2011

Does it Matter Who I Work For and Who I Work With? The Impact of Owners and Coworkers Birthplace and Race on Hiring and Wages

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May, 2011

Abstract

This paper investigates the effect of firm owners and coworkers on hiring patterns and wages. Firstly, I explore the potential mechanisms generating their interrelation. Using a search model where social networks reduce search frictions, I develop the theoretical implications of social ties between owners and workers for individual labor market outcomes. In the model, wages are derived endogenously as a function of the efficiency of the social ties of current employees. Firms decide whether to fill their vacancies by posting their offers or by using their current workers' connections. As a result, individuals with a more efficient connection tend to receive higher wages. These findings highlight the potential importance of social connections and social capital for understanding employment opportunities and wage differentials. Secondly,using a unique matched sample from an employer-employee administrative database and a survey of characteristics of small firm owners, I analyze the impact of the birthplace of employers and individual coworkers (native versus immigrant) on firm hiring patterns and average log wages. First, I explore the effect of owner type on the composition of new hires. The results show that firms with immigrant owners are more likely to hire immigrant workers. Moreover, among immigrant owners, this prevalence is especially strong for Hispanic and Asian workers. I also find that the probability that a new hire is a native, non-Hispanic white or black is higher for native firms. Second, I estimate the impact of owners and coworkers place of birth on wage differentials across worker types, controlling for workers' human capital. The results illustrate that much of the difference between the log annual wage of immigrants and natives comes from immigrants' propensity to work in non-native owned firms, which pay the lowest average wages. Interestingly, though, native workers holding a job in immigrant firms are paid less than immigrant workers. The paper concludes by discussing the extent to which the empirical findings can account for the model.

Keywords: immigration, wage differential, hiring process, social networks, small firms.
JEL Classification: J15, J21, J31, J61, R23.

*Disclaimer: This work is unofficial and thus has not undergone the review accorded to official Census Bureau publications. All results have been reviewed to ensure that no confidential information is disclosed. The views expressed in the paper are those of the authors and not necessarily those of the U.S. Census Bureau.

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1 Introduction

This paper analyzes the effect of the birthplace of firm owners and coworkers on hiring patterns and wages. As of 2007, immigrant workers represented 15% of the U.S. population. The impact of large inflows of immigrants and their assimilation into the host economy has been a primary area of study in the labor literature. How such large flows of workers are incorporated into the labor market and interact with various businesses and workers is of special interest. The role of business owners in the patterns of hires and earnings in the labor market has played an important role in this literature. In particular, some studies have found that the type of manager recruiting new workers is a determinant of the firm's workforce composition. For instance, Carrington and Troske [1995] and Giuliano and Ransom [2008] have found that females and blacks are disproportionatly employed by female and black supervisors respectively. Meanwhile, Stoll et al. [2004] found that black businesses receive more applications from black workers and employ more black workers than other businesses.

This paper explores the potential mechanisms explaining the interconnection between owner's and coworkers' characteristics and workers' hiring patterns and wages. Recent work has used the idea of networks in the labor market to explain labor market inequalities as a function of differential social capital (social resources, network structures, network resources). Minority individuals are generally connected to other minority-group workers who cannot provide them with the opportunity to change their employment outcomes. Hispanics and blacks are disadvantaged because they are likely to match with same-kind job contacts, and end up working in lower wage workplaces where other Hispanics and blacks work (Elliot [2001]). Following this thought stream, I use a search model where social networks reduce search frictions to develop the theoretical implications of social ties between owners and workers for individual labor outcomes. The model helps provide insights into what assumptions would be necessary to account for the qualitative patterns in the empirical analysis. In the model, wages are derived endogenously as a function of the efficiency of the social ties of current employees. Firms can fill their vacancies either by posting offers or by using their current workers' connections. As a result, individuals with better connections tend to have higher wages. Two forces drive that result. First, current workers provide a costless recruitment mechanism to the firm. Second, workers will produce more new hires in the future and for those unemployed, a better social connection would result in more job offers.

Using a unique matched sample from an employer-employee administrative database and a survey of characteristics of small-firm owners, this study analyzes the impact of the type of employers and individual coworkers (natives versus immigrants, or ethnic groups) on firm hiring patterns and workers' average log wages. Firm types are defined by the type of owner (immigrant-owned versus native-owned), while ''coworker" refers to the fraction of same-kind fellow workers holding a job in the same firm. The share of immigrant coworkers in the firm is called the *coworker index*.[1] This index intends to capture, in a general way, the effect of coworkers in the establishment's dynamics. The particularity of the index is that we are able to account for all existing coworkers, including their characteristics, before an individual is hired. We connect owner and firm characteristics (place of birth, size and industry) with workers' characteristics (wage, age, education, and place of birth) to test different assumptions about firm hiring patterns and the wage differentials of workers of different types. Given the unique features of the matched database, the data allows asking whether there exist wage premia associated with being an immigrant and with working for or with other immigrants.

The type of a new hire can be affected by the type of employer in different ways. First, social networks, segregated by race or similar background, could be used by job seekers and by employers when looking for new candidates. Ethnic communities provide a network for immigrant entrepreneurs to find workers, to sell ethnic goods, and to obtain credit. Second, matching productivity generated by employer-employee similarity could motivate owners to employ same-kind individuals. In certain industries the use of a common language may be important for productive efficiency. Third, employer tastes might bias them to employ workers of a similar kind. Employer discrimination could generate scope for segregation.[2] However, coworker effects could compensate for the presence of employer discrimination. In fact, for all types of owners the share of similar coworkers increases the probability of being hired in the firm. We also control for specific characteristics in the firm, such as the fraction of English speakers, to identify the possible scope for matching productivity. This paper focuses on the importance of social ties in the process of recruitment when firms use current employees' social connections to help find and identify new candidates. However, employers may use this mechanism differently for different worker types, depending on their ability to take advantage of their workers' connections. For instance, given their cultural, linguistic, and social backgrounds, immigrant employers have an advantage, compared to natives, in exploiting their immigrant workers' social connections.

[1] In this Chapter, the expressions *firm type* and *owner type* are used to explain that firm's owners correspond to one of the following groups: native-only, immigrant-only, and mix owned firms.

[2] Lang [1986]

Our results suggest that immigrant owners are three percentage points more likely than native owners to hire other immigrants, even after controlling for industry, firm size, geographic concentration of immigrants in the population, population density, and the legal form of organization of the firm. Looking at ethnic/race groups, immigrant owners (Hispanic/Asian owned firms) are 3 to 4 percentage points more likely than native owners (white and black owned firms) to hire Asians and Hispanics versus blacks and whites. Both, native and immigrant owners, hire white non-Hispanic workers, but native owners have a higher probability of having white workers as new hires. These results are based on both linear probability models and a multinomial logit specification that accounts for the simultaneity of choosing from different types of workers.

Among our strongest findings are the existence of a persistent pattern of hiring similar types and the smaller effect of the share of dissimilar coworkers on the likelihood of hiring a particular individual. For instance, the share of similar coworkers at the time of recruitment increases the probability of hiring a worker of a type by around 60%. The probability is higher when the owner is similar to the new hired. Additionally, this probability is different whether the employer is immigrant versus native. Immigrant businesses show higher chances of hiring a new immigrant, Hispanic or Asian compared to native businesses, even after looking whether they have similar workforce distribution at the time of a new recruitment.

To study the wages of employees, one must understand the role of employers in wage-setting, which necessitates gathering wage data by employer and having detailed information about the employer. Immigrant workers tend to have lower average wages than native workers. Many authors have used a human capital approach to explain that wage gap and have found that skill accounts for almost two thirds of the wage difference between Hispanics and white Non-Hispanics.[3] Meanwhile, the residual unexplained wage gap has traditionally been used to claim the existence of racial/ethnic discrimination in the labor market. Other authors have found that industry wage-differentials are to a very large extent explained by the characteristics of workers and the contribution of industry to wage setting is much smaller after looking at both person and that industry effects.[4] However, these studies don't rule out a significant impact of firm-level effects on wage formation.[5] The results in this paper suggest that much of the difference between the log annual wages of immigrants and natives comes from immigrants' propensity to work in non-native owned firms, which pay the lowest average log annual wages. Interestingly,

[3] Borjas [1994], Trejo [1997], Chiswick [1978], Borjas [2003] among others.

[4] Abowd et al. [1999]

[5] These authors obtained that the average of the difference in wages paid to an identical worker employed at two different firms in France was 20%-30%.

though, native workers holding a job in immigrant firms are paid less than immigrant workers. After controlling for typical human capital variables, full-time immigrant workers earn about 8% less than native workers ($3,293 less each year). When working for native employers this difference increases to 11%. Meanwhile, immigrant workers earn 10% more than native workers in immigrant owned firms ($4,398 more each year).

To the best of our knowledge, no previous study has analyzed the link between employer and coworkers' birthplaces and employees' employment opportunities and wages in a large set of industries and geographic locations. This research provides initial steps on that branch of analysis. These findings suggest that social connections and social capital may be important for understanding employment opportunities and wage differentials.

The remainder of the paper is organized as follows. Section 2 reviews previous work on the relation between workers and types of firms, ethnic economies and 'ethnic matching' between supervisors and employees, the usage of networks, and network effects on hiring procedures and workers' wages. It also discusses the importance of analyzing small businesses when looking at the impact of immigration. 3 develops a theoretical framework to analyze the matching process between heterogeneous workers and firms by introducing the efficiency of current workers' social ties as a form of social network. Section 5 examines the data and presents basic descriptive statistics on owners' and workers' characteristics. Next, section 6 presents preliminary information on workers' average earnings by worker type and by different levels of coworker shares. Section 7 is divided in two sections. The first part analyzes whether the type of employer and coworker characteristics affect the composition of new hires in firms. The second part evaluates the impact of firm owner type on employees' log annual earnings controlling for worker human capital. Section Section 8 concludes.

2 Literature Review

Because no single theory exists to explain the effect of firm owners and coworkers on hiring patterns and wages, I draw on the literature of several related fields to motivate my hypotheses on the subject. Those literatures include ethnic economy theories dealing with ethnic/immigrant concentration, theories of firm wage differentials and hiring procedures, and network theories.

Immigrants tend to work in low-wage/low-productivity firms, low-pay occupations, and in firms with a high percentage of immigrant workers.[6] Some researchers have found occupational and ethnic coworker concentration in the United States (Andersson et al. [2007], Patel and

[6] Borjas [1994], Borjas [2003], Andersson et al. [2007], and Andersson et al. [2008].

Vella [2007], and Light [2006]) and in other countries (Barr and Oduro [2000] and Andersson and Wadensjó [2001]). The literature has attempted to explain workers' concentration by skill, race, and sex.[7] Hellerstein and Neumark [2007] analyzed ethnic segregation in the United States and found a substantial degree of segregation in the workplace. They claim that even though workplace segregation partially results from residential segregation (*spatial mismatch* explanation) and from ethnically correlated skills, there seem to be other mechanisms that suggest the presence of *immigrant social connection* effects. In an extensive analysis of racial and ethnic segregation across U.S. workplaces, they found that a large degree of segregation remains even after accounting for metropolitan areas, and that very little of this segregation can be explained by observed differences in education and occupations. Language, however, seems to be a significant factor for immigrant segregation. Lang [1986]'s theory provides an explanation for worker segregation by language groups. When there are transaction costs associated with employees of different language groups working together, there is scope for segregation. Employers of each language group have incentives to fully segregate to avoid the cost of needing employees who can be the bridge between different language groups.

Despite findings on immigrant concentration at different levels, we cannot be sure that immigrants are more likely to work for immigrant bosses and that such a pattern would affect individuals' labor market outcomes. There is no evidence that immigrant businesses are distributed differently across industries, sizes, or skills, than native businesses.

A recent group of studies analyzes the matching process between managers and workers by racial group. Giuliano et al. [2006] found a significant effect of race and ethnicity on hiring procedures. For example, in locations with large Hispanic populations, Hispanic managers tend to hire more Hispanics and fewer whites than white non-Hispanic managers. In a more recent analysis, Giuliano and Ransom [2008], looks at the effect of manager ethnicity on hires, separations and promotions across different occupations in a U.S. retail firm. Whites were more likely to leave stores where managers were Hispanics than when they were white. Their work is very relevant, however they only focus on the effect of the manager race on the hiring decisions. Their studies do not consider the coworker effect. That is, they don't study the effect of the fraction of similar coworkers holding a job in the firm when a new worker is hired. This coworker effect can also differ across all types of owners. They do not consider at the effect of the firm workforce composition and the possible effects of coworker on new hires.

There has not yet been a connection established between owner's nativity and the type of

[7] Kremer and Maskin [1996], Hellerstein and Neumark [2003].

workers employed at a firm and the employee earnings. Nevertheless, the literature treats motivations for supervisor-employee matching. First, firm owners could have preferences for employing individuals of their own type or with the same background. Second, the types of goods offered by immigrant firms may differ from those offered by native firms. In immigrant that specialize in producing ethnic goods, immigrant workers have a comparative advantage over native workers in these firms. The differences between products can result in different worker composition.[8] However, none of these reasons have obvious predictions on workers' earnings. That an employer has a preference for a certain group does not necessarily imply higher wages for that group. The distribution of workers and employers in the market also affects the labor market equilibrium.

In sociology literature, there have been a limited number of studies that provide some insights on the tendency of immigrants to work for immigrant firms. For instance, in Los Angeles, in 1989, 30 percent of employed Koreans held jobs in firms owned by fellow Koreans even though Koreans composed only one percent of the Los Angeles County population.[9] According to Cardenas and Hansen [1988], during the 1980s, Mexican immigrant employers were most likely to hire Mexican, whether legal or undocumented, and favorably evaluate their quality. Porter and Wilson [1980] find two relevant patterns in the Cuban immigration to Miami during the 1960s. First, Cubans worked with other Cubans. Second, almost one-third of the Cubans worked for Cuban employers. The phenomenon of immigrants hiring immigrants is not limited to coethnic relationships between employees and employers. Other researchres have found that employers from one immigrant group often hire workers from other ethno/racial groups.[10] In Los Angeles, during the nineties, 51% of the garment factories were owned by Asians with most of their employees being Hispanics. Ethnic networks alone cannot expand the supply of coethnic-accessible jobs. Generally, the number of jobs offererd by ethnic-specific owned firms is not equal to the number of possible candidates from the same ethnic group in the local communitiy. Business leaders from ethnic groups whose rates of entrepreneurship are higher than other groups, find it increasingly difficult to limit hiring to members of their own groups. Ethnic crossover can expand the economic opportunities provided by immigrant-owned business. Immigrant workers often join networks that generally cross ethnic boundaries. Using the Garment Industry in Los Angeles as an example, Light [2006] analyzes immigrant ownership economies consisting of immigrant employers plus their immigrant but not coethnic employees. He finds that this type

[8] Andersson and Wadensjó [2001]
[9] Min [1989].
[10] Massey [1999], Massey et al. [1987].

of economy explains part of the garment industry's growth during early 1990s in Los Angeles.

