Essentializing Origins: Ethnoracialization of Immigrants in the U.S. Context

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ABSTRACT

Using U.S. Census data fitted into a series of cross sectional quantitative models, this dissertation estimates how *ethnoracialization* molds immigrants' socioeconomic outcomes, after controlling for their demographic and human capital endowments and the spatial context in which they live. Although extensive research exists on the relationship between human capital, income and social status and the unequal socioeconomic outcomes of immigrant groups, little attention has been given to how the ethnoracial heterogeneity within and between immigrant groups affects unequal outcomes. To contribute to fill this void, this dissertation presents three analyses that build on one another by exploring how ethnoracialization helps shape socioeconomic outcomes through time and space while paying particular attention to the interaction between country of origin, race, English proficiency, legal status, and the educational attainment of immigrants. The studies find evidence that strongly suggest the presence of structural ethnoracialization at the national, regional and metropolitan scales that mediates the economic integration of immigrants, especially those with high levels of education, into the U.S. economy. Specifically, results point to a patterned division of outcomes where immigrants from some Asian countries such as India and China are positively ethnoracialized, and consistently place at the top of all measured outcomes (income, socioeconomic status, occupational status, and skill-job matching probabilities), while Latin Americans, especially Mexicans and Central American, who tend to be negatively ethnoracialized, place at the bottom.

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INTRODUCTION

The unprecedented globalization experienced in the last five decades has been accompanied by a similar rise in human migration and economic inequality. In United States (U.S.) the tensions created by these interacting processes exist within a historical context of *racialization* that has shaped and is shaped by how immigrant identities are imagined and simplified. Oftentimes this process of essentialization stems from stereotypical preconceptions assigned to immigrants depending on their country of origin, their culture, their race, or a mixture of these ascriptions, which are conceptualized in this study as the process of *ethnoracialization*. This dissertation seeks to provide a theoretical and empirical framework for this social process by meticulously studying the effects of the intersection between immigration, ethnoracialization, and inequality, in a holistic and multiscalar fashion. Using U.S. Census data fitted into a series of cross sectional quantitative models, this dissertation estimates how demographic and human capital endowments of immigrants and the spatial context in which they exist, shape their unequal socioeconomic outcomes vis-à-vis different dominant groups in a patterned and predictable manner imbued by the positive and negative effects of ethnoracialization. Although extensive research has been made on some of these relationships, such as human capital on income and status and the unequal outcomes of immigrant groups, little attention has been given to how the ethnoracial heterogeneity within and between immigrant groups affects unequal outcomes. To fill this void, this dissertation presents three analyses that build on one another by exploring how ethnoracialization mediates socioeconomic outcomes in a fluid manner through time and space.

Chapter I starts by setting the theoretical foundation for defining and utilizing the concept of *ethnoracialization* within the context of immigration and inequality using an epistemological and an empirical approach. With an in-depth review of available literature and a national multi-decade analysis of the between (ethnic) and within (racial) variation in income and status outcomes of major immigrant groups. The main objective in this chapter is to disrupt the assumed heterogeneity of immigrant ethnic groups by factoring in their internal racial differences. With findings that clearly evidence an unequally biased socioeconomic system that rewards some and punishes others based on biocultural characteristics, Chapter I provides extensive evidence to the process of ethnoracialization of immigrants, which challenge personal-endowment-centric theories. In Chapter II the focus is narrowed geographically and contextually by exploring the inequality of socioeconomic status outcomes (based on occupation, education and income) for immigrants in the U.S. West Coast labor market, reducing some of the widely variant ethnoracialization of similarly labeled groups at a regional level. For example, being Latino/Hispanic has a very different meaning in Los Angeles as compared to Miami, yet results from Chapter I would suggest that the socioeconomic outcomes of immigrants belonging to this panethnic identity are very similar across the U.S. landscape. Chapter II also prioritizes the "ethno" in ethnoracialization, as racial distinctions are not clearly delineated across the main immigrants groups, thus, ethnicity, defined by continental origin, becomes the main analytical driver of unequal outcomes. Chapter III delves deeper into one of the more interesting findings in Chapter II, that inequality of socioeconomic outcomes has a direct relationship with level of education, meaning that more disparate occupational status returns occur at the highest levels of human capital attainment. This is in clear contradiction to what most economists would maintain, and sets the stage for an even more focused analysis of ethnoracialization in the labor market. Thus, the population of interest in this last study are the highly educated immigrants who reside in the main U.S. metropolitan areas where high tech industries are the main drivers of the economy. To complement the analyses in Chapters I and II, which looked at inequalities in socioeconomic returns to endowments, Chapter III measures the probabilities of immigrants of

Asian and Latin American origin to match their advanced education to corresponding jobs in STEM-related fields. Contextual variation is brought to the forefront in this chapter, as sociospatial controls are integrated in a multilevel model to capture the effects of living and working in "unique" innovative metropolitan areas. The ultimate goal of this last study is to provide definitive evidence that even when immigrants have achieved the highest levels of human capital, and live in the most progressive urban centers in the country, some groups still cannot escape the external limitations imposed on them by a structurally ethnoracialized system. In the following paragraphs I will describe the three chapters in more detail an present some of the main findings of each study.

Chapter I. Migration, Inequality, and Ethnoracial Stratification

This chapter analyzes the relationship between inequality, international migration, and ethnoracialization in the United States, from 1970-2010. Informed by current scholarship and based on pooled U.S. Decennial Census and ACS data, this study uses extensive empirical analysis to explore the historical trends of disparate socioeconomic outcomes between and within immigrant groups vis-à-vis U.S.-born, non-Hispanic whites. The chapter departs from previous studies that conceive of national immigrant groups as racially homogeneous; assume that human capital is the best predictor of immigrants' incorporation in the host society; and only consider inequality between groups neglecting to examine the significance of within group inequality. Through the use of Average Marginal Effects of two-way interacted OLS models the study finds that race effects vary across ethnonational groups, so *ethnoracialization* seems to be a better analytical concept to explain the dynamics of racialized inclusion and exclusion determining patterned and secular socioeconomic inequalities between and within groups. Results challenge established notions of human capital as the most effective equalizer, as average gains from education, language proficiency, and naturalization are distributed unequally across ethnoracially-bounded groups. While non-white Asian and most white European immigrants exhibit the highest status and income, Latin-American-origin groups (US- and foreign born), regardless of their race, are significantly more likely to earn less and have a lower socioeconomic status than any other ethnic groups, ceteris paribus.

Chapter II. Racialization of Immigrant Ethnicity and Occupational Attainment in the Western U.S. Labor Market

This paper explores how immigrants' ethnic identification influences their occupational status attainment in the United States' labor market. Single year data from the American Community Survey from 2008 to 2018 are pooled to compare how European-born workers fare vis-à-vis other immigrant workers according to their continental ethnic origin. It uses educational attainment, immigration status, and English proficiency to predict the variance in occupational status between and within ethnic groups. The analysis is based on a nested three-block ordinary least squares regression (OLS), and an interacted model between the three main predictors and the ethnic group identifiers. The findings confirm the significant effect of education, immigration status, and English proficiency on occupational status scores. As expected, increases in education, holding a legal immigration status, and being fluent in English have positive effects on occupational status attainment, other things being equal. This positive relationship, however, is not equally manifested across ethnic groups. The study reveals that the explanatory power of these personal endowments is significantly reduced among some ethnic groups, strongly suggesting a patterned and significant effect of labor market discrimination. Contrast analysis of the predictive margins of the four-way interacted model provides further support of the effects of negative exclusionary discrimination against some immigrant groups, most evident in Mexicans and Central Americans. Interestingly, highly educated Mexicans and Central Americans, who, despite their legal status, and English fluency, tend to be more likely to work in lower status occupations than any other ethnic group. This finding questions previously established notions according to which maximizing human capital, possessing legal immigrant status, and being fluent in English pave the way to the successful integration of immigrants into the U.S. labor market. This study, thus, provides much needed empirical evidence supporting theories of ethnoracialization of the U.S. labor market.

Chapter III. Ethnoracialized STEM Roots: Skill-Job Mismatch among High-skilled Immigrants in U.S. Innovative Metropolitan Areas

This chapter explores the relationship between ethnoracialization and the occupational matching of STEM-educated immigrants across the most innovative U.S. metropolitan areas. Contrary to the commonly held assumption that education seeds equality, the results suggest that ethnoracialization significantly shapes well-known patterns of rewards and advantages and losses and disadvantages across immigrants possessing the highest human capital endowments. Evidence shows that local contexts, including ethnic residential segregation, innovation of place of work, and individual-level characteristics, have little effect on altering these patterns of ethnoracial inequality creating a notion of the deep roots of ethnoracial segregation in historical processes of structural inclusion/exclusion in the U.S. labor market. Using a comparative approach across the main immigrant sending countries from Asia and Latin America, the study finds that matching discrepancies are mostly the result of structural or institutional discrimination that favors Asians. Specifically, results from this study show that among Asian and Latin American immigrants, those from India and China, are the main beneficiaries of positive ethnoracialization as they are able to match their STEM education with a STEM occupation with an average of 50 percent higher odds than most other Asia-born immigrants, and 60 to 70 percent higher than those born in Latin America—*ceteris paribus*. Socio-spatial measures do not explain these differences, as they account only for the language proficiency variance between ethnic groups, and are greatly outperformed by the prevailing positive and negative effect of the ethnoracialization of immigrant cognitive abilities in the U.S. labor market.

Conclusion

The consistency of the findings in the three chapters provide ample evidence of the positive and negative influence of ethnoracialization of immigrants in the U.S. - In broad terms Asian immigrants are imagined as a model minority and Latin American immigrants as a weight to society and in return we observe Asians at the top of every measure of socioeconomic integration where Latinos are undoubtedly excluded. This could be easily explained by the overrepresentation of Indian and Chinese immigrants among the highly educated which affords them high-skill, high-status, and high-pay tech jobs, and by the equally salient representativeness of Mexicans and Central Americans with low educational attainment in low-skill, low-status, low-pay service jobs. However, this argument falls apart when Asian and Latin American immigrants with not only an equivalent level of education, but also comparable demographic characteristics, English proficiency, and legal status are compared and the disparate outcomes prevail. Geographic differences do not seem to reshape the bipolar patterns drawn indelibly by ethnoracialization, as the three studies show unequal outcomes at all and every single scale after controlling for all other factors. Ethnoracialization is, thus, deeply rooted in the structure of U.S. labor markets and society, and as a self-validating process, it has only gotten worse in the last half century in par with increases of its intersecting global processes of immigration and inequality.

CHAPTER 1:
Migration, Inequality, and Ethnoracial Stratification1

INTRODUCTION

This article analyzes the relationship between socioeconomic inequality, international migration, and ethnoracial stratification. The theoretical and practical implications of this relationship is critical especially in highly racialized societies with substantial immigrant population like the U.S. Recent scholarship questions extant literature on the relationship between race and inequality, suggesting that the effects of race on the distribution of societal rewards are not fixed, but variable and mediated by ethnicity in a process dubbed ethnoracialization (Brown and Jones 2015, Leeman 2018, Ong and Gonzalez 2019). In this sense, new immigration flows significantly affect ethnoracial relations and stratification (Jaynes 2000, Kretsedemas 2018, Waters and Eschbach 1995). Informed by current scholarship and based on U.S. Census data, this article addresses three main questions. First, to what extent race (being white or non-white) has a similar (positive or negative) effect on the distribution of income and socioeconomic status across ethnic groups, ceteris paribus? Second, how does the intersection of ethnicity and race affect inequality within U.S.- and foreign-born groups? Finally, is human capital (i.e., education, legal status, English proficiency) an equalizing factor across and within groups regardless of their ethnoracial identification?

The U.S. is the most unequal among the world's wealthiest societies (Alvaredo et al. 2017, Piketty 2014, Piketty, Saez and Zucman 2018, Smeeding 2005, Volscho and Kelly 2012),

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as well as the world's top destination of global migration. By 2018, the U.S. Gini coefficient was 41.4, ranking the country closer to well-known, significantly unequal countries such as Kenya (40.8), Peru (41.5), and the Dominican Republic (41.9), than to other rich societies such as Japan (32.9), Canada (33.3), and the European Union's 30.3 (Eurostat 2021, World Bank 2021). On the other hand, by 2019, the U.S. counted some 44.9. Million immigrants, or 13.7 percent of the population, a proportion not seen in the country for a century (U.S. Census). Driven by growing immigration, the country's level of ethnoracial diversity has reached a historical high: by 2018, the proportion of people self- identified as members of ethnoracial minorities represented two-fifths (39.3 percent), more than two-and-a-half times higher than the proportion registered four decades earlier (14.6 percent).[1]

Predictably, the burden of rising inequality particularly affects ethnoracial minorities. Indeed, prior studies show that African Americans and people of Latin American origin are the most negatively affected by this trend (Bonilla-Silva 2018, Hoynes, Miller and Schaller 2012, Mandel and Semyonov 2016, Muñoz et al. 2015, Telles and Ortiz 2008). A majority of these studies, however, center on inequality among U.S.-born people. On the other hand, most research on immigration and inequality in the U.S. focuses on either how immigrants (conceived as an exogenous economic factor) affect domestic inequality, or how they are incorporated into U.S. society. The former is dominated by economic accounts, chiefly focuses on the effects of immigration on domestic labor markets, while the latter adopts a more sociological perspective and tends to focus on immigrants' sociocultural and economic integration.

Despite epistemic differences between these economic and sociological accounts, they both share two general analytical assumptions. First, they implicitly assume that immigrants who are from the same country of origin are racially homogeneous; second, they understand human capital to be the best predictor of migrants' socioeconomic performance independent from other immigrant characteristics like race and ethnicity. These two assumptions, we argue, are questionable, notwithstanding abundant empirical evidence demonstrating the significance of race and ethnicity as determinants of social patterns of the uneven distribution of opportunities and rewards across ethnoracial groups.

The U.S., in short, provides unequal, ethnoracialized opportunity structures to immigrants. Specifically, opportunities and rewards afforded to immigrants are contingent on how they are identified racially (i.e., white or non-white), a perception which in turn is mediated by a societal valuation of their ethnic identity (i.e., where they come from), irrespective of their actual human capital endowments and capabilities. In other words, immigrants' national identification, as constructed by receiving society, shapes racialized perceptions of, and practices towards them upon arrival. As such, being a white, or non-white immigrant has not a fixed meaning and preordained effect on her socioeconomic positionality, for it depends on how society values her national origin. In this sense, society's perception and regard of, say, a white British immigrant are significantly different from its perception and regard of a white Mexican immigrant, ceteris paribus. Conversely, receiving society's perception of immigrants is not fixed and solely based on their geocultural origins – i.e., country of origin, language, cultural practices, and so forth, as current analytical accounts assumed. Rather, opportunities and societal rewards afforded to immigrants change over time as society values and prizes, or devalues and denigrates their *ethnic* and *racial* origins and identification. The social stratification process engendered by the intersection of migrants' national origin and racial identification is captured by the term *ethnoracialization* (for previous definitions and usage of ethnoracialization see, Alcoff 2009, Leeman 2018, Ong and Gonzalez 2019). Paraphrasing Brubaker, our approach moves away from "attempts to specify what an ethnic or racial group or nation *is*" to an attempt "to specify how ethnicity, race, and nation *work*" (Brubaker 2009: 29, emphasis added) in structuring inequality. It is important to note that ethnoracialization is not intended to replace the importance and relevance of race and ethnicity as independent social dimensions, for they are key analytical concepts that illuminate particular dynamics shaping social stratification. Ethnoracialization helps illuminate the variegated construction and effects of the historically contingent race-ethnicity relationship on immigrants' unequal access to societal opportunities, recognition, and rewards.

An abundant literature shows a wide socioeconomic gap separating Latin Americans from other more successful immigrant groups. Most accounts explaining these disparities focus on the differential in average human-capital endowments, and on migrant-selectivity differences, ignoring the role that ethnoracialization may play in structuring immigrants' mode and relative success of incorporation. A few studies, meanwhile, demonstrate the significance of racialization on immigrant inequality (Frank, Akresh and Lu 2010, Maldonado 2009, Massey 2013, Villarreal and Tamborini 2018, Wong et al. 1998, Zhou 2012). More recently, some analysts have shown the role of ethnoracialization as a key mechanism of inclusion and exclusion among immigrants in the U.S. (Alcoff 2009, Saéns and Douglas 2015, Brown & Jones 2015, Flores-Gonzalez 2017, Ong and Gonzalez 2019). With the exception of Ong and Gonzalez (2019), for the most part, these studies use and define ethnoracialization as a generic theoretical concept to study immigrant and minority groups, such as Asian Americans and Latinx, but fall victim to the previously mentioned analytical fallacy of homogenizing immigrant national groups. We first address the race-inequality nexus by examining contemporary disparities between immigrant national groups' household income and socioeconomic status, controlling for their heterogeneous ethnoracial composition, using cross sectional repeated data collected by the U.S. Decennial Census and the ACS. Second, we examine how the intersection of ethnicity and race affects inequality within U.S.- and foreign-born groups.

The third question this study addresses is whether human capital effectively equalizes groups with similar endowments across ethnoracial lines, as the literature predicts. Often, analysts use the average levels of education and immigration status across national groups to explain differences in group's average socioeconomic outcomes. If this is the case, we could expect that migrants with similar human capital attributes (e.g., the same immigrant status, level of education, and level of English fluency) would earn similar incomes and attain similar socioeconomic status, regardless of their national ethnicity and racial identification. Race scholars have argued against this expectation due to dominant racial discrimination; however, the evidence provided to support this point has been mostly limited to white-black comparisons. By including U.S.-born minorities and all immigrant groups in the analysis, and controlling for their racial identification (white vs. non-white), sociodemographic characteristics, and human capital endowments, this study contributes to a better understanding of the effect of ethnoracialization on inequality, especially as it relates to the foreign-born.

We use two measures of inequality: Annual household income and socioeconomic status. Guided by contributions from existing scholarship on inequality, migration, racialization, and ethnoracialization, our study confirms some previously reported findings about the human capital/economic returns relationship, presents evidence that questions the equitability in the distribution of these returns, and makes three important contributions to our understanding of the migration-inequality nexus in the U.S.

The average predictive margins estimated from OLS models confirm that gender, human capital, and race are indeed key determinants of U.S. inequality structures. As expected, human capital, as a general factor, has a negative relationship with inequality (higher levels of education render lower levels of inequality and vice versa), while being female and identified as non-white are positively associated with inequality (women face higher inequality than men, as non-whites do vis-à-vis whites). Not surprisingly, the marginal effect results also show a stratification system dependent on origin with some Asian and European immigrant national groups earning the highest household income and holding the highest socioeconomic status, while their Latin American counterparts, especially Mexicans and Central Americans, consistently receiving the lowest incomes and having the lowest status, ceteris paribus.

On the other hand, when the interaction ethnicity*race (i.e., ethnorace) is introduced, the model reveals that race has different effects on different national immigrant groups. While for many groups, race is significantly associated with the allocation of socioeconomic rewards (i.e., non-whites receive lower rewards than their white coethnics, ceteris paribus), for other groups, race has either not significant effect, or its effects are mixed – i.e., affects negatively the income of non-whites from certain national origins, but makes no difference in their socioeconomic status.

Overall, Latin American immigrants, as well as U.S.-born people of Latin American descent, regardless of their racial identification (white or non-white), are significantly more likely to earn less and have a lower socioeconomic status than any other ethnic groups, after controlling for age, gender, education, household structure, citizenship status, English proficiency, and region of residence.

In sum, evidence demonstrates that race does not operate as an independent factor affecting similarly socioeconomic inequality between and within ethnic groups. Rather, its effect, or lack of, is mediated by its intersection with ethnicity. As such, we demonstrate how the concept of *ethnoracialization* captures the fluid dynamics of inclusion and exclusion engendered by race. The theoretical and practical implications of our findings should spur the expansion of inequality research to critically include consideration of the pervasive effects of ethnoracialization on the production and reproduction of inequality between groups until now perceived as ethnoracially homogeneous.

BACKGROUND

The study of inequality and social stratification has historically been at the center of sociological inquiry, from the classical works of Marx and Weber to those of Bendix and Lipset, Blau and Duncan, and Wright. Among social scientists, there is not a commonly accepted threshold separating tenable from untenable levels of socioeconomic inequality. Yet there is a consensus that growing inequality disrupts access to opportunities and resources and skews the distribution of societal rewards, leading to a more polarized social stratification structure, while inducing political instability and economic inefficiency (Galbraith 2016, Solt 2008, Stiglitz 2013, Western and Pettit 2010). Recently, the study of inequality has moved to center stage across the social sciences not only because of its explosive growth worldwide, but also because of mass protests against it that spread across the world in the aftermath of the Great Recession of 2008 (Gaby and Caren 2016, Giugni and Grasso 2015, Giugni and Grasso 2016, Yagci 2017). In 2011 alone, tens of thousands of people gathered to demand more equality and inclusion, from Cairo's Tahrir Square, to Madrid's Puerta del Sol, to London's St Paul's, and New York's Zuccotti Park. Their motto, "we are the 99 percent," launched in opposition to the plutocratic “one percent” (those who own a vastly disproportionate share of wealth and power), became the signature shorthand expression of the rebellion against contemporary inequality. Meanwhile, dense volumes on the subject by national and international economists became overnight bestsellers and the topic of radio and television talk shows.

In analyzing this trend, most recent scholars of inequality have tended to privilege macro structural explanations. Accordingly, the adoption of free market-centered economic and social public policies that promote deregulation, along with the contraction of state intervention across the world (first introduced since the late 1970s and accelerated after the end of the Cold War), led to a sharp and steady increase in the unequal distribution of income and wealth across countries, with a tiny minority of the population accumulating a disproportionate amount of the national income and wealth (Alvaredo et al. 2017, Franzini and Pianta 2016, Held and Kaya 2007, Huber and Solt 2004, Jacobs and Myers 2014, Piketty 2014, Stiglitz 2007, 2013, Volscho and Kelly 2012). This approach contrasts somewhat with more common, conventional micro-level studies, which favor a closer look at the determinants, dynamics, and on-the-ground experiences of inequality. In the United States, the vast majority of these studies focuses on the social determinants of inequality across different social groups. Special emphasis has been put on understanding inequalities between categorically defined groups (Cotter, Hermsen and Vanneman 1999, Massey 2007, Tilly 1999), especially by gender and race (men and women and mostly white-black socioeconomic outcomes) (Leicht 2008, Massey 2007, Ridgeway 2011).

Sociological research has demonstrated how categorical inequalities are constructed and reinforced not only in the everyday interactions of marginalized groups with members of the dominant group, but also institutionally through employers’ quotidian decisions about whom to hire for what positions, and under what conditions, and more generally through how employers selectively grant or deny access to opportunities and rewards. Accordingly, microsocial studies center on analyzing outcome differences such as income, educational, and occupational attainment and health wellbeing, between men and women, whites and blacks, and immigrants and natives, controlling for a host of covariates.

As increasing inequality becomes a generalized concern across societies, it is important to note that the goal is not to achieve absolute equality. For inequalities are inherent to the human condition, and social structures are shaped by the diversity of people's capabilities, potentials, drive, and desires, and their variation and value across social spaces and societies (Sen 1999). The main concern, rather, has to do with understanding what factors determine a *systematic*, *patterned*, and *socially structured* uneven distribution of economic resources and societal opportunities and rewards across different categories of persons and groups in specific societies at particular times. In this sense, the sociological study of inequality should expand beyond a purely economic focus on determining differences in wealth and income. Scholars should broaden their focus to also examine the socially induced differences between individuals and groups that shape quality of life and general wellbeing. Socioeconomic status, in a Weberian sense, is associated with sociopolitical power, social recognition, and productive skills. These unevenly distributed dimensions are intrinsically linked to the production and reproduction of economic inequality (Fraser 1995, Lamont, Beljean and Clair 2014). In keeping with this approach, we focus on socioeconomic inequality, defined as unequal access to economic attainment (i.e., income) and social recognition and standing (i.e., social status) between and within ethnoracial groups, particularly immigrants.

Racialization, Ethnoracialization and Inequality

A vast literature has demonstrated a significant and persistent relationship between inequality and race. Until recently, however, most of this literature zeroed in on African Americans, whose experience has thus far been shaped by a widespread institutionalized discriminatory and exclusionary treatment in economic and social interactions that has pushed them into a persistently disadvantageous position in society. However, racial exclusion is a global process. The question then is how does immigrants' individual racial identification affect their mode of incorporation? At present, dominant analytical models do not allow us to answer this question, for they assume that immigrant national groups are not only ethnically, but also racially homogeneous (Brown and Jones 2015). By definition, then, race is rendered analytically irrelevant for understanding immigrants' mode of incorporation into receiving societies.

The concept of ethnoracialization seems the most appropriate to guide the exploration of the migration-inequality relationship (Gans 2017, Alcoff 2009, Saéns and Douglas 2015, Brown & Jones 2015, Flores-Gonzalez 2017, Ong an Gonzalez 2019). We conceive of ethnoracialization as a process of differentiating and stratifying groups of people according to perceived patterns of difference along two main dimensions, phenotypical (racial) and sociocultural (ethnic). Contrary to conventional racialization analyses, however, we posit that race, and the concomitant processes of racialization and racist exclusion/inclusion practices, do not constitute a singular, monolithic, and independent dimension. Rather, the socially constructed meaning of race (as expressed by biological features, such as skin color or phenotype) is mediated by the perceived ethnic and cultural characteristics of the racialized group, including geographic origins, nationality, language, religion. Borrowing from Omi and Winant (1994: 111), we postulate that these arbitrarily constructed differences are interpreted as the manifestation of “profound differences” situated *within* ethnoracially identified persons, including qualities such as intelligence, physical ability, temperament, ethics, sexuality, and the like. Ethnoracialization thus constructs some sociocultural groups as “races” possessing significantly and immutably different capabilities and, therefore, deserving different societal opportunities and rewards, regardless of their actual individual sociodemographic endowments and abilities.

The study of ethnoracialization emerges as part of the growing sociological interest in uncovering general social mechanisms that produce and reproduce inequality (Lamont, Beljean and Clair 2014). Research on racialization beyond race has unveiled critical processes and mechanisms that contribute to the persistence of system-wide inequalities — from cognitive classification processes that allow people to identify and categorize others and, thus, justify their inclusion/exclusion (Maldonado 2009, Massey 2007), to nation-state bureaucracies and methods (such as the census and the law) that define, categorize, and unequally distribute resources to groups at the meso and macro levels (Omi and Winant 1994, Wimmer 2013). The study of ethnoracialization calls attention to the fluidity of racial categorizations within and between different ethnic groups, and their embeddedness in power relations across time and space (Saperstein and Penner 2012).

This is particularly evident when examining the migration-inequality relation. Some analyses treat migration reductively, as formed by a uniform group of foreign-born people, disregarding their national origins or racial identification (Cotter, Hermsen and Vanneman 1999, Milanovic 2016, Piketty 2014). Other studies, however, focus on how sociological dimensions such as ethnicity intersect with immigration to shape inequality levels between different immigrant groups (Massey 2013). This study, on the other hand, accounts for the inter- and intra-group racial and ethnic heterogeneity as a key determinant of unequal distribution of societal rewards, opportunities, and recognition. What do we know about the effect of the interaction between ethnicity, race, and inequality?

Migration, ethnoracialization, and Inequality

Many scholars agree that the mass displacement of people across national borders "is a powerful symbol of global inequality" and a clear reflection of its global dimensions (Black, Natali and Skinner 2005: 1, Faist 2016, Faist 2019). Yet no scholarly consensus exists about the direction of migration's effect on inequality in receiving societies. This lack of scholarly consensus is in part due to the diversity of epistemic approaches and plurality of foci among students of the migration-inequality nexus. Scholars of migration and race studying this issue examine the effects of immigration on receiving society's economy, look at immigrants' socioeconomic mode of incorporation into receiving society, and analyze their social standing as members of minority, underrepresented groups. Our inquiry brings these disparate foci together to contribute to a better understanding of the contemporary migration-inequality nexus in the United States.

One approach, mainly dominated by economists, is mostly concerned with immigration's economic effects on dimensions such as local wages, employment, and job stability (Alsalam and Smith 2005, Peri 2016, Xu 2018). Some economists posit that global migration is the "seemingly more peaceful form of redistribution and regulation of global wealth inequality" (Milanovic 2016, Piketty 2014: 538), and as one of the best ways to reduce global poverty (Pritchett 2006: 87). However, in the United States, the scholarship on this is mixed. Some analysts posit that immigration has a significant and positive impact on inequality (Borjas 2014, Hibbs and Hong 2015, Reed 1999, Xu, Garand and Zhu 2016), while others claim that its effects are negligible (Card 2009, Mason 2014, Peri 2007, Peri 2016), or even negative (Card and Peri 2016, Foged and Peri 2015, Milanovic 2016, Pritchett 2006). Borjas, for example, has persistently argued that immigration increases inequality. In general, Borjas considers that immigration across the board has a negative effect, for "low-skill immigrants will typically harm low-skill natives, while skilled immigrants will harm skilled natives," thus increasing inequality (Borjas 2007a: 5).

Meanwhile, accounts countering this assessment argue that immigration's impact on economic inequality is negligible or negative, for immigrants' work tends to complement, rather than displace native workers, often, engendering further economic opportunities, including increasing employment and salary growth. Overall, however, and irrespective of their assessment, most economic analyses tend to assume that immigrant workers are more or less perfect substitutes for U.S.-born workers with similar human capital characteristics (Card and Peri 2016, Ottaviano and Peri 2012). In keeping with this assumption, one could expect that immigrants' socioeconomic position should be similar to that of their U.S.-born counterparts, with similar levels of education and other human-capital characteristics.

Despite differences in how they assess the migration-inequality nexus, most economic studies tend to share two significant epistemic limitations. First, they neglect to take into account the effect of receiving societies' ethnoracialized perception and treatment of immigrants according to their racial identity and national origin. Such perception selectively provides or denies immigrants equal access to socioeconomic opportunities and rewards. Indeed, ethnoracialized stereotyping informs the categorization of immigrants, which results in unequal access to opportunities across immigrant national groups. As migration scholar Roger Waldinger points out about the ontological consequences of racialization of ethnicity:

> In a racialized society like the United States, entire ethnic groups are ranked according to sets of socially meaningful but arbitrary traits; these rankings determine fitness for broad categories of jobs. All other qualifications equal, members of the top-ranked group are picked first when employers decide whom to hire; the rest follow in order of rank (Waldinger and Lichter 2003: 8).

