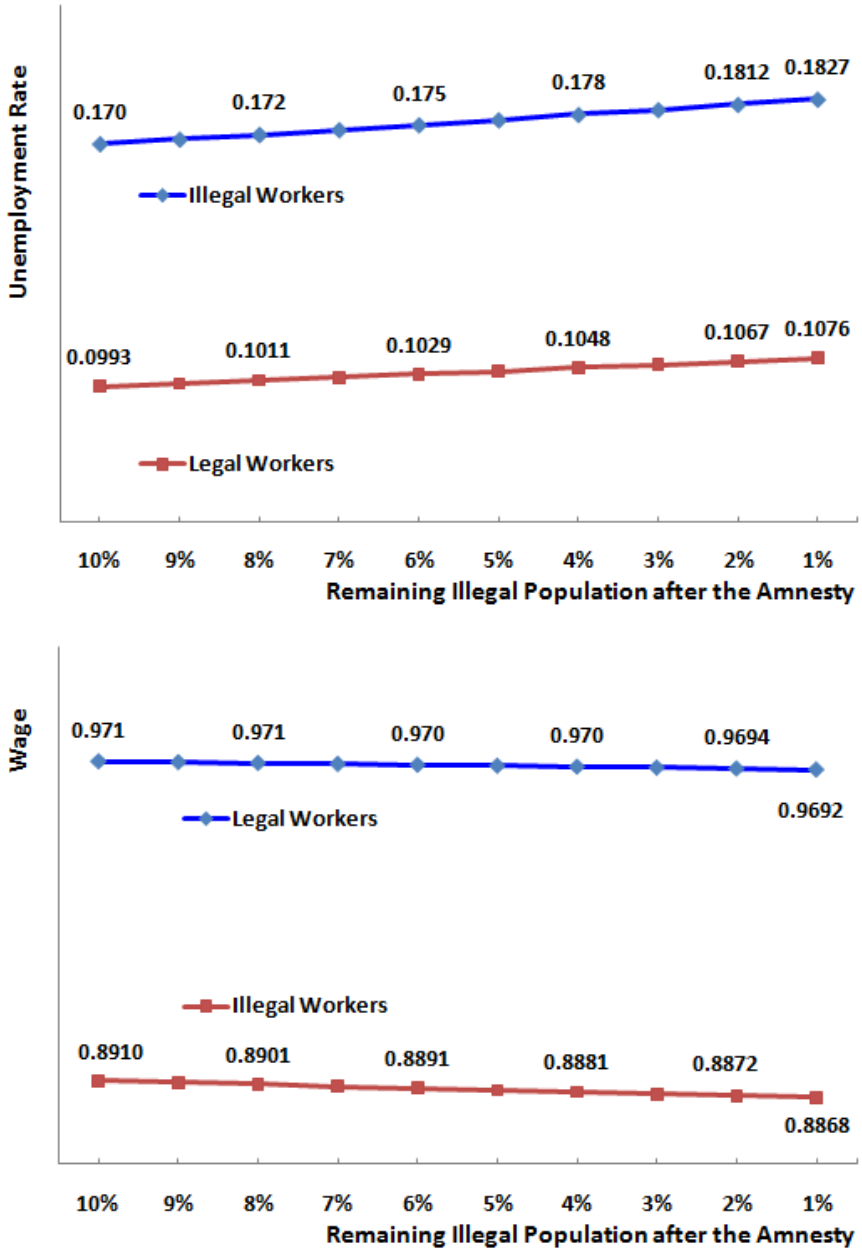


Table 3: Model's Predictions - Tighter Border Enforcement Increasing Migration Costs

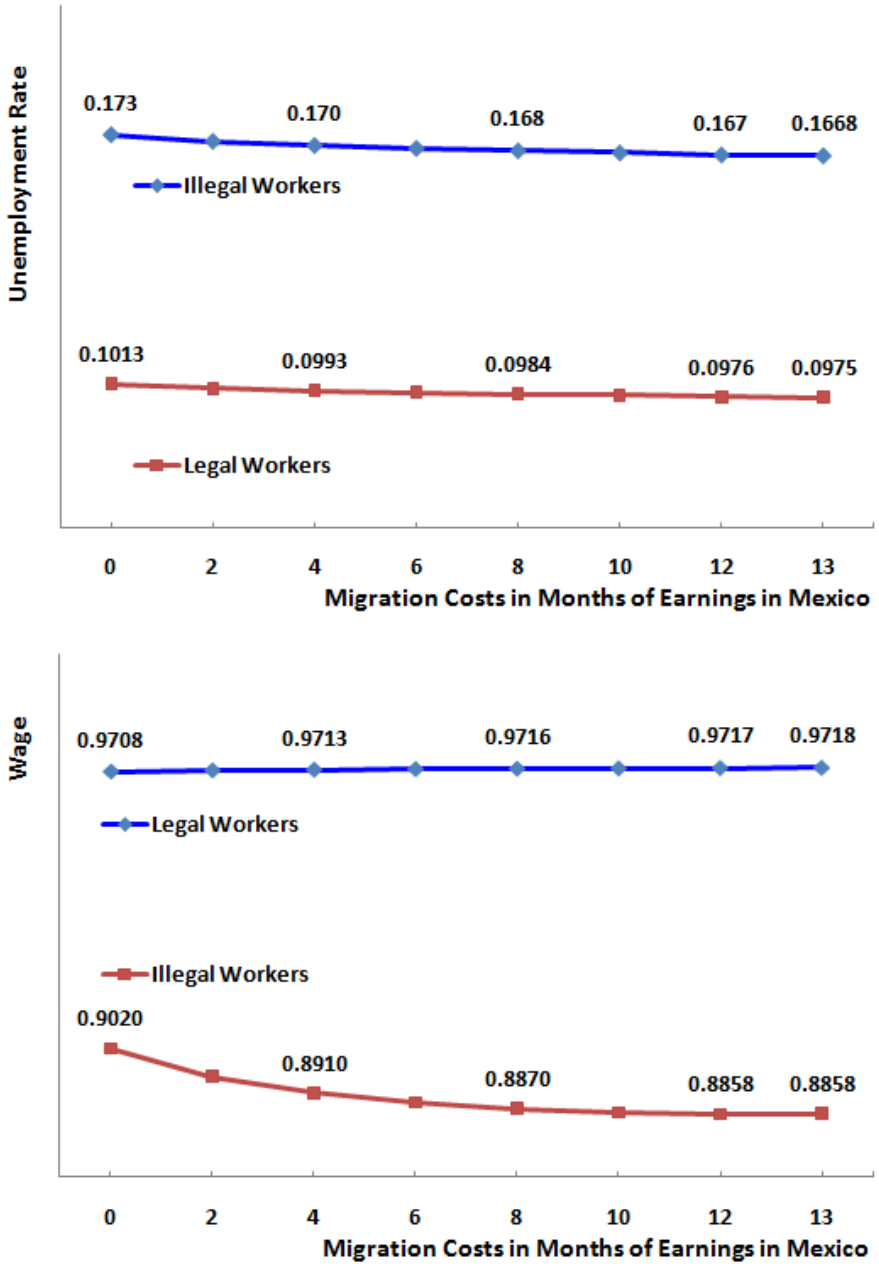
	Migration Costs (Months of Earnings in Mexico)		Difference
	4	8	
Vacancy/unemployment ratio	0.720	0.734	0.014
Probability of filling vacancy	0.428	0.425	0.016
Probability of finding a job	0.308	0.312	-0.015
Unemployment rate legal	9.9%	9.8%	-0.09%
Unemployment rate illegal	17.0%	16.8%	-0.15%
Wage legal	0.971	0.972	0.03%
Wage illegal	0.891	0.887	-0.45%
Wage gap	9.0%	9.5%	0.5%
Average wage	0.965	0.964	-0.04%
Optimal to migrate US (ε_M)	0.281	0.229	-0.052
Optimal to stay in US (ε_{US})	0.844	1.147	0.302
Proportion of illegal workers US	8.9%	9.2%	0.3%
Welfare employed legal	236.4	236.5	0.05%
Welfare employed illegal	197.2	195.2	-0.98%
Welfare unemployed legal	235.7	235.8	0.05%
Welfare unemployed illegal	195.4	193.5	-0.97%

2.4.2 Results: Effect of Tighter Border Enforcement

Table 3 shows the effect of an increase in border enforcement that doubles migration costs. Migration costs are measured in months of earnings in Mexico prior migration. The results show that this policy would decrease market tightness, decrease the probability of filling a vacancy $p(\theta)$ from 42.8 percent to 42.5 percent, and increase the probability of finding a job $q(\theta)$ from 30.8 percent to 31.2 percent. The increase in the probability of finding a job decreases the unemployment rate of legal workers by 0.09 percent and the unemployment rate of illegal workers by 0.15 percent.

The results show that higher migration costs decrease $\overline{\varepsilon}_M$ and increase $\overline{\varepsilon}_{US}$, which implies that fewer individuals in Mexico find it optimal to migrate and more workers in the U.S. find it optimal to stay in the U.S. The overall effect of the increase in border enforcement is an increase in the number of illegal workers in the U.S. (e_I+u_I) from 8.9 percent to 9.2 percent. These results highlight the importance of accounting for return migration when estimating

Figure 2: Effect of Tighter Border Enforcement on Wages and Unemployment Rates for Legal and Illegal Workers.



the effects of different immigration policies. While tighter border enforcement deters workers from crossing, it also decreases return migration increasing the illegal population in the U.S.

The results also show that the increase in the illegal population in the U.S. increases the wages of natives by 0.03 percent. The increase in the probability of finding a job improves workers' outside options, and therefore, increases their wages.

Finally, with respect to the wages of illegal workers, the increase in migration costs generates two opposing effects on workers' outside options, and therefore, on their wages: on the one hand, the increase in the probability of finding a job improves workers' outside options, on the other hand, higher migration costs worsen workers' outside options since workers are less likely to undertake multiple trips to the U.S. The results show that the latter effect dominates; doubling migration costs due to tighter border enforcement decreases the wages of illegal workers by 0.45 percent.[16]

2.5 MODEL WITH ILLEGAL WORKERS PAYING PAYROLL TAXES

While some illegal workers, such as day laborers and domestic workers are paid in cash off the books, estimates suggest that between 50 and 75 percent of the undocumented workers in the U.S. pay payroll taxes.[17] Illegal workers frequently obtain formal jobs using false social security numbers or social security numbers that belong to someone else. They have payroll taxes withheld as any other legal worker in the U.S., however, in order to avoid detection, they do not file for tax refunds or unemployment benefits.

In the following section I modify the model to study the effect of an amnesty in an economy where firms can hire illegal workers "off the books", paying them under the table and avoiding the payment of payroll taxes; or "on the books", using false social security

[16] Figure 2 shows the effect of increases in border enforcement measured by increases in migration costs. Migration costs are measured in months of earnings in Mexico (horizontal axis). The graph at the top shows the unemployment rates of legal (natives) and illegal workers. The graph at the bottom shows the wages of legal (natives) and illegal workers. In the baseline scenario migration cost are set at 4 months of earnings.

[17] According to Stephen Goss, chief actuary with the Social Security Administration, as many as 75 percent of the undocumented workers pay payroll taxes (Porter (2005)). A recent review by the Congressional Budget Office (2007) shows that income tax compliance rates are typically estimated to fall between 50 and 75 percent among unauthorized immigrants.

numbers pretending they are legal aliens.

2.5.1 Model

For simplicity, I will assume that there is no movement of workers between Mexico and the U.S. Each period firms post a certain number of vacancies and a matching function determines the flow of new matches between firms and workers. When firms post vacancies, they only know the conditional probability that the match will be formed with a legal or an illegal worker. Once the match is formed, firms realize the worker's type. If the match is done with an illegal worker, the firm decides if the worker is hired on or off the books.

In this setting a fixed payroll tax (T) is levied on firms for all legal workers and for the illegal workers hired on the books. The tax revenue is used to pay for the unemployment benefits of legal workers (b_U). Now, the income of unemployment of legal workers will include two components: income received from unemployment insurance (b_U) and the value of leisure (b_O). For illegal workers, the income of unemployment will be the value of leisure (b_I). The value functions of unemployed legal and illegal workers are given by

$$U_L = (b_U + b_O) + \beta(qW_L + (1-q)U_L) \text{ and}$$

$$U_I = b_I + \beta(q(\gamma W_I^T + (1-\gamma)W_I^{NT}) + (1-q)U_I),$$

where γ is the proportion of workers hired by firms on the books, and W_I^T and W_I^{NT} represent the value of an illegal worker employed on and off the books respectively.

The value functions of employed legal workers, employed illegal workers on the books, and employed illegal workers off the books are given by

$$W_L = w_L + \beta\left(\delta_L W_L + (1-\delta_L)U_L\right),$$

$$W_I^T = w_I^T + \beta\left(\delta_I W_I^T + (1-\delta_I)U_I\right) \text{ and}$$

$$W_I^{NT} = w_I^{NT} + \beta\left(\delta_I W_I^{NT} + (1-\delta_I)U_I\right),$$

where w_I^T and w_I^{NT} are the wages received by illegal workers on and off the books.

The firm's value functions are given by

$$J_L = y - w_L - T + \beta \left(\delta_L J_L + (1 - \delta_L) V \right),$$

$$J_I^T = y - w_I^T - T + \beta(\delta_I J_I^T + (1 - \delta_I) V) \text{ and}$$

$$J_I^{NT} = y - w_I^{NT} + \beta \left(\delta_I J_I^{NT} + (1 - \delta_I) V \right),$$

where J_I^T and J_I^{NT} represent the value of a firm matched with an illegal worker on and off the books, and T is the amount of the payroll tax.

The value of a firm with an open vacancy can be written as

$$V = -c + \beta p \left(a J_L + (1 - a) \left\{ \gamma J_I^T + (1 - \gamma) J_I^{NT} \right\} \right) + \beta (1 - p) V$$

where $p(\theta)$ is the probability of filling a vacancy, $(1 - a)$ is the conditional probability that the match will be formed with an illegal worker, and γ is the conditional probability that the match with the illegal worker will be on the books. With respect to creation of new jobs I assume free entry into the economy, which implies that firms create job vacancies until any incremental profit is exhausted ($V = 0$).

Wages are determined by Nash bargaining, the solution is to set w_L, w_I^T and w_I^{NT} to maximize the product surpluses

$$\max_{w_L} (W_L - U_L)^{1-\eta} (J_L - V)^{\eta},$$

$$\max_{w_I^{NT}} (W_I^{NT} - U_I)^{1-\eta} (J_I^{NT} - V)^{\eta} \text{ and}$$

$$\max_{w_I^T} (W_I^T - U_I)^{1-\eta} (J_I^T - V)^{\eta}.$$

In this model, the payroll tax is used to pay for the unemployment benefits of legal workers. In steady state, tax revenue must equal tax expenditures. Therefore, the steady state condition is given by

$$u_L b_L = T(\mu_L - u_L) + T\gamma(\mu_I - u_I)$$

where the expenditure in unemployment benefits for legal workers is equal to the tax revenue generated by the payroll tax levied on legal workers and on illegal workers on the books.

Table 4: Parameters and Targets in a Model with Illegal Workers Paying Payroll Taxes

Parameter	Value	Source
Output	$y = 1$	Normalization
Discount Factor	$\beta = 0.996$	Pissarides (09)
Bargaining parameter	$\eta = 0.5$	Pissarides (09)
Destruction rate Legal	$1 - \delta_L = 0.034$	Shimer (04)
Destruction rate Illegal	$1 - \delta_I = 0.063$	EMIF 93-05
Proportion of illegal workers "on the books"	$\gamma = 0$	Previous model
Legal Population US	$\mu_L = 0.94$	CPS 00-10
Illegal Population US	$\mu_I = 0.06$	DHS(05&06)
Unemp Income Legal $b_L = b_U + b_O$	$b_L = 0.71$	Hal & Milgrom (08)
Unemp Income Legal: Unemployment benefits	$b_U = 0.36$	Department of Labor
Unemp Income Legal: Leisure	$b_O = 0.35$	Difference
Parameter	**Value**	**Calibration Target**
Unemp Income Illegal: Leisure	$b_I = 0.043$	Unemployment rate $u = 0.10$
Vacancy cost	$c = 0.35$	Wage gap $\frac{w_L}{w_I} - 1 = 0.09$
Parameter Matching Function	$\iota = 0.738$	Market tightness $\theta = 0.72$

2.5.2 Quantitative Analysis

2.5.2.1 Fixed and Calibrated Parameters The new parameters and calibration targets are summarized in Table 4. The proportion of legal and illegal workers μ_L and μ_I are set at 0.94 and 0.06 respectively. In this model μ_L represents the number of legal workers in the U.S. and μ_I represents the number of Mexican workers in the U.S. Since in this model there is not movement of workers between Mexico and the U.S., now μ_I does not include workers in Mexico. The income of unemployment for legal workers is set at $b_L = 0.71$ following Hall and Milgrom (2008). The income of unemployment is divided into two categories, income received from unemployment insurance (b_U) and the value of leisure (b_O). The income received from unemployment insurance b_U is set at 0.36, the average unemployment insurance replacement rate for the U.S. between 1975 and 2004 according to the Department of Labor. Since $b_L = b_U + b_O$, the income from leisure b_O is set at 0.35. Finally, I set $\gamma = 0$; a scenario where firms hire illegal workers off the books and only pay taxes for their legal workers.

The parameter of the matching function is set at $\iota = 0.738$, the vacancy posting cost is set at $c = 0.35$, and the income of unemployment for illegal workers is set at $b_I = 0.043$. These parameters are chosen calibrating them to match the wage gap between legal and illegal workers ($\frac{w_L}{w_I} - 1 = 0.09$), the U.S. unemployment rate ($u = 0.10$) and labor market tightness ($\theta = 0.72$). The targets used for the calibration are the same used in the previous specification of the model. While the first two calibrated parameters are similar to the ones obtained in section 2.4, the income of unemployment for illegal workers is significantly lower because this new setting does not account for the possibility of return migration and illegal workers have less alternative options.

2.5.2.2 Results: Changes in the Proportion of Illegal Workers Paying Payroll Taxes Table 5 shows the effect of changes in the proportion of illegal workers paying payroll taxes or on the books (γ) .[18] The results show that illegal workers in jobs off the books earn higher wages than illegal workers on the books since a proportion of the payroll tax levied on the last group is transferred to workers.

