Education-Occupation Mismatch and Social Networks for Hispanics in the US: Role of Citizenship

Kusum Mundra*
Department of Economics, Rutgers University, Newark and IZA, Bonn Germany
kmundra@newark.rutgers.edu

and

Fernando Rios-Avila
Levy Economics Institute at Bard College
friosavi@levy.org

June 2020

JEL Codes: J15, J24, J61

Keywords: Education-Occupation Mismatch, Horizontal Mismatch, Social Networks, Hispanics, Citizenship

* Corresponding author. Department of Economics, 360 Dr. Martin Luther King Jr. Blvd., Newark NJ 07102-1801.

ABSTRACT

In this paper we examine the education and occupation mismatch for Hispanics in the US using a novel objective continuous mismatch index and explore the role of immigrants' social networks on this mismatch. We explore whether having a larger social network helps Hispanics in finding jobs that better match with their skill and education levels or whether living in areas with larger concentration of Hispanics leads to more competition for the same jobs in the labor market. Given that the legal status of immigrants influence how the social networks are leveraged and their impact on labor market outcomes, we focus on the citizenship status for Hispanics. The quality of match between Hispanic's college degree major and occupation is measured using one of the continuous indices proposed in Rios-Avila and Saavedra-Caballero (2019) and calculated using pooled data for all college graduates in the US from 2010 to 2017. The Hispanic networks measures are constructed as the share of Hispanic population who are 25 years or older with respect to the total population of the same age and the second measure only includes Hispanics with at least a bachelor's degree using the weighted pooled data from 2010 to 2015. We find that networks have a positive impact on the job-match quality, but mostly for Hispanic citizens and this effect is stronger when the networks constitutes of at least a college degree. This shows that Hispanic citizens living in higher concentration of Hispanic college graduates are better able to leverage their networks or their networks are better able to match them with jobs closer to their field of specialization and skill set.

1. INTRODUCTION

With increasing technology and investment in higher education around the world there has been increasing incidence of job education/skill mismatch. In particular, the occupation and education gap for immigrants is quite stark in their destination countries because skills and labor market experience are not completely transferred across borders as well as the lack of English proficiency for many immigrant groups. This mismatch in the labor market is costly not only to the individuals in terms of lower earnings (Altonji et al., 2016, and van der Werfhorst, 2002) and diminished job satisfaction (Cabral, 2005; Belfield and Harris, 2002), but also to the firms and the country for not employing individuals at their most productive jobs and investing on their employee's firm specific trainings. This mismatch not only effects individual's well being and income but also effect their overall social mobility and economic assimilation as well as integration rates for immigrants. In this paper, we examine the education and occupation mismatch for Hispanics in the US using a novel continuous objective mismatch index and explore the role of their social networks play in this mismatch.

Using the continuous index of mismatch proposed in Rios-Avila and Saavedra-Caballero (2019), we explore whether having a larger social network helps Hispanics in finding jobs that better match with their skill and education levels or if living in areas with larger concentration of Hispanics leads to more competition for the same jobs in the labor market. Both finding a better job match and a higher competition in the local labor market will be more severe if the individual's network is similar to her in skill and education level, which makes this an empirical question. There is a big literature on the role of social networks in labor market outcomes for both immigrants and natives (Granovetter 1995, Munshi 2003, Vella and Patel 2013 to name a few). In addition, there is a big literature on measures and determinants of mismatch for general population (Nordin et al. 2010, Robst 2007 to name a few) and as well as for immigrants and the effect of this mismatch on worker earnings (Chiswick and Miller 2009, 2010a, 2010b). However, not much is known on how networks influence the education and occupation mismatch.

The percentage of immigrants who are college educated has increased rapidly in the US over last two decades. Similar patterns have been observed for Hispanics, both immigrants and citizens, although they remain behind of the US average[1]. More than their native-born counterparts, many high-skilled immigrants work in jobs for which they are over-credentialed and/or overqualified. Some empirical research bears out anecdotal stories of immigrant taxi drivers with graduate degrees or graduates working in kitchen. Given that the legal status of immigrants influence how the social networks are leveraged and their impacts on labor market outcomes we focus on the citizenship status for Hispanics. Hispanics in the US have significant proportion of citizens through amnesties as well as second third generation and well as the highest proportion of undocumented immigrants in the US.

This research is very timely and would help us to understand the role of potential social networks on the extent of education- occupation mismatch for Hispanic natives and immigrants. Given that social networks help individuals labor market outcomes, our research question is: Are workers who have access to large social networks, an informal job search method, more likely to be employed in the jobs that better match the individual's education and skills? To answer this empirical question, we analyze a sample of Hispanic people living in the US, who have at least a Bachelor's degree and were interviewed in the American Community Survey in 2016 and were living in an MSA that is identifiable in the ACS survey consistently since 2010. The quality of the match between Hispanic's College Degree and their occupation is measured using one of the indices proposed in Rios-Avila and Saavedra-Caballero (2019) using pooled data for all college graduates in the US from 2010 to 2017, and using 2010-2015 data to estimate potential Hispanic networks at the MSA level.

2. BACKGROUND AND LITERATURE REVIEW

The literature identifies two types of education-occupation mismatches: vertically mismatched or horizontal mismatch. The idea of over education /required education /under education (ORU) framework are based on the idea of vertical mismatch (Chiswick and Miller

[1] Brookings (2011) report using widely-used measure of over qualification shows that nearly half (49 percent) of high-skilled immigrants are overqualified for their jobs (i.e., their educational attainment is at least one standard deviation above the mean attainment for their occupation).46 About one in nine (11.3 percent) is greatly overqualified (i.e., two or more standard deviation above the mean), whereas These figures are one-third of natives are (36.1 percent) are overqualified, and 6.1 percent greatly overqualified.

1999) where employees level of education is compared to the average level of education in her occupation. Horizontal mismatch on the other hand is a measure of how close are the skills and knowledge workers obtain in their field of education, and the skills and knowledge that are required by an specific occupation/job (Robst 2007). Horizontal mismatch is very relevant for college educated employees because many majors prepare them with general education for different jobs requiring minimum college degree qualification but their field of education does not teach them job specific skills. Moreover, there is an excess supply of certain majors in the labor market and there is an excess demand of jobs requiring completely different majors and skill set (Machin & McNally, 2007). This often varies with the labor market institutions and whether there is a recession or boom. Employees often make their major choices with an expectation of finding future employment, but often because of labor market institutions or the macro conditions there might be less demand for the jobs in their field compared to some other fields. Both vertical mismatch and horizontal mismatch, which is more relevant for college and higher graduates is costly for both employees because its results in underutilization of skills and lower pay. Also, for firms who have employees lacking the job specific skills and they have to invest in job specific training.

Mismatch, whether vertical or horizontal is explained by search theory. Under the presence of labor market frictions, employees may enter the labor market and find themselves choosing jobs for which they are overeducated or horizontally mismatched, but over time, they may find a better match to their level of education or field (Groot & Maasen van der Brink 2000). Human capital theory proposes that due to friction in the labor market workers might take jobs for which they are over educated, but expect to gain job specific training for future job growth. On the other hand, undereducated workers might substitute job specific training for their lack of education and for potential job mobility (Sicherman 1991). For immigrant's formal education and degree attained as well as home country labor market experience are often not transferable across borders so immigrants are often both vertically as well as horizontally mismatched. Immigrants' ability also plays an important role, both for overeducated and undereducated immigrants, as well the selection of immigrants from their home country, in determining the mismatch and its negative impact on earnings (Chiswick and Miller 2010a). There is ample evidence that many immigrants due to their status in their destination countries or language proficiency are over educated for their jobs or not employing their skills in the most productive jobs and have lower earnings.

To keep up with economic and technological growth schools and universities provide improved and advanced skills so that recent graduates are considered over educated than the earlier cohorts in existing occupation (Kirker et al. 2000). This incidence of over education due to technological growth for immigrants is determined by the level of development and growth in the immigrant home country.[2] Chiswick and Miller (2009) also propose screening theory where the employer hires, both natives and immigrants based on formal education, but with time has more information on the ability and skill levels of employees and promotes or demotes individuals based on more information of the worker ability and this may reduce mismatch.