The cited studies have been limited to small samples from a particular geographic areas and specific groups of firms and immigrants. Most of them also focus on a particular period of time, with a cross-sectional view of the distribution of workers and firms. Seemingly, their analyses intended not to look beyond the segregation aspect and to analyze the possible causes and consequences of those patterns. Unlike previous studies, this paper uses a representative group of areas, industries and workers, and it analyzes the flow of hiring and the effect of employer-employee type matches on wages. The underlying hypothesis in the analysis is that workers and employers made different use of their social connections in the market, which led to a particular hiring pattern by each firm type.

On wage effects, previous research has suggested that much of the unexplained variation in wages among employees is linked to characteristics of their firms, such as size and industry.[11] Not only individual characteristics explain wage differentials between immigrants and natives, but potentially so do other characteristics, such as the birthplace or ethnicity of employers and coworkers. Unfortunately, most wage databases come from household surveys of individuals who earn wages (Decennial Census and CPS), rather than from establishment surveys of wage-paying employers; they provide little employer-specific information, except for industry and, in some cases, firm size.

3 An Exploratory Model

3.1 Setup

In this section I explore the potential mechanisms underlying the results of the previous section. Using a search model where social networks reduce search frictions, I develop the theoretical implications of social ties between owners and workers for individual labor outcomes. In the model, wages are derived endogenously as a function of the efficiency of the social ties of current employees. Firms can choose to fill their vacancies either by posting offers or by using their current workers' connections. As a result, individuals with better connections have higher wages. Individual with more ties would find more candidates for the firm, but he would have more opportunities when he becomes unemployed. The model intends to illustrate the matching process between workers and businesses incorporating the existence of networks and firm's choice of hiring procedure. A firm chooses its recruitment policies (formal vs. informal) when

[11] [Groshen, 1990, 1991a,b], Abowd et al. [1999], Abowd et al. [2004] among others.

filling a particular vacancy, considering the capacity of their employees to find candidates for the position.

There has been previous theoretical work analyzing the impact of firm and coworker types on the information structure of job finding and the link between job search, job matching and social networks. Holzer [1987] is the first theoretical discussion of firms' hiring procedures. He proposes a model in which the firm maximizes expected profit considering recruitment costs and worker's expected productivity. However, no implications for wages were analyzed. Networks may reduce costs and the uncertainty about workers' productivity (Holzer [1987], and Simon and Wagner [1992]). Since screening workers, negotiating wages, supervising, and enforcing contracts are all part of the administrative costs of a firm[12], firm owners may improve efficiency by using network connections available to workers with similar social backgrounds. That is, information networks may work better within groups (ethnic/race of employers and employees) than between them. [13]

A second group of studies consider job information networks as exogenous and investigate the impact of networks on wages ([Montgomery, 1991, 1992], and Mortensen and Vishwanath[1994]). In these models, the equilibrium wage distribution increases with the probability that an offer comes from a contact. Montgomery further evaluates the link between wages and the strength of social ties (strong versus weak). Even though more recent studies have explicitly modeled the structure of networks to analyze the effect of network dynamics on wages and unemployment [Calvo-Armengol and Jackson, 2004, 2007], the assumption of an exogenous job information network is still very useful to analyze wage and vacancy outcomes. Models with detailed specifications of network topology treat labor markets as a black box. There is ex ante wage dispersion and an exogenous arrival rate of job offers. It is assumed that wages are function of the network size and that individuals randomly choose the number of social contacts from the total population of workers.

In this model, I endogenize labor market outcomes (wages and vacancies) but assume an exogenous job information network[14]. The aim of this model is to illustrate in a simple way the effect of social networks on labor outcomes with different firm and worker types to develop patterns consistent with the findings in the previous section.

[12]Very relevant for small businesses because of the lack of scale economies

[13]In this analysis I consider the heterogeneous group of immigrants as an homogeneous group. In the empirical approach, I also separate groups by their race or ethnicity

[14]Other models fully describe the topology of the networks. However, in the framework of this paper, trying to endogenize networks would make it impossible to find a closed form solution. The simplicity of the model presented here allows us to draw strong implications without losing the relevant characteristics of the process.

Inspired by Holzer [1987] and Fontaine [2006], I consider a search model that includes firm's hiring decisions and the use of current workers' social ties. I include different types of firms and multiple networks. A in Fontaine [2006], the matching function is derived from an urn-ball process.[15] This process provides a microfoundation for the matching process and considers the coordination failure that arises from congestion externalities.[16] A underlying assumption in the model is that the levels of vacancies and unemployment are very high, holding their ratio (market tightness) constant. In this limiting case, the urn-ball matching function exhibits constant returns to scale. Wages are a result of bargaining between workers and employers.

There are two types of firms (o) denoted as native-owned (n) and immigrant-owned (f), and two types of workers (i) denote as natives (n) and immigrants (f). The number of each type of worker is exogenously given by L_i, and the number of type i workers among the unemployed is u_i. Workers and firms are risk neutral, live infinitely and have a common discount rate r. There is free-entry, and δ_o represents the number of type o firms in steady state. Only unmatched workers engage in search. Unemployed workers receive a value of leisure b, and workers are separated from jobs at the exogenous rate s. Jobs are vacant or occupied.

Each existing worker generates applicants for the employer at an exogenous rate ρ_{io}, which depends on worker (i) and employer (o) types. This factor is common to all firms with type o. Therefore, ρ_{io} represents what Fontaine calls network efficiency. Network efficiency can be considered to be a function both of the number of workers of type i in the firm and their social ties with same-type unemployed workers, and of the employer o's ability to use his employees' (type i) connections. An employee of a given group transfers job offers only to unemployed workers belonging to the same group. If he doesn't find an unemployed worker from his group, the job offer is lost. All types of employed workers produce y. In addition to relying on coworker referrals, firms can advertise a job vacancy at a cost c. These posted offers are sent randomly the u unemployed workers. θ_i represents market tightness for workers of group i. v_o is the number of vacancies posted by firm of type o.

As previously noted, the matching function is derived from an urn-ball process (binomial

[15] In the typical urn-ball process, there are U unemployed workers and V vacancies. Each unemployed worker submits an application. These applications are randomly distributed across the V vacancies with the restriction that any particular worker send at most one application to any particular vacancy. Each vacancy then chooses one application at random and offers that applicant a job. A worker may get more than one offer. In that case, the worker accepts one of the offers at random. Urn-ball process introduces a new coordination problem, because there could be multiple applications of job seekers but only one firm will hire the individual.

[16] This failure arises when workers apply to some vacancies without knowing where other workers applied, so that as a result there are multiple applications to some vacancies and zero to others. Therefore, the group of vacancies without applicants remains unfilled. For more detail refer to Albrecht et al. [2003].

distribution). However, in this model, unemployed workers are considered the urns and job offers the balls. Unemployed workers receive offers from two sources: from posted vacancies and from similar-type current workers in the firm. $\frac{1}{u}$ is the chance that any unemployed worker receives an offer from a posted vacancy and $\frac{1}{u_i}$ is a type-i unemployed worker's probability of receiving an offer from social ties to a particular existing worker at the firm. Given the randomness of vacancies offered to unemployed workers, the probability that no firms' offers reach an unemployed worker of type i is given by $\prod_{o\in n,f}^{o}(1-\frac{1}{u})^{v_o}(1-\frac{1}{u_i})^{\rho_{io}L_i}$. With this in mind, we can then derive the probability that an unemployed worker from group i receives at least one offer.

$$C_i = 1 - \prod_{o\in n,f}^{o}(1-\frac{1}{u})^{v_o}(1-\frac{1}{u_i})^{\rho_{io}L_{io}} \tag{1}$$

where, C_i represents the probability that a unemployed worker receives at least one job offer. In a labor market in which vacancies and unemployment are arbitrarily large but finite, holding market tightness unchanged, this distribution can be approximated by a Poisson distribution.

$$C_i \approx 1 - \exp\left(-\theta_i\right) \tag{2}$$

where $\theta_i = \frac{\sum_o p_i v_o + \sum_o \rho_{io}L_{io}}{u_i}$ and $p_i = \frac{u_i}{u}$

The probability that an offer is matched to an unemployed worker of type i is given by the matching function in equation (3). This function exhibits constant returns to scale. An increase of ρ_{io} will translate into an increase in the number of offers to a particular worker in group i. Workers receive offers from formal and informal channels, but only accept one offer. Therefore, an increment in the probability of finding a candidate through current workers increases the number of offers received by unemployed workers through informal channels.

$$m(\theta_i) = u_i C_i \frac{1}{\sum_o p_i v_o + \sum \rho_{io}L_{io}} = \frac{1}{\theta_i}(1-\exp\left(-\theta_i\right)) \tag{3}$$

$m(\theta_i)$ is the expected number of workers hired of type i. It can be shown that $\partial m(\theta_i)/\partial\theta_i < 0$ (i.e. firms find it harder to find a worker the tighter is the market).

$$\frac{\partial m(\theta_i)}{\partial\theta_i} = \frac{\theta_i exp(-\theta_i) - (1-exp(\theta_i))}{\theta_i^2}$$

which is negative as long as $1-exp(-\theta) > \theta exp(-\theta_i)$. When $x = 0$, $xexp(-x)-(1-exp(-x)) = 0$. The derivative of this function is negative with respect to x for $x > 0$.

$\theta_i m(\theta_i)$ is the exit rate from unemployment for an individual i. The total number of matches is the sum of the contact rates within each social group. $M = \sum_o \sum_i (p_i v_o + \rho_{io} L_{io}) m(\theta_i)$.

On the workers' side, denote U_i as the present discounted utility of an unemployed worker and W_{io} as the present discounted value of an employed worker holding a job, with $\omega(.)$ being the wage rate for worker type i in firm type o.

$$rU_i = b + \theta_i m(\theta_i)(E[W_{io} - U_i]) \tag{4}$$

$$rW_{io} = w_{io} + s(U_i - W_{io}) \tag{5}$$

An important assumption of the model is that firms choose v_o taking into account that employees also produce applicants. Therefore, employers face the following a profit maximization problem:

$$V_o(L_{io}) = Max_{v_o \geq 0} \left[y(\sum L_{io}) - \sum w_{io} L_{io} - c v_o + rV(L_{io}) \right]$$

subject to

$$\dot{L}_o = \sum_i (\rho_{io} L_{io} + v_o) m(\theta_i) - sL_o$$

$$\dot{L}_o = \sum_i \dot{L}_{io}$$

The firm is interested in L_{io} given ρ_{io}. $V(L_{io})$ is the firm expected profit. Solving the Bellman Equation and using Kuhn-Tucker conditions I obtain:

$$\begin{aligned} \frac{c}{m(\theta_i)} &= \frac{y - w_{io}(.)}{r + s - \rho_{io} m(\theta_i)} \iff v_o > 0 \\ \frac{c}{m(\theta_i)} &> \frac{y - w_{io}(.)}{r + s - \rho_{io} m(\theta_i)} \iff v_o = 0 \end{aligned}$$

Firms will post a vacancy if and only if the cost of posting the vacancy is equal to the value of filling the vacancy. If v_o different to zero, in each period a firm o chooses the number of advertised vacancies, so it controls the increment of its total number of employees. In this way, the firm indirectly influences the number of applicants the social network will produce.

Wages are subject to a bargaining process and the firm can refuse to hire a matched candidate. The surplus of each match is shared according to the Nash solution of the bargaining problem, with $\beta \in [0, 1]$ representing the bargaining weight of firms.

$$\beta J_{io} = (1 - \beta)(W_i - U_i) \tag{6}$$

where J_o is the expected value of a filled job with a worker type i for a firm o. An individual will accept an offer if it is above the bargained wage. Using equations 6, 4, 5, and 6 we derive the wage implied by Nash bargaining.

$$w_{io} = b + \beta \frac{r + s + \theta_i m(\theta_i)}{r + s + \beta\theta_i m(\theta_i) - (1-\beta)\rho_{io} m(\theta_i)} (y - b) \tag{7}$$

The arrival rate of job offers from a firm o to an unemployed worker of type i is directly proportional to the number of people in the network (group i) who are employed in firm o. An interpretation for ρ_{io} is that it represents the capacity of workers and employers to take advantage of the groups' social connections. I express ρ_{io} using the following functional form.

$$\rho_{io} = f(\rho_i, \rho^o) \tag{8}$$

where ρ_i is the connections that current workers of type i has, and it can be affected by the number of current employees in each type of firm o, while the employer's ability to take advantage of his current employees' social ties is represented by ρ^o. Firms are not necessarily able to exploit their employers social ties because they may lack familiarity with their employees' cultural background, language, social patterns, and other factors.

Proposition 3.1. *In partial equilibrium, taking θ as given, and for a given y,c,b, and s, wages are an increasing function of the efficiency of the social network ρ. A higher network efficiency induces a higher job matching rate for the firm with no additional cost. Using equation 7 we can compute the derivative of wages with respect to social network efficiency as follows:*

$$\frac{\partial w_{io}}{\partial \rho_{io}} = \frac{\beta(1-\beta)m(\theta_i)(y-b)}{[r + s + \beta\theta_i m(\theta_i) - (1-\beta)\rho_{io} m(\theta_i)]^2} > 0$$

The increase on the efficiency of networks for a worker type i in a firm o generates a higher number of expected matches for workers of type i, given them a better bargaining position in the firm. Therefore, we would expect the probability of hiring an immigrant worker to be higher the larger the amount of immigrant workers already employed by a firm. This is what we would call the 'coworker effect'. Additionally, when group i has more efficient social ties, and the owner is also more efficient in taking advantage of these social ties to find new workers, firms find even more costless to use current employees' connections to find candidates. Workers of type i would provide more candidates to the firm, therefore, the probability of this group being hired by the firm will be higher than otherwise.

There are two forces generated by any increment in ρ_{io}. On one side, it increases the job offers using informal channels, more candidates are found using current workers. On the other side, it decreases the number of vacancies advertised because firms find more costly to post a vacancy compared to use informal channels. This substitution effect guarantees the uniqueness of the equilibrium.

Proposition 3.2. *In equilibrium, labor market tightness adjust so that the expected cost of an advertised vacancy equals the expected profit of a filled position. Using results from the firm's problem (equation 6) with $v_o > 0$, and wage bargaining results (7), I obtain:*

$$\frac{c}{m(\theta_i)} = \frac{(1-\beta)y - b}{r + s + \beta\theta_i m(\theta_i) - (1-\beta)\rho_{io} m(\theta_i)} \tag{9}$$

The solution is defined only when the right hand side of Equation (9) is positive, that is, when the marginal value of a filled position is positive. This holds provided that $r+s+\beta\theta_i m(\theta_i)-(1-\beta)\rho_{io}m(\theta_i) > 0$. Assuming a $\bar{\theta}_i$ such that $r+s+\beta\bar{\theta}_i m(\bar{\theta}_i)-(1-\beta)\rho_{io}m(\bar{\theta}_i) = 0$, then for values of $\theta \in [\bar{\theta}, +\infty]$, the expression is increasing in θ, so that the marginal value of a filled vacancy is decreasing with respect to θ, while the cost of a filling vacancy increases with higher values of θ.