The results show that an increase in the proportion of illegal workers on the books decreases market tightness (θ) , decreases the probability of finding a job $q(\theta)$, and increases unemployment rates.

Changes in the proportion of illegal workers on the books will affect wages in two ways: First, the decrease in market tightness and increase of the unemployment rates worsen workers' outside options decreasing their wages (outside options effect). Second, the increase in the number of illegal workers on the books will increase tax revenue because now more workers pay the payroll tax (tax effect). Since illegal workers are not eligible for unemployment benefits, the amount of the tax necessary to pay for the unemployment benefits of legal workers decreases. Since part of the tax is paid by firms and part is paid by workers in form of lower wages, the increase in γ will increase the wages of the workers subject to payroll taxes (legal workers and illegal workers on the books).

While we can conclude that the wages of illegal workers off the books will decrease due

[18] The wage gap between legal and illegal workers is calculating according to $(w_L/((\gamma w_I^T + (1-\gamma)w_I^{NT}) - 1$. The welfare for employed legal workers (W_I) is given by $(\gamma W_I^T + (1-\gamma)W_I^{NT})$.

Table 5: Effect of Changes in the Proportion of Illegal Workers Paying Payroll Taxes

	Proportion of Illegal Workers Paying Payroll Taxes				
	0	0.25	0.5	0.75	1
Vacancy/unemployment ratio	0.720	0.719	0.718	0.7175	0.7167
Probability of filling vacancy	0.4559	0.4561	0.4564	0.4566	0.4568
Probability of finding a job	0.3282	0.3280	0.3278	0.3276	0.3274
Unemployment rate legal	9.386%	9.392%	9.397%	9.403%	9.408%
Unemployment rate illegal	16.10%	16.11%	16.12%	16.13%	16.14%
Wage legal	0.9389	0.9394	0.9398	0.9403	0.9407
Wage illegal "off" the books	0.861	0.858	0.855	0.852	0.848
Wage illegal paying tax	0.843	0.840	0.837	0.834	0.831
Wage gap	9.0%	10.1%	11.1%	12.2%	13.2%
Average wage	0.93429	0.93424	0.93419	0.93415	0.93411
Tax	0.0373	0.0368	0.0363	0.0358	0.0353
Tax revenue	0.03176	0.03178	0.03180	0.03182	0.03184
Welfare employed legal	229.4	229.5	229.6	229.7	229.8
Welfare employed illegal	182.7	181.0	179.4	177.8	176.2
Welfare unemployed legal	228.8	228.9	229.0	229.1	229.2
Welfare unemployed illegal	180.6	179.0	177.3	175.8	174.2

to the lower outside options effect, the impact on the wages of legal workers and illegal workers on the books will depend on the magnitude of the two effects (lower outside options effect and tax effect). Table 5 shows that for legal workers the tax effect dominates, and an increase of γ increases their wages (w_L). On the other hand, for illegal workers on the books the outside option effect dominates and an increase of γ decreases their wages (w_I^T).

2.5.2.3 Results: Effect of an Amnesty Table 6 shows the effect of an amnesty decreasing the illegal population from 6 percent to 1 percent for different values of γ (proportion of illegal workers on the books). Column A shows the baseline scenario when all illegal workers are paid under the table ($\gamma = 0$) and column B shows the effects of the amnesty on different variables with respect to the baseline scenario. Columns C through F show baseline scenarios and effects of the amnesty for $\gamma = 0.5$ and $\gamma = 1$.[19]

[19] Table 26 in the Appendix shows the effects of an amnesty, first, if we leave the amount of the payroll tax fixed, and second, if we allow the tax to adjust to make the revenue from payroll taxes equal to the

Table 6: Effect of an Amnesty in a Model with Illegal Workers Paying Payroll Taxes

	A	B	C	D	E	F
	Baseline	Difference	Baseline	Difference	Baseline	Difference
Proportion workers paying tax	0	0	0.5	0.5	1	1
Vacancy/unemployment ratio	0.720	-0.137	0.718	-0.135	0.7167	-0.1338
Probability of filling vacancy	0.4559	0.0422	0.4564	0.0418	0.4568	0.0415
Probability of finding a job	0.3282	-0.0376	0.3278	-0.0373	0.3274	-0.0370
Unemployment rate legal	9.39%	1.09%	9.40%	1.08%	9.41%	1.07%
Unemployment rate illegal	16.10%	1.71%	16.12%	1.70%	16.14%	1.69%
Wage legal	0.9389	-0.72%	0.9398	-0.80%	0.9407	-0.87%
Wage illegal "off" the books	0.8613	-1.43%	0.8547	-1.51%	0.8485	-1.64%
Wage illegal paying tax	0.8426	-1.75%	0.8366	-1.89%	0.8308	-2.06%
Wage gap	9.02%	0.78%	11.14%	1.02%	13.22%	1.37%
Average wage	0.9343	-0.314%	0.9342	-0.307%	0.9341	-0.300%
Tax	0.037	12.95%	0.036	15.64%	0.035	18.30%
Tax revenue/expenditure	0.03176	17.53%	0.03180	17.42%	0.03184	17.32%
Welfare employed legal	229.4	-0.93%	229.6	-1.00%	229.8	-1.06%
Welfare employed illegal	182.7	-3.26%	179.4	-3.51%	176.2	-3.85%
Welfare unemployed legal	228.8	-0.95%	229.0	-1.0%	229.2	-1.09%
Welfare unemployed illegal	180.6	-3.4%	177.3	-3.6%	174.2	-4.0%

The results show that an amnesty decreases the probability of finding an illegal worker with a low outside option and therefore, decreases θ. The decrease in θ generates an increase in unemployment. According to the model, the decrease in θ will be smaller for larger values of γ. If γ is low, which implies, a large number of illegal workers are employed off the books, an amnesty reducing the illegal population will generate a large decrease in θ. On the other hand, if γ is high, and therefore, a large proportion of the illegal workers work on the books (and firms are already paying taxes for those workers), the amnesty will generate a smaller decrease in the number of vacancies and θ.

The decrease in θ decreases the probability of finding a job (q) and increases the unemployment rate of legal and illegal workers. Since the decrease of θ is smaller for large values of γ, the increase in unemployment rates will also be smaller for higher values of γ.

expenditure of unemployment benefits for all legal workers. The results show that the tax adjustment further decreases the wages of all types of workers as result of the amnesty.

Effect of an Amnesty on the Wages of Legal Workers

The wages of legal workers are affected in two ways. First, the increase in the unemployment rate worsens workers' outside options decreasing their wages (outside options effect). Additionally, the fact that now there is a larger number of unemployed legal workers, the amount of the tax necessary to pay for unemployment benefits will go up, decreasing even more the wages of legal workers (tax effect).

The magnitude of the decrease in the wages of legal workers for different values of γ depends on the magnitude of the outside options effect and the tax effect. On the one hand, the decrease of θ and the increase in unemployment rates are smaller for large values of γ. Therefore, the decrease in wages due to worse outside options should be lower for high values of γ. On the other hand, an amnesty increasing the legal population increases the number of workers paying taxes but also the number of workers claiming unemployment benefits. If a large proportion of illegal workers were paying the tax before the amnesty (high γ), the amnesty will only increase unemployment claims, and therefore, the amount of the tax. Since part of the tax is paid by the firm and part of the tax is paid by workers, a higher tax implies lower wages for legal workers. The results show that the second effect dominates, and the decrease in the wages of legal workers is larger for higher values of γ.

Effect of an Amnesty on the Wages of Illegal Workers Paying Payroll Taxes

The decrease in their wages is larger than that observed among legal workers but due to the same mechanisms. First, higher unemployment rates worsen outside options decreasing their wages, and second, due to higher taxes necessary to pay for unemployment benefits of the newly legalized immigrants. The magnitude of the decrease in their wages for different values of γ depends on the magnitude of the outside options effect and the tax effect (the outside options effect is larger for low γ but the tax effect is smaller for low γ). The results show that the tax effect dominates, and the decrease in the wages of illegal workers on the books is larger for higher values of γ.

Effect of an Amnesty on Wages of Illegal Workers off the Books

The decrease in their wages is larger than that observed among legal workers, but lower

than those observed among illegal workers on the books. The reason is that they are only affected by the first mechanism (decrease in outside options). Since they are working off the books, the increase in taxes necessary to pay for unemployment benefits does not affect their wages. The results show that an amnesty would decrease the wages of illegal workers off the books, and the effect is going to be larger for low values of γ.

Summarizing, it is important to account for the fact that a proportion of illegal workers are working on the books and therefore pay payroll taxes in order to measure the effect of an amnesty on the wages of workers. The results show that the larger the proportion of illegal workers paying taxes, the larger will be the amount of the tax necessary to pay for the increase in unemployment claims (the amnesty will not change the number of workers paying taxes but will increase the number of workers claiming for unemployment benefits), and therefore, the larger will be the decrease in the wages of legal and illegal workers in the economy.

2.6 CONCLUSIONS

I analyze the effects of two immigration policies, an amnesty and an increase in border enforcement, on the labor market outcomes of U.S. natives and Mexican immigrants. Even though changes to the immigration system have potentially large implications, little research has been devoted to analyze the effects of different policies on the U.S. labor market. In this paper I use a Mortensen-Pissarides style labor market model to estimate the effects of those policies on the wages and unemployment of legal and illegal workers. One distinctive characteristic of my model is that it accounts for return migration, an important feature when studying illegal immigration due to the high mobility between Mexico and the U.S. observed among undocumented workers.

This paper highlights a new channel through which natives and illegal workers interact in the economy. In this model, natives benefit from the presence of illegal workers in the labor market. The presence of illegal workers increases firm's incentives to open vacancies (since

their probability of finding a worker with a low outside option increases), which increases the wages of natives and decreases their unemployment rate. Hence, an amnesty granting legal status to a proportion of the illegal population would decrease the wages of natives and increase their unemployment rate.

Moreover, this paper points out the fact that immigration policies might have unintended effects. The model shows that an increase in border enforcement has an ambiguous effect on the number of illegal workers in the economy. While tighter border enforcement deters illegal migration of prospective workers, it also changes incentives for those already in the U.S. by decreasing return migration. In the event that tighter border increases the number of illegal workers, the model predicts that it will increase the wages of natives and have an ambiguous effect on the wages of illegal workers. Quantitative results show that tighter border enforcement increases the number of illegal workers, increases the wages of natives and decreases the wages of illegal workers.

These results are consistent with the findings of existing studies. The fact that natives benefit from the presence of illegal workers in the labor market is in line, although due to a different mechanism, to the result of Ottaviano and Peri (2010). They find that the 1990-2006 immigration wave to the U.S. will have a small positive effect on the average wages of natives in the long run. Moreover, relative to the ambiguous effect of tighter border enforcement on the flows of illegal immigrants, my results are in line with the findings of Angelucci (2005). She studies the impact of enforcement on 1972-1993 migration net flows finding that increases in border controls deter migrants from crossing the border illegally, but lengthen their duration in the U.S.

Additionally, in this paper I emphasize the importance of accounting for the fact that a proportion of illegal workers have formal jobs and pay payroll taxes. The results show that the smaller the proportion of illegal workers paid off the books, the larger will be the decrease in wages generated by a decrease in the number of illegal workers in the economy.

There are three extensions to this paper that are of potential interest. First, relax the assumption of having constant returns to scale in the aggregate economy. The results of this model represent the long run equilibrium where we have a perfectly elastic capital supply and do not consider the negative effect of having more workers in the economy in the short

run.

Second, allow some Mexican immigrants to enter the U.S. legally (e.g. workers with temporary work permits or workers with tourist visas), and then overstay. Even though these workers represent a small fraction of the illegal immigrant population in the U.S., their expected utility of working illegally in the U.S. is higher than that of workers who enter illegally and could impact workers' behavior.

Finally, it would also be interesting to investigate the effect of alternative immigration policies, for example, policies intended to change firms' incentives to hire illegal workers. Such policies include the implementation of audits and workplace raids to firms suspected of hiring illegal workers, or increases in penalties to firms hiring illegal workers. Even though the Immigration Reform and Control Act of 1986 (IRCA) legally mandates that U.S. employers verify the employment eligibility status of newly-hired employees, the implementation and enforcement of such policies have not been successful in the past.

3.0 EFFECT OF LEGAL STATUS ON THE WAGES OF MEXICAN IMMIGRANTS IN THE UNITED STATES

3.1 INTRODUCTION

Immigration from Mexico to the United States (U.S.) is a topic of great interest for policy-makers and academics. Mexico is the most important source country for U.S. immigration, accounting for 34.0 percent of total immigrant arrivals since 1990.[1] In 2009, the 11.5 million Mexican immigrants living in the U.S. represented 29.9 percent of the U.S. foreign-born population and 10.6 percent of the total population of Mexico.[2] One important feature of Mexican immigration is that a high percentage of new arrivals enter the U.S. illegally.[3] Estimates from the Department of Homeland Security (DHS) suggest that in January 2010 the number of illegal Mexican workers in the U.S. was 6.6 million, which represents 61.5 percent of the total unauthorized population in the U.S.[4]

Even though the evidence has shown that legal workers earn on average higher wages than illegal workers, the issue becomes to identify the factors generating those differences. For instance, wage differentials could be explained by differences in migrants' characteristics such as age, education, or English proficiency. Additionally, illegal workers are likely to concentrate in a few specific low-paying activities, activities that have become identified as traditional illegal migrant' jobs due to the existence of migration networks. Moreover, these

[1] Hanson, G. (2006).

[2] Tables 27 and 28 in the Appendix provide recent estimates of the number of illegal immigrants, Mexican illegal immigrants and foreign born in the US.

[3] Passel, J. (2006) found that in recent years about 80 to 85 percent of the immigrants coming from Mexico have entered the United States undocumented.

[4] Neither the Census Bureau nor any other U.S. government agency counts the illegal migrant population. Hoefer, Rytina, and Campbell (2011) subtract the estimated legal-immigrant population from the total foreign-born population and the residual is considered as the unauthorized migrant population.

differences could be associated with discrimination in the labor market against illegal workers. Finally, firms incurring additional expenses from employing undocumented workers, such as fines and costs of avoiding prosecution, may be willing to employ undocumented workers only if their wage is low enough to compensate for such costs.

Which of these factors is correct has important implications for the analysis of the impact of immigration on wages, unemployment, and the overall U.S. labor market. Over the last three decades, the ratio of illegal to legal immigrants has increased significantly. Therefore, if for example, the earnings of illegal workers are lower due to different observable characteristics, the increase in their proportion should not have affected wage rates apart from the effect of increasing the supply of immigrant labor. However, if undocumented workers earn lower wages due to their illegal status, then the growing prevalence of undocumented migrants in the U.S. labor force should have depressed wage rates beyond the effect attributable to increased numbers of immigrants alone.

In this paper I estimate the effect of legal status on the wages of Mexican immigrants in the U.S. using a rich dataset of Mexican migrants, controlling for possible selection biases, and exploiting the random variation in legal status that comes from a change in the U.S. migration policy.

The lack of reliable, representative data on the illegal population has been one of the factors that have made the issue of whether undocumented migrants earn lower wages a matter of some debate. Whereas previous studies, using the U.S. Census of Population and Housing or the U.S. Current Population Survey (CPS) have analyzed immigrants' characteristics and earnings, those surveys do not ask individuals explicitly about their legal status. Alternative sources of information used to study illegal immigration have also included small samples of non-random illegal workers in specific locations, apprehended migrants, workers who returned to Mexico or legalized immigrants, which are not representative of the immigrant population working in the U.S.

In this paper I use data on Mexican migration from the Survey of Migration to the Northern Border (EMIF). The EMIF is a cross-sectional survey conducted ten times between 1993 and 2005. Among the advantages of using this survey are that it asks migrants about their legal status, identifies return migrants, and is conducted among Mexican migrants, both

temporarily and permanently settled in the U.S. Moreover, since the survey is conducted in Mexico and by the Mexican government, as opposed to that of the U.S., illegal immigrants should feel little concern about the legal consequences of their responses.

Migration is a selective process; therefore, controlling for selection biases is crucial. People who migrate to a foreign country are not a random selection from the population at origin; they might differ in terms of observable characteristics, but also in terms of unobservable qualities such as ability or motivation. Individuals migrating with and without documents may also be selected into the workforce in different ways. Barriers to entry for illegal workers significantly increase migration costs which may make illegal immigrants more highly selected with respect to factors like motivation and risk-taking propensity. Finally, it is important to consider the fact that a proportion of the immigrant population obtained legal status after entering the U.S. illegally. If more motivated workers are also more likely to obtain legal status, the gains from legal status would also be biased.

I estimate the effect of legal status on the wages of immigrants using regression analysis. In order to control for selectivity of workers migrating legally and illegally to the U.S., I restrict the sample to include only workers who entered the U.S. illegally. By the time of the survey, some workers are still working without documents, but others obtained legal status and constitute the comparison group. Additionally, in order to test for selectivity in the population obtaining legal status after entering the U.S. illegally, I use a sample of workers who obtained legal status under the 1986 Immigration Reform and Control Act (IRCA). IRCA provides us with a legalization procedure that is exogenous to migrants' characteristics since eligibility was based on time of arrival to the U.S. Using matching estimators and propensity-score matching techniques, I compare individuals obtaining legal status through IRCA and other legalization programs in order to test for selectivity among workers obtaining legal status through different channels. Finally, using matching estimators for a sample of workers who obtained legal status through IRCA, and an appropriate control group of illegal workers, I estimate the effect that receiving legal status has on the wages of the workers legalized under IRCA.

The results show that legal workers earn higher wages than illegal workers, especially those working in the production and service sectors. Controlling for observable characteristics

and occupation decreases the wage differential between legal and illegal workers but does not eliminate it. Moreover, discrimination against illegal workers does not seem to explain the wage differences between legal and illegal workers, since the wage gap is only observed among workers in specific occupations. For individuals working in the production sector, the wage gap between legal and illegal migrants is 18.3 percent among supervisors, 11.5 percent among regular workers, and 1.1 percent among assistants and apprentices. For workers in the agricultural sector or providing domestic services there are no significant differences in the wages of legal and illegal workers.