There has been steady increase in the literature on the incidence of match or mismatch, determinants of this mismatch, and the effect of this mismatch on worker earnings. In addition, for immigrants their education levels, skills and home country experience are not often perfectly transferred across borders as well as there is selection on who immigrates from their home countries. Nordin et al. (2010) examines the income penalty of education and occupation mismatch for Sweden across gender for higher education degrees and find that income penalty is twice as large as the one found by Robst (2007) for US men, whereas Swedish women have the same penalty as US counterparts. Dajalstaed (2011), also for Sweden, find that the vocationally educated workers have a higher match compared to general education level and that immigrants have a higher mismatch than natives. For the immigrants in major destination countries studies have shown existence of mismatch, similar determinants of this mismatch across countries, and a significant wage penalty due to this mismatch. Chiswick and Miller (2009) find that for US high skilled immigrant males there is significant presence of over education compared to the average level of education required for the jobs they are employed in. Moreover, the levels of over education have no influence on their earnings and so they are underpaid. However, longer the immigrants are in the US their extent of mismatch goes down and there is significant increase in earnings. Similarly, for Canada examining the determinants of job-education mismatch and its impact on earnings Sharaf (2013) find that two-thirds of recent immigrants are overeducated with a wage loss of 8% while under-educated immigrants loses around 2% on average. They also find that higher proficiency in English and immigrants who just arrived are over educated for their jobs but over time they assimilate and their job mismatch is significantly reduced. For UK Campbell

[2] For the detail survey and meta-analysis on vertical and horizontal mismatch see (Hartog, 2000; McGuinness, 2006;

(2013.) find that the level of mismatch significantly varies by the region of origin of the different immigrant groups highlighting that the immigrant groups are selected differently based on their origin and that play a significant role in the incidence and degree of mismatch. They find that immigrants from EU accession countries of Central and Eastern Europe are more significantly over educated for their jobs that other recent EU migrants in UK and are concentrated in jobs that where wages are not high for over education. Moreover, for non-graduate occupations these immigrants, even if over-educated, face substantial wage penalties compared to UK natives.

2.1. Role of social networks

Since labor market frictions are important determinants of both vertical and horizontal mismatch, type of job search and referral methods used will influence the incidence as well as the degree of mismatch for both natives and immigrants. It is well established that individual social networks play an important role in their employment, though we do not know much on how these social networks effect the degree of education and occupation mismatch. Is it that using informal job search method, like social networks, increases the likelihood of employment but workers end with a job where they are over educated or have a large horizontal mismatch? Or rather, does living in areas with larger potential networks reduce market frictions improving the likelihood to work in better job matches?

An individual's network is a part of his or her social capital and is important for both natives and immigrants in their labor market outcomes. The most influential definition of social networks is provided by Granovetter (1973, 1982) who distinguishes different types of networks based on the strength of the ties between their members. Granovetter defines that strong ties are typically maintained with family members, whereas weak ties are maintained with friends and acquaintances. Distinguishing between weak and strong ties Granovetter(1995) finds that more than fifty percent of jobs in neighborhoods are found through contacts and weak ties networks because those networks have larger access to information on job openings that strong ties networks do not. Similar findings using different methods and measures of the strength of social networks are also seen in Holzer (1988), Montgomery (1991), Ionnides and Loury (2004) to name a few. For the U.S., Falcon and Melendez (2001) and Elliott (2001) show that Latinos are more likely to use individual social contacts and insider referrals to find jobs. For the U.K., Patacchini and Zenou

(2012) show that the higher the residential proximity of individuals from the same ethnic group, the higher the probability of finding jobs through social contacts.

Immigrants rely on their social networks, particularly of their compatriots for their economic as well as social assimilation in the United States. Owing to the different definitions of networks and the variety of methodologies employed, there is a wide range of findings regarding the impact of social networks on migrants' earnings in the literature. For instance, Massey et al. (1987) used data from the Mexican Migration Project and defined social networks as kinship, friendship, and paisanaje (i.e.,fellow citizens). Orrenius (1999), however, defined family networks as having a relative with U.S. migration experience, whereas Chiswick and Miller (1996) showed that migrant groups tend to live in the areas where many others speak their language (i.e., areas with a high linguistic concentration). This tendency may reduce migrants' incentive to learn the new language and may explain why migrants living in ethnic enclaves earn less than their counterparts living in areas where English is spoken more frequently. In contrast, Mouw (2003) found that, once unobserved worker characteristics are controlled for, the use of contacts positively affects wages. Finally, using the MMP data, Munshi (2003) found evidence of a higher likelihood of holding a higher-paying, nonagricultural job among migrants with larger networks. However, Patel and Vella (2013) show that networks have a strong effect on immigrants' occupational choice and wages. US census data show that the occupational choices of new immigrants are driven by the occupation of their compatriots and immigrants who choose similar occupations have a greater positive earning effect.

Despite the different network measures used in the literature, the common finding is that networks unambiguously increase the chances of immigrants' employment, with mixed findings on the effect on earnings. Social networks with similar characteristics group helps in finding employment through informal channels but also possibly leads to poor education and skill job match and lower earnings. Bentolila et al.(2010) using samples from the U.S. and Europe show that workers who found jobs using contacts show 1-2 percent lower unemployment duration but report a significant mismatch between their productive advantage and their occupational choice. Specifically, they find that workers who used contacts to find jobs earned 2.5 percent lower wages than those who found jobs without using contacts. In a theoretical model of heterogeneous workers and firms and links between workers representing favoring relationship Horvath(2014)show that networks might lead to a higher mismatch. However, if the fraction of ties with similar agents (*homophilly*) increases, the level of mismatch decreases. So if the employee's social networks was more similar to her in terms of skill, characteristics, culture, language her networks will be able to match her with jobs more accurate with her education and skill level. This is why immigrant networks with compatriots helps in better job match for immigrants because compatriots have more information on the home country education and experience.

On a similar vein there has been increasing evidence on the higher quality of networks having more effective role in the labor market outcome. Social networks play an important role for individuals in the labor market because they help to reduce job search cost by providing access to information that facilitates the job search process, however, the effect of networks on employment outcomes depends on the initial state of the networks and on the length the agent has been unemployed. The longer an individual is unemployed, the lower are her chances of finding a job due to duration dependence but also because the quality of networks worsens and her networks are less helpful in job searches (Calvo-Armengol and Jackson 2004; Mundra and Rios-Avila 2018). So homophilly, influencing the quality of networks is important in how networks effect the individuals employment prospects as well as education and job matching.

There is an increasing literature on how the individual's human capital skills as well as their legal status influence on how they leverage their social networks in job search and labor market outcomes. There is well established evidence of migrants' unauthorized status adversely affecting their earnings in the United States (e.g., Bean et. al. 1988; Winegarden and Khor 1991).[3] However, differences in human capital—such as migrants' English proficiency—explain only 48% of the log-wage gap between unauthorized and legal male migrants (Rivera-Batiz 1999). Therefore, although some studies have found that most background information is insignificant in determining migrants' earnings (e.g., Kossoudji and Ranney 1986), migrants' legal status may affect their earnings independently of their personal and human capital characteristics. Similarly,

[3] Unauthorized migrants lack appropriate work documentation and are exposed to workplace vulnerabilities that may translate to a greater difficulty in finding employment or to lower wages compared with legal migrants. In this vein, Rivera-Batiz (1999) found that male Mexican legal migrants earn, on average, 41.8% more than unauthorized workers.

legal status influences the effect of social networks in the labor market outcomes. Distinguishing between networking differences between unauthorized and legal migrants or the distinct impact that these networks may have on their respective wages. Amuedo-Dorantes and Mundra (2007) found that both family and friend networks have a significant positive effect on earnings for both legal and undocumented immigrants, though the strong family networks improve earnings for legal migrants by a larger magnitude than the unauthorized immigrants. So a citizen will have a better and more effective networks that they can leverage in their employment and earning prospects and possibly have higher quality networks. Citizens compared to non-citizens can leverage their higher quality networks to reduce the labor market frictions and provide better information on their labor market skills to the employer and in turn possibly leading to lower education-occupation mismatch.

3. Measuring the Education-Occupation Quality Match

Broadly, there are two methods for measuring the degree of relatedness or match quality between education and occupation (horizontal match/mismatch). On the one hand, authors like Robst (2007a, 2007b) and Yuen (2010) use subjective measures, where people are asked their beliefs on whether or not their educational background is related to their jobs. On the other hand, Nordin et al. (2010) and Marin and Hayes (2017) suggest the construction of more objective measures of match quality, using information on the observed distribution of workers with different fields of study across occupations. This paper takes the same approach as in Rios-Avila and Saavedra-Caballero (2019), which is similar in spirit to Nordin et al. (2010), constructing a match quality indices based on the observed distribution of individuals across occupations and fields of study. The intuition behind the construction of the index can be described as follows.