Proposition 3.3. *Unemployment rate in equilibrium is obtained by equating the flow out of employment to the flow into the unemployment for each type i and is a function of the market tightness and the exit rate.*

$$u_i = \frac{s}{s + \theta_i m(\theta_i)} \tag{10}$$

Recall that $\theta_i m(\theta_i)$ is the unemployment exit rate. Using lemma (3.3), as ρ_{io} increases, the equilibrium exit rate $\theta_i m(\theta_i$ increases reducing u_i.

The model has implications the effect of social interactions on market wages that can be compared to our empirical findings below. Different types of firms pay different wages to similar workers (observable characteristics). Among subgroups with the same y, h, s, firm-group combinations with higher ρ_{io} will have higher wages and a lower unemployment rate. From Lemma (3.1) we can see that workers of type i with a ρ_{io} higher than that of other types in the same firm will receive higher wages. If ρ_{io} are such that $\rho_{nn} > \rho_{ff} > \rho_{fn} > \rho_{nf}$, there will be a distribution of wages in which natives are paid higher wages when working for native firms, but are paid lower when they work for immigrant-owned businesses. Similarly, immigrants are paid better when working for immigrant employers. Within a firm, workers of different groups are paid differently because their social ties differ in their level of efficiency. That is, foreign-born and native workers receive different wages when working for an immigrant firm because links between immigrant employers and immigrant workers result in more worker referrals. Additionally, workers with higher offer arrival rates earn more in equilibrium. These findings highlight the potential importance of social connections and social capital for understanding workers' employment opportunities and wage differentials.

4 Empirical Approach

4.1 On the use of social networks

Recent work has suggested that supervisor-employee ethnic matching could result from the use of networks.[17] On the one hand, according to several sociological studies on the ethnic economy, ethnic solidarity serves to provide entrepreneurs with privileged access to immigrant labor and to legitimize paternalistic work arrangements (Sanders and Nee [1987] and Model [1997]). Different firms have different recruitment processes, generating an initial sorting of workers types. On the other hand, networks can also have an impact on wages, providing better matches and more opportunities to the individual. Ethnic networks can generate informal sources of capital formation and captive markets, making these firms more self-sufficient and flexible (Volery [2005]). Social capital becomes another form of capital resource.[18].

Immigrant entrepreneurs can take advantage of their language, cultural background and affinities, to have access to different ethnic groups. Their immigrant status can give them privileged access to sources of labor less available to native entrepreneurs. Immigrant entrepreneurs routinely employ coethnics (including relatives) at rates vastly above chance levels. The most important network relationships are based on kinship, friendship, and paisanaje (the feeling of belonging to a common community of origin).[19] Immigrant economies rely upon networks to locate jobs. On the one hand, referrals by friends or coworkers remove some of the uncertainty associated with finding a job with unfamiliar employers and increase the chance of finding a better job match. On the other hand, immigrant entrepreneurs tend to rely on their current employees to help fill their vacancies. Workers tend to refer individuals that are 'similar' to them, from the same group, or with the same characteristics. Referral coworkers could also provide informal training, show the new worker how to perform the job, and have a good interaction with the new hire. Moreover, referral coworkers indirectly accept responsibility for new hires. Employers realize that this practice is beneficial for them as well. Little cost or effort need be expended when new workers are located through employee contacts.

Previous empirical findings show that Hispanic men report more frequent use of friends and relatives for job search than non-Hispanic whites, and are also significantly more likely to have

[17] Networks is not a new concept in the literature. Sociologists have investigated the origins and creation of social networks for more than 40 years. Rees[1966] draws attention to differences among workers and their use of available information (formal and informal sources). Job referral is also extensively used in the labor market, as well as family networks (Granovetter [1995]).

[18] Social capital in its simplest form is a social network of strong and weak social ties (Light and Gold [2000]).

[19] Massey[1980].

obtained their most recent job through personal contacts. Hispanics use informal contacts 32.8 percent more than white non-Hispanics and blacks.[20]. Recent Latino immigrants are more likely than blacks or Latino natives to use personal contacts to find jobs(Elliot [2001]). Weak English skills explain much of this difference. However, this difference does comes not only from the use of job networks by workers, but also from a greater reliance on referrals in small workplaces in combination with a concentration of recent immigrants in small firms. Employers also have a role in this process given that firms' hiring procedures will affect individuals' likelihood of receiving offers from jobs heard about through friends and relatives.

4.2 Small firms

My focus on small firms is motivated by tow observations. First, in larger firms, the separation between ownership and management could detach the firm's hiring process from owner characteristics. As Haltiwanger [2006] points out, however, in small firms the decision process is likely dependent on owner ability and characteristics. When dealing with each worker, small firm owners could project their tastes and managerial abilities in the hiring and production process of the firm. Since it is usually the business owner who makes such choices, the identification of the person responsible for hiring decisions is easier and more relevant for small firms.

Second, immigrant workers are more likely than natives to work in small firms. Andersson et al. [2007] find that there is a significant market segmentation that appears in any detailed distribution of workers in firms. Immigrants are more likely to be employed in firms with less than 10 employees, 70% of immigrants work for small firms. Meanwhile, more than 60% of native workers are employed at firms with more than 100 employees. The labor force changes generated by immigration inflows are thus borne primarily by smaller, younger firms. These firms are more sensitive to immigration shocks. If we only look at aggregate numbers (including small and big firms), immigration effects will be obscured.

5 Data and Measures

5.1 Sources

In this paper, I use three different databases to match owners' characteristics to workers' characteristics. First, I use the Characteristics of Business Owners Survey (CBO) from 1992, and then match this survey with administrative data from the IRS (Business Register) for the years 1992

[20] Holzer[1987b], Smith [2000]

to 1996. To obtain workers characteristics, I use information from the Longitudinal Household-Employer Dynamics (LEHD) database for the years 1992 to 1996. In this section, I give a brief description of each database, limitations and discuss how I construct relevant variables used in the regressions.

The *Characteristics of Business Owners (CBO)* is produced by the Bureau of the Census. The 1992 release of CBO was the final version of this survey, which formerly was conducted every five years. This survey was conducted in 1996, along with the economic census, while the questions in the survey refer to the business' and owners' information for years 1992 and 1994. The CBO is a supplement to the Survey of Minority-Owned Business Enterprises (SMOBE) and Survey of Women-Owned Businesses (WOB). The survey universe considered was ''any business which files an IRS form 1040, Schedule C (individual proprietors or self-employed persons); form 1065 (partnership); or form 1120S(Subchapter S corporation) in 1992.''.[21] It considers as business owners those who filed business tax forms as owners of the firm, excluding non-S corporations, with at least 500 dollars in yearly business receipts, and with the largest employment size category equal to five hundred. Note, that non-S corporations generally have investors, not decision-making owners, and thus this group is not in the CBO survey's universe. However, excluding non-S corporations often excludes the largest employers, making comparisons of small and large business owners difficult. The CBO provides details about both business owners and their businesses. The unique firm identifier is the CFN (Census File Number). At the cross-sectional level this number is unique for each firm.

According to a CBO publication cited in of the Census [1997], almost 62% of the 78,147 firms' surveys [22] and 59% of the 116,589 owners' surveys were returned. One possible reason of this low rate of reply is the difficulty of finding owners of exiting firms after 3-4 years. Almost 70% of all businesses present in 1992 was still in operation in 1996. This rate is lower for minority-owned firms (around 66%). Given weighted results, the survey indicates that in 1992, 20% of owners were in firms with employees. According to the minority-firm surveys, women, Asian, Pacific Islanders, American Indian, black, and Hispanic owners were typically underrepresented in the larger employment size classes. Hispanic-owned firms were 3.68% of all employer firms, but just 2.04% of firms with 100 or more employees. Additionally, 90.6% of business owners were born in the United States, while 9.4% percent were foreign born. [23] The percentage of native-owned

[21] Characteristics of Business Owners 1992:CBO092-1. U.S. Bureau of the Census (September 1997) and Headd [1999].

[22] This is translated into 63% of the 41,297 employer firm surveys.

[23] A foreign born is an individual that was born outside the USA. CBO has a particular question on whether the owner was born in the US or abroad.

firms was higher in the case of larger firms (94.5%). In this paper we focus only on employer firms.

On average, there exists more than one owner per firm. Looking at CBO(1992), more than 52% of the firms are employers, and almost 41% of employer firms are have one owner. Employer firms tend to have more owners than non-employer firms. Based on previous research using the CBO [24], I consider the CBO as a sample of firms even though it is essentially a sample of firm owners. The resulting complication is that I need to make assumptions to identify the owner characteristics for multiple-owner firms. As a first attempt , I consider three types of firms: only-native-owned, only-immigrant-owned, and mix-owned. Using this classification, more than 85% of employer firms has 1 or 2 owners for all types.

This database has some limitations. First, in the 1992 survey the CBO's sample universe omits chapter C corporations. This group of corporations corresponds to bigger businesses; therefore, comparison between small and large businesses in the CBO must be done with care. Second, even though I have each firm's average payroll, I know nothing about the interfirm distribution of payroll between different types of workers. Third, this survey has zero information on human capital or occupational characteristics of workers. I try to overcome some of these limitations by merging CBO with data from Bureau of Labor (UI and ES202) as described below.

The second database used in this paper is the Census Bureau's *Standard Statistical Establishment List* (SSEL) or *Business Register* (BR).[25] This data has cleaner information on firms given that the source of the SSEL is at the administrative level. This database works as a register of active employer business establishments[26] in the United States and its territories. The unit of information is an enterprise, which can be associated with one or more establishments and with one or more EIN entities (Employer Identification Number). [27] In this paper we concentrate on those businesses organizations associated with only one EIN and one establishment, known as *single-establishment enterprises* or *single-unit firms*.[28] All of the small firms in this paper correspond to single-unit establishments. The hypothesis that firm owners are the ones making the

[24] Carrington and Troske [1995]

[25] Walker [1997] has an extensive discussion on the Census Bureau's Business Register. The initial source of information on businesses is the IRS(Parker and Spletzer [2000]). The SSEL receives three main files from IRS; the Business Master File (BMF), with information on name, addresses and legal form of organization; the Payroll Tax Return File (Form 941) containing quarterly payroll and first quarter employment (including March 12th employment); and the Annual Business Income Tax Return Files with information on receipts/revenues, industry classification. For all three sources, EIN is the primary business' id.

[26] Active employer business establishments are those with payroll at anytime during the past three years, or with an indication that the business expects to hire employees in the future.

[27] An EIN entity is an administrative unit assigned by IRS for tax purpose. Under the Federal Insurance Contributions Act (FICA) every organization with paid employees has to obtain an EIN.

[28] All the matches between CBO(1992) and SSEL(1992) are in this category.

main contracting decisions in a firm is more plausible in firms with only one establishment than otherwise. In the case of younger and smaller firms, this restriction does not exclude many firms. [29] Additionally, businesses have a CFN (Census File Number) as an identifier, which is unique for single-unit businesses. To follow the firm across time, the longitudinal identifier for each firm is called alpha; which corresponds to the first 6 digits of firms' EIN. In the sample, I only follow firms that survived the entire period 1992 to 1996. Because most non surviving firms did not respond to the CBO survey and the weights are constructed such that this pattern is considered, the weighted results are not impacted by this exclusion.[30]

I take data on industry, legal form of organization and employment from the SSEL files. See Appendix B for specific description of these variables. Because of the time difference between the year of information and the year in which the CBO survey was conducted, a significant part of information on employment is compared with the SSEL's information on the firm's employment and sales[31]. I use the common unique firm identifier (CFN) to match CBO with SSEL.[32] Then I follow the firm across time until 1996[33].

The second set of information is associated with the characteristics of workers. This information comes from the *Longitudinal Employer-Household Dynamics* database. Information on workers comes from the Unemployment Insurance wage records for a group of states[34] and the ES202 data.

Based on availability, I use data from eight States for the years 1992 to 1996. The list of states includes high immigrant concentration and low immigrant concentration areas (California, Idaho, Illinois, Maryland, North Carolina, Oregon, Wisconsin, and Washington). These files contain person identifiers that allow researchers to track a worker's quarterly earnings within a State across years. I sum over quarters to obtain each worker's annual earnings. This database also contains firm identifiers that allow for an exact link between the UI files and other data sets. The business level identifiers in UI files are State Employer Identification Numbers (SEINs). Therefore, one can match the UI data with the ES202 data, using SEIN to get information on the

[29] Haltiwanger et al. [2005]

[30] Headd [1999].

[31] The CBO is a retrospective survey. The response rate is affected by the survival rate of the firm and the extent to which owners can accurately recall past information.

[32] I use businesses' CFN, which are the Census Bureau's preferred intra-year, cross-dataset link. The CFN contains the EIN firm identifier and is unique for single-unit firms.

[33] To illustrate the groups of firms included in both databases, I include a short discussion on firms matching rate in the Appendix A

[34] More detailed analysis on these records is presented in Abowd et al. [2006], and additional information on date of birth, place of birth, and gender are obtained for almost all workers in the sample after linking UI wage records to Census data. 98% of all private, non-agricultural employment is covered by the employer reports.

EIN, and compare it with the data previously matched using CBO(1992) and Business Register. For single-unit firms, the units of observation at the firm level used for CBO, SSEL and LEHD are generally similar.

The UI wage records contain virtually all business employment for the sample states. Earnings reports from I records are more accurate than survey-based earnings data, and one can obtain information for each worker in a specific firm (or establishment).

Using this database, I follow firms across time from 1992 to 1996 using the unique identifier within the state. I end up using only those firms that survived during the entire period and did not change ownership. This group represents 95% of the initial set of firms in 1992.[35] Finally, the data set used in this study is unique in the sense that it contains data from each firm on output and inputs used in the production process, as well as data on earnings and some demographic characteristics of each worker in the firm. I use the years 1992 to 1996 for the analysis mainly because information about owners' place of birth (i.e. being born in or outside the US) only available in the Characteristics of Business Owners Survey in 1992. My data tracks the total payroll and workforce composition of each firm from 1992 to 1996.

The drawback of using UI data is its lack of certain demographic information on workers such as education and occupation. However, the staff at the LEHD has overcome this limitation by imputing education using administrative data from the Census Bureau containing information such as date of birth, place of birth, geographic area, industry, and sex. In this paper,I use this imputed information on education[36] used in previous work for LEHD research. This variable is a proxy for individuals' human capital. I am aware that the lack of occupational information could be a relevant drawback of the data given that prior research has documented an important role for occupational segregation in creating different workers' wage gaps. We might think that immigrants tend to concentrate in low-skilled occupations relative to natives. However, as Troske [1999] and Carrington and Troske [1995] point out, occupations and job titles are less likely to be sharply defined in small firms, and as a result there could be less occupational segregation in small firms compared to large firms. Despite this limitation, we have to keep in mind that we can account for other workers' characteristics, such as age, sex and imputed education. Given that workers have varying preferences for place of work depending on the disutility of commuting and amenities of particular areas, the areas where they would be willing to work are better represented by their actual place of work than their place of residence. Therefore, I need data on

[35]Few firms were dropped because, initially, the survey's rate of response was highly correlated with the firms survival rate, so that most of the firms with information in the survey are surviving businesses.