Prime illustrations of the fluid construction of ethnoracialized categorical inequality are the "model minority" labeling, where Asian immigrants in the U.S. are conceived of as entrepreneurial, technologically-savvy, scientifically-oriented, and assimilable (Wong et al. 1998); while, say, Mexicans are conceived of as unsophisticated, adept manual laborers and socioculturally unassimilable (Huntington 2004). As Massey has pointed out, the socially constructed boundaries demarcating categorical groups are legitimized through discourses that associate mostly positive attributes (e.g., intelligence, entrepreneurship, honesty, and so forth) with high-status in-group members, while members of low-status out-groups are perceived in largely negative terms (e.g., unintelligent, incompetent, lazy, dishonest, and so forth) (Massey 2007). This leads to the exclusion of low-status out-group members and shaping an unequal distribution of societal resources.

Second, most economic, and non-economic-focused studies presuppose that people hailing from the same country of origin form a homogeneous racial collective. This conception, informed by what some analysts dub methodological nationalism (Amelina et al. 2012, Wimmer and Glick-Schiller 2002), leads scholars to view immigrants as part of discrete national groups within which ethnoracial differences are either non-existent, or are deemed irrelevant.

Epistemologically, thus, immigrants' national identity is constructed and operationalized as a singular identity – i.e., immigrants are Mexican, English, German, Indian, tout court. The epistemic implications of this construct are significant because they blind analysts from examining potential patterns of inequalities *within* national immigrant groups due to not just sociodemographic differences (i.e., human capital), but to exclusionary processes of racialization (i.e., white vs non-white conationals).

Assimilation, human capital and ethnoracialization

Sociological literature on the incorporation of immigrants, on the other hand, has been dominated by assimilation theory (Alba and Nee 1997), a perspective that has been widely criticized, but still remains the canonical interpretation of how immigrants' incorporation process plays itself out. Assimilation theory privileges sociocultural and human capital characteristics as the main determinants of immigrant integration into receiving society. As such, immigrants' English-language proficiency and level of education are key indicators predicting the pace and success of assimilation. Accordingly, higher levels of education and full language proficiency are expected to facilitate swifter integration and social mobility in the host society (Borjas 2014, Gordon 1964). And as race, ethnicity, and racialization are not considered determining factors in this process, a key assumption at the core of assimilation theory is that immigrants have a single national identity and allegiance (Pickus 1998, Schuck 1998). Accordingly, national identity and national citizenship are defined as well-bounded characteristics, such that acquiring new ones implies abandoning those held previously. Therefore, becoming a naturalized U.S. citizen is a crucial measure of assimilation, and acts as a doorway to unfettered access to socioeconomic opportunities and rewards. Given all the above assumptions, naturalized and English-language- fluent immigrants are expected to be as socioeconomically successful as U.S. natives, ceteris paribus.

Critical assessments of classical immigrant assimilation theory argue that it cannot explain the experience of current immigrants' conditions and prospects in the U.S. Because it is based on the early experience of European immigrants, it predicts the eventual erosion of socioeconomic, cultural, and political differences between immigrants and their descendants, and the native population, such that immigrants and their descendants eventually come to resemble the dominant white, Anglo-Saxon and Protestant native population (Gordon 1964). More recently, however, several scholars have introduced a revised version of assimilation theory, arguing that it remains valid for the twenty-first century. The main difference with the original version, they argue, is that the mainstream population, as they call it, is much more diverse, including non-Protestant people. More significantly for our study, according to this new version, racism does not impede the incorporation of minorities, because racist practices are prevented by affirmative action policies and civil rights laws (Alba and Nee 2003). In the same vein, other scholars argue that this "return of assimilation" theory represents a "more analytically complex and normatively defensible understanding" of migrants' incorporation in receiving societies (Brubaker 2001: 543). For this renewed version of assimilation, Brubaker posits, the normative focus moves "from *cultural* to *socio-economic* matters," coupled with a "continuing robustness of processes of linguistic acculturation" (emphasis in the original, ibid.). Accordingly, assimilation theory shifts from expecting immigrants' complete absorption into U.S. society, to "focusing on a process of becoming similar (in some respect, to some reference population)" (ibid. p. 542). According to this view, we should expect that immigrants, regardless of their national origin and racial identification, would achieve similar levels of, say, average household income and socioeconomic status as their U.S. counterparts with the same social and educational characteristics.

Recent evidence lends support to some of these expectations. A study of migration in 27 countries in the European Union, for example, found that immigrants who have acquired citizenship and speak the dominant language perceive less discrimination. However, it also found that immigrants coming from socio-economically more developed countries with higher living standards (and who, for that reason, are "more comparable" to the native population) are less likely to perceive discrimination and more likely to have a social status similar to that of their native counterparts (André and Dronkers 2016).

The prevailing disregard for the potential effects of immigrants' own racial identity in the process of incorporation, including vis-à-vis their own conationals, in a ethnoracialized receiving society, we argue, obnubilates the analysis of the migration-inequality relationship (Bobo and Charles 2009, Bonilla-Silva 2018, Maldonado 2006, Marable 2006). As recent research in the emerging field of colorism demonstrates, light-skinned people, including white immigrants, tend to do better than dark-skinned ones (Faught and Hunter 2012, Hannon 2015, Perreira, Wassink and Harris 2018, Villarreal and R. 2018). This seems to be confirmed by case studies showing that dark-skinned Mexican Americans tend to do worse than their light-skinned counterparts in multiple dimensions of social life, including occupational attainment, income, and experiencing discrimination (Allen, Telles and Hunter 2000, Arce, Murguia and Frisbie 1987, Telles and Murguia 1990a). For instance, based on data from a national survey of males of Mexican origin in the U.S., Telles and Murgia (1990a: 694) found that "dark and native American-looking individuals of Mexican descent suffer significantly greater earnings disadvantages than their lighter and more European-looking counterparts." A similar finding was reported by Espino and Franz (2002), who found that darker-skinned Mexican and Cuban immigrants (respectively the first and seventh largest immigrant groups in the country) face significantly lower occupational prestige scores than their lighter-skinned counterparts, after controlling for factors shaping labor market performance. Other studies have also shown that other Latino groups, such as Puerto Ricans (Aranda and Rebollo-Gil 2004), Dominicans

(Itzigsohn 2009), and Central Americans (Rodríguez and Menjívar 2009), are also frequently negatively racialized.

In sum, ethnoracialization appears to closely articulate and shape the migration-inequality nexus. Paraphrasing Herbert Gans, we argue that ethnoracialization begins with the "voluntary or involuntary" arrival of new immigrants, whose origin in mostly non-white nations, makes them "different and underserving" (Gans 2017: 342). However, as discussed earlier, along with exclusionary processes, ethnoracialization can also be associated with processes facilitating the socioeconomic inclusion of some immigrant groups, as receiving societies perceive them as, borrowing from Gans, similar and deserving. Contemporary migration thus constitutes the fuel par excellence for the construction of ethnoracial diversity and inequality in U.S. society. Indeed, immigrants from Latin America, Africa, and some Asian countries are often perceived and treated as culturally, racially, and socially inferior and unrelated to receiving society, and are categorized as ethnic minorities. This perception and institutional treatment contrasts with those given to immigrants from the global North or select Asian countries, which are mostly non-white, such as India, China, and Korea (Rissing and Castilla 2014). These disparate ethnoracial perceptions significantly affect immigrants' mode of socioeconomic incorporation. To some extent, they suggest the emergence, as Bonilla-Silva (2002) proposes, of a new racial stratification structure. While the U.S. Census and the ACS do not have data on people's skin color, for our analysis we use people's racial self-identification to measure race and dichotomize it as white and non-white.

DATA AND METHODS

Data

Original data come from the Integrated Public Use Microdata Series (IPUMS) (Ruggles et al. 2018), 1 percent weighted sample of people who are between 18 and 65 years of age, are economically active, and have positive incomes. These data are taken from pooled U.S. Decennial Census from 1970 to 2000 and the 2010 American Community Survey (ACS). After data reduction, the pooled subpopulation includes harmonized data on some 5.5 million observations for the 40-year period (see Table A1.1 in the Appendix).

For variance estimation, we take into account that IPUMS data are drawn from complex design samples in which individual-level data are clustered by household, are stratified, and have different sampling probabilities. As a result, variance is drawn from primary sampling units (PSUs) that are weighted and summed across strata, rather than individual-level observations, which implies that error terms are no longer independent from one another. This, in turn, means that degrees of freedom are no longer derived from the sample size but are calculated as the number of PSUs minus the number of strata, minus the number of terms in the model (Lee and Forthofer 2006: 58). To achieve unbiased and conservative error estimates, we use Taylor-series variance estimation procedures. Our models' conditional means and variances are estimated using the design-weighted least squares (DWLS) method included in Stata's complex survey analysis command *svy* (Stata 15). This command makes full use of the sample expansion weights and the STRATA and CLUSTER technical variables provided by IPUMS-USA to compute linear regression coefficients and their respective standard errors.

Analytical Approach

Our goal is to capture the determinants and evolution of social inequalities along distinct temporal and spatial dimensions at both the individual and group levels. We operationalize migration as a heterogeneous process (patterned along a plurality of ethnic, racial, class, and sociodemographic characteristics) whose relationship with inequality is embedded in and influenced by historically changing structural conditions. Our analysis follows a two-step process. We first develop a set of models that use a conventional approach to immigration, that is, they measure immigration as if it were made up of homogeneous national (i.e., ethnic) groups with no internal racial differentiation; we then deploy a second set of models that includes the moderating effect of immigrants' racial identification; all while controlling for human capital characteristics and region of residence. We explain each of these models below.

Dependent variables

Informed by sociological research on stratification, we use two dependent variables in order to generate a more nuanced picture of the relationship between migration and inequality. Our main measurement of inequality is a synthetic socioeconomic index, the Hauser Warren Socioeconomic Index (HWSEI). This index is designed to measure individuals' socioeconomic status or what, in general terms, could be construed as social class (Hauser and Warren 1997). HWSEI is a composite measure provided by the weighted sum of occupational education and occupational earnings based on the occupational prestige classification scheme of the 1989 General Social Survey (GSS) and the 1990 census. By integrating education and earnings into the construction of occupational prestige, this index allows for a more holistic, sociological interpretation of socioeconomic inequality.

The second dependent variable is household income, measured as inflation-adjusted household annual income (HHINC) in 1999 dollars.[2] We choose household, rather than individual income, because it constitutes a better sociological dimension of people's living conditions, as it measures the amount of pooled resources nominally available to each individual. However, it is important to point out that household income is not exempt from measurement errors, some of which stem from the fact that IPUMS income data is top coded. This means that the effect of extremely high incomes in the estimation is excluded, artificially reducing inequality. This, we argue, makes our results even more significant. A log-transformation was performed on HWSEI and HHINC to smooth the distribution of both dependent variables and to reduce the effect of those individuals with a "0" or very low score, which positively skewed the distribution of the variables.

Independent Variables

We divide our independent variables into four main blocks: sociodemographic, socio-spatial, ethnoracial, and temporal. In the first set of OLS models (Table 1.2), we use U.S.-born, non-Hispanic (USNH) males as the reference group. Sociodemographic variables include age, sex (female=1), household characteristics, educational attainment, English proficiency (non-fluent=1), legal status (non-naturalized citizen=1), and race (non-white=1). To control for household characteristics, we include a member count in Household Size and an identifier of Two-headed Household (yes=1). Educational attainment is operationalized as a categorical variable (less than high school (reference), high school diploma, some college, college diploma, and more than college). Educational attainment, English proficiency, and legal status measure human capital.[3]

For our first set of models, which focuses on ethnicity, we dichotomize the U.S.-born population into U.S.-born non-Hispanic (reference group) and U.S.-born Hispanic.

Immigrants' ethnicity is operationalized from their country of origin. However, we limit the number of countries in the models to the top three sending countries from the three main continents of origin, Europe, Asia, and Latin America (the UK, Germany, and Italy; China, India, and the Philippines; and Mexico, the Central American Northern Triangle (El Salvador, Guatemala, and Honduras), and Cuba). Those coming from other countries are included under a separate variable (other European; other Asia, other Latin American). Given their low numbers in the sample, we grouped immigrants from the rest of the world (Africa, Oceania, and other parts) into a single "Other Immigrants" category.

Meanwhile, we use socio-spatial variables to capture the relationship between place of origin and U.S. residence and inequality. They include the dichotomized categories of the U.S. Census' nine geographical divisions to control for region of residence at the time of the census (Pacific [reference], New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, and Mountain). As indicated earlier, we also consider immigrants' country and continent of origin, as a socio-spatial category associated with the way the receiving society perceives them. Finally, we use census year as a temporal control variable.

Models

First, we start the exploration with OLS models to estimate the mean log household earnings (log HHINC) and log Hauser-Warren Index of Socioeconomic Inequality (log HWSEI) for U.S.-born and immigrant national (i.e., ethnic) groups from 1970 to 2010. Second, also using OLS models, we introduce the moderating effect of the race*ethnicity interaction, controlling for the other variables in the original model. We assume that any differences found in this second set of models could be due to differential human capital levels across groups, in addition to race and ethnicity. Hence, we add controls for multiple human capital factors (i.e., education, legal status, English fluency) to ethnicity*race as predictors of household income and socioeconomic status.

Results from the first set of OLS models (Table 1.2) show a significant uneven distribution of inequality among immigrant national groups, such that some immigrants, particularly those coming from Latin America, consistently do worse than immigrants from other parts of the world, ceteris paribus (a detailed description of these results is presented in the next section).

However, while robust, these initial models do not account for the moderating effects of race and, thus, do not address a key concern guiding our inquiry, namely, the role that immigrants' racial identification plays in structuring patterns of socioeconomic disparities. This limitation could render regression main effects insufficient to reach valid conclusions regarding a possible ethnoracialization of inequality. We thus develop a second set of models adding the *ethnicity*race* interaction term to account for this effect (Table 1.3). For ease of interpretation and visualization, we graph the ratio of each immigrant group's average predictive margin of household income and socioeconomic status to USNHW's, based on the results from the OLS model (Figures 1.2 and 1.3).

RESULTS

Table A1.1 in the Appendix presents the definition and general frequency distribution of the variables in the model. The observations in the pooled sample are almost evenly divided by gender (45 percent female). Over one half of the sample has at least a high school diploma, almost one quarter have college or higher levels of education, and another quarter have some college education. Around 28 percent of the total sample is non-white and over one-third (36 percent) are immigrants, a figure that confirms immigration's role in the growth of ethnoracial minority groups during the 1970-2010 period. Overall, immigrants constitute around 15 percent of the total sample, with the largest proportion hailing from Latin America (43 percent) and Asia (25 percent). Europeans represent around one-fifth of all immigrants. Mexico is by far the largest migrant-sending country (26 percent), followed by the Central American Northern Triangle (El Salvador, Guatemala, and Honduras, 5 percent), and the Philippines (4 percent).

Descriptive statistics and historical trends

Descriptive statistics in Table 1.1 show the evolving distribution of the DVs and of select sociodemographic covariates for the three largest immigrant continental groups (Asians, Europeans, and Latin Americans) and U.S.-born, non-Hispanics (USNHs). These data indicate that overall average log of annual household incomes (log HHINC) and socioeconomic status (log HWSEI) are higher in 2010 than in 1970. However, such growth follows an unequal, stratified pattern across groups, in which European and Asian immigrants take the top positions, while Latin Americans remain consistently at the bottom. By 2010, Asian immigrants rank at the top, as they have the highest average socioeconomic status (3.609915 log HWSEI, or a 37 score in 2010, a 13 percent increase from 1970) and household income (10.91729 log HHINC, or
$55, 121, in 1999 dollars, a 25 percent increase from 1970). Asian immigrants are followed by European immigrants and USNHs. At the opposite end of the distribution, Latin American immigrants show the lowest log scores in both average socioeconomic status (3.219465 log HWSEI, or 25 score in 2010, a paltry one percent increase from 1970) and household income (10.46902 log HHINC, or $35,208, in 1999 dollars, a 3 percent *decline* from their average

household income in 1970).

Not surprisingly, and as predicted by most existing studies, descriptive data of covariates in Table 1.1 reveal patterns that seem to explain the unequal patterns just described. For example, the average level of education of every group between 1970 and 2010 significantly increases, suggesting a continuous positive selectivity of all immigrants, a trend also reported by recent studies (Card and Raphael 2013). This increase in average education, however, follows the same unequal growth pattern of the dependent variables, with Asian immigrants consistently located at the top of the educational attainment distribution. Over one-half of Asians (52 percent) report having a college degree or higher level of education in 2010 (16 points higher than forty years earlier), 20 points higher than U.S.-born, non-Hispanics (32 percent) the same year. At the other end of the educational spectrum, Latin Americans report the lowest educational attainment with just 11 percent reporting high educational attainment in 2010, 2 points higher than they had in 1970. Conversely, Latin Americans present the highest proportion of people with the lowest educational attainment. Similarly, Latin Americans also present the highest (and increasing) rate of non-naturalized people (71 percent in 2010) and persistent high levels of lack of English proficiency. These characteristics compare unfavorably to those of European and Asian immigrants, whose proportion of non-naturalized and non-fluent English speakers tend to be much lower.

Interestingly, however, the proportion of non-naturalized citizens and non-fluent English speakers among Europeans and Asians move in opposite directions during the period under study. So while the proportion of the non-naturalized Europeans significantly increases (from 32percent to 55 percent), that of Asians' substantially decreases (from 60 percent to 42 percent), at a time when immigration from Asia is the fastest growing in the U.S. (Batalova, Shymonyak and Mittelstadt 2018). Similarly, while the proportion of non-fluent English speakers among Europeans has slightly increased, that of Asians' has significantly decreased.

The unequal and patterned distribution of educational attainment, naturalization, and language proficiency roughly follows the distribution pattern of the two dependent variables and coincides with existing arguments and empirical findings in the literature emphasizing the significant and positive effect of human capital on immigrants' economic attainment and social status. In sum, these descriptive statistics show that Asian and Latin American immigrants represent ideal examples supporting the predictions of assimilation theory and human-capital-based arguments. How do these general, bivariate trends relate to immigrants' racial identification?

Descriptive statistics show a general increase in racial diversity since 1970 (Table 1.1). For example, while less than one percent of European immigrants identify themselves as non-white in 1970, 6 percent do so in 2010. Similarly, the proportion of non-whites among Asians and Latin Americans also significantly increases during this period. This trend produces a rather mixed picture vis-à-vis the changes observed in the dependent variables: A greater presence of non-whites among Europeans and Asians seems to coincide with these groups' increasing average household income and socioeconomic status, as well as with increasing within-group income inequality. On the contrary, a greater proportion of non-white Latin Americans coincides with a drop in the group's average household income, a meager improvement in their average socioeconomic status, and decreasing within-group income inequality.

Before we address these paradoxical patterns using multivariable analyses, we briefly examine the historical context and patterns in which the relationship between racial identification and household income and socioeconomic status is embedded.

Table 1.1 about here

Figure 1.1 provides a general picture of historical changes in the distribution of the two dependent variables by immigration and racial identification. Figure 1.1a shows a patterned stratification of average log household income (log HHINC) by continent of origin and racial identification during the 1970-2010 period. Accordingly, non-white immigrants tend to do worse than both their continental counterparts and U.S.-born, non-Hispanic whites (USNHW). The exceptions to this pattern are non-white Asians, who are the top average household income earners by 2010, after being almost at the bottom of the income distribution 40 years earlier.

Latin Americans, regardless of their race, consistently remain at the bottom throughout the period. The difference between the average income of white and non-white Latin American household gradually decline to the point of almost disappearing in the last decade.

Induced by the Great Recession, all groups saw their average household income decline in the last decade, with white and non-white Latin American and white Asian households experiencing the sharpest income reduction. It is important to emphasize here that the largest intra-group income gap occurs between white and non-white Asian households. Together, these results confirm recent accounts about the uneven effect of the great recession on minority groups in the U.S. and offer some initial clues to explain increasing economic inequalities within panethnic immigrant groups (Kochhar and Cilluffo 2017, Kochhar and Cilluffo 2018).

Historical trends in the distribution of socioeconomic status (log HWSEI) seem to reproduce the unequal, stratified trends observed in the evolution of household income, albeit in a more polarized manner. Indeed, Figure 1.1b reveals that when comparing socioeconomic status by immigrants' continent of origin (ethnicity) and race (white vs non-white), white Asians are at the top throughout the 1970-2010 period (3.6083 log HWSEI in 1970 and 3.605 in 2010). By 2010, they were followed by non-white Asians, white and non-white Europeans, and USNHWs, respectively. Meanwhile, Latin Americans remain far at the bottom, with non-white Latin American immigrants showing the lowest, and most stagnant, socioeconomic status (3.1751 and 3.1855 log HWSEI, in 1970 and 2010, respectively). White Latin Americans follow a declining path getting closer to the socioeconomic status of their non-white counterparts following a pattern of declining internal inequality. Meanwhile, the gap separating Latin Americans' socioeconomic status from the rest of the population seems to be widening at an increasing pace, forming what appears to be a bipolar distribution by 2010 (Figure 1.1b). The multivariable analyses that follow are modeled to uncover the determinants of these patterns of inequality. The first set of OLS models includes sociodemographic and spatial variables and immigrants grouped into single national (ethnic) groups, assuming no internal racial differentiation, as the current literature sees them. The second set of models measures the moderating effect of race on each national group (ethnicity*race interaction), while controlling for all the covariates in the original model.

Figure 1.1 about here

Ethnicity and inequality

Tables 1.2 presents the results of the first set of OLS models. Column I presents results for log HHINC for the full 1970-2010 period, while column II presents the results for log HWSEI. These results confirm that gender, race, household structure, and social capital are significantly correlated with both DVs.

To begin, holding all the other variables constant, women appear to endure a significant economic disadvantage throughout the entire period, as their mean household income is 4 percent (($e^{-.045} - 1$)*100= - 4.4) smaller than that of USNH males. Moreover, looking at the historical trend (data not shown), this disadvantage seems to be increasing as women's household income in 2010 was 7 percent smaller than that of USNH men, as compared to just 2 percent smaller 40 years earlier. Meanwhile, women's socioeconomic status has continued to lag behind that of USNH males, as their HWSEI score is 3 percent smaller for the period.

These initial models also confirm the overall significance of race on inequality, as being non-white appears negatively associated with both log HHINC and log HWSEI. Meanwhile, household structure, as measured by its size and headship characteristics, is also significantly associated with inequality, as larger households tend to earn higher incomes (Table 1.2, column I), but have lower socioeconomic status (Table 1.2, column II). Conversely, single-headed households are significantly penalized in terms of income and status, as their average income is almost two-fifths smaller (($e^{(-.484)}$ -1)*100 = - 38) than the average earnings of two-headed households, while their average HWSEI score is 4 percent lower than the latter's.

OLS model results in Table 1.2 also show that educational attainment, as predicted by existing literature, represents the most powerful factor associated with higher household income and socioeconomic status. Higher skilled people tend to have significantly higher than average household earnings and socioeconomic status than lower skilled ones, ceteris paribus.

OLS models also show an uneven socio-spatial distribution of inequality across the U.S. Overall, the Pacific Division (the reference)[5] offers the highest average household income, followed by the New England Division.[6] Meanwhile, the West South Central

Division[7] appears to be the most unequal in terms of household income, all other variables held constant.

Our main interest, however, centers on the mean (β coefficient) of log household income and log HWSEI for ethnic groups. The full OLS model results reveal a stratified distribution of inequality across ethnonational groups from across different regions of the world. Ceteris paribus, OLS estimates indicate that European and Asian immigrants would earn the highest average household incomes (Table 1.2, column I). Immigrants from India and the UK appear at the top, as their average household earnings are the highest, respectively, at 23 percent and 19 percent higher than USNH's. Then again, the average household income of the vast majority of Latin American immigrants, as well as that of U.S.-born Hispanics' (USHs) are significantly lower than that of the reference group. However, immigrants from Central America's Northern Triangle are the only Latin Americans who show a slightly higher average HHINC (4 percent) than USNH's. By far, Mexican immigrants earn the lowest average household income (some 12 percent lower than that of the reference group).

The distribution pattern of socioeconomic status reproduces that of household income's. In effect, the OLS model for socioeconomic status (Table 1.2, column II) shows that most European, all Asian, as well as all "other immigrants" (i.e., immigrants from other parts of the world) have higher average log HWSEI than that of the reference group, after controlling for all the other variables. Once again, Indians possess the highest mean log HWSEI, followed by UK immigrants and "other" Asian immigrants. In sum, these findings confirm that Asian immigrants possess the highest average socioeconomic position in the U.S.

The only ethnic groups showing a negative log HWSEI coefficient are Italian and "other" European immigrants, as well as Latin Americans, with the exception of Cubans, whose mean socioeconomic status is not statistically different from that of the USNHs. Thus, on average and after controlling for all other variables, Mexicans are less likely to have a higher socioeconomic status than any other immigrant group.

Yet our central question remains: How does race moderate the effect of ethnicity on inequality as measured by the two dependent variables? That is what the next set of models address.

Table 1.2 about here

Ethnoracial identification and inequality

In order to measure the moderating effect of race, we run OLS models using the same covariates included in the initial models plus the interaction ethnicity*race. To examine the interaction effects, we use Average Marginal Effects (AMEs), which produce a single quantity summary that reflects the full distribution of X values. AMEs average across the variability in the fitted outcomes, capturing variability better than marginal effects at means (Leeper 2018: 8). Table 1.3 shows the OLS β average predictive margins of the adjusted log household income (column I) and log socioeconomic status (column III) across ethnoracial groups, net of all the covariates. To facilitate the interpretation of the results, we also include the equivalent income value in 1999 U.S. dollars (column II) and Hauser-Warren SEI scores (column IV). In addition, to better capture distribution patterns, we include Figures 1.2 and 1.3, which respectively show the ratio of the average annual HHINC and average HWSEI scores of each group to those of the reference group (USNHW), based on the full model results.

AMEs results display a more nuanced stratification system than the one produced by initial models. The average predictive margins confirm that, ceteris paribus, race is a statistically significant factor shaping inequality between and within ethnic groups. Overall, they confirm that European and Asian immigrant groups locate at the top, while Latin Americans and U.S.-born non-whites and Hispanics stay at the bottom.

Non-whites, with a few exceptions, exhibit lower mean household incomes and socioeconomic status than their white ethnic counterparts. However, the effect of race is not consistent, as it affects ethnic groups differently, which supports our expectation that race is not a fixed, rigid factor affecting all ethnic groups equally. For example, departing from the dominant white-advantage trend, non-white Italian, Indian, and Filipino immigrants appear to earn a significantly higher average household income than both their white conationals and the reference group, ceteris paribus (Table 1.3, column I). On the other hand, while the average household income that non-white British immigrants earn is significantly higher than that of USNH whites, it is significantly lower than that of the white British. These mixed patterns occur during a period when the proportion of non-whites and the average level of education significantly increased across all immigrant groups (see Table 1.1). In turn, the high socioeconomic position of Asians also coincides with U.S. mainstream's changing perceptions of Asians from being considered undesirable and unassimilable "others," to be seen as a model minority and selectively targeted for recruitment into high-tech occupations and for giving them preferential treatment in the allocation of work permits and resident visas (Ho 2003, Rissing and Castilla 2014, Torres 2017).

After controlling for all the variables in the model, non-white Indians appear to have the highest average household income ($69,334), some 40 percent higher than U.S.-born, non-Hispanic whites ($49,613), the control group (Table 1.3, column II). Meanwhile, U.S.-born, non-Hispanic non-whites, U.S.-born Hispanics, and all Latin American immigrants earn the lowest average household incomes, with white and non-white Mexican households earning less than half of non-white Indians and around one third less than USNH whites (Table 1.3, column II). Tellingly, U.S.-born, non-Hispanic non-whites' average household income ($34,338) is similar to that of white and non-white Mexican immigrants ($33,793 and $34,857), albeit lower than that of white and non-white U.S.-born Hispanics and other Latin American immigrants. To better appreciate the unequal distribution pattern of average household income, Figure 1.2 presents the ratio of the average household income of each ethnoracial group to that of the reference, based on the results from the full OLS model. The significantly diverse effect of race across ethnic groups is evident.

Table 1.3 and Figures 1.2 about here

OLS models on HWSEI, for the most part, reproduce the patterns observed for HHINC's (Table 1.3, columns II and IV, Figure 1.3). In effect, most Asian and a select group of European immigrant groups, as well as white immigrants from other parts of the world, exhibit average socioeconomic status higher than that of USNHW, ceteris paribus. Once again, Latin Americans, as well as USNH non-whites and people of Latin American descent, consistently do worse than any other groups holding the lowest average socioeconomic status. White and non-white Indians, as well as white Filipinos, white Chinese, and whites from other Asian countries hold higher status than USNH whites. Meanwhile, non-white Filipinos and non-whites from other Asian countries possess a similar socioeconomic status as USNH whites. Among Europeans, only white and non-white British and white Germans hold average HWSEI scores higher than that of USNH whites. Non-white Indians exhibit the highest socioeconomic status, with a HWSEI score 31 percent higher than that of the control group, while Mexicans and

Central Americans possess the lowest.

Figure 1.3 about here

Race and within-group inequalities

Based on the full model, Table A1.2 (in the Appendix) presents the simple contrasts of the marginal linear predictions of the log HHINC and log HWSEI decomposing the effect of race within each group, using whites as the reference. From these results we identify three different types of racial effects, which are summarized in Table 1.4. First, for three groups (Italians, Indians, and Central Americans), out of the 16 being analyzed, race is not statistically significant in determining either average HHINC or HWSEI of coethnics, ceteris paribus. Incidentally, the first two national groups in this category locate at the top of the income and socioeconomic status distribution, while the last locates at the bottom end of it. Italians, whose average socioeconomic status is significantly lower than that of USNH whites, despite earning a higher average household income than them, until relatively recently, used to be one of the most racialized and stigmatized European immigrants (Gambino 1974, Staples 2019). Incidentally, Central Americans experience a similar fate of negative stereotyping and discriminatory marginalization today. In contrast, white and non-white Indians, who until 1965 were officially excluded from membership in the U.S. polity, are now the top household earners and hold the highest socioeconomic status today. In sum, for these immigrant groups what determines their socioeconomic inclusion or exclusion is their national identity (where they are from), rather than their racial identification, keeping all the other covariates constant. This suggests some sort of ethnic essentializing, in which race does not seem to play a role in determining patterns of inequality. As such, social stratification follows a pattern determined by societal valuation: Some groups are at the top, while others are at the bottom, due to characteristics appreciated as intrinsically associated with their national identity.