If we assume a static labor market where the number of jobs available by occupation and number of workers with specific types of education are fixed and exogenous, then the following identity must hold.

$$\sum_{i \in OCC} p_O(i) = \sum_{j \in fld} p_F(j) = 1 \qquad (1)$$

Where $p_O(i)$ is the proportion of workers in occupation i, and $p_F(j)$is the proportion of workers with field of degree *j*. If the distribution of jobs were given at random, disregarding any differences in productivity, skill or wages related to fields of degrees or occupations, the joint probability of finding a worker with a field of degree j working in an occupation i will be given by:

$$p_{OF}(occ = i, fld = j) = p_{OF}(i,j) = p_O(i) \times p_F(j) \qquad (2)$$

Where $p_{OF}(i,j)$ is the probability of a person working in occupation *i* with a field of degree *j*.

As described in the literature, the empirical and theoretical evidence suggests this is not the case. The field of degree plays an important role in how workers are matched to jobs, because different fields are likely to provide specific skill sets to workers that are more valuable in some occupations, but less valued in others. This will create an automatic attraction between specific occupations and workers with specific fields of degree, as workers seek to maximize their wages given their set of skills and employers seek hiring the most productive workers for a given occupation. In this regard, in a frictionless market, we should expect to find everyone in a specific field working in the most related occupation, with a zero probability of finding someone working on an occupation that is unrelated to their field.

Due to frictions in the labor market and the presence of other factors that both workers and employers may consider at the time of hiring, one might expect that the observed distribution of workers across fields of degrees and occupations reflects a mixture of labor market frictions and a job matching maximizing behavior. Nevertheless, under the assumption that, on average, individuals with field of education *j* prefer to work in occupation *i* because they believe that occupation is the best match for their skill set, the observed distribution of workers across fields of degrees and occupations $p_{OF}(i,j)$ can be used to create indices of education-occupation match quality (I_{MQ}). In specific, we construct an index that uses the ratio of the observed proportion of workers with education *j* in occupation *i*, divided by the expected proportion under the assumption of no assortive matching, as a proxy for job-match quality:

$$I_{MQ}(i,j) = \frac{p_{OF}(i,j)}{p_O(i) \times p_F(j)} \qquad (3)$$

Intuitively, values above one of this index suggest that a particular occupation and field of degree combination is a *good match*, because the likelihood of seeing that particular combination is better than the benchmark of no assortative matching or random matching. Similarly, values below one would indicate that particular combination is a *bad match,* because it is observed in at a frequency below the benchmark of random matching.

These index is similar in spirit to the categorization used in Nordin et al. (2010), where fields of study and occupation pairs are classified as matched, weakly matched, or mismatched based on overall density and some arbitrary criteria (Nordin et al. 2010, 1050). In contrast, this index does not depend on any subjective criteria. As it will be described in the data section, a monotonic transformation of this index is used for the rest of the analysis.

4. Data and Summary Statistics

4.1. Data

Data for this paper comes from the American Community Survey (ACS) for the years 2010 to 2017, obtained from the Integrated Public Use Microdata Series (IPUMS) (Ruggles et al. 2017). The ACS is the largest ongoing national survey in the U.S., collecting data from 3.5 million households each year since 2005, replacing the decennial census's long form.

From 2009 onwards, all individuals who participated in the survey and have at least a bachelor's degree were asked to specify their major, even if they had a higher education degree, such as a master's or PhD. While persons in the survey could provide multiple answers regarding their field of bachelor's degree, the information in the ACS data provides details of the first two fields reported on the survey form. In 2010, the census codes used for the classification of fields of bachelor's degree changed, and so to maintain a consistent classification we use data from 2010 onwards.

Since, the aim of the paper is to analyze the quality of the education-occupation match for the core of the labor force in the United States, the construction of the index of match quality only uses data for individuals between 25 to 64 years of age and with at least a College degree. This index is constructed for the whole population in the United States and does not differentiate across any groups. Because information regarding occupation is not available for individuals who have never worked or have been unemployed for longer than five years, they were excluded from the sample. However, we do include in the sample the information on individuals who are currently unemployed and for whom the information on their last occupation is available.

In order to obtain the most accurate measures possible, the estimation of our indices of education-occupation match quality uses pooled data for the years 2010 to 2017. This gives us a sample of 3,918,914 observations. For the estimation of the indices, the proportions of people by occupation and field of bachelor's degree are calculated using weighted data. For the construction of the matching quality indice (I_{MQ}) we used the detailed fields of bachelor's degree (173 fields) and detailed occupation categories (453 occupations). Since only 10 percent of the sample declared a second field of bachelor's degree, the index is constructed using only the first declared field of degree. Finally, because the index has a skewed distribution, for the purposes of the analysis, a monotonic transformation is applied:

$$SI_{MQ}(i,j) = \frac{\ln\left(I_{MQ}(i,j)\right) - E\left(\ln\left(I_{MQ}(i,j)\right)\right)}{Var\left[\ln\left(I_{MQ}(i,j)\right)\right]^{0.5}} \; for\ k = 1,2$$

where the mean and standard deviation are estimated using the pooled data for 2010–17, using each field of degree and occupation combination as unit of observation. The transformed indices $F_k(i,j)$ are z-scores that preserve the interpretation as before. Where is k- this transformation for every occupation??

For the main variable of interest, we construct two measures of Hispanic networks at the metropolitan areas (MSA) level. The first measure is defined as the share of Hispanic population who are 25 years old or older with respect to the total population of the same age. The second measure is constructed in the same way restricting the sample further to the population with at least a bachelor's degree. The measures are constructed using weighted pooled data from 2010 to 2015, using only metropolitan areas that are identified through all the years between 2010 to 2017.

For the econometric analysis we restrict our sample to data to the civilian population for the years 2016 and 2017, for the Hispanic population between 25 to 64 years of age, who have at least a bachelor's degree and whose information on their current or last job occupation information is available. Given the restrictions of the measure of Hispanic networks, the sample is restricted to the population living in metropolitan areas that are consistently identified in the ACS from 2010 to 2017. The index of match quality is assigned to each observation in the sample based on their field of degree and occupation classification

4.2. Summary Statistic

Highly educated Hispanics are considerably different from the average Hispanic. Between 2016 and 2017, people who identified themselves as Hispanic represented approximately 16.6% of the working population between the ages of 25 to 64. Among highly educated workers, those with at least a College degree, they represent only 8.4% of the sample, with the population of Hispanic non-citizens being the least represented in population within the highly educated population.

Table 1 provides summary statistics of the Hispanic sample for citizens and non-citizens. In the weighted sample just over 63% of Hispanic are citizens and predominantly composed by whites (73%) and women (56%). Hispanic non-citizen are older whereas citizens are relatively younger. While most of Hispanics in the sample are married (60%), Hispanic citizens in the sample are more likely to be single than non-citizens. Only 4% of the sample identifies themselves as veterans, with a larger presence of veterans among citizens.

Looking into Hispanics skills variables we find that the English language shows one of the largest differences among Hispanic citizens and non-citizens. While only 5% of Hispanic citizens indicate to have some difficulty speaking English, 34% of non-citizens Hispanic indicate having difficulty in speaking English. A comparable share of citizens and non-citizens Hispanics indicate to be attending school (10%), have a graduate degree (33%) or having any type of disability (3.6%). However, a somewhat larger share of Hispanic citizens indicate to be currently working (or worked last time) in a wage paid job (93% vs 88%) or to have worked in an occupation that has a larger share of workers with at least a Bachelor degree (a measure proxy for vertical matching). Finally, in regards to household characteristics, there is a larger share of Hispanic citizens that are homeowners (68% vs 61%) and who live in households without children (55% vs 50%) or no adults (24% vs 20%).

