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Education-occupation mismatch and social networks for Hispanics in the U.S.: role of citizenship

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ABSTRACT

Using a sample of college-educated Hispanics from the 2016–2017 American Community Survey we examine the role of potential social networks on the education-occupation mismatch for Hispanics in the U.S. To do this, we use a novel data-driven index to measure the degree of education-occupation mismatch, while potential networks are measured using the share of Hispanics at the MSA level. We find that networks improve job-match quality for college-educated Hispanics, with effects that are significantly larger for Hispanic citizens when networks consist of the proportion of Hispanics with college degrees. Our findings are robust to other indices of education mismatch.

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1. Introduction

With increasing technology and investment in higher education worldwide, there has been a rise in the incidence of job and education/skill mismatch. In particular, the education-occupation gap for immigrants is quite stark in their destination countries because skills and labor market experiences are not completely transferrable across borders and in addition there is 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, Kahn, and Speer 2016; and Van de Werfhorst 2002) and diminished job satisfaction (Vieira 2005; Belfield and Harris 2002) but also to the firms and the country for not employing individuals at their most productive jobs. Education-occupation mismatch not only affects an individual's well-being and income but also affects 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 U.S., a group that constitutes a large and relatively homogenous subpopulation in the country, using a novel continuous objective mismatch index and explore the role their social networks play in this mismatch and how this differs between citizens and non-citizens.

There is a large literature on the role of social networks in labor market outcomes for both immigrants and natives (Granovetter 1995; Munshi 2003; Damm 2009; Beaman 2012, Patel and Vella 2013, Schmutte 2015; Hensvik and Skans 2016; Battisti, Peri, and Romiti 2022 to name a few). In addition, there is a well-established literature on measures and determinants of education-occupation

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mismatch for the general population (Nordin, Persson, and Rooth 2010; Robst 2007) as well as for immigrants and the effect of this mismatch on worker earnings (Chiswick and Miller 2009, 2010a, 2010b; Green, Kler, and Leeves 2007; Nielson 2011; Darko and Abrokwa 2020; Carmichael, Darko, and Kanji 2021). Despite this research, not much is known about how social networks influence education and occupation mismatch.

The percentage of the college-educated population, for both U.S. citizens and immigrants, has increased rapidly in the U.S. over the last two decades. However, compared to their native-born counterparts, many high-skilled immigrants work in jobs for which they are overqualified. Similar patterns have been observed for Hispanics, both immigrants and citizens, although they remain behind the U.S. average.[1] Hispanics originate from non-English speaking countries and even if they constitute a large vintage immigrant group having a long immigration history in the U.S., they also earn significantly less than white non-Hispanic natives in the U.S..[2] While other minority groups could be of interest, the Hispanic population is the largest and most representative/visible minority in the U.S. Moreover, unlike other ethnic/migrant groups, Hispanics are also characterized by a common language, which makes them a homogenous group to analyze. Furthermore, Hispanics also tend to rely on their social networks for job-search in the U.S. (see Munshi 2003; Amuedo-Dorantes and Mundra 2007).

Using the continuous index of mismatch proposed in Rios-Avila and Saavedra-Caballero (2019), this study explores two research questions. First, we explore whether having a larger social network helps Hispanics find jobs that better match their skill and education levels, or whether living in areas with a larger concentration of Hispanics leads to more competition for the same jobs. Second, we analyze if the role of social networks on education-occupation mismatch varies across citizenship status, as citizens may have better access to particular job markets. Both, finding a better job match and facing higher competition in the local labor market could be affected if the individual's network is similar to her in skill and education level, which makes this an empirical question. Given that the legal status of immigrants influences how they leverage their social networks for labor market outcomes, we focus on the citizenship status for Hispanics and distinguish between native citizens, naturalized citizens, and non-citizens.

This research is timely and will help us understand the role of social networks on the extent of education-occupation mismatch for Hispanic natives and immigrants. Given that social networks improve individual employment outcomes (Montgomery 1991; Munshi 2003; Schmutte 2015; Dustman et al. 2016; and Battisti, Peri, and Romiti 2022, to name a few). Our research question is whether workers who have access to large social networks, providing a larger pool of informal job search opportunities, are more likely to be employed in jobs that better match the individual's education and skills and how this varies with their citizenship status. To answer this question, we analyze a sample of Hispanics in the U.S. with at least a bachelor's degree from 2016 to 2017 American Community Survey (ACS). The quality of the match between the college degree and occupation for Hispanics is measured using the indices proposed in Rios-Avila and Saavedra-Caballero (2019) and calculated using pooled data for all college graduates in the U.S. from 2011 to 2015. We use ACS data from 2011 to 2015 or 2015 5 yr ACS data to estimate potential Hispanic networks as a general share of Hispanics at the MSA level as well as the share of Hispanics at the MSA level with at least a college degree.

2. Background and literature review

The literature identifies two types of education-occupation mismatches: vertical mismatch and horizontal mismatch. Vertical Mismatch is based on the idea of over-education/required education /under-education (ORU) framework (Chiswick and Miller 1996) where employees' level of education is compared to the average level of education in their occupation. Horizontal mismatch, on the other hand, is a measure of how close the knowledge and skill that workers obtain in their field of education are to the skills and knowledge that are required by a specific occupation/job (Robst 2007).

Both vertical mismatch and horizontal mismatch are costly for both employers and employees because it results in underutilization of skills and lower pay. Also, firms that have employees lacking job-specific skills or are undereducated need to invest in job-specific training, to compensate for the job mismatch (Groot and Maassen van den Brink 2000).

Much of the research on education skill mismatch among immigrants shows that job-education mismatch is highest for new immigrants and decreases over time as immigrants assimilate. Chiswick and Miller (2009) find that among the high skilled immigrants in the U.S. there is a significant presence of over-education mismatch compared to citizens. However, the longer the immigrants are in the U. S. the extent of mismatch decrease and earnings increase proportionately. 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' wage loss is around 2% on average and similar to the U.S. over time as immigrants assimilate, their job mismatch is significantly reduced. For UK Campbell (2013) finds that the immigrant groups are selected differently based on their origin and this plays a significant role in the incidence and degree of mismatch. Examining the case of recent immigrants in Australia Green, Kler, and Leeves (2007) finds that over-education is greater among immigrants from non-English speaking countries and hence non-English speaking countries earn consistently lower than English-speaking immigrants and natives. Similar findings are shown in Nielson (2011) for Denmark where foreign-educated immigrants benefit the least from over-education. Dahlstedt (2011) finds that vocationally educated workers in Sweden find better job-matches compared to workers with general education training and that immigrants have a higher mismatch than natives.

In contrast with vertical-mismatch, there is research focused on analyzing the alignment between the skills individuals obtain through their college studies, and the skills required by the occupations they end up working at. Horizontal-mismatch is very relevant for college graduates because the skills acquired through a college degree may be different from the skills required in their current jobs. Moreover, there is an excess supply of certain majors in the labor market and an excess demand for jobs requiring completely different majors and skill sets (Machin 2004). This often varies with the labor market institutions and whether there is a recession or boom. Employees often choose their fields of study with the 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 of education. There has been extensive work done on vertical mismatch but not on horizontal mismatch.

Most research on horizontal mismatch is based on the creation of objective measures based on job evaluation by *experts*, who define the education requirement of detailed occupations. One such example is the Occupational Information Network[3], which provides information on the types of tasks and skills required for a detailed list of occupations. Although this approach is based on arguably objective assessments made by experts, the cost of maintaining an up-to-date dataset is prohibitive, and it still depends on the subjective options (Hartog 2000).

There has been a steady increase in the literature on the incidence of education-occupation mismatch, the determinants of this mismatch, and the effect of this mismatch on worker earnings. Robst (2007) focusses on horizontal mismatch by examining how closely an individual's degree is related to her job using subjective questions from the National Survey of College Graduates and examines the effect of this mismatch on their earnings. This subjective measure, used by Robst (2007a, 2007b) and Yuen (2010), where people are asked their beliefs on whether or not their educational level and background match their job responsibilities and requirements. The main drawback of this approach is that responses may be inaccurate due to misinformation about the job (Leuven and Oosterbeek 2011) or because respondents may tend to overstate the requirements for their jobs (Borghans and de Grip 2000; Hartog 2000). In either case, this may lead to bias estimates.

Other measures of mismatch use statistical methods based on realized matches. Nordin, Persson, and Rooth (2010) and Marin and Hayes (2017) suggest the construction of such kind of measures of match quality using the information on the observed distribution of workers with different fields of study across occupations. The rationale behind the construction of the index is that higher the concentration of workers with a particular field of education background working in a particular occupation is, the higher is the matching quality. In contrast, combinations that are observed with less frequency will be associated with lower matching quality. Nordin, Persson, and Rooth (2010) examines the income penalty of education and occupation mismatch for Sweden across gender for higher education degrees and find that the income penalty is twice as large as the one found by Robst (2007) for U.S. men, whereas Swedish women have the same penalty as U.S. counterparts. Darko and Abrokwa (2020) study the effect of vertical educational mismatch on earnings in Ghana, using a data-driven measure based on the notion that, for a given occupation category, the best type of education match is the one that is observed the most often. Similar to Nordin, Persson, and Rooth (2010) we construct a match quality index based on the observed distribution of individuals across occupations and fields of study.