The second type of effects reflect existing expectations according to which race reliably determine inequality. Here, ceteris paribus, race consistently eclipses ethnic identification in shaping socioeconomic outcomes, regardless of people's group affiliation. The majority of the U.S. population falls into this category, including USNH, Germans, Filipinos, Cubans, as well as "other" immigrants from Asia, Latin America, and other regions of the world. Germans are the only Europeans in this group. Incidentally, the majority of non-white Germans are of African descent, as are non-white Cubans and "other" Latin Americans, all of whom tend to earn lower household incomes and hold lower socioeconomic status. Contrary to the first category, here race seems to override ethnicity in structuring patterns of intra-group inequality. But this racialized inequality does not necessarily follow the U.S. conventional racialization pattern (whites do better than non-whites). Indeed, non-white Filipinos on average earn a significantly higher household income, although they seem to hold lower socioeconomic status, on average (see Table 1.3).

For the third group, race has a mixed effect on inequality outcomes: Race significantly affects the income of white and non-white coethnic households, but is not statistically correlated with socioeconomic status. This is the case of U.S.-born Hispanics, British, Chinese, and Mexican immigrants, as well as immigrants from other European countries. With the exception of non-white Mexicans, non-whites in all the groups show lower household incomes than their white coethnics. This mixed effect of race suggest the intersection of two different logics of stratification. On the one hand, for the most part, race seems to work in the economic realm as expected, with whites earning higher incomes than non-white coethnics, thus, helping to maintain internal inequality and racial divisions. On the other, ethnicity, rather than race, determines the group's socioeconomic position, regardless of the racial identification of its members, while keeping all the other variables constant.

Table 1.4 about here

The robustness and consistency of our results point out to the importance of ethnoracialization as an uneven and fluid process structuring socioeconomic inequality between and within U.S.- and foreign-born groups. OLS coefficients and predictive average marginal effects reveal that human capital is not rewarded equally across ethnoracial groups. These findings confirm that, ceteris paribus, Latin American immigrants (most especially Mexicans) and U.S.-born Hispanics (or Latinos) and USNH non-whites, persistently receive the least rewards for their human capital endowments in comparison to all other ethnoracial groups. This is true even at the top of the human capital distribution, that is, among the most skilled and "most assimilable" immigrants.

Moreover, data not shown here, consistently indicate that this disadvantage also stubbornly persists for these ethnoracial groups at every level of formal education: From High-School dropouts, to High-School graduates, to those with some college education, to college graduates. In the case of Mexicans, paradoxically, these data also suggest that the higher their level of education, the bigger their disadvantage vis-à-vis equally trained USNH whites.

DISCUSSION AND CONCLUSIONS

Our study presents comparative evidence showing the persistence of ethnoracial inclusion and exclusion across multiple national-origin groups during a four-decade period. In keeping with expectations from assimilation theory, it could be assumed that antidiscrimination and affirmative action legislation would prevent racial and ethnic exclusion. Therefore, one could find that immigrants with similar human, cultural, and legal capital endowments (i.e., similar level of education, English proficient, and being naturalized U.S. citizens) would attain similar household income and socioeconomic status. Consistent with extant literature on racial exclusion, the evidence shows, that despite antidiscrimination policies, a persistent marginalization of most non-white (with the exception of Asians) and Latin-American-origin people, as their human capital is rewarded at a lower rate than that of their counterparts. On the other hand, and consistent with race scholarship findings, we expected that in an ethnoracialized society like the U.S., phenotypical features (i.e., race) would be the main factor structuring socioeconomic opportunities, regardless of people's ethnic origins (Bonilla-Silva coloristic stratification in the U.S.). Yet the evidence shows that the normative expectation of white-inclusion and non-white-exclusion does not pan out to dominate the experience of Asian immigrants and Latin-American-origin people.

Results demonstrate the significant, albeit uneven, fluid role that race plays in determining the allocation of societal rewards, net of groups' human capital endowments and sociodemographic characteristics. As such, race works differently across ethnic groups: Being identified as white or non-white appears to carry with it different practical implications for different groups. Nationality thus emerges as a crucial site mediating the meaning and effects of racialization as a positive, negative, or neutral attribute.

In light of existing knowledge, it is reasonable to posit that, ceteris paribus, the effect of race is contingent on its intersection with ethnicity, inasmuch as society selectively perceives, values, and rewards some ethnic groups above others. This historically-embedded process, ends up penalizing the members of some groups who are perceived as unworthy (or unassimilable, in the case of immigrants) and thus denied equal access to societal opportunities and rewards, while preferring and rewarding other groups by rendering them as superior, special, or of equal worth as the dominant group. As such, the human capital endowments of the former are devalued, which leads to their secular marginalization, while the latter's are praised, which paves the way to their successful incorporation. Thus, rather than working as a singular, absolute categorical determinant of inequality, race and its effects are contingent on people's ethnic (i.e., national) origins or ancestry, rather than on their actual physical or biological characteristics alone (i.e., white vs non-white). In this sense, in contemporary U.S. society, the meaning and opportunities granted to, say, a non-white British, or a non-white Indian immigrant are far superior than those afforded to a white Mexican or Central American, or a U.S.-born white Hispanic with similar human capital level. For this reason, we argue, our findings provide strong support for ethnoracialization as a process that overlaps with, but is distinct to, racialization.

Ethnoracial categorization and discrimination is not a static and well-bounded process that allows us to categorically define people according to their physical appearance or skin-color tone in isolation of other socially-binding, non-physical characteristics. Accordingly, our findings suggest that the social meaning assigned to people's phenotype is actually mediated by people's sociocultural characteristics, such as nationality (i.e., ethnicity), language, religion, names, and accents, among others. Ethnoracialization, thus, explains the reasons why the effects of racial identification among Asian immigrants seem to follow a different, almost diametrically opposite direction than the one observed among Latin American immigrants and U.S.-born people of Latin American descent. Ethnoracialization constitutes a more nuanced alternative- analytical category to the color-coded stratification proposed by Bonilla-Silva (2002), which privileges skin color as the sole dimension of racial inclusion/exclusion.

Contrary to explanations proposed by economists and assimilation scholars, we find that socioeconomic inequalities across racial and ethnic groups cannot be fully explained by differences in human capital. Our findings suggest that exogenous contextual factors explain significant differences in average household income and socioeconomic status across ethnoracial groups, rather than different levels of human capital endowments. Indeed, after controlling for human capital and other sociodemographic and socio-spatial characteristics, ethnoracialization appears to be the mechanism shaping the unequal distribution of social and economic rewards across ethnoracial groups in the U.S. We find that human capital, widely accepted as one of the most powerful mechanisms of social mobility and immigrant assimilation, proves to work as expected for some immigrant groups but not for others, ceteris paribus. For some Latin American immigrants, most especially Mexicans, the higher their human capital, the more distant they seem to be from matching the household income and socioeconomic status of USNHWs who possess similar endowments. The opposite is true for most Asian and European immigrants, regardless of their racial identification. This finding coincides with results from recent studies, one of which concludes that "the gap in earnings between Hispanic and black immigrants on the one hand, and white and Asian immigrants on the other, is even larger among men with a college degree than among those without one" (Villarreal and Tamborini 2018: 707). Similarly, in reference to the persistent effect of race and ethnicity on U.S. inequality, another study posits that "even when we control for education, we find that the wealth of college-educated Whites is more than 13 times greater than college-educated Blacks and Latinx. In fact, Whites without a high school degree have significantly more wealth, on average, than Black and Latinx college graduates" (Carter 2018: 24).

Immigrants coming originally from different Latin American countries, despite their significant national sociocultural differences, appear to have successfully been constructed as forming a singular ethnoracial group in the U.S. As a result, they and their offspring seem to face a similar socioeconomic fate, as earlier studies report. Over a decade ago, in reference to the experience of racialized exclusion expressed by Latin American immigrants and their offspring, Alejandro Portes concluded that "The initially implausible but socially created belief that Hispanics are a race has definite consequences on the plans, perceptions, and actions of young people adapting to mainstream U.S. society" (Portes 2007: 287). Similarly, Telles and Ortiz (2008) argue that the fact that many or most Mexican Americans are perceived as nonwhite could negatively affect the entire group by further ethnoracializing them. Ortiz and Telles' (2017) findings on the exclusion of Mexican Americans, lend further support to our own results on the marginalization of U.S.-born Hispanics. Their study reports "virtually no generational progress between the second and third generations on a wide range of socioeconomic indicators," while third-generation Mexican Americans appear to have "hit a ceiling in U.S. society" (452). They further suggest that this ethnoracializing process also affects other Latino groups, such as Central Americans, Dominicans, and Puerto Ricans (453). The othering (Schwalbe et al. 2000) of Latin-American-origin people, particularly those from Mexico, help explain their persistent exclusion. Oppressive othering is expressed in the racialized construction of Mexicans as an inferior ethnoracial group as articulated in public narratives describing them as uneducated and criminals, which provide legitimacy to official and non-official practices of exclusion.

Despite the trend towards the homogenization of continental and national groups, the evidence shows that racial identification (white vs non-white) remains a powerful mechanism of inclusion and exclusion and a significant determinant of intragroup inequality. For very few groups (Italians, Indians, and Central Americans) race proves to be not significant for explaining within-group inequalities. However, for the majority, racial identification is a significant determinant of within-group inequalities, as non-white-average-household income and status tends to be lower than those of white coethnics. Some case studies have reported this intragroup, race-driven inequality process among Mexican-origin people in the U.S. They found that dark- skinned Mexican Americans and Mexican immigrants earn significantly lower incomes “than their lighter and more European-looking counterparts primarily because of labor market discrimination” (Espino and Franz 2002, Telles and Murguia 1990b: 694).

What are the macrosocial implications of this ethnoracial process of inclusion and exclusion, in light of the immigration-driven, growing diversity of the U.S. population?

According to sociologist Eduardo Bonilla-Silva, demographic changes and increasing ethnoracial diversity, including Latinos surpassing African Americans as the largest minority group, leads to the end of the U.S. bi-racial (white-black) order and its evolution “into a complex tri-racial system.” He describes such tri-racial system as formed by “whites” at the top (including European-American whites, European immigrants, some Asian-origin people, and “assimilated white Latinos”), “honorary whites” in the middle (including “light-skinned Latinos” and some Asian-origin people), and “collective blacks” at the bottom (including African Americans, “dark- skinned Latinos,” some Asian-origin people, and African immigrants) (Bonilla-Silva 2002: 4).

This racial taxonomy, Bonilla-Silva argues, determines U.S. socioeconomic stratification system. Yet, he recognizes, his broad argument is “hard to verify empirically” (Ibid. p. 5). Our results provide partial support to this argument, as far as pointing at the end of the U.S. bi-racial stratification order. Yet we question some of the main assumptions informing it: First, Bonilla-Silva's tri-racial system only considers racial variation among Latin American-origin people, but not among other groups. By doing so, the model assumes, second, that all European immigrants are white, which our study refutes. Finally, the proposed model seems to equate race with color, inadvertently simplifying the complex and fluid construction of race as it intercepts with ethnicity, as documented here.

Proposing an alternative U.S. racial stratification model is beyond the scope of this paper. However, the evidence suggests a reconfiguration of the U.S. stratification system in which significant numbers of non-whites (e.g., non-white British and Italians, and white and non-white Asians) become part of a new dominant elite, while, many white Latin-America-origin people end up at the bottom along with some non-white Europeans (e.g., non-white Germans and non-whites from other European countries), African Americans, and other minorities.

Two decades ago, questioning the validity of the white-black racial paradigm, which legitimizes the argument that U.S. society is free of class divisions, Jaynes (2000: 9) argued that this paradigm "will survive only if all new immigrant groups become successful in the United States, leaving the black poor at the bottom of the social structure. If, however, significant proportions of some immigrant groups join poor African Americans at the bottom, a new paradigm of race and class relations may emerge." The evidence presented here lends support to Jaynes' prediction.

This ethnoracialized stratification system has not only ontological, but epistemological consequences. For it affects not just immigrant national groups' mode of incorporation, but also seems to shape scholars' research agenda. Indeed, research on Asian and European immigration is greatly skewed toward the study of the highly skilled, while that on Latin American immigration is almost exclusively focused on poor and uneducated workers. This lopsided approach flights in the face of the fact that, numerically, there are many more highly-skilled immigrants in the U.S. from, say, Mexico than from countries such as the UK, Germany, Canada, or Korea (reference withheld). Such a skewed research agenda, we posit, unwittingly contributes to the consolidation of ethnoracialized stereotypes and exclusionary practices.

Looking forward, in order to better understand the growing inequality gap in U.S. society and its implications, scholars should seek to tease out the dynamics and fluid effects of the intersection of inequality and racial and ethnic identification. This task requires more focused, comparative inquiries deploying multiple methodological strategies and, ideally, conducted by multidisciplinary research teams. To close, we want to recall the late Samuel Huntington's admonition, which although motivated by quite a different preoccupation calls attention to the urgency of addressing the secular and intensifying marginalization of Latin-America-origin people in the U.S.: "If this trend continues, the cultural [and socioeconomic] division between Hispanics and Anglos could replace the racial division between blacks and whites as the most serious cleavage in U.S. society" (Huntington 2009).

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ENDNOTES

[1] "Minority" refers to people who report their ethnic and racial identity as something other than non- Hispanic White alone in the decennial census (U.S. Census Bureau, decennial census of population, 1970 (5 percent sample), 1980 to 2010).

[2] Household Income includes the total income of the householder and all other individuals 15 years old and over in the household, whether they are related to the householder or not. Total income is the sum of the amounts reported separately for wage, salary, and all other kind of income, including all type of public assistance support.

[3] Research shows that immigrants typically receive no return to their pre-migration experience (Friedberg 2000). Following Friedberg's we argue that immigrants' human capital is reduced to their formal educational attainment, language skills, and legal status. Immigrants' number of years in the U.S. was not included as a covariate in the model due to high collinearity with age. [4] The VFR two-stage estimator is appropriate here as the variance estimators in Stata's **svy** command are generalizations of White's heteroskedasticity-robust estimators, and therefore, correct for the heteroskedasticity in the error terms by design.

[5] Alaska, California, Hawaii, Oregon, and Washington.

[6] Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont.

[7] Arkansas, Louisiana, Oklahoma, and Texas.

Table 1.1. Descriptive statistics for an analysis of the effects of migration on annual household income (HHINC) and socioeconomic status (HWSEI), 1970-2010

	1970				2010			
	US Non-Hisp	Europe	Asia	Latin America	US Non-Hisp	Europe	Asia	Latin America
Log HHINC	10.68655 (.0010457)	10.79816 (.0056156)	10.68467 (.0149945)	10.49479 (.0107581)	10.748 (.0013243)	10.89446 (.0067633)	10.91729 (.0053352)	10.46902 (.0041114)
Variance of log HH Income	.5630378	.5127759	.6619485	.6040769	.8703233	.7890835	.8055824	.4831805
Log HWSEI	3.434229 (.0005143)	3.369643 (.003358)	3.48618 (.0097404)	3.204965 (.0054197)	3.552063 (.0004998)	3.586376 (.0030948)	3.609915 (.0025393)	3.219465 (.0015916)
Variance of log HWSEI	.1586236	.2032851	.2935255	.2032151	.1579612	.173644	.198026	.1534863
Age	39.11 (.0158567)	44.61 (.0983662)	38.07 (.2057074)	37.89 (.141482)	41.01 (.016743)	42.61 (.0875599)	41.78 (.0579517)	38.65 (.0480169)
Female	.384 (.0004158)	.3984 (.0030365)	.3791 (.0069655)	.3738 (.0048213)	.4821 (.0004699)	.4740 (.0029449)	.4692 (.0018766)	.3882 (.001567)
More than College	.0567 (.0002967)	.0710 (.0018546)	.2312 (.0073725)	.0521 (.002613)	.1090 (.00036)	.1981 (.0027141)	.2242 (.002151)	.0336 (.0006524)
College	.0746 (.0003377)	.0574 (.0016613)	.1238 (.0056728)	.0351 (.0021646)	.2101 (.0004996)	.2228 (.0028931)	.2980 (.0023056)	.0725 (.0009932)
Some College	.1386 (.0004386)	.1220 (.0023311)	.1493 (.0060171)	.1013 (.0035583)	.2770 (.0005631)	.2364 (.003038)	.1854 (.0019578)	.1438 (.0014291)
High School	.3752 (.000619)	.2758 (.0032697)	.2020 (.0066927)	.2095 (.0049495)	.3550 (.0006063)	.2979 (.0033302)	.2115 (.0021649)	.3365 (.0020227)
Less than High School	.3549 (.0006278)	.4738 (.0037959)	.2936 (.0080646)	.6020 (.006264)	.0489 (.0002857)	.0449 (.0014852)	.0810 (.0014999)	.4136 (.0022725)
Non-white	.1093 (.0002907)	.0060 (.0006118)	.6393 (.009056)	.0672 (.0035963)	.1521 (.0005541)	.0625 (.0018558)	.8872 (.0017833)	.3885 (.0027087)
Non-citizen	n.a.	.3164 (.0037313)	.5997 (.0086976)	.6576 (.0063001)	n.a.	.5542 (.0037111)	.4172 (.0027517)	.7124 (.001987)
Non-fluent in English	.0012 (.0000423)	.1965 (.0029718)	.4457 (.008757)	.6828 (.0055596)	.0040 (.0000728)	.2239 (.0032352)	.3915 (.0026974)	.6712 (.0020646)
n (subpopulation obs.)	686,706	20,735	4,039	8,005	1,100,798	31,743	66,310	98,131
N (subpopulation size)	68,670,600	2,073,500	403,900	800,500	109,725,508	3,256,178	7,053,084	12,775,081

US population 18 to 65 years old in the labor force and with positive incomes.
Standard errors in parentheses

Table 1.2. U.S.: OLS Beta regression coefficients of the log Adjusted Household Annual Income (HHINC) and log Hauser Warren Socioeconomic Index (HWSEI) on sociodemographic, geospatial, and ethnic-origin characteristics of population 18 to 65 years old in the labor force, 1970-2010

	Log HHINC Full Model β	Log HWSEI Full Model β
	I	II
Sociodemographic		
Age	0.041***	0.016***
	(0.000)	(0.000)
Age*Age	-0.000***	-0.000***
	(0.000)	(0.000)
Female	-0.045***	-0.027***
	(0.001)	(0.000)
Household Size	0.172***	-0.012***
	(0.000)	(0.000)
Single-headed household	-0.484***	-0.038***
	(0.001)	(0.000)
Non-white	-0.191***	-0.060***
	(0.001)	(0.000)
Non-fluent in English	-0.169***	-0.110***
	(0.002)	(0.001)
Non-citizen	-0.109***	-0.035***
	(0.003)	(0.001)
Educational Attainment		
More than College	0.807***	0.747***
	(0.002)	(0.001)
College Diploma	0.652***	0.565***
	(0.001)	(0.001)
Some College	0.352***	0.317***
	(0.001)	(0.001)
High School Diploma	0.227***	0.150***
	(0.001)	(0.000)
Sociospatial		
U.S. region of residence		
New England Division	0.012***	0.010***
	0.002)	(0.001)
Middle Atlantic Div.	-0.018***	-0.003***
	(0.002)	(0.001)
East North Central Div.	0.083***	0.025***
	0.002)	(0.001)
West North Central Div.	-0.184***	-0.037***
	(0.002)	(0.001)
South Atlantic Div.	0.119***	0.009***
	0.002)	(0.001)
East South Central Div.	0.274***	0.042***
	(0.002)	(0.001)
West South Central Div.	-0.182***	0.003***
	(0.002)	(0.001)
Mountain Div.	0.158***	0.012***
	0.002)	(0.001)
Ethnonational groups		
US-born population		

US-born Hispanic	-0.076***	0.003***
	(0.002)	(0.001)
Foreign-born population		
United Kingdom	0.175***	0.060***
	(0.006)	(0.003)
Germany	0.114***	0.024***
	(0.005)	(0.002)
Italy	0.104***	-0.045***
	(0.007)	(0.003)
Other European countries	0.046***	-0.015***
	(0.004)	(0.002)
India	0.203***	0.106***
	(0.008)	(0.003)
China	0.044***	0.030***
	(0.009)	(0.003)
Philippines	0.151***	0.009**
	(0.006)	(0.003)
Other Asian countries	0.053***	0.048***
	(0.004)	(0.002)
Mexico	-0.131***	-0.031***
	(0.004)	(0.001)
CANT§	0.039***	-0.027***
	(0.008)	(0.003)
Cuba	-0.062***	0.003
	(0.008)	(0.003)
Other Latin American countries	-0.014**	-0.021***
	(0.005)	(0.002)
Other countries	0.056***	0.027***
	(0.004)	(0.002)
Time period		
1980	0.056***	-0.005***
	(0.001)	(0.001)
1990	0.066***	-0.021***
	(0.001)	(0.001)
2000	0.129***	-0.012***
	(0.001)	(0.001)
2010	0.021***	-0.031***
	(0.001)	(0.001)
Constant	9.346***	2.979***
	(0.005)	(0.002)
Observations	8,198,932	8,136,894

Standard errors in parentheses.
Data source: 1 percent sample pooled from 1970-1990 US Decennial Census and 2000-2010 ACS.
Reference variables: Less than High School for educational attainment, Pacific Division for U.S. region of residence, and US-born Non-Hispanic males for ethnonational groups. For the full model, 1970 is the reference for time period.

§ CANT = Central American Northern Triangle (Honduras, Guatemala, El Salvador).

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.3. OLS Beta Average Predictive Margins of the log Adjusted Household Annual Income (HHINC) and log Hauser Warren Socioeconomic Index (HWSEI) on sociodemographic, geospatial, and ethnoracial characteristics of population 18 to 65 years old in the labor force, 1970-2010.

	Log HHINC		Log HWSEI	
	Full Model β	1999 US$	Full Model β	HWSEI Score
	I	II	III	IV
US-born Non-Hisp White	10.812*** (0.001)	49,613	3.532*** (0.000)	34
US-born Non-Hisp Non-White	10.444*** (0.002)	34,338	3.387*** (0.001)	30
US-born Hisp White	10.612*** (0.003)	40,619	3.420*** (0.001)	31
US-born Hisp Non-White	10.532*** (0.004)	37,496	3.394*** (0.002)	30
UK White	10.989*** (0.007)	59,219	3.629*** (0.003)	38
UK Non-white	10.922*** (0.031)	55,381	3.658*** (0.014)	39
German White	10.857*** (0.006)	51,896	3.550*** (0.003)	35
German Non-white	10.582*** (0.028)	39,419	3.488*** (0.012)	33
Italian White	10.890*** (0.008)	53,637	3.348*** (0.004)	28
Italian Non-whites	10.915*** (0.085)	54,995	3.435*** (0.035)	31
Other Euro White	10.871*** (0.004)	52,628	3.492*** (0.002)	33
Other Euro Non-white	10.649*** (0.029)	42,150	3.449*** (0.012)	31
Indian White	10.945*** (0.041)	56,670	3.782*** (0.020)	44
Indian Non-white	11.149*** (0.009)	69,494	3.799*** (0.004)	45
Chinese White	10.934*** (0.052)	56,050	3.629*** (0.029)	38
Chinese Non-whites	10.790*** (0.010)	48,533	3.504*** (0.006)	33
Filipino White	10.870*** (0.032)	52,575	3.584*** (0.016)	36
Filipino Non-white	11.049*** (0.007)	62,881	3.538*** (0.004)	34
Other Asian White	10.832*** (0.009)	50,615	3.623*** (0.004)	37
Other Asian Non-white	10.804*** (0.005)	49,217	3.522*** (0.002)	34
Mexican White	10.428*** (0.004)	33,793	3.166*** (0.002)	24
Mexican Non-whites	10.459*** (0.005)	34,857	3.141*** (0.002)	23
CANT White§	10.550*** (0.011)	38,177	3.182*** (0.004)	24

CANT Non-white§	10.554*** (0.011)	38,330	3.157*** (0.004)	23
Cuban White	10.659*** (0.009)	42,574	3.424*** (0.004)	31
Cuban Non-white	10.520*** (0.027)	37,049	3.352*** (0.012)	29
Other Latin American White	10.697*** (0.007)	44,223	3.407*** (0.003)	30
Other Latin American Non-whites	10.593*** (0.009)	39,855	3.320*** (0.004)	28
Other Immigrants White	10.898*** (0.005)	54,068	3.580*** (0.003)	36
Other Immigrants Non-whites	10.626*** (0.006)	41,192	3.433*** (0.002)	31
Observations	8198932		8136894	

Standard errors in parentheses
Data source: 1 percent sample pooled from 1970-1990 US Decennial Census and 2000-2010 ACS.
Reference variables: Less than High School for educational attainment, Pacific Division for U.S. region of residence, and US-born Non-Hispanic males for ethnonational groups. For the full model, 1970 is the reference for time period.
§ CANT = Central American Northern Triangle (Honduras, Guatemala, El Salvador).
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.4. Summary of the effect of racial identification on socioeconomic inequality within ethnoracial groups – Non-whites vs whites

Effect	HHINC	HWSEI	Cases
No effect	•	•	Italian, Indian, CANT
Negative effect	–	–	**USNH**, German, Filipino, Other Asian, Cuban, Other Latin American, Other immigrants
Mixed effect	–	•	**USH**, UK, Other European, Chinese, Mexican

- No significant statistical difference

– Significant negative statistical difference

Table A1.1. Summary Statistics and Variable Definitions.

Variable	Definition	Mean	SE	Min	Max
Dependent Variables					
Hauser Warren Socioeconomic Index (HWSEI)	Log transformation of occupational status provided by the weighted sum of occupational education and occupational earnings based on the occupational classification scheme of the 1989 General Social Survey (GSS) and the 1990 census.	3.495	.000423	1.96431	4.38863
Household Income (HHI)	Log Transformation of self- reported total household income of previous calendar year, adjusted for inflation.	10.756	.000000	-.26919	14.3972
Independent Variables					
Sociodemographic					
Age (years)	Respondent's age	38.725	.006114	15	65
Sex	Female=1; Male=0	.449	.000176	0	1
Non-Citizen	Non-naturalized=1; Naturalized=0	.068	.000166	.06816	.06880
Non-English Fluent	Non-fluent=1; Fluent=0	.063	.00016	.06288	.06349
Household Size	Number of individuals residing in the household	2.600	.001052	1	10
Two- Headed Household	Two-headed HH=1; Other=0	.661	.049320	0	1
Education	Respondent's educational attainment				
Less than High School	Yes=1; No=0 (reference category)	.159	.000187	0	1
High School Graduate	Yes=1; No=0	.365	.000249	0	1
Some College	Yes=1; No=0	.239	.000219	0	1
College Diploma	Yes=1; No=0	.150	.000184	0	1
Postgraduate Education	Yes=1; No=0	.088	.000143	0	1
Race (US-Born)					
Non-Hispanic White	Yes=1; No=0 (reference category)	.718	.000240	0	1
Non-Hispanic Black	Yes=1; No=0	.096	.000151	0	1

Non-Hispanic Asian	Yes=1; No=0	.007	.000049	0	1
Non-Hispanic Other Race	Yes=1; No=0	.011	.000062	0	1
Hispanic White	Yes=1; No=0	.031	.000100	0	1
Hispanic Non-White	Yes=1; No=0	.016	.000078	0	1
Sociospatial					
US region of residence					
Pacific Division	Yes=1; No=0 (reference category)	.156	.000214	0	1
New England Division	Yes=1; No=0	.055	.000137	0	1
Middle Atlantic Division	Yes=1; No=0	.151	.000217	0	1
East North Central Division	Yes=1; No=0	.171	.000226	0	1
West North Central Division	Yes=1; No=0	.073	.000160	0	1
South Atlantic Division	Yes=1; No=0	.175	.000225	0	1
East South Central Division	Yes=1; No=0	.058	.000138	0	1
West South Central Division	Yes=1; No=0	.104	.000182	0	1
Mountain Division	Yes=1; No=0	.058	.000139	0	1
Ethnoracial					
Immigrants' continental origin					
Europe	Yes=1; No=0	.023	.000081	0	1
Asia	Yes=1; No=0	.029	.000099	0	1
Africa	Yes=1; No=0	.004	.000040	0	1
Latin America	Yes=1; No=0	.080	.000153	0	1
Other World Regions	Yes=1; No=0	.012	.000067	0	1
Immigrants' ethno-national origin by race (Main countries of origin by continent)					
UK White	Yes=1; No=0	.003	.000027	0	1
UK Non-White	Yes=1; No=0	.000	.000008	0	1
German White	Yes=1; No=0	.004	.000032	0	1
German Non-White	Yes=1; No=0	.000	.000010	0	1
Italian White	Yes=1; No=0	.002	.000026	0	1
Italian Non-White	Yes=1; No=0	.000	.000003	0	1

Other European White	Yes=1; No=0		.012	.000063	0	1
Other European Non-white	Yes=1; No=0		.000	.000011	0	1
Indian White	Yes=1; No=0		.000	.000006	0	1
Indian Non-white	Yes=1; No=0		.004	.000042	0	1
Chinese White	Yes=1; No=0		.000	.000004	0	1
Chinese Non-white	Yes=1; No=0		.003	.000038	0	1
Filipino White	Yes=1; No=0		.000	.000007	0	1
Filipino Non-White	Yes=1; No=0		.005	.000049	0	1
Other Asian White	Yes=1; No=0		.004	.000034	0	1
Other Asian Non-white	Yes=1; No=0		.012	.000069	0	1
Mexican White	Yes=1; No=0		.016	.000091	0	1
Mexican Non-white	Yes=1; No=0		.013	.000085	0	1
Central Amer. Northern	Yes=1; No=0		.003	.000042	0	1
Triangle White* Central Amer. Northern	Yes=1; No=0		.003	.000047	0	1
Triangle Non-white* Cuban White	Yes=1; No=0		.003	.000034	0	1
Cuban Non-white	Yes=1; No=0		.000	.000012	0	1
Other Latin-American White	Yes=1; No=0		.006	.000052	0	1
Other Latin-American Non-white	Yes=1; No=0		.004	.000046	0	1
All other Immigrants White	Yes=1; No=0		.006	.000036	0	1
All other Immigrants Non- white	Yes=1; No=0		.010	.000056	0	1
n (unweighted sample)		5,524,767				
N (Pop)		560,993,137				

* Central American Northern Triangle includes immigrants from El Salvador, Guatemala, and Honduras.