4.3 Horizontal job match: What do they study and where to they work?

Table 2 provides the average score of the matching index and its distribution across Hispanic citizen and non-citizen group. On average, Hispanic citizens work in jobs that better match their educational background compared to non-citizens. Hispanic citizens matching quality score is 0.117 standard points higher than that of non-citizens, a difference that is statistically significant at conventional levels. To have a more concreate idea of how Hispanic workers fare based on the matching index, a simple classification of the standardized index of matching quality is created. Mismatch would be considered if a person has an index below 0, weak mismatch if the index is between 0 and 1, weak match if its between 1 and 2, and match if its 2 or higher. Table 2 shows that 4.5% more Hispanic citizens work for a weak-match job or better, compared to non-citizens.

Since the index of matching quality is constructed based on the distribution of population across occupations and fields of education, we provide a brief overlook of the distribution of Hispanics across aggregated occupations and fields of education groups. These distributions are provided in Figures 1 and 2.

Based on the statistics from our weighted sample, the three most important occupations among Hispanics are: Management and Business; Education; and Clerical support, accounting for 39% of the Hispanic workforce. These three occupations represent a 7.3% larger share among Hispanic citizens (41.7%), but people working in them have an average matching score which is 0.3 points below that of the overall Hispanic population average.

From the relative distribution of Hispanic citizens and non-citizens[4] across occupations, we find that the protective services, legal occupations and social show the largest discrepancies in favor of Hispanic citizens. These occupations show average matching scores at least 0.3 points

[4] The relative distribution is measured as how much larger or smaller is the share of Hispanic citizens (non-citizens) working in a given occupation, or with a given field of studies, compared to the overall total.

higher than the average. On the other hand, occupations that are mostly favored by non-citizens, with maintenance and constructions showing the largest discrepancies, also characterized for being occupations with below average matching scores. The only occupation that is relatively favored by non-citizens and has an above average matching score is Architecture and Engineering, which represents less than 3% of sample. Overall, it may seem that noncitizen Hispanics are more likely to work in occupations that have low scores of matching quality.

Following a similar analysis as the one done for the distribution across occupations, Figure 2 provides some statistics regarding the distribution of Hispanics across fields of degree. By a large margin, the most common Major among Hispanic is business, representing 23.5% of the sample. There is a slightly larger share of Hispanic non-citizens in this major (26.7%), and people working in this field have a matching score that is 0.193 points below the average. The two next most important fields are education and engineering, with engineering being favored by Hispanic non-citizens, representing just over 18% of the sample and showing above average matching scores. Based on the aggregate Major distribution, 12 out of 20 Majors that are favored by Hispanic citizens have below average matching scores. In contrast, only 3 out of 13 fields favored by Hispanic non-citizens have a below than average matching score. (what does this mean – in terms of analysis. That education is fine for non-citizens compared to citizens but due to frictions they end up in mismatched occupations).

4.4 Hispanic Potential Networks and Horizontal matching

Since our main goal in this paper is to examine the role of Hispanic concentration (potential Hispanic networks) on the likelihood that a Hispanic individual may work on a job that is good match to his or her educational background we look at a summary of the various concentration levels and the degree of mismatch. The quality of the match is based on the constructed Standardized Matching index. Because the distribution of both the proxy for networks are highly skewed, due to the presence of metro areas that are historically Hispanic, we classify them in 7 groups as detailed in Figures 3 and 4 ranging from 0-5% to 40+%.

From Figure 3, examining the average score of the job matching index across the size of the Hispanic network, measured by the overall Hispanic concentration ratio, suggests that both Hispanic citizens and non-citizens have lower matching scores if they live in metropolitan areas with a high concentration of Hispanics. Only when the size of the network is very large, above 30%, we see a positive impact on the average matching quality. However, if we measure Hispanic concentration by the share of Hispanics with a College degree, we see that Hispanic citizens seem to benefit slightly from living in areas with moderate network sizes (15-20% or higher), with a more ambiguous impact for Hispanic non-citizens (see Figure 4).

5. Econometric Model and Results

In order to test the impact that networks have on the quality of the job match quality among Hispanic, we estimate an ordinary least squares model where the dependent variable is the Index of Match quality we described in section 3. For controls we use all variables described in the summary statistics, with the exception of the share of workers with a College degree working in a given occupation. To account for state specific unmeasured factors, we include state fixed effects. There might be unobserved state level factors, for instance labor market institutions, and which effects both Hispanic concentration and Hispanic settlement in the state and thus including state level fixed effects in our model we aim to attenuate the omitted variable and reverse causality bias in the model. Finally, we also control for detailed field of education fixed effects to control for the fact that certain fields of study are highly specialized, and workers in that field are most likely to work in a good matched job.

Table 3 provides the results from the model estimation based on the specifications described above but including only state fixed effects. Columns 1-3 reports results for the overall Hispanic concentration as network proxy, and columns 4-6 using the concentration of Hispanic among people with at least a College degree. The models are estimated for the citizens and noncitizens separately, but a pooled result is also provided.

The results regarding the control variables are consistent across citizens and non-citizens, and are comparable to the results reported in Rios-Avila & Saavedra-Caballero (2019) for the overall population in the U.S., with a few exceptions. As expected from the summary statistics, Hispanic citizens are more likely to work in a job that is a better match for their field of degree compare to non-citizens. While women are more likely to work in a match of lesser quality compared to men, the opposite seems to be the case when looking at the Hispanic citizen sample. Being nonwhite or indicating to "speak English well" do not appear to have a negative impact on the job match.[5] Finally, while the presence of 2 or more children in the household seems to have a

[5] The main category regarding Domain of English language is if the individual speaks only English at home, or if he considers to speak it VERY well.

negative impact on the quality of the job match for non-citizens, it appears to have no impact for Hispanic citizens.

In regards to the role of networks on the degree of mismatch across citizenship status among Hispanic, the results suggest that the broad measure of Hispanic networks (concentration of Hispanic living in a given metropolitan area) has a small negative insignificant relationship with the quality of their job match. Interestingly, the impact seems to be positive for Hispanic citizens, with the impact being statistically significant when there are more than 30% of Hispanic people living in the metropolitan area.

One may consider that using the overall concentration of Hispanic people within a metropolitan area to be a poor measure of networks, in particular for highly educated workers. This may be the case because people with less than a College degree may not have access to the information and leads to jobs that people with higher education degrees are looking to work for. In this regard, a better measure of networks is the concentration of Hispanic workers among the population with at least a College degree.

Using this alternative measure of Hispanic networks we find that networks have a positive impact on the quality of the job match for both citizens and non-citizens. Among non-citizens, the impact is observed only when the network size is larger than 40%.[6] For Hispanic citizens, networks now appear to have a positive impact on the job match starting at 10% of Hispanic concentration. Excluding the estimates regarding the largest network size (40%+), the results suggest that the impact does not increase with network size, and that having a network larger than 10% may increase the job match index in about 0.11 points. At 40% or more, however, the results suggest an improvement on the match quality index of 0.2 points.

Table 4 provides the estimates of the same specification used in Table 3, reporting the results that control Hispanics with at least a College degree, but controlling for detailed fields of degree fixed effects. If we consider fields of study exogenous for all people in the sample, controlling for this fixed effects would allow us to analyze to what extent networks relates the

[6] The five Metropolitan areas that have this large network size are Brownsville-Harlingen, El Paso, Laredo and Mcallen-Edinburg-Mission in Texas, and El Centro in California,

likelihood of a Hispanic worker to work for good job match, given that their fields of degrees is already fixed. The results from this estimation are consistent with those in table 6. The main difference is that we now observe that the presence of more than 2 children in the household has a negative impact on the job match quality. In regards to the impact of networks, the results suggest a somewhat larger impact on the job match quality compared to the estimations in table 3.

Among Hispanic non-citizens, networks seem to have a small, positive, but mostly not statistically significant effect improving the job match quality. A noticeable exception is when for metro areas where the networks are larger than 40%. Taking the results face value indicate that living in areas with such high concentration highly educated Hispanic workers improve the index of matching quality in 0.185 points. Turing to Hispanic citizens, controlling for fields of degree fixed effects show that the previous results are robust. Networks appear to have a positive effect on job-match quality. Hispanic citizens living in areas with small networks (5-10%) have an average job match quality score that is 0.06 points higher compare to areas with smaller concentrations of Hispanic. This impact seems to increase slightly with the network size up to 0.15 points when looking at areas with the largest Hispanic networks.