[36]See Lengermann et al. [2004] for details on the imputation.

individuals' place of work. Location of the firm is obtained using the LEHD database.

5.2 Construction of ex post weights

A relevant technical issue that arises in the process of using different databases, especially when a survey is included, is the change of sample frame used by the survey database. Additionally, for smaller geographic areas, differences in industry and geographic information, along with differences in the scope of industries covered , lead to dissimilarities in the universe considered by the LEHD data and surveys based on the Economic Census.[37]

In the design of the CBO survey, four panels were created in addition to divisions by employer status (employer versus non-employer), 2-digit industry and state. These panels consider racial categories using owners' social security and the SSN categories: Asian, Asian-American / Pacific Islander, Hispanic, Black, and White. These groups were created by the Survey on Minority Businesses. Therefore, small firms and minority-owned firms are over-represented in the survey.

The difference between the universe and sampling frames used in the CBO survey implies that our matched analysis sample will not be representative. Specifically, the sample frame used in the CBO will over-represent small, minority-owned businesses when linked with the UI database. To deal with this issue, I follow Abowd et al. [2007] and build *ex post* weights that control for the firms' size, 2-digit industry code, legal form of organization, and employer status. I follow previous research in the sense that I first construct the fractions of firms in all the categories in the universe of ES-202.[38] This represents the numerator in the ex post weight.[39] Then, I compute the same fractions for the final matched data and use this fraction as the denominator of the ex post weight. This weight has the property that the distribution of employment by each category reflects the size distribution of ES-202 considered universe.

The second section of the adjustment procedure considers the construction of an inverse mills ratio. I use a probit estimation that considers the probability of being matched as a function of log of employment, legal form of organization, owner's place of birth (in or out the US), and log of sales per employee. This section intends to account for the CBO survey's sampling frame and the possible selection bias generated by the effect of unobservables on firms exiting from the

[37]LEHD database covers partially agriculture and public administration industries. Surveys based on the Economic Census tend to over-represent businesses in areas with high density population.

[38]The universe of ES-202 is single-unit firms with more than one employee (coworker can be computed only for these firms) and less than one thousand employees, and are in Economic Census in-scope industries in 1992.

[39]The universe is all business in the ES-202 with more that 2 employees, not in Agriculture, Mining, nor Public Administration.

universe considered to design the sample of the CBO survey. This inverse mills ratio is included in all regressions. For more details see appendix.

5.3 Firms

To compare the full CBO sample to the final matched sample used in the analysis, I look at descriptive statistics for a set of variables. The final match uses LEHD information from 8 states[40], which includes high and low immigration states. For these states I obtain workers' and firms' information. Firms from the agriculture, mining and public administration sectors are not included. Additionally, only single-unit businesses are considered. The original matched sample in the analysis has 7,200 firms, representing 339,040 workers from 1992 to 1996. All results are weighted by the adjusted-weight discussed in section 5.2.

Table(1) shows two blocks of summary statistics. One block (CBO-SSEL) contains the employer firms matched from the CBO survey and the BR, while the second block (Sample(CBO-LEHD)) contains the final matched sample, consisting of the subset of CBO-SSEL data matched to the LEHD. For each block, this table presents the distribution of firm type across firm size categories and sectors, together with the average number of owners, average share of immigrant workers, de-meaned average log sales per employee, average percentage of immigrants in the county the firm is located and the counties surrounding this location, and the percentage of each type of firm. Total population and share of immigrant workers are constructed from the public 1990 Census, and are based on all Census counties surrounding the location of the firm. Immigrant firms have a higher proportion of immigrants in the local population than native and mixed firms. Because immigrants also tend to be geographically segregated, I will use this variable to control for differences in firms' local workforce.

In the firm, the workforce of the average immigrant-owned firm contains 38% immigrant workers. By race the composition is 41% white, 20% Hispanic, 18% Asian, 7% black, and 13% others. The distribution of firms across sectors and firm sizes for each type of firm is very similar, except for the tendency of immigrant-owned firms to be in retail or services, and this distribution is only slightly changed after matching the original database with the LEHD database.

From the table we observe that immigrant-owned firms' log of sales per employee is slightly higher than native-owned firms. Actually, on average, native owned firms have the lowest log labor productivity. In general, firms are concentrated in size categories with fewer than 50 employees. Meanwhile, all firm types are more represented in sectors such as Services, Retail,

[40]Those states with available data in 1992

Manufacturing and Construction. Sole proprietorships represent more than 50% of immigrant and native firms. The average number of owners by firm type (owner type) keeps very similar levels as the unmatched sample. The average number of owners by owner birthplace is similar, except, as expected, for mix-owned firms which by definition have two or more owners. Table (1) illustrates that this patterns are similar in the original CBO sample and the final matched CBO-LEHD sample.

In the original matched data there is a percentage of firms with unknown owners' place of birth. I decide to exclude this group from further analysis. Given that, on average, the characteristics of this unknown group are similar to the rest of the sample (see Appendix(C) for t-tests and a chi-square analysis), I don't expect this exclusion will dramatically affect my findings.

I also drop those firms with less than two employees and I only consider male workers. Workers should have at least one coworker, and the analysis of earnings is net of other labor supply factors that could affect female workers differently. After these restrictions, the final sample is reduced to *4,478 firms* and *214,398 workers* from 1992 to 1996.

5.4 Workers

Among the relevant workers' characteristics available in my data are age, immigration status (place of birth), date of entry in the US (date of SSN application), education, quarterly wage, and race. I sum over quarters to obtain each worker's annual earnings, and then compute real earnings based on 1992 dollars. The data set used for the analysis includes all male workers with positive earnings. On the distribution of workers, Table (2) and Figure (1) show the proportions of workers by age, race, sex, education, owner type,size, and sector. Additionally, I report the mean age, education and earnings of both immigrants and natives and of all workers in the reduced sample. In the data, foreign workers represent almost 24% of the total number of workers.

Similar to previous studies, on average, although differences don't seem to be large, foreign born workers tend to be less educated, younger and tend to have lower income than native workers(Borjas [1994]). The fraction of workers across age categories, however, is similar for both types of workers in age categories 40 years and more.

The share of workers with a high school diploma or less is over 60% for both immigrant and natives. Immigrants are more concentrated in the high school dropout and high school graduate categories. Looking at sectoral distribution, both foreign and native workers are concentrated in Construction, Manufacturing, Retail and Services, with natives more likely to be in Construction while immigrants in Manufacturing.[41] For small businesses, foreigners seem more likely to be working for immigrant than for native owners, while the opposite is true for native workers. 43% of immigrant workers are employed in immigrant firms and 49% are employed in native firms.

Most of the immigrants are Hispanics or Asians, while natives are mainly either white or black. Although there is a fraction of native-Hispanic and native-Asian workers, these proportions are less than 5%. The racial and ethnic categories follow the SSA codes, which form a set of mutually exclusive and collectively exhaustive categories. I also include information on whether the worker is full or part time. A worker is full time if he or she has worked during the full year (worker has positive earnings all four quarters). Most of the survey corresponds to information from firms located in MSAs. However, I include a variable that identifies those firms and workers located outside a MSA. Almost 90% of the workers holds jobs in a firm located inside a MSA.

Looking at place of birth in detail, Mexican, Salvadorian, Indian, and Chinese workers are the most represented immigrant groups in the data. At the national level, these are also the largest immigrant groups in the US according to Census 1990. In the data, native owners employ almost 75% of the total workforce.

5.5 Measuring coworker share

I follow Andersson et al. [2008]'s measure of coworker share. The immigrant coworker share is considered as a measure of exposure where the worker himself is excluded.

$$COW_{ij} = \frac{1}{emp_j - 1} \sum_{emp_j}^{k \neq i} I_k \tag{11}$$

Where I_k is one when the worker is an immigrant. Therefore, this measure will contain the fraction of immigrant coworkers of an employee in a firm. This measure is generally used in concentration analysis. Here I use it as an indication of workforce composition in the firm.

6 Analysis of New Hires, Earnings of Workers and Skill Distribution

6.1 New Hires

For the analysis of hiring procedures, I look at the type, race and ethnic composition of new hires by type of owner. During the period of analysis (1992-1996), there were 147,373 new hires.

[41] One explanation for this pattern is that informal and undocumented immigrants workers are not largely covered by the database.

I identify a new hire in the data by following a firm and looking at those workers that accessed the sample during the period of analysis. I track information on each new worker. Table (3) shows the distribution of new hires by type of owner. While new hires include a large share of natives for every type of owner, the proportions of newly hired immigrants for immigrant and mixed-owned firms (more than 30%) are almost three times the proportion of immigrants hired in native-owned firms (almost 12%).

The second section of Table (3) displays the composition of new hires by race and ethnicity. Hispanics and Asians correspond to more than 35% of immigrant-owned firms' new hires. Again, this represents almost three times the proportion hired by native firms. Both immigrant and native firms hired more new workers later in the sample period as the economy recovered from the 1991-1992 recession (see Figure 1).

6.2 Earnings of Workers

In this section, I look at workers' earnings. On average, immigrant workers have lower wages than natives. Most of the explanations given by the literature are based on human capital formation. Immigrants have lower host country abilities and generally less education than natives. However, even after controlling for some of these characteristics, immigrants tend to receive lower wages than observationally similar natives (Borjas [1994]). But do workers receive different wages than their counterfactual group regardless of who they work for? To answer this question I undertake two different exercises. First, I look at the average real log annual earnings of each worker type across owner types. I also look at these statistics for different groups of firms defined by the fraction of similar coworkers in the firm. This analysis is a first look at the impact on firm owner types on earnings. Second, I estimate owner type wage effects after controlling for a number of firm and worker characteristics, and evaluate the sources of wage differentials.

The natural log of real annualized earnings of each worker comes from LEHD-UI records.[42] Table (4) shows how average wages change according to the type of owner. The last column of the table shows the t-test computed for worker type wages for each owner type. A t-test can reject the null hypothesis that the mean of immigrant worker wages and the mean of native worker wages are the same at the 90% level.

Looking at Table (4) we notice three relevant outcomes for wage differential analysis. First,

[42]When we take the average log annual earnings for each type of firm, we find that it is slightly below the log of annual payroll per employee in the SSEL database. According to internal documentation on the ES202/SSEL joint project, annual payroll in SSEL files includes non-wage payments, such as benefit payments, retirement pension funds, annuity funds, supplemental benefit funds, etc, which are not included in the UI files.

immigrants are paid slightly less by native than by immigrant owners. In general, they are paid the lowest when working for native owners. Second, native workers are paid significantly less in immigrant owned businesses. Third, on average native owned firms pay more than immigrant owned firms. Fourth, mix-owned firms significantly pay less to immigrant workers. However, these firms employ a lower proportion of immigrant workers than immigrant-owned firms.

In sum, immigrant workers end up receiving lower log annual earnings than native workers. If we combine the first three outcomes, we can see that much of the difference between the log annual wages of immigrants and natives comes from immigrants' propensity to work in immigrant owned firms. These firms pay the lowest wages, and the difference in immigrant earnings between immigrant and native firms is small. Additionally, native owned firms pay immigrant workers less than native workers (see Table(4)).

It is important to highlight the relevance of having actual earnings of each employee at the firm level, so we can exploit these variations to identify the effect of owner types on individuals' wages. Therefore, individual level wages are used in the regressions analyzed in the next sections. Table (4) would not be possible if we didn't have data on both employers and employees' characteristics. Our unique database allows us to compare average earnings between workers of different types holding a job in the same type of firm, and workers of the same type (native or immigrant) working for different types of owners.

I now perform a similar exercise, but separating firms by the share of coworkers similar to the worker (see Table 5). I use the median value over time of coworker shares at each firm. This measure is different from the measure of immigrant coworker share defined previously, in that I define as coworker share the share of workers that are of a similar type to the worker in a specific firm. For instance, the coworker share of a native worker is the share of native born workers in the firm excluding the worker. The second column (%) shows the percentage of workers of each type in the firm accordingly below or above the coworker share median. We can see in the table that the previous findings remain valid. Foreign-born employers pay the lowest wages, on average. However, for businesses with coworker share below the median, immigrant employees working for immigrant employers are paid slightly more than immigrant employees working for native employers. Additionally, workers are paid more when working with similar coworkers. When workers' coworker share is below the median, employers pay lower annual wages. More than 65% of the businesses have a mixed workforce, that is, the share of immigrant coworker is neither one nor zero ($0 < share < 1$).

The outcomes in these tables do not control for individuals' characteristics, so we don't know the profiles of native and foreign employees holding jobs in these businesses. Nevertheless, these findings are striking. Immigrant owners pay the lowest on average. Furthermore, they are able to pay natives less than the rest of the market. This motivates the question of what type of native workers work for immigrant employers.

6.3 Sorting by Skill

Sorting by skill is a possible cause of sorting by owner type. The incentive to combine workers of identical skills within the same firm has been documented previously (Kremer and Maskin [1996]). Job descriptions and skill requirements are also a concern as characteristics of employers and employees are correlated. Additionally, if firms of different types have different skill mix productivity, immigrant owners could use more intensively labor than native businesses, immigrant employers would tend to hire more and low-skilled workers than native firms. Immigrants, Hispanics, and other minority groups have, on average, lower skill so they may tend to work in low-skill sectors and low-skill jobs regardless of the owner type. Immigrant owners, on the other hand, may tend to concentrate in low-skill sectors because they also have low skill levels. Table (6) shows workers' distribution by owner's skill requirement. The skill requirement for a firm is computed using Census 1990 data after compiling the share of workers by industry at the 2-digit level that have low educational attainment(less than high school) and high educational attainment(more than high school). High skill industries are those in which more than 50% of workers have at least high school diploma. The remaining industries are low skill. The idea is to illustrate whether specific owner and worker types are concentrated in a particular skill group.

Not surprisingly, the table shows that low-education industries have higher fraction of immigrant workers than firms in high-education industries. Immigrant firms continue to have a bigger proportion of immigrant workers, except for mix-owned businesses. Results are similar breaking down by workers' race. However, it is worth mention that immigrant-owned firms are more than 60% of the group of low-skill.

To account for part of this pattern, I latter in the regressions include the share of workers in the firm in four education categories: high school dropouts, high school graduate, some college, and college graduate.

7 Empirical Analysis

7.1 Methodology

The ideal data to analyze the effect of owners, coworkers, and social connections on individual labor market outcomes requires information on individuals' labor market histories, earnings, and, specifically, the employer's source of ex-ante information about the job seekers that apply to its open vacancies. With this information we would be able to measure for the actual hiring policies that firms use to find new workers. Unfortunately, I don't have detailed data on hiring procedures used by firms. However, I do have a good deal of valuable information on the firms and workers. The workers in each sample firm can be divided into different categories such as native and foreign-born, or by race/ethnicity[43] to infer workers' and candidates' likely social connections. This, together with information on the type of owner, will help infer the use of social ties in the firm's hiring process and its effect on workers' earnings. More specifically, network structure refers to the number of ties an individual has (Smith, 2000). In this paper, I try to identify the impact of networks by using the proportion of coworkers who are potentially tied to newly hired worker. Besides identify the type of owner for whom the employee works, I use the proportion of similar employees in the firm at the time the new worker is hired as a measure of the network link between coworkers, employers, and the new worker.