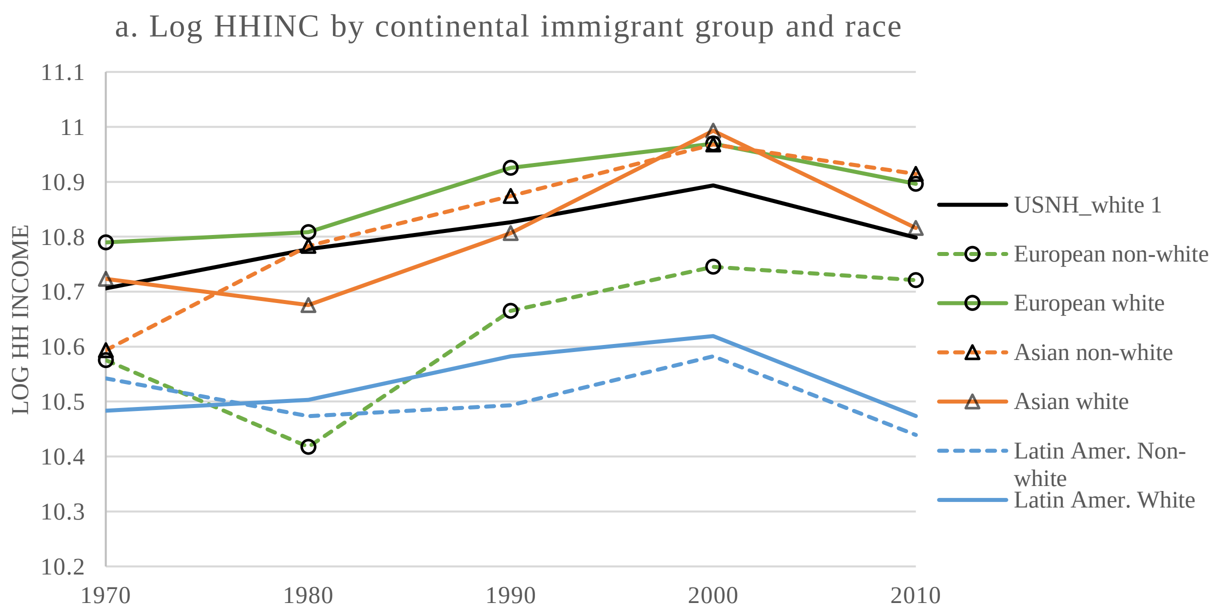
Note: 1% sample IPUMS USA Decennial Census Data, 1970-2010; subpopulation 18-65 years old in the labor force with positive incomes.

Table A1.2. Simple contrasts of marginal linear predictions of log HHINC & log HWSEI that decompose Race effects within ethnoracial groups using whites as reference.

	Log HHINC	Log HWSEI
	I	II
(Non-White vs White) US-born Non-Hispanic	-0.22588***	-0.0738***
	(0.00152)	(0.0005)
(Non-White vs White) US-born Hispanic	-0.06953***	-0.0017
	(0.00430)	(0.0016)
(Non-White vs White) UK	-0.06895*	-0.0180
	(0.02733)	(0.0118)
(Non-White vs White) German	-0.12568***	-0.0244*
	(0.02449)	(0.0098)
(Non-White vs White) Italian	0.04790	0.0257
	(0.07159)	(0.0293)
(Non-White vs White) Other Euro	-0.15246***	-0.0133
	(0.02588)	(0.0096)
(Non-White vs White) Indian	0.03767	-0.0171
	(0.03653)	(0.0157)
(Non-White vs White) Chinese	-0.15711***	-0.0267
	(0.04349)	(0.0193)
(Non-White vs White) Filipino	-0.07707**	-0.0633***
	(0.02694)	(0.0127)
(Non-White vs White) Other Asian	-0.02883**	-0.0277***
	(0.00924)	(0.0033)
(Non-White vs White) Mexican	-0.02859***	-0.0022
	(0.00625)	(0.0021)
(Non-White vs White) CANT	-0.02689	-0.0070
	(0.01405)	(0.0048)
(Non-White vs White) Cuban	-0.06854**	-0.0368***
	(0.02482)	(0.0099)
(Non-White vs White) Other LatinAm	-0.06852***	-0.0146***
	(0.00970)	(0.0038)
(Non-White vs White) Other Immigrants	-0.24859***	-0.0812***
	(0.00692)	(0.0027)

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 1.1. U.S.: Log HH Income and log HWSEI by Continental Immigrant Groups and Race, 1970-2010



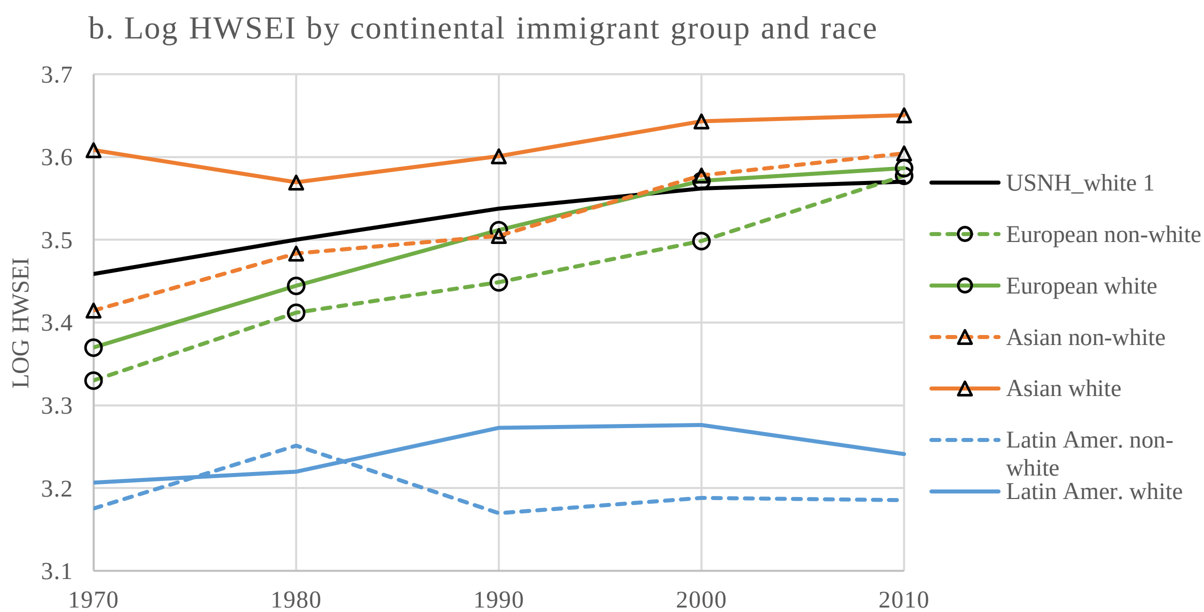


Figure 1.2. HHINC Ratio of ethnoracial groups' to USNHW's (1999 US$), based on full OLS model - 1970-2010

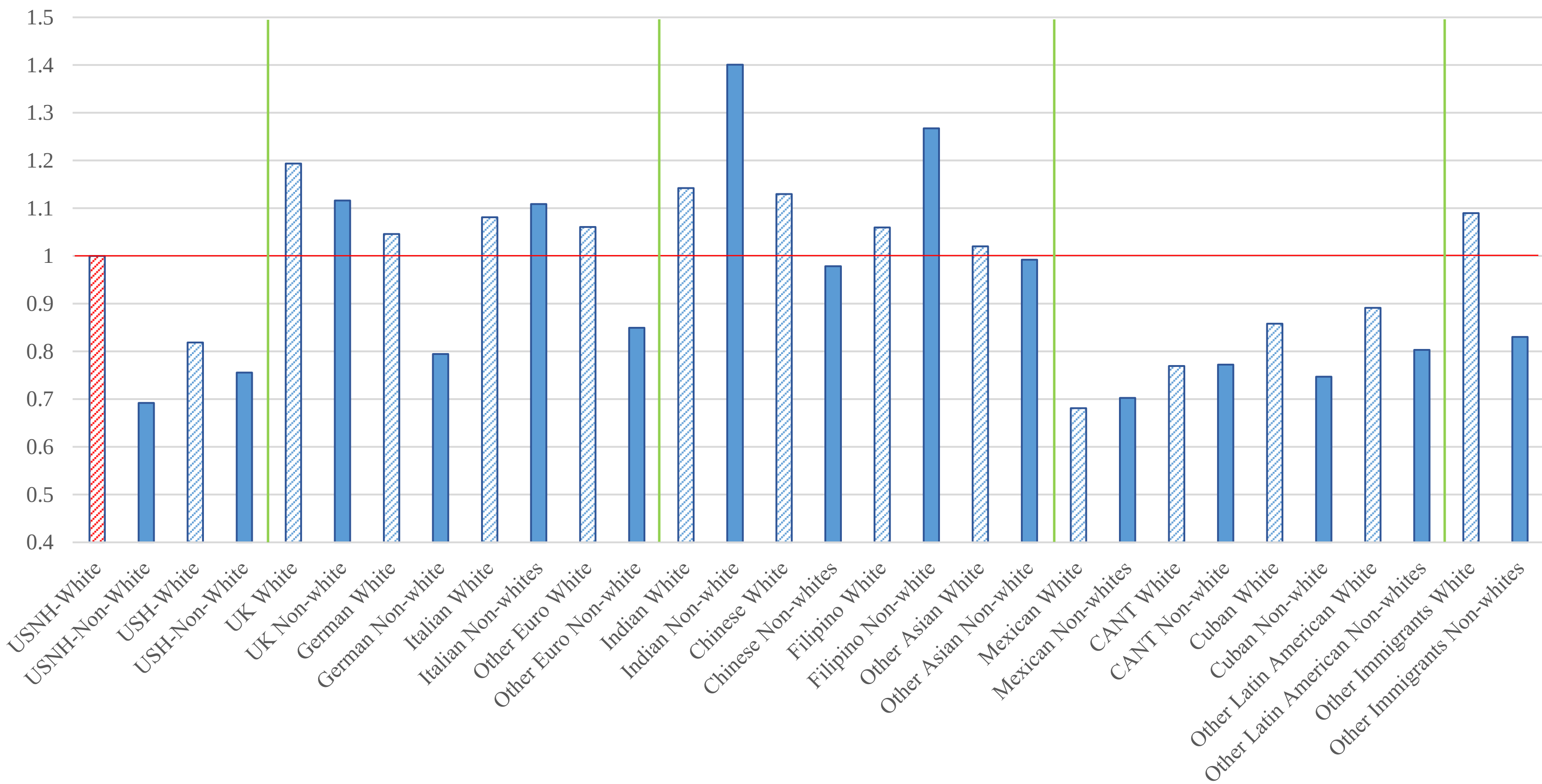
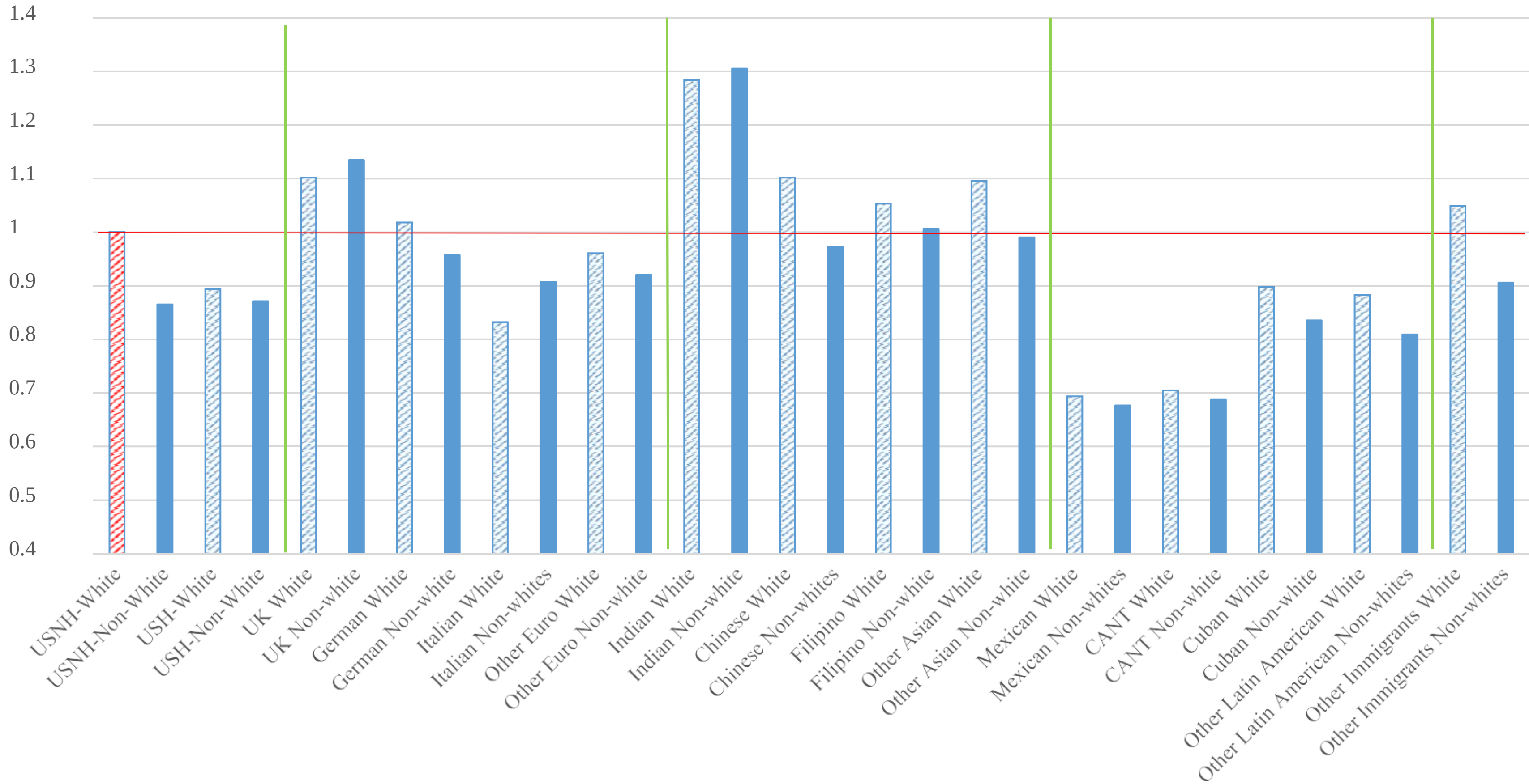


Figure 1.3. U.S.: HWSEI Ratio of ethnoracial groups' to USNHW's, based on the full OLS model - 1970-2010



CHAPTER 2:
Racialization of Immigrant Ethnicity and Occupational Attainment in the Western U.S. Labor Market

INTRODUCTION

The impact of ethnoracializing immigrant labor force on their occupational status has yet to be thoroughly explored. This article uses a quantitative approach to provide empirical evidence of the socioeconomic effects of working in the U.S.' ethnoracialized context, while being cognizant of the important effect of human capital endowments and other employee characteristics on the occupational status of immigrants. The main contribution of this study to existing literature is to challenge the accepted and widely proven notion that education (both how much of it and where it was attained), language proficiency, and legal status, are the main drivers of high levels of occupational status; not because they are not so, but rather, because there are systematic differences in how diverse ethnoracially divided sub-populations are rewarded for maximizing these endowments. In other words, the relationship between worker characteristics and their occupational status is not only mediated by the skills brought to the table by immigrant workers, but also by how these workers are perceived and (de)valued by employers due to their ethnoracial origin.

Dominant narratives of labor market social relations disregard the mounting research on the demand-side (employer) effect on differential outcomes, which since the early 70's has been referred to as *labor market discrimination* (Ashenfelter and Rees 2015, Becker 1971). Consequently, Western developed labor markets are framed as being rational, objective, and disembedded from social contexts (including racialized prejudices); while workers, who cannot escape their social condition, absorb their employers' subjectivities. The analytical approach of my research originates from this epistemological tension, and makes the argument that as a social institution (Hughes 1949), the labor market has inherent ontological inefficiencies that produce and reproduce racialized discriminatory practices that militate against the supposedly leveling effects of neutral factors such as human capital.

RESEARCH PLAN

To examine how the racialized U.S. social context in which the labor market operates affects the occupational status attainment of native and immigrant ethnic groups, this paper measures the effect of the interactions between the ascribed and achieved characteristics of workers on labor market outcomes as a marker of socioeconomic status differentials. As ascribed characteristics I include the socio-demographic markers of gender, age, and marital status, and the cultural conditions of nativity and ethnic identity. As the achieved characteristics I control for the socioeconomic achievements of workers regarding their educational attainment and where this education was obtained; and their assimilatory practices such as English proficiency and legal status. Aside from providing compelling empirical evidence of the racialization of ethnicity (ethnoracialization), my main contribution to the literature is bridging established opposing analytical perspectives that rarely communicate with one another and have two main shortcomings. The first perspective is a *supply-side* approach and frames labor market outcome inequalities as being mainly the result of differences in worker's acquired skills, assuming that the labor market is a space free of subjective social action. The second perspective comes from a *demand-side* approach and starts with the assumption that discrepancies in labor market outcomes of equally skilled employees are based mainly on systematic or institutionalized practices that ascribe racialized characteristics to employees depending on their ethnic origin. These ascriptions result in a clear division of labor, with some groups being rewarded with a higher occupational status, and others, while equally endowed, being penalized. This paper examines the rationality and objectivity of the market as proposed by supply-side market fundamentalists by using empirical analysis of the effect of human capital on market outcomes when other factors of influence are controlled for, and by measuring how these effects are moderated by immigrant-specific achieved characteristics across ethnic groups. Additionally, this paper addresses the shortcomings of demand-side market structuralist and post-structuralist research, which tends to sample on the dependent variable by selecting only those marginalized populations whose detrimental labor market outcomes are evident. This bias in research design mechanically eliminates some of the variance of the outcome variable, which can exaggerate the magnitude and significance of the findings and may result in a confirmation bias and false inferences. To avoid this common mistake, I include quantitative analyses of occupational status attainment of ***all*** the working population in the ACS, both native and immigrant, and grouped by ethnic origin. To further prevent biasing my findings, I also include a broad range of occupational status determinants deemed important by labor market researchers in several disciplines. By addressing the abovementioned research flaws, the resulting findings can be readily incorporated into discussions of occupational attainment inequality by scholars with different epistemological backgrounds and research agendas.

The results presented here support previous findings of the significant effect of human capital accumulation for predicting occupational status differentials between ethnic groups. In addition, results also show the moderation effects of English fluency, legal immigrant status, and educational origins discussed in the literature. However, once respondents are grouped by ethnic origin, and interactions between the main predictors are factored in, three main patterns of the racialization of ethnicity emerge. First, immigrant workers with a low level of education are more likely to have occupational status scores that differ relatively little from natives', regardless of English fluency or legal status. This suggests that, in aggregate terms, the low skill segment of the labor market is rather inclusive and, in a sense, seems to adhere well to conventional conceptions of free labor market ideals. Second, as educational attainment of workers increases, the labor market becomes less impartial and the negative effects of discrimination are increasingly manifested for racialized immigrant ethnic groups, especially Mexicans and Central Americans. Third, and finally, the moderating effects of indicators of assimilation, namely, English language proficiency and legal immigrant status, on socioeconomic status are highly dependent on workers' level of education and ethnic identification. While highly educated Asian and European immigrants reap the rewards of being fluent in English, independent of their legal immigration status, highly educated Mexicans and Central Americans are not rewarded for their fluency in English and are penalized excessively for being undocumented. These trends strongly suggest that the U.S. labor market is not only stratified by human capital achievement, fluency in English, and access through immigration documentation, but also by the subjective negative preconceptions that employers, coworkers, and clients have about the ethnically racialized work force.

The paper is structured as follows. The first section defines the main concepts and theoretical principles; reviews the literature on labor market outcome differentials from which two main hypotheses are derived. The second section describes the data and methods utilized. The third, and last section, presents a discussion of the implications suggested by the study's findings and draws some general conclusions.

ANALYTICAL BACKGROWND

Before delving into theoretical, methodological, and analytical discussions, I provide the definitions of the main sociological concepts, utilized in this paper. *Ethnicity* is defined by Martin N. Marger as a socially constructed categorization applied to groups within a larger society that are usually bound by "unique culture, sense of community, ethnocentrism, ascribed membership, and territoriality" (2003:15). Of special relevance to this paper is the territorially based sense of community that set the boundaries of the twelve ethnic groups included in the analysis. For the native-born, a real or imagined common ancestry served as a delimiter, and for immigrants, their continental region of birth. Next, *Racialization*, is a highly contested concept in sociological theory and practice (for a thorough overview of the term's history and development see Murji and Solomos 2005) and as such, it needs to be carefully defined. I use racialization beyond its racial conception and focus on its similar shared effect on ethnic determinism. In accordance, the race construct as an analytical concept in this paper is deliberately minimized from the framework as the ethnic categorization is seen to subsume it (Bonacich 1972:548). Floya Anthias and Nira Yubal-Davis, argue that linking the racialization process to only the social construction of race and its implications would "exclude the experiences of immigrant ethnic groups […], which construct them as inferior, but not on the premise of a supposed racial categorization, but as cultural, political or national outsiders and undesirables" (1992:11). Departing from Anthias and Yubal-Davis, I propose that the going beyond race in the definition of racialization is not tied only to a construction of inferiority and undesirability, as this misses the effects of positive ethnic ascriptions, such as the *model minority* phenomenon. Thus, racialization is the process of essentializing groups on the basis of assumptions about its members' positive or negative physical or cultural variations, the meanings of these perceptions, and their concomitant effects. *Ethnoracialization* is, then, the process by which stereotyped traits and expected behaviors are attributed to groups that share a common immediate or historic geographic origin and are deemed inferior or superior, undeserving or deserving, and undesirable or desirable.

The theoretical framework guiding this study evolved from the field of economic sociology of immigration introduced by Portes, Roberts, Sassen, and Granovetter among others in their 1995 seminal book titled after the field's name (Portes 1995). The authors challenged the neoclassical economic notions of a rational and impartial value-free labor market providing extensive theoretical and empirical evidence of the strong influence of the social environment on economic decisions, experiences, and outcomes of labor market participants. However, the Weberian and Schumpeterian principles bridging the economic and the social schools of thought in Portes' volume tend to remain partial to the moral virtues of labor demand-side actors rather than exposing their sometimes irrational and prejudicial nature. As indicated by Merton in his foreword and replicated by the authors throughout the book, Schumpeter went "to some pains to exclude ethnic variation in his analysis of class formation" (Merton in Portes 1995:vii). The result of steering away from acknowledging the role of ethnoracialization on uneven labor market outcome trends results on an economic sociology of immigration that places most of its explanatory power on social and cultural capital differentials between immigrant groups; which tends to engage authors in "blaming the victim" narratives.

In order to deconstruct workers as the sole social agents responsible for their fate in the labor market, I complement the analytical reach of the economic sociology of immigration by focusing the analysis on the ascribed characteristics on which workers have no influence, namely their ethnic origin. In this way, the variance remaining after controlling for the main drivers of occupational status in the literature can be attributed to the subjective perceptions of those who employ them, contract them, or work alongside them. To support this analytical jump, I employ the principles of Giddens' theory of structuration, which posits that, "structural properties of social systems exist only in so far as forms of social conduct are reproduced chronically across time and space" (Giddens 1984:xxi). Adjusting this philosophical approach to the specific inefficiencies of the labor market, I propose that the patterned and predictable occupational status inequalities that immigrant workers from disparate ethnic groups experience, result from the temporal and spatial cumulative effect of employers' actions and behaviors at the individual and institutional levels. These actions and behaviors are informed and inform the day to day interactions between employers and employees and the social context they occupy, which in turn are subject to racialized perceptions of "the other" that negatively or positively affect their access to, and outcomes from, labor market participation. The main thesis that I propose is, therefore, composed of three premises that encapsulate the cyclical progression of the racialization phenomena as a structured positive feedback loop. First, the cumulative essentialization of certain groups by dominant social agents has resulted in an increasingly ethnically racialized U.S. social context. Second, this ethnic racialization percolates and affects the labor market as an institution embedded in a U.S. social system conformed, in some part, by agents of racialization. This racialization may be positive or negative and it influences the selectivity of recruiting workers, how they are perceived, and how they are compensated in the labor market accordingly. And third, the socioeconomic outcomes of a partial labor market affect racialized immigrant minority groups in a patterned and measurable manner. For negatively stereotyped ethnic groups racialization further decreases their occupational status attainment. For positively racialized ethnic groups labor market outcomes may even surpass those of the dominant group. Hence, ethnoracialization reinforces the negative or positive stereotypical perceptions about ethnic groups that constantly fashion and refashion the social constructions of their members at the different levels of social interaction, from the individual to the broader social context.

Variability of outcomes in the labor market

Between- and within-group differences in labor market outcomes have been thoroughly researched. Studies have been informed primarily by two schools of thought: those that focus on a “rational” labor market, where the characteristics of the labor force are the primary source of variation; and those that explore the “irrational” mostly unobserved characteristics of employer behavior as an important factor in market outcome discrepancies (Zschirnt and Ruedin 2016, Vernby and Dancygier 2019). Convergence between these two schools of thought can be traced back to over 60 years ago, when economists such as Gary S. Becker, in 1957, and Kenneth Arrow, in 1973, started modeling the irrationality of labor market discrimination within the assumptions of a rational profit-seeking neoclassical paradigm (Arrow in Ashenfelter and Rees 2015:3-34, Becker 1971). Sociologist responded by pointing out the limitations of assuming neoclassic simplifications when analyzing complex social relationships, especially with regards to multiple ethnic groups (Reder in Ashenfelter and Rees 2015:34-42) or ethnic antagonism in wage differentials (Bonacich 1972). This resulted in an ongoing epistemological division that, interestingly, did not split the camps by disciplinary affiliation but rather lured most quantitative sociologist towards considering rational justifications rather than irrational behaviors as explanatory variables of the variation of labor market outcomes (perhaps influenced by heavy critique from authors such as Smith 1990). This division, I argue, is not delimited by contrasting methodological selections and theoretical formulations, but rather by the attribution of responsibility for outcome discrepancies to either the supply-side (personal endowments or contextual differences) or the demand-side (employer and institutional subjective tastes or preferences) of the labor market. I consider this often ignored epistemological dichotomy to be of great academic, political, and societal relevance, as it guides how research is conducted and interpreted, how policies are designed and applied, and how people construct their perceptions of the "other" within and outside the labor market.

Research supporting supply-side correlates dominates academic developments. Specific to immigrants in the U.S. labor market, immigration economists tend to maintain the ideological principle of a rational labor market, and focus on the endogenous human and cultural capital characteristics of immigrants—educational attainment, skills, work experience (for opposing sentiments towards immigration that, nevertheless, share the same neoclassical assumptions see Borjas 2014, and Card and Peri 2016). Other economists expand on the explanatory power of personal endowments by adding language as the main indicator of assimilation and occupational success (Chiswick and Taengnoi 2007, Day and Shin 2005, Lewis 2011). Most economic sociologists and economic geographers acknowledge that the labor market is imperfect, they account for the relevance of personal endowments, but give primacy to contextual exogenous factors such as geographic differences as predictors of economic integration (Sassen in Portes 1995:87-127, Stolzenberg 1990). Sociologists have also contributed to this literature by integrating structural characteristics that affect group's outcomes differently, such as social and cultural capital (Aguilera and Massey 2003, Hall and Farkas 2008, Fernandez-Kelly in Portes 1995:213-47). Regardless of their analytic approach, methodology, or disciplinary affiliation, authors from the above-mentioned disciplines tend to share an understanding of the labor market in which employers are seen as impartial and their actions isolated from affecting their employees' occupational status achievement. For example, Borjas (2014, 2016) dismisses discrimination against immigrants in the U.S. labor market as a phenomenon unique to underdeveloped countries of origin. To him, Mexican immigrants' poor economic outcomes "could have been the result of social, cultural, and economic barriers that they faced [back in Mexico]—barriers that might perhaps disappear after they moved to the United States" (Borjas 2016:82). Aside from the clear misconception that the U.S. economy may not impose social, cultural, and economic barriers on Mexican immigrants; the previous quote implies that since Mexican workers come from a socially, culturally, and economically inferior country, their skills and capabilities are, in consequence, also inferior. This *inferiorization* of the Mexican and Latino workforce is key to their ethnoracialization in the broader social context (Anthias 1992, Murji and Solomos 2005:13), and consequential to their reduced labor market outcomes as evidenced by quantitative (Bohara and Davila 1992, Espino and Franz Michael 2002, Telles and Murguia 1990) and qualitative (Donato, Stainback and Bankston in Zúñiga and Hernández-León 2005:73-103) research.

Research that evaluates labor outcome variation as a function of unobserved demand-side inefficiencies is significant in its findings but less abundant in the literature (Goodwin-White 2008, Reimers 1983). The main difficulty limiting researchers is quantifying the role of employers in labor market outcome discrepancies. Therefore, most research of this phenomenon focuses on pre-hire labor market interactions measured as discrimination of immigrants at either the time of processing the legal documentation for employment (Rissing and Castilla 2014) or at the time of job applicant selection and hiring (Bertrand and Mullainathan 2004, Pager 2007). Research on the racialization of ethnicity in the U.S. labor market has, consequently, depended on scarce qualitative studies that, although highly informative, are geographically constrained and suffer from sampling bias reducing their generalizability (Smith 1990).