6. Conclusions

Social networks play a very significant role in job search, though may often lead to lower earnings. This raises an important question do people who rely on their social networks (a group of same ethnicity, language, or country of origin to name a few) to find jobs end up with jobs where they are poorly matched to their skills and field of education or are they better matched. This is important to study because levels of education as well as skills are on the rise and so is significant occupation-field mismatch or job –education mismatch, which is costly to both individuals and firms.

Using data from the American Community Survey we construct an index of objective matching quality to assess the role that Hispanic networks have on the likelihood that a person works for an occupation that is better suited to her educational background. Using the concentration of Hispanic workers among the population with tertiary education as the proxy of networks we find that networks seem to have a positive impact on the job-match quality, but mostly for Hispanic citizens. This shows that Hispanic citizens are better able to leverage their networks or their networks are able to match them better with jobs closer to their field of specialization and skill set. Also, citizens have a better quality networks that is potentially able to provide the Hispanic citizens with better job information and matching. We don't have this information but Hispanic citizens would also tend to have better human capital skills such as higher quality of degree education and possibly education in the US and also better job market experience, which helps their Hispanic networks to place them in jobs that fit their field of specialization more than their non-citizen counterparts.

References

Amuedo-Dorantes, C. and K. Mundra 2007. "Social Networks and Their Impact on the Employment and Earnings of Mexican Immigrants," *Demography*.

Bean, F.D., L.B. Lowell, and J.L. Taylor. 1988. "Undocumented Mexican Immigrants and the Earnings of Other Workers in the United States." *Demography* 25:35–52.

Borjas, G.J. 1987. "Self-selection and the Earnings of Immigrants." *American Economic Review* 77:531–53.

Calvo-Armengol, A. and M. Jackson, 2004. "The Effects of Social Networks on Employment and Inequality," *American Economic Review*, 94(3): 426-454.

Campbell, S. 2013. "Over-education among A8 migrants in the UK," DOQSS Working papers 13-09, Department of Quantitative Social Science-UCL Institute of Education, University College London.

Chiswick, B. R. and P. W. Miller, 1996. "Ethnic Networks and Language Proficiency Among Immigrants," *Journal of Population Economics*, 9(1): 19-35.

———. 2009. "The International Transferability of Immigrants' Skills." Economic Education Review, 28: 162-169.

———. 2010a. "Educational Mismatch: Are High-Skilled Immigrants Really Working at High-Skilled Jobs and the Price They Pay If They Aren't?." in Barry R. Chiswick edited *High Skill Immigration in a Global Labor Market*, Washington DC, American Enterprise Institute Press, 111-154.

———. 2010b. "The Effects of Educational-Occupational Mismatch on Immigrant Earnings in Australia, with International Comparison," *International Migration Review*, 44(4):869-898.

Chiquiar, D. and G.H. Hanson. 2005. "International Migration, Self-selection, and the Distribution of Wages: Evidence From Mexico and the United States." *Journal of Political Economy*, 113:239–81.

Cingano, F. and A. Rosolia, 2012, "People I Know: Job Search and Social Networks," *Journal of Labor Economics*, 30(2): 291-332.

Dahlstedt, I. 2011. "Occupational Match: Over and Under Educated among Immigrants in the Swedish Labor Market." *Journal of International Migration and Integration*,

Elliott, J. R., 2001. "Referral Hiring and Ethnically Homogeneous Jobs: How Prevalent Is the Connection and for Whom?" *Social Science Research*, 30(3), 401-425.

Falcon, L. M. and E. Melendez, 2001. "*Racial and ethnic differences in job searching in urban centers" in Urban inequality: Evidence from Four Cities*, ed. Alice O'Connor, Chris Tilly, and Lawrence Bobo. New York: Russell Sage Foundation.

Farber, H. and R. Valletta, 2015. "Do Extended Unemployment Benefits Lengthen Unemployment Spells? Evidence from Recent Cycles in the U.S. Labor Market," *Journal of Human Resources*, 50(4): 873-909.

Granovetter, M.S. 1973. "The Strength of Weak Ties." *American Journal of Sociology* 78:1360–80.

———. 1982. "The Strength of Weak Ties: A Network Theory Revisited." Pp. 105–30 *in Social Structure and Network Analysis*, edited by P.V. Marsden and N. Lin. Beverly Hills, CA: Sage Publications.

———. 1995. "*Getting a job: A study of contacts and careers*. Chicago: University of Chicago Press. 2nd Edition.

———. 2007b. "Education, college major, and job match: gender differences in reasons for mismatch." *Education Economics* 15(2): 159–75.

Groot, W., & Maassen van den Brink, H. 2000. "Over education in the labor market: A meta-analysis." *Economics of Education Review*, 19(2): 149–158.

Hartog, J. 2000. "Over-education and earnings: Where are we, where should we go?" *Economics of Education Review*, 19(2): 131–147.

Holzer, H. 1988. "Search method use by unemployed youth," Chiswick, B. R. and P. Miller 2009. "The international transferability of immigrants' human capital." *Economics of Education Review*, 28:162-169.

Horvath, G. 2014. "Occupational Mismatch and Social Networks." *Journal of Economic Behavior and Organization*, 106: 442-468.

Kiker, B. F., Santos, M. C., & Mendes De Oliveira, M. 2000. "The role of human capital and technological change in overeducation." *Economics of Education Review*, 19(2):199-206.

Lemieux, T. 2014. "Occupations, fields of study and returns to education." *The Canadian Journal of Economics/Revue Canadienne d' Economique* 47(4): 1047–77.

Marin, A., and S. Hayes. 2017. "The Occupational Context of Mismatch: Measuring the Link between Occupations and Areas of Study to Better Understand Job-Worker Match." *Canadian Journal of Sociology/Cahiers Canadiens de Sociologie* 42(1): 1–22.

Munshi, K. 2003. "Networks in the Modern Economy: Mexican Migrants in the U.S. Labor

Market." *The Quarterly Journal of Economics* 118:549–99.

Nordin, M., I. Persson, and D. Rooth. 2010. "Education–occupation mismatch: Is there an income penalty?" *Economics of Education Review* 29(6): 1047–59.

Rios-Avila, F. and F. Saavedra-Caballero. 2019. "It Pays to Study for the Right Job: Exploring the Causes and Consequences of Education-Occupation Job Mismatch" Working paper 922, Levy Economics Institute: Annandale on Hudson, NY.

Robst, J. 2007a. "Education and Job Match: the Relatedness of College Major and Work." *Economic of Education Review* 26(4): 397–407.

———. 2007b. "Education, college major, and job match: gender differences in reasons for mismatch." *Education Economics* 15(2): 159–75.

Ruggles, S., K. Genadek, R. Goeken, J. Grover, and M. Sobek. 2017. "Integrated Public Use Microdata Series (IPUMS): Version 7.0 [dataset]." Minneapolis: University of Minnesota. https://doi.org/10.18128/D010.V7.0.