Following each firm, from 1992 to 1996, I obtain the number of employees who work for the firm and their earnings. I also have the total number of workers possessing any given set of demographic characteristics at each period of time. Following the definition of networks used in previous literature, I compute the share of similar coworkers for each new hire at each firm in each period, assuming that a background implies at least a weak network connection between individuals.[44]

A key challenge in linking owners and employees is that the characteristics of both owners and employees may be correlated with other characteristics of a workplace and its location. Section 6.3 above gives preliminary evidence on sorting by skill. The correlation between owner and employee types could also be a result of residential segregation of workers and owners (spatial mismatch). Job descriptions and skill requirements are also a concern, as characteristics of

[43] White, Black, Hispanic, and Asian.

[44] At this point, it is worth to mention that even though immigrants are very diverse and it is a group that reflects a multiple gamma of ethnic/cultural backgrounds, not necessarily captures by the denomination of being foreign-born, it is also true that immigrants tend to have similar strategies to enter into the labor market regardless of their cultural background. Using migrant networks is one common factor among foreign-born workers, especially for new immigrants (Porter and Wilson [1980], Light [2006]).

employers and employees are correlated. Immigrants, and in particular Hispanics, tend to be low skilled and therefore are likely to work in low-skilled sectors and low-skilled jobs regardless of the owner type. However, at the same time, immigrant owners could tend to concentrate in low-skill sectors, perhaps because they also have low skill levels.

Because the proportions of immigrants are unequally distributed across sectors and regions , I control for the 2-digit industry and geographic location of each firm. There exist sectors such as Retail, Services and Construction where immigrants represent a significant proportion of the workforce [45]. We also see this pattern in the geographic distribution of the immigrant population. For instance, according to Census 2000, cities such as Los Angeles and New York represented more than 30% of the total immigrant population in the country. To account for these concerns I need to control for fixed attributes of the workplace and the local labor market, and also for local trends in labor pool demographics. Therefore, I estimate the model controlling for characteristics of the firm (F_j) and local community (Z_j). These controls include the immigrant workforce population and population density in the local community, 2-digit industry code dummies, firm's size (log of reported employment), and legal form of organization. I also include the share of the firm's workers in the four education categories discussed previously.

Previous research has remarked the impact of English language ability in the use of networks and the level of wages for immigrant workers. I capture this feature by interacting the 2-digit industry dummy with a English speaker dummy. This interaction intends to capture whether language is used differently at work.

In the wage regressions, I also control for individual characteristics (X_j), including worker's age, education and a dummy for working full time. The composition of the labor pool might also be affected by changes over time in labor supply and demand. For example, white natives may be more likely to work in low-wage retail jobs when labor markets are weak. Therefore, I also include a dummy variable for each of the years in the sample (M_t) to control for national fluctuations in the labor market.

The identification strategy exploits variation across owner types for otherwise similar firms. By controlling for a rich set of firm characteristics I can narrow the possible alternative explanations for any residual correlation between owner type and worker outcomes.

[45] This can be also related to the fact that these sectors are also highly represented by relatively smaller firms than in Manufacturing, for instance.

7.1.1 Analysis of firms hiring patterns

This section starts by looking at the hiring patterns of the firm, estimating a model that predicts the probability that a newly hired employee is an immigrant. Firm hiring decisions indirectly reflect the way owners can use current employees to fill their job vacancies. I use a linear probability model to estimate the likelihood that a newly hired worker is of a particular type (immigrant or from a specific race/ethnic group).[46]

Pr(new hire= group$_i$)$_{kjt}$=

$$c + B_1 * O_j + \delta * W_{jt-1} + B_2 * O_j * W_{jt-1} + \Phi * F_j + Z * Z_{kj} + T * M_t + \epsilon_{kjt} \tag{12}$$

In a regression with both owner type and coworker share included, the estimated coefficient on owner type will capture only the direct impact of owner type on hiring, not the total effect, which will include both the direct effect and the indirect effect coming through owner type's effect on coworker share. The use of employee referrals can be correlated with the type of owner and can affect hiring pattern if owners have the tendency to hire same-group individuals. When employees tend to refer same-group workers, the owner type's effect may be amplified. If we believe that the share of similar coworkers is a good proxy for social connections, these exercises illustrate the combined result of owner effect and hiring patterns.

O_j is a vector of dummy variables for owner type. Where k, j and t designate the worker, firm type, and time respectively. When group i refers to an immigrant, and immigrant-owned firms are the omitted group. B_1 represents the vector of coefficients associated with the impact of owner type on hiring. The elements of this vector are expected to be negative when the omitted group is the same type as the new hire. For instance, the coefficient on native owners would be negative if immigrant-owned firms are more likely to hire new immigrant workers. W_{jt-1} corresponds to the vector of the proportion of workers of type each type i at the firm in the previous period. An interaction between owner type and W_{jt-1} is included to asses differences in use of current employees' networks across owner types. I also control for firm characteristics F_j, year dummies M_t, and local community information and state dummies Z_{kj}.

I assume that the error (ϵkjt) in equation 12 are independent and identically distributed across firms, but not within firms. To correct for non spherical disturbances, I estimate Huber-White robust standard errors clustered by firm. This procedure is used in all subsequent estima-

[46]I use a linear probability model over a Probit (Logit) model because I don't need to restrict the sample to firms that hire at least one new worker of each type. This restriction could introduce sample selection bias because firms with zero hiring could have a completely different policy than those with a least one new hire.

tions. I cluster the errors by firm since firms in the sample may have hired more than one worker and thus may have repeated observations.

For purposes of analysis, I estimate different versions of equation (12) and look at the impact of the addition of controls on the estimate of B_1 and B_2. The first regression includes only year dummies; subsequent specifications add controls one by one. Most of the literature on hiring networks argues that current workers' referrals are more important to firm hiring patterns than owners' personal networks. Owners are likely to hire individuals from their residential area. However, current workers have a larger and more diverse set of connections that can be exploited by the firm. I am not able to disentangle these effects directly. Nevertheless, by allowing owners of different groups to make use of their workers' social ties differently, the estimated interaction effects can measure the ability of owners to use social ties.

Table (7) shows the probability of a new hire being an immigrant given the characteristics of the firm, its community and the share of coworkers in the firm. Controlling only for year dummies, native owners are 25 percentage points less likely to hire a new immigrant worker than immigrant firms. This difference is significantly reduced, to 3.5 percentage points, when we include the share of immigrant coworkers. The inclusion of other characteristics of the firm and the local community has smaller impacts the relative likelihood of native versus immigrant owners hiring a new immigrant worker. There is a positive and significant impact on the probability of the new hire being an immigrant when the proportion of workers in the firm with low education (high school dropout) increases. The owner effect diminishes and the difference in the probability of hiring a Hispanic between immigrant and native owners is 2.5 percentage pointas. The coworker effect is smaller too. Although, we can see the same significant 'persistence' in the pattern of workers hired by each type of firm. The interaction effect between owner and coworker slightly decreases for both mix and native owners. However, the pattern remains equal. The share of similar type coworker is smaller in mix and native owned firms than in immigrant owned firms. Immigrant employers can take advantage more efficiently of its current immigrant workers than other types of employers. We should be cautious when analyzing these results. I control for a vast series of covariates to control for all possible observables that can be correlated to employer and employee effect, however, the presence of unobservables correlated to firm and worker interactions can bias the results. As another exercise, I compute the firm fixed-effect version of the model by including firm dummies. The last column of Table (7) shows the results. The share of immigrant coworkers in the firm at the time of the new hire remains positive, high, and significant.

7.1.2 Hiring Process by Race/Ethnicity

I next consider the probability that a new hire comes from a particular race/ethnic group: white, black, Hispanic and Asian. That is, I estimate equation (12), setting i equal to a particular racial category. Tables 8 and 9 show the effect of owner types and share of type i coworkers, and other type of coworkers, at the time of hiring on the probability that a new hire is Hispanic, Asian, white, or black respectively.

The likelihood of a new worker being Hispanic significantly decreases when the employer is native. This result holds even after including a exhaustive list of controls(Table 8). The direct impact of owner type is reduced, however, once we control for the share of Hispanic coworker. For instance, having Hispanics as current employees in the firm increases the probability that the new worker to be Hispanic (by up to 88% in immigrant owned firms). The impact of Hispanic coworkers is smaller for native owned firms. In section (6.3) we discussed the distribution of workers by average industry-level skill requirement. As a proxy to control for this effect, I include the share of workers by four educational attainment at the firm and the fraction of workers of similar type in the local community. The results show that a higher share of low-educated workers in the firm increases the probability that the new worker is Hispanic. I also include the share of workers of each group race. The inclusion of these shares decreases the impact of the similar coworker share.

Looking at Asian new hires (Table 8), we again find that native employers are less likely to hire Asian workers. The inclusion of additional controls reduces the difference in probability of hiring an Asian between immigrant and native owned firms. Another interesting result is that Asians are less likely to be hired in firms with bigger proportion of workers with education attainment below the high school level.

Whites and blacks are more likely to be hired by native firms (See Table (9)). However, the probability that a new hire is black or white depends on the share of blacks or whites in the firm at the time of the recruitment process. The significance of the immigrant owner effect on black hiring vanishes when I include the coworker share in the regression. The column called FE shows the results of the regression after including firm fixed effects. The persistence of hiring patterns slightly decreases but it is still high and significant. The largest drop is presented by the probability of blacks to be hired when the share of coworker whites increases.

I also experiment with estimating a multinomial logit model to account for the case that employers may simultaneously choose among different types of workers. The estimation sample is then restricted to firms that hire at least one worker of each race group during the period 1992-1996. This restriction eliminates more homogeneous firms. The new sample contains 2,662 firms. I investigate how the owner type and share of different types of workers at the time of hiring affects the type/race of the new hire. I estimate a model[47] that aims to reveal whether the birthplace of the employer affects the likelihood that a new worker is of the same type as opposed to other types, conditional on having accessed to the firm during the period of analysis and controlling for the characteristics of the worker and the firm.

Pr(new hire is worker type: $i)_{kjt}$ =

$$\frac{exp(c^i + B_1^i * O_j + \delta^i * W_{jt-1} + \Phi^i * F_j + Z^i * Z_{kj} + T^i * M_t + \epsilon^i_{kjt})}{\sum_{s=1}^{5} exp(c^s + B_1^s * O_j + \delta^s * W_{jt-1} + \Phi^s * F_j + Z^s * Z_{kj} + T^s * M_t + \epsilon^s_{kjt})} \tag{13}$$

with $i = 1, ..., 4$ for the four race groups: white, black, Asian, and Hispanic. This procedure makes very strong assumptions with respect to the relevance of other alternatives. The odds ratio of any two options is assumed independent of the other alternatives. This feature is important to consider when more than two alternatives are included. To test the Independence of Irrelevant Alternatives assumption, I conduct a Hausman test by excluding each outcome category in turn. The test indicates that I cannot reject the null hypothesis that the odds of one outcome happening are independent of other alternatives. Additionally, I perform Wald tests for combination of categories. The tests reject the null hypotheses that all coefficients associated with a given pair of outcomes are zero (except intercepts). I cluster the errors by firm since observations within firms are not independent. The results for this regression are shown in Tables (10) and (11).

Table (10) shows the change in log odds comparing two alternatives. The change in log odds between hiring a white worker versus hiring a Hispanic or an Asian decreases when the firm is immigrant-owned. The share of white coworkers significantly increases in the log odds of a white being hired. I also show the predicted hiring probabilities for each owner type (Table 11) computed at the means of all firms and dummy variables. Immigrant owners are 3 percentage points more likely to hire Asians and Hispanics than native firms. These results support the analysis in the previous section.

7.1.3 Workers' earnings and analysis of results

I estimate the effects of owner type and coworkers on workers' compensation by using a human capital approach. The dependent variable is the natural logarithm of workers' real annual wages.

[47] I specifically estimate a mixed logit model that incorporates both characteristics of the individual and the alternatives.

The regression includes dummy variables for owner type, the share of same kind coworkers, worker type, and other firm characteristics. Using wage estimates at the individual level, we can evaluate the impact of owners' characteristics on wage differentials by using equation (14).

$$\begin{aligned} ln(w_{kjt}) = \quad & c + \beta_1 * I_k + X_k^{'} * B_2 + O_j^{'} * B_3 + I_k * O_j^{'} * B_4 + COW_{kj}^{'} * B_5 + I_k * COW_{kj} * B_6 + \\ & O_j^{'} * COW_{kj}^{'} * B_7 + I_k * O_j^{'} * COW_{kj}^{'} * B_8 + F_j^{'} * \Phi + Z_{kj}^{\prime} * Z + T * M_t + \mu kjt \end{aligned} \tag{14}$$

where k identifies information on the worker and j refers to information on the firm. w_{kj} stands for worker k's log real annual earnings at firm j. I_k is a dummy variable for whether the worker is an immigrant. In an effort to establish how much the immigrant earnings differential is due to differences in predetermined personal characteristics, I add a vector X_i of employee characteristics including age, age squared, education, sex, and race. O_j is a vector of dummy variables for owner type: with B_3 their corresponding coefficients. COW_{kj} stands for the proportion of immigrant coworkers in the firm (explained in section 5.5). The expected sign for β_1 is negative, assuming that immigrants earn lower wages, and its significance indicates that there is enough variation across the different worker types. With the inclusion of owner type dummies, the estimate of β_1 will represent the difference in wages between immigrants and natives in native owned firms. The sum of β_1, and the B_3 and B_4 coefficients corresponding to an immigrant owned firm will be positive if immigrant workers earn higher wages when working for immigrant-owned businesses than native workers in an immigrant firm. The coworker share accounts for the potential impact on wages of having better connections to similar types of workers in the firm. The interaction between COW_{kj} and the vector of owner types is included to asses whether the effect of coworkers differs according to the type of employer that is hiring the employee. I explore a 3-way interaction among owner type, worker type, and the immigrant coworker share. In equation (14), $B_2 X_k$ absorbs the effects of variations in personal characteristics. We would expect estimates of β_1 and the vector B_3 to change after including workers' characteristics. It is equal to one according to each owner's type represented in the sample, B_3 is the vector of coefficients associated with those dummy variables.

We should be aware of the potential presence of omitted variable bias. Unobservable characteristics could bias estimated coefficients in equation (14). Ignoring these unobservables could causes us to overestimate the impact of owner type and immigrant coworkers on individual earnings. High ability workers of type k should look for firms that pay higher earnings. If native-owned firms offer higher wages and employ these high ability workers, the estimated model would not be capturing the effect of owner type on workers' earnings; rather it would be capturing individuals' ability to find better jobs. Also, worker preferences and comparative advantage can influence the results. Variations in preferences for particular job characteristics across different workers could provide an alternative explanation for both earnings differentials and sorting. To account for some of this variation, I include the fraction of workers in the firm with education lower than high school, equal to high school, higher than high school with some college, and equal to college or higher. The omitted category is the group of college graduate.