This paper's major contribution to the literature is to address and mitigate immigrant labor demand-side limitations. Using quantitative analysis that controls for the main correlates proposed by labor supply-side literature, I question whether a substantial residual occupational-status inequality suggests the existence of labor demand subjectivities. With this aim in mind, I posit two main hypotheses that guide my analysis. First, *human capital and demographic characteristics are awarded or penalized at significantly different rates across ethnic groups in the U.S. West Coast labor market, which is partially influenced by the racialization of ethnicity (between-group differentials)*. Second, *labor market discrimination is not only evident at the between-group level, where some groups are constructed positively and others negatively, but also within ethnic groups, where the personal endowments of group members are awarded or penalized in patterns directly related to their degree of racialization (within-group differentials)*.

I use a well-established occupational status score to estimate the effect of ethnicity on labor market outcomes. I include the influence of worker's observed characteristics, such as productivity-related personal endowments, as independent variables. Variance in the coefficients of these ascribed and acquired traits and their interactions is measured by their effect on the occupational-status dependent variable. Estimated variance comes from workers' observed characteristics and employers', clients' and coworkers' unobserved discriminatory actions. In the following section, I describe the operationalization of the two hypotheses, the data used for the analysis, and the methodology.

DATA AN METHODS

Data

Data come from the pooled 2008-2019 1% American Community Survey (ACS) provided by the Integrated Public Use Microdata Series (IPUMS) (Ruggles et al. 2021). The region of analysis includes the Western U.S. States of California, Washington, and Oregon. This region was selected to represent the diverse labor markets around the US that are major recipients of immigrants from all ethnicities with very different labor endowments. For example, the Silicon Valley in California, and Seattle in Washington State attract highly educated European, Chinese, Indian and Mexican immigrant workers; while, the California Central Valley, Washington State's Yakima Valley attract a significant amount of low-skilled Mexican agricultural and service workers. This heterogeneity of the sample is important to avoid selection bias. After data cleaning and preparation, this subsample includes harmonized data on over 3.9 million observations, of which a subpopulation of 2.6 million is included in the final analysis. This universe consists of men and women aged 15 to 65 who are in the labor force and had worked the previous year to the survey[2]. Analysis is representative of an estimated pooled population of 283 million across the twelve survey years. Variance is calculated using replicate weights provided by IPUMS, which reflect the complex survey design of the ACS.

The outcome variable for the study is the Nam-Powers-Boyd (NPB) occupational status score, 1990 basis. It is a scale from 0 to 100 that approximates the percentage of labor force participants with a combined level of education and income below each occupation defined by the U.S. census. The scores given to ACS occupations are provided by IPUMS and were

[2] Although most research on labor market phenomena restricts the sample to those aged 25 to 65 and not in school I want to measure the occupational status at all stages in the career path captured by the Nam-Powers-Boyd occupational status score.

calculated according to Nam and Boyd (2004). This scale assigns equal weight to educational attainment and earnings, is independent of occupational definition changes, and is void of subjective interpretations of prestige and social standing as compared to other socioeconomic indexes such as Duncan's or Hauser-Warren's. In this regard, the NPB score avoids categorical measures of status that draw their boundaries arbitrarily following researcher choices and instrumentally biasing the results. This is particularly evident in occupational skill research, where "high skill" and "low skill" categorizations reflect the preconceptions of the social scientist about different occupations, which are then unavoidably transmitted to their findings. To avoid this bias while maintaining a sense of stratification, I use the NPB score, which, in comparison, is obtained using only mathematical manipulation of census count data to provide a "pure socioeconomic" scale (Nam and Boyd 2004:333).

The data is grouped according to *Ethnic Origin*. This variable conceptualizes people in the ethnoracialized U.S. context, where natives' identities are constructed from racially based ancestry, and immigrant identities are constructed from their immediate geographic origin. Thus, ethnoracial categories of US-born individuals are operationalized to represent their hyphenated ancestral ethnic origin. Summary statistics of the variables used in the analysis grouped by ethnicity are provided in Table 2.1**.**

Table 2.1 about here

Descriptive findings

ACS data summarized in Table 2.1 reveals that among the U.S.-born groups, non-Hispanics have the highest average occupational status scores and those of Latino origin have the lowest. Remarkably, European, Asian, and "other" immigrants have higher average occupational status scores than native-born non-Hispanics. This preliminary finding may support notions of immigration that claim that some migrants, especially European and Asian, have unique characteristics that make them more productive and therefore more successful in the host labor market. With European and Asian immigrants scoring over 57 points, they, on average, are in occupations that are ranked over 14 points higher than native Latinos, and 20 points higher than Latin American immigrants (after averaging the scores of the three Latin American ethnic groups= 37). These differences between ethnic groups are very significant in the socioeconomic standing of workers. Mexican immigrants have the lowest average NPB occupational status score (28.1), which is equivalent to a barber (NPB 26) as compared to say, a mapping technician (NPB 58), the equivalent to the European and Asian average. Race-wise the relationships are less conclusive as the majority of the population self-reports to be White (66%). Asian and African immigrants are the exception, but they still have surprisingly high percentages of White members (10% and 30%, respectively). Within Latinos, a little over half are White (55%), and most of the rest (42%) self-report as mixed race, or do not fit the Census defined racial categories. While these results may suggest the racialization of ethnicity, the influence of other predictors of occupational status is also evident. Differences in educational attainment, English language proficiency, and legal status across ethnic groups mirror the trends of occupational status scores. Asian immigrant's share of members with a college degree or higher is three times higher than that of Latino-Americans, and ten times higher than that of Mexican immigrants. While half the Asian immigrants have a college degree or higher educational attainment, only 5 percent of the Mexican immigrants do. Almost 70 percent Mexican immigrants do not speak English fluently, while 81 percent European immigrants do. Interestingly, South American immigrants have better English skills than Asian immigrants despite having a lower average occupational status score. With regards to legal status, over 80 percent of all non-Latino immigrant groups have legal documents, while 64 percent Central American and 58 percent Mexican immigrants do. From this descriptive profile it is plausible to conclude that occupational status variation is determined more by the characteristics of the labor supply than on discrimination from those who demand it. However, while bivariate descriptions provide some context of the form, direction and strength of association between independent variables and the dependent variable, they do not consider how these predictors vary together. Multivariate analysis is then required to have a more holistic idea of the relationship.

Analytical approach

I divide the analysis in three stages that include the occupational status predictors. The stages include an educational attainment stage, racial and ethnic origin stage, and a labor market access stage. These stages are operationalized using a three nested-model approach and analyzed using multivariate ordinary least squares regression (OLS). An OLS model is the most appropriate instrument for analyzing the NPB dependent variable, for it is continuous and ranging from 1 to 100. Moreover, coefficients from OLS regressions are easily interpretable. Mean scores from single males in California with less than a high school diploma surveyed in 2008 provide the group of reference. In the full model, being US-born and white and non-Hispanic is added to these parameters. Although this method of quantitative analysis is well accepted by social scientists, it is not without its flaws. First, only easily measurable and publicly available independent variables can be used. This may result in missing important predictors in the analysis, such as personality traits, social capital, and luck. Second, the actual process of ethnoracialization is not measurable by this method, only its outcome, resulting in inferences with a high degree of speculation. Third, regression coefficients in large samples are always artificially significant, as p-values deflate to zero in observation thresholds with much lower *N*'s than ACS samples. Nevertheless, considering the many limitations, this study provides a "good enough" model in the standard by which statistical models are measured in the social sciences[3], and I additionally quantify the sensitivity and magnitude of the effects, rather than their statistical significance alone[4].

Empirical model

The first stage of the nested model, Table 2.2 (Model 1), includes demographic, temporal and spatial information that serve as controls for the independent variables. This stage includes *Educational Attainment* as a categorical variable coded as: (1) Less than High School Diploma, (2) High School Diploma, (3) Some College, (4) College Graduate, and (5) Postgraduate Diploma. As has been noted, education is one of the strongest predictors of occupational status (Friedberg 2000) and it is, therefore, chosen to guide further analysis.

The second stage (Model 2) nests Model 1 by adding the *Race* and *Ethnic Origin* variables to determine how occupational status is influenced by racial and ethnic group membership once I control for all other factors. Following the theory of ethnic antagonism (Bonacich 1972), for the U.S.-born population I use U.S. Census racial categorization and construct ethnic groups from the commonly used dichotomization of being Hispanic or not. For immigrants, their place of birth at the continental scale defines their ethnic group. Immigrants are

[3] For a discussion of what constitutes a "good enough" model, a "best" model, and the "correct" model see Cheng J, Edwards LJ, Maldonado-Molina MM, Komro KA, Muller KE. Real Longitudinal Data Analysis for Real People: Building a Good Enough Mixed Model. *Statistics in medicine*. 2010; 29(4):504-520. doi:10.1002/sim.3775.
[4] See Mingfeng Lin, Henry C. Lucas, Jr., Galit Shmueli. Too Big to Fail: Large Samples and the P-Value Problem. *Information Systems Research*. 2013; ISSN 1526-5536 (online):1-12

divided into *Europeans*, *Asians*, *Africans*, *South Americans, Central Americans, Mexicans,* with foreign individuals born in all other regions being labeled *"Other"*. Mexican immigrants are included as a separate ethnicity due to the size and influence of this immigrant population in the U.S. context of ethnoracialization.

The third stage (Model 3) nests the previous models by including the immigrant-specific characteristics that are considered to be detrimental for occupational status attainment. Lack of English fluency, and attaining all education abroad are operationalized as controls, and lacking legal status is chosen as the explanatory variable. The ACS provides five English proficiency categories in the *speakeng* variable. U.S. Census research suggests that the only two English proficiency adjacent groups that demonstrate a significant gap in earnings are those who speak "very well" versus those who speak "well" (Day and Shin 2005:6). Following this finding, researchers of occupational status attainment dichotomize the English language proficiency and have found English fluency to be a highly influential predictor of occupational status (Chiswick and Taengnoi 2007, Day and Shin 2005, Lewis 2011). As this stage incorporates immigrant specific disadvantages in occupation status attainment, I construct a *Not English Fluent* dummy. I dichotomize the original *speakeng* variable and code it 0 if the respondent speaks only English or speaks it "very well", and 1 otherwise. Source of educational attainment is an important predictor of occupational status attainment (Friedberg 2000); it is dichotomized as 1, *Educated Abroad,* and 0, education attained in the U.S. Since this information is not included in the ACS dataset, I calculated it following Chiswick and Taengnoi (2007), where education is assumed to be attained continuously from age six , so "if age at migration is greater than the years of schooling plus six, it is assumed that all schooling took place abroad" (Chiswick and Taengnoi

2007:23)[5]. Legal status has also been shown to have a significant effect on labor market outcomes (Hall and Greenman 2015, Rissing and Castilla 2014). The "Naturalized Citizen" category within The *Citizenship* variable in the ACS is the only indicator of immigrant legal status. However, there is no variable that distinguishes non-citizen legal residents from unauthorized immigrants. To estimate an undocumented population researchers use *Logical Edits* and *Probability Edits* (Pastor and Scoggins 2016); which consist on drawing available information from the dataset that is likely to qualify non-citizens as legal permanent residents (LPRs). For example, being in the military, receiving most types of government assistance, immigrating before 1982 or being Cuban are all characteristics of LPRs. After running the logical edits, the remaining non-citizens form the *Undetermined Legal Status*[6] identifier used as the last explanatory variable in this stage[7]. The full model (Model 3) provides the occupational status variation as influenced by all the independent variables concomitantly in the three stages.

Table 2.2 about here

[5] Contrary to Chiswick and Taengnoi's (2007) findings, and in agreement with Friedberg (2000), I find that the source of education is a significant predictor of occupational status. Chiswick's contradictory findings may be related to the model design. Chiswick used a multinomial logistic regression on broadly and arbitrarily defined high skill occupational categories, removing the hierarchical structure of the outcome variable (all occupations are assumed to have the same socioeconomic status, since they are all labeled "high skill"). This results on the counterintuitive notion that "odds of being in a certain occupation do not vary with the source of education, other things being the same" (Chiswick and Taengnoi, 2007, p.23). An OLS regression of the hierarchically defined NPB dependent variable demonstrates significant unit changes influenced by educational source differentials.

[6] Previous research from Pastor and Scoggins (2016) go further by calculating *Probability Edits*. These use a separate dataset that includes indicators of legal residence to calculate the probability of being undocumented, and through multiple imputation of missing values or applying logistic coefficient estimates (Pastor and Scoggings, 2016), they assign a legal status to non-citizens not captured by the Logical Edits. I avoided this step as it is based on the assumption that undocumented status is a homogeneous statistically transferable characteristic between differently designed and gathered datasets, which is highly unlikely.

[7] I refrain from labeling this resulting group as "undocumented immigrants", since a Wald Test comparing this subgroup to Mexican Consular ID data, which is assumed to be comprised mostly of undocumented Mexicans (Massey, Douglas S., Jacob S. Rugh and Karen A. Pren. 2010. "The Geography of Undocumented Mexican Migration." *Mexican Studies/Estudios Mexicanos* 26(1):129-52. doi: 10.1525/msem.2010.26.1.129.), shows significant differences between the two groups in both educational and occupational skills.

EMPIRICAL ANALYSIS

Main Effects

Model 1 in Table 2.2 shows, in tune with structuration theory, that spatial and temporal variables are important predictors of occupational attainment. We can see some of the effects of the 2008 great recession in the decreasing average status achievement of the population at each survey year; with slow recovery in 2013. Compared to California, living in Washington increases the mean occupational status score by half a point, while living in Oregon has the opposite effect, which could reflect the types of jobs available for immigrants in these states and the high selectivity of the Washington labor market compared to a more diverse California. These demographic differences between states become relevant when we include ethnoracial and labor market effects in the nesting models, as living in California gives the greatest average advantage increasing the occupational status score by up to 3 points over the less diverse states. Model 1 also reaffirms the importance of educational attainment, as having college degree or more education (43-College, 55-Postgraduate) more than triples the effect of just having a high school diploma (14), and almost doubles the effect of attending some college (24); when having less than a high school education is the reference category and all other factors are controlled for. Adding race and ethnicity in Model 2 and immigrant-specific negative qualifiers in Model 3 increase the explanation of the variance. Increments in pseudo R^2 are significant with F (11, 79) = 7064.67, $p< 0.001$ for Model 2 and F (3, 79) = 12918.68, $p< 0.001$ for Model 3. After holding all other occupational status predictors constant in Model 3, Latino immigrants, on average, have the lowest occupational status scores. Blacks are the worse off of all racial groups. Their occupational status score is, on average, four points lower than that of Whites. US-born Latinos also do worse than Non-Latino natives, an effect shared with their immigrant counterparts. Four immigrant ethnic groups—Europeans, Asian, African, and Others (mostly Canadians)—have higher average occupational scores than the reference group in the full model, all else being equal. On the other hand, Asian are the most likely to have the highest average occupational scores among all racial groups, *ceteris paribus*.

The models in Table 2.2 also show that when we add labor market limiting factors to ethnic group identification (from Model 2 to Model 3), some patterns emerge that support the bifurcated effects of ethnoracialization. For all non-Latino ethnic groups the introduction of labor market limitations removes their "ethnic penalty" and their nativity effect on occupation status goes from negative to positive after being *awarded* an average of 4 NPB points. For US-born and immigrant Latinos the ethnic penalty remains significant, so despite a small improvement, the ethnoracializing effect on them stays negative after including the influence of immigrant characteristics that limit these groups' labor market access.

Based on these findings one can plausibly conclude that my first hypothesis is supported (*Ethnic discrimination affects between-group occupational attainment discrepancies*). However, skeptics of the racialization of ethnicity phenomenon could argue that the main effects shown in Table 2.2 do not account for the interactions between predictors, and that main regression effects are not enough to establish valid inferences. Intuitively this argument makes sense. Studies have shown that language fluency affects various skill-level workers differently, and that legal status also has different effects depending on educational attainment. To address these potential shortcomings, I ran a four-way interaction model on only on the foreign-born, as the two higher-level effects—legal status[8] and English Proficiency—are immigrant specific. These higher level moderators are then interacted with the main predictors, resulting in estimates that measure the

[8] To include the effects of the different nativity and immigrant legal status categories in the interacted model I use the *Citizen* variable in the ACS and recoded "non-citizens" to include the "undetermined legal status" identifier obtained by logical edits. To simplify the interacted model this variable is dichotomized.

moderation effects of ethnic origin on educational attainment, while simultaneously factoring in the effects of legal status and English proficiency. The post-estimation predictive marginal contrasts of this fully interacted model are displayed in Figure 2.1[9]. In it, I show the individual contrasts of ethnicity that decompose each combination of the levels of education, language, and legal status using European immigrants as reference. These results demonstrate that, contrary to previous accounts, immigrant ethnic groups do not show the same returns to their "human capital investments". Evidently, immigrants from some ethnic groups, regardless their formal level of education and English proficiency are penalized rather than rewarded in the higher skill segments of the U.S. West Coast labor market. An explanation of the linear predictive margins graph and analysis of its findings follows.

Figure 2.1 about here

Interaction Effects

Interactions between the 4 predictors of interest are used to answer the question: in terms of occupational status attainment, how does the effect of ethnic group membership and educational attainment depend on the respondent's, immigration legal status and fluency in English? A brief answer is that the higher the education, the more determinant between- and within-group differential become. Within-group variance is particularly influenced by English fluency and legal immigrant status. Figure 2.1 plots the occupational status outcomes of the different ethnic groups by legal status and English proficiency. It divides the population into five subgroups each representing an educational attainment category. The zero gridline in the Y-axis represents the linear predictive margin of equally endowed European immigrants' occupational

[9] The output from this model is extensive and hard to interpret. A table including main and interacted marginal effects can be supplied upon request.

status score at each level of education, fluency, and legal status. The further a point is from this line, the larger the difference between the group's predictive margin and the reference group. Capped spikes represent confidence intervals at 95 percent, when these cross the zero Y gridline, the difference in marginal outcomes between the ethnic group and reference group are statistically insignificant.

At first glance, Figure 2.1 reveals striking differences in the predicted marginal occupational status achievements between European immigrants and ethnic groups across educational categories, validating education as the main source of outcome variance. However, the impact of the education effect is not what most scholars would expect. The higher the education, the more disperse the predictive margins between the groups and European immigrants are. In a sense, education is the great un-equalizer, as trends in the interactions between the predictors get amplified with each increase in level of education. More importantly, the higher the educational attainment the larger the contrast within and between groups, as the vertical spread of the points increases overall.

This vertical spread results from the interaction between education and language, which gives support to the literature on the importance of English language proficiency in labor market outcomes. However, this interaction does not result in a similar trend for all groups (see Figure 2.2). Highly educated, non-LPR Asian and "other" immigrants, independent of their English fluency, have higher occupational status scores on average than highly educated European immigrants, after controlling for all other factors. In contrast, although non-LPR Mexican, South and Central American immigrants that speaking English fluently enjoy a slight occupational status advantage over their non-English fluent counterparts, this language premium is not nearly enough to bridge the average occupational status gap between them and European immigrants.

The interaction between educational attainment and immigrant legal status can be derived from simultaneous changes within ethnic group predictive margins in the X- and Y-axes. This results in a negatively sloped diagonal tendency for most immigrant ethnic groups (declining immigration "legality" corresponds to decreasing occupational status achievement, all other things equal), validating the importance of legal immigrant status on occupational status achievement. As with English fluency, the general trend is highly influenced by differences in educational attainment (see Figure 2.1). Among the least educated, immigrants with undetermined legal status fair similarly to their LPR counterparts. As educational attainment increases, however, the negative effect of not being a naturalized immigrant or a permanent legal resident on occupational status attainment gets amplified. This trend is epitomized when we see that the worst off subgroups, in terms of predictive occupational status margins differences with European immigrants, are non-LPR *highly-educated* Mexicans and Central Americans that do not speak English fluently. These findings provide support for my second hypothesis, that *within group endowment differences affect groups' occupational status differently*, as illegality and lacking English fluency have a significantly more negative effect for Latin American immigrants, most especially Mexicans and Central Americans. To showcase this phenomenon more tangibly the linear marginal prediction contrasts between European Immigrants and other immigrant groups with the same level of education and varying English fluency and immigrant legal status are examined in detail next.

Select Findings

First, the effect of English fluency is measured among highly educated immigrants with undetermined legal status. As Figure 2.2 shows for Asians[10] and "other" immigrants within this

[10] Since Indians and Chinese were awarded about 60% of the H-1B visas available to foreign workers from 2001 to 2015, totaling over one million between the two countries (Pew Research Center 2017 http://pewrsr.ch/2qbBwGn), they are

subgroup English fluency is rewarded with a 5 and 9 point premium respectively. Interestingly, in this subgroup Asian and "Other" immigrants are not penalized for not being English fluent; they are in fact awarded about the same average score as if they were LPRs (5 and 6 points respectively). Put simply, regardless of their language skills, non-naturalized Asian and mostly Canadian immigrants, on average, fare better in the U.S. West Coast labor market than European immigrants. In contrast, for Mexicans and Central Americans in the subgroup, English fluency does not improve their outcomes over European Immigrants as they, on average, score 16 and 23 points lower in their marginal predicted occupational status contrast (see Figure 2.2). What is truly shocking is that Mexicans and Central Americans within this group suffer an occupational status penalty *ten to thirty times larger* (-31 and -36 points respectively) than their Asian and mostly Canadian counterparts for not speaking English fluently.

Figure 2.2 about here

Second, I explore the effect of immigrant legal status on occupational status attainment by only focusing on non-LPR immigrants that are highly educated and do not speak English fluently. The comparison subgroup, namely those with all the negative immigrant traits, remains the same as in the previous analysis. Asian and "Other" immigrants within this subgroup that are LPRs are rewarded on average with 7 points respectively over European immigrants (see Figure 2.3). For Mexicans and Central Americans the opposite is the true. Having an undetermined legal status, on average, doubles the negative effect (-31 and -35 points respectively) of their already

certainly overrepresented in the "undetermined legal status" category. However, rather than seeing this as detrimental to my findings, I interpret this as showing the selectivity practices of the U.S. government officials giving preference to immigrants of some nationalities over others.

negative difference (-16 and -20 points) with European immigrants' occupational status scores, after controlling for all other determinants (see Figure 2.3).

Figure 2.3 about here

DISCUSSION AND CONCLUSIONS

The implications of the findings presented in the previous section are surprising and concerning. To begin, they strongly suggest ethnoracialization in the U.S. West Coast. The material consequences of this discrimination is not only evident in labor market outcomes but in academic debates and the broader social context. Historically, as the "grand mixer of peoples" (Hughes 1949), the labor market has been characterized by segregationist and discriminatory practices. Although there is evidence of desegregation in the labor market since Title VII of the Civil Rights Act (Tomaskovic-Devey et al. 2006), it is evident that the increase in diversity and representation of historical minorities in the labor market has not made this into a social institution free of discrimination. Labor market relationships between those who demand labor and those that supply it are deeply affected by the social structure that embeds them. The negative perceptions of the Latino ethnicity have spillover effects on immigrants who would otherwise be desirable and productive workers due to their high education, legal documentation, and English proficiency. To uncover this prevalent discriminatory environment, I reveal that, after controlling for demographic, geographic, temporal factors and more importantly—level of education, legal status and English proficiency—Mexican and Central American immigrants have the lowest average occupational status scores of all ethnic groups. This, I argue, is a consequence of the racialization of Mexican and Central American ethnicity, which supports the growing body of literature on the creation of a Latino underclass (De Genova 2004, Massey and Pren 2012).

Patterns

The patterns of labor market ethnoracialization synthetized from the previous examples and the results shown in Figure 2.1 are clear. For Asian and “other” immigrants the subjectivity of the labor market is shown to work in their favor bringing to mind model minority and middleman minority narratives (Hirschman and Wong 1986, Sakamoto, Goyette and Kim 2009). For Mexicans and Central Americans discrimination has devastating effects, strongly suggesting the racialization of their ethnicity. In general terms, being a ethnoracialized Latino: can diminish the human capital gains from higher education that Borjas (2016) exalts; can nullify the language premium found to be so significant by Chiswick and Taegnoi (2007) and Lewis (2011); and can erase the benefits of becoming a legal permanent resident discussed by Rissing and Castilla (2014). That Mexicans and Central Americans do worse in every regard than all other ethnic groups when other factors are set equal is the most telling factor about the impacts of the ethnoracialization of an entire ethnic group, a process that, as structuration theory suggests, is not linear and produces and reproduces discrimination at the individual and institutional levels, across time and space in a positive feedback loop. As such, the racialization of Latino ethnicity has consequences that expand beyond the labor market social institution.

Implications

In a political environment increasingly deterministic about who is deserving or undeserving, about who belongs and who does not; racialized immigrant groups pay the price for the discriminatory constructions of their identity and worth. Before even entering the labor market, the ethnoracialization of their identity has lasting effects on their ability to succeed in the host society. Rissing and Castilla (2014) show how government agents from the U.S. Department of Labor engage in discriminatory practices by denying permanent work visas to suitable applicants from Latin American countries at a higher rate than applicants from other nationalities, after controlling for key factors. Once in the labor market, Latino workers are imagined as low skilled, unproductive, and a burden to native workers (Borjas 2016). Since Latinos are the most numerous immigrant group in the West Coast labor marker their exclusion from equal market gains affects the socioeconomic status of the population as a whole. Mexicans and Central American immigrants exhibit higher levels of poverty, geographic segregation and social exclusion. Aside from the negative socioeconomic consequences of Latino racialization, this ethnic group also suffers from mental health disorders resulting from high rates of perceived discrimination (Pérez, Fortuna and Alegria 2008).

In the academic sphere the effects of preconceiving Latinos as an inferior group in the study design are also evident and result in dire consequences for this population. Aside from the explicit racialization of Latino immigrants demonstrated by Borjas "uniformly dismal view about immigration" (Card and Peri 2016:22), a more subtle form of discrimination in research finding interpretation and explanation can be perceived with careful inspection of the literature. Surprisingly, studies that are framed and showcased as uncovering discrimination against certain groups are filled with stereotyped assumptions that reflect the researchers' subjective construction of the Latino population. Many of authors reviewed lessen or completely dismiss the role of employers by either simplifying relationships by removing them from a historical context, or proposing overly complex explanations in order to circumvent evident findings of discrimination. One example is given from Stolzenberg (1990) in his analysis of occupational achievement of Latino men in the U.S. He finds strong evidence for discrimination after controlling for key variables and geographic distribution—"for not speaking English very well, [Latinos] pay roughly twice the penalty in SEI paid by white non-[Latinos], and the Latino disadvantage in earnings and weeks worked is even larger" (1990:151). This finding, however, does not compel him to fully internalize the role that discrimination plays in penalizing Latino ethnicity as he follows with, “this greater penalty may result from unmeasured correlates of poor English fluency among white [Latinos] but not among other whites” (1990:151) Further into his discussion, Stolzenberg argues that “selective migration might produce unusual educational or occupational distributions of ethnic groups in the United States, but those effects would not be directly due to ethnicity”(1990:152). Evidently, Stolzenberg assumes that his findings are not rigorous enough to support a theory of racialization of ethnicity, and to him, the selectivity against a specific group, all other things being equal, is free from discriminatory practices against Latinos (seeRissing and Castilla 2014 who reject Stolzenberg's assumption). These subtle discriminatory practices result in a myopic, ahistorical and decontextualized analysis that, at best, normalizes government discriminatory practices and at worst, feeds into the rhetorical nationalistic discourses of exclusion that have gained prevalence in the current political culture.

Limitations and future Research

Further research on the racialization of Latino ethnicity is important in order to address the dire consequences of the phenomenon discussed in the previous section. Strictly quantitative data analysis has many limitations. As pointed out by Justus Veenman, “as the method aims at revealing the existence of discrimination, another drawback is that it provides us with product variables rather than process variables. It is therefore not possible to acquire information about the actual discrimination acts, let alone information about the motives behind these acts” (Veenman 2010:1809). Still, revealing discrimination by quantifying its impact on all major ethnic groups in the U.S. West Coast labor market, is a worthwhile endeavor that can have significant implications in future debates and research on labor market discrimination.

To capture the process of racialization rather than merely the outcome a mixed-methods study in which a survey of discriminatory practices from both labor demand and supply sides is informed and analyzed by quantitative methods would be of great use. However, as the time needed for, and cost of such study may make it too difficult of an endeavor, other more accessible approaches may be favored. More detailed quantitative research of the effects of ethnoracialization of the Latino ethnicity should use as dependent variables other measures of socioeconomic inequality such as income, a poverty dummy, and/or composite measures of occupational prestige such as the Houser-Warren SEI score. To capture other dimensions of the racialization process not included or not deeply analyzed in this study, the effect of racial categorization and gender discrepancies should be included in the interacted model as independent variables. To capture the geographic influence on the variance of the outcomes geospatial analysis that includes Public Use Microdata Area (PUMA) should be conducted. To remove the regional and temporal constrains for generalizability of the findings, data of the whole country and period of at least 50 years is preferable. Lastly, to increase specificity and generalizability even further, one avenue for future research is to look at a finer breakdown of country of origin – particularly for Asians (e.g. filipino vs Japanese vs Indian etc) and to explore comparisons with other countries' contexts, such as the racialization of Turkish ethnicity in Germany, would be highly beneficial.