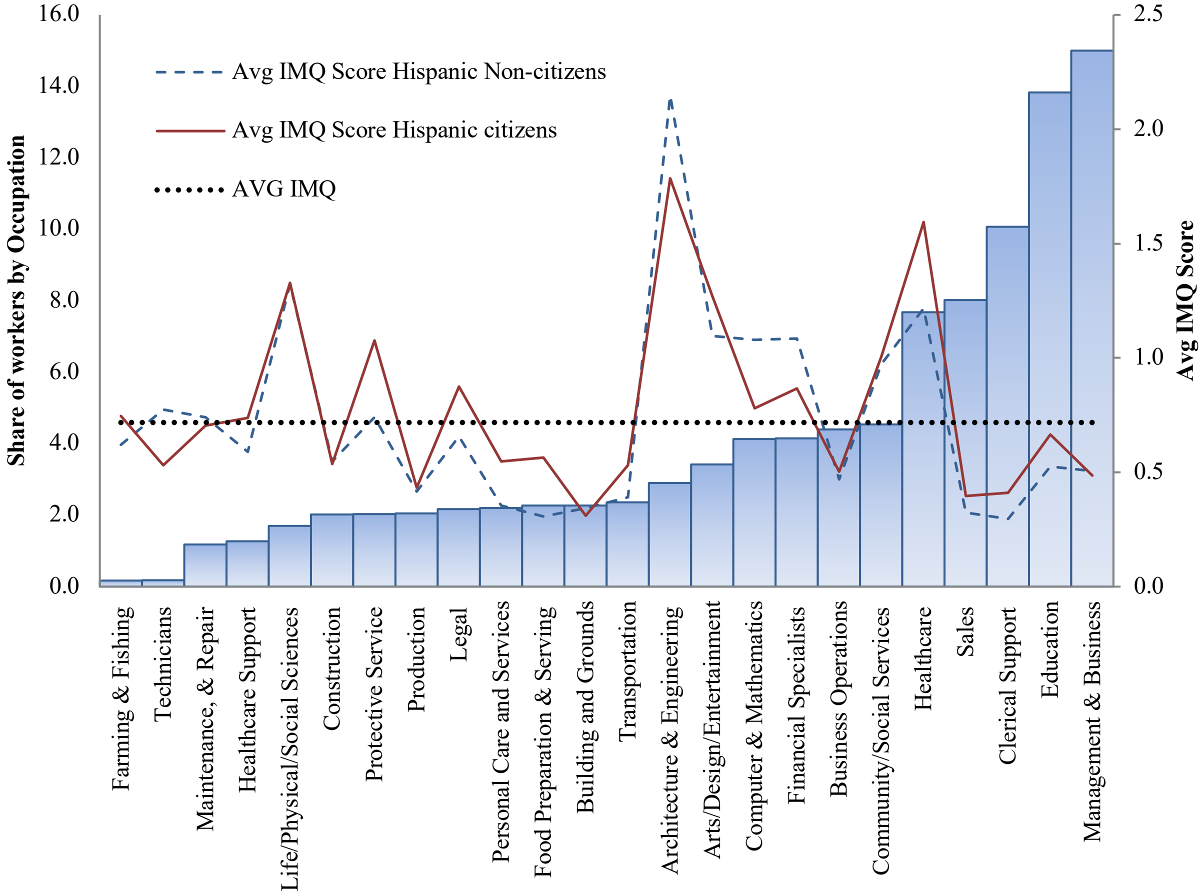
Sharaf, M. F. 2013. "Job Education Mismatch and Its Impact on the Earnings of Immigrants: Evidence from recent arrivals to Canada." *ISRN Economics*, Hindawi Publication.

Sicherman, N. 1991. "Overeducation in the labor market." *Journal of Labor Economics*, 9(2):101–122.

Somers. M. A., S. J. Cabus, W. Groot and H. M. Brink 2016. "Horizontal Mismatch between Employment and the Field of Education: Evidence from a Systematic Literature Review."

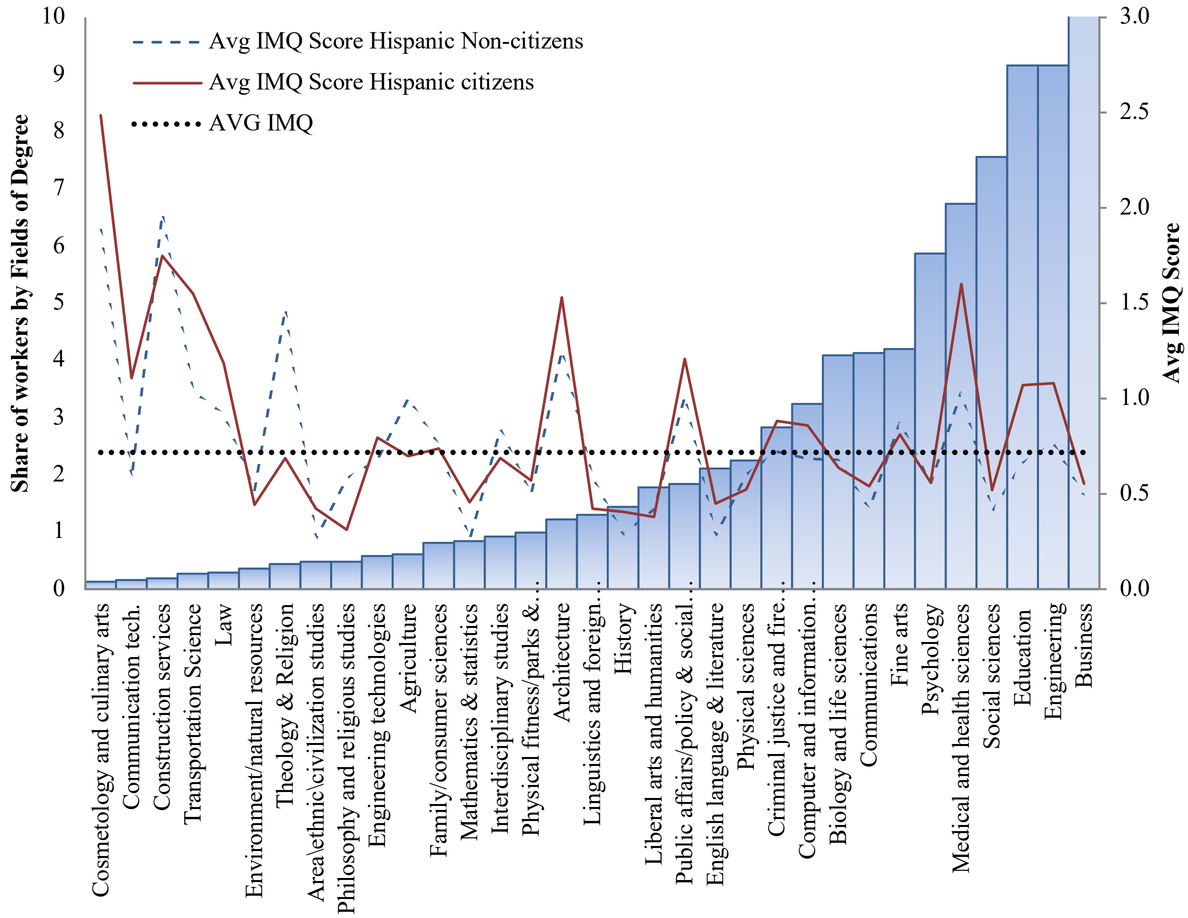
Yuen, J. 2010. "Job–education match and mismatch: Wage differentials." *Perspective on Labour and Income* 11: 1–26.

Figure 1. Distribution of Hispanic by occupation.



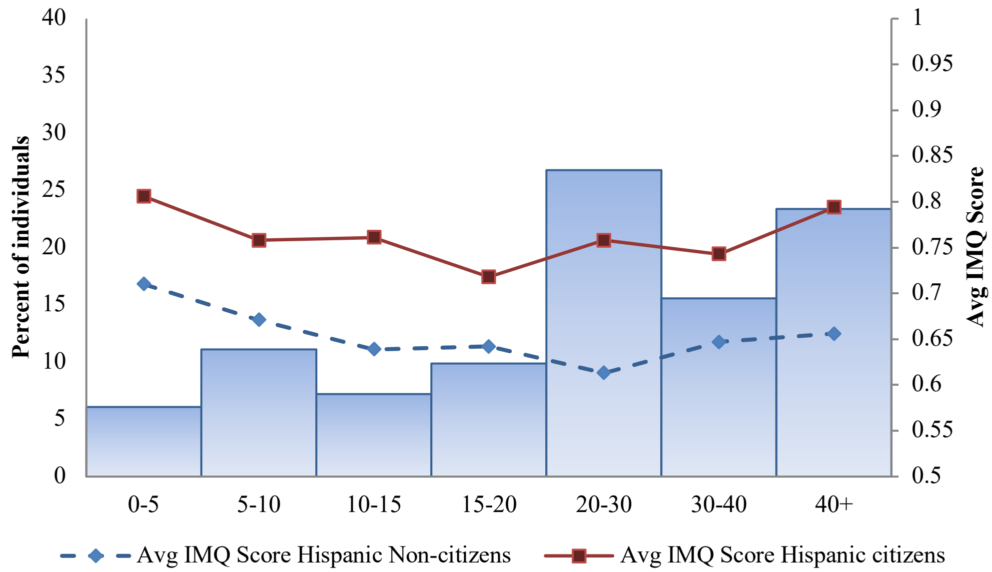
Note: All statistics are estimated using sample weights. The Average IMQ is calculated as the weighted mean of the matching index for all observations in a given occupation by citizenship status