2.1. Social networks, labor market outcomes, and mismatch

Since labor market frictions are important determinants of both vertical and horizontal mismatch, the 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 social networks play an important role in employment outcomes, though we do not know much about how these social networks affect the degree of education and occupation mismatch across citizenship. Does using informal job search methods, like social networks, increase the likelihood of employment, but workers end up with jobs where they are over-educated or have a larger horizontal mismatch? Or rather, does living in areas with larger potential networks reduce market frictions, increase information flow and improve the likelihood of working in better job matches? This is important to understand for both immigrant labor market outcomes as well as immigrant and minority integration in the host countries. In this paper, utilizing a data-driven measure of occupation-education mismatch, we examine the role of networks on horizontal mismatch in the context of immigrants. Carmichael, Darko, and Kanji (2021) shows that workers in Kenya and Ghana, who use social networks in finding jobs, pay a wage penalty if they are overeducated. Chort (2017), using subjective measures of mismatch, finds that people who use networks have a lower probability of vertical mismatch, but there is no significant effect on horizontal mismatch. In addition to proposing a new statistical measure of horizontal mismatch, this paper examines the role of social networks on the mismatch for Hispanics in the U.S. In particular, exploring the role of citizenship, given the heterogeneity between non-citizen immigrants, naturalized citizens, and born U. S. citizens.[4]

The most influential definition of social networks is provided by Granovetter (1973, 1982) who distinguishes between weak and strong ties. He 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-tie 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) Dustman et al. (2016) 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. Using employer-employee matched data for a MSA in Germany, Dustman et al. (2016) show, workers earn higher wages and stay longer at a job, if they obtain jobs through referrals,. Schmutte (2015) using social network quality in small neighborhoods find that workers move to higher-paying firms when their neighbors work at higher-paying firms and local referral networks help match high-ability workers to high-paying firms.

Immigrants rely on the social networks of their compatriots for their economic as well as social assimilation in the United States. Because of 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, but there is a consensus that networks improve migrants' employment outcomes (Munshi 2003; Damm 2009; Dustman et al. 2016 to name a few). Chiswick and Miller (1996) implicitly define immigrant networks based on the language immigrants speak and find that immigrants living in areas with high linguistic concentration earn less than their counterparts where English is spoken more frequently.[5] In contrast, Mouw (2003) finds that, once unobserved worker characteristics are controlled for, the use of contacts positively affects wages. Using Mexican Migration Project data, Munshi (2003) shows that there is a higher likelihood of holding a higher-paying, nonagricultural job among migrants with larger networks. Similarly, Patel and Vella (2013) show that networks have a strong effect on immigrants' occupational choices and wages. U. S. 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. However, Aslund and Skans (2010) using Swedish data finds that labor market ethnic segregation is related to adverse labor market outcomes, and overexposure of immigrants to other immigrants versus natives is negatively correlated with group employment levels and wages.

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, though not much is known about how social networks influence education-occupation mismatch for immigrants. Social networks with similar characteristics help in finding employment through informal channels but may lead to poor education and skill job match and lower earnings. Using samples from the U.S. and Europe Bentolila, Michelacci, and Suarez (2010) 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. Carmichael, Darko, and Kanji (2021) finds that workers in Ghana and Kenya rely heavily on social networks to find jobs but earn less when they are over-educated and even when exactly matched. However, Damm (2009) using data on Danish refugees show that ethnic networks help in job information which increases job-worker match quality and immigrant wages. Chort (2017) using survey data for immigrants examines the role of social networks on vertical and horizontal mismatch and finds that there are higher chances of horizontal mismatch when workers rely on their migrant networks for jobs, but it lowers the chances of vertical mismatch. While Chort (2017) provides evidence on the role of networks on both horizontal and vertical mismatch, the definitions of horizontal mismatch are constructed in a way similar to Nordin, Persson, and Rooth (2010), where horizontal mismatch is defined based on ad hoc classification rules. In this paper, we propose a data-driven objective measure of horizontal mismatch.

If an individual's social networks are similar to hers in terms of skill, characteristics, culture, and language, then networks will be more conducive in matching her with jobs closer to her education and skill level. In a theoretical model of heterogeneous workers and firms, and links between workers representing favoring relationships, Horvath (2014) shows that networks might lead to a higher mismatch. However, if the fraction of ties with similar agents (*homophily*) increases, the level of mismatch decreases. This is why immigrant networks with compatriots help find better job matches because compatriots have more information on the home country's education and experience, which can be leveraged on providing job leads. Similarly, there has been increasing evidence of the higher quality of networks having a more effective role in the labor market outcome. Calvo-Armengol and Jackson (2004) and Mundra and Rios-Avila (2020) show that the longer an individual is unemployed, the lower 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. Examining political refugees resettled in the U.S., Beaman (2012) finds that the labor market outcomes of refugees depend on the vintage of network members. If the refugees' network consists of recent members, the labor market outcomes are inferior, however greater number of tenured members improves the probability of employment and raises member wages.

There is a growing literature on how the individual's human capital skills as well as their legal status influence 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 U. S. (see Bean, Lowell, and Taylor 1988; Winegarden and Khor 1991; Amuedo-Dorantes and Mundra 2007).[6] 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, even if 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, legal status influences the effect of social networks on 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 strong family networks improve earnings for legal migrants by a larger magnitude than the undocumented immigrants. As a result, citizens will have better and more effective networks, which 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, thus in turn leading to a lower education-occupation mismatch. This paper will add an important dimension to the role of citizenship and how it further helps in improving labor market outcomes and integration of immigrants and minorities in the host country.

3. Measuring the education-occupation quality match

This paper takes the same approach as in Rios-Avila and Saavedra-Caballero (2019), which is similar in spirit to Nordin, Persson, and Rooth (2010), constructing a match quality index based on the observed distribution of individuals across occupations and fields of study. The rationale behind the construction of the index is that the higher the concentration of workers with a particular field of education background working in a particular occupation, the higher is the matching quality. In contrast, combinations that are observed less frequently will be associated with a lower match quality. The specifics of the approach are described next.

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

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

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, and 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:

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

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 a natural affinity 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 to hire the most productive workers for a given occupation. In a frictionless market we will expect to find everyone in a specific field working in the most related occupation, with a zero probability of finding someone working in an occupation that is unrelated to their field. Thus, a higher matching quality implies that a worker finds a job that pays the highest wage given his skill and that an employer finds the most productive worker, given the set of job requirements.

Due to frictions in the labor market as well as 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 degree and occupations reflects a mixture of labor market frictions and job matching maximizing behavior. Nevertheless, under the assumption that on average, individuals with field of education j work in occupation i because that is the best match for skill sets and wages, 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}). Specifically, 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 assortative matching, as a proxy for job-match quality:

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

Intuitively, values above one for the index given in equation (3) suggest that a particular occupation and field of degree combination is a *good match* because the likelihood of seeing that particular combination is higher than the benchmark of no assortative matching or random matching. Similarly, values below one would indicate that a particular combination is a *bad match* because it is below the benchmark of random matching. This index is similar in spirit to the categorization used in Nordin, Persson, and Rooth (2010), where fields of study and occupation pairs are classified as matched, weakly matched, or mismatched based on overall density and some arbitrary criteria. In contrast, we propose a continuous index that can be used to rank occupation and education in terms of their matching quality.

4. Data and summary statistics

4.1. Data

Data for this paper comes from the American Community Survey (ACS), 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 every year since 2005. From 2009 onwards, all individuals who participated in the survey and had at least a bachelor's degree were asked to specify their major, or field of degree or study, even if they had a higher education degree, such as a master's or Ph.D. 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. To obtain a large enough sample to capture the full joint distribution of individuals across occupations and fields of education we use the ACS 5-year sample for the years 2011–2015. This represents approximately 5% of the population, with sample weights that have been calibrated to represent the population for the entire 5-year period.

Since the paper aims to analyze the quality of the education-occupation match for the core of the labor force in the U.S., the construction of the index of match quality uses data for individuals between 25 and 64 years of age and with at least a college degree. This index is constructed for the whole population in the U.S. and does not differentiate across any demographic nor ethnic groups. Because information on 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 information on individuals who are currently unemployed and for whom the information on their last occupation is available.

For identification of the Hispanic subsample we use a question of self-identification, and whether the person interviewed considers him/herself to be of Hispanic, Latino, or Spanish origin. The Census Bureau definition identifies individuals of Hispanic, Spanish, or Latino Origin according to their country of origin, based on ancestry, linage, heritage, nationality group, or country of birth. Similarly, citizenship status is identified based on self-identification, where individuals are asked if they are citizens born in the U.S. or its territories, from U.S. parents, naturalized citizens, or not U.S. citizens.

4.2. Matching index

To obtain the most accurate measures possible, the estimation of our indices of education-occupation match quality uses the ACS 5-year sample corresponding to 2011–2015, which gives us a sample of 2,400,300 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 index (I_{MQ}) we used a reclassification of fields of bachelor's degree (91 fields) and the aggregated occupation categories (63 occupations). Since 10 percent of the sample declared a second field of bachelor's degree, the construction of the index is adjusted as follows.

$$I_{MQ}(i, j) = \frac{p_{OF}(i, f_1 = j \mid f_2 = j)}{p_O(i) \times p_F(f_1 = j \mid f_2 = j)} \tag{4}$$

where f_1 and f_2 denote the first and second field of degree respectively. This adjustment considers the full labor force coming from field of education j, regardless if a person declares it as the first or second field of education. If a person declares two fields of education, then we calculate two matching indices for the person given her occupation and assign this individual the highest of the two indices. In other words, the assigned index corresponds to the one that shows the best matching between occupation and field of education.