Characteristics of firms (F_j) and of local community (Z_j) are also included. These controls include the population share of each group in the local community, population density, firm's size (log of reported employment), and legal form of organization. M_t are year dummies.

The first column of Table (12) shows results from a baseline model including immigrant status, individual age, education, and part-time status, but excluding other variables of interest. The table reports the betas estimated by equation (14). To make the analysis, I transform these unstandardized β coefficients with the usual formula $[(e^{\beta}-1)*100]$, I can analyze the percentage change in wages associated with a 1-unit change in a continuous independent predictor variable. In the case of a dichotomous independent variable, I interpret the percentage wage difference in the target category compared to the reference category. After controlling by typical human capital variables, full-time immigrant workers earn about 8% less than native workers (3,293 dollars less each year). When working for native employers this difference increases to 11%. Meanwhile, immigrant workers earn 10% more than native workers in immigrant owned firms (4,398 dollar more each year).

The human capital results in Table (12) are consistent with the literature. Age positively affects wages but at a decreasing rate. Education is significant and positive. Part-time workers earn less than full-time workers. The inclusion of additional independent variables does not modify these patterns. After controlling for individual characteristics, immigrant workers are paid less than native workers in native firms, but they receive a significantly higher wage than native workers when working for immigrant firms. The inclusion of the share of immigrant coworkers produces interesting results. Immigrants earn more when working for immigrant employers and when the immigrant coworker share increases. The opposite is true for native workers. In general, a native worker receives higher wages if he or she works for a native firm with a low share of immigrant workers.

These results are striking in two senses. One, the ability to look at individual wages and identify the types of firm owners is only possible with this database. We have individual earnings for each firm. Although immigrants are paid less on average, they find themselves in a better position when working for immigrant firms. Second, we can look at the entire workforce and identify the individuals' types of coworkers in the firm. This allows us to make inference on the impact of social ties on worker wages.

8 Conclusion

This paper explores the analysis of

Using a matching framework, This paper explores the potential mechanisms explaining the interconnection between owner's and coworkers' characteristics and workers' hiring patterns and waget. Furthermore, it takes advantage of unique employee and employer matched micro-data from the U.S. Census Bureau to examine the effect of owner types and coworker types on firms' hiring patterns and workers' earnings. Particular attention was paid to the nativity of employers and to the share of similar coworkers (by nativity and ethnicity) at firms when new workers are hired. I examined the effect of those variables on hiring rates and on the wage differential between immigrants and natives.

There would be a distribution of wages in which workers are paid higher when working for same-type owners. Within a firm, workers of different groups are paid differently because their social ties differ in their level of efficiency. That is, foreign-born and native workers receive different wages when working for an immigrant firm because links between immigrant employers and immigrant workers result in more worker referrals. Additionally, workers with higher offer arrival rates earn more in equilibrium.

Firms with high share of skilled workers have incentive to use referrals, because the chances of finding another skilled worker through referral are higher than through the market (posting vacancies). This is true as long as the probability of referring a high skilled worker is higher than the distribution of skilled workers in the market. Nevertheless, even an immigrant firm with a low level of skilled workers could be able to generate a more efficient connection with its current workers if it can exploit the rate of worker replication.

In sum, the better the employer can get information from its current employees, in this case the better immigrant firms obtain information from its current immigrant employees, the lower the uncertainty on the expected productivity, the lower the informational cost, and the lower the recruitment cost. The informal mechanism would be relatively more efficient than the use of formal recruitment processes. The more skilled workers the firm has the higher the incentives to use informal channels to reproduce the characteristics of its current workers.

In general, employees' wages are affected by the type of owner of the firm. For native employees the effect on wages is higher when working for immigrant employers. Natives are paid lower when working for immigrant employers, and in these firms natives have lower average earnings than immigrants. One explanation for these findings is that immigrant bosses have a better understanding of and networking with the immigrant community, and, therefore, can better find and contract immigrant workers than native-owned firms. Why can't native-owned firms quickly adjust and find this cheaper labor? Lack of language knowledge and lack of networking make it harder for native bosses to find immigrant workers. This findings justify further analysis of differences in contracting ability across employers. The evidence that the type of owner matters for wage differentials among workers also implies an important role for personnel policy.

In addition to examining the effect of owners and coworkers on differences between immigrants and natives, I evaluate the effect on ethnically(racially) different groups. Individual's race is an important source of variation across workers. The evidence suggests that employers tend to hire workers from the same ethnic group. A significant persistence in the hiring process is observed across all types of owners, even after controlling for firm fixed effects. Immigrant owners tend to hire more Hispanics and Asians, while native owners hire more blacks and whites.

By shedding light on the ways workers and employers interact in the labor market to affect job and wage outcomes, this research makes a contribution to the sociology, labor economics, and demography literatures. It also opens up numerous avenues for future research. On the microeconomic side, we can further evaluate job flows and wage profiles of workers inside different types of firms. The analysis of assimilation can also take advantage of the results presented here, to further our understanding of adjustment process of new immigrant workers. The empirical analysis in this paper makes some progress toward mitigating biases of skill sorting. This paper controls for a broad number of observable characteristics that try to capture other explanations for segregation. However, if owner unobservable characteristics are correlated to worker characteristics, the results of the analysis would be biased. Different empirical approaches such as instrumental variable or fixed-effect approaches could be good options in future research, although this would demand a more exhaustive matched database that follows workers after leaving the firm and firms after ownership changes. Increasing the scope of the analysis by looking at one industry could also provide information on the costs and benefits of firm recruitment processes. For instance, we could examine with more detail the effect of worker type concentration on firms' labor productivity. On an aggregate view, we can evaluate the effect of large flows of immigrants on the economy with the combined analysis of push and pull factors. Immigrant firms and immigrant workers seem to match quickly in the labor market. The analysis on unemployment and aggregate vacancies in the labor market can be extended to incorporate the findings in this paper.

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Table 1: *Descriptive Statistics - CBO(1992) and Sample/Matched Firms*

	CBO(*)					Matched Sample(CBO-LEHD)				
Distribution/Type of firm	**Mix**	**Immigrant**	**Native**	**Unknown**	**ALL**	**Mix**	**Immigrant**	**Native**	**Unknown**	**ALL**
Size (%)										
2-4	26.52	49.30	42.51	46.43	44.66	16.67	37.27	33.60	33.29	33.79
5-9	18.06	20.90	21.35	20.91	21.05	18.75	21.53	20.97	20.33	20.79
10-19	23.48	14.68	16.69	15.00	15.90	18.75	18.44	18.02	17.40	17.88
20-49	18.18	10.70	12.10	10.95	11.59	28.13	14.25	16.72	16.89	16.58
50-99	6.94	2.97	4.56	4.26	4.26	9.90	5.67	6.65	6.78	6.59
100+	6.82	1.46	2.79	2.45	2.54	7.81	2.84	4.03	5.31	4.37
Sector (%)										
Construction	6.49	5.07	12.74	10.41	10.58	5.73	4.71	13.49	9.38	10.06
Manufacturing	20.26	10.35	13.89	13.59	13.38	25.00	15.93	17.65	18.36	17.76
Transp. & Utility	5.45	2.83	7.43	6.73	6.43	5.21	2.77	7.58	6.91	6.34
FIRE	19.22	19.73	17.14	19.24	18.36	18.75	22.18	19.03	22.24	20.84
Retail	17.14	29.68	19.73	23.17	22.47	14.58	29.85	16.42	21.34	20.83
Wholesale	6.10	3.19	6.18	5.21	5.36	7.81	3.55	5.30	4.44	4.70
Services	25.32	29.16	22.89	21.65	23.43	22.92	21.02	20.54	17.33	19.49
Legal Form (%)										
Sole Proprietorship	-	62.40	51.43	29.15	50.48	-	62.40	51.43	29.15	50.64
Partnership	28.51	12.58	12.26	18.69	12.97	28.51	12.58	12.26	18.69	12.99
Corporation (**)	71.94	24.10	25.01	52.16	27.36	71.94	25.01	25.01	52.16	36.37
l(sales/employment) (1)	11.64	11.60	11.48	11.54	11.54	11.73	11.59	11.57	11.63	11.64
	(1.17)	*(1.17)*	*(1.05)*	*(1.15)*	*(1.11)*	*(1.08)*	*(1.19)*	*(1.05)*	*(1.18)*	*(1.13)*
Immigrant in the neighborhood(***) (%)	13.47	22.15	12.43	15.06	12.90	14.03	21.17	11.34	15.07	12.80
In MSA (%)	92.01	96.50	90.07	80.60	92.41	91.30	97.37	93.01	81.71	92.85
Average Number of Owners	3.58	1.57	1.88	1.80	1.84	3.78	1.55	1.95	1.83	1.87
Average Share of imm. Workers (%)	.	.	.	.	.	33.00	38.05	11.55	28.00	26.00
Unweighted distribution of firms(%)	2.03	14.94	45.87	37.16	100	2.84	18.10	42.54	36.53	100
Weighted distribution of firms(%)	2.01	13.50	78.60	5.89	100	2.84	12.89	77.92	6.40	100
# of Firms (sample) unweighted			38,980					7,985		
# of Observations (sample) unweighted			38,980					339,040		

NOTE: Statistics based on weighted outcomes unless the contrary is indicated. (*) Single-unit firms that matched with SSEL. (**)Only S- Corporation . (***)Using Census 1990, computed percentage of immigrant population in the surroundings counties around the firm. (1)Source SSEL: Sales (total receipts/sales), and employment (Employment March12th).

Table 2: *Descriptive Statistics - Characteristics of Workers*

	Indiviudal		All
	IM	US	
MEAN (std)			
Age	34.01	34.14	34.11
	(13.33)	*(12.02)*	*(13.13)*
Education	13.04	13.16	13.13
	(2.76)	*(2.94)*	*(2.79)*
Log(annual earnings)	8.30	8.32	8.33
	(1.87)	*(1.68)*	*(1.84)*
DISTRIBUTION (%)			
AGE			
Under 25	18.09	24.43	22.91
25-39	51.64	43.03	45.10
40+	30.26	32.54	31.99
EDUCATION			
High School Dropout	8.89	7.41	7.77
High School Graduate	59.27	59.26	59.26
Some College Education	30.81	32.00	31.71
College Graduate	1.04	1.33	1.26
SECTOR			
Construction	7.92	18.37	15.85
Manufacturing	37.08	26.13	28.76
Transportation and Utilities	3.81	7.11	6.31
Wholesale	14.17	14.16	14.16
Retail	19.33	16.63	17.28
FIRE	1.36	1.58	1.52
Services	16.34	16.03	16.10
SIZE			
2-4	2.18	1.65	1.78
5-9	4.70	4.23	4.34
10-19	9.27	9.32	9.31
20-49	19.32	21.23	20.77
50-99	18.96	18.91	18.92
100+	45.57	44.66	44.88
RACE			
White	17.36	75.07	61.18
Hispanic	47.21	4.85	15.04
Asian	22.76	0.93	6.18
Black	1.71	11.21	8.92
Other	10.88	4.67	6.16
TYPE OF OWNER			
Immigrant	42.70	12.10	19.46
Mixed	8.34	5.67	6.31
Native	48.96	82.23	74.22
Part-time	43.67	37.39	38.90
In MSA	97.23	83.38	86.71
All	24.06	75.94	100

Note: Number of observations equal to 214,398 workers. Statistics based on weighted outcomes. Standard Deviations in parenthesis. Male workers with positive earnings in a year. Log annual wage in 1992 dollars.

Table 3: *Average Race and Ethnic Composition of New Hires by Owner's Type*

	Owner Type			
Worker type/ race/ethnicity	Immigrant	Mixed	Native	All
Immigrant	**33.30**	37.10	11.56	14.80
Native	66.70	**62.90**	88.44	85.20
Hispanic	**20.14**	22.32	10.14	11.50
Asian	**16.09**	12.78	2.65	4.26
White	48.20	49.80	**73.61**	70.40
Black	6.49	8.41	**8.68**	8.46
Other	9.09	6.70	4.92	5.38

Note: Number of Observations equal to 147,373. Male workers with positive earnings in a year.

Table 4: *Means Earnings by Owner and Worker Type*

Variable=log(annual earnings)	**(%)**	**Mean**	**STD**	**T-test**
owner = Immigrant				
Immigrant	50.30	8.35	*1.47*	
Native	49.70	8.12	*1.67*	
All	**100.00**	**8.23**	**1.64**	**24.20**
owner = Mix				
Immigrant	35.94	8.52	*1.86*	
Native	64.06	9.04	*1.71*	
All	**100.00**	**8.71**	**1.82**	**-16.07**
owner = Native				
Immigrant	15.87	8.32	*1.73*	
Native	84.13	8.38	*1.88*	
All	**100.00**	**8.37**	**1.73**	**-5.83**

Note:STD indicates standard deviation. Log annual wage in 1992 dollars. Using workers during the period 1992-1996.(*)T-tests are computed on the difference between average wages of immigrant and native workers for each specified owner type.

Table 5: *By Coworker Share: Mean Earnings by Owner and Worker Type*

	Coworker Share					
	Below the median			**Above the median**		
Variable=log(annual earnings)	**(%)**	**Mean**	**STD**	**(%)**	**Mean**	**STD**
owner = imm						
Native	33.64	7.37	*1.71*	66.36	7.67	*1.53*
Immigrant	66.69	7.98	*1.68*	33.31	8.19	*1.34*
all	**48.09**	**7.74**	**1.51**	**51.91**	**7.82**	**1.70**
owner = mix						
Native	26.42	7.90	*1.79*	73.58	8.39	*2.98*
Immigrant	66.36	8.67	*1.63*	33.64	6.91	*1.21*
all	**39.07**	**8.32**	**1.75**	**60.93**	**8.13**	**1.98**
owner = usa						
Native	6.96	7.74	*1.81*	93.04	8.38	*1.89*
Immigrant	91.48	7.80	*1.77*	8.52	7.68	*1.96*
all	**20.33**	**7.78**	**1.79**	**79.67**	**8.31**	**1.92**

Note: STD indicates standard deviation. Log annual wage in 1992 dollars. Statistics based on estimation sample: all male individuals working between 1992 and 1996.

Table 6: *Worker types distribution by owner's skill requirement*

	Low-Skill Industries				High-Skill Industries			
Worker / Owner	**Immigrant**	**Native**	**Mixed**	**All**	**Immigrant**	**Native**	**Mixed**	**All**
Immigrant	38.60	11.60	27.50	15.40	33.70	9.20	41.60	11.50
Native	61.40	88.40	72.50	84.60	66.30	90.80	58.40	88.50
Race/ethnicity								
Hispanic*	19.23	10.12	16.78	11.40	17.73	6.44	20.05	7.43
Asian	18.22	2.63	8.23	4.64	17.09	2.97	24.30	4.34
Black	5.38	6.83	7.62	6.68	6.45	10.84	4.45	10.42
White (non-hispanic)	48.71	76.18	61.38	72.47	52.22	75.49	42.07	73.28
Other**	8.46	4.25	5.98	4.80	6.51	4.27	9.12	4.53
All	**70.83**	**54.16**	**62.24**	**100.00**	**29.17**	**45.84**	**37.76**	**100.00**

Note: Using Census 1990 information on workers' education attainment by industry, industries are separated into High Skill and Low Skill. High skill refers to those industries in which more than 50% of workers have at least a high school diploma. Otherwise we define the industry as low skill. (*) Hispanic refers to all races with ethnic group Hispanic. (**) The group Other includes Native American and otherwise unclassified racial groups. Native-American workers represented only 0.5% of the total sample.