Additionally, the results show that the wage gap is larger among individuals working in "formal" jobs. While it is true that some illegal workers are paid off the books, an important number of undocumented workers get formal jobs using false social security numbers. The evidence supports the idea that firms may hire undocumented workers in formal jobs if their wage is low enough to compensate for the additional expenses that firms incur from hiring undocumented workers (e.g. tax burden, fines or costs of avoiding prosecution). The wage gap between legal and illegal workers is 9.4 percent for workers in formal jobs, and is not statistically significant for workers in informal jobs.

Finally, the results show that, once we control for observable characteristics, there is no evidence of selectivity among Mexican workers obtaining legal status.

3.2 LITERATURE REVIEW

The economic performance of the immigrant population and the effect of legal status on the wages of U.S. migrants had been topics of widespread interest for many years. Illegal immigration, by its nature, is not easily measurable. Unfortunately, the lack of reliable, representative data on the subject has made the issue of whether undocumented immigrants earn lower wages due to their illegal status a debated topic.

To circumvent the scarcity of information, researchers have drawn conclusions from different types of studies. First, researchers have gathered small, non-random samples of undocumented immigrants in specific locations in certain sectors of the economy. For example,

Taylor (1992), using data from a survey of California farm workers conducted in 1983, finds that the earnings of illegal workers are significantly lower than those of legal workers in high-skill farm jobs. He finds that illegal workers earn 29 percent less than legal workers in jobs that require firm-specific human capital such as foreman, or machine-operator; but, those differences are not statistically significant for workers in low-skill jobs.

A second strategy for studying wages of undocumented migrants has been to estimate wage regressions using mainly data gathered in sending regions, such as western Mexico. Massey (1987) examines the extent to which illegal status lowers wage rates among immigrants using the Mexican Migration Project (MMP), a household survey conducted in 1982 and 1987 in rural communities of western Mexico with high rates of migration to the U.S. In this paper he finds that legal status has no direct effect on the wages of Mexican immigrants in the U.S. Moreover, he finds that legal status has little effect on the kinds of jobs that migrants take in the U.S., but it does play an important role in determining the length of time that immigrants stay in the country.

A third strategy to study the wage effects of obtaining legal status has included the analysis of samples of legalized workers. Cobb-Clark and Kossoudji (2002), using the Legalized Population Surveys (LPS), a survey conducted among illegal immigrants who received amnesty under IRCA, estimate the wage benefit of legalization as approximately 6 percent. According to Hanson (2006), there are two factors that could have caused this relatively modest wage gain. First, if the three years covered by the LPS is not long enough for individuals to realize the wage benefits associated with obtaining legal status, and second, if formerly undocumented individuals are negatively selected with respect to unobserved skills. Unfortunately, these studies might suffer from selection biases that undermine the validity of reported findings and create apparent contradictions in the results.

Migration is a selective process; people who migrate are not a random selection from the population at origin, individuals migrating with and without documents may also be selected into the workforce in different ways. Additionally, a large proportion of the immigrant population obtained legal status after entering the U.S. illegally; reasons why properly control for possible selection biases along with appropriate methods to correct for selectivity are necessary to accurately estimate the effect of legal status on the wages of immigrants.

3.3 DATA

The data on Mexican migration comes from the Survey of Migration to the Northern Border (EMIF), a cross-sectional survey conducted ten times between 1993 and 2005 that samples the flows of migrants between Mexico and the U.S. in the northern border region of Mexico.[5] The survey is conducted in eight Mexican border cities.[6] Within each city, individuals are sampled at different locations including bus stations, airports, train stations, international bridges, ports of entry and Mexican customs inspection stations. The EMIF is a very rich database; it identifies illegal workers, temporary workers and return migrants, individuals that represent an important part of the U.S. labor force.

The survey consists of four different questionnaires,[7] but I only use the one conducted among Southward-bound migrants returning from the U.S. This section of the EMIF contains information on wages, legal status and time in the U.S., as well as many other socioeconomic characteristics such as age, years of schooling and marital status. It includes individuals twelve years of age or older who were not born in the U.S. and who do not live in the city in which the survey was conducted. Within this sample I further impose some sample exclusion restrictions, I limit the sample to male immigrants (accounting for 90 percent of the sample), born in Mexico (accounting for 99.9 percent of the sample) who arrived into the U.S. after 1954. Table 28 in the appendix gives a description of some of the variables included in the survey.

I define temporary migrants as those who report Mexico as their country of residence. One of the advantages of using country of residence as a proxy for temporary or permanent status is that it provides a measure of intention or identification with a U.S. residence, an improvement over other measures frequently used in the literature such as time in the U.S.

[5] Each phase of the survey lasted one full year. The dates of application are shown in the appendix, Table 29.

[6] The border cities where the survey is conducted are: Reynosa, Matamoros, Nuevo Laredo, Piedras Negras, Cuidad Juarez, Nogales, Mexicali and Tijuana. According to the Secretaria del Trabajo y Prevision Social, these cities account for more than 90 percent of the migration flux from Mexico to the U.S.

[7] The survey includes 4 questionnaires: one for Northward-bound immigrants (with destinations in either Mexican border cities or the U.S.), one for Southward-bound immigrants from Mexican border cities, one for Southward-bound immigrants returning from the U.S. and finally one for immigrants returned to Mexico by the U.S. Border Patrol.

Table 7: Summary Statistics

Variables	All Immigrants		Legal		Illegal	
	Mean	SD	Mean	SD	Mean	SD
Legal	64.5%	0.478	100%	0.000	0%	0.000
Age	35	10.32	38	10.0	30	8.79
Married	74.1%	0.438	83.5%	0.371	57.1%	0.495
With Family in US	85.0%	0.357	89.9%	0.301	76.0%	0.427
Temporary	37.3%	0.484	20.2%	0.401	68.5%	0.465
Return Migrant	29.2%	0.454	14.5%	0.353	55.8%	0.497
Years of schooling	7.14	3.59	7.30	3.68	6.86	3.39
School in US	4.3%	0.202	5.9%	0.235	1.3%	0.114
No educated	5.3%	0.225	4.8%	0.215	6.3%	0.243
Elementary dropout	20.2%	0.402	20.1%	0.401	20.3%	0.403
Elementary graduated	25.0%	0.433	24.8%	0.432	25.2%	0.434
Secondary dropout	9.5%	0.293	9.1%	0.287	10.2%	0.303
Secondary graduated	20.6%	0.404	20.0%	0.400	21.6%	0.412
High school dropout	6.8%	0.252	6.5%	0.247	7.4%	0.261
High school graduated	7.9%	0.270	8.8%	0.284	6.4%	0.244
College dropout	2.6%	0.158	3.1%	0.174	1.5%	0.122
College graduated	2.0%	0.141	2.6%	0.159	1.0%	0.101
Contract	25.4%	0.435	33.6%	0.472	10.3%	0.304
Benefits	41.5%	0.493	55.3%	0.497	16.5%	0.371
Hours worked	8.59	1.651	8.59	1.546	8.57	1.825
Days worked	5.53	0.742	5.52	0.726	5.54	0.770
Monthly earnings[1]	1,500	998.0	1,652	1,082	1,222	746.6
Hourly Wage[1]	7.67	12.73	8.53	15.41	6.11	4.55
Professional/Managerial	7.5%	0.263	10.0%	0.300	2.9%	0.167
Commerce/retail	3.8%	0.191	4.3%	0.202	2.9%	0.169
Services	15.7%	0.363	13.7%	0.344	19.2%	0.394
Agriculture	23.8%	0.426	21.9%	0.414	27.2%	0.445
Industry	48.8%	0.500	49.5%	0.500	47.4%	0.499
Time in US (last entry years)	1.85	3.625	1.78	3.89	1.98	3.07
1 year or less	17.8%	0.383	6.0%	0.238	39.2%	0.488
Between 2-5 years	18.5%	0.388	12.2%	0.327	29.9%	0.458
Between 6-10 years	21.4%	0.410	24.7%	0.431	15.4%	0.361
Between 11-16 years	21.4%	0.410	27.6%	0.447	10.0%	0.300
More than 16 years	20.9%	0.407	29.4%	0.456	5.4%	0.226
Time in US (first entry years)	10.12	8.39	13.04	8.07	4.82	6.01
Year of First Entry in the US	1989	8.9	1986	8.3	1995	7.0
Cohort arrived before 1984	27.7%	0.447	38.2%	0.486	8.4%	0.278
Cohort arrived 1985-1990	26.7%	0.442	33.3%	0.471	14.6%	0.353
Cohort arrived 1991-1996	22.6%	0.418	19.9%	0.399	27.6%	0.447
Cohort arrived 1997-2005	23.0%	0.421	8.6%	0.280	49.4%	0.500
Number of observations	29,621		16,147		13,474	

[1] Dollars of 2001.

Return migrants are workers returning to Mexico who plan to settle there permanently and have no intention to return to work in the U.S. in the near future. Finally, using information on last month's earnings, I estimate hourly wages using the number of hours worked per day and number of days worked per week reported by workers.[8]

One of the limitations of using the EMIF is that it only includes Mexican workers who return to Mexico and misses all those workers who never return. In order to examine how the wages of Mexican workers surveyed by the EMIF mirror those that have been found in the literature using other datasets, I use information from the CPS available since 1994. Figure 6 in the appendix shows average hourly earnings for different cohorts of Mexican male migrants from the CPS, and Figures 7, 8 and 9 show average hourly earnings of workers from the EMIF. When we compare all workers from both surveys (Figures 6 and 7) we can observe similar trends in their wages, however, the wages from the EMIF are lower for all cohorts of entry (Figure 10).

Given that the likelihood of observing illegal, temporary workers is lower in the CPS than in the EMIF, and that those groups of workers are the ones more likely to earn lower wages, I also compare the trends on the wages observed from the CPS with the wages of legal workers settled permanently in the U.S. from the EMIF (Figures 6 and 8). Now there are not differences in the wages of workers who entered before 1990, and for the two most recent cohorts, the wages from the EMIF are even higher than those observed from the CPS. The comparison by cohort of entry is shown in Figure 11. These results suggest that, even though the EMIF only includes Mexican workers who return to Mexico and misses the workers who never return, the wages of legal permanent workers observed in the EMIF are similar to those of the workers survey by the CPS, a survey that includes a representative sample of the Mexican workers permanently settled in the U.S.

Additionally, in order to have a representative sample of the legal and illegal immigrant population in the U.S., I restrict the sample to include only workers who travel to Mexico for personal reasons (individuals who visit Mexico due to an unexpected event, an emergency)

[8]The variable measuring workers' wages in the U.S. appears to contain important coding errors. In the majority of cases, errors occurred by a miscoding of the unit of time for which the reported wage was paid. Some respondents reported their hourly wages; others reported daily, weekly, quarterly and monthly wages. For this reason, I estimate hourly wages using last month's earnings, number of hours worked per day and number of days worked per week.

eliminating workers traveling to Mexico for vacations (who are more likely to be legal workers and have higher wages), and individuals who return to Mexico because they lost their jobs or could not find one (and are more likely to be undocumented and earn lower wages). Finally, a selection issue can arise if workers are more or less likely to cross depending on their characteristics such as legal status or earnings, since they might appear in the sample at different rates. For example, illegal workers might be more likely to cross back and forth if they earn low wages since the opportunity cost of being caught is lower; or if they earn high wages, and can afford to pay smugglers' fees more often. In order to address this problem, using the number of times that each worker has entered and exited the U.S., I estimate their probability of being observed in the sample and construct a set of weights using the inverse of that probability.[9]

Table 7 provides descriptive statistics for legal and illegal migrants. It is interesting to note that 45 percent of the sample entered the U.S. illegally, 45 percent respond that Mexico is their country of residence (temporary workers), 37 percent of the workers in the sample are return migrants and more than 50 percent of the individuals in the sample have six years of schooling or less. On average, Illegal migrants are younger, less educated and more likely to be temporary workers and return migrants.

On average, legal workers earn $8.06 per hour while illegal workers earn $6.30 per hour (in 2001 U.S. dollars), 51 percent of the legal workers reported to have some benefits and only 17 percent of the illegal population. Regarding occupation, 47 percent of the individuals in the sample work in production, 25 percent in agriculture, and 21 percent work in the services sector. Finally, 17 percent of the legal workers report they have been in the U.S. less than five years, and 32 percent more than 16 years. In contrast, 67 percent of the illegal workers report they have been in the U.S. less than five years, and only 6 percent more than 16 years.

[9] A more detailed explanation of the construction of the weights is provided in the Appendix.

3.4 EMPIRICAL SPECIFICATION

3.4.1 OLS Regression

In order to test if legal status impacts the wage rate of workers I use OLS regressions controlling for factors likely to influence migrants' wages. Given that a non-random selection of workers migrating legally and illegally to the U.S. might bias the results, I restrict the sample to include only workers who entered the U.S. illegally. By the time of the survey, some workers are still working without documents, but others report that they have obtained legal status and constitute the comparison group.[10]

In Model 1 the dependent variable is the logarithm of the real wage of individual i observed in year t. The regressors include dummy variables for legal workers, marital status, and family in the U.S., age, and the logarithm of the real state minimum wage. I also include dummy variables for different educational attainments, time that workers have been in the U.S. and controls for occupation. Finally I include dummy variables for temporary workers and return migrants, controls for the year in which the survey was conducted, controls for the state in which respondents work and an error term.

$$\begin{aligned}\log w_{it} \;=\; & \alpha + \beta * legal + \delta * age + \varphi * married + \kappa * familyUS + \psi * \log \min wage + \\ & \sum_{j=1}^{8} \rho_j * education_i + \sum_{j=1}^{4} \phi_j * timeUS_i + \sum_{j=1}^{5} \kappa_j * occupation_i + v * temporary + \\ & \lambda * ret\_migrant + \varpi * year + \varkappa * state + \varepsilon_{it}\end{aligned}$$

In Model 2, in order to capture the wage gap between legal and illegal workers in different occupations, I include all regressors included in Model 1 and interactions of the legal variable with six different major occupation groups: professional/technicians, services, production, sales, agricultural, and other activities.[11] For Model 3, within the six major occupation groups, I construct twelve more detailed categories to estimate the wage gap between legal and illegal workers. I classify individuals into the following occupations: professionals,

[10] Large differences with respect to the unrestricted estimation will provide evidence of selection, which would imply that wage gaps can not only be attributed to legal status, but also to important difference in the unobserved characteristics of workers migrating legal and illegally to the U.S.

[11] A detailed description of the occupations included in each group is provided in Table 28 in the appendix.

technicians, service providers, domestic service providers, sales managers, sales workers, supervisors in production, workers in production, assistants and apprentices in production, agricultural foreman, agricultural laborers, and other activities.

In Model 4, to further analyze if the variables analyzed in Model 1 such as education or time in the U.S. impact differently the wages of legal and illegal workers, I estimate OLS regressions separately for legal and illegal workers. In this Model the dependent variable is the logarithm of real wage and the independent variables are those included in Model 1.

Finally, to further analyze if the effect of legal status is different for individuals working in formal jobs (e.g. workers with formal contracts who receive fringe benefits), in Model 5 I include all regressors included in Model 1, a dummy variable for workers with formal jobs, and interactions of the variable formal with dummies for legal and illegal workers.

3.4.2 Testing for Selectivity

In order to test for selectivity among individuals obtaining legal status, I use the 1986 IRCA's legalization program, a program that granted amnesty to approximately 2.7 million illegal workers. Eligible immigrants were individuals who were unlawfully residing in the U.S. before January 1, 1982 (main legalization program or Pre-1982), and individuals employed in seasonal agricultural work for a minimum of 90 days in the year prior to May, 1986 (SAW program). IRCA provides us with a legalization procedure that is exogenous to migrants' characteristics since eligibility was based on time of arrival to the U.S.

In the EMIF migrants do not report how they obtained legal status, however, starting on 1997, the EMIF asks how many years ago individuals obtained legal status. Using that information, as well as the year of first entry, I select the migrants that were most likely to be legalized under IRCA. Table 30 in the appendix shows the number of workers legalized per year according to the EMIF.[12] The workers who obtained legal status between 1988 and

[12] According to the EMIF the number of workers who obtained legal status increases significantly in 1986, peaks in 1988 and decreases the following years. However, according to the INS (Table 6) IRCA applicants received permanent residence starting in 1989. This mismatch might be explained by the fact that IRCA was passed into law on November 6, 1986, the application period ran from May 5, 1987 to May 4, 1988, and migrants might be reporting any of those years instead of the year in which permanent residence was granted. For that reason, to avoid any risk of misidentification, the workers who obtained legal status between 1988 and 1991, and entered the U.S. illegally between 1978 and 1981 will be considered the migrants most likely to be legalized under IRCA.

1991, and entered the U.S. illegally between 1978 and 1981 will be considered the migrants most likely to be legalized under IRCA. Alternative comparison groups are also tested as robustness checks.

Matching estimation and propensity score techniques are used to estimate the average effect of a program or treatment, allowing for heterogeneous effects, assuming that sample selection is due to observable rather than unobservable differences. Previous studies have found that bias-adjusted propensity-score matching perform comparatively well relative to non-experimental methods which frequently tend to overstate the differences between the treatment and control groups (McKenzie, Gibson, and Stillman (2006)).[13] In this case, to evaluate the impact on job market outcomes associated with receiving permanent residence under IRCA, I would need data on the job market outcomes that those workers would have obtained if they had received legal status through other legalization channels. Since this counterfactual is not observed, I compare labor market outcomes of workers legalized under IRCA with workers with who obtained legal status through other legalization programs.

First, I estimate the differences in earnings of workers legalized under IRCA (main legalization program or Pre-1982) and workers who obtained legal status through other programs (workers who entered the U.S. illegally between 1978 and 1981 and received permanent residence between 1978 and 1985 or between 1992 and 1994).[14] Additionally, I estimate the difference in the earnings of workers who obtained legal status through the IRCA agricultural SAW program and agricultural workers who obtained legal status through other programs (workers who entered illegally between 1982 and 1985 and received legal status between 1978 and 1985 or between 1992 and 1994). These comparisons will show if there is evidence of selectivity among Mexican workers obtaining legal status if the outcomes of workers legalized

[13] McKenzie, Gibson, and Stillman (2006) estimate the wage effects of obtaining legal status using a migrant lottery among Tongans willing to migrate to New Zealand. They estimate gains from migration by comparing the incomes of migrants to those who applied to the lottery but whose names were not selected. They also consider the earnings of individuals who did not apply for the lottery to assess the degree to which non-experimental methods can provide an unbiased estimate of the income gains from migration. Their results show that migrants are positively selected in terms of observed and unobserved skills. Non-experimental methods overstate the gains from migration, while a good instrumental variable, difference-in-differences and bias-adjusted propensity-score matching perform comparatively well.