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Table 2.1. Summary Statistics by Ethnic Group—Post-Estimation Population Means and Percentages

	US Non-Hispanic	US Hispanic	Euro Immigrant	Asian Immigrant	African Immigrant	Other Immigrant	Central-American Immigrant	South-American Immigrant	Mexican Immigrant	Total
Occupational Status (0-100)	55.31 (0.027)	43.02 (0.049)	59.13 (0.123)	57.24 (0.063)	52.89 (0.277)	59.50 (0.213)	31.85 (0.106)	50.91 (0.244)	28.10 (0.046)	
Year										
2008	56.42%	12.49%	2.63%	10.22%	0.60%	0.93%	2.71%	0.71%	13.28%	22,978,302
2009	56.05%	12.54%	2.59%	10.34%	0.57%	0.95%	2.91%	0.69%	13.37%	22,930,166
2010	54.87%	13.38%	2.59%	10.72%	0.59%	0.94%	2.84%	0.75%	13.33%	22,796,069
2011	54.28%	14.04%	2.62%	10.86%	0.65%	0.91%	2.82%	0.73%	13.09%	22,890,761
2012	53.96%	14.55%	2.65%	10.87%	0.65%	0.92%	2.81%	0.78%	12.82%	23,076,649
2013	53.48%	15.02%	2.62%	10.87%	0.69%	0.89%	2.77%	0.79%	12.87%	23,165,652
2014	53.12%	15.58%	2.58%	10.92%	0.63%	0.87%	2.70%	0.76%	12.84%	23,411,208
2015	52.47%	16.13%	2.58%	11.16%	0.67%	0.92%	2.68%	0.73%	12.66%	23,753,247
2016	52.24%	16.50%	2.57%	11.17%	0.72%	0.91%	2.74%	0.73%	12.43%	23,997,300
2017	51.78%	17.55%	2.63%	11.35%	0.74%	0.89%	2.61%	0.80%	11.65%	24,407,351
2018	51.47%	17.80%	2.57%	11.36%	0.78%	0.91%	2.64%	0.81%	11.67%	24,608,274
2019	51.10%	18.42%	2.49%	11.40%	0.88%	0.97%	2.71%	0.77%	11.25%	24,743,705
State										
California	46.26%	18.35%	2.51%	12.38%	0.63%	0.86%	3.37%	0.86%	14.78%	218,456,328
Oregon	80.47%	5.56%	2.22%	3.88%	0.43%	0.81%	0.61%	0.34%	5.68%	23,004,279
Washington	76.02%	5.17%	3.25%	7.27%	1.09%	1.30%	0.63%	0.40%	4.86%	41,298,077
Age	40.79 (0.013)	33.45 (0.023)	42.72 (0.055)	43.29 (0.025)	41.42 (0.110)	43.28 (0.092)	41.50 (0.053)	43.09 (0.101)	40.65 (0.025)	
Female	47.37%	47.70%	45.84%	48.41%	42.44%	46.73%	42.13%	48.42%	37.55%	282,758,684
Married	48.01%	35.31%	61.93%	67.79%	58.51%	60.15%	50.65%	57.71%	58.75%	282,758,684
Race										
White	81.02%	59.99%	93.46%	10.21%	29.85%	58.11%	45.69%	63.22%	57.15%	
Black	7.69%	0.91%	1.39%	0.13%	63.23%	10.33%	2.03%	0.86%	0.24%	
Asian	6.32%	0.83%	2.16%	86.42%	4.42%	23.79%	0.40%	2.92%	0.15%	
Other	4.97%	38.27%	2.99%	3.23%	2.50%	7.77%	51.88%	33.00%	42.46%	
Education										
No HS Dip.	15.87%	12.29%	0.67%	6.43%	0.28%	0.32%	9.70%	0.36%	54.08%	31,161,794
	3.28%	8.80%	2.87%	6.48%	4.46%	3.83%	38.97%	5.29%	47.35%	

HS Diploma	50.18%	21.29%	1.92%	7.26%	0.49%	0.74%	3.05%	0.65%	14.41%	83,170,414
	27.64%	40.71%	21.79%	19.52%	21.25%	23.66%	32.75%	25.33%	33.68%	
Some College	59.63%	19.29%	2.41%	8.39%	0.69%	0.89%	1.83%	0.78%	6.09%	75,150,647
	29.68%	33.32%	24.70%	20.37%	26.93%	25.83%	17.70%	27.49%	12.87%	
College Dip.	64.57%	9.07%	3.14%	16.50%	0.93%	1.18%	1.00%	0.92%	2.70%	60,444,985
	25.85%	12.61%	25.90%	32.23%	28.96%	27.51%	7.77%	26.05%	4.58%	
Grad. Dip.	62.31%	6.05%	5.52%	20.18%	1.08%	1.52%	0.66%	1.03%	1.65%	32,830,844
	13.55%	4.57%	24.75%	21.40%	18.40%	19.18%	2.81%	15.84%	1.52%	
Non-Fluent	0.63%	5.75%	18.61%	38.77%	23.64%	7.27%	64.18%	33.42%	68.14%	
Educ. Abroad	NA	NA	54.14%	60.07%	68.46%	53.92%	66.90%	60.96%	64.25%	
Undet. Immig. Status	NA	NA	14.11%	15.10%	12.24%	16.79%	36.12%	20.05%	42.09%	
Total	150,971,470	43,504,283	7,328,929	30,949,717	1,932,562	2,594,207	7,757,320	2,131,131	35,589,065	282,758,684

Standard errors in parenthesis. Source: American Community Survey 2008-2019

Between-group percentages calculated row-wise using row total. Within-group percentages calculated column-wise using column total.

Table 2.2. Nested Regression of Occupational Status Score on Education, Legal status, and Ethnic Origin; Controlling for Time, Place, and Demographic characteristics in Western USA 2008-2013.

Nam-Powers-Boyd Occupational Status Score, 1990 basis	Model 1 Educational Attainment	Model 2 Race and Ethnic Origin	Model 3 Labor Market Limitations
Year (reference 2008)			
2009	-0.513*** (0.091)	-0.455*** (0.087)	-0.467*** (0.086)
2010	-0.964*** (0.090)	-0.840*** (0.087)	-0.866*** (0.087)
2011	-1.237*** (0.093)	-1.078*** (0.088)	-1.120*** (0.088)
2012	-1.417*** (0.097)	-1.224*** (0.091)	-1.282*** (0.089)
2013	-1.278*** (0.096)	-1.058*** (0.091)	-1.135*** (0.090)
2014	-1.398*** (0.088)	-1.141*** (0.084)	-1.253*** (0.084)
2015	-1.451*** (0.093)	-1.155*** (0.089)	-1.280*** (0.087)
2016	-1.588*** (0.087)	-1.270*** (0.080)	-1.405*** (0.080)
2017	-1.718*** (0.090)	-1.388*** (0.084)	-1.553*** (0.083)
2018	-1.947*** (0.086)	-1.592*** (0.079)	-1.769*** (0.077)
2019	-1.943*** (0.083)	-1.591*** (0.082)	-1.789*** (0.080)
State (reference- CA)			
Oregon	-0.678*** (0.064)	-3.063*** (0.065)	-3.170*** (0.065)
Washington	0.506*** (0.047)	-1.644*** (0.049)	-1.708*** (0.047)
Age	1.292*** (0.008)	1.576*** (0.008)	1.652*** (0.008)
Age^2	-0.013*** (0.000)	-0.017*** (0.000)	-0.017*** (0.000)
Female	-1.435*** (0.027)	-1.564*** (0.027)	-1.598*** (0.027)
Married	3.053*** (0.033)	3.519*** (0.033)	3.727*** (0.033)
Education (Reference- Less than High School)			
High School	14.07*** (0.057)	8.595*** (0.058)	5.687*** (0.065)
Some College	24.39*** (0.058)	17.67*** (0.059)	14.18*** (0.065)
College Diploma	42.74*** (0.058)	35.14*** (0.062)	31.49*** (0.068)
Postgrad Diploma	54.81*** (0.056)	47.03*** (0.059)	43.15*** (0.067)
Race (Reference-White)			
Black		-3.868*** (0.085)	-3.902*** (0.085)
Asian		-0.033 (0.065)	0.920*** (0.064)
Other		-0.840*** (0.052)	-0.772*** (0.052)
Ethnic Origin (Reference US-Born Non-Hispanic)			
US-Born Hispanic		-3.308*** (0.054)	-2.969*** (0.055)
European Immigrant		-1.896*** (0.095)	2.317*** (0.102)
Asian Immigrant		-4.241*** (0.078)	0.959*** (0.078)
African Immigrant		-4.077*** (0.193)	1.131*** (0.191)
Other Immigrants		0.538** (0.164)	3.575*** (0.163)

Central American Immmgt		-11.86*** (0.108)	-4.356*** (0.104)
South American Immgt		-6.787*** (0.214)	-1.120*** (0.204)
Mexican Immigrant		-13.46*** (0.051)	-5.950*** (0.062)
Not Fluent in English			-8.235*** (0.071)
All Education Abroad			-4.535*** (0.065)
Undetermined Legal Status			-1.753*** (0.068)
Constant	-4.578*** (0.187)	-0.236 (0.190)	1.129*** (0.191)
Observations	3,867,755	3,867,755	3,867,755
Population Size	405,457,086	405,457,086	405,457,086
Subpopulation Obs.	2,645,514	2,645,514	2,645,514
Subpopulation Size	282,758,684	282,758,684	282,758,684
Block df	21	11	3
Design df	79	79	79
F; Pr>*F*	78832.44; 0	7064.67; 0	12918.68; 0
Pseudo R^2	0.41	0.43	0.44
Change in R^2		0.02	0.01

Standard errors in parentheses. Calculated using balanced repeated replication (BRR).
Model uses US-born Males as the demographic reference, California as the base spatial reference, 2008 as the base temporal reference and low education as the educational skill reference. European Americans are the reference of block 3

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 2.1. Contrasts of predictive margins of NPB Occupational Status Score

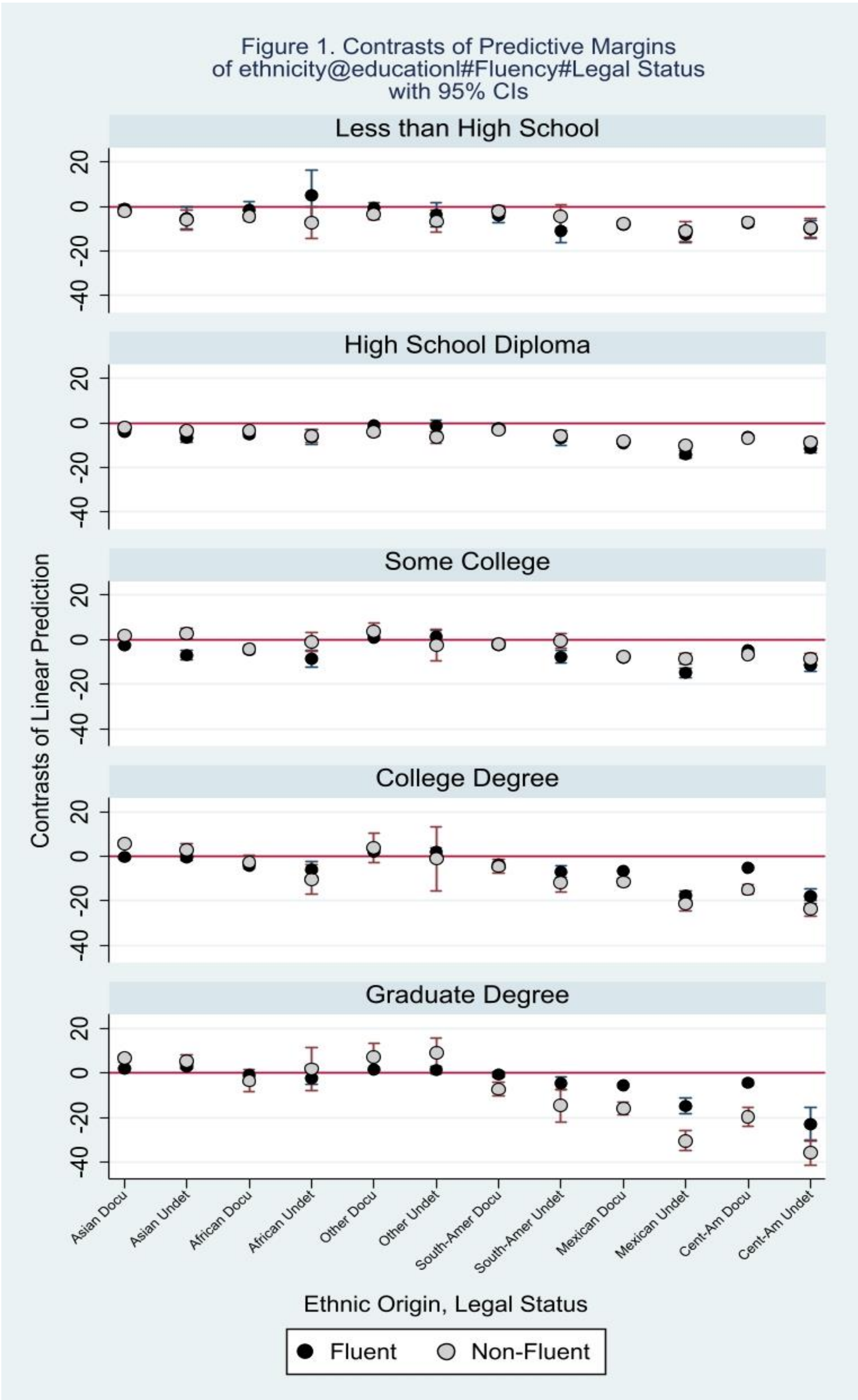
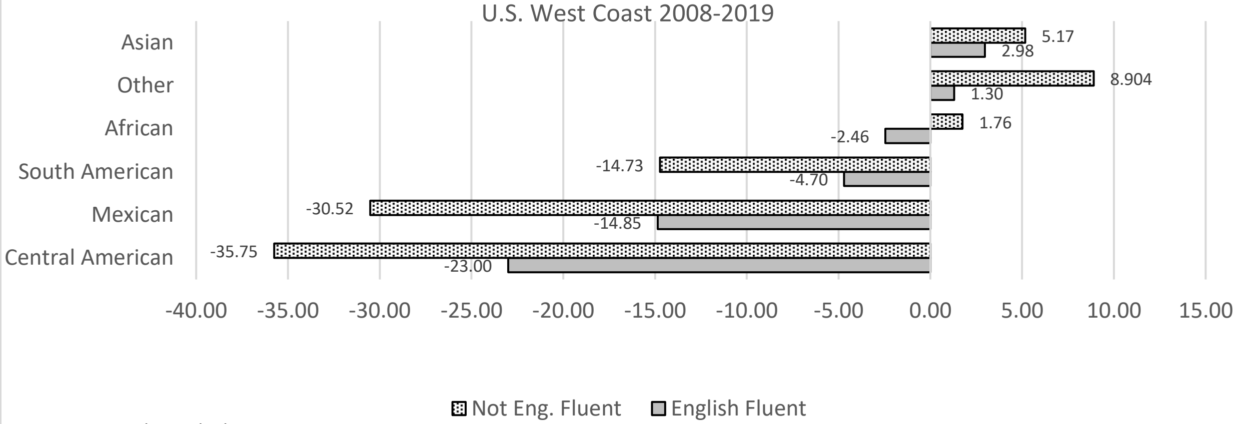
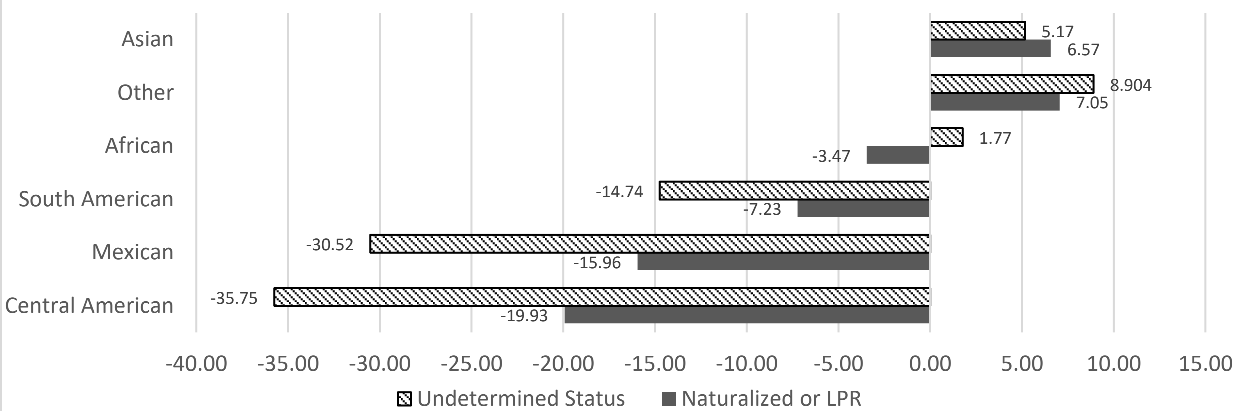


Figure 2.2. Linear Marginal Prediction Contrasts of Highly educated European Immigrants vs. Other Highly Educated Immigrant Groups with Undetermined Legal Status. U.S. West Coast 2008-2019



Source: Author calculations using ACS

Figure 2.3. Linear Marginal Prediction Contrasts of Non-fluent Highly Educated European Immigrants vs. Other Highly Educated Immigrant Groups. U.S. West Coast 2008-2019



Source: Author calculations using ACS

CHAPTER 3:
Ethnoracialized STEM roots-
Skill-Job Mismatch among High-skilled Immigrants in U.S. Innovative Metropolitan Areas

INTRODUCTION

The purpose of this study is to explore the effects of the ethnoracialization of highly skilled immigrant on their probability of educational-occupational matching (henceforth referred as "matching") in their places of work and residence in the U.S. I interrogate two dominant scholarly arguments. First, that college and postgraduate degrees are tools for reducing inequality of socioeconomic outcomes evenly across immigrant groups, as educational investments are thought to provide a more secure path to rewarding employment and upward mobility, and, second, that spaces of innovation where these immigrants work and reside are fertile ground for progressive thinking and inclusion.

I use a decade of U.S. Census survey data on immigrants who hold a degree in science, technology, engineering, math (STEM), or related fields[11], and who live in the top 35[12] most innovative cities in the U.S. (hereafter the "subpopulation") to estimate the probabilities of matching their education with a STEM-related occupation while controlling for a host of individual-level factors identified in the literature as predictors or mediators of socioeconomic integration. I limit my analysis to individuals from Asian and Latin-American countries, who

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[11] STEM and STEM-related occupations: computer and mathematical occupations, engineers, engineering technicians, life scientists, physical scientists, social scientists, science technicians, and STEM managers, architects, health care practitioners, health care managers, and health care technicians. STEM STEM-related degrees: Animal Sciences, Food Science, Plant Science and Agronomy, Soil Science, Environmental Science, Architecture, Communication Technologies, Computer and Information Systems, General Engineering, Engineering Technologies, Library Science, Biology, Mathematics, Military Technologies, Nutrition Sciences, Neuroscience, Mathematics and Computer Science, Cognitive Science and Biopsychology, Interdisciplinary Social Sciences, Multi-disciplinary or General Science, Physical Sciences, Nuclear, Industrial Radiology, and Biological Technologies, Psychology, General Social Sciences, Transportation Sciences and Technologies, Communication Disorders Sciences and Services, Medical Technologies Technicians, Pharmacy, Pharmaceutical Sciences, and Administration, Actuarial Science, Business Economics, Management Information Systems and Statistics. Source: https://www.census.gov/library/publications/2013/acs/acs-23.html

[12] Originally 50, but missing data on 15 Metropolitan Areas in the ACS reduced the study to 35.

have been identified in previous research as exhibiting, respectively, the strongest positive and negative effects of ethnoracialization on their social and economic wellbeing (Guarnizo and Becerra (Forthcoming)).

For the geographic component, I interrogate two contrasting theories on the effect of spatial characteristics on the socioeconomic outcomes of their residents. The first is market segmentation (Peck 1996), which argues that labor market discrimination is shaped by the geographic spaces of unique local labor markets. If this were the case, then we could expect to find significant variance between the average matching outcomes across MSAs due to the unique influences of sociospatial externalities within places where immigrants reside and work. The uniqueness of local labor markets is not put in question here, rather the degree to which this distinctiveness has an effect on the patterns of unequal valuation of ethnoracialized immigrants' STEM degrees at the time of finding a job. The second theory, creative class exceptionalism (Florida 2002, Fischer and Hout 2006:51–52), argues that innovative spaces attract creative individuals who tend to exhibit progressive values such as inclusiveness and tolerance, and thus transfer these characteristics to the places they populate in masse. If this were the case, the cumulative biases from employers' ethnoracializing of job applicants should be reduced and we would expect differences in average labor matching probabilities among highly educated ethnic groups to vary insignificantly across innovative urban areas, regardless of ethnic background.

I use two logistic modeling strategies to analyze the data in order to capture variability in highly-skilled migrants' labor matching probabilities vis-à-vis those from India, who for that last three decades, have had the highest success integrating to the top of the socioeconomic hierarchy in the host society (Guarnizo and Becerra (Forthcoming)). The first set of logistic models estimates temporal effects and the individual-level influence of demographic characteristics and human capital endowments on matching odds and serves as a frame of reference for the following models. The second set of models use a multilevel mixed effects[13] structure to include random effects at the second level which capture the average variance across metropolitan statistical areas (MSAs) and ultimately factor in the sociospatial context to which high-skilled immigrants are exposed at their place of work and residence. The geographic controls include the proportion of total population in MSAs that are immigrant, or that self-identify as either Asian or Latino, or that have a high occupational earnings status. Additionally, I include controls of ethnic segregation of measured by the Dissimilarity Indexes between Whites/Asians and Whites/Latinos.

To outline the research approach, I start with the analytical background that guides this research. Once the stage is set, I introduce the data, provide a summary of the descriptive statistics and the output from the models. To close, I delve into the analysis and implications of these results, providing some recommendations for future research.

RESEARCH PLAN

Before outlining my research agenda I will define the concept of *ethnoracialization* as it applies in this paper. Ethnoracialization is a fluid relational process of othering by assigning racial meaning to groups of people who share a common ethnic origin, using real or imagined prototypes to dictate their level of social inclusion or exclusion. Here “othering” is defined as the “making up of people” (Omi and Winant, 2014, pp 105) by constructing differences that bound the “normalcy” of the dominant group based on phenotypes, behaviors, principles or values; in this sense, ethnoracialization is a political process as it reflects power differentials that follow an

[13] I use Stata’s Melogit command. All code available upon request. StataCorp. 2021. *Stata Statistical Software: Release 17*. College Station, TX: StataCorp LLC.

explicit or implicit agenda. I underscore three characteristics of ethnoracialization in this definition: that it is a fluid process, evolving and devolving through time and space (Guarnizo and Becerra (Forthcoming)); that it can be a positive or negative valuation of a group (ibid., Becerra (Forthcoming)); and that race, as a phenotypical identifier, may or may not be an essential component in its constitution (Anthias and Yubal-Davis 1992). The latter is a key departure between ethnoracialization and the concept of racialization (Omi and Winant 1994), and allows me to bypass the epistemological inadequacies of institutionally imposed artificial self-identification of race in U.S. surveys. Although some studies have uncovered the effects of ethnoracialization on socioeconomic outcomes (Ong and Gonzalez 2019, Guarnizo and Becerra (Forthcoming), Becerra (Forthcoming)), others, the personal and contextual influences of human capital endowments and spatial composition on skills matching probabilities (Wang and Lysenko 2014), the combination of both approaches as they apply to the mode of incorporation of STEM-trained immigrants into the high-skilled labor market has not been attempted until now. STEM occupations require especial attention because they include jobs that matter for regional dynamism and prosperity; and they pay high wages for workers. Groups who are shut out from this sector will most likely have less chances at economic incorporation than those who secure STEM jobs. Therefore, the matching of immigrants' STEM education to a suitable career in STEM is crucial to maximize their socioeconomic outcomes. It could matter for workers if their ambitions are not met, which is especially relevant for immigrants, as their options of horizontal displacement to other lucrative non-STEM careers could be limited if their job is attached to their Visa or specific work permit. Aside from the benefits to those matched on their skills, matching could matter for the economy, as lost talent does not generate high returns and could limit innovation.

Literature on the effects of spatial segregation on labor market outcomes and minorities' employment opportunities focuses on educational, class, racial, and ethnic differences between the dominant group of White males and the minority groups. This approach has only revealed a partial account of the processes imbued in ethnoracialization. The findings of these studies give us insights on the majority/minority binaries, and some information about within group inequalities; however, by not comparing the effects *between minorities,* even if relative to Whites, some of the key processes of inclusion and exclusion are ignored (Wang and Lysenko, 2014).

Wright et al. examined job-matching in immigrants with STEM degrees as a homogenous group and found that those who live in tech-dense metropolitan areas have similar chances of matching in their major domains as their White-male counterparts (Wright et al. 2017). However, to my knowledge, there are no systematic studies of how nationally distinct immigrant groups fare in these spaces of innovation. Research on the native population provides some clues, which suggest that U.S.-born Latino men that have a STEM degree are less likely than U.S.-born White and Asian men to work in their field of study (Beede et al. 2011, Wright et al. 2017, Wang and Lysenko 2014). Additionally, Guarnizo and Becerra (Forthcoming), and Becerra (Forthcoming) found evidence of lower earnings and socioeconomic status of highly educated Latino immigrants compared to those of Asian and European origin, all else being equal. This study will, therefore, provide much needed evidence of the effect that ethnoracialization of high-skilled immigrants has on facilitating or restricting the job matching probabilities of this subpopulation, and determine if patterns of success or failure across highly educated ethnonational immigrant groups are affected by the regional labor market characteristics.

I will test two main hypotheses:

I. *The ethnoracialization of highly educated immigrant workers improves the chances of matching of positively constructed groups while decreasing the chances of matching of those imagined as less capable.*

This assignation, however does not follow a simple Asian (racial)-Latino (ethnic) dichotomy but rather is defined by ethnonational distinctions.

II. *Patterns of divergent matching outcomes across ethnonational groups are not place-of-residence specific, but rather the result of structural inequalities that permeate every innovative metropolitan labor market across the country*.

Accordingly, a negatively ethnoracialized highly educated immigrant could reside in the most diverse and inclusive neighborhood in the U.S. and work in the most vibrant and innovative labor market, and still have dramatically lower chances of matching their education with a suitable career than an equally educated immigrant from a country that is positively constructed by the host society.

If hypothesis II is supported by the analysis, then I offer an alternative explanation to the structural rather than localized effect of ethnoracialization of immigrant STEM graduates—that of institutional racism through statistical discrimination. The U.S. immigration authorities that grant work-visas and permits engage in o biased selectivity of applicants based almost exclusively on their country of birth (Rissing and Castilla, 2014). The result, I argue, is a STEM labor market that is overrepresented by immigrants from two countries: India and China, not because of an intrinsic supremacy in STEM knowledge and capabilities but a political agenda characteristic of ethnoracialized selectivity (Chen and Buell 2018, Tu and Okazaki, 2021). Prior research suggests the success of Indians and Chinese in STEM fields could be due to social (Luek 2017) and professional networks (Lysenko and Wang 2020), however, this research does not consider the value of the networks of other ethnic groups making it impossible to suggest they are more or less efficient than say, Latin American networks. Others focus on the impact of immigration policy and history, as U.S. employers and authorities are known to target workers for H1-Bs from particular countries with large STEM educational pools, which has resulted on immigration industries in particular countries that have developed in response to US visa policy/labor demand (Indians in tech; Filipinos in health, etc). Then again, in principle, these historical policies are imbued with ethnoracialized valuations of immigrants by their country of origin, a practice explored further later I this study.

ANALYTICAL BACKGROUND

The matching between education and employment of immigrants (Handel 2003, Chiswick and Miller, 2010) and the ethnoracialized patterns shaping socioeconomic outcomes are well established and thoroughly researched by academics in different disciplines (Becerra (Forthcoming), Kim 2015, Sakamoto et al. 2009). Similarly, the effect of space, deriving from places of work and residence, on the economic and social integration of immigrants has been the center of theoretical and empirical debates for the last 60 years (Danziger and Weinstein 1976; Price and Mills 1985). However, no major empirical work has been done to unify these efforts to better understand the potential effects of ethnoracialization on STEM labor markets. Studies of these markets tend to focus on the native population. Meanwhile, most studies of the relationship between space and ethnoracialization have focused on the urban underclass (Fortuijn et al. 1998). I build on research that synthetizes the geographical effect of metropolitan compositions on the skill-job matching probabilities of immigrants (Wright et al 2017, Wang and Lysenko 2014, Baum et al. 2008), by adding an ethnoracialization framework that differentiates between ethnonationally grouped immigrants and captures the heterogeneity in personal and regional influences.

The effect of ethnoracialization on matching

Although previous research on occupational matching suggests that there is a correlation between education and successful matching, little attention has been given to how this process unfolds among ethnonationally identified high-skilled immigrant workers in innovative urban areas. The effects of racialization on native-born minorities' employment opportunities are evident, even within the "tolerant and progressive" *creative cities* (Florida, 2002), as the low likelihood of Latinos and Blacks to work in STEM occupations is significant (Beede et al. 2011). Studies of the matching probabilities of minorities with a STEM degree to a STEM occupation in metropolitan areas with varying STEM occupational density and size, in part support evidence of ethnoracially uneven outcomes (Wright et all, 2017). All else being equal, U.S.-born Blacks and Latinos have 20 and 30 percent lower probability, respectively, of matching their credentials with employment than equally qualified US-born non-Hispanic Whites. US-born Asians, who are racialized positively, have over 20 percent higher probability than U.S.-born non-Hispanic Whites to be matched to a STEM job, *ceteris paribus*. Here ethnoracialization seems to have a significant influence on employment opportunities in metropolitan areas by including some and excluding others. Wright's study, unintentionally, also exemplifies findings that, due to research design choices, conceal the influence of racialization across immigrant ethnonational groups. In the study, foreign-born STEM graduates are operationalized as a single homogenous group, resulting in a probability of occupational matching slightly higher than that of the reference White males (for STEM agglomerated metros). Had immigrants been divided into representative ethnic groups, such as Asian, Latino, and European, perhaps results of their matching probabilities would mirror those of their native coethnics. This study aims to build on Wright et al.'s findings by integrating the ethnoracial heterogeneity of highly skilled immigrant workers in the analysis of their matching probabilities.