Figure 2. Distribution of Hispanic individuals by Fields of Degree



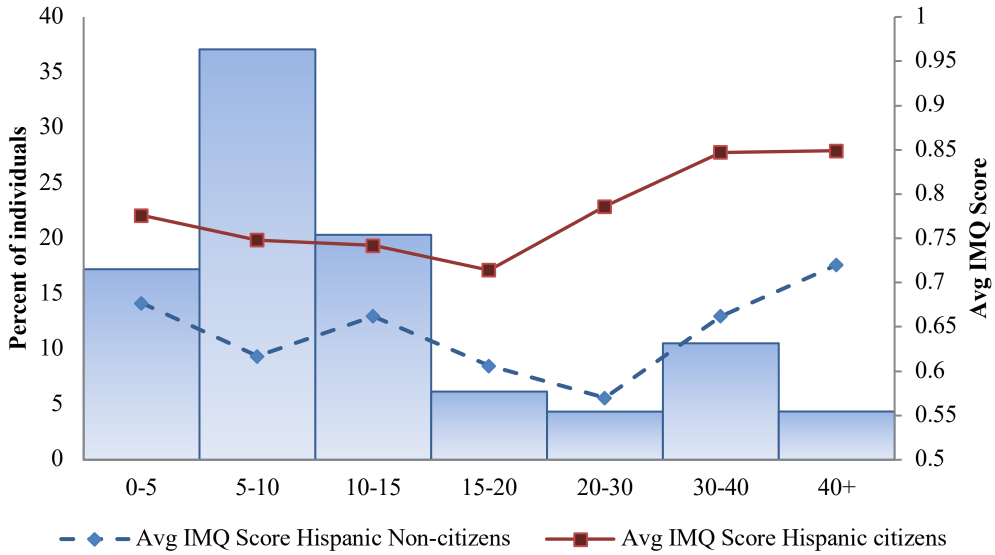
Note: All statistics are estimated using sample weights. The Average IMQ is calculated as the weighted mean of the matching index for all observations in a given field of education. The share of Hispanic in Business (not shown) is 23.5%.

Figure 3. Average Matching Quality Score (IMQ) by Share of Hispanics in MSA



Note: All statistics based on sample weighted data. Share of Hispanics is calculated for individuals 25 – 65 years old

Figure 4. Average Matching Quality Score (IMQ) by Share of Hispanics with a College Degree



Note: All statistics based on sample weighted data. Share of Hispanics is calculated for individuals 25 – 65 years old with a College degree.

Table 1. Summary Statistics by immigration status.

	Non Citizen		Citizen		All Hispanic	
	Mean %	Std Error	Mean %	Std Error	Mean %	Std Error
Demographics						
Non Citizen					36.8%	(0.0018)
Citizen					63.2%	(0.0018)
Gender						
Male	46.3	(0.0031)	42.8	(0.0023)	44.1	(0.0019)
Female	53.7	(0.0031)	57.2	(0.0023)	55.9	(0.0019)
Age Group						
25-34	23.0	(0.0026)	39.1	(0.0023)	33.2	(0.0018)
35-44	29.4	(0.0028)	28.6	(0.0021)	28.9	(0.0017)
45-54	28.7	(0.0028)	20.4	(0.0019)	23.4	(0.0016)
55-64	18.9	(0.0024)	12.0	(0.0015)	14.5	(0.0013)
Race						
White	71.7	(0.0028)	74.2	(0.0021)	73.3	(0.0017)
Non-White	28.3	(0.0028)	25.8	(0.0021)	26.7	(0.0017)
Marital Status						
Married	66.8	(0.0029)	55.4	(0.0024)	59.6	(0.0019)
Other	14.6	(0.0022)	11.7	(0.0015)	12.7	(0.0013)
Single	18.6	(0.0024)	32.9	(0.0022)	27.6	(0.0017)
Is a veteran	2.2	(0.0009)	5.4	(0.0011)	4.2	(0.0008)
Education and Skills						
Domain of English Language						
Speaks English very well	66.2	(0.0029)	94.8	(0.0011)	84.2	(0.0014)
Speaks English well	20.6	(0.0025)	4.3	(0.0010)	10.3	(0.0011)
Speaks English but not well	13.3	(0.0021)	0.9	(0.0004)	5.5	(0.0009)
Currently attending School	8.9	(0.0018)	10.6	(0.0015)	10.0	(0.0011)
Has a Graduate Degree (Master or Phd)	34.3	(0.0029)	32.8	(0.0022)	33.4	(0.0018)
Has any difficulty (disability)	3.3	(0.0011)	3.8	(0.0009)	3.6	(0.0007)
Current or last job was a wage paid job	87.9	(0.0020)	93.1	(0.0012)	91.1	(0.0011)
%of workers with a College Degree in Occupation	45.0	(0.0024)	55.7	(0.0017)	53.6	(0.0011)
Household Characteristics						
House Tenure						
House Owner	61.2	(0.0030)	68.1	(0.0022)	65.6	(0.0018)
Household Composition						
No Children	50.3	(0.0031)	55.5	(0.0024)	53.6	(0.0019)
At least 1 Child 0-18	21.9	(0.0026)	18.4	(0.0018)	19.7	(0.0015)
2+ children 0-18	27.8	(0.0028)	26.1	(0.0021)	26.7	(0.0017)
No other adult	20.1	(0.0025)	24.3	(0.0020)	22.7	(0.0016)
at least 1 other Adult in HH (25-64)	63.0	(0.0030)	61.5	(0.0023)	62.0	(0.0018)
2+ other Adults in HH (25-64)	16.9	(0.0023)	14.2	(0.0017)	15.2	(0.0014)
1+ Elderly in the household	2.2	(0.0009)	2.3	(0.0007)	2.2	(0.0006)
Observations	25948		44504		70452	

Note: Standard errors of the mean in parenthesis. Statistics are created using weighted data.

Table 2. Match quality scores among Hispanics, by citizenship Status.

Job Match Scores	**Non citizen**	**Citizen**	**All**
Mismatch (0 or lower)	24.3%	22.4%	23.1%
Weak Mismatch (0 to 1)	48.7%	46.0%	47.0%
Weak Match (1 to 2)	15.0%	17.2%	16.3%
Match (2 or higher)	12.1%	14.4%	13.5%
Average SI_{MQ}	0.6452	0.7621	0.7176

Note: All statistics are obtained sample weights

Table 3. Role of Social Networks in Job Match quality for Hispanics: by citizenship status