[14] It is important to note that the in the analysis involving workers legalized under the agricultural SAW program I only include those workers who by the time of the survey are still working in the agricultural sector. All those workers who received permanent residence under the SAW program and changed their occupation after receiving legal status are not included in the sample.

under IRCA are statistically different to the outcomes of workers with similar characteristics, who entered the U.S. during the same period of time, and obtained legal residence through other legalization programs.

3.4.3 Estimating a Wage Gap for Legalized Workers under IRCA

Finally, using the sample of workers who obtained legal status through IRCA (Pre-1982) and appropriate control groups of illegal workers, I also estimate the wage gap between legal and illegal workers. This exercise will not only serve as a falsification test to the analysis of selectivity among Mexican workers obtaining legal status, but also, will provide an estimation of the gains from legal status using workers for whom legal status is exogenous to their personal characteristics. The comparison group consists of a sample of illegal workers who entered the U.S. prior to January 1, 1982 and did not apply to IRCA.

Again, matching techniques seem to be the best estimation method. It is important to note that according to the law, in order to apply to IRCA workers had to prove they had a "continuous physical presence in the United States, except for brief, casual, and innocent travel abroad." When the Immigration and Naturalization Service (INS) issued regulations to implement the law, the INS deemed ineligible for legalization all persons who left the U.S. without permission after Nov. 6, 1986.[15] For this reason, some migrants were rejected by the INS after filing applications; others were rejected by INS clerks without even being permitted to file an application, and other migrants never even applied after they heard the INS was denying amnesty to anyone who had left the country temporarily.[16] This evidence explains why it is not surprising to see in the EMIF a number of illegal immigrants who entered the U.S. prior to 1981 did not obtain legal status under IRCA. Those workers might

[15] Several lawsuits contested this advance-permission regulation and the courts invalidated the regulation twelve days before the deadline to file applications for legal resident status.

[16] In 2000, Congress enacted the Legal Immigration and Family Equity Act Amendments known as the LIFE Act. Among the benefits the law conferred was temporary restoration of the expired 1986 law permitting certain illegal immigrants to become lawful permanent residents. Specifically this amnesty bill was for those who had been told that they were not eligible for permanent residency under IRCA. Applicants had to prove that they entered the United States before January 1, 1982, resided continuously in the US in an unlawful status until May 4, 1988, and that they were continuously present in the US from November 6, 1986, until May 4, 1988. The late amnesty bill of 2000 gave legal status to approximately 400,000 illegal aliens.

have not been eligible due to temporary absences without permission from the INS, and by the time of the survey we still observe them working illegally in the U.S. For those reasons, this group of illegal workers represents an appropriate comparison group.[17] However, if the sample of illegal workers includes individuals who decided not to apply to IRCA, for example, individuals with criminal records who knew their applications would be rejected, the estimated wage gap would overestimate the real gap.

3.5 RESULTS

3.5.1 Economic Performance of Mexican Legal and Illegal Immigrants in the U.S.

In this section I analyze how the economic performance of Mexican immigrants has evolved over time, and to what extent legal status impacts their wage rates. Figure 12 in the appendix shows that the wages of legal and illegal workers have increased during the period of analysis (1993-2005) and, as has been documented in the literature, that illegal workers earn the lowest wages. Without controlling for other factors, the wages of illegal workers have been on average 24 log points lower than those of legal workers. In order to measure if this difference persists once factors likely to influence migrants' wages are controlled for, I run different OLS specifications. Given that non-random selection among workers who migrate legally and illegally might potentially bias the estimates, I restrict the sample to include only workers who entered the U.S. illegally.[18] By the time of the survey, some workers are still working without documents, but others report they have obtained legal status and constitute the comparison group.

Table 8 shows the results from Model 1. Once we control by migrants' characteristics,

[17] If workers did not applied to IRCA due to temporary absences they are an appropriate comparison group (the continuous permanent residence was required from the moment IRCA was passed into law and the time of application). If workers did not applied for other reasons, for example, having a criminal record, then the sample of illegal workers might be negatively selected and the results would overestimate the gains from legal status.

[18] Regressions including workers who entered the U.S. legally and illegally showed similar results. The evidence suggests that observable characteristics seem to be controlling for any selectivity between workers migrating legally and illegally to the U.S.

Table 8: Model 1

Independent Variable	Coef		Std Error
Legal	0.075	***	0.019
Age (10 years)	-0.03	***	0.001
Married	0.02		0.018
With Family in US	0.03		0.019
Temporary Worker	-0.13	***	0.018
Return Migrant	-0.04	**	0.02
Log state min wage	0.13		0.138
Education (ref=None)			
Elementary dropout	0.046		0.037
Elementary graduate	0.104	***	0.038
Secondary dropout	0.183	***	0.046
Secondary graduate	0.17	***	0.039
High school dropout	0.202	***	0.047
High school graduate	0.226	***	0.044
Some college	0.255	***	0.058
College graduate	0.409	***	0.123
Time in US (ref= less than 2 years)			
2-5 years in US	0.034	*	0.019
6-10 years in US	0.058	***	0.022
11-16 years in US	0.084	***	0.023
>16 years in US	0.137	***	0.027
Occupation (ref=Professional/Managerial)			
Sales	-0.24	***	0.06
Services	-0.26	***	0.049
Agriculture	-0.384	***	0.052
Production	-0.175	***	0.047
Other Activities	-0.46		0.282
Constant	1.678	***	0.24
Controls by Year	Yes		
Weights	Yes		
Observations	10,204		
Adj R^2	0.1908		

*** Significant at 0.01 level, ** 0.05 level, * 0.10 level.

legal workers earn wages 7.5 log points higher than illegal workers. The results also show that wages increase systematically with education and with time in the U.S. Individuals with 2-5 years of experience earn wages 3.4 log points higher than recently arrived workers, while workers with more than 16 years in the U.S. earn wages 13.7 log points higher than newly arrived workers.

The results show that the wages of temporary workers are 13 log points lower than those of permanent workers, a result that can be explained if temporary workers have restricted mobility and incentives to take jobs that require little investment in education or training. Finally, the results show that wages of return migrants are 4 log points lower than those of workers who stay in the U.S. This evidence is in line with the "Disappointment Theory of Migration" (Herzog and Schottman, 1982) which maintains that people engage in return migration because they "failed"; they could not find employment or could earn only low wages at the target location. People move with the intention of settling in the new location but have limited information before migration and may miscalculate the benefits of migration.

Model 2 estimates the wage gap between legal and illegal workers in six major occupation groups. The results (Table 9) show that the gap is larger for those working in sales (16 log points), production (9.9 log points), and services (6.7 log points). For individuals working in the agricultural sector and as professionals/technicians the wage gap is 2.8 log points and 7.2 log points respectively, however, these differences are not statistically significant.

In Model 3 I estimate the wage gap between legal and illegal workers in twelve more detailed categories according to their occupation. The results (Table 10) show that the gap is larger among sales workers (17.7 log points), supervisors in production (16.8 log points), workers in production (10.9 log points), and workers in the service sector (8.9 log points). For professionals, technicians, sales managers and agricultural supervisors, the estimated wage gaps are 16.7, 1.7, 10.3 and 13.6 log points respectively; however, these differences are not statistically significant. In these occupational categories large standard errors can be associated to the small number of observations and specifically, to the small number of illegal workers in these categories. Finally, for laborers in the agricultural sector, workers providing domestic services, and individuals working as assistants in production the wage gap is small and not statistically significant (0.5, 2.4 and 1.1 log points respectively).

Table 9: Model 2

Independent Variable	Coef		Std Error
Legal*Profesional	0.072		0.09
Legal*Sales	0.16	**	0.074
Legal*Services	0.067	**	0.033
Legal*Agriculture	0.028		0.031
Legal*Production	0.099	***	0.023
Age (10 years)	-0.03	***	0.001
Married	0.019		0.018
With Family in US	0.032	*	0.019
Temporary Worker	-0.128	***	0.018
Return Migrant	-0.041	**	0.02
Log state min wage	0.134		0.138
Education (ref=None)			
Elementary dropout	0.044		0.036
Elementary graduate	0.102	***	0.038
Secondary dropout	0.181	***	0.046
Secondary graduate	0.168	***	0.039
High school dropout	0.2	***	0.047
High school graduate	0.225	***	0.044
Some college	0.253	***	0.057
College graduate	0.409	***	0.123
Time in US (ref= less than 2 years)			
2-5 years in US	0.036	*	0.019
6-10 years in US	0.059	***	0.022
11-16 years in US	0.084	***	0.023
>16 years in US	0.137	***	0.027
Occupation (ref=Professional/Managerial)			
Sales	-0.303	***	0.09
Services	-0.257	***	0.075
Agriculture	-0.355	***	0.075
Production	-0.193	***	0.073
Other Activities	-0.499	***	0.094
Constant	1.675	***	0.245
Controls by Year	Yes		
Weights	Yes		
Adj R^2	0.1912		

*** Significant at 0.01 level, ** 0.05 level, * 0.10 level.

Table 10: Model 3

Independent Variable	Coef		Std Error
Legal * Professional	0.167		0.159
Legal * Technician	0.017		0.091
Legal * Sales Managers	0.103		0.147
Legal * Sales Workers	0.177	**	0.082
Legal * Services	0.089	**	0.037
Legal * Domestic Services	0.024		0.06
Legal * Agricultural Supervisor	0.136		0.114
Legal * Agricultural Laborer	0.005		0.032
Legal * Supervisor in Production	0.168	***	0.059
Legal * Workers in Production	0.109	***	0.026
Legal * Assistants in Production	0.011		0.038
Elementary dropout	0.045		0.037
Elementary graduate	0.096	**	0.038
Secondary dropout	0.164	***	0.045
Secondary graduate	0.159	***	0.038
High school dropout	0.19	***	0.047
High school graduate	0.208	***	0.044
Some college	0.237	***	0.058
College graduate	0.288	**	0.129
Occupation (ref=Professional)			
Tecnician	-0.267	**	0.133
Sales Managers	-0.314	**	0.149
Sales Workers	-0.579	***	0.123
Services	-0.473	***	0.109
Domestic Services	-0.466	***	0.113
Agricultural Supervisor	-0.504	***	0.139
Agricultural Laborer	-0.577	***	0.109
Supervisor in Production	-0.429	***	0.115
Production Workers	-0.39	***	0.107
Assistant in Production	-0.443	***	0.11
Other Activities	0.718	***	0.193
Constant	1.888	***	0.252
Controls by Year	Yes		
Weights	Yes		
Adj R^2	0.2053		

*** Significant at 0.01 level, ** 0.05 level, * 0.10 level.

Table 11: Model 4

	LEGAL			ILLEGAL		
	Coef		Std Error	Coef		Std Error
Age (10 years)	-0.035	***	0	0.006		0
Married	0.056	***	0.02	-0.02		0.02
With Family in US	0.036		0.03	0.032		0.02
Temporary	-0.156	***	0.02	-0.077	***	0.03
Return Migrant	-0.087	***	0.03	-0.038	*	0.02
Education (ref=None)						
Elementary dropout	0.046		0.04	0.039		0.04
Elementary graduate	0.115	***	0.04	0.083	*	0.04
Secondary dropout	0.184	***	0.05	0.044		0.05
Secondary graduate	0.175	***	0.04	0.100	**	0.05
High school dropout	0.268	***	0.05	0.104	*	0.06
High school graduate	0.226	***	0.05	0.126	**	0.06
Some college	0.301	**	0.08	0.185	***	0.07
College graduate	0.448	***	0.08	0.341	***	0.1
Time in US (ref= less than 2 years)						
2-5 years in US	0.036		0.03	0.035	*	0.02
6-10 years in US	0.07	**	0.03	0.087	***	0.02
11-16 years in US	0.094	***	0.03	0.064	**	0.03
>16 years in US	0.164	***	0.03	0.085	**	0.04
Occupation (ref=Professional)						
Technicians	-0.254	***	0.08	-0.22	*	0.12
Sales Managers	-0.163		0.1	-0.31	**	0.15
Sales Workers	-0.336	***	0.09	-0.5	***	0.11
Services	-0.399	***	0.07	-0.38	***	0.09
Domestic Services	-0.505	***	0.08	-0.39	***	0.1
Agricultural Supervisor	-0.414	***	0.08	-0.4	***	0.12
Agricultural Laborer	-0.58	***	0.07	-0.49	***	0.09
Supervisor in Production	-0.248	***	0.08	-0.31	***	0.1
Production Workers	-0.31	***	0.07	-0.29	***	0.09
Assistant in Production	-0.428	***	0.07	-0.36	***	0.09
Constant	1.747	***	0.27	2.161	***	0.33
Observations	10,341			4,658		
Adj R^2	0.209			0.158		

*** Significant at 0.01 level, ** 0.05 level, * 0.10 level.

In Model 4, to further analyze if the covariates impact differently the wages of legal and illegal workers, I estimate Model 1 separately for both groups of workers. Table 11 shows that temporary migrants earn lower wages than their settled counterparts. Illegal temporary workers earn wages 7.7 log points lower than settled illegal workers, while legal temporary migrants earn wages 15.6 log points lower than settled legal workers. The results also show that wages of return migrants are lower than those of workers who stay in the U.S. Legal return migrants earn wages 8.7 log points lower than legal workers who stay in the U.S., and illegal return migrants earn wages 3.8 log points lower than the illegal workers who decide to stay. Finally, wages increase systematically with education and with experience in the U.S., two results that are especially strong among legal workers.

Finally, the results from Model 5 (Table 12) show that the wage gap between legal and illegal workers is 9.0 log points for workers in formal jobs, and is not statistically significant for workers in informal jobs. This evidence is in line with the idea that firms may be willing to employ undocumented workers only if the wage is lower so as to compensate for the additional cost that firms incur when hiring illegal workers. Such costs might include tax burden, fines and costs of avoiding prosecution, costs that are higher when undocumented workers have formal jobs.

3.5.2 Testing for Selectivity among Workers obtaining Legal status

In order to evaluate the effect of the potential bias generated if workers with more unobserved ability are more likely to obtain legal status, I use the 1986 IRCA's legalization program to test for selectivity in the population obtaining legal status. Tables 13 and 15 report summary statistics for the treatment and control groups. For the workers legalized under IRCA Pre-1982 the control group is a sample of workers who entered the U.S. illegally during the same period of time and obtained legal status between 1978 and 1985 or between 1992 and 1995. For the agricultural workers legalized under SAW, the control group is a sample of workers who entered the U.S. between 1982 and 1986 and received legal status between 1978 and 1985 or between 1992 and 1995.

Table 14 shows the estimated wage gap between workers legalized under IRCA (PRE-

Table 12: Model 5

Independent Variable	Coef		Std Error
Legal*Formal	0.09	***	0.02
Legal*Informal	0.023		0.016
Formal	0.063	***	0.019
Age (10 years)	-0.003	***	0.001
Married	0.022	*	0.012
With Family in US	0.02		0.016
Temporary Worker	-0.112	***	0.013
Return Migrant	-0.039	***	0.014
Log state min wage	0.141		0.088
Education (ref=None)			
Elementary dropout	0.039	*	0.021
Elementary graduate	0.09	***	0.021
Secondary dropout	0.157	***	0.026
Secondary graduate	0.15	***	0.022
High school dropout	0.177	***	0.029
High school graduate	0.186	***	0.026
Some college	0.212	***	0.04
College graduate	0.267	***	0.047
Time in US (ref= less than 2 years)			
2-5 years in US	0.024		0.024
6-10 years in US	0.052	*	0.023
11-16 years in US	0.075	***	0.023
>16 years in US	0.121	***	0.025
Occupation (ref=Professional)			
Technicians	-0.363	***	0.049
Sales Managers	-0.323	***	0.064
Sales Workers	-0.551	***	0.052
Services	-0.51	***	0.044
Domestic Services	-0.521	***	0.048
Agricultural Supervisc	-0.49	***	0.05
Agricultural Laborer	-0.655	***	0.044
Supervisor in Producti	-0.41	***	0.046
Production Workers	-0.41	***	0.043
Assistant in Productic	-0.515	***	0.046
Other Activities	-0.446	***	0.101
Constant	1.922	***	0.159
Controls by Year	Yes		
Weights	Yes		
Observations	10,196		
Adj R^2	0.1918		

Table 13: Summary Statistics: IRCA(PRE-1982) vs Legal Workers

Year Obtained of Legal Status						
	1978-1985		1986-1991 IRCA (PRE-1982)		1992-1995	
	Observations	133	Observations	543	Observations	189
Year of	Wage	2.09	Wage	2.04	Wage	2.18
Arrival	Years schooling	6.28	Years schooling	6.18	Years schooling	6.73
1978-1981	Age	43.23	Age	43.18	Age	42.56

1982) and the control group. The covariates used are age, age squared, years of schooling, years of schooling squared, number of years in the U.S., and number of years since legal status was granted. I also include dummy variables for eleven different occupations, the number of jobs the migrant has had in the U.S., and dummy variables for temporary workers, workers with family in the U.S., phase of the survey in which the interview was conducted, and the state of the U.S. the where the migrant works. Using the methodology provided by Abadie et al., (2004), I estimate the average treatment effect for the treated (ATT) using bias-corrected exact matching and estimate the standard errors allowing for heteroskedasticity.[19] I use four matches to estimate the conditional variance functions given that four matches seem to include sufficient information without matching unlike individuals. Additionally, as robustness check I also analyze the sensitivity of the estimator to the number of neighbors used in forming the match estimating the gap with up to five matches. The results show that there are no significant differences in the earnings of the workers from the treatment and the control group.

Table 14 also shows estimates of the wage gap using propensity score matching estimation. I use a logit specification to estimate the propensity score; however estimations using a probit model provide similar results. The estimations are performed following the methodology provided by Becker and Ichino (2002). The ATT is estimated using the same covariates from the specification above and four matching methods: nearest neighbor, stratification, kernel and radius matching. It is important to mention that the common support condition

[19] According to Abadie et al., (2004), bootstrapping methods for estimating the variance of matching estimators do not necessarily give correct results.