The proposed index provides an ordinal classification of the occupation-education match and as constructed is highly skewed, and so we use a monotonic transformation that will simplify its use and interpretation in our analysis. Specifically:

$$PI_{MQ}(i, j) = E(I_{MQ} \leq I_{MQ}(i, j)) * 100 \tag{5}$$

This transformation represents the share of people, based on ACS 2011–2015 data, who have an index of matching quality lower than $I_{MQ}(i, j)$, multiplied by 100. As stated before, the index of match quality is assigned to each observation in the sample based on their occupation classification, and field of degree. For those with two fields of education, only the highest index is used.

4.3. Hispanic networks

We construct two measures of Hispanic networks at the MSA level, also using the 5-year ACS data. The first measure is defined as the share of Hispanics among the population 25 years of age or older. The second measure is constructed in the same way, but further restricting the sample to the population with at least a bachelor's degree, which constitutes the share of Hispanics in the population with at least a college degree. For the econometric analysis, we restrict our sample to the civilian Hispanic population for the years 2016 and 2017 between 25 and 64 years of age, who have at least a bachelor's degree, and whose information on their current or last job occupation is available.

For the analysis to examine the role of Hispanic networks on their occupation-education mismatch we use a sample from 2016 to 2017. This may limit the impact of short-term endogenous factors that would affect immigrant networks and labor market match quality, which is constructed using 2011–2015 data. However, estimations should only be considered as a partial-correlations, and not necessarily as capturing causal effects. Given the restrictions of the measure of Hispanic networks, the sample is restricted to the population living in metropolitan areas that are identified in the ACS from 2011 to 2017.

4.4. Summary statistics

In 2016 and 2017, people who identified themselves as Hispanic represented approximately 16.6% of the working population between the ages of 25–64, however, among highly educated workers, those with at least a college degree represent only 8.4% of the sample, with the population of Hispanic non-citizens being the least represented. Table 1 provides summary statistics of the Hispanic sample for native citizens, naturalized U.S. citizens, and non-U.S. citizens. In the weighted sample, about 62% of Hispanics are U.S. citizens who are predominantly composed of whites (72%) and women (54%). Non-Citizens, and especially naturalized citizens, are older than natives. While most Hispanics in the sample are married (56%), Hispanic U. S. born citizens are more likely to be single

Table 1. Summary statistics by immigration status.

	Native Citizen		Naturalized		Non-Citizen		All Hispanic	
	Mean %	Std Error	Mean %	Std Error	Mean %	Std Error	Mean %	Std Error
Demographics								
Citizen							61.9	(0.0018)
Naturalized Citizen							21.9	(0.0016)
Non-Citizen							16.2	(0.0014)
Gender								
Male	44.5	(0.0024)	45.3	(0.0039)	52.2	(0.0050)	45.9	(0.0019)
Female	55.5	(0.0024)	54.7	(0.0039)	47.8	(0.0050)	54.1	(0.0019)
Age Group								
25-34	41.0	(0.0023)	18.6	(0.0031)	31.6	(0.0046)	34.6	(0.0018)
35-44	29.4	(0.0022)	29.3	(0.0036)	32.8	(0.0047)	30.0	(0.0017)
45-54	19.2	(0.0019)	30.6	(0.0036)	24.8	(0.0043)	22.6	(0.0016)
55-64	10.4	(0.0014)	21.5	(0.0032)	10.9	(0.0031)	12.9	(0.0013)
Race								
White	73.0	(0.0021)	70.6	(0.0036)	68.2	(0.0046)	71.7	(0.0017)
Non-White	27.0	(0.0021)	29.4	(0.0036)	31.8	(0.0046)	28.3	(0.0017)
Marital Status								
Married	51.8	(0.0024)	64.0	(0.0038)	62.6	(0.0048)	56.2	(0.0019)
Other	12.3	(0.0016)	17.5	(0.0030)	13.0	(0.0034)	13.6	(0.0013)
Single	35.8	(0.0023)	18.4	(0.0031)	24.3	(0.0043)	30.2	(0.0017)
Is a veteran	5.3	(0.0011)	3.3	(0.0014)	0.5	(0.0007)	4.1	(0.0007)
Education and Skills								
Domain of English Language								
Speaks English very well	95.0	(0.0010)	76.7	(0.0033)	45.8	(0.0050)	83.0	(0.0014)
Speaks English well	4.1	(0.0009)	17.0	(0.0030)	25.2	(0.0043)	10.3	(0.0011)
Speaks English but not well	1.0	(0.0005)	6.3	(0.0019)	29.0	(0.0045)	6.7	(0.0009)
Currently attending School	10.6	(0.0015)	8.8	(0.0022)	8.2	(0.0027)	9.8	(0.0011)
Has a Graduate Degree (Master or Phd)	30.8	(0.0022)	33.9	(0.0037)	29.1	(0.0045)	31.2	(0.0017)
Has a Second field of degree	10.0	(0.0017)	8.4	(0.0025)	7.2	(0.0030)	9.2	(0.0012)
Has any Disability	3.7	(0.0009)	3.4	(0.0014)	2.6	(0.0016)	3.5	(0.0007)
Current or last job was a wage paid job	93.2	(0.0012)	88.6	(0.0025)	86.5	(0.0034)	91.1	(0.0011)
Household Characteristics								
House Owner	64.9	(0.0023)	68.8	(0.0037)	38.4	(0.0048)	61.5	(0.0018)
Household Composition								
No Children	55.9	(0.0024)	51.4	(0.0040)	49.5	(0.0050)	53.9	(0.0019)
At least 1 Child 0–18	18.2	(0.0018)	21.4	(0.0032)	22.2	(0.0041)	19.6	(0.0015)
2 + children 0–18	25.9	(0.0021)	27.2%	(0.0035)	28.3	(0.0045)	26.5	(0.0017)
No other adult	27.7	(0.0021)	22.9%	(0.0033)	25.4	(0.0043)	26.3	(0.0017)
at least 1 other Adult in HH (25-64)	57.7	(0.0023)	60.2%	(0.0039)	58.1	(0.0049)	58.3	(0.0019)
2 + other Adults in HH (25-64)	14.6	(0.0017)	16.9%	(0.0030)	16.5	(0.0037)	15.4	(0.0014)
1+ Elderly in the household	2.3	(0.0007)	3.0%	(0.0014)	1.5	(0.0012)	2.3	(0.0006)
Observations	44770	16017	10085	70872				

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

than non-citizen or naturalized citizens. Only 4% of Hispanics identified themselves as veterans, with a larger presence of veterans among U.S.-born citizens.

Looking into Hispanic skill variables we find that the English language shows one of the largest differences across citizenship status. Among Hispanic naturalized citizens, only 6% indicate having some difficulty speaking English, whereas that figure is 29% for non-citizens and only 1% for Hispanic natives. Among the three groups, the percentage who have a Graduate Degree are very comparable; 34% for naturalized citizens, 31% for natives, and 29% for non-citizens. However, a somewhat larger share of Hispanic U.S.-born citizens (natives) than naturalized or non-citizens are currently working (or worked last time) in a wage-paid job (93% vs 88% vs 86%). Finally, regarding household characteristics, there is a larger share of Hispanic citizens than non-citizens who are homeowners (68% vs 38%) and who live in households without children (55% vs 50%) or no other adults (28% vs 25%)

4.4.1. Horizontal job match: what do they study and where do they work?

Table 2 provides the average score of the matching index and its distribution across Hispanic citizens (natives), naturalized citizens, and non-citizens. On average, Hispanic natives and naturalized citizens work in jobs that better match their educational background compared to non-citizens. The matching quality score for U.S.-born citizens is 1.2 points higher than naturalized citizens and 5.8 points higher than non-citizens. This difference is statistically significant at conventional levels. For convenience, we recode the index into four groups: a mismatch if a person has an index between 0 and .25, a weak mismatch if the index is between 0.25 and 0.5, a weak match if the index is between 0.5 and 0.75, and a match if the index is 0.75 or higher. Table 2 shows that 8.7% more U.S.-born citizens work for a weak-match job or a match, compared to non-citizens.

We provide a brief overlook of the distribution of Hispanics across aggregated occupations and fields of education groups in Figures 1 and 2. Based on the statistics from our weighted sample, the three most important occupations representing 39% of the Hispanic workforce are: Management and Business, Education, and Clerical Support. These three occupations represent a 12.8% larger share among Hispanic citizens (41.7%) compared to non-citizens. People working in these occupations have an average matching score of 49.1, which is 3.3 points below that of the overall Hispanic population average.

From the relative distribution of Hispanic by citizenship status[7] across occupations, we find that protective services, legal occupations, and social services show the largest differences across citizenship status for Hispanics. These occupations show average matching scores that are slightly higher than the average. On the other hand, occupations that are mostly favored by non-citizens, show below-average matching scores and maintenance and construction shows the largest differences across citizenship status. The only occupation that is relatively favored by non-citizens over citizens and has an above-average matching score is architecture and engineering, which represents less than 3% of the sample. Overall, it seems that noncitizen Hispanics are more likely to work in occupations that have low matching scores.