Table 7: *Linear Estimates of the Effect of Owner Type on the Probability that a New Hire is an Immigrant*

	(1)	(2)	(3)	(4)	(5)	(6)	FE
Owner Mix	-0.0374***	-0.0519***	-0.041***	-.0034**	-0.0037**	-0.00313**	
	0.0056	*0.0057*	*0.0065*	*0.001*	*0.001*	*0.001*	
Owner Native	-0.2539***	-0.2358***	-0.0351***	0.0342***	-0.033***	-0.0254***	
	0.003	*0.0032*	*0.0031*	*0.0009*	*0.0004*	*0.0014*	
Share of Immigrant Coworkers			0.9961***	0.782***	0.7724***	0.7132***	0.6715***
when hired			*0.0056*	*0.002*	*0.0101*	*0.0234*	*0.0435*
Share of Coworkers when hired					-0.0125**	-0.0094**	
* Owner Mix					*0.005*	*0.005*	
Share of Coworkers when hired					-0.0711***	-0.0378***	
* Owner Native					*0.003*	*0.0041*	
Corporation						-0.00085*	
						0.0033	
Sole Proprietorship						0.0026	
						0.003	
log(employment)						0.003	
						0.002	
Share of workers with HSD (firm)						0.0021**	
						0.0004	
Share of workers with HSG (firm)						-0.0012	
						0.001	
Share of workers with SCG (firm)						0.005	
						0.006	
Population % immigrant in neighborhood(+)						0.0162**	
						0.0068	
Population in neighborhood(+)						0.0004***	
						0.00	
In MSA						-0.005***	
						0.0009	
Constant	0.3709***	0.4081***	0.0211***	0.0989***	0.0969***	0.0285**	0.1575*
	0.0032	*0.099*	*0.0039*	*0.002*	*0.0016*	*0.0069*	*0.781*
year dummies	yes	yes	yes	yes	yes	yes	yes
Industry dummies	-	yes	yes	yes	yes	yes	-
Industry*English speaker dummy	-	-	-	yes	yes	yes	-
R-Square	*0.27*	*0.29*	*0.32*	*0.34*	*0.35*	*0.38*	*0.41*

Note: Reference group is immigrant firms.Reference Sector is Services. The number of observations is 147,373. Standard Errors are Huber-White robust standard errors, corrected for firm clustering. (+) Neighborhood is defined counties adjacent to the county where the firm is located. Population in 100,000's. FE represents the firm fixed-effect model. ***significant at 1%, ** significant at 5%, * significant at 10%.

Table 8: *Linear Estimates of the Effect of Owner Type on the Probability that a New Hire is Hispanic*

	Hispanic						Asian					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**FE**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**FE**
Owner Mix	0.0214***	0.012	0.0077	0.014	-0.0694		-0.029***	-0.0280***	0.002	0.001	0.007	0.1948
	0.0041	*0.01*	*0.005*	*0.0357*	*0.054*		*0.0032*	*0.0032*	*0.003*	*0.002*	*0.002*	*0.254*
Owner Native	-0.0903***	-0.0872***	-0.0412***	-0.0245**	-0.0172**		-0.1245***	-0.1114***	-0.054**	-0.052**	-0.06**	
	0.003	*0.003*	*0.003*	*0.001*	*0.001*		*0.002*	*0.002*	*0.002*	*0.002*	*0.014*	
Hispanic Coworkers when hired			0.9441***							-0.743***	-0.712***	-0.622***
			0.0054							*0.0079*	*0.008*	*0.008*
Asian Coworkers when hired				-0.628***	-0.526***	-0.504***			0.8194***			
				0.013	*0.023*	*0.029*			*0.031*			
White Coworkers when hired				-0.703***	-0.681***	-0.596***				-0.7876***	-0.741***	-0.6715***
				0.0095	*0.0075*	*0.0197*				*0.0071*	*0.0072*	*0.0074*
Black Coworkers when hired				-0.879***	-0.725***	-0.616***				-0.8795***	-0.8214***	-0.7631***
				0.0123	*0.0134*	*0.0212*				*0.0083*	*0.0081*	*0.0083*
Hispanic Coworkers when hired *			0.0621**							-0.0197	-0.0556	
Owner Mix			*0.031*							*0.0303*	*0.041*	
Asian Coworkers when hired *				0.1060**	0.093**				0.007			
Owner Mix				*0.0483*	*0.034*				*0.002*			
White Coworkers when hired *				0.0185	0.0175					-0.0746***	-0.076***	
Owner Mix				*0.0384*	*0.0434*					*0.0022*	*0.0022*	
Black Coworkers when hired *				0.137	0.105					0.032	0.0404	
Owner Mix				*0.0845*	*0.0945*					*0.0446*	*0.0536*	
Hispanic Coworkers when hired *			0.0869***							-0.0064	-0.0064	
Owner Native			*0.043*							*0.0185*	*0.0185*	
Asian Coworkers when hired *				-0.113***	-0.102***				-0.152***			
Owner Native				*0.0295*	*0.0243*				*0.013*			
White Coworkers when hired *				-0.148**	-0.124**					-0.0158	-0.031	
Owner Native				*0.062*	*0.056*					*0.0154*	*0.0221*	
Black Coworkers when hired *				-0.094*	-0.097*					-0.0076	-0.0095	
Owner Native				*0.04*	*0.04*					*0.02*	*0.02*	
log(employment)					0.0013**						0.0014**	
					0.00						*0.00*	
Share of workers with HSD (firm)					0.0012***						-0.0012**	
					0.0005						*0.0001*	
Share of workers with HSG (firm)					0.0025***						-0.000	
					0.0003						*0.00*	
Share of workers with SCG (firm)					0.0030***						-0.0013**	
					0.0008						*0.00*	
Working Pop. % immigrant in neighborhood (+)					0.0561**						0.024*	
					0.0245						*0.001*	
Working Pop. % Hispanic in neighborhood (+)					*0.094****							
					0.002							
Working Pop. % Asian in neighborhood (+)											0.043**	
											0.01	
Constant	0.1920***	0.1243***	0.9702***	0.8454***	0.9511***	0.8411***	0.1495***	0.112**	0.065**	0.095***	0.094***	0.097
	0.0032	*0.009*	*0.08*	*0.1616*	*0.171*	*0.201*	*0.0018*	*0.0562*	*0.02*	*0.01*	*0.01*	*0.081*
year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry dummies	-	yes	yes	yes	yes	-	-	yes	yes	yes	yes	-
State dummies	-	-	yes	yes	yes	-	-	-	yes	yes	yes	-
Other controls (+)	-	-	-	-	yes	-	-	-	-	-	yes	-
p-value	*0.0001*	*0.002*	*0.0001*	*0.003*	*0.003*	*0.01*	*0.0001*	*0.002*	*0.0001*	*0.003*	*0.003*	*0.01*
R-Square	*0.22*	*0.29*	*0.31*	*0.34*	*0.42*	*0.35*	*0.26*	*0.31*	*0.34*	*0.35*	*0.37*	*0.38*

Note: Reference group is native firms.Reference Sector is Services. The number of observations is 147,373. Standard Errors are Huber-White robust standard errors, corrected for firm clustering. (+) Other controls include: location in a MSA dummy, legal form of organization, population in thousands in the neighborhood, interaction between 2-digit industry dummy and English speaker dummy. Neighborhood is defined as the adjacent counties to the county where the firm is located. Population in 100,000's. ***significant at 1%, ** significant at 5%, * significant at 10%.

Table 9: *Linear Probability: Effect of Owners types on the Probability that a New Hire is Black*

	White						Black					
	(1)	(2)	(3)	(4)	(5)	FE	(1)	(2)	(3)	(4)	(5)	FE
Constant	0.4407***	0.4112***	0.9702***	0.8747***	0.915***	0.71*	0.0689***	0.0269***	0.0867***	0.4116***	0.4116***	0.3145
	0.004	*0.127*	*0.08*	*0.2327*	*0.237*	*0.33*	*0.0026*	*0.0077*	*0.01*	*0.1612*	*0.1612*	*0.201*
Owner Mix	0.0197***	0.0518***	0.0077	-0.0007	-0.012		0.0197***	0.0044	0.0034	0.0139	0.0139	
	0.0074	*0.0073*	*0.005*	*0.02*	*0.02*		*0.0044*	*0.0045*	*0.005*	*0.0619*	*0.0619*	
Owner Native	0.2633***	0.2307***	0.0412***	0.0391***	0.0233***		0.0231***	0.0312***	0.0235***	0.0345***	0.0345***	
	0.004	*0.004*	*0.003*	*0.009*	*0.010*		*0.002*	*0.002*	*0.003*	*0.013*	*0.013*	
Hispanic Coworkers when hired				-0.8325***	-0.8197***	-0.147***				-0.8262***	-0.8321***	-0.7143***
				0.0255	*0.0257*	*0.0276*				*0.0299*	*0.0337*	*0.034*
Asian Coworkers when hired				-0.6869***	-0.6904***	-0.5821***				-0.8516***	-0.8363***	-0.6523***
				0.0211	*0.0213*	*0.0234*				*0.0269*	*0.0302*	*0.032*
White Coworkers when hired			0.8861***							-0.9126***	-0.9073***	-0.2834***
			0.0279							*0.0252*	*0.0284*	*0.054*
Black Coworkers when hired				-0.8936***	-0.8654***	-0.6634***			0.9513***			
				0.0375	*0.0378*	*0.465*			*0.0345*			
Hispanic Coworkers when hired *				-0.1247***	-0.1252***					-0.1465**	-0.1098	
Owner Mix				*0.05*	*0.0566*					*0.071*	*0.0926*	
Asian Coworkers when hired *				-0.2546	-0.2212					-0.1272**	-0.0145	
Owner Mix				*0.0507*	*0.0518*					*0.0707*	*0.0822*	
White Coworkers when hired *			0.1015***							-0.1249**	-0.0202	
Owner Mix			*0.0454*							*0.0705*	*0.0823*	
Black Coworkers when hired *				-0.047	-0.0236				0.0923***			
Owner Mix				*0.1047*	*0.1048*				*0.034*			
Hispanic Coworkers when hired *				0.0351*	0.0390*					0.0009	0.0048	
Owner Native				*0.017*	*0.017*					*0.03*	*0.03*	
Asian Coworkers when hired *				0.0996**	0.1154**					0.0898	0.0707	
Owner Native				*0.0363*	*0.0364*					*0.103*	*0.0384*	
White Coworkers when hired *			0.077***							0.0386	0.0584**	
Owner Native			*0.0354*							*0.026*	*0.0293*	
Black Coworkers when hired *				0.0194	0.0257				0.1298***			
Owner Native				*0.0386*	*0.0388*				*0.023*			
log(employment)					0.0061**						0.0082***	
					0.00						*0.00*	
Share of workers with HSD (firm)					-0.0018***						0.0011***	
					0.0008						*0.0005*	
Share of workers with HSG (firm)					-0.0024***						-0.0001	
					0.0005						*0.0001*	
Share of workers with SCG (firm)					-0.0046***						0.0005	
					0.0012						*0.0008*	
Working Pop. % immigrant in neighborhood (+)					-0.1471***						-0.0362*	
					0.036						*0.01*	
Working Pop. % white in neighborhood (+)					*0.0754****							
					0.023							
Working Pop. % black in neighborhood (+)											0.095***	
											0.01	
year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry dummies	-	yes	yes	yes	yes	-	-	yes	yes	yes	yes	-
State dummies	-	-	yes	yes	yes	-	-	-	yes	yes	yes	-
Other controls (+)	-	-	-	-	yes	-	-	-	-	-	yes	-
p-value	*0.0001*	*0.002*	*0.0001*	*0.003*	*0.003*	*0.01*	*0.0001*	*0.002*	*0.0001*	*0.003*	*0.003*	*0.01*
R-Square	*0.27*	*0.31*	*0.33*	*0.35*	*0.39*	*0.41*	*0.21*	*0.23*	*0.31*	*0.31*	*0.33*	*0.34*

Note: Reference group is native firms.Reference Sector is Services. The number of observations is 147,373. Standard Errors are Huber-White robust standard errors, corrected for firm clustering. (+) Other controls include: location in a MSA dummy, legal form of organization, population in thousands in the neighborhood, interaction between 2-digit industry dummy and English speaker dummy. Neighborhood is defined as the adjacent counties to the county where the firm is located. Population in 100,000's. ***significant at 1%, ** significant at 5%, * significant at 10%.

Table 10: *Multinomial Logit Model: Effects of Owner Type and Coworkers on Type of New Hires*

	Change in log odds comparing alternative 1 to alternative 2					
coworker	White to Black	White to Asian	White to Hispanic	Black to Hispanic	Black to Asian	Asian to Hispanic
White	**-1.97*** **	**2.32*** **	**3.53*** **	1.44*	0.53	0.92
	0.646	*0.761*	*0.421*	*0.71*	*0.723*	*1.017*
Black	**-5.352*** **	1.186	2.145***	**7.456*** **	**5.456*** **	1.014
	0.892	*1.086*	*0.661*	*0.957*	*0.968*	*1.131*
Asian	-1.391	**-7.243*** **	0.041	1.433	-5.682***	**7.126*** **
	0.951	*1.001*	*0.591*	*1.108*	*0.946*	*1.143*
Hispanic	-0.236	*-0.086*	**-3.675*** **	**-3.127*** **	0.15	**-3.654*** **
	1.03	*1.102*	*0.527*	*1.09*	*0.952*	*1.361*

Notes: Notes: Other controls include log of employment, percentage of immigrant workers in the surrounding counties, population in the county, legal form of organization, Msa location, 2-digit industry, interaction 2-digit industry and English speaker dummy, state and year dummies. Results from race/ethnicity 'others' are not shown. Number of observation 135,583 workers, and 2,662 firms. Robust standard errors in italic allow for arbitrary correlation within the same firm. * significant at 10%,** significant at 5%, *** significant at 1%.