Table 14: Matching Estimation IRCA (PRE-1982) vs Legal Workers

Propensity Score	ATT	Std. Err.
Stratification matching	-0.031	0.036
Kernel-based matching	-0.037	0.037
Nearest neighbor matching	0.006	0.046
Matching Estimator	**Coef.**	**Std. Err.**
SATT 1	0.005	0.045
SATT 2	-0.002	0.041
SATT 3	-0.008	0.04
SATT 4	-0.02	0.04
SATT 5	-0.018	0.04
OLS	**Coef.**	**Std. Err.**
OLS	-0.019	0.033

Table 15: Summary Statistics IRCA(SAW) vs Legal Workers

	1978-1985		1986-1991 IRCA (SAW)		1992-1995	
Year of Arrival 1982-1985	Observations	26	Observations	196	Observations	43
	Wage	1.67	Wage	1.71	Wage	1.91
	Years schooling	5.08	Years schooling	5.26	Years schooling	6.3
	Age	44.46	Age	39.45	Age	39.26

Table 16: Matching Estimation IRCA (SAW) vs Legal Workers

Propensity Score	ATT	Std. Err.
Stratification matching	0.013	0.072
Radius matching	0.029	0.079
Kernel-based matching	0.023	0.083
Nearest neighbor matching (RD)	0.001	0.064
Matching Estimator	Coef.	Std. Err.
SATT 1	0.014	0.12
SATT 2	0.049	0.101
SATT 3	0.055	0.1
SATT 4	0.017	0.103
SATT 5	-0.018	0.104
OLS	Coef.	Std. Err.
OLS	0.059	0.082

was imposed and the balancing property was set and satisfied in all the models.[20] The results show no significant differences in the earnings of the treatment and the control group.

Next, I estimate the wage gap between agricultural workers legalized under IRCA SAW program and the control group. Table 16 shows the estimates obtained using bias-corrected matching as well as propensity score. The results show that there are no significant differences in the earnings of the treated and control group.

Based on the previous results, we can conclude that there is no evidence of selectivity among Mexican workers obtaining legal status. The estimates show that the outcomes of workers legalized under IRCA are no statistically different than those of workers with similar characteristics who obtained permanent residence through other legalization programs. These results suggest that the observable characteristics of migrants seem to be controlling for any type of selection among workers obtaining legal status. According to the Bureau of Consular Affairs during the period of analysis most of the legalizations have been done under provisions which give priority to those who have immediate relatives and family already in the U.S. These two methods do not seem to increase the chances of legalization for those with more unobservable abilities.

[20] The common support test verifies that the overlapping assumption is satisfied and the balancing property verifies that the covariates are balanced within each block, that is, that the difference between the average of the covariates for the treatment and control groups within each block is small.

Table 17: Summary Statistics Legal (IRCA PRE-1982) and Illegal Workers

Legal Workers (IRCA PRE-1982)		
Year of Arrival 1978-1981	Observations	543
	Wage	2.04
	Years schooling	6.18
	Age	43.18
Illegal Workers		
Year of Arrival 1978-1981	Observations	86
	Wage	1.75
	Years schooling	5.44
	Age	41.8

3.5.3 Estimating a Wage Gap for Legalized Workers under IRCA

Finally, using again matching estimators for the sample of workers who obtained legal status through IRCA (PRE-1982), and a sample of illegal workers who entered prior to January 1, 1982 and did not apply to IRCA, I estimate the wage gap between legal and illegal workers. As mentioned before, this is an appropriate control group since their legal status seems to be exogenous to personal characteristics; a number of migrants were not eligible for IRCA due to temporary absences from the U.S. However, if the sample of illegal workers includes individuals who decided not to apply to IRCA, for example, individuals with criminal records who knew their applications would be rejected, the wage gap would be overestimated, and the results obtained would represent an upper bound for the real gap. Table 17 reports summary statistics for the treatment and control groups.

Table 18 shows the estimated wage gap. The covariates used are age, age squared, years of schooling, years of schooling squared, and number of years in the U.S. I also include dummy variables for eleven different occupations, the number of jobs that migrants have had in the U.S., and dummy variables for temporary workers, workers with family in the U.S., phase of the survey in which the interview was conducted, and the state of the U.S. where migrants work.

The ATT estimated using bias-corrected exact matching shows a gap of 15.5 log points while matching using different number of covariate matches show a statistically significant

Table 18: Matching Estimation IRCA (PRE-1982) vs Illegal Workers

Propensity Score	ATT		Std. Err.
Stratification matching	0.138		0.094
Radius matching	0.131		0.099
Kernel-based matching	0.177		0.089
Nearest neighbor matching	0.115		0.115
Matching Estimator	Coef.		Std. Err.
SATT 1	0.155	**	0.079
SATT 3	0.135	*	0.08
SATT 5	0.135	*	0.079
SATT 7	0.136	*	0.078
SATT 10	0.147	*	0.078
OLS	Coef.		Std. Err.
OLS	0.097		0.067

wage gap between 13.5 and 14.7 log points. Table 18 also shows estimates of the wage gap using propensity score matching estimation using the same covariates from the specification above. The ATT estimated using nearest neighbor matching shows a gap of 11.5 log points, stratification matching a gap of 13.8 log points, kernel matching a gap of 17.7 log points, and radius matching a gap of 13.1 log points.

Based on the previous results, we can conclude that once I control for different individual characteristics, legal workers earn wages 12 to 17 log points higher than those of illegal workers. This gap seems to be robust since different matching techniques provided similar results, and unbiased, since legal status is granted based on date of arrival and is exogenous to migrants' characteristics.

3.6 CONCLUSIONS

I estimate the effect of legal status on the wages of Mexican immigrants in the U.S. using Mexico's Survey of Migration to the Northern Border. I control for possible selection biases and test for selectivity in the population obtaining legal status using the 1986 IRCA's

legalization program along with matching estimation techniques.

The results show that legal workers earn higher wages than illegal workers, especially those working in the production and service sectors. Controlling for observable characteristics and occupation decreases the wage differential; however, we still observe a significant wage gap. Moreover, the results show discrimination against illegal workers does not seem to explain the wage differences between legal and illegal workers, since the wage gap is only observed among workers in specific occupations. Finally, the results show that the wage gap is larger among individuals working in "formal" jobs. While it is true that some illegal workers are paid off the books, an important number of undocumented workers get formal jobs using false social security numbers. The evidence is in line with the idea that firms may hire undocumented workers in formal jobs if the wage is lower so as to compensate for the additional expenses that firms incur from hiring undocumented workers (e.g. tax burden, fines or costs of avoiding prosecution).

The results also show that temporary migrants earn lower wages than their settled counterparts, a finding that can be explained if temporary workers have restricted mobility and incentives to take jobs that require little investment in education or training. Additionally, I find that return migrants earn lower wages than those of workers who decide to stay in the U.S. This evidence is in line with the "Disappointment Theory of Migration" that maintains that people engage in return migration because they "failed"; they could not find employment or could earn only low wages at the target location. Finally, it is interesting to note that wages increase systematically with education and with experience in the U.S.; these results that are especially strong among legal workers.

I test for selectivity in the population obtaining legal status using the 1986 IRCA's legalization program, which provides us with a legalization procedure that is exogenous to migrants' characteristics. Using matching and propensity score estimation, I find no evidence of selectivity among Mexican workers obtaining legal status. The estimations show that the outcomes of workers legalized under IRCA are no statistically different than those of workers with similar characteristics who obtained permanent residence through other channels. These results suggest that the observable characteristics of migrants seem to be controlling for any type of selectivity among workers obtaining legal status.

Finally, I estimate a wage gap between workers legalized under IRCA and an appropriate group of illegal workers. The results show that once I control for different individual characteristics, there is a significant gap in the wages of legal and illegal workers of 12 to 19 percent. This gap seems to be robust since different matching techniques provided similar results, and unbiased, since legal status is granted based on date of arrival and is exogenous to migrants' characteristics.

Given the large number of Mexican migrants working in the U.S. labor market, a better understanding of their characteristics and job market outcomes is an issue of great relevance for Mexico and the U.S. A deeper knowledge of the benefits of having legal status and the characteristics of those obtaining legal status can provide policymakers with useful information to better estimate, not only the implications of the current immigration policy, but also the impact that future changes to the U.S. immigration policy could have on the U.S. labor market.

4.0 WHO STAYS AND WHO GOES BACK HOME? EVIDENCE FROM MEXICAN IMMIGRANTS IN THE U.S.

4.1 INTRODUCTION

To better understand the dynamics of the immigrant flow, it is essential to analyze the characteristics of return migrants. Return migration is an important phenomenon that has received little attention in the literature even though it involves a large share of migrants and has large social, economic, and cultural impacts on both, the home and host countries. If long-term settlement is not a random process, return migration will not only affect the composition of the immigrant population and their use of social services in the host country, but also the economic development in the home country through remittances and investment.

In this paper I study return migration of Mexican migrants in the United States. Borjas and Bratsberg (1996) show that the return migration process accentuates the type of selection that originally characterized the immigrant flow. According to their theoretical prediction, if the immigrant flow is positively selected, the outmigrants should be less skilled than the immigrants who remain in the United States (U.S.). If the immigrant flow is negatively selected, the outmigrants will be more skilled than the immigrants who remain in the U.S.

In this paper I test Borjas and Bratsberg's prediction. I use data from the Survey of Migration to the Northern Border (EMIF) together with a selection model to infer the unobservable skills of Mexican immigrants and the unexpected component of their earnings in the U.S. I test for differences in the observable skills, unobservable skills, and uncertainty component associated with U.S. earnings of return migrants and migrants who stay in the U.S.

The results show that immigrants are negatively selected relative to the Mexican popula-

tion. Consistent with Borjas and Bratsberg's prediction, return migrants are relatively more skilled than the typical immigrant. Moreover, workers who face more negative unexpected conditions in the U.S. are those who find it optimal to return to Mexico.

4.2 LITERATURE REVIEW

Despite the practical importance of return migration, little is known about the selection process guiding the outmigration decision of the foreign born. An important body of literature has considered return migration as a cost-benefit decision, where individuals decide to stay or return in order to maximize their expected lifetime earnings. Sjaastad (1962) provides a theoretical framework for the decision to migrate where individuals calculate their present discounted value of expected returns in different locations, and migration occurs if the returns in a potential destination, net of migration costs, are larger than the returns in their home country.

According to this view, immigrants originally move in response to higher wages in the host country, which they expect to yield higher lifetime earnings. In the absence of a reduction in the binational wage differential, return migration should only occur if a migrant's expectations for higher earnings are not met, if wages are lower than expected, or if the psychic costs of moving are higher than anticipated. In this sense, return migrants are view as "failures", what Duleep (1994) calls "mistaken migrants", and Herzog and Schottman (1982) call "disappointed migrants".

However, these predictions are often not compatible with the empirical evidence. Some authors have provided explanations to rationalize the fact that migrants return, despite persistently higher wages in the host country. Djajic and Milbourne (1988) assume that different preferences for consuming at home and at the destination may be responsible for temporary migration. Dustmann (1995, 1997) shows that high purchasing power of the host country currency at home, and higher returns to human capital in the home economy, are some of the motives behind return migration. Mesnard (2004) analyzes how capital market imperfections influence return migration and shows that return migration may be one way

to overcome capital constraints.

An alternative view of return migration is known as the "Target Income Theory of Migration" (Stark 1991, Borjas 1994, Hill 1987, Lindstrom 1996, Massey et al. 1993). This theory states that immigrants move to accumulate savings to invest in their home countries. That is, migrants plan to stay in the host country as long as is required to accumulate enough savings to reach a particular level of income. Once reaching the target, they return to their place of origin. This theory assumes that immigrants have a strong preference for remaining in their home country and migrate due to limited wage opportunities at home.

Borjas and Bratsberg (1996) present a model that incorporates both theories of return migration. First, return migration may have been planned as part of an optimal life-cycle residential location sequence, where some immigrants migrate to the U.S. for a few years, accumulate financial resources or other types of capital, and then return to the source country. Alternatively, return migration might occur if immigrants based their initial migration decision on erroneous information about economic opportunities in the U.S. This model predicts that return migration accentuates the type of selection that originally characterized the immigrant flow. The authors confirm their theoretical predictions by calculating outmigration rates for immigrants from 70 source countries using data from the 1980 U.S. Census.

Two studies that empirically analyze the selection process guiding return migration are Borjas (1989) and Jasso and Rosenzweig (1988). In the Borjas' study, return migration is inferred from sample attrition in a longitudinal data set of foreign born scientists and engineers. He finds that the least successful scientists and engineers are most likely to drop out from the sample, and concludes that the outmigration process is one in which "failures" leave the U.S. In contrast, Jasso and Rosenzweig observe the naturalization decision of immigrants, and infer that those who do not naturalize are most likely to leave the country. In their study, it is the most skilled workers who do not naturalize, and are most likely to be outmigrants.

4.3 BORJAS AND BRATSBERG'S MODEL

Individuals in the home country (country 0) consider the possibility of migrating, either temporarily or permanently to the host country (country 1). The log earnings distributions in the source and home countries are given by:

$$\begin{aligned} w_0 &= \mu_0 + \upsilon \\ w_1 &= \mu_1 + \lambda\upsilon + \varepsilon_1 \end{aligned}$$

where μ_0 is the mean log income in the source country, and μ_1 is the mean income that would be observed if all persons in the source country (Mexico) migrate to the host country (U.S.). The parameter λ represents the rate of return to skills in the U.S. relative to that in Mexico. The parameter υ reflects ability or skills that are transferable across countries and is assumed to be known to the individual. The parameter ε_1 reflects an uncertainty component due to misinformation or luck in U.S. earnings, and is assumed to remain unknown unless the individual migrates to the U.S. The random variables υ and ε_1 measure deviations from mean incomes, have zero means and finite variances, and are assumed to be independent.

Workers in Mexico can migrate temporarily to the U.S. followed by a permanent return to Mexico. The log earnings associated with this alternative are given by:

$$w_{10} = \pi w_1 + (1 - \pi)(w_0 + k)$$

where π and k represent the time that the individual stays in the U.S. and the gain to a temporary stay. Both parameters are constant among individuals.

Assuming risk neutrality, a person migrates to the U.S. if the expected value of the maximum between the wage from migrating permanently and temporarily to the U.S., exceeds the wage in Mexico net of migration costs:

$$E\left[max\left\{w_1 - M, w_{10} - M - R\right\}\right] > w_0,$$

where M and R are time equivalent measures of migration cost to the U.S. and remigration costs to Mexico.[1]

Individuals who migrate to the U.S. will return to Mexico if they migrated in the first place, and if the actual available income in the U.S. is lower than the potential income in Mexico.

$$E\left[max\left\{w_1 - M, w_{10} - M - R\right\}\right] > w_0$$

and

$$max[w_0 - R, w_{10} - R] > w_1.$$

Combining the last two expressions it can be found that an individual will stay in Mexico if

$$\upsilon(\lambda - 1) \leq (\mu_0 - \mu_1 + \kappa) + \frac{M + R + \kappa}{\pi};$$

will migrate to United States if:

$$\upsilon(\lambda - 1) > (\mu_0 - \mu_1 + \kappa) + \frac{M + R + \kappa}{\pi},$$

and will return to Mexico if:

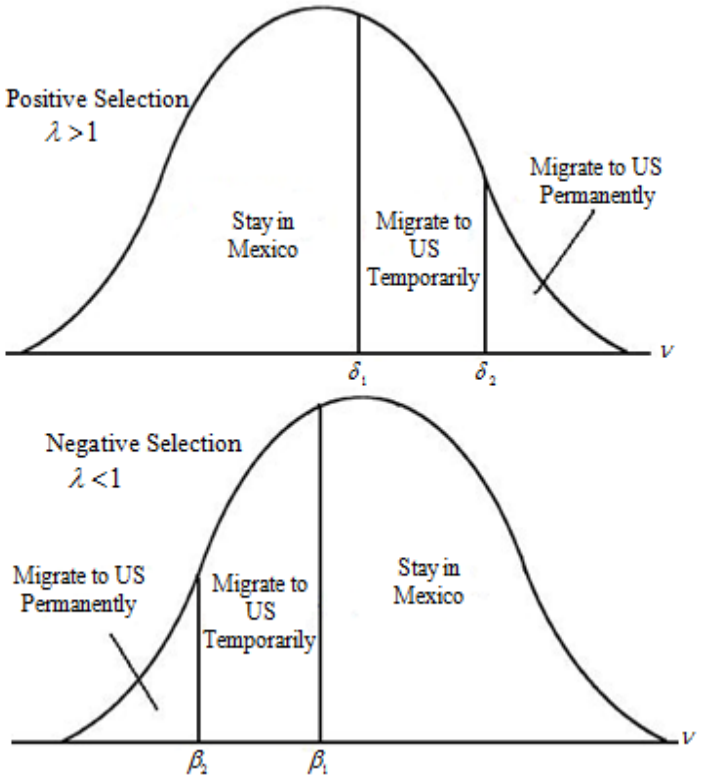
$$(\mu_0 - \mu_1 + \kappa) + \frac{M + R + \kappa}{\pi} < \upsilon(\lambda - 1) < (\mu_0 - \mu_1 + \kappa) - \frac{R}{1 - \pi} - \varepsilon_1.$$

Figure 3 shows the skill sorting in human capital model when immigrants are positively selected ($\lambda > 1$) and negatively selected ($\lambda < 1$) when there is not uncertainty in the migration decision. If the immigrant flow is positively selected, the outmigrants should be less skilled than the immigrants who remain in the United States. If the immigrant flow is negatively selected, the outmigrants will be more skilled than the immigrants who remain in the U.S.

Return migration can also arise as immigrants attempt to correct mistakes in the initial immigration decision. The introduction of uncertainty in U.S. economic opportunities does not alter the type of selection that characterizes the immigrant flow because individuals

[1] According to Borjas and Bratsberg the decision is made by comparing the maximum of the expectation of the wages if migration is permanent or temporary and the wage in the source country net of migration costs: $max[Ew_1 - M, Ew_{10} - M - R] > w_0$. However these differences do not change the predictions of the model.