	Network: % Hispanic in MSA			Network: % Hispanic with a College degree in MSA		
	Non Citizen	**Citizen**	Total	**Non Citizen**	**Citizen**	Total
	(1)	(2)	(3)	(4)	(5)	(6)
Is a Citizen			0.0319*			0.0314*
			[0.0118]			[0.0118]
Female	-0.0980*	0.0246^	-0.0227+	-0.0983*	0.0242^	-0.0229+
	[0.0159]	[0.0133]	[0.0102]	[0.0159]	[0.0133]	[0.0102]
Age: 35-44	-0.0754*	-0.0748*	-0.0735*	-0.0752*	-0.0757*	-0.0737*
	[0.0234]	[0.0175]	[0.0140]	[0.0234]	[0.0175]	[0.0140]
Age: 45-54	-0.147*	-0.126*	-0.135*	-0.147*	-0.127*	-0.135*
	[0.0242]	[0.0199]	[0.0152]	[0.0241]	[0.0199]	[0.0152]
Age: 55-64	-0.106*	-0.0915*	-0.0966*	-0.108*	-0.0931*	-0.0979*
	[0.0280]	[0.0250]	[0.0184]	[0.0280]	[0.0249]	[0.0184]
Non White	-0.0574*	-0.01	-0.0296*	-0.0563*	-0.0113	-0.0285+
	[0.0176]	[0.0148]	[0.0114]	[0.0177]	[0.0149]	[0.0114]
Marital Status: Other (not married)	-0.0387	-0.0549+	-0.0468*	-0.0396	-0.0551+	-0.0473*
	[0.0253]	[0.0249]	[0.0178]	[0.0253]	[0.0248]	[0.0178]
Marital Status: Other (Single)	-0.0454^	-0.0595*	-0.0547*	-0.0467^	-0.0604*	-0.0556*
	[0.0252]	[0.0193]	[0.0152]	[0.0251]	[0.0193]	[0.0152]
Is a veteran	-0.0186	-0.03	-0.03	-0.0131	-0.0262	-0.0306
	[0.0570]	[0.0318]	[0.0277]	[0.0571]	[0.0318]	[0.0277]
Domain of English: (Only English or very well)						
Speaks English Well	-0.187*	-0.01	-0.138*	-0.188*	-0.00961	-0.140*
	[0.0198]	[0.0308]	[0.0166]	[0.0198]	[0.0308]	[0.0166]
Speaks English, but not well	-0.349*	-0.265*	-0.336*	-0.350*	-0.268*	-0.337*
	[0.0207]	[0.0573]	[0.0189]	[0.0207]	[0.0573]	[0.0189]
Attending School	-0.0884*	-0.144*	-0.123*	-0.0868*	-0.143*	-0.122*
	[0.0283]	[0.0197]	[0.0162]	[0.0283]	[0.0197]	[0.0162]
Has a Graduate Degree (Master or Phd)	0.0538*	0.0545*	0.0579*	0.0544*	0.0549*	0.0584*
	[0.0175]	[0.0141]	[0.0110]	[0.0175]	[0.0141]	[0.0110]
Has any difficulty (disability)	-0.100+	-0.112*	-0.107*	-0.100+	-0.111*	-0.107*
	[0.0399]	[0.0323]	[0.0253]	[0.0399]	[0.0324]	[0.0253]
Current or last job was a wage paid job	0.0802*	0.0811*	0.0840*	0.0821*	0.0826*	0.0854*
	[0.0217]	[0.0246]	[0.0164]	[0.0217]	[0.0247]	[0.0164]
Is a Home Renter	-0.0469*	-0.0676*	-0.0607*	-0.0457*	-0.0675*	-0.0600*
	[0.0173]	[0.0148]	[0.0112]	[0.0172]	[0.0148]	[0.0112]
At least 1 Child 0-18	-0.032	0.00	-0.01	-0.0322	-0.0019	-0.0138
	[0.0207]	[0.0182]	[0.0137]	[0.0207]	[0.0182]	[0.0137]
2+ children 0-18	-0.0601*	-0.01	-0.0294+	-0.0603*	-0.0118	-0.0293+
	[0.0208]	[0.0181]	[0.0137]	[0.0208]	[0.0181]	[0.0137]
at least 1 other Adult in HH (25-64)	0.028	-0.02	0.00	0.0277	-0.0158	0.00127
	[0.0246]	[0.0196]	[0.0153]	[0.0246]	[0.0196]	[0.0153]
2+ other Adults in HH (25-64)	-0.0789*	-0.0649*	-0.0723*	-0.0797*	-0.0657*	-0.0732*
	[0.0269]	[0.0231]	[0.0175]	[0.0269]	[0.0230]	[0.0175]
1+ Elderly in the household	-0.0995^	-0.0864+	-0.0911*	-0.0994^	-0.0880+	-0.0922*
	[0.0566]	[0.0383]	[0.0320]	[0.0567]	[0.0383]	[0.0321]
Network Size*						
5-10 % of Hispanics in MSA	-0.0394	0.0037	-0.0136	0.00983	0.0432	0.0282
	[0.0592]	[0.0473]	[0.0371]	[0.0438]	[0.0372]	[0.0283]
10-15 % of Hispanics in MSA	-0.0315	0.0426	0.0117	0.0729	0.101+	0.0890*
	[0.0560]	[0.0487]	[0.0368]	[0.0520]	[0.0427]	[0.0330]
15-20 % of Hispanics in MSA	-0.0552	0.0070	-0.0249	0.0123	0.0453	0.0331
	[0.0644]	[0.0520]	[0.0403]	[0.0596]	[0.0483]	[0.0376]
20-30 % of Hispanics in MSA	-0.0194	0.0695	0.0290	-0.0313	0.117+	0.0807+
	[0.0593]	[0.0494]	[0.0381]	[0.0776]	[0.0498]	[0.0403]
30-40 % of Hispanics in MSA	-0.00659	0.101+	0.0543	0.0667	0.109+	0.0756+

	[0.0626]	[0.0515]	[0.0398]	[0.0577]	[0.0526]	[0.0384]
40% + of Hispanics in MSA	0.0043	0.106+	0.0574	0.154+	0.200*	0.187*
	[0.0591]	[0.0503]	[0.0382]	[0.0662]	[0.0535]	[0.0417]
State FE	X	X	X	X	X	X
Observations	25948	44504	70452	25948	44504	70452

Note: Robust Standard errors using sample weights. ^ p<0.1 + p<0.05 * p<0.01. * Columns 1, 2 and 3, measure Network size as the overall share of Hispanic living in an MSA. Columns 4, 5 and 6 uses the share of Hispanics among the population with a college degree.

Table 4. Role of Hispanic Networks on the Job Match quality across citizenship status

	Network: % Hispanic with a College in MSA		
	Non Citizen	Citizen	Total
Is a Citizen			0.0578*
			[0.0113]
Female	-0.0960*	-0.0361*	-0.0596*
	[0.0164]	[0.0130]	[0.0103]
Age: 35-44	-0.0628*	-0.0575*	-0.0594*
	[0.0224]	[0.0161]	[0.0131]
Age: 45-54	-0.152*	-0.114*	-0.133*
	[0.0234]	[0.0184]	[0.0145]
Age: 55-64	-0.122*	-0.125*	-0.122*
	[0.0271]	[0.0233]	[0.0175]
Non White	-0.0522*	-0.0272+	-0.0332*
	[0.0170]	[0.0136]	[0.0107]
Marital Status: Other (not married)	-0.0417^	-0.0779*	-0.0603*
	[0.0236]	[0.0231]	[0.0167]
Marital Status: Other (Single)	-0.0401^	-0.0339^	-0.0365+
	[0.0238]	[0.0176]	[0.0142]
Is a veteran	-0.00715	-0.0366	-0.0316
	[0.0538]	[0.0283]	[0.0254]
Domain of English			
(Baseline speaks only English)			
Speaks English Well	-0.216*	-0.0541^	-0.178*
	[0.0192]	[0.0292]	[0.0161]
Speaks English, but not well	-0.361*	-0.327*	-0.361*
	[0.0207]	[0.0578]	[0.0191]
Attending School	-0.0955*	-0.145*	-0.126*
	[0.0271]	[0.0185]	[0.0154]
Has a Graduate Degree (Master or Phd)	0.0486*	0.0591*	0.0591*
	[0.0169]	[0.0134]	[0.0105]
Has any difficulty (disability)	-0.101+	-0.114*	-0.110*
	[0.0403]	[0.0307]	[0.0249]
Current or last job was a wage paid job	0.0804*	0.033	0.0593*
	[0.0212]	[0.0254]	[0.0164]
Is a Home Renter	-0.0485*	-0.0450*	-0.0522*
	[0.0165]	[0.0136]	[0.0106]
At least 1 Child 0-18	-0.0279	-0.0241	-0.0241^
	[0.0200]	[0.0167]	[0.0129]
2+ children 0-18	-0.0683*	-0.0478*	-0.0538*
	[0.0197]	[0.0167]	[0.0128]
at least 1 other Adult in HH (25-64)	0.0176	-0.0112	-0.00389
	[0.0232]	[0.0181]	[0.0143]
2+ other Adults in HH (25-64)	-0.0983*	-0.0807*	-0.0983*
	[0.0260]	[0.0212]	[0.0165]
1+ Elderly in the household	-0.0953^	-0.0605^	-0.0759+
	[0.0548]	[0.0349]	[0.0306]
Network Size			
5-10 % of Hispanics in MSA	0.0164	0.0666^	0.0492^
	[0.0416]	[0.0340]	[0.0263]
10-15 % of Hispanics in MSA	0.0828^	0.120*	0.112*
	[0.0496]	[0.0390]	[0.0307]
15-20 % of Hispanics in MSA	0.0111	0.0436	0.0356
	[0.0562]	[0.0443]	[0.0349]
20-30 % of Hispanics in MSA	0.00352	0.152*	0.121*
	[0.0739]	[0.0455]	[0.0375]
30-40 % of Hispanics in MSA	0.0629	0.118+	0.0824+
	[0.0534]	[0.0481]	[0.0353]

40% + of Hispanics in MSA	0.185* [0.0634]	0.153* [0.0488]	0.177* [0.0388]
State FE	x	x	x
Field of Degree Grouped FE			
Field of Degree detailed FE	x	x	x
Observations	25948	44504	70452

Note: Robust Standard errors using sample weights. ^ p<0.1 + p<0.05 * p<0.01.