The effect of place on matching

High-skilled immigrants concentrate in large metropolitan areas (Abel et al. 2012). These areas are also the drivers of technological development (Florida, 2002). Opportunity cost theory would tell us that living near an innovative place where vast wealth is being created and where more progressive open-minded people tend to live would increase the chances of a minority group to have a good job, a good salary and a good quality of life overall, compared to those living in less innovative metropolitan areas (Bettencourt et al., 2007). Recent empirical evidence shows otherwise, countering previously reported arguments on the alleged inclusiveness of creative spaces (Florida, 2017, Peck 2005). In turn, the opportunities usually associated with living and working in innovative urban hubs are highly ethnoracialized making them readily available to some and denied to others, ceteris paribus. To explain this phenomenon researchers have developed a myriad of theories of ethnic segregation (for places of residence), and labor market segmentation (for places of work), each with its own assumptions of the positive or negative effect of occupying ethnoracialized spaces. I, however, pose that ethnoracialization is so deeply entrenched in the national labor structure of the U.S, that spatial distribution and geographic characteristics may play a smaller role on socioeconomic outcome disparities than the subjective characterizations of immigrant groups. Next, I will briefly describe the tenets of some of these theories and how they could be applied in the analysis of disparate rates of matching success between ethnonational immigrant groups across different locations.

Studying the influence of local labor market segmentation due to supply and demand factors on the socioeconomic outcomes of workers is very complex. On one hand, supply and demand systems cannot be properly understood in isolation from each other as life at work and at home cannot be completely disassociated—"the economic dimensions of life cannot be divorced from the social dimensions, while neither should be lifted out of spatial context" (Hanson and Pratt, 1992, pg. 374). On the other hand "the supply-and demand-sides of the labor market differ in terms of their dynamics as well as their structure" and are perceived as relatively autonomous from one another (Peck, 1989 pg.46). Moreover, theories argue that processes of labor market segmentation are shaped by and within the geographic spaces of unique local labor markets wherein modes of reproduction and production exist in a unique dialectical relationship and are influenced by the historical use of these specific spaces (Peck 1996). It is in these local labor market spaces, labor geographers argue, that broader processes of segmentation are uniquely channeled to influence labor market and economic outcomes experienced by workers in place. It is, therefore, necessary to utilize a regional scale, in which these three dimensions—place of work and residence, supply and demand of labor, and labor market independence—are captured and analyzed in a relational manner.

Adding to the complexity of socio-spatial relationships, research in empirical economic literature suggests that "immigrants and natives, including natives of the same ethnicity as immigrants, do not respond to the same locational criteria" (Sassen, 1995). This difference in responses is due to a myriad of cultural, economic, geographical and social characteristics (Wright and Ellis 2000, Wang and Lysenko 2004). It is, therefore, important to explore how spatial characteristics related to the local distribution of ethnoracialized minorities affect the matching probabilities of *each* immigrant group within spaces of innovation.

To untangle these intricate relationships I fit survey microdata of high-skilled immigrants with substantial temporal and spatial coverage using quantitative models that aim to estimate the source of the variance in the matching outcome while simultaneously controlling for important human and spatial factors. In the next sections I will describe the data, the summary statistics, the models' design, and the empirical findings.

The effect of ethnoracialization on structural inequality

The best example of the reaches of ethnoracialization at the structural level is institutional racism at the time of granting work-visas or permits by U.S. authorities, which impacts immigrants matching probabilities before they enter the STEM labor market. On the one hand, research indicates that U.S. Labor Department officials use statistical discrimination to grant or reject approval of employment-linked nonimmigrant visas which is dependent on national origin (Rissing and Castilla 2014). Mexicans, for example, were 35 percent less likely to be granted approval than equally qualified Canadians (the reference group), who in turn where 18 percent less likely than Indians, all else equal. In the specific case of H-1B work visas, a lottery is supposed to eliminate selectivity bias, but the pool of "qualified applicants" is comprised of over 85 percent Indians and Chinese[14]. It is not surprising then that Indian and Chinese immigrant applicants were awarded about 60% of the H-1B visas available to foreign workers from 2001 to 2015, totaling over one million between the two countries, while Mexicans were awarded a little over 1 percent[15]. On the other hand, the Department of Homeland Security (DHS) grants a work permit labeled Optional Practical Training (OPT) for international students who attend or graduate from U.S. universities. The DHS offers a STEM-specific OPT, which in 2019 recruited

[14] https://www.uscis.gov/sites/default/files/document/reports/h-1b-petitions-by-gender-country-of-birth-fy2018.pdf
[15] Pew Research Center 2017 http://pewrsr.ch/2qbBwGn

almost half of the total 150,000 OPT participants, of which two thirds constitute Indian and Chinese students. Indians constitute about 60 percent[16]. In 2018 since March 2016, OPTs grant a 36- month extension in their stay to students that have secured a STEM position[17]. This information allows me to speculate that the majority of highly qualified Indian and Chinese immigrants in the U.S. have entered the STEM labor market through paths guarantee employment, which results in a disproportionate success in finding a job that matches their education compared to the remainder of ethnonational STEM-related job hopefuls. These selection processes are heavily influenced by immigrants' countries of origin demonstrating a cycle of ethnoracialized stratification that runs deep into the fabric of U.S. Institutions. Although this paper does not provide further direct evidence of structural racism, the goal is to demonstrate that other explanations for the patterns of unequal matching hypothesized fall empirically short when compared to ethnoracialization and structural discrimination, mostly through a process of elimination.

DATA AND METHODS

Data

This study uses two pooled American Community Survey (ACS) 5-year datasets, 2010-2014 and 2015-2019 (Ruggles et al. 2021), providing a full decade of microdata on immigrants. ACS 5-year data files have the advantage of not restricting small area geographies with low population and, crucial for this project, providing the maximum information about small population groups, relative to the ACS single year file[18]. To eliminate noise in the variance, I only include in the analysis immigrants from Asian and Latin American countries aged 25-65 that hold a STEM-

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[16] https://www.cato.org/blog/facts-about-optional-practical-training-opt-foreign-students
[17] I reduce some of the OPT effect by excluding those who identify as students from the analysis.
[18] ACS General Handbook 2018. Ch03
https://www.census.gov/content/dam/Census/library/publications/2018/acs/acs_general_handbook_2018_ch03.pdf

related college degree[19], who live in the top 35 most innovative metropolitan areas in the U.S. (see Innovation Ranking below), and who are active in the labor force (excluding active students). After data cleaning and case selection, the subpopulation of interest comprises 174,000 observations, who, after weights are applied, represent just over 2 million individuals.

Innovation Ranking

The measure of innovation that ranks the top 35 most innovative cities in the U.S. comes from the 12th annual Cities Classifications & City Rankings from the Innovation Cities™ Index, which *2thinknow* has calculated since 2007[20]. Using 162 standard indicators, three main categories were created: *Cultural Assets* (arts communities, civic organizations, museums, music events, galleries, political protests, books, media, availability of information, and sports), *Human Infrastructure* (mass transit, finance, universities, hospitals, rail, roads, law, commerce, start-ups, healthcare, and telecommunications), and *Networked Markets* (geography, economics- exports and imports, technology, market size, geo-political factors, and diplomacy). This holistic measure of innovation provides a strong basis for spatial selection beyond simple economic or demographic indicators, assuring to capture some heterogeneity in the places in which high-skilled immigrants work and live.

Dependent variable: STEM degree-occupation matching

To measure the probability of immigrants matching their educational investments with occupational gains, I generated a matching indicator that assigns a "1" to workers that have equal or greater occupation attainment in STEM with respect to their college degree in a STEM field, and "0" to all others. Since the selected subpopulation comprises only STEM field college

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[19] Some of these graduates also have postgraduate degrees, but the field of study is not identified in the ACS. Thus, postgraduate degree is used as a control foreducational attainment but not necessarily STEM specialization.
[20] https://www.innovation-cities.com/index-2019-global-city-rankings/18842/

graduates, individuals who work in STEM occupations without a STEM college degree are not included in the analysis. Note that this exclusion eliminates people without a STEM college degree who may go into graduate school in a STEM-related major and have a high chance of matching to a STEM occupation. The matching measure makes the reasonable assumptions that the goal of those who graduated with STEM degrees is to end in STEM occupations, and that having a STEM occupation constitutes a move upward in socioeconomic status. The weighted proportions and counts within each ethnonational category are shown in Table 3.1. A deliberate decision was made to unify all STEM and STEM-related occupation within one category as the intention of this study is not to focus on the different value society gives to the different STEM fields, but to the value that high skills labor demand assigns to the educational attainment of different ethnoracial immigrants groups. The recommendations provided by The Office of Management and Budget [21] determined that STEM includes computer and mathematical occupations, engineers, engineering technicians, life scientists, physical scientists, social scientists, science technicians, and STEM managers. And that STEM-related occupations consist of architects, health care practitioners, health care managers, and health care technicians. Based on these recommendations, STEM occupations and degree fields were coded using IPUMS variables *occ2010* and *degfield* respectively.

Independent variables: first and second level fixed and random variables

The level one indicators include demographic, ethnoracial, temporal, spatial evenness, and human capital measures. The temporal control *multiyear* is the actual year of survey that builds each 5-year ACS file. Demographic variables are *age* and its squared term to account for quadratic shape, *female*—which is IPUMS' sex variable recoded as 0 for men and 1 for women,

[21] www.bls.gov/soc/#crosswalks

married an indicator of marital status, and *non-White* is the racial control. The ethnic origin predictor is specified differently in the models, in one, it identifies the *continent of origin* of immigrants—including Europe, Asia, Africa, South America, Central America and Caribbean, and “others”, and in the other models it identifies *the country of origin*—including India, China, Philippines, Korea, Vietnam, Japan, and other Asian countries, Mexico Cuba, and South and Central American countries combined. Human capital consists of a proxy for receiving *education abroad* (see Dissertation Paper II), *college diploma*—which for this subpopulation is the lowest educational attainment, a proxy for *undetermined legal status* derived from logical edits (see Dissertation Paper II), a *non-fluent* in English dichotomy obtained by recoding IPUMS variable *speakeng* as 0 for those who are fluent or native speakers and 1 for speaking well or worse.

The level two variables include socio-spatial characteristic of metropolitan statistical areas (MSAs), which the U.S. Office of Management and Budget (OMB) delineates based on the geographic sphere of influence of the main cities in the U.S., based on where most people live, work, and conduct business in urban centers. Proportions of different demographic groups were calculated by MSA for each 5-year ACS file. These groups include immigrants, Asians, Latinos, and people with high occupational earnings status[22], and are transformed to mean centered percentages to be meaningful in the binary outcome model. A state-level *coastal* indicator that is 1 for metropolitan areas in East or West coasts states and 0 for all others is included to test for a broader national spatial polarization of innovation. Lastly, measures of ethnoracial spatial evenness are included to go beyond simple ethnoracial concentrations and provide actual

[22] Defined as workers with one standard deviation above the mean occupational status from the IPUMS’ *erscor90* variable.

measures of neighborhood-level spatial segregation, which are provided by the Dissimilarity Index described in detail below.

Dissimilarity Index

This index is a measure of spatial segregation that calculates the differences in residential patterns of one racial/ethnic group in relation to another. Dissimilarity measures the percentage of a group's population that would have to move in or out of a neighborhood for each neighborhood to have the same percentage of that group as the metropolitan area that contains it. The index ranges from 0.0 (complete integration) to 1.0 (complete segregation). This index provides important information about the spatial ethnic segregation to which immigrants are exposed to in the places where they work and live. Even if a person does not live in a highly segregated neighborhood, the spill-over effects of such neighborhood being in an ethnically segregated MSA are assumed to be significant as the person would most likely interact with employers and coworkers that do live in segregated neighborhoods. The Dissimilarity Index of MSAs using 2010 Census data is publicly available from the Diversity and Disparities project at Brown University[23]. Due to the focus on positive and negative ethnoracialization exemplified by the contrasting experience of Latino and Asian immigrants, I only selected the Dissimilarity indexes of all White/Asians, and White/Latinos living in the U.S., independent of nativity, to capture the effect on matching of living in ethnoracially segregated innovative metropolitan areas.

Descriptive findings

Summary statistics of weighted counts and proportions are provided in Table 3.1, for level 1 predictors, and in Table 3.1 for level 2 predictors. Proportions across ethnonational groups of

[23] https://s4.ad.brown.edu/projects/diversity/Data/data.htm#WP

educational/occupational matching reveal low levels of matching within all groups, from 60 percent down to 25, and overall only 48 percent have a successful match. There are, however, stark differences between ethnonational groups, providing some grounds to **hypothesis I**, as Asians, in general, have between two and three times higher STEM matching proportions than Latinos. The relatively high proportions of Indians, Chinese, and Vietnamese who have a successful match could explain their dominance in the high skilled immigrant labor market and provides evidence to the bipolarity of the ethnoracialization process.

Table 3.1 shows that during the past decade STEM educated Asian and Latino immigrant populations have remained evenly distributed within groups. Overall, however, this subpopulation has grown substantially at a rate of 40 percent in this period ((443,443-316,085)/316,085 *100) compared to all immigrants' growth of 3 percent[24] . Patriarchal divisions of labor from the countries of origin are replicated, as there are roughly two times more males than females in this subpopulation, with female proportions ranging from 30 percent in Indians to 45 percent in Filipinos. In summary, demographic summary statistics paint a picture of this subpopulation as mostly married males in their 40s, which, for Indians and Chinese, contrast with the general perception of immigrant tech workers being young recent graduates.

Table 3.1 around here

A glance of the human capital summary statistics provides some mixed evidence of the effect of education on matching probabilities. In Table 3.1, Indians and Chinese have the highest educational attainment with over 60 percent of them holding a postgraduate degree, mirroring the patterns of skill-matching and supporting established notions of the importance of post-graduate

[24] https://www.migrationpolicy.org/article/frequently-requested-statistics-immigrants-and-immigration-united-states-2020.

education on STEM careers. Only 22 percent of Filipinos, on the other hand, have a graduate degree, which is about half of the proportion of their successful matches. This, in combination with South American proportions of postgraduates, who in contrast have 17 percent less matches than postgraduates, offer some evidence of the divergent effect of human capital for differently ethnoracialized groups. The total subpopulation has an uneven distribution of educational origin, with Indians and Vietnamese in the extremes at 72 and 24 percent respectively getting their education abroad. Despite the high contrast between the two groups, this variable is the result of logical edits so these statistics should be taken with skepticism until a direct measure of educational origin can confirm them. Similar is the case of the legal status identifier, as the variable does not differentiate directly between, say, undocumented immigrants and work-visa holders, and the status for these contrasting groups is both labeled "undetermined". However, the contrasting figures from Vietnamese at only 3.7 percent undetermined legal status and Indians and Mexicans at over 30 percent, suggest differences between the paths to permanent residency across immigrant groups that affect the chances of integration into the STEM labor market. Additionally, most, if not all immigrants with "undetermined" legal status face precarious conditions, even if the hold valuable documents such as H-1B visas or OPT permits, as these are temporary, meaning that conditions may change drastically for those who hold them (Gonzalez 2020 and 2021). Lastly, one of the most influential human capital endowments for immigrant success, according to the literature, is fluency in English and in this subpopulation over 80 percent of Indians, Filipinos, and "Other Asian" groups speak very well or better, while half of Cubans, and a third of Central Americans do not. Taking this information at face value, we could conclude that the differences in matching are, therefore, not ethnoracial in nature, but rather explained by a combination of different human capital achievements that give Asian groups an advantage over Latin Americans when matching their education with a STEM occupation. Multivariate and multilevel analysis will confirm or deny this initial presumption.

Consistent with mounting evidence to the problematic racial and ethnic categorization in Census data (Strmic-Pawl 2018; Prewitt 2013), Table 3.1 shows the heterogeneity of ethnonational groups that are mostly lumped together into a single race for Asians, or a single ethnicity for Latinos. Every major high-skilled immigrant-sending Asian nation except for Japan self-identify as non-White almost exclusively (> 98 percent). Most people from "other Asian" nations, on the other hand, consider themselves White, with only 37 percent of them claiming other race. Similarly, the majority of highly-skilled immigrants from Latin America self-identify as White (75 percent on average), which could either be the result of racial segregation and discrimination in Latin America creating a racialized pre-migration selectivity bias or, as some analysts have argued, an effect of White being racialized as having higher education and socioeconomic status in the U.S. imagination, inducing this elite ethnic group to self-identify as White. Despite their self-racialization, it is clear that Latin American immigrants are not ethnoracialized as Whites by the U.S. society (Guarnizo and Becerra (Forthcoming)), so that over 90 percent of Cubans, for example, self-classifying as White has little effect on their matching probabilities.

Socio-spatial measures of context

The "compositional" measures of interest in this study—ethnic and status concentration, and ethnic segregation—aim to capture the influence of context in the matching probabilities and are included in Table 3.1. Ethnic concentration and occupational status are provided as percentages within MSAs and ethnic segregation by their averaged neighborhood-level dissimilarity index. No evident patterns were recognized in a close inspection of these summary statistics (Appendix

1), and a model regressing innovation rankings on the socio-spatial variables confirmed this lack of lineal correlation (output not included). This provides some evidence that compositional and segregation measures may not be as influential for highly educated immigrants who may be more residentially integrated with Whites and less influenced by ethnic segregation than low-skilled migrants in U.S. metropolitan areas.

Descriptive statistics have provided mixed evidence about the human capital, socio-spatial, and ethnoracialization influence on matching proportions. While increases in matching may correspond with higher proportions of graduate degrees, these relationships are not reflected across ethnonational groups, lending some support to hypothesis I about the ethnoracialization process. English proficiency, however, seems to account for these discrepancies giving credence to theories of human capital endowments. For hypothesis II, no spatial patterns of influence were detected, but to confirm or deny these interpretations it is necessary to analyze the combined effects of the different influential factors while controlling for others with a multiscalar approach. I do so in the following section.

Table 3.2 about here

Empirical models

To analyze the main two hypotheses of this study, four different models using two modeling techniques are designed. First, to test the conception that race is subordinate to ethnicity for the matching across high skilled immigrant groups, I use a larger sample that includes STEM college graduate individuals from all immigrant groups, and use European immigrants as the reference for their racial similarity with the dominant group in the host society. I built a logistic model (Model 1, Table 3.3) that regresses the dichotomous measure of matching success on ethnoracial origin, which is defined by the interaction between ethnicity (continental origin) and race (non-

White), while controlling for temporal demographic, and human capital variables. I graph the contrasts of marginal predictive probabilities of Model 1 in Figure 3.1 to make the main and interaction effects easy to interpret.

Figure 3.1 about here

Second, to test the design that uses national origin categorization as more powerful at capturing heterogeneity within ethnoracial groups than continental origin categories, I run another logistic regression of matching on the interaction between country of origin and fluency in English while controlling for all other factors. For ease of interpretation of the interacted model, the margins of the predicted probabilities are calculated and their marginal probability contrasts graphed in Figure 3.2. Third, to measure the effect of the variance between metropolitan areas, I include a mixed effects multilevel model[25] with random MSA-level intercepts and the same first level fixed effects as in Model 2. Fourth, in Model 4 I test the sociospatial composition context by adding second-level predictors of ethnoracial concentration and occupational status within MSAs. I also add the White/Asian and White/Latino dissimilarity indexes to this model to test the hypothesis that uneven distribution of the ethnic and racial groups within neighborhoods in the top innovative MSAs is influential on matching across co-ethnic immigrant groups. All second-level predictors are mean-centered so that the modeled estimates have substantive meaning at the random intercepts. As the output of Model 4 does not reflect independent odds ratios for MSA, only the variance of their random intercepts, I graph the

[25] To reduce the bias in the variance components of small cluster sizes during pseudo-maximum-likelihood estimation, person-level weights were scaled using Rabe-Hesketh and Skrondal's Method 1. This adjustment makes the sum of the 1st-level weights equal the effective sample size of their corresponding MSAs (Rabe-Hesketh, S., and A. Skrondal. 2006. Multilevel modelling of complex survey data. Journal of the Royal Statistical Society, Series A 169: 805–827).

average change in probability of matching within MSAs across ethno-racial groups by education and English proficiency, also known as the contrasts of marginal predicted means (Figure 3.3).

Figure 3.2 and 3.3 about here

EMPIRICAL ANALYSIS

The analysis of the models described above is done in three steps. First, I evaluate the results of the ethno-continental model (Model 1) to determine if the elimination of the race predictor is supported in this subpopulation. Second, I analyze the logistic and the mixed effects multilevel models (2-4) in Table 3.3 to see the changes in explanatory power and variance of each additional set of predictors. However, since some interactions are included in the fixed effect models and the effects of the random intercepts are hard to synthetize from the model output, I move to analyze their contrasts of predictive margins and marginal means in **Figures 2** and **3** respectively[26]. Analysis provided below.

The race # ethnicity interaction

Contrasts from Figure 3.1 show that highly skilled non-white immigrants from Asia are the only group that has a positive difference with European Whites, with 20 percent higher odds of matching (exp(0.18)). All Latino immigrant groups exhibit the opposite relationship, irrespective of race or language, demonstrating a strong ethnoracialized pattern and confirming previous findings (Guarnizo and Becerra (Forthcoming)). The only group whose race seems to be a determinant factor on matching probabilities, *ceteris paribus,* is again, Asian immigrants. However, recalling from Table 3.1 we realize that the "White/non-White" distribution among

[26] Model 3 in Table 3 is excluded from the analysis of contrasts, as its results look exactly the same as the full model which includes 2nd level spatial predictors.

Asians is driven by ethnonational distinctions, and Whites, in the majority, are composed of immigrants from Middle Eastern countries. Middle Eastern immigrants are not generally associated with the Pan-Asian identity as socially constructed in the U.S. and are even classified as being racially White in the U.S. Census[27]. We also know that although Latinos are more racially heterogeneous with nontrivial representation in every race (Table 3.1), they are in essence racialized as "non-White" as a group, even when the majority of them self-identify as White. The idea of a privileged race or skin color in high-skills immigrant selection is also debunked by these findings as Cubans, who almost unanimously self-identify as White, have much lower match odds than Filipinos, who are racialized as darker Asians (Espiritu 1994). These results confirm the inadequacy of race to differentiate between groups in any better way than national origin would, as the ethnoracial identity of immigrants is not racial in nature but rather linked to their racialized national origin. Thus, the concept of ethnoracialization is again proven to provide be a more robust and meaningful framework in which to study immigrant unequal outcomes, and therefore, validates my decision to exclude race from the analysis of this subpopulation going forward. With respect to the influence of language proficiency on matching probabilities across ethnoracial groups, we see from Figure 3.1 that there are no significant differences between ethno-continental groups. In the next section I examine this finding further by exploring if this lack of effect is really the case or if it is a result of aggregating groups with contrasting English skills.

[27] https://www.census.gov/topics/population/race/about.html

Ethnonational multilevel models

Level 1 effects

Throughout the models it is evident that aside from 2019, the temporal effect on matching is not significant when we control for all other factors with p values > 0.05. Rather than interpreting this finding as a rejection of the fluidity of ethnoracialization with respect to time, I pose that this is the result of the structural discrimination perspective on job-matching. Legislation that could affect the matching outcomes of this population by ethnonational origin during the last decade has only reinforced established trends. During the Obama administration high-skilled immigration increased but remained highly ethnoracialized prioritizing Indian Chinese STEM students and workers. The effects of recently passed laws under the Fairness for High-Skilled Immigrants Act of 2020[28] may create some waves in the future, but they most likely will be in the direction of further ethnoracialized polarization. Two of the main changes that the Act proposes are removing per-country limitations on employment-based visas, and increasing the per-country numerical limitation for family-sponsored immigrants which are expected to help those ethnonational groups with established high-skilled immigration paths, namely Indians and Chinese.

Demographically, the odds of matching decrease on average by about 4 percent by every year increase in age, women have 33 percent less odds of matching than men and marriage increases the odds by about 25 percent, all other things equal. The gender disparity in the relationship between STEM education and occupation is alarming and is sure to be an influential factor in mediating ethnoracialization *within* ethnonational groups. Indeed, research suggests that some of the gains in gender equality in the last 30 years are dwarfed by the increasingly

[28] https://www.congress.gov/bill/116th-congress/house-bill/1044/text

divergent outcomes between men and women within different income brackets across U.S. regional geographies, especially at the top of the occupational hierarchy (Goodwin-White, 2018) However, the gendered component of skills-matching goes beyond the scope of this paper, and will be the main focus of a future study.

With regards to human capital, I find evidence that immigrant ethnoracialization through structural discrimination in STEM work-visa and permit may play a considerable role in the matching probabilities as, contrary to expectations, acquiring one's education abroad increases the odds of matching by 15 percent, all other things equal. Assuming that this variable is a good approximation to actual degree origin suggests that immigrants that come with work visas, which require an advanced degree and an employer to act as sponsor, may bypass the intense competition as they enter the dynamic labor markets in innovative metropolitan areas. It is also evident that after controlling for all other factors, having a postgraduate degree is extremely advantageous, as they have 57 percent higher odds of matching their STEM education with a STEM job, than those with only a college degree. Aside from an 11 percent decrease in odds of matching in the full model (Model 4), legal status is not significant in this subpopulation, pointing to a possible spatial effect that limits the integration of undocumented and "nonimmigrant" STEM applicants into STEM careers. The main effects show that, in line with ethno-continental aggregate results, lack of fluency in English reduces the odds of matching by 30 percent, other things being equal. However, we will explore how this influence is mediated by education and ethnonational origin after integrating spatial controls in the full model.

The effect of country of origin on matching odds, using Indians as reference, uncovers the inequalities that are prevalent in this subpopulation, usually hidden in research by aggregate racial grouping. Models 2, 3, and 4, in Table 3.1 present consistent differences across ethnonational groups regardless of the modeling technique utilized, providing solid evidence to *hypothesis I*, especially the value of disaggregating racial Asians and ethnic Latinos. Positive ethnoracialization clearly does not benefit immigrants from all Asian countries equally. All else being equal, Filipinos, Koreans, Japanese, and all "other Asians" have between 40 and 60 percent lower odds of matching that Indians regardless of which controls are used. The only ethnonational group that has better odds of matching than Indians are Vietnamese immigrants, at 16 percent above the reference group—which could be related to their high level of citizenship though naturalization (96 percent from Table 3.1). Chinese, as expected, do not have significantly different odds from those of Indians, especially when controlling for the MSA random slopes. Comparisons to Latin American groups draw more striking evidence of the impact of negative ethnoracialization in varying degrees. As shown in Table 3.3 there is a reduction in odds of matching by 54 percent in Cubans all the way down to 71 percent-plus for Mexicans and Central Americans in the full model, which controls for all other temporal, spatial, demographic, and human capital characteristics. These results are shocking, and not only confirm the ethnoracialized selection bias at the top of the educational skills hierarchy favoring Indians and Chinese over other Asian groups, but an outright systematic and pervasive discrimination against Latino high skilled immigrants whose educational attainment is devalued when trying to land jobs that match their skills. This phenomenon is further examined below, where I analyze the multilevel mixed model estimates and show how persistent inequality patterns are even when controlling for local labor market and ethno-spatial characteristics.

Contrast of margins at Level 1 and Level 2

Controls for spatial ethnic segregation and concentration of coethnic groups and high-profile workers at the metropolitan scale were included to explore if they explained some of the variance in matching outcomes. The intraclass correlation (ICC) was calculated in an unconditional intercept-only model to measure if clustering data within MSAs explained a significant portion of the observed variance across the fixed (individual-level) predictors. The ICC was 0.0363, lower than what is considered clear evidence of clustering (0.05) (Heck et al. 2014), still, it is close enough to warrant the analysis of spatial effects. Figures 3.2 and 3.3, respectively, graph the contrasts of marginal predicted matching probabilities and marginal means across MSAs (in logit scale), decomposed by ethnonational groups' education and English proficiency. Figure 3.2 uses the estimates from Model 2, where only person-level fixed effects were estimated, without any level 2 spatial predictors. The contrasts show that although having a postgraduate degree does improve the matching probabilities some, the pattern of their contrasts remains almost identical regardless of level of education. Except for Chinese and Vietnamese immigrants, when compared to Indians, all other groups do progressively worse as we move right along the positive to negative ethnoracialization axis (in the Asian to Latino direction). Surprisingly, the effect of English fluency for Latinos is opposite than expected, especially among postgraduate workers, as those who are non-fluent have about 10 (exp(0.1)) percent higher odds of matching than fluent (Figure 3.2). This language paradox, however, is completely erased when we factor in spatial controls in Figure 3.3, pointing to the influence of spatial compositional and segregationist characteristics of MSAs. From Model 4 in Table 3.3, we can conclude that the difference in matching probabilities between fluent and non-fluent immigrants is being driven by increases in the averages of Latino proportion of the population, decreasing proportion of immigrants, and increasing proportion of high occupational earnings status workers. Thus, places with proportionally more Latinos, less immigrants in general, and more workers in high paying occupations seem to be more tolerant of language barriers. Other than eliminating the fluency effect, including the level 2 controls only slightly diminishes the vertical spread of matching probabilities. The pattern of ethnoracialization on matching outcomes across all ethno-national groups remains unaltered from previous results. This finding offers support to *hypothesis II* and we can, therefore, conclude that the MSA-specific spatial characteristics controlled for in this study are less influential on matching probabilities than the positive or negative ethnoracialization of immigrants common to all STEM labor markets in this study.

DISCUSSION

The model outcomes described above reveal some alarming patterns. At the onset of this study I expected to find matching differences across ethnonational groups, but the magnitude observed and consistency across models is surprising. My aim with this study was to demonstrate that discrepancies in matching odds are not the result of different personal characteristics of immigrant workers, or the specific characteristics of local labor markets where the live and work, but rather the manifestation of structural discriminatory practices based on ethnoracial signals at different instances of the job-matching process. These biased preconceptions about immigrants, which are ascribed to individuals depending on their nationality, fit clearly within the framework of ethnoracialization as I defined it at the beginning of the paper.

Consistent with *hypothesis I*, disparate matching outcomes not only vary dramatically between the commonly used ethnoracial categories of Asian/Latino, but vary substantially within these categories as well. Indian and Chinese clearly dominate skill-job matching in the STEM labor market among immigrants, while most Latin Americans with STEM education are relegated to non-STEM careers. Also, validating *Hypothesis II*, mixed effects multilevel modeling demonstrate that spatial characteristics, such as ethnic segregation and concentration of key groups within innovative metropolitan areas, do not explain the patterns of unequal matching success across ethno-national groups. This is not to say that space and place are irrelevant, as regional variation seems to fully explain the English fluency effect and about 10 percent of the matching probability contrasts and between Indians (the reference) and immigrants in all other ethnonational groups in the study. Yet, space is clearly secondary to the structural and entrenched ethnoracialization that permeates all STEM labor markets producing and reproducing the patterns of unequal matching probabilities across all major metropolitan areas.