Figure 3: Skill Sorting in Human Capital Model



migrate in order to maximize their expected value of income. After arrival in the U.S., the immigrant makes a random draw from the $g(\varepsilon)$ density, and reconsiders the profitability of his original decision. The decision of whether to return to Mexico depends on whether the draw is favorable or unfavorable. Figure 4 shows that only those persons who have relatively unfavorable draws become return migrants.

The skill composition of the return migration flow in this model is identical to the sorting implied by the human capital model. In particular,

$$E(\upsilon|\text{ Migrate and Stay}) > E(\upsilon|\text{ Migrate and Return}),\text{ for } \lambda > 1$$

and

$$E(\upsilon|\text{ Migrate and Stay}) < E(\upsilon|\text{ Migrate and Return}),\text{ for } \lambda < 1.$$

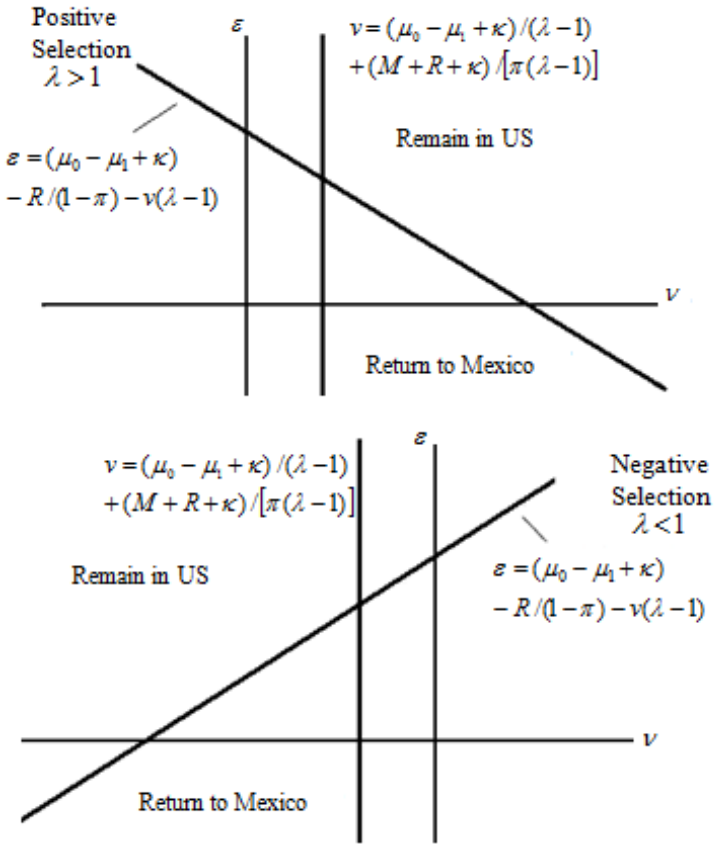
If $\lambda > 1$, return migrants are relatively unskilled workers (selected from a skilled immigrant flow), while if $\lambda < 1$, return migrants are relatively skilled workers (selected from an unskilled immigrant flow). As before, return migration accentuates the selection that characterizes the original immigration. Figure 4 shows that the random variable υ for return migrants is truncated from above when $\lambda > 1$, and υ is truncated from below when $\lambda < 1$.

4.4 DATA

Data on Mexican population is from the 1995 Mexican population and dwelling count, and the 2000 Mexican Census. Data on Mexican migration comes from the Survey of Migration to the Northern Border (EMIF), a cross-sectional survey conducted ten times between 1993 and 2005 that samples the flows of migrants between Mexico and the U.S. in the northern border region of Mexico.[2] The EMIF contains information of wages in Mexico prior migration, wages in the U.S., as well as many other characteristics such as age and education. Additionally, in the survey it is possible to identify workers by legal status and return migrants.

[2]The survey is conducted in eight Mexican border cities. Within each city, individuals are sampled at different locations including bus stations, airports, ports of entry and Mexican customs inspection stations.

Figure 4: Skill Sorting Uncertainty Model



I impose some sample restrictions. I limit the sample to workers who migrated to the U.S. after 1992, who were working in Mexico prior migration, and report their wages. I also restrict the sample to include migrants who worked at least 30 days in the U.S. and report their wages, and who were surveyed by the EMIF within the first three years of U.S. residency. "Return migrants" are workers returning to Mexico who plan to settle there permanently and have no intention to return to work in the U.S. in the near future. Migrants who "Stay in the U.S." are workers who are visiting Mexico but will return to work either temporarily or permanently to the U.S.

Hourly wages in the U.S. are estimated using migrants' information on last month's earnings, number of hours worked per day and number of days worked per week.[3] A selection issue can arise if workers with different characteristics are more or less likely to cross the Mexico-U.S. border, since they might appear in the sample at different rates.[4] In order to address this problem, using the number of times that each worker has entered and exited the U.S., I estimate their probability of being observed in the sample and construct a set of weights using the inverse of that probability.

Table 19 provides descriptive statistics for all immigrants, return migrants, migrants who stay in the U.S. Immigrants have on average 6.15 years of schooling, their average wage in the U.S. is $5.75 per hour (in 2001 U.S. dollars), and their wage in Mexico prior migration was $1.65 per hour (in 2001 U.S. dollars). It is important to note that while 12.9 percent of the immigrants entered the U.S. legally, by the time of the survey 27.7 percent are authorized to work in the U.S. Return migrants are slightly less educated; earn lower wages in the U.S., but report higher wages in Mexico prior migration.

[3] For workers reporting daily, quarterly or monthly wages in Mexico, hourly wages are estimated assuming they work eight hours per day, six days per week and 4.33 weeks per month.

[4] For example, illegal workers might be more likely to cross back and forth if they earn low wages in the US since the opportunity cost of being caught is lower; or if they earn high wages, and can afford to pay smugglers' fees more often.

Table 19: Summary Statistics Return Migrants and Migrants who Stay in the U.S.

	All Immigrants		Return Migrants		Migrants Stay in US	
	Mean	SD	Mean	SD	Mean	SD
Characteristics						
Legal at Survey	27.7%	0.45	23.9%	0.43	40.0%	0.49
Legal at Entry	12.9%	0.33	11.4%	0.32	17.5%	0.38
Return Migrant	75.7%	0.43	100.0%	0.00	0.0%	0.00
Age	33.2	10.5	33.2	10.4	33.4	10.7
Married	69.2%	0.46	70.1%	0.46	66.8%	0.47
Family in US	77.7%	0.42	76.7%	0.42	80.5%	0.40
Female	2.0%	0.14	1.6%	0.13	3.2%	0.18
Years of schooling	6.15	3.40	6.12	3.34	6.25	3.61
No education	8.3%	0.28	7.9%	0.27	9.5%	0.29
Elementary dropout (<6y)	25.8%	0.44	25.9%	0.44	25.8%	0.44
Elementary graduate (6y)	28.3%	0.45	28.8%	0.45	26.4%	0.44
Secondary dropout (7-8y)	8.4%	0.28	8.5%	0.28	8.2%	0.27
Secondary graduate (9y)	18.4%	0.39	18.8%	0.39	16.9%	0.37
High school dropout (10-11y)	3.8%	0.19	3.7%	0.19	4.1%	0.20
High school graduate (12y)	4.8%	0.21	4.4%	0.21	6.1%	0.24
Some College (13-15)	1.2%	0.11	1.0%	0.10	1.9%	0.14
College graduate (>=16y)	0.9%	0.10	0.9%	0.09	1.2%	0.11
Earnings						
Wage US[1]	5.75	4.59	5.68	4.81	6.00	3.91
Wage Mexico[1]	1.65	4.26	1.71	4.54	1.48	3.30
Occupation in US						
Professional/Technicians	1.8%	0.13	1.5%	0.12	3.0%	0.17
Sales	1.7%	0.13	1.6%	0.12	2.1%	0.14
Services	21.3%	0.41	21.5%	0.41	19.9%	0.40
Agricultural	34.5%	0.48	35.2%	0.48	32.8%	0.47
Production	40.6%	0.49	40.2%	0.49	42.2%	0.49
Other Activities	0.1%	0.03	0.1%	0.04	0.0%	0.00
Observations	5,538		4,144		1,394	

[1]In 2001 US Dollars. Wages in Mexico prior migration.

4.5 EMPIRICAL SPECIFICATION

I will use Borjas and Bratsberg's selection model along with data of Mexican immigrants and the Mexican population to infer the unobservable transferable skills of immigrants and the unexpected component of their earnings in the U.S. To determine the type of selection process guiding the outmigration decision of Mexican immigrants, I test for significant differences in the unobserved skills and the uncertainty component of return migrants and migrants who stay in the U.S. The wage equations in Mexico and the U.S. are given by:

$$w_{0i} = \alpha_0 + \beta_0 X_i + \upsilon_i \tag{4.1}$$

and

$$w_{1i} = \alpha_1 + \beta_1 X_i + \lambda \upsilon_i + \varepsilon_{1i} \tag{4.2}$$

where w_{0i} is the logarithm of the hourly wage in Mexico of individual i, w_{1i} is the logarithm of the hourly wage in the U.S. of individual i, X_i is a set of individual observable characteristics such as age, years of schooling, gender, marital status, and state; υ_i represents unobserved workers' transferable skills, λ is the rate of return to skills in the U.S. relative to Mexico, and ε_{1i} is a random shock.

Step 1

Using equation (4.1) and data from the 1995 Mexican Population and Dwelling Count and the 2000 Mexican Census, I estimate the returns to observable characteristics for the Mexican population. I restrict the sample to include individuals who work, report their wage and are aged 16 to 65. I run this regression separately for year 1995 and 2000, and obtain a set of coefficients for each year.

Step 2

For the sample of Mexican immigrants surveyed by EMIF, I find the returns to observable and unobservable characteristics in the Mexican labor market. I use information of wages in Mexico prior migration (w_{0i}), a set of personal characteristics (X_i), and the rate of return to observable characteristics in the Mexican labor market (the coefficients obtained in the

previous step). The estimated unobservable transferable skills ($\widehat{\upsilon_i}$) for Mexican immigrants are given by:

$$\widehat{\upsilon_i} = w_{0i} - (\widehat{\alpha_0} + \widehat{\beta_0} X_i).$$

For workers who entered the U.S. between 1993 and 1997 I use the coefficients obtained in the regression for the Mexican population in 1995. For workers who entered after 1997 I use the coefficients obtained in the regression with data from 2000.

Step 3

The next step is to find the rate of return to observable (β_1) and unobservable characteristics (λ) in the U.S. labor market for the sample of immigrants. Using information of migrants' wages in the U.S. (w_{1i}), a set of individual observable characteristics (X_i), and their unobservable skills ($\widehat{\upsilon_i}$), I estimate the following wage regression:

$$w_{1i} = \alpha_1 + \beta_1 X_i + \lambda \widehat{\upsilon_i} + \varepsilon_{1i}. \tag{4.3}$$

The coefficient associated with $\widehat{\upsilon_i}$ is the rate of returns to skills in the U.S. relative to Mexico (λ), and the residuals obtained (ε_{1i}) can be interpreted as the uncertainty component associated with immigrants' U.S. earnings

$$\widehat{\varepsilon_{1i}} = w_{1i} - \widehat{\alpha_1} - \widehat{\beta_1} X_i - \widehat{\lambda} \widehat{\upsilon_i}.$$

I test for significant differences in the transferable skills ($\widehat{\upsilon_i}$) and the uncertainty component ($\widehat{\varepsilon_{1i}}$) between return migrants and migrants who decide to stay in the U.S. Moreover, I test if the selection process is different between workers migrating legally and illegally to the U.S.

Alternatively, if we change Borjas and Bratsberg's model, and we allow for shocks in the Mexican labor market equation (4.1) becomes:

$$w_{0i} = \alpha_0 + \beta_0 X_i + \upsilon_i + \varepsilon_{0i}. \tag{4.4}$$

If we assume that the unobservable skills υ_i are uncorrelated with workers' observable characteristics X_i, and that the estimated unobservable skills $\widehat{\upsilon_i}$ are uncorrelated with the error term $\widehat{\varepsilon_{0i}}$, in step 2 we will only be able to estimate $\widehat{\upsilon_i + \varepsilon_{0i}}$ instead of $\widehat{\upsilon_i}$ with

$$\widehat{\upsilon_i + \varepsilon_{0i}} = w_{0i} - (\widehat{\alpha_0} + \widehat{\beta_0} X_i).$$

Therefore, the equation (4.3) for the U.S. labor market becomes

$$w_{1i} = \alpha_1 + \beta_1 X_i + \lambda \widehat{\chi_i} + u_i \tag{4.5}$$

where

$$\widehat{\chi_i} = \widehat{\upsilon_i + \varepsilon_{0i}} \text{ and } u_i = \varepsilon_{1i} - \lambda \widehat{\varepsilon_{0i}}.$$

In this setting, since $\widehat{\chi_i}$ and u_i are correlated, the results will suffer of attenuation bias. If λ is positive, $\widehat{\lambda}$ will tend to underestimate λ, if λ is negative, $\widehat{\lambda}$ will overestimate the rate of returns to skills in the U.S. relative to Mexico.

One caveat of this study is that it only includes immigrants who entered the U.S. since 1992 due to data availability. While this analysis can be extended to analyze future waves of immigrants, the selectivity of previous cohorts cannot be determined. Estimates suggest that almost half of the Mexican workers migrating to the U.S. return to Mexico within twelve months, therefore, analyzing the behavior of immigrants who entered the U.S. during a 10 year window, provide a representative picture of the selection process guiding return migration.

Table 20: Education and Earnings of Immigrants and Mexican Population

	Mexican Population		Immigrants
	1995	2000	EMIF
Years of schooling	8.77	8.94	6.15
	(4.22)	(4.44)	(3.40)
Wage Mexico[1]	2.19	2.12	1.65
	(3.51)	(9.01)	(4.26)
Wage U.S.[1]	-	-	5.75
	-	-	(4.59)
Observations	61,118	355,054	5,538

4.6 RESULTS

4.6.1 Selectivity of Mexican Workers Migrating to the U.S.

The results show that the immigrant flow of Mexican workers is negatively selected in terms of their observable and unobservable skills. Table 20 shows that the number of years of education for immigrants is significantly lower than the average years of schooling for the Mexican population. While the average educational attainment in Mexico was 8.77 in 1995 and 8.94 years in 2000, the average years of schooling among Mexican workers who migrated between 1992 and 2005 is only 6.15 years. Additionally, Mexican workers are negatively selected based on their unobservable transferable skills. Table 21 shows that while the average unobserved skills is zero for the Mexican population, the average skills for Mexican immigrants is -0.248 and this difference is statistically significant.

The rate of return to unobserved transferable skills in the U.S. relative to Mexico is estimated to be 0.085. Since the rate of return to skills is higher in Mexico than in the U.S., workers with more skills have little incentive to migrate to the U.S. Additionally, the estimated rate of return to one year of schooling is $\beta_0^{yschool} = 0.10$ in Mexico, and $\beta_1^{yschool} = 0.03$ in U.S.

Table 20 also shows that the wages of immigrants in Mexico (prior migration) are lower than the average wages for the Mexican population. Those differences in wages can be ex-

Table 21: Unobserved Skills of Immigrants and Mexican Population

	Immigrants EMIF[1]	Mexican Population[1]	Difference[2]
Unobserved transferable skills	-0.248 (0.91)	0.00 (0.00)	-0.248*** (0.002)

[1]Standard deviations in parenthesis. [2]Standard error in parenthesis.

*** Significant at 0.01 level.

plained due to different observable characteristics like age or education, or due to differences in the unobservable skills. In order to test the source of the wage differential, I estimate the wages that immigrants would earn if they had similar characteristics to the average Mexican resident (eliminate differences in terms of observable characteristics). The results show that the differences in wages are mainly due to differences in unobservable skills. Figure 5 shows the average wages for the Mexican population, the wages that migrants earned in Mexico, and the wages that those migrants would earn if they had characteristics similar to the ones of the average Mexican resident. Even if we compensate migrants for their differences in observable characteristics, their wages are still significantly lower than the wages of the Mexican population.

4.6.2 Selectivity of Return Migration

Table 22 shows the years of education and the unobserved skills for return migrants and migrants who stay in the U.S. Migrants who stay are slightly more educated; however, the difference in years of schooling is not statistically significant. For both groups of workers the value of their unobserved skills is negative, which implies that both groups of migrants are negatively selected relative to the Mexican population. However, the value of the unobserved skills is higher (less negative) among return migrants, which implies that return migration intensifies the negative selection that originally characterized the immigrant flow.

Table 22 also shows the uncertainty component (ε). The results show that migrants who decide to return to Mexico are those with lower values of ε. Therefore, workers who faced

Figure 5: Wages in Mexico: Immigrants prior Migration and Mexican Population

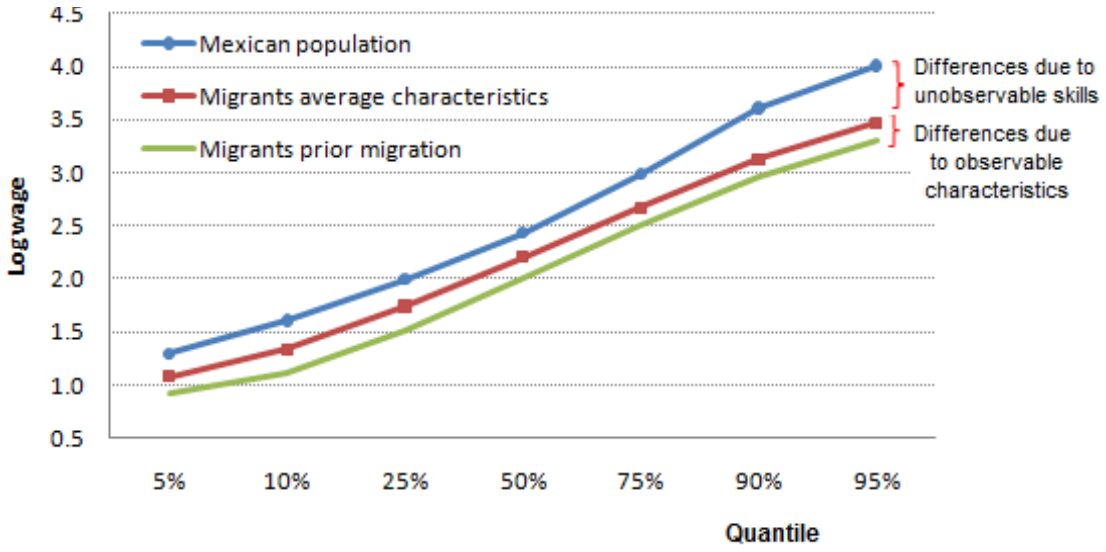


Table 22: Education, Unobserved Skills and Uncertainty Component of Return Migrants

	Immigrants EMIF		
	Return Migrants[1]	Migrants Stay[1]	Difference[2]
Years of schooling	6.116	6.252	-0.137
	(3.34)	(3.61)	(0.17)
Unobserved skills (υ)	-0.182	-0.446	0.264***
	(0.85)	(1.07)	(0.05)
Uncertainty component (ε)	-0.025	0.078	-0.103***
	(0.65)	(0.59)	(0.03)
US earnings ($\lambda\upsilon + \varepsilon$)	-0.041	0.040	-0.081***
	(0.66)	(0.60)	(0.03)
Observations	4,144	1,394	

[1]Standard deviations in parenthesis. [2]Standard errors in parenthesis.