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

Job Match PIMQ Scores	Native Citizen	Naturalized	Non-Citizen	All
Mismatch (0-0.25)	23.76%	26.06%*	29.68%*	25.22%
Weak Mismatch (0.25–0.50)	24.89%	23.58%*	27.72%*	25.07%
Weak Match (0.50–0.75)	27.52%	27.87%	26.95%	27.51%
Match (0.75–1)	23.83%	22.49%*	15.65%*	22.21%
Average SI_{MQ}	50.3	49.1*	44.6*	49.1
P10	10.5	9.2*	8.8*	10.5
P50	50.6	50.6	43.2*	50.6
P90	90.0	88.7*	82.7*	90.0
Standard Deviation	28.4	28.6	27.1*	28.4

Note: All statistics are obtained using sample weights. * indicates if the difference is significant with respect to U.S. born citizen at 10%.

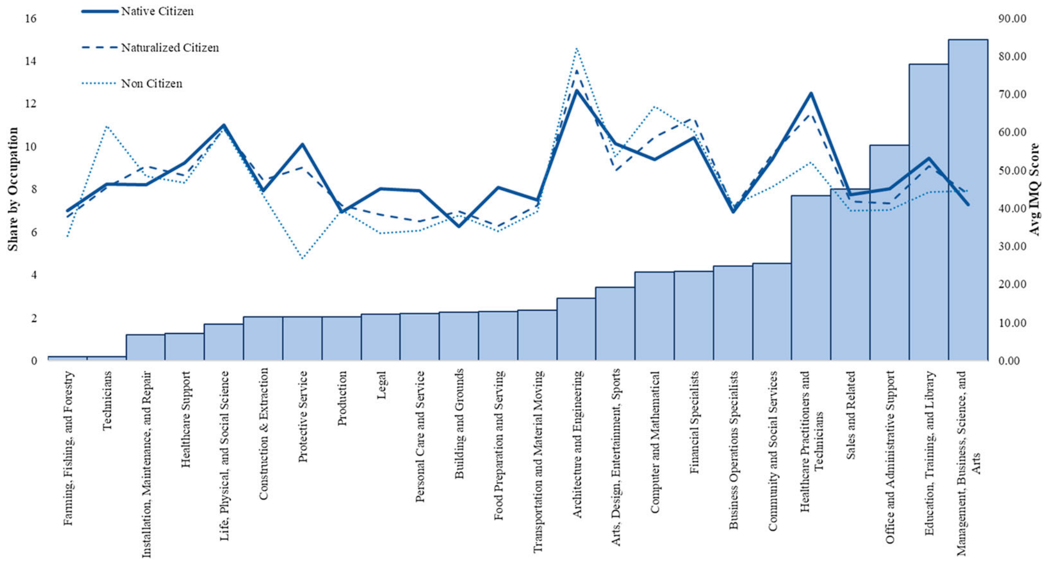


Figure 1. Distribution of Hispanics by occupation. Note: All statistics are estimated using sample weights. The Average IMQ is calculated as the weighted mean of the matching index for all observations in a given occupation by citizenship status. Population shares are plotted against the left axis, whereas the IMQ score by citizen Status uses the right axis.

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 Hispanics is business, representing 22.6% of the sample.

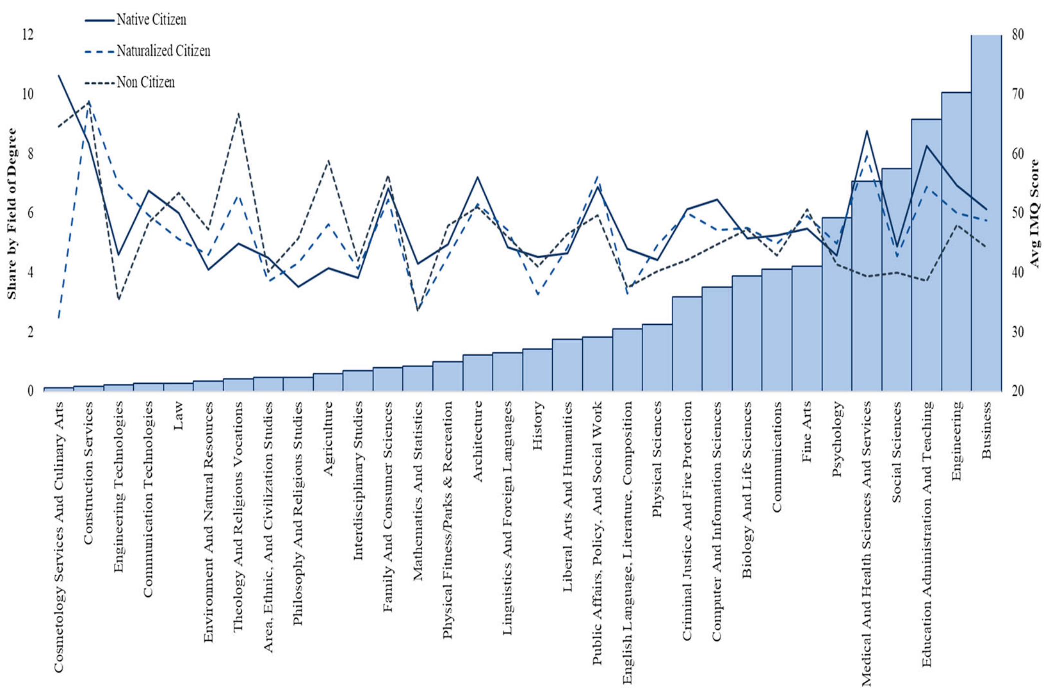


Figure 2. Distribution of Hispanic individuals by field of degree. Note: All statistics are estimated using sample weights. The Average IMQ is calculated as the weighted mean of the matching index for all observations in a given field of education. The share of Hispanics in Business (not shown) is 23.5%. Population shares are plotted against the left axis, whereas the IMQ score by citizen Status uses the right axis.

There is a slightly larger share of Hispanic non-citizens in this field (26.6%), and people working in this field have a matching score that is just below the average. The next two most important degree fields are education and engineering and engineering is favored by Hispanic non-citizens, representing just over 19% of the sample and showing above-average matching scores. We find that U. S. born citizens have better matching scores in 15 of 32 fields compared to Hispanic naturalized citizens and non-citizens, whereas Hispanic non-citizens have better matching scores only in 10 out of 32 fields.[8]

4.5. Hispanic social networks and horizontal matching

Because our main goal in this paper is to examine the role of Hispanic concentration (potential Hispanic networks) on the likelihood that a Hispanic individual works at a job that is a 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 rank-matching index. The distribution of proxy for networks is highly skewed due to the presence of metro areas that are historically Hispanic and so we classify them into 7 groups as detailed in Figures 3 and 4 ranging from 0–5% to 40+%.

Figure 3 shows the average score of the job matching index across the size of the Hispanic network, measured by the overall Hispanic concentration ratio, suggesting that Hispanic 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 becomes very large, above 30%, do we see a positive correlation with average matching quality. Among the U. S, born citizens and naturalized citizens, however, we do not see any clear trends between matching quality and the share of Hispanics at the MSA level.

On the other hand, if we measure Hispanic concentration by the share of Hispanics with a college degree, we see that Hispanic citizens benefit even in areas with moderate network sizes (15–20% or higher). We find that the positive correlation between social networks and decreasing education-occupation mismatch is stronger for college-educated Hispanics, when their networks consist of

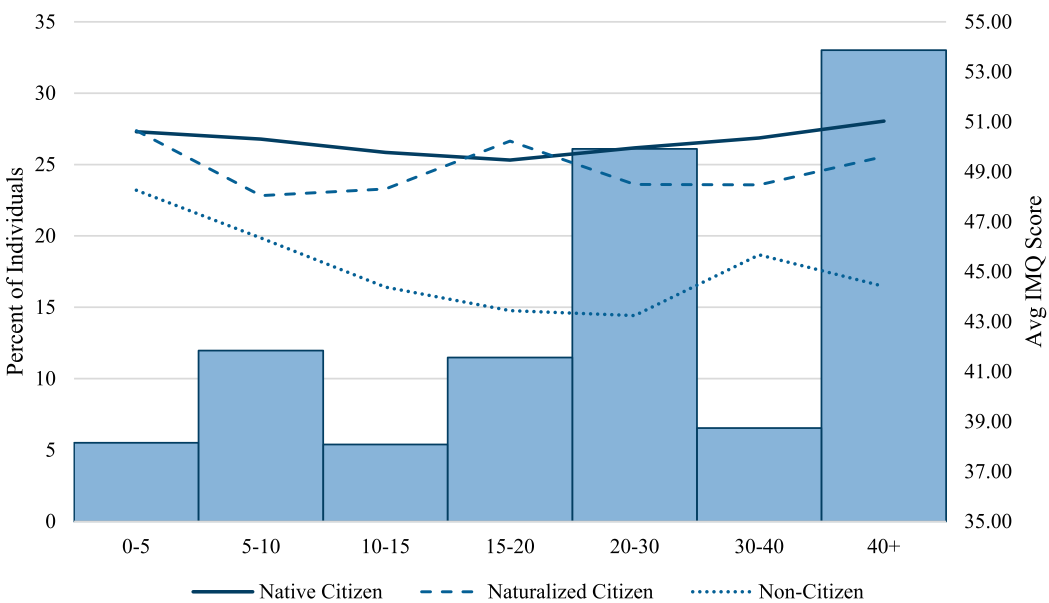


Figure 3. Average matching quality score (IMQ) by share of Hispanics in MSA. Note: All statistics are based on sample-weighted data. The share of Hispanics is calculated for individuals 25–65 years old. Population shares are plotted against the left axis, whereas the IMQ score by citizen Status uses the right axis.