According to findings in this study, Indians and Chinese's higher odds of matching are not well explained by any of the demographic or human capital characteristics that I controlled for, or the socio-spatial context to which they are exposed. Thorough analysis has been made about the apparent exceptionality of some Asian-American groups, who have surpassed U.S.-born Whites in various measures of achievement (Lee and Zhou 2015, Kim 2015). However, these explanations apply to multigenerational upward mobility, and are not easily applicable to 1st generation immigrants. Analysis presented in this paper also weakens the "model minority" myth as we see Koreans, Filipinos, and especially Japanese not able to match their credentials with a suitable job at the rate that Indians and Chinese do. As cultural or cognitive superiority is not an empirically valid cause, only one explanation comes to mind to explain the privileged position of Indians and Chinese at the top of the high-killed immigrant labor market and the inability of Mexicans and Central Americans to succeed as a group—Structural or Institutional discrimination.

The most influential effect of ethnoracialization seems to occur even before immigrants set foot in the U.S. Institutional or structural discrimination engenders from U.S. authorities ethnoracialized selections of immigrants by choosing who deserves approval and who does not based on socially constructed preconceptions about the meaning ascribed to national origin, which should be irrelevant when evaluating the qualifications of an applicant. Putting it simply, among equally qualified immigrants with STEM degrees, those from India and China are highly desired, those from other Asian countries are welcomed, while those from South America are accepted, and those from Central America and Mexico are rejected. Each of these degrees of acceptance brings with it a slew of imagined attributes that justify the discriminative process for the ethnoracializing brain. What is worse, is that negatively ethnoracialized immigrants carry with them these misplaced judgements on their individual capabilities throughout their careers, affecting their socioeconomic integration in the long run. In the case of Mexican and Central American immigrants, the overly negative ethnoracialization of their identity as the group with less skills has unsurmountable damaging effects.

Seemingly, nowhere in the creative-class development model is there room for a systematic inclusion of Latin American immigrants into high-tech careers. Despite a considerable numerical presence among the highly educated in the U.S.[29], Latinos are still ethnoracialized as uneducated, which may influence high-tech employers at the time of hiring their equally ethnoracialized immigrant coethnics. Economists call this *statistical discrimination*; meaning that employers make judgments about unobservable characteristics of applicants based on stereotypes of the group the applicant belongs to (Arrow 1971, Wright et al. 2017). As a consequence of being at the receiving end of negative ethnoracialization and structural discrimination the probability of most Latin American, and specially Mexican and Central American immigrants to land a STEM job that matched their credentials is extremely low. Not only would most jobs in high tech industries be already committed to mostly Indian and Chinese

[29] According to 2017 ACS data of college educated population Latino= 4.8 million; Asian= 6.3 million; Black 5.2 million Source: https://factfinder.census.gov

H-1B and OPT recipients, but they would also be competing with native applicants who have language, educational prestige, and social capital advantages. As a result, discouraged Latino workers would be forced to accept positions below their cognitive capabilities in other fields or return to their countries of origin (Akee, and Jones 2019). In this scenario, the advantages of acquiring advanced degrees in STEM fields and living in a tech-dense metropolitan area would be eclipsed by the pervasive negative ethnoracialization of Mexican and Central American immigrants to which they are subjected at every stage in their integration journeys. Unfortunately, for Latinos in cities where tech companies agglomerate this means they get displaced further into the "service underclass" (Scott, 2012), where they may work in the same spaces and places as the creative class, but at polar opposites with regards to occupation, income, and social status. The implication of this structural discrimination is, therefore, that high-skilled Latino immigrants would be as likely to suffer the deleterious effects of ethnoracialization on spatial segregation, lower wages, unaffordable or inappropriate housing, dead-end occupations, as their low-skilled counterparts and other U.S.-born coethnics.

Limitations and future research

Although the findings of this study are robust and compelling, there are some limitations with regards to data, design, and analysis. Future research in the topic of educational-occupational matching of immigrants should aim at reducing the uncertainty created by data limitations when creating both outcome and predictor variables. As mentioned in the Data section of this paper, many of the codification decisions with regards to educational origin, what constitutes a STEM career, and even what socio-spatial variables were selected have an impact on the output of the models which may bias the analysis. There are ongoing efforts to use the restricted version of the National Survey of College Graduates (NSCG) linked to the ACS to study the relationship between STEM education, careers and socioeconomic outcomes. This would allow researchers to identify the postgraduate degree field and include it in the matching odds, utilize consistent education/occupation codes, determine the source of education with certainty, create a longitudinal dataset that can follow immigrants at different life-stages, and use more refined geographic information for spatial controls. How significant these data quality improvements may be in reducing the so far strong effect of Ethnoracialization on matching probabilities is yet to be determined. Additionally, one important finding that I scarcely mention in this study, due to time and space limitations, is the sizeable effect of sex on matching probabilities. Gendered inequality among high-skilled immigrants needs to be explored further, as this population may combine the undervaluing of women's cognitive capabilities in the host society with the negative effect on women immigrants whose employment patterns may reflect gendered societal inequalities carried from their country of origin. Lastly, this study frames spatial segregation and concentration as mere controls. For a more substantial geographic epistemological impact it is important to run interactions or fully stratified models using these socio-spatial characteristics to incorporate the geographic concept of spatial heterogeneity and estimate how the influence of a factor (i.e. ethnoracialization) may differ based on geographic conditions.

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Table 3.1. **Summary Statistics by Ethnic Group—Post-Estimation Population Means and Percentages**

Variable		Indian	Filipino	Chinese	Korean	Viet-namese	Japanese	Other Asian	Mexican	Cuban	South American	Central American	Total
Educ/Occ Match		63.02%	40.66%	56.79%	38.84%	55.86%	34.91%	42.84%	25.15%	26.32%	29.62%	23.64%	48.20%
Year													
	2010	26.87%	8.75%	17.81%	5.96%	6.10%	2.19%	11.72%	5.91%	2.98%	8.75%	2.97%	316085
	2011	27.08%	8.22%	18.35%	5.48%	6.21%	2.21%	11.30%	5.95%	3.04%	9.55%	2.61%	318007
	2012	28.74%	8.16%	16.95%	5.32%	5.58%	2.22%	11.50%	6.03%	3.24%	9.26%	3.00%	332405
	2013	29.13%	7.30%	17.77%	5.37%	6.26%	1.85%	10.99%	6.52%	3.05%	8.91%	2.84%	344703
	2014	30.57%	7.46%	17.51%	5.06%	5.66%	2.14%	10.99%	5.99%	2.70%	9.05%	2.87%	350730
	2015	30.28%	7.33%	18.31%	4.90%	5.31%	1.89%	11.09%	6.47%	2.78%	8.93%	2.70%	371991
	2016	30.95%	6.68%	17.75%	4.91%	5.08%	2.04%	11.20%	6.01%	3.06%	9.53%	2.79%	385273
	2017	31.87%	6.49%	17.70%	4.74%	4.87%	1.84%	11.08%	6.06%	2.85%	9.39%	3.11%	414041
	2018	31.00%	6.05%	18.11%	4.77%	5.08%	1.91%	10.88%	6.18%	3.12%	10.21%	2.68%	433895
	2019	31.58%	6.30%	17.96%	4.71%	4.66%	1.69%	11.24%	6.33%	2.92%	9.73%	2.89%	443443
Age		39.53	46.27	42.87	43.46	43.67	44.46	43.60	42.10	47.93	44.19	42.89	
Female		30.32%	44.48%	39.64%	35.51%	36.99%	32.67%	31.86%	32.61%	37.19%	37.98%	36.41%	
Married		84.05%	72.68%	75.46%	74.37%	71.61%	71.69%	71.23%	64.05%	63.90%	68.18%	60.63%	
Edu Abroad		72.27%	64.52%	58.96%	46.65%	23.95%	57.46%	51.12%	51.73%	65.86%	63.63%	41.74%	
Postgraduate		61.70%	22.47%	68.53%	46.75%	33.89%	45.58%	52.52%	31.79%	35.83%	46.22%	34.42%	
Undet Legal		32.76%	14.42%	18.91%	18.12%	3.70%	25.85%	14.10%	30.38%	23.28%	21.39%	23.11%	
Non-Fluent		11.69%	16.14%	33.96%	35.86%	33.00%	34.18%	15.80%	34.33%	50.41%	24.97%	30.23%	
Non-White		99.22%	98.30%	99.39%	98.99%	99.57%	85.84%	37.47%	30.05%	6.64%	25.99%	39.70%	
Coastal		65.77%	81.44%	81.25%	80.66%	75.01%	81.18%	76.07%	56.82%	92.16%	80.44%	79.66%	
Total		1112609	266312	661670	188575	201205	73528	415006	228303	110182	347501	105682	3710573

Table 3.1. Summary Statistics of Socio-spatial measures by MSAs

Top 33 Most Innovative Metropolitan Statistical Areas in the U.S.	White /Asian Dissim.	White /Latino Dissim.	Percent Asian	Percent Latino	Percent Immig.	Percent High Occupational Earnings Status
Albany-Schenectady-Troy, NY	40.50	38.85	4.13	5.07	8.23	20.30
Allentown-Bethlehem-Easton, PA-NJ	35.68	55.43	2.74	15.86	9.35	16.21
Austin-Round Rock, TX	38.27	43.23	5.32	32.21	16.15	23.71
Baltimore-Columbia-Towson, MD	40.89	39.76	5.35	5.67	11.18	24.12
Boston-Cambridge-Newton, MA-NH	43.38	59.58	7.43	11.73	19.16	25.74
Buffalo-Cheektowaga-Niagara Falls, NY	51.00	50.74	2.88	4.79	6.71	16.65
Charlotte-Concord-Gastonia, NC-SC	41.17	47.64	3.43	9.99	10.36	19.66
Chicago-Naperville-Elgin, IL-IN-WI	42.72	56.32	6.28	21.95	18.50	20.25
Dallas-Fort Worth-Arlington, TX	44.49	50.27	6.48	28.86	19.34	20.25
Denver-Aurora-Lakewood, CO	30.03	48.78	4.09	23.02	13.38	24.45
Durham-Chapel Hill, NC	41.94	47.98	4.32	12.97	14.40	23.57
El Paso, TX	20.53	43.26	1.17	82.22	26.80	12.90
Houston-The Woodlands-Sugar Land, TX	48.72	52.51	7.42	37.07	24.11	19.55
Jacksonville, FL	34.61	27.59	3.73	8.63	10.22	18.87
Los Angeles-Long Beach-Anaheim, CA	45.73	62.15	15.55	45.29	34.49	18.07
Miami-Fort Lauderdale-West Palm Beach,	32.71	57.36	2.39	45.02	41.12	17.34
Minneapolis-St. Paul-Bloomington, MN-WI	39.56	42.50	6.23	5.77	10.92	22.21
New York-Newark-Jersey City, NY-NJ-PA	50.41	62.00	10.54	24.40	29.95	20.95
Orlando-Kissimmee-Sanford, FL	32.29	40.20	4.17	30.29	19.05	17.54
Philadelphia-Camden-Wilmington, PA-NJ-D	40.26	55.06	5.59	9.29	11.25	20.92
Pittsburgh, PA	48.86	28.56	2.20	1.73	4.24	19.36
Portland-Vancouver-Hillsboro, OR-WA	31.53	34.26	6.79	12.01	13.78	20.85
Providence-Warwick, RI-MA	36.49	60.11	2.83	12.34	13.79	16.82
Raleigh, NC	43.93	37.13	5.16	10.53	12.68	25.24
Riverside-San Bernardino-Ontario, CA	38.18	42.36	6.66	50.02	22.43	13.40
Sacramento--Roseville--Arden-Arcade, CA	46.77	38.85	13.43	21.38	19.51	20.21
San Antonio-New Braunfels, TX	36.14	46.08	2.38	55.82	13.61	15.81
San Diego-Carlsbad, CA	44.28	49.61	11.69	33.65	25.09	20.96

San Francisco-Oakland-Hayward, CA	44.28	49.59	25.44	22.27	31.89	27.94
San Jose-Sunnyvale-Santa Clara, CA	43.03	47.62	34.98	26.32	39.81	33.15
Seattle-Tacoma-Bellevue, WA	33.87	32.80	13.56	9.98	19.78	24.83
Tampa-St. Petersburg-Clearwater, FL	33.10	40.67	3.28	18.86	14.66	18.48
Washington-Arlington-Alexandria, DC-VA-	36.86	48.30	9.92	15.70	24.40	29.76

Sources: Ethnic proportions from the 2014 and 2019 5-year ACS; Dissimilarity Index from the Diversity and Disparities project at Brown University using 2010 Census.

Table 3.3. Multilevel Mixed Effects model odds ratios of STEM Education-Occupation matching on ethnoracial characteristics controlling for time, space, demographic and geospatial predictors in the U.S., 2010-2014 and 2015-2019.

STEM Education-Occupation Match (0-1)	Model 1 Logistic Ethno-Continental	Model 2 Logistic Ethnonational	Model 3 Mixed Logistic Person	Model 4 Mixed Logistic, Spatial
Year of Survey				
2011	1.020 (0.026)	1.000 (0.031)	1.011 (0.031)	1.009 (0.031)
2012	1.008 (0.025)	0.999 (0.030)	0.999 (0.028)	0.996 (0.027)
2013	0.972 (0.024)	0.983 (0.029)	0.981 (0.024)	0.979 (0.024)
2014	0.975 (0.024)	0.996 (0.029)	0.992 (0.027)	0.986 (0.026)
2015	0.998 (0.024)	0.991 (0.029)	0.985 (0.031)	0.974 (0.034)
2016	1.029 (0.025)	1.052 (0.030)	1.040 (0.027)	1.029 (0.027)
2017	0.983 (0.023)	0.974 (0.028)	0.956 (0.023)	0.947 (0.027)
2018	1.011 (0.024)	1.012 (0.028)	0.998 (0.025)	0.988 (0.029)
2019	1.097*** (0.025)	1.116*** (0.031)	1.091** (0.028)	1.076* (0.031)
Age	0.957*** (0.004)	0.962*** (0.005)	0.960*** (0.009)	0.956*** (0.009)
Age # Age	1.000*** (0.000)	1.000* (0.000)	1.000 (0.000)	1.000* (0.000)
Female	0.668*** (0.007)	0.670*** (0.009)	0.666*** (0.031)	0.676*** (0.031)
Married	1.261*** (0.017)	1.286*** (0.021)	1.256*** (0.026)	1.257*** (0.026)
Educated Abroad	1.167*** (0.014)	1.178*** (0.017)	1.146*** (0.039)	1.152*** (0.040)
Only College Degree	0.543*** (0.006)	0.554*** (0.007)	0.566*** (0.023)	0.566*** (0.023)
Legal Status Undetermined	0.909*** (0.013)	0.992 (0.017)	0.953 (0.050)	0.963 (0.051)

Non-English Fluent	0.664***	0.672***	0.692***	0.699***
	(0.009)	(0.025)	(0.022)	(0.023)
Non-White	0.902			
	(0.050)			
Continental Origin (reference: Euro immigrants)				
Asian Immigrants	1.055*			
	(0.028)			
African Immigrants	1.026			
	(0.047)			
Other Immigrants	1.006			
	(0.032)			
South American Immigrants	0.684***			
	(0.020)			
Mexican Immigrants	0.620***			
	(0.022)			
Cent. Amer. & Caribbean Immigrants	0.681***			
	(0.023)			
Race # Ethnicity				
Non-White # Asian	1.952***			
	(0.118)			
Non-White #African	1.031			
	(0.080)			
Non-White # Other	0.884			
	(0.061)			
Non-White # South American	1.201*			
	(0.096)			
Non-White # Mexican	1.002			
	(0.087)			
Non-White # Cent. Amer. & Caribbean	0.836*			
	(0.069)			
Country of Origin (Reference: Indian)				
Filipino		0.673***	0.667***	0.664***
		(0.019)	(0.050)	(0.050)
Chinese		0.842***	0.967	0.958
		(0.019)	(0.068)	(0.067)
Korean		0.508***	0.550***	0.545***

	(0.018)	(0.042)	(0.041)
Vietnamese	1.082*	1.158*	1.159*
	(0.039)	(0.065)	(0.065)
Japanese	0.403***	0.453***	0.449***
	(0.023)	(0.032)	(0.032)
Other Asian	0.553***	0.560***	0.561***
	(0.014)	(0.030)	(0.030)
Mexican	0.331***	0.278***	0.275***
	(0.012)	(0.015)	(0.015)
Cuban	0.488***	0.458***	0.460***
	(0.026)	(0.048)	(0.049)
South American	0.358***	0.377***	0.375***
	(0.010)	(0.034)	(0.034)
Central American	0.317***	0.293***	0.292***
	(0.016)	(0.017)	(0.017)
Fluency # Nationality			
Non-Fluent # Filipino	0.864*		
	(0.062)		
Non-Fluent # Chinese	1.420***		
	(0.066)		
Non-Fluent # Korean	1.069		
	(0.071)		
Non-Fluent # Vietnamese	1.412***		
	(0.093)		
Non-Fluent # Japanese	1.287**		
	(0.123)		
Non-Fluent # Other Asian	0.892		
	(0.056)		
Non-Fluent # Mexican	0.531***		
	(0.043)		
Non-Fluent # Cuban	0.497***		
	(0.046)		
Non-Fluent # South American	0.635***		
	(0.046)		
Non-Fluent # Central American	0.442***		
	(0.055)		
Spatial Controls			
In Coastal States			0.977
			(0.053)

Pct. Latino in MSA				1.007**
				(0.002)
Pct. Asian in MSA				1.009
				(0.005)
Pct. Foreign in MSA				0.984**
				(0.005)
Pct. High Occupational Earnings Score in MSA				1.027***
				(0.007)
Avg. White/Asian Dissimilarity in MSA				0.997
				(0.004)
Avg. White/Latino Dissimilarity in MSA				0.991**
				(0.002)
Variance of MSA Random Intercept			1.037*	1.010**
			(0.015)	(0.003)
Observations	2,012,926	2,012,087	2,013,052	2,012,124

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 3.1. Contrast of Predictive Margins of Matching

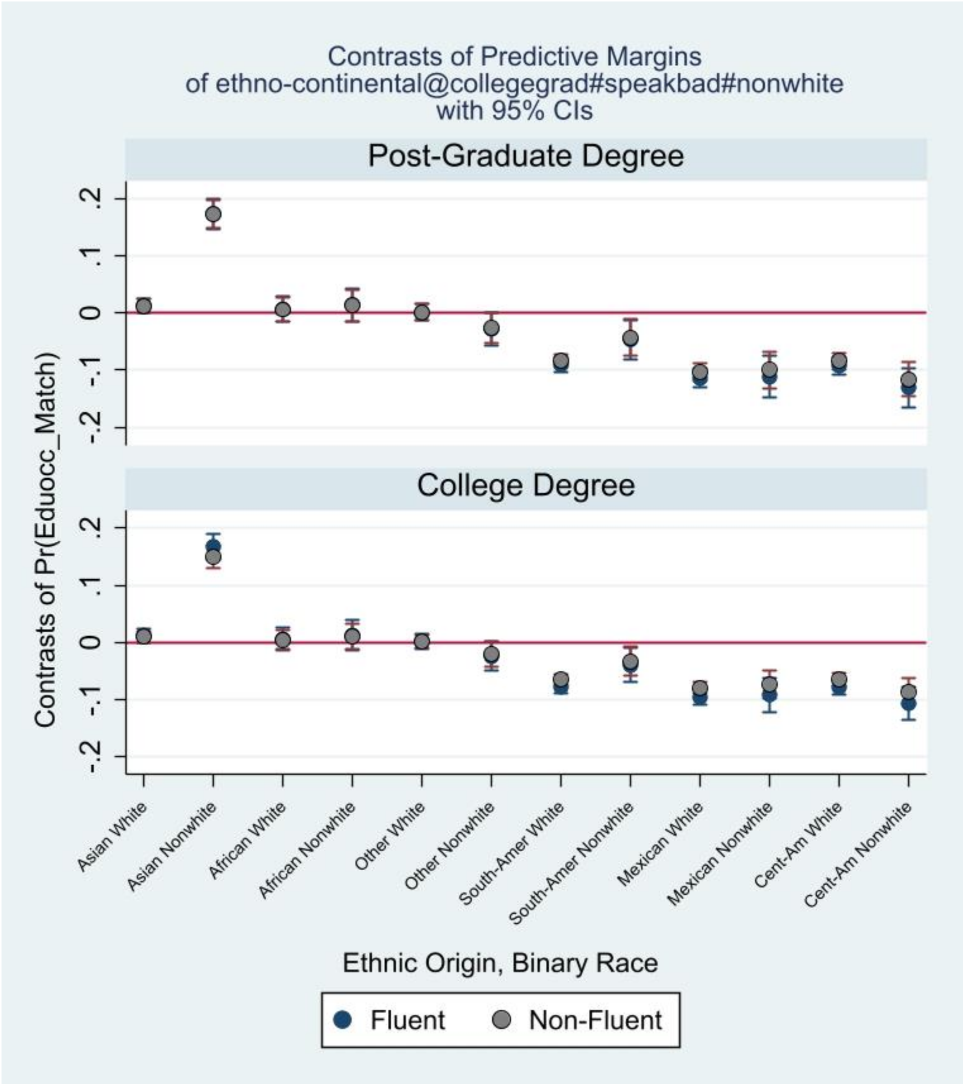


Figure 3.2 Logit contrasts of matching.

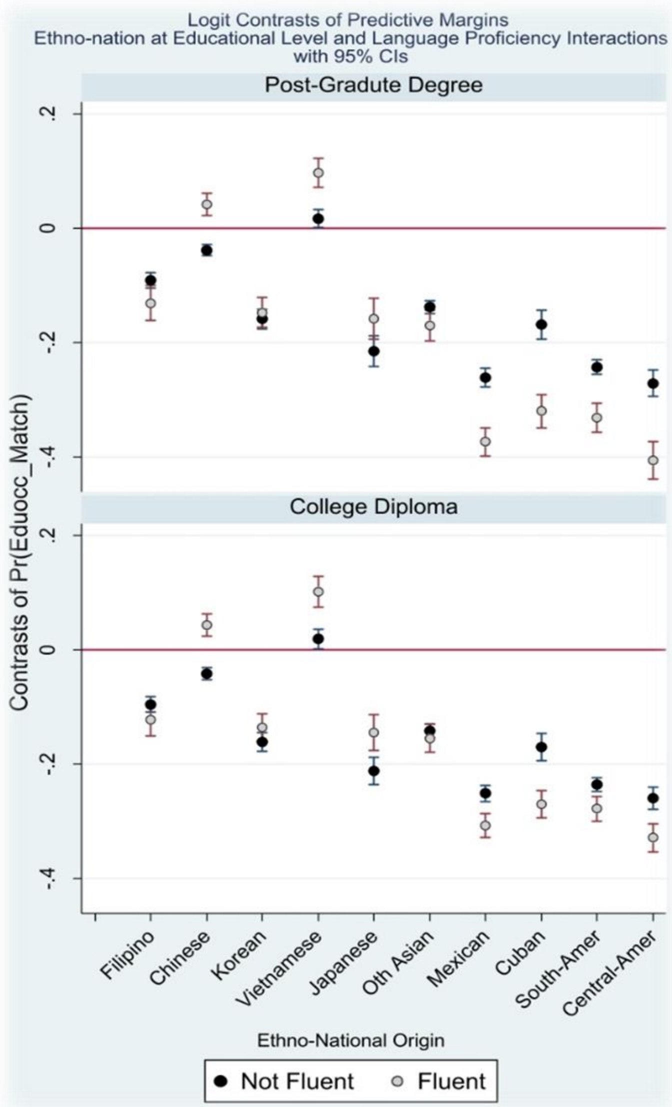
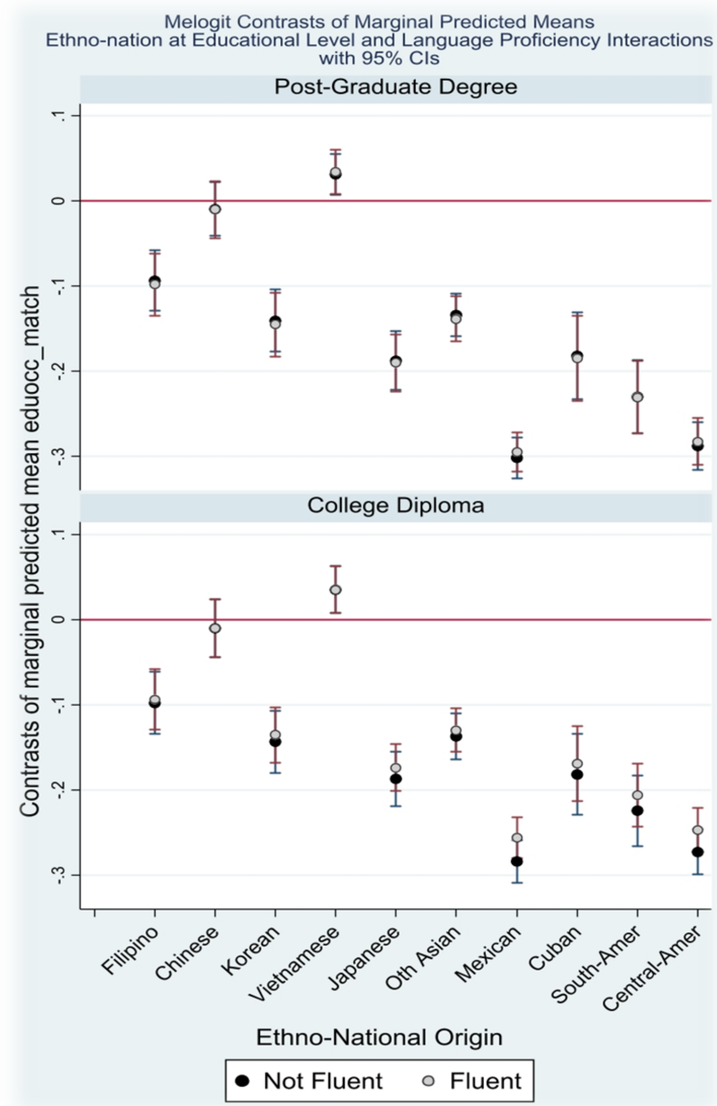
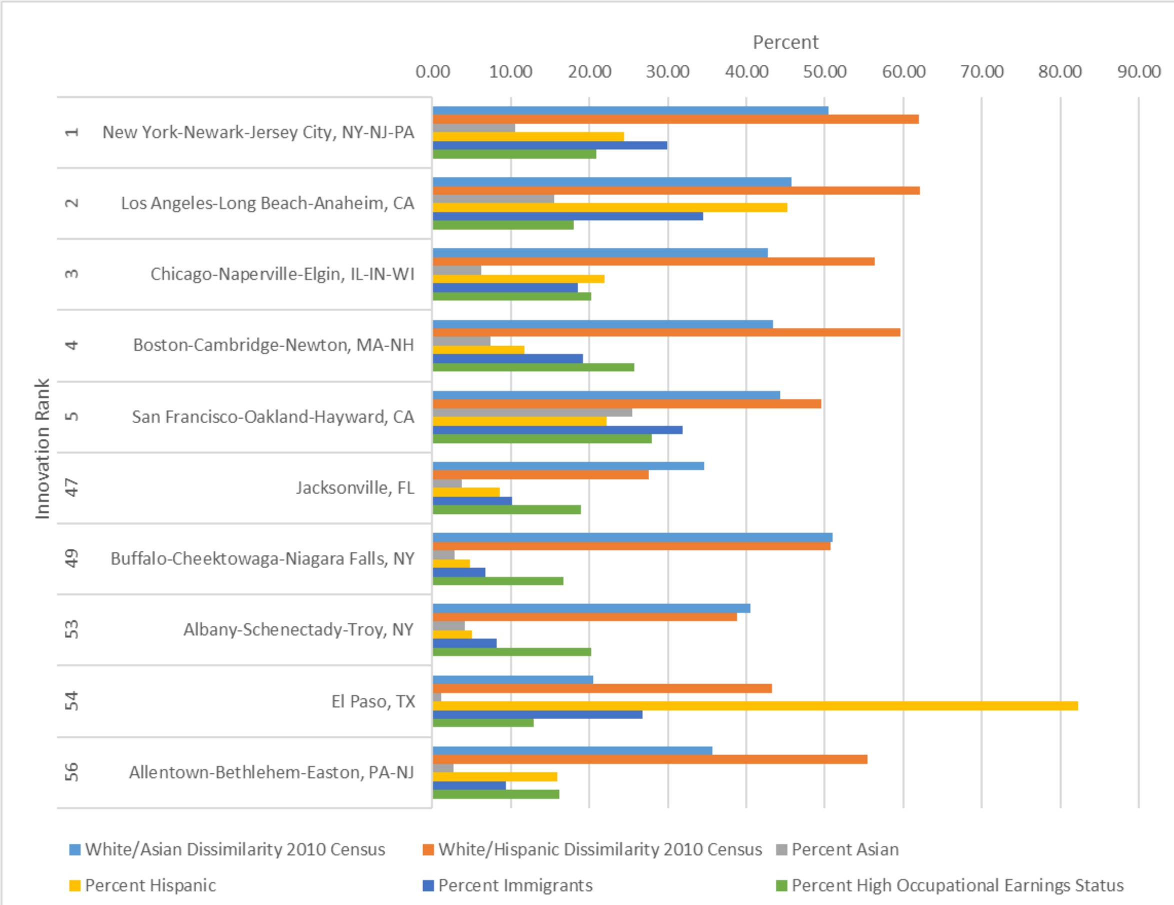


Figure 3.3. Mixed Effect Logit contrasts of matching



A 3.1. Spatial characteristics of top 5 and bottom 5 MSAs ranked by innovation



Sources: Ethnic proportions from the 2014 and 2019 5-year ACS; Dissimilarity Index from the Diversity and Disparities project at Brown University using 2010 Census; and Innovation ranking from the Innovation Cities™ Index, 2017.