***Significant at 0.01 level.

unfavorable conditions or bad luck in the U.S. are more likely to become return migrants. Finally, since the return migrants are more skilled (highest υ's) than the ones who stay, and the ones who faced unfavorable conditions or bad luck (lowest ε's) it is not evident if the earnings associated to unobserved skills and the uncertainty component of those who return home are higher or lower than those who stay in the U.S.

$$(\lambda\upsilon + \varepsilon|stay) \lesseqgtr (\lambda\upsilon + \varepsilon|return)$$

Table 22 shows that the U.S. wages ($\lambda\upsilon + \varepsilon$) of return migrants are lower than the wages of those who stay in the U.S., therefore, the uncertainty effect dominates.

4.6.3 Differences among Legal and Illegal Workers

Previous studies analyzing the selectivity of Mexican immigrants to the U.S. have pointed out that the type of selection is determined by workers' migration costs. Chiquiar and Hanson (2005) construct a model that incorporates migration costs and find that the selection of workers from Mexico depends on the size of migration costs and how they vary with skills. If illegal workers face higher migration costs than legal workers, the type of selectivity observed among both groups of workers might differ. Gonzalez (2011) finds evidence of intermediate selection among Mexican immigrants in terms of education; however, this selectivity becomes more negative when he analyzes the selectivity of illegal workers. In light of this evidence, it becomes a relevant issue to study the type of selection guiding the return migration decision of legal and illegal workers. In this section I test for differences in the observable and unobservable skills, as well as in the uncertainty component associated with U.S. earnings of return migrants and migrants who stay by legal status. In this section legal status is considered at the moment of entry. While most of the workers have the same legal status during their time in the U.S., some of them obtained legal status after entering illegally and others overstay their work permits and work undocumented at the time of the survey.

Table 23 shows the differences in the characteristics of legal and illegal workers. Illegal workers are less educated and have higher unobserved transferable skills than legal workers.

Table 23: Education, Unobserved Skills and Uncertainty Component by Legal Status

	Immigrants EMIF		
	Legal[1]	Illegal[1]	Difference[2]
Years of schooling	6.811	6.054	0.757***
	(3.97)	(3.30)	(0.25)
Unobserved transferable skills (υ)	-0.346	-0.232	-0.113*
	(0.92)	(0.91)	(0.06)
Uncertainty component (ε)	0.016	-0.002	0.018
	(0.67)	(0.63)	(0.04)
Observations	572	5,018	

[1] Standard deviations in parenthesis. [2] Standard errors in parenthesis.
*** Significant at 0.01 level, * significant at 0.1 level.

With respect to the uncertainty component, there are not significant differences between legal and illegal workers.[5]

Table 24 reports years of schooling and unobserved skills for return migrants and migrants who stay in the U.S. by legal status. Migrants who stay in the U.S. are slightly more educated; however, the difference in years of schooling is not statistically significant for legal and illegal workers. For legal workers, the value of the unobserved skills is negative, and there are not significant differences between return migrants and migrants who stay. For illegal workers the value of the unobserved skills is also negative, but is higher (less negative) among return migrants. These results suggest that return migration accentuates the negative selection that originally characterized the immigrant flow in terms of unobservable skills, particularly among illegal workers. Illegal return migrants have more unobservable skills than the illegal workers who stay in the U.S.

Table 25 shows the value of the uncertainty component ε. Among legal and illegal workers, return migrants are those with lower values of ε. Workers who faced unfavorable conditions or bad luck in the U.S. return to Mexico, and that effect is stronger among legal workers.

[5] The proportion of workers who entered the U.S. illegally is 89.8 percent. The only reference is reported by Passel, J. (2006) who reports that in recent years about 80 to 85 percent of the immigrants coming from Mexico entered the US undocumented.

Table 24: Education and Unobserved Skills of Return Migrants by Legal Status

	Education		Unobserved skills (υ)	
	Legal	Illegal	Legal	Illegal
Return Migrants	6.748	6.035	-0.284	-0.169
Standard Deviation	(3.77)	(3.27)	(0.84)	(0.85)
Observations	382	3758	382	3758
Stay in US	6.948	6.105	-0.470	-0.441
Standard Deviation	(4.38)	(3.41)	(1.06)	(1.08)
Observations	187	1209	187	1209
Difference	-0.201	-0.070	0.186	0.272***
Standard Error	(0.620)	(0.162)	(0.132)	(0.048)

***Significant at 0.01 level, *significant at 0.1 level.

Table 25: Uncertainty Component and U.S. Earnings of Return Migrants by Legal Status

	Uncertainty component (ε)		US earnings ($\lambda\upsilon + \varepsilon$)	
	Legal	Illegal	Legal	Illegal
Return Migrants	-0.052	-0.022	-0.076	-0.036
Standard Deviation	(0.679)	(0.649)	(0.687)	(0.655)
Observations	382	3739	382	3739
Stay in US	0.151	0.063	0.111	0.025
Standard Deviation	(0.628)	(0.584)	(0.636)	(0.588)
Observations	187	1203	187	1203
Difference	-0.203**	-0.084***	-0.187**	-0.061**
Standard Error	(0.090)	(0.029)	(0.092)	(0.029)

***Significant at 0.01 level, **significant at 0.05 level.

Finally, Table 25 shows that the U.S. wages ($\lambda\upsilon + \varepsilon$) of return migrants are lower than the wages of those who stay in the U.S. for both groups of workers. The results show that the uncertainty effect dominates; even though return migrants have higher unobservable skills, they earn lower wages in the U.S. because they also face more adverse conditions. This result is especially strong among legal workers.

4.7 CONCLUSIONS

This paper examines the return migration behavior of Mexican migrants in the United States. I test Borjas and Bratsberg's (1996) theoretical prediction that the return migration process accentuates the type of selection that originally characterized the immigrant flow. According to their model, if the immigrant flow is positively selected, the outmigrants should be less skilled than the immigrants who remain in the U.S. If the immigrant flow is negatively selected, return migrants will be more skilled than the immigrants who remain in the U.S.

I use the Survey of Migration to the Northern Border together with a selection model to infer the unobservable skills and the unexpected component of their earnings in the U.S. of return migrants and migrants who stay in the U.S. The results show that the immigrant flow of Mexican workers is negatively selected, workers migrating from Mexico to the U.S. are those with lower observable and unobservable skills. In terms of earnings in Mexico, the wages of immigrants are lower than the average wage of Mexican residents. While part of the wage differential is explained by differences in their observable characteristics, most of the difference is associated to differences in their unobservable skills.

The evidence is consistent with Borjas and Bratsberg's prediction, return migration accentuates the negative selection that originally characterized the Mexican immigrant flow. Return migrants are relatively more skilled than the typical immigrant; workers with the lowest unobservable skills are the ones who find optimal to reside in the United States. Additionally, I test how U.S. opportunities impact the return migration decision of immigrant workers. The results show that return migrants are workers who earned lower wages and faced more unfavorable conditions in the U.S.

The large increase in the proportion of Mexican immigrants who enter the U.S. illegally; the increases in migration costs faced by illegal workers due to tighter border enforcement, and the fact that the type of selection that characterizes the immigrant flow depends on the size of migration costs, heighten the importance of studying the type of selection determining the return migration decision of legal and illegal workers.

The evidence shows that return migration accentuates the negative selection that characterizes the immigrant flow in terms of unobservable skills, particularly among illegal workers. Illegal workers with the highest skill levels are the ones who find it optimal to return to Mexico. In terms of the unexpected component of U.S. earnings, return migrants faced more unfavorable conditions in the United States, and that effect is stronger among legal workers.

There are two important caveats to these results. First, this study only includes immigrants who entered the U.S. between 1993 and 2005. While this analysis can be extended to analyze future waves of immigrants, the selectivity of previous cohorts cannot be determined. Second, I analyze the selectivity of return migration using legal status at the time of entry. However, an important number of immigrants who enter the U.S. illegally obtain legal status once in the U.S., and also, a number of legal workers overstay and work without documents. As a further extension, the selectivity among workers who change their legal status after entry should be considered.

5.0 APPENDIX

5.1 APPENDIX TO CHAPTER 1

Table 26: Effect of an Amnesty with and without Tax Adjustment

	All workers "off" the books			All workers pay tax		
		Effect Amnesty			Effect Amnesty	
	Baseline	NoTax Adj	Tax Adj	Baseline	NoTax Adj	Tax Adj
Vacancy/Unemployment ratio	0.720	-0.124	-0.137	0.717	-0.117	-0.134
Probability filling a vacancy	0.456	0.038	0.042	0.457	0.036	0.041
Probability finding a job	0.328	-0.034	-0.038	0.327	-0.032	-0.037
Unemployment rate legal	9.39%	0.97%	1.09%	9.41%	0.92%	1.07%
Unemployment rate illegal	16.10%	1.53%	1.71%	16.14%	1.44%	1.69%
Wage legal	0.939	-0.2%	-0.7%	0.941	-0.2%	-0.9%
Wage illegal off books	0.861	-1.3%	-1.4%	0.848	-1.2%	-1.6%
Wage illegal paying tax	0.843	-1.3%	-1.7%	0.831	-1.2%	-2.1%
Wage initially illegal	0.861	7.1%	6.6%	0.831	10.6%	9.9%
Wage gap	9.0%	1.2%	0.8%	13.2%	1.1%	1.4%
Average wage	0.934	0.2%	-0.3%	0.934	0.4%	-0.3%
Tax	0.037	0	12.9%	0.035	0	18.3%
Tax revenue	0.032	4.2%	17.5%	0.032	-0.6%	17.3%
Tax expenditure	0.032	16.2%	17.5%	0.032	15.6%	17.3%
Government deficit	0	0.004	0	0	0.005	0
Welfare employed legal	229.4	-0.4%	-0.9%	229.8	-0.4%	-1.1%
Welfare employed illegal	182.7	-2.9%	-3.3%	176.2	-2.7%	-3.8%
Welfare unemployed legal	228.8	-0.5%	-1.0%	229.2	-0.5%	-1.1%
Welfare unemployed illegal	180.6	-3.0%	-3.4%	174.2	-2.9%	-4.0%
Welfare firm hire legal worker	0.63	9.2%	8.2%	0.63	8.6%	7.3%
Welfare firm hire illegal worker	2.08	7.9%	8.9%	2.01	7.5%	8.0%

5.2 APPENDIX TO CHAPTER 2

Table 27: Estimates of the Number of Illegal Immigrants in the US (I)

Publication	Institution	Year of Data	Foreign Born	From Mexico	Illegal	Illegal from Mexico
Unauthorized Immigrant Population: National and State Trends, 2010	The Pew Hispanic Center	March 2010	40.2 million		11.2 million	6.5 million
Estimates of the Unauthorized Immigrant Population Residing in the US: January 2010	Department of Homeland Security	January 2010			10.79 million	6.64 million
Statistical Portrait of the Foreign-Born Population in the US, 2009	The Pew Hispanic Center	2009	38.45 million	11.48 million		
Estimates of the Unauthorized Immigrant Population Residing in the US: January 2009	Department of Homeland Security	January 2009			10.75 million	6.65 million
Estimates of the Unauthorized Immigrant Population Residing in the US: January 2008	Department of Homeland Security	January 2008			11.6 million	7.0 million
Estimates of the Unauthorized Immigrant Population Residing in the US: January 2007	Department of Homeland Security	January 2007			11.8 million	7.0 million
Mexican Immigrants in the United States	Migration Policy Institute	December 2006	37.5 million	11.5 million		
Estimates of the Unauthorized Immigrant Population Residing in the US: January 2006	Department of Homeland Security	January 2006			11.6 million	6.6 million
Estimates of the Unauthorized Immigrant Population Residing in the US: January 2005	Department of Homeland Security	January 2005			10.5 million	6 million
		January 2000			8.5 million	4.7 million

Table 28: Estimates of the Number of Illegal Immigrants in the U.S. (II)

Publication	Institution	Year of Data	Foreign Born	From Mexico	Illegal	Illegal from Mexico
The Size and Characteristics of the Unauthorized Migrant Population in the US: Estimates Based on the March 2005 Current Population Survey	The Pew Hispanic Center	March 2005	37 million		11.1 million	6.2 million
		Projected March 2006			11.5 to 12 million	
		Census 2000			8.4 million	4.7 million
Estimates of the Size and Characteristics of the Undocumented Population	The Pew Hispanic Center	March 2004	36 million	11.2 million	10.3 million	5.9 million
Backgrounder: Homeward Bound Recent Immigration Enforcement and the Decline in the Illegal Alien Population	Center for Immigration Studies	August 2007			12.49 million	
		May 2008			11.17 million	
Illegal Migration from Mexico to the United States," Journal of Economic Literature	UCSD and NBER	2004	34 million	10.5 million		
Where Immigrants Live An Examination of State Residency of the Foreign Born by Country of Origin in 1990 and 2000	Center for Immigration Studies	1980		16% of the foreign born		
		1990		22% of the foreign born, 4.36 million		
		2000		30% of the foreign born, 9.33 million		
		2015		45% of the foreign born		
		2000				Roughly 50%
		Between 90-00				+2.8 million
Historical Census Statistics on the Foreign-born Population of the United States: 1850-1990	US Census Bureau	1990	19.8 million			
The Foreign-Born Population: 2000	US Census Bureau	March 2000	31.1 million	30% of foreign born, 9.2 million		
The Foreign-Born Population in the United States: 2003	US Census Bureau	March 2003	33.5 million			

Table 29: Description of the Variables

Variables	Description
Educational Attainment	No education, Elementary dropout (<6 years), Elementary graduate (6 years), Secondary dropout (<9 years), Secondary graduate (9 years), High school dropout (<12 years), High school graduate (12 years), Some College (13-15 years) and College graduate (16 or more).
Legal	With documents to work in the US at the time of the survey
Temporary	Report Mexico as their country of residence
Permanent	Report US as his country of residence
Return Migrant	Dummy variable=1 for respondents who plan to settle in Mexico permanently. Dummy variable=0 for those respondents who plan to stay for a short period of time in Mexico and will go back to work in the US
Time US	Groups generated according to the number of years that worker have been in the US: with less than 2 years, 2-5 years, 6-10 years, 11-16 years and more than 16 years
Cohort of Entry	Groups generated according to their year of arrival: Cohort 55-84, Cohort 85-90, Cohort 91-96 and Cohort 97-05
Hourly Earnings	Last month earnings divided by the number of hours worked per month
Occupation US:	
Professional / Technicians	**Professional:** Management, teachers, accountants and artists **Technicians:** Engineering technicians, automotive service technicians, office and administrative support occupations
Services	**Services:** Workers in transportation services, protective services, food and beverage serving workers, cooks and food preparation workers, cleaning and maintenance workers, personal care services, landscaping and grounds keeping workers **Domestic Services**: Maids, housekeeping services and other domestic workers
Production	**Supervisors in production:** Supervisors and machinery operators. **Workers in production:** Assemblers and fabricators, food processing workers, metal workers, plastic workers, and construction workers **Helpers and Assistants in production**
Sales	**Sales Managers:** Sales representatives, supervisors and managers **Sales Workers:** Cashiers, demonstrators, product promoters, door-to-door sales workers, news and street vendors.
Agricultural	**Agricultural Foreman:** Supervisors and equipment operators **Agricultural Laborers:** Farm workers, harvest workers, and laborers

Table 30: Dates of Application of the EMIF

Survey Phase	**From**	**To**
Phase I	28-Mar-93	27-Mar-94
Phase II	14-Dec-94	13-Dec-95
Phase III	11-Jul-96	10-Jul-97
Phase IV	11-Jul-98	10-Jul-99
Phase V	11-Jul-99	10-Jul-00
Phase VI	11-Jul-00	10-Jul-01
Phase VII	11-Jul-01	10-Jul-02
Phase VIII	11-Jul-02	10-Jul-03
Phase IX	11-Jul-03	10-Jul-04
Phase X	11-Jul-04	10-Jul-05

Table 31: Persons Granted Legal Status from EMIF

1950-1980	177
1981	26
1982	49
1983	60
1984	92
1985	164
1986	**256**
1987	**370**
1988	**495**
1989	**325**
1990	**363**
1991	**288**
1992	241
1993	232
1994	246
1995	233
1996	190
1997	177
1998	147
1999	112
2000	94
2001	71
2002	52
2003	31
2004	9

Table 32: Persons Granted Permanent Residence by Fiscal Year under IRCA

Fiscal Year	IRCA (TOTAL)	IRCA (PRE-1982)	SAWs
1989	478,883	**478,882**	1
1990	880,940	**824,272**	56,668
1991	1,134,509	**215,399**	919,110
1992	165,089	47,915	117,174
1993	16,702	16,702	0
1994	4,083	4,083	0
1995	2,898	2,898	0
1996	3,037	3,037	0
1997	1,300	1,300	0
1998	820	818	2
1999	6	4	2
2000	271	267	4
2001	192	189	3
	2,688,730	1,595,766	1,092,964