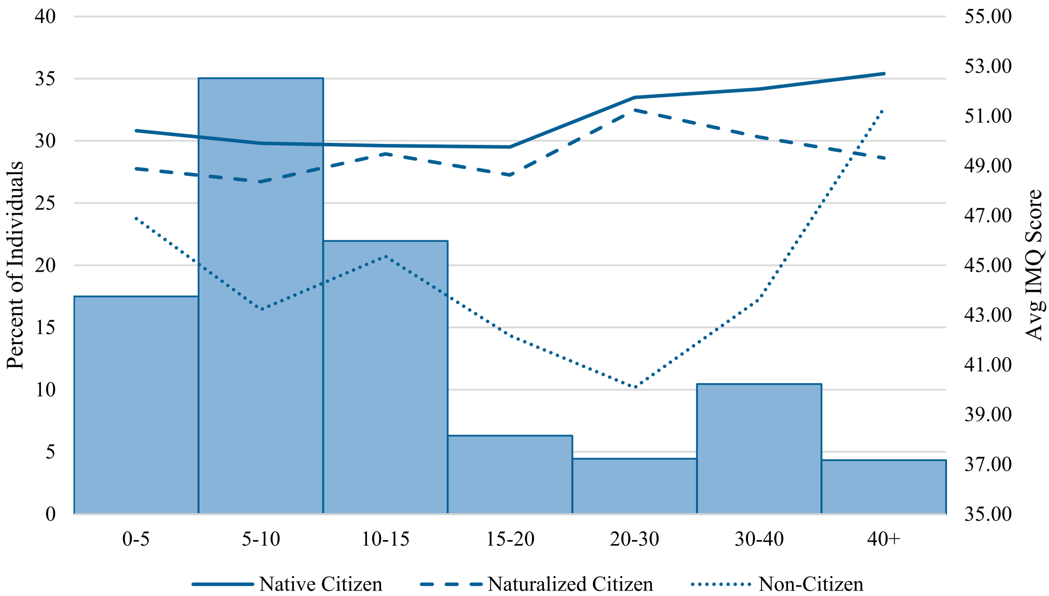


Figure 4. Average matching quality score (IMQ) by share of Hispanics with a college degree. Note: All statistics are based on sample-weighted data. The share of Hispanics is calculated for individuals 25–65 years old with a College degree. Population shares are plotted against the left axis, whereas the IMQ score by citizen Status uses the right axis.

people with similar education levels (college education or higher). We also observe moderate correlations for naturalized citizens but with declining effects, if they live in areas with a high concentration of Hispanics with a college degree. For Hispanic non – citizens, we see an increase in job match quality, only in areas with large networks of Hispanics with a college degree (20–30% or higher), see Figure 4.

5. Econometric model

To test the impact that networks have on the quality of the job match among Hispanics, we estimate a linear regression model where the dependent variable is the Rank Index of Match quality ($PIMQ_i$), described in section 3, as a function of our Hispanic network variable. Separate regressions are estimated using both the general Hispanic network variable, and the variable constructed using Hispanic with at least a college degree.

$$PIMQ_i = \beta_0 + \beta_1 Network_{msa} + \beta_2 X_i + \delta_s + unemp_{msa} + \varepsilon \quad (6)$$

Network is the main variable of interest and is measured as the share of the population at the MSA level. Vector *X* includes age, marital status, gender, level of education, disability, and veteran status. Given the strong role of educational background and the limitations associated with communication barriers and time restrictions, we also control for current school attendance, if the person has a graduate degree (Master or PhD), if he/she works in a wage-paid job (rather than being self-employed) and self-perceived domain on the English language. On the lines of Valletta (2013), *X* also includes whether the individual is a renter or not because if the individual is a homeowner, they are less mobile in the labor market and this will be an important determinant of their labor market mismatch. To account for other factors that could potentially affect why people work in certain occupations, given their educational background, we include in *X* individual characteristics that could increase (or reduce) frictions in the labor market we also control for household structure characteristics, including the presence of children, other adults, and elderly in the household.

Using pooled cross-section data for 2016 and 2017, treating each sample as independent brings the sample to 70,872 observations.[9] To account for state-specific unmeasured factors, such as labor market institutions, we include state-level fixed effects (δ_s). This may attenuate omitted variables and reverse causality bias in the model caused by state-level factors that affect both Hispanic concentration and Hispanic job market decisions. To control for other costs associated with frictions in the local labor market, we also include MSA-specific unemployment rate ($unemp_{msa}$). We estimate model in equation (6) separately for the U. S. born citizen, naturalized citizen, and non-citizens samples, using both measures of networks. All models are estimated using survey weights and we report Huber-White robust standard errors.

To address the fact that some individuals may be more inclined to study highly specialized fields and are most likely to work in a good-matched job, we also estimate models controlling for detailed field of degree fixed effects. This allows us to reduce the impact of self-selection into specific fields of study driven by factors such as individuals choosing broader fields of study because they are more adaptable to the fluctuating labor market demand, or choosing highly specialized fields because of potential earnings premiums or employment prospects.

6. Results and discussion

Table 3 provides raw differences on the role of network size on our index of matching quality while controlling for state fixed effects only and the models are estimated across citizen status separately. Columns 1–3 report results for the overall Hispanic concentration as a network proxy, and columns 4–6 use the concentration of Hispanic with at least a college degree. We find that Hispanic networks, especially when they are defined using people with at least a college degree, have a positive effect on the match quality of a job among Hispanics who are native citizens. Even though native citizens and naturalized citizens have the same rights and opportunities, our results suggest that Hispanic networks are positively correlated with matching quality only among native citizens. Once we restrict the network definition using Hispanic with at least a college degree, the partial correlations with matching quality increases. This effect could be linked to the improvements in labor market information between populations with similar educational backgrounds.

Table 4 provides the results from the model estimation using all relevant control factors including state fixed effects and estimated for U.S.-born native, naturalized citizens, and non-citizens for both network measures. Examining the role of networks on the degree of job mismatch suggests that the broad measure of Hispanic networks (concentration of Hispanic living in a given metropolitan area) have a small, negative, and insignificant relationship with the quality of the job match among non-citizens. Interestingly, the impact seems to be positive and significant for Hispanic citizens who live in metropolitan areas with 30% or higher Hispanic population. The estimates for naturalized citizens also suggest a slightly positive effect but is statistically insignificant.

Using the concentration of all Hispanic people within a metropolitan area could be a poor measure of networks for highly educated workers. This may be the case because people without a college degree may not have access to information, or leads on jobs, for Hispanics with higher levels of education. 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 natives and naturalized citizens. For example, compared to living in MSA's with the lowest concentration of Hispanic college graduates, living in a MSA with a concentration of 20-30% of Hispanics increase the job match quality index by 4.3 and 4.8 points among native and naturalized citizens, respectively. This effect seems to be larger among natives and increasing with network size. Among non-citizens, the impact is observed only when the network size is larger than 40%.[10]

The findings for other variables are as expected. Similar to what is well known, racial and ethnic discrimination factors lead to adverse labor market outcomes for non-white individuals. Although non-whites are about 30% of the sample, a relatively large proportion, there may be job market

Table 3. Raw differences in match quality and network size.

	Network: % Hispanic in MSA				Network: % Hispanic in MSA with a College degree			
	Native Citizen	Naturalized Citizen	Non-Citizen	All	Native Citizen	Naturalized Citizen	Non-Citizen	All
Network Size (Base 0-5%)								
5–10	0.419	−2.823	−4.064*	−0.883	1.627*	1.059	−2.731	0.742
	[1.192]	[2.094]	[2.374]	[0.951]	[0.951]	[1.611]	[1.806]	[0.741]
10–15	0.434	−1.160	−7.136***	−1.173	2.707+	2.005	0.726	2.181**
	[1.446]	[2.423]	[2.763]	[1.121]	[1.083]	[1.836]	[2.110]	[0.849]
15–20	1.167	−0.0733	−4.617*	−0.188	2.468**	1.050	−1.516	1.520
	[1.379]	[2.410]	[2.754]	[1.098]	[1.255]	[2.179]	[2.514]	[0.994]
20–30	2.417***	−0.00930	−4.352*	0.675	3.975***	3.716	−4.516	2.707**
	[1.358]	[2.356]	[2.617]	[1.076]	[1.299]	[2.813]	[3.208]	[1.073]
30–40	3.253**	−0.930	−3.302	1.238	4.050***	2.951	0.856	2.890***
	[1.516]	[2.629]	[2.994]	[1.205]	[1.369]	[2.033]	[2.391]	[1.018]
40+	4.001***	−0.373	−2.436	1.817*	5.519***	2.300	6.167+	4.805***
	[1.370]	[2.326]	[2.640]	[1.081]	[1.381]	[2.407]	[2.692]	[1.094]
Citizenship Status (base Born Citizen)								
Naturalized Citizen				−1.298***				−1.286***
				[0.333]				[0.333]
Not a Citizen				−5.848***				−5.816***
				[0.373]				[0.374]
Constant	47.99***	49.68***	48.18***	49.70***	48.21***	47.57***	45.21***	48.89***
	[1.173]	[2.047]	[2.236]	[0.932]	[0.831]	[1.409]	[1.527]	[0.652]
State FE	x	x	x	x	x	x	x	x
Observations	44770	16017	10085	70872	44770	16017	10085	70872

Note: Dependent variable: Index of Matching quality. *** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$

Table 4. 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		
	Native Citizen (1)	Naturalized Citizen (2)	Non Citizen (3)	Native Citizen (4)	Naturalized Citizen (5)	Non Citizen (6)
Female	1.146***	−1.109**	−3.679***	1.138***	−1.131**	−3.731***
	[0.343]	[0.560]	[0.653]	[0.343]	[0.561]	[0.650]
Age: 35–44	−1.560***	−1.012	−3.117***	−1.587***	−1.018	−3.082***
	[0.450]	[0.890]	[0.862]	[0.450]	[0.890]	[0.862]
Age: 45–54	−2.192***	−2.860***	−5.210***	−2.221***	−2.880***	−5.159***
	[0.509]	[0.893]	[0.942]	[0.509]	[0.892]	[0.942]
Age: 55–64	−1.488**	−1.987**	−5.392***	−1.544**	−2.030**	−5.465***
	[0.640]	[0.997]	[1.190]	[0.639]	[0.996]	[1.187]
Non-White	−0.209	−1.190*	−1.451*	−0.160	−1.146*	−1.396*
	[0.388]	[0.630]	[0.726]	[0.388]	[0.631]	[0.724]
Marital Status (Base: married)						
Other	−0.980	−0.231	−2.285**	−0.976	−0.252	−2.272**
	[0.639]	[0.897]	[1.082]	[0.639]	[0.898]	[1.078]
Single	−1.497***	−1.631*	−2.880***	−1.494***	−1.656*	−2.852***
	[0.503]	[0.926]	[0.973]	[0.503]	[0.926]	[0.970]
Is a veteran	−1.389*	−0.271	−12.10***	−1.419*	−0.274	−11.46***
	[0.791]	[1.621]	[4.009]	[0.792]	[1.620]	[4.043]
Domain of English: (Only English or very well)						
Speaks English Well	−0.230	−5.168***	−4.602***	−0.298	−5.174***	−4.703***
	[0.779]	[0.748]	[0.814]	[0.781]	[0.747]	[0.812]
Speaks English, but not well	−6.918***	−11.39***	−8.237***	−7.030***	−11.37***	−8.275***
	[1.645]	[1.056]	[0.811]	[1.644]	[1.054]	[0.808]
Attending School	−2.724***	−2.243+	−1.898	−2.715***	−2.237**	−1.855
	[0.546]	[1.011]	[1.186]	[0.547]	[1.012]	[1.181]
Has a Graduate Degree (Master or Phd)	0.672*	0.653	1.499**	0.691*	0.628	1.578*
	[0.363]	[0.583]	[0.733]	[0.363]	[0.583]	[0.729]
Has Secondary field	6.207***	3.775***	8.177***	6.187***	3.810***	8.168***
	[0.480]	[0.844]	[1.097]	[0.480]	[0.846]	[1.098]
Has any Disability	−2.172**	−2.404*	0.981	−2.165**	−2.393*	1.061
	[0.870]	[1.383]	[1.850]	[0.870]	[1.381]	[1.866]
Current or last job was a wage paid job	2.117***	1.811**	1.834**	2.130***	1.854***	1.989**
	[0.623]	[0.805]	[0.910]	[0.623]	[0.804]	[0.909]
Is a Home Renter	−1.686***	−2.713***	0.155	−1.682***	−2.709***	0.220
	[0.391]	[0.650]	[0.702]	[0.391]	[0.649]	[0.700]
# of Children						
At least 1 Child 0–18	0.237	−0.125	−1.238	0.263	−0.106	−1.245
	[0.469]	[0.737]	[0.848]	[0.470]	[0.738]	[0.845]
2 + children 0–18	0.557	−0.844	−1.506*	0.560	−0.837	−1.505*
	[0.467]	[0.745]	[0.867]	[0.467]	[0.745]	[0.866]
# Adults						
at least 1 other Adult in HH (25-64)	−0.732	1.363	−0.232	−0.715	1.385	−0.212
	[0.504]	[0.875]	[0.982]	[0.504]	[0.877]	[0.978]
2 + other Adults in HH (25-64)	−2.121***	−0.967	−4.643***	−2.087***	−0.967	−4.549***
	[0.610]	[0.992]	[1.160]	[0.609]	[0.994]	[1.153]
1+ Elderly in the household	−0.981	0.298	−3.899	−0.955	0.313	−4.091
	[1.043]	[1.825]	[2.813]	[1.040]	[1.832]	[2.837]
MSA U. rate	−0.0222	0.200	0.677**	−0.108	0.0827	0.357
	[0.135]	[0.221]	[0.324]	[0.147]	[0.235]	[0.334]

(*Continued*)

Table 4. Continued.

	Network: % Hispanic in MSA			Network: % Hispanic with a College degree in MSA		
	Native Citizen (1)	Naturalized Citizen (2)	Non Citizen (3)	Native Citizen (4)	Naturalized Citizen (5)	Non Citizen (6)
Network Size*						
5-10% of Hispanics in MSA	0.305	−2.295	−2.149	1.662^	1.954	−1.051
	[1.183]	[2.085]	[2.287]	[0.947]	[1.571]	[1.776]
10-15% of Hispanics in MSA	0.509	0.0506	−3.087	2.923***	3.171*	2.407
	[1.442]	[2.395]	[2.681]	[1.083]	[1.797]	[2.068]
15-20% of Hispanics in MSA	0.988	1.682	−1.999	2.771+	1.642	0.124
	[1.371]	[2.386]	[2.715]	[1.284]	[2.151]	[2.506]
20-30% of Hispanics in MSA	2.324*	1.906	−1.037	4.270***	4.774*	−3.130
	[1.352]	[2.336]	[2.602]	[1.308]	[2.800]	[3.247]
30-40% of Hispanics in MSA	3.141**	0.633	−0.807	4.225*	4.121+	2.466
	[1.513]	[2.601]	[2.938]	[1.395]	[2.019]	[2.397]
40% + of Hispanics in MSA	3.983***	1.492	0.567	6.053***	3.798	7.917***
	[1.368]	[2.309]	[2.610]	[1.469]	[2.517]	[2.789]
Constant	48.14***	50.26***	51.21***	48.52***	49.36***	50.88***
	[1.588]	[2.715]	[3.003]	[1.356]	[2.234]	[2.515]
State FE	X	X	X	X	X	X
Observations	44770	16017	10085	44770	16017	10085

Note: Dependent variable: Index of Matching quality. Robust SE in brackets. *** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$.

frictions that force them to work in occupations with lower-quality of job match. The estimated correlation, however, is insignificant among natives. We also observe that older individuals, except for the 55–64 age group, are more likely to work in jobs of lesser match quality compared to younger individuals. While this could indicate that older individuals have difficulty in finding jobs that match their educational background, it may also be the case that as they gain more experience, they might end up in jobs that are different from their original fields of education, but closer to the skills acquired through their job experience.

Non-citizens and naturalized – citizens Hispanic women are more likely to work in a match of lesser quality compared to men, whereas the opposite seems to be the case when looking at the Hispanic native citizen sample. It is often the case that women, in particular married women, face stronger frictions in the job market compared to men, which may drive them to work in jobs that have a lower quality match compared to men. This seems to be the case for naturalized citizens, with a stronger (negative) effect among non-citizens. On the other hand, we also observe that on average, single and separated people work in jobs that are worse matches to their educational background. It is possible that single individuals, who may be more financially constrained compared to married individuals, may be willing to work in jobs that may differ from their fields. This, however, is in contrast with the results observed across age groups.

English language skills have a large impact on the job match quality. Among Hispanic native citizens, those who 'speak English well' seem to fair just as well compared to those who speak only English at home. Among naturalized and non-citizens, however, the gap is large and significant, with a reduction of almost 5 points in the matching quality index. As expected, across all models, not being able to speak English well in the U.S. greatly reduces the job match quality. It is important to note that among noncitizens, about 30% indicate they do not speak English well.

Education background is strongly related to individual job match. People with a post-graduate degree, are slightly more likely to work in a better-match job. Interestingly, we find that individuals with a second field are far more likely to work in a better job match. This could be explained either by the added skill specificity of a post-graduate degree, or that individuals with two degrees have a broader set of skills compared to individuals with only one field.[11] We also find that individuals with a disability have a significantly lower match.

The findings regarding family structure variables also have expected signs. Larger families, either based on the number of adults or the number of children, are related to worse job matches, especially among non-citizens. We also find that more than two children below 18 years of age significantly lower job match quality for non-citizens, but not for citizens. Having more than 2 children in that age group might be imposing more household constraints and fewer resources to cope with for non-citizens versus citizens. In some cases, individuals might be stuck in jobs with a lower match because these jobs give more flexibility with their schedules to better serve their household. Having a larger family may also reduce job mobility of individuals, increasing their likelihood to be stuck in lesser-quality jobs.

In terms of other household characteristics, we observe that being a home-renter is negatively correlated with job match quality. Although we expected that homeowners are likely to suffer from a home-lock effect, it seems that the responsibilities associated with homeownership motivate workers to find better job matches, which in turn will lead to higher earnings.

6.1. Role of field of degree

One limitation of the specification used for Table 4 is that we do not control for the field of degree people have. This may generate a bias on the results if people select themselves to study particular fields of education because of their career prospects and earning potential. To address this potential bias, we include in the model field of education fixed effects and the results are given in Table 5. We focus on the estimates that use share of Hispanics with at least a college degree, as the measure of networks.

Controlling for degree field fixed effects allows us to analyze to what extent networks relate to the likelihood of Hispanic workers with a college degree to work for a job match after considering the differences across their fields of study. The results of these estimations are consistent with those in Table 4, other than for some control variables. In contrast with the model without field of education fixed effects in Table 4, we find that U.S. native citizen women no longer fair better than men. This suggests that women may select themselves into fields of education that have better job match prospects, for instance nursing, especially among natives but not among naturalized citizens and non-citizens. Lastly, the improved job match index that was observed among people who worked in a wage-paid job in Table 4 is no longer observed among native citizens. Though, it is still seen among naturalized and non-citizen Hispanics.

Among Hispanic non-citizens, networks seem to have a small and mostly insignificant effect on job match quality. As before, a noticeable exception is living in metro areas where networks are larger than 40% increases the index of matching quality by 7.4 points. For Hispanic native and naturalized citizens, controlling for fields of degree fixed effects shows that the results in Table 3 are robust. Networks appear to have a positive effect on job-match quality, which increases with network size. However, the effect seems to reach a maximum of just above 4 points, when considering networks larger than 20%.

6.2. Robustness: alternative measure of matching quality

As described in the methodological section the matching quality index we propose has advantages over other approaches in the literature because it provides a data-driven measure that uses combinations of occupations and educational backgrounds. There is a possibility, however, that our results are driven by the methodological decisions in the construction of the index, and not by the expected patterns in the data. To provide additional robustness, we compare the estimates on the effect of

Table 5. Role of social networks in job match quality: controlling for field of degree.

	Network: % Hispanic with a College degree in MSA		
	Native Citizen (4)	Naturalized Citizen (5)	Non-Citizen (6)
Female	−0.389	−2.687***	−2.272***
	[0.350]	[0.592]	[0.676]
Age: 35–44	−1.691***	−1.229	−2.786***
	[0.426]	[0.851]	[0.842]
Age: 45–54	−2.744***	−3.386***	−4.931***
	[0.486]	[0.864]	[0.918]
Age: 55–64	−2.981***	−2.826***	−5.156***
	[0.612]	[0.967]	[1.163]
Non-White	−0.499	−1.083*	−1.219*
	[0.364]	[0.612]	[0.702]
Marital Status (base Married)			
Other	−1.306**	−0.820	−2.087**
	[0.610]	[0.871]	[1.040]
Single	−0.630	−1.010	−2.491*
	[0.477]	[0.880]	[0.928]
Is a veteran	−1.600**	−0.653	−11.25***
	[0.750]	[1.522]	[3.939]
Domain of English:			
(Only English or very well)			
Speaks English Well	−1.130	−5.602***	−4.894***
	[0.756]	[0.731]	[0.791]
Speaks English, but not well	−8.426***	−11.87***	−7.795***
	[1.668]	[1.061]	[0.799]
Attending School	−2.603***	−2.637***	−0.975
	[0.519]	[0.955]	[1.148]
Has a Graduate Degree (Master or Phd)	1.767*	1.479+	2.093*
	[0.358]	[0.579]	[0.720]
Has Secondary field	8.225***	6.291***	9.349***
	[0.440]	[0.800]	[1.088]
Has any Disability	−2.101**	−2.414*	1.345
	[0.841]	[1.379]	[1.830]
Current or last job was a wage paid job	0.520	1.362*	1.918**
	[0.650]	[0.798]	[0.887]
Is a Home Renter	−0.923**	−2.433***	0.459
	[0.369]	[0.631]	[0.673]
# of Children			
At least 1 Child 0–18	−0.348	−0.0246	−1.407*
	[0.445]	[0.715]	[0.832]
2+ children 0–18	−0.502	−1.014	−1.916**
	[0.442]	[0.723]	[0.832]
# Adults			
at least 1 other Adult in HH (25-64)	−0.373	1.189	0.0323
	[0.479]	[0.843]	[0.942]
2+ other Adults in HH (25-64)	−2.131***	−1.735*	−4.340***
	[0.572]	[0.971]	[1.123]
1+ Elderly in the household	−0.544	0.745	−3.183
	[0.970]	[1.748]	[2.704]
MSA U. rate	−0.156	0.00812	0.379
	[0.142]	[0.235]	[0.331]
Network Size*			
5–10 % of Hispanics in MSA	1.946+	2.021	−1.485
	[0.887]	[1.534]	[1.784]
10–15 % of Hispanics in MSA	3.229***	3.330*	1.953
	[1.019]	[1.754]	[2.080]
15–20 % of Hispanics in MSA	2.469+	1.046	−0.176
	[1.211]	[2.056]	[2.481]
20–30 % of Hispanics in MSA	4.212***	5.151*	−3.643
	[1.223]	[2.658]	[3.173]
30–40 % of Hispanics in MSA	4.163***	3.402*	2.361

(*Continued*)

Table 5. Continued.

	Network: % Hispanic with a College degree in MSA		
	Native Citizen (4)	Naturalized Citizen (5)	Non-Citizen (6)
	[1.333]	[1.984]	[2.409]
40% + of Hispanics in MSA	4.344***	3.577	7.382***
	[1.378]	[2.449]	[2.792]
Constant	50.55***	51.29***	49.50***
	[1.317]	[2.202]	[2.510]
State FE	X	X	X
Field of education	X	X	X
Observations	44770	16017	10085

Note: Robust Standard errors in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Hispanic networks based on our proposed measure of matching index to a modified index based on the one proposed in Darko and Abrokwa (2020).

Darko and Abrokwa (2020) study the effect of vertical educational mismatch on earnings in Ghana, using a data-driven measure. The index the authors propose is based on the notion that, for a given occupation category, the best type of education match is the one that is observed the most often. Thus, they construct an index as the ratio between: (1) the share of workers with education background j in occupation i, $share_{educ=j|occ=i}$ divided by (2) the maximum share of across all education backgrounds but in the same occupation:

$$DI_{occ} = \frac{share_{educ|occ}}{\max\limits_{educ} share_{educ|occ}}$$

We argue that this definition only considers the employer's side of the story (occupation) and that one should also consider the match quality index from the perspective of the workers as well. The best occupation match for someone with a given education background is the one where they work most frequently. Thus, the index would be the ratio of (1) the share of workers in occupation i, with education background j, $share_{occ|educ}$, divided by (2) the maximum share of across all occupations but with the same educational background:

$$DI_{educ} = \frac{share_{occ|educ}}{\max\limits_{occ} share_{occ|educ}}$$

For our robustness analysis, we combine these indices of matching quality using the geometrical mean of both $DI_{QM} = (DI_{occ} * DI_{educ})^{1/2}$. In addition, we impose the same nonlinear transformation we applied to our index, such that the standardized index is defined as:

$$DPI_{MQ}(i, j) = E(DI_{QM} \leq DI_{MQ}(i, j)) * 100$$

We call this the modified Darko and Abrokwa Index, which is now fully comparable to our index. As shown in Figure 5, there is strong agreement across both indices, with a weighted correlation of 0.93. This suggests that both indices identify similar patterns in terms of what pairs of occupation and education backgrounds are considered good matches vs bad matches. We do observe that our index assigns higher matching scores to some occupation and education combinations, which are not identified as such based on Darko and Abrokwa (2020). However, those are mostly cases with a small number of observations for those particular combinations.

To provide further evidence of the robustness of our results, we replicate previous models, accounting for all demographic controls as well as state and field of degree fixed effects, using the modified Darko and Abrokwa index of job match quality as the dependent variable. The

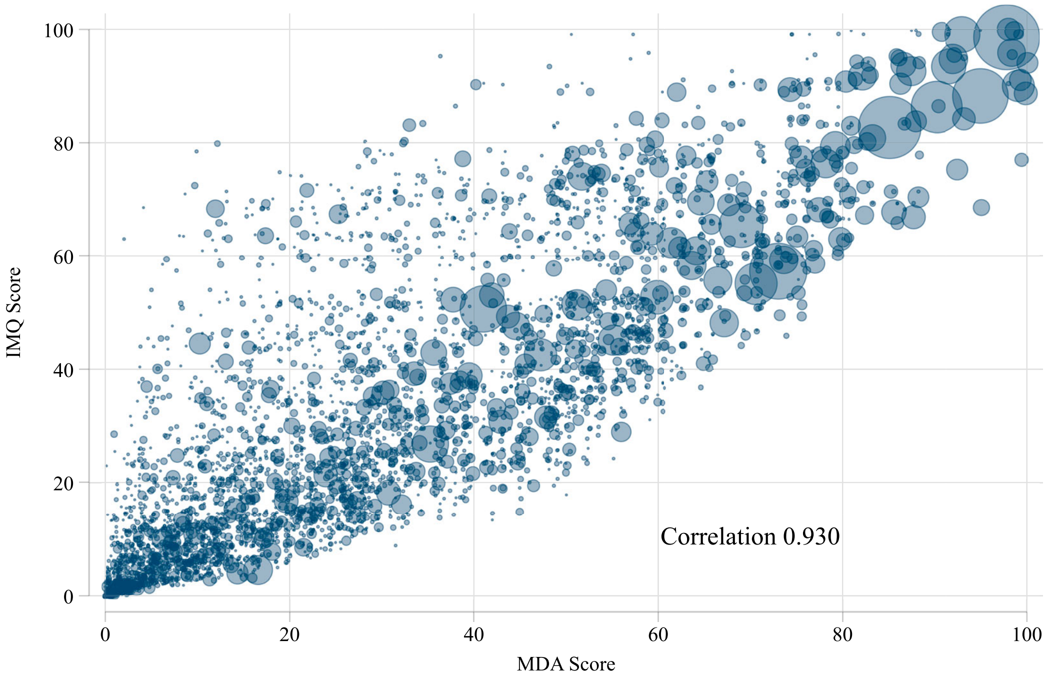


Figure 5. Proposed IMQ score with modified Darko index. Note: Weighted scatterplot based on sample: MDA – Modified Darko-Abrokwa Index.

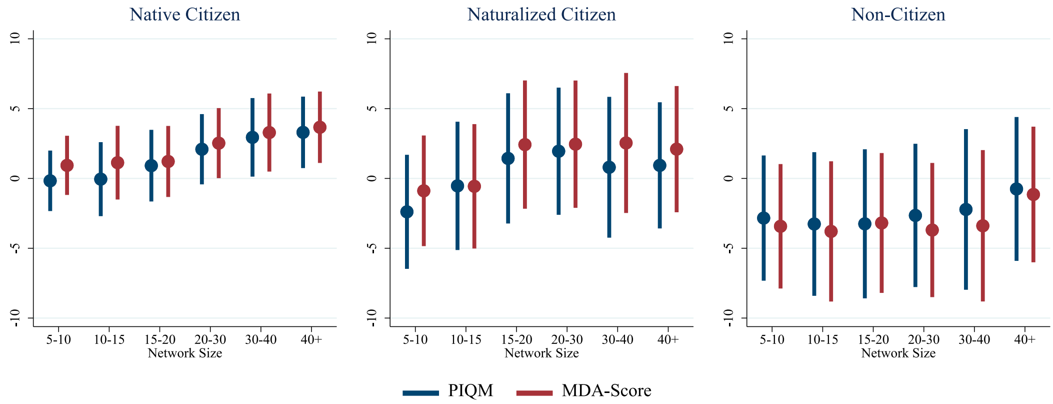
results are illustrated in Figure 6. We find that the point estimates and confidence intervals of our proposed index and modified Darko & Abrokwa coincide with our results quite closely, with only small differences in the point estimates. This confirms our conclusions that Hispanic networks have an impact on the quality of the occupation-education match. But mostly on native-born and naturalized citizens. For non-citizens, networks have a significant effect on the job match quality but only for those living in the MSA with the largest concentration of Hispanics with a college degree.

7. Concluding comments

There is a consensus that social networks play an important role in job search, facilitating access to information and leads, and increasing the likelihood of finding jobs. However, there is limited research focus on understanding the quality of those jobs networks facilitate. In this regard, this paper raises an important question: Do social networks help people find jobs that are a better match to their skill sets?. This question is important to study because levels of education and skills are on the rise and so is the level of education-occupation mismatch, which is costly to both individuals and firms. We examine this issue focusing on the case of college-educated Hispanics in the U.S., with a particular focus on the role of citizenship on the extent of education-occupation mismatch and the differences in how the social networks are correlated with the horizontal mismatch across native, naturalized, and non-citizens.

Horizontal mismatch is very relevant for college graduates because the skills acquired through college may be different from the skills required in their current jobs. To construct this index, we use pooled data from the 5 yr 2015 ACS to construct an objective index of horizontal matching quality using data on all individuals in the ACS between 25 and 64 years of age. This index uses the observed distribution of occupations and educational backgrounds to assess it a particular occupation-education combination is a strong or a weak job match. We use this index to examine the role

a) Network: Share of Hispanics in MSA



b) Network: Share of Hispanics with College Degree in MSA

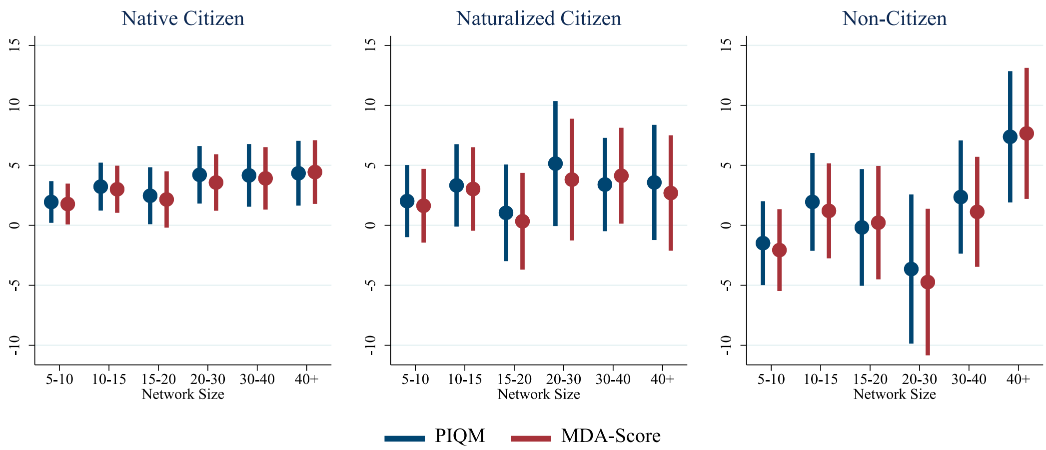


Figure 6. The role of networks on job match quality. (a) Network: Share of Hispanics in MSA; (b) Network: Share of Hispanics with College Degree in MSA

of social networks for college-educated Hispanics in the U.S. Our refined measure of social networks at the MSA level is the Hispanic share of the total population of 25 years and older and with at least college education.

From the econometric analysis using ACS for 2016 and 2017 and the social networks measure of the proportion of Hispanics with at least college education, we find that networks have a positive impact on the job-match quality for both citizens and non-citizens. Among non-citizens, the impact is observed only when the network size is larger than 40%, whereas for citizens, networks now appear to have a positive impact on the job match at a low 10%. Also, having a network larger than 10% may increase the match quality index by about 0.11 points. At 40% or more, however, the results suggest an improvement in the match quality index of 0.2 points. These results are robust when we control for the field of education.

This finding 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 access to better quality networks potentially providing Hispanic citizens with better job information and matching. Although we do not have information in our sample, Hispanic citizens may also have access to better quality education than their non-citizen counterparts. Moreover, citizens may have better U.S. job market experience, which helps their Hispanic networks to place them in jobs that fit their field of specialization more than non-citizens. This paper also highlights another channel through which citizenship is beneficial in the labor market and for economic and social well-being.

Notes

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) and about one in nine (11.3 percent) is greatly overqualified (i.e., two or more standard deviation above the mean). Whereas, one-third natives (36.1 percent) are overqualified, and 6.1 percent natives are greatly overqualified.
2. See Mora and Davila 2018 report Economic Policy Institute: https://www.epi.org/publication/the-hispanic-white-wage-gap-has-remained-wide-and-relatively-steady-examining-hispanic-white-gaps-in-wages-unemployment-labor-force-participation-and-education-by-gender-immigrant/
3. O*NET replaces the Dictionary of Occupational Titles. https://www.bls.gov/careeroutlook/1999/Spring/art01.pdf
4. There is some work showing the role of networks on over education, Kalfa and Piracha (2018) and Kucel and Byrne (2008) show that social networks increase overeducation in Australia and UK respectively.
5. Massey et al. (1987) using data from the Mexican Migration Project defined social networks as kinship, friendship, and paisanaje (i.e., fellow citizens) and Orrenius (1999) defined family networks as having a relative with U.S. migration experience.
6. 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.
7. The relative distribution is measured by how much larger or smaller is the share of Hispanic native citizen, naturalized, and non-citizens working in a given occupation or with a given field of studies, compared to the overall total.
8. Table A in the Appendix gives the occupation distribution of Hispanics for citizens and non-citizens. Table B gives similar College degree distribution.
9. Model estimations using 2016 and 2017 data separately provide qualitatively similar results to our pooled model, and is given in the appendix.
10. The five MSA areas that have this large network size are Brownsville-Harlingen, El Paso, Laredo and Mcallen-Edinburg-Mission in Texas, and El Centro in California,
11. One should consider, that by construction, having a second degree will guarantee a better job match index. As explained in the methodological section, in the case of individuals with a secondary field of degree, the index of match quality is assigned based on the best match of the two fields.

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