Table 11: *Multinomial Logit Model: Predicted Probability of Covariates*

	Workers			
Owner	White	Black	Asian	Hispanic
Native	0.740	0.120	0.031	0.100
Immigrant	0.710	0.102	0.060	0.126
Mix	0.690	0.119	0.052	0.134

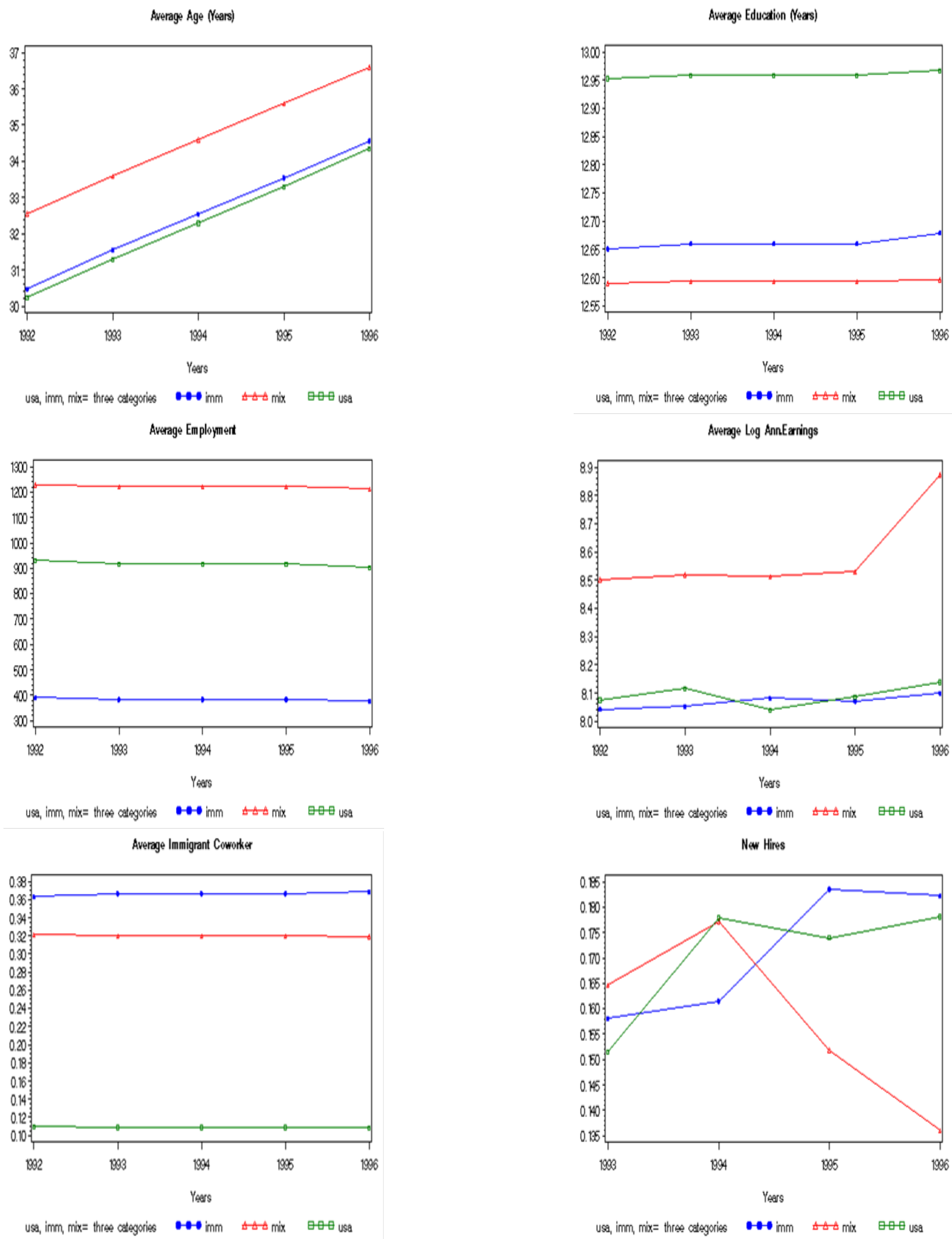
Note: Based on multinomial logit predictions of the race of new hires from previous table.

Table 12: *OLS Results: Effect of Owner Type and Coworker Share on Log Real Annual Wages*

	(1)	(2)	(3)	(4)	(5)
Immigrant	-0.08***	-0.1503***	-0.1205***	-0.1171***	-0.1017***
	0.007	*0.0069*	*0.0073*	*0.0025*	*0.0008*
Age	0.0806***	0.080***	0.0803***	0.0802***	0.0749***
	0.0007	*0.0007*	*0.0007*	*0.0006*	*0.0008*
Age square (′)	-0.080***	-0.080***	-0.080***	-0.080***	-0.080***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*
Education	0.506***	0.506***	0.511***	0.504***	0.484***
	0.0007	*0.0007*	*0.0007*	*0.0007*	*0.0007*
Partime	-2.1847***	-2.1805***	-2.1792***	-2.1783***	-2.1240***
	0.0044	*0.0044*	*0.0044*	*0.0036*	*0.0049*
Owner Mix		0.1808***	0.1615***	0.1407***	0.0936
		0.0128	*0.013*	*0.0481*	*0.0155*
Owner Immigrant		-0.1191***	-0.1443***	-0.1495***	-0.1087***
		0.0097	*0.0101*	*0.017*	*0.012*
Owner Mix*Immigrant		0.0054	-0.0007	0.1866	0.1368
		0.0224	*0.02*	*0.251*	*0.243*
Owner Immigrant*Immigrant		0.3205***	0.3030***	0.3174***	0.3131***
		0.0251	*0.0153*	*0.017*	*0.0252*
Imm.Coworker			-0.1398***	-0.2457***	-0.3797***
			0.0163	*0.0203*	*0.0276*
Imm.Coworker*Immigrant			0.09***	0.12***	0.1520***
			0.013	*0.011*	*0.02*
Imm.Coworker*Oimm				-0.0966***	-0.2925***
				0.036	*0.0734*
Imm.Coworker*Omix				-0.095**	-0.1359
				0.0582	*0.0513*
Imm.Coworker*Oimm*					0.6456***
Immigrant					*0.1285*
Imm.Coworker*Omix*					-0.3285
Immigrant					0.641
Constant	10.665***	10.7015***	10.686***	10.653***	10.615***
	0.26	*0.262*	*0.263*	*0.241*	*0.235*
Year dummies	yes	yes	yes	yes	yes
2-digit industry dummies	yes	yes	yes	yes	yes
Other controls	no	no	no	no	yes
R-Square Adjusted	0.25	0.27	0.28	0.31	0.35

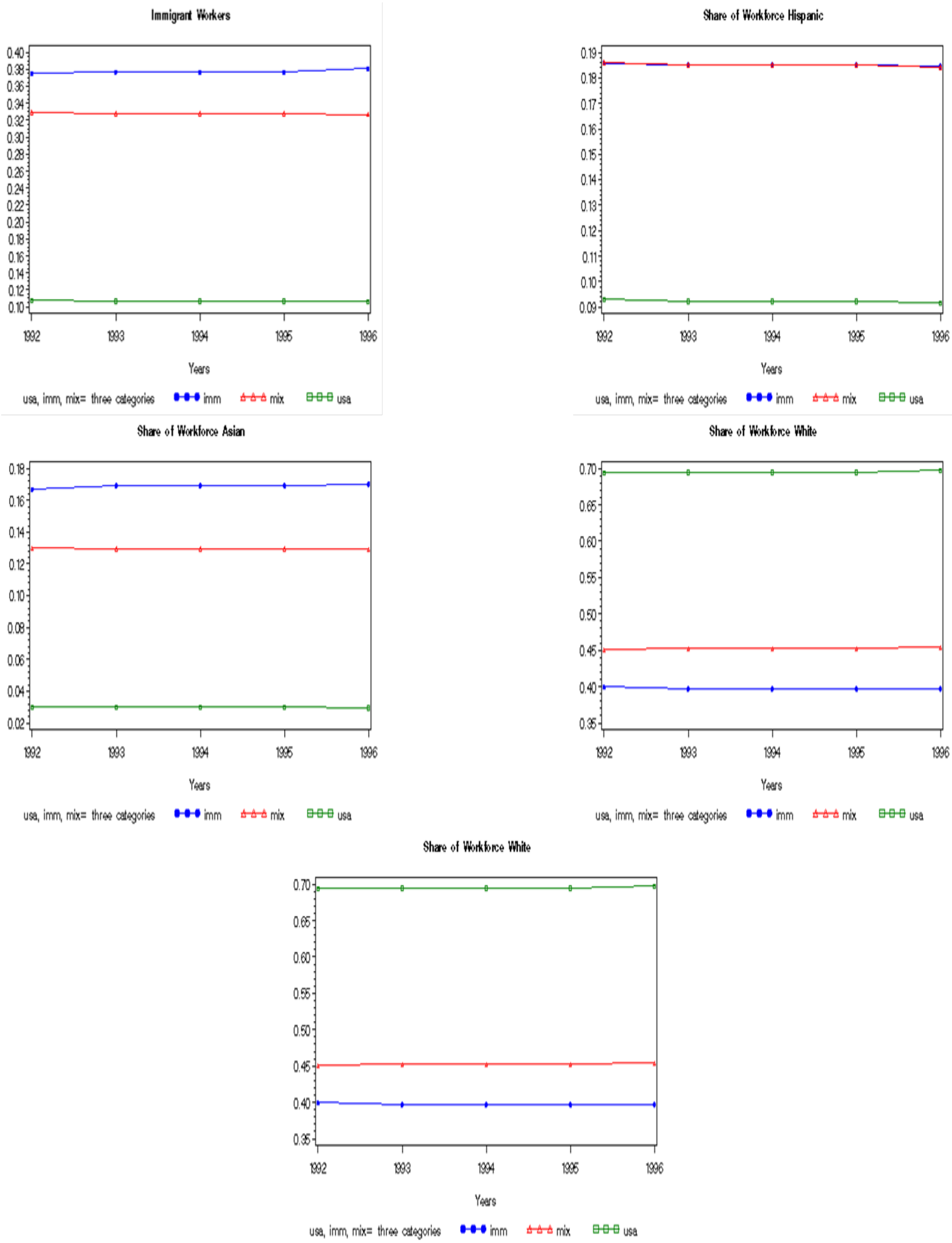
Note: The number of observations includes 214,398 workers. Standard Errors are Huber-White robust standard errors, corrected by firm clustering. Reference group are full time native workers in native firms. (+) Neighborhood is defined as the contiguous counties to the county where the firm is located. Population in 100,000's. (′) $Age * 10^2$.
***significant at 1%, ** significant at 5%, * significant at 10%.

Figure 1: Workforce Characteristics of Immigrant, Mix and Native Firms



Note: Weighted share and percentage. Base on years 1992-1996.

Figure 2: Workforce Characteristics of Immigrant, Mix and Native Firms Cont...



Note: Weighted share and percentage. Base on years 1992-1996.

APPENDIX

A Matching Rate

To have an idea of the groups of firms included in both database, I include a short discussion on firms matching rate. Mostly, matches between CBO and SSEL in 1992 are employer firms (See Table(A-1)). However, there is a small portion of non-employers that match with SSEL[48]. The matching rate, although very high, is not 100%. There is a group of industries that are not included in SSEL such as Private Households (88), and Direct Sellers (5963) that are included in the CBO. The matching rate increases with the number of owners of the firm. Number of owners in the firm and size of the firm are also relatively proportional.

Table A-1: *Matching and Non-matching rate of firms in CBO and SSEL(single-unit)*

	CBO: One Owner	
	Non-Employer	**Employer**
Non-matches	99.28	10.79
Matches	0.72	89.21

	CBO: Two Owners	
	Non-Employer	**Employer**
Non-matches	79.23	2.55
Matches	20.77	97.45

	CBO: Multiple Owners	
	Non-Employer	**Employer**
Non-matches	88.31	3.92
Matches	11.69	96.08

Source: Authors calculation based on CBO(1992) and SSEL(1992).

B Definitions

Standard Statistical Establishment List (SSEL).

- Sales: Following Spletzer [1998], I consider the variable sales as to the sum over ACSR1, ACSR2, ACSR3. We can include ACSR4 for Corporations and Partnerships. Spletzer [1998] gives a more detailed information on the sale data in the SSEL. For single establishment file has sales data. This variable contains data for the Value of Shipments, Sales, Receipts, or Revenue. It may include ''total revenues, gross income, operating receipts (gross receipts or sales less returns and allowances), interest income, and gross rents". In 1992, 80.1 percent of SSEL single establishments have current year sales data. When matched with CBO we obtain sales data for all firms. Spletzer [1998] compared the values for Employment, Payroll, and Sales between SSEL and the Economic Census. He found that, for 1992 and single establishments in Maryland, the number for the two first match well. However, the numbers for sales and sales per worker shows a difference above 8%. He speculates that the difference is coming from distint definitions, specifically for commissions for wholesalers ''that sell as an agent for another company (Type of Operation code=43 or 46)."
- For the employment variable I use the sum of ACEMP and AC943E.

C Unknown-Owned Firms

Before continuing with the analysis, it is worthy of attention to mention that there exists a group of undefined firms for which owners' nativity is unknown. Mostly, this group corresponds to firms that did not answer the survey (CBO). 95% of the owners of these firms did not answer the survey. I obtained

[48]The SSEL in 1992 seems to include those nonemployer firms that were subject to Federal Income Tax[49].

information on their distribution, size, sales and payroll using SSEL and EC in 1992. At a glance, from Table(1) the distribution of this type of firms across size and sectors is similar to the rest of the group. For further analysis, I compute a t-test of equality of productivity proxies and earnings per employees means between the unknown-owned firms and a weighted average value of the productivity proxies and earnings of the other three groups. A t-test cannot reject the null hypothesis that the mean of labor productivity (t-test=-0.89), and logarithm of earnings per employee (t-test=2.2) of unknown-owned firms and the rest of the groups are the same at the 90% level. The average number of owners and the average share immigrant workers at the firm is also similar when we compare unknown-owned firms with the average of immigrant, mix and native-owned firms.

Additionally, a chi-square test over unknown-owner firms' and the rest of the group's distribution across categories (size and sector) cannot reject the hypothesis that unknown-owned firms and the total of firms excluding unknowns are similarly distributed across the categories size and sector presented in Table(1) at the 90% level. The Pearson chi-square for the size distribution is 9.02 (Pr=0.11). For the distribution across sectors, the Pearson chi-square with 6 degree of freedom is equal to 16.02 (Pr=0.08). Like the other firms types, unknown-owned firms are highly represented in Wholesale, Manufacturing, Services and Retail. At the same time, more than 70% of unknown-nativity employers are businesses with less than 20 employees.

It is very relevant for us to know whether the owner (or owners) of the firm was (were) born in the USA or otherwise. We cannot identify this profile for the group unknown. Given that the characteristics of the unknown group are very similar, in average, to rest of the sample, I decide to drop these observations. For the rest of the paper, we only consider those groups for which nativity is obtained (three groups of firms: native-owned, mix-owned, and immigrant-owned).

D Weights and selection

According to Heckman(1979), I obtain the probit estimate from the probit selection equation in order to estimate the inverse mills ratio. The probability of being a matched firm in the sample is estimated as a function of the characteristics of the firm: size, industry, legal form of organization, geographic location, owner type, and continuing or exiting firm.

$$\lambda(z) = \frac{\phi(z)}{\Phi(z)} \tag{A-1}$$

where $\Phi(.)$ is the standard normal cfd, $\phi(.)$ is the standard normal density and z is $x^{'}\beta/\sigma$. The covariates x are the ones discussed above and the coefficients are estimates of the probit model.