Figure 6: Wages of Mexican Workers by Year of Arrival CPS 1994-2005

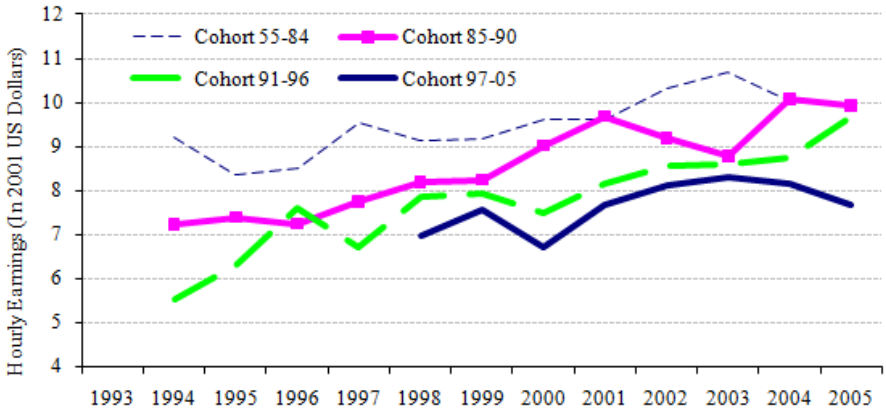


Figure 7: Wages of Immigrants by Year of Arrival EMIF 1993-2005

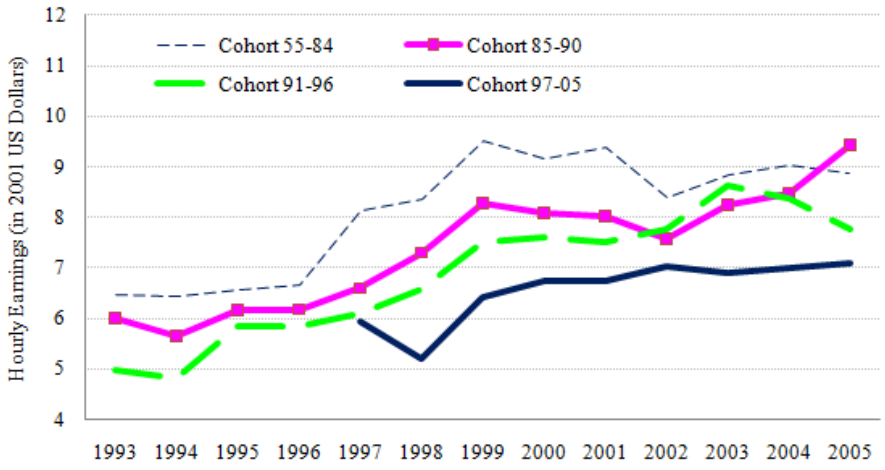


Figure 8: Wages for different Cohorts of Mexican Legal Permanent Immigrants (EMIF)

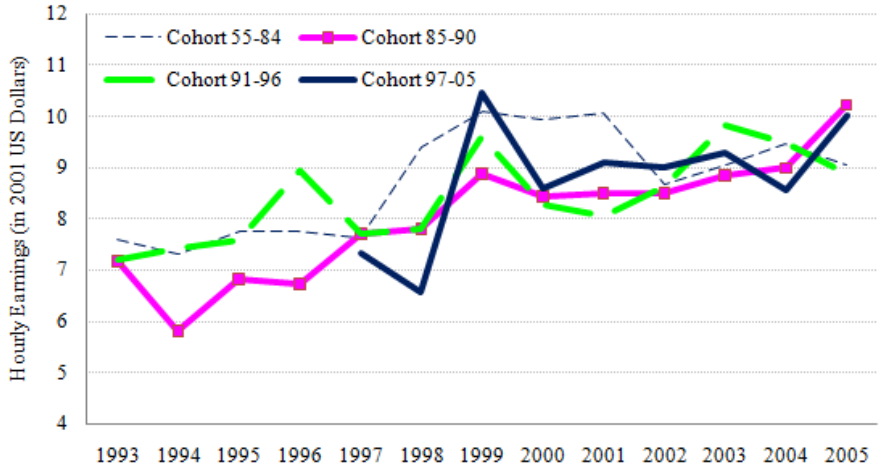


Figure 9: Wages for different Cohorts of Mexican Illegal Immigrants (EMIF)

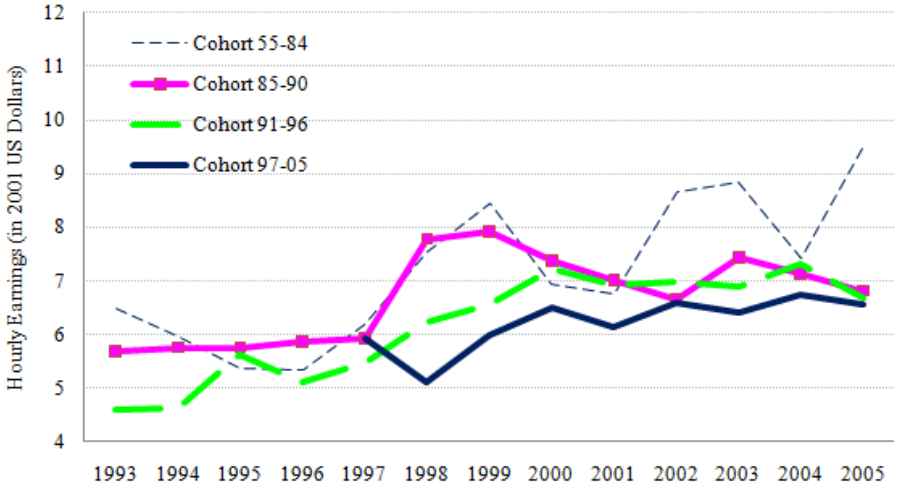


Figure 10: Wages by Cohort of Entry (CPS) vs All Migrants (EMIF)

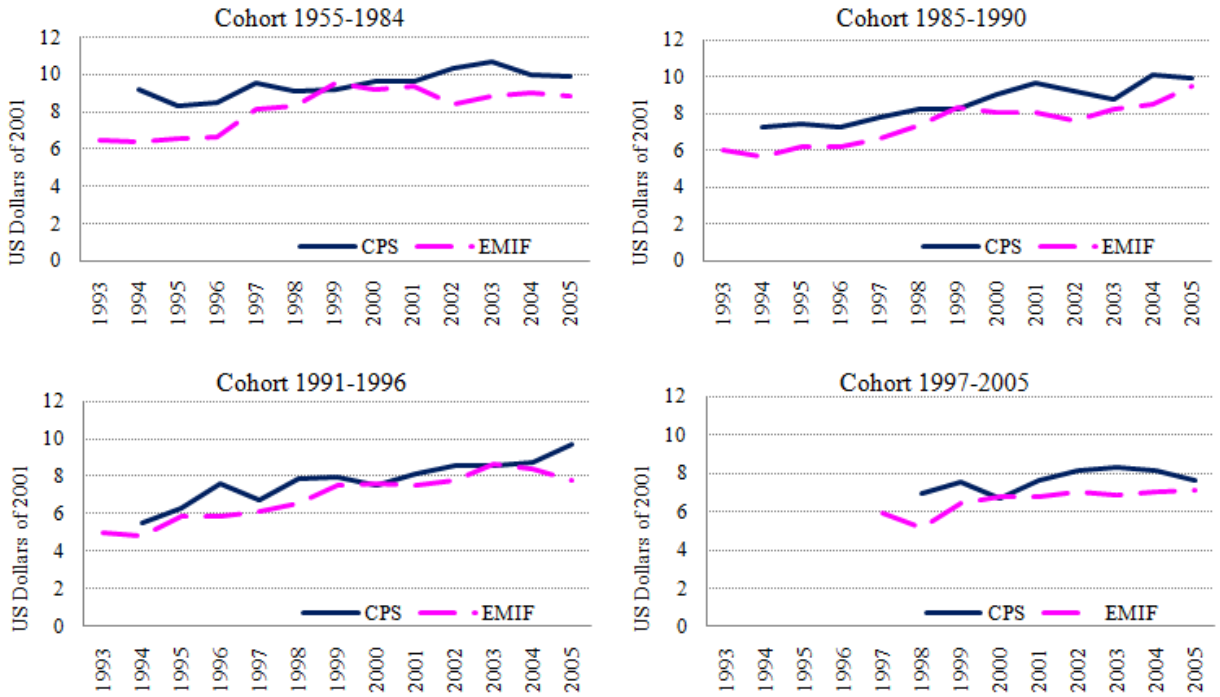


Figure 11: Wages by Cohort of Entry (CPS) vs Legal Permanent Migrants (EMIF)

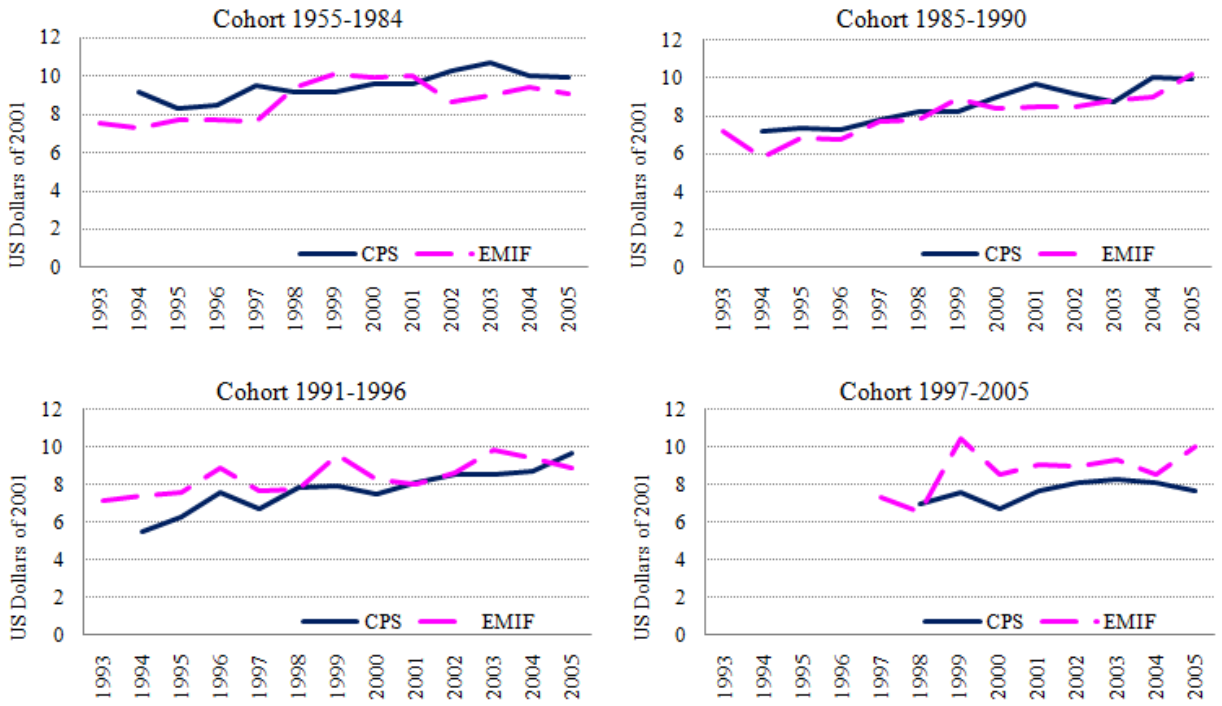
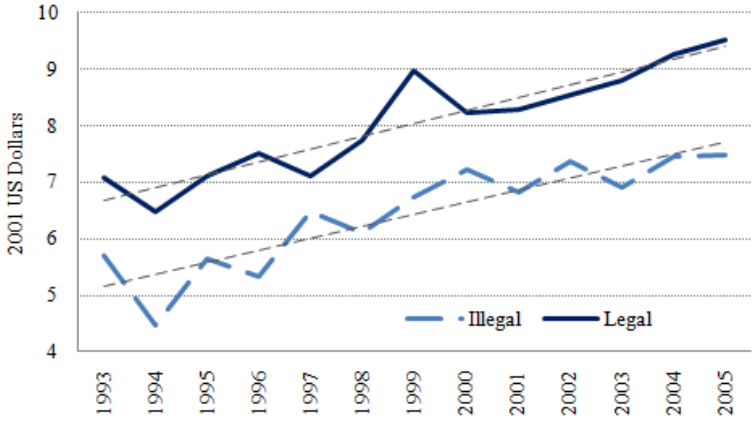


Figure 12: Wages of Legal and Illegal Mexican Immigrants in the United States



5.2.1 Construction of Weights

A selection issue can arise if workers are more or less likely to cross depending on their characteristics such as legal status or earnings, since they might appear in the sample at different rates. In order to address this problem, using the number of times that each worker has entered and exited the U.S., I estimate their probability of being observed in the sample and construct a set of weights using the inverse of that probability.

$$\text{Entries per year}_i = \frac{\text{Number of entries}_i}{\text{Number of years in US}_i}$$

for individual i observed in year t.

$$\text{Probability of being observed}_i = \frac{\text{Entries per year}_{it}}{\sum_{i=1}^{i=n} \text{Entries per year}_{it}}$$

$$\text{weight}_i^{\text{Prob Entry}} = \frac{1}{\text{Probability of being observed}_i}$$

5.2.2 Matching Estimators and Propensity Score

Formally, let y_{1i} be the outcome with treatment, y_{0i} the outcome without treatment and x denote a vector of observed covariates. Also let w be a binary treatment indicator, where $w = 1$ denotes treatment (i.e. legal) and $w = 0$ otherwise (i.e. illegal). To measure the effect of the treatment, we are interested in the difference in the outcomes $y_1 - y_0$. However, since y_1 and y_0 are not observed at the same time, the quantity of interest becomes the average treatment effect on the treated (ATT) which is defined as:

$$ATT = \tau_{P,T} = E[y_{1i} - y_{0i}|w_i = 1]$$

The treatment effect can be identified non-parametrically by imposing two assumptions: the conditional independence and the overlap assumptions. The first assumption states that conditional on the covariates x_i, w_i and (y_{1i}, y_{0i}) are independent.

$$(y_{1i}, y_{0i}) \perp w_i | x_i$$

The second assumption states that for any value of x, there are some units that are treated and other units that are not.

$$0 < P[w_i = 1 | x_i] < 1$$

Given that eligibility to IRCA's legalization program was exclusively based on date of arrival to the U.S. (treatment group), we can presume that the conditional independence assumption is satisfied. Additionally, one test that can be used to assess the validity of this assumption is to compare the impact of treatment for different control groups. For that reason, when I test for selectivity among workers obtaining legal status after entering the U.S. illegally, and when I estimate the gain from legal status among workers legalized under IRCA, results using two different control groups are analyzed (ineligible migrants, eligible non-applicants and applicants for legal status under IRCA). With respect to the overlap assumption, different tests to verify that the assumption is satisfied are also performed (e.g. comparison of the distribution of the covariates for the treatment and control groups and estimation under common support for the treatment and control groups).

5.2.2.1 Matching Estimator As was mentioned before, since only one of the potential outcomes y_1 or y_0 is observed for each individual, matching estimators impute the missing outcome for each i by finding other individuals whose covariates are similar, but who were not exposed to the treatment. In other words, using average outcomes of individuals with "similar" characteristics, we can estimate the wage that workers legalized under IRCA would have earned if they had obtained legal status through other channels.

Under the conditional independence and overlap assumptions, the matching estimator for the average treatment effect on the treated is

$$\widehat{ATT}_{MATCH} = \frac{1}{N} \sum_{i|w_i=1} \widehat{\mu}_1(x_i) - \widehat{\mu}_0(x_i)$$

Another characteristic of the matching method is that it allow us to estimate "exact matching" using as matches observations of the opposite treatment status with the exact same values of the regressors and also "inexact matching" if we use units that have "close" covariate matches. An issue that arises with the inexact matching method is that we will introduce a bias if we use as matches units that do not have exactly the same covariates, x_i, as unit i. In this paper I use a bias corrected matching estimator suggested by Abadie and Imbens (2006) which calculates a counterfactual adjusted for the difference in the covariates between a unit and its matches.

5.2.2.2 Propensity Score Rosenbaum and Rubin (1983) define the propensity score as the conditional probability of treatment given the covariates

$$p(x) = Pr[w = 1|x].$$

The key result of Rosenbaum and Rubin is that if the balancing hypothesis[1] is satisfied,

$$wi \perp x_i|p(x_i)$$

and if the conditional independence assumption is true

$$(y_{1i}, y_{0i}) \perp w_i|x_i$$

then treatment status, w_i, is independent of the potential outcomes (y_{1i}, y_{0i}) conditional on the propensity score $p(x)$

$$(y_{1i}, y_{0i}) \perp w_i|p(x_i).$$

Thus, rather than conditioning on the covariates, x, we can condition on the propensity score, $p(x)$, to estimate the treatment effects.

[1] The balancing hypothesis implies that observations with the same propensity score must have the same distribution of observable (and unobservable) characteristics independently of treatment status. In other words, for a given propensity score, exposure to treatment is random and therefore treated and control units should be on average observationally identical.

Today there exist numerous methods for using the propensity score; however, one of the methods that has attracted most research interest in recent years is to use it in conjunction with a matching method. One approach is to use nearest neighbor matching in which the set of matches for unit i, $J_M(i)$, is defined as the M observations in the opposite treatment group with the smallest values of the scalar distance

$$||p(x_1) - p(x_i)||.$$

Once this set of M nearest neighbors has been constructed, we can compute the ATT using inexact matching based on the covariates x_i. Another approach is to use radius matching which is comparable to nearest neighbor matching but rather than define the M closest neighbors, it only use matches that are within some predefined interval r such that

$$J_M(i) = \{i = 1, 2, .., N | W_1 = 1 - W_i \ , ||p(x_1) - p(x_i)|| < r\}$$

While radius matching give equal weight to every match that lies within $J_M(i)$, there is another method named kernel matching that determines the weight that each match receives based on the distance of the match from the original unit.

Finally, another method for using the propensity score is known as stratification or blocking. The idea is that, based on the propensity score, the data is divided into B blocks so that the probability of treatment is approximately the same across observations in a block. The estimate of the population ATT is determined by averaging the estimates within each block and weighting by the share of the sample observations that fall in that block. When using this method, I check whether the covariates are balanced, that is, whether the difference between the average of the covariates for the treatment and control groups within each block is